Market Contraction and Innovation Divergence: The Impact of the US–China Trade War on Chinese Innovation*

Xiao Ma   Yueyuan Ma   Hanyi Tao   Yiran Zhang

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Abstract

This paper studies the impact of the US import tariff on the intensity and direction of innovation in China during the trade-war. Empirically, we break down patent abstracts into technical terms through textual analysis, enabling a comparison of innovation directions between Chinese and US firms based on the similarity of these terms. We find that greater exposure to US import tariffs lowers similarity—especially with recent US patents—and reduces Chinese patent filings. To interpret these patterns, we build a heterogeneous firm model where firms endogenously allocate innovation effort across product features and make export decisions. Tariff shocks alter innovation by shifting export demand. Quantitatively, this demand channel explains 21% of the decline in China–US innovation similarity. Moreover, changes in innovation intensity and direction reduce Chinese exports by 3.3% by 2021, with shifts in innovation direction alone contributing 14% of the decline.

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*Xiao Ma: Peking University. Email: xiaoma@phbs.pku.edu.cn, Yueyuan Ma: UC Santa Barbara. Email: yueyuanma@ucsb.edu. Hanyi Tao: ShanghaiTech University. Email: taohy@shanghaitech.edu.cn. Yiran Zhang: Fudan University. Email: yiran_zhang@fudan.edu.cn. We thank Loren Brandt, Jie Cai, Murat Celik, Rafael Dix-Carneiro, Gordon Hanson, Guangzhou Hu, Yang Jiao, Bingjing Li, Hong Ma, Ivan Png, Natalia Ramondo, Michael Song, Gonzalo Vazquez-Bare, Xiaodong Zhu, Johannes Van Biesebroeck, and seminar/conference participants at CUHK Shenzhen, Fudan, HKU, Tsinghua, CICM, CEIBS, and CESI for helpful comments. All potential errors are our own.

1 Introduction

Many economists view the rise of globalization, particularly in terms of cross-border trade, as a new "stylized" fact of economic development (Jones and Romer, 2010). However, after decades of trade liberalization especially since the Uruguay Round (Caliendo, Feenstra, Romalis and Taylor, 2015), this trend has slowed recently, largely due to escalating trade conflicts. A notable event is the US-China trade war, which began as the Trump administration imposed tariffs on imported steel and aluminum in early 2018 and subsequently imposed additional tariffs on Chinese goods and export sanctions on specific Chinese firms, particularly in high-tech and industrial sectors (Bown, 2021). The primary aim of this trade conflict was to address what the US considered unfair practices by China, such as intellectual property theft, forced technology transfer, and trade imbalances, while also considering national security concerns about China's technological advancements. In retaliation, China imposed higher tariffs on US products, particularly agricultural products.

Given that technology is a key point of contention in the conflict and innovation acts as a pivotal catalyst for technological progress, this paper aims to investigate the following two questions: What impact does the US import tariff have on the innovation intensity and trajectory of Chinese firms? How does the tariff shape the performance of Chinese firms through the innovation channel?

To address these two questions, this paper first constructs a matched dataset that contains comprehensive details on the operational activities, patent filings, and export and import volumes of all publicly listed Chinese firms for each year from 2000 to 2021.[1] We utilize the number of patent applications as an indicator of firms' innovation intensity and take firms' R&D cost in their annual report as a complementary measure. In order to assess the technological trajectory of Chinese firms' innovations, we adopt a novel text-based metric that evaluates the similarity between Chinese patents and patents from other major patenting regions worldwide, such as the US, Europe, Japan, and South Korea. Specifically, we employ the Term Frequency-Inverse Document Frequency (TF-IDF) method, a widely recognized statistical technique in the field of natural language processing, to transform patent abstracts into vectors, which correspond to the frequency distribution of informative technical terms. Subsequently, we calculate the cosine similarity between vectors of patents filed by Chinese firms and those originating from other countries. This text-based metric sheds light on the technological alignment between Chinese and foreign patents, providing valuable insights into the trajectory of Chinese innovation progress.

[1] The export and import volumes are drawn from China's Customs Trade Data and are available only for the period between 2000 and 2016.

To empirically assess the impact of US import tariffs on Chinese firms' innovation intensity and direction, we follow the prior literature (e.g., Fajgelbaum, Goldberg, Kennedy and Khandelwal, 2020) by leveraging the quasi-experimental setting of the trade war, while accounting for other aspects of this trade conflict. We measure firm-level exposure to the trade war using changes in US import tariffs, China's retaliatory tariffs, the number of products subject to US export controls, and an indicator for whether a firm was sanctioned by the US government. The analysis employs a First-Difference approach, defining trade shocks as the changes in average tariff rates, export control coverage, and sanction status between the post–trade war period (2018–2021) and the pre–trade war baseline (2014–2017). To address potential endogeneity arising from trade volume responses, tariff exposure is calculated based on firms' pre-war trade composition by product.

Our regression analysis reveals that increases in US import tariffs significantly reduce the innovation intensity of Chinese listed firms and contribute to technological divergence from US patents. Specifically, a 10-percentage-point increase in export-weighted US tariffs leads to a 10.88% decline in firms' patent filings and a 9.51% decline in R&D expenditures. It also reduces the similarity between Chinese patents and US patents filed in the preceding five years by 2.58% relative to the historical average. This divergence is especially pronounced with respect to more recent US patents, suggesting a stronger departure from the technological frontier. These findings indicate that the demand shock induced by US tariffs weakens Chinese firms' incentives to maintain competitiveness in the US market.

Allowing for heterogeneous effects of the trade war, we find that the adverse impact of US import tariffs on both patent filings and technological similarity intensifies over time, leading to a widening divergence in the innovation trajectories of the two countries. By contrast, China's retaliatory tariffs do not significantly influence Chinese firms' patent output or their technological similarity with recent or historical US patents.

We further examine the impact of rising US import tariffs on the similarity between Chinese patents and those originating from Europe, Japan, and South Korea, while controlling for changes in tariffs directly with these regions. The results show a decline in patent similarity with varying magnitudes, indicating the multi-dimensional nature of innovation. Specifically, a 10-percentage-point increase in US import tariffs leads to a 2.69% decrease in similarity to European patents filed in the past five years, a 2.46% decrease in similarity to Japanese patents, and a statistically insignificant 1.49% decrease in similarity to South Korean patents. However, after controlling for the firm's innovation similarity to the US, the effect on patent similarity with other regions disappears. This suggests that the growing divergence between Chinese innovation and that of other regions is largely driven by the widening gap between Chinese and US innovations, aligning with recent findings that highlight the importance of securing innovation approval in the US for gaining access to global markets (Gong, Li, Manova and Sun, 2023).

Which technological domains are Chinese firms diverging from, and which type of Chinese firms are most affected to higher US import tariffs? Our analysis finds that patent similarity between Chinese firms and the leading US innovators—defined as the 20 largest patentees in each IPC class—declines most sharply when tariffs rise. Moreover, Chinese firms of lower TFP witness a greater reduction in patent applications, and their innovation activities shift further away from those of the leading US innovators. The results indicate that divergence is sharpest at the US technological frontier, with less productive firms particularly vulnerable to US import tariffs.

A notable example of a shift in innovation direction is DJI, the world's largest civilian-drone maker. After US Section 301 actions raised the tariff burden on Chinese drones—from an initial 25% in 2018 to a cumulative rate of roughly 170% by 2025— DJI channeled its camera and video transmission systems emphasizing high-resolution imaging and long-distance transmission suited to professional filmmaking and expansive urban or rural environments in the US to emphasizing low-latency performance and signal stability. DJI also channeled its R&D away from hobby-grade quadcopters aimed at American consumers and toward agricultural and enterprise platforms serving precision-farming markets in Asia, Latin America, and Europe.[2] This example illustrates how a firm's innovation strategy is heavily influenced by the preferences of the markets it serves. To systematically analyze the mechanism by which tariff shocks impact firms' innovation activities, we develop a partial equilibrium model that focuses on multi-product, multi-destination firms facing heterogeneity in consumers' preferences across export markets. In the model, each of firms' products is represented by a vector of features, which correspond to the vectorized patent texts in the TF-IDF method. The productivity of each feature is contingent upon both the firm's overall innovation intensity and the innovation direction on the vector space. Firms make decisions on both the intensity and direction of innovation and their participation in the export market for each product. Unlike conventional trade models that assume symmetric preferences across destination countries, our model integrates distinct country-specific tastes for each product's feature. Consequently, changes in import tariffs directed at specific destinations not only influence the overall level of innovation intensity through shifts in the total market size but also redistribute innovation

[2]The company doubled its domestic sales of crop-spray Agras drones in the first year after the tariff hike and continued to expand the line; by the end of 2024, over 400 000 DJI agricultural drones were operating worldwide.

efforts across different product features. Specifically, our model predicts that an increase in tariffs on Chinese exports to the US would reduce innovation intensity among Chinese firms and prompt a reorientation of Chinese innovations away from US consumers' preferences.

To evaluate the effectiveness of the model in explaining the impact of the tariff shock and to assess the role of innovation decisions in shaping firms' performance in response to the trade shock, we conduct a quantitative analysis based on the model. We calibrate the model to the data moments before the trade war, with heterogeneity in consumers' preferences inferred from the initial TF-IDF vectors of firms' patent applications and firms' product sales across three destination markets (China, the US, and the Rest of World). We then perform simulation exercises to understand firms' decision-making with and without the unexpected changes in tariffs during the trade-war period. The model predicts a 0.56% decline in Chinese patents' similarity to US innovations, following a 10% increase in US import tariffs, compared to a 2.68% decline observed empirically. Thus, the demand channel as specified in the model explains 21% of the observed divergence in innovation direction between China and the US.

Further counterfactual analysis highlights the significant role of firms' innovation decisions in determining their export performance in response to tariff shocks. By 2021, changes in innovation intensity and direction result in a 3.5% decline in Chinese firms' export sales to the US, with 14% of this decline—equivalent to a 0.5% reduction—driven by shifts in R&D direction. Moreover, the adverse effect of innovation on export performance intensifies over time, indicating that the innovation channel both prolongs and amplifies the trade war's negative impact.

Related Literature. Our paper is related to several strands of the literature. First, this paper closely connects with the growing literature on understanding the effects of the trade war (e.g., Amiti, Redding and Weinstein, 2019; Fajgelbaum et al., 2020; Fajgelbaum, Goldberg, Kennedy, Khandelwal and Taglioni, 2023; Bonadio, Huo, Kang, Levchenko, Pandalai-Nayar, Toma and Topalova, 2024; Chor and Li, 2024), especially from the perspective of Chinese firms (e.g., Benguria, Choi, Swenson and Xu, 2022; Jiao, Liu, Tian and Wang, 2022; Ju, Ma, Wang and Zhu, 2024; Benguria and Saffie, 2025). Most of these existing studies focus on its impact on global trade patterns and welfare, taking a short-run perspective by presuming firms' productivity as given, largely due to the data limitations.[3] The longer-term effects of the trade war are still not fully understood, especially from reductions in investments and capacities (see Fajgelbaum and Khandelwal, 2022,

[3]One exception is Benguria et al. (2022), who show that higher trade policy uncertainty induced by the trade war affects firm investments.

for a review). Our paper contributes to this literature by examining the dynamic impact of the trade war on firm production capacity through innovation. Analyzing patent data with a textual analysis approach, we show that the trade war affects both the quantity and, more novelly, the direction of innovations, and demonstrate that accounting for productivity dynamics amplifies its negative effects on firms' trade behavior.

Our paper contributes to the directed-technological-change (DTC) tradition that links market size to the orientation of innovation (Acemoglu and Linn, 2004). Empirically, trade liberalization has been shown to shape R&D and productivity for US producers (Autor, Dorn, Hanson, Pisano and Shu, 2020), Canadian firms (Lileeva and Trefler, 2010), and European companies (Bloom, Draca and Van Reenen, 2015; Aghion, Bergeaud, Lequien and Melitz, 2018), while impacting the quantity and quality of Chinese patents (Liu and Qiu, 2016; Bombardini, Li and Wang, 2017; Liu, Lu, Lu and Luong, 2021). We extend this literature by examining the reverse shock—US import tariff hikes that shrink a major export market—and by moving from coarse patent counts to a TF-IDF embedding of patent abstracts that pinpoints where in technology space firms innovate. Theoretically, this fine-grained approach extends DTC analysis from factor- or sector-biased change to the micro-level allocation of innovation within technology space.

Finally, our paper contributes to the literature on patent content measurement by integrating textual analysis into a quantitative economic model using a hedonic demand approach (Lancaster, 1966; Pellegrino, 2025). Previous studies on patents have largely focused on structural information, such as patent counts, citations, and technology classifications (Hu and Jefferson, 2009; Lerner and Seru, 2017). Correspondingly, innovation models have primarily emphasized the quantity or quality of innovation. However, a wealth of information is embedded in the unstructured data of patent texts. Recent research has begun to develop new measures by analyzing text similarity between patents and product files, as well as between earlier and later patents, to assess their scientific or commercial value and direction (Comin and Hobijn, 2010; Hoberg and Phillips, 2016; Gentzkow, Kelly and Taddy, 2019; Bloom, Hassan, Kalyani, Lerner and Tahoun, 2021; Kelly, Papanikolaou, Seru and Taddy, 2021). To our knowledge, no study has yet mapped the outcomes of textual analysis algorithms onto economic models. Our paper bridges this gap by linking word frequencies from the TF-IDF method to the preferences of the markets where firms sell their goods. This allows for a direct quantification and evaluation of how shifts in market preferences, driven by tariff shocks, influence the direction of innovation. Additionally, this paper expands the literature by incorporating patents from multiple patent offices, including those in China, Japan, Korea, and Europe, and develops a text-based metric to assess technological similarities between patents across countries beyond the US.

The rest of the paper is organized as follows. Section 2 describes the background of the US-China trade war, the data sources, and the methods to construct key variables in the empirical analysis. Section 3 introduces the empirical strategy and presents the impact of the trade war on Chinese firms' innovation intensity and direction. Section 4 lays out a quantitative model to unveil the mechanisms in the empirical analysis. Using the calibrated model, we quantify the impact of the trade war through the demand channel in Section 5. Section 6 concludes.

2 Context and Data

In this section, we begin by outlining the background of the US-China trade war. Next, we discuss the data sources and detail how the key measures used in the empirical analysis are constructed.

2.1 Products Affected in the US-China Trade War

We provide a brief summary of the main rounds of tariff escalation during the trade war in Appendix A. Table 1 presents the products most significantly affected by the tariff escalation. The products are defined by the Harmonized System (HS) codes, a standardized numerical method of classifying traded goods. We compute the difference between the average tariff from 2018 to 2021 and the 2017 tariff for each 8-digit HS code, identifying the products with the largest positive changes. This analysis is conducted for both exports to the US and exports to China. As shown in Table 1, among Chinese goods exported to the US, manufacturing products, especially electrical and power equipment, experienced the largest increase in tariffs. Among US goods exported to China, agricultural products were imposed the highest tariff increases.

In addition to tariffs, the US government—under the authority of the Export Control Reform Act of 2018 (ECRA)—implemented export controls through the Commerce Control List (CCL) and imposed sanctions on Chinese firms via the Entity List. These measures aim to restrict Chinese companies from purchasing US-origin goods and technologies, particularly those with potential military applications or those that could enhance China's surveillance capabilities.

Table 1: Products with Largest Increases in Tariff, in Percentage Points

Export to the US		Export to China	
HS Product	Tariff Change	HS Product	Tariff Change
Generators	45.0%	Meat, of swine	55.0%
Electric accumulators	45.0%	Offal, edible	55.0%
Electrical apparatus	35.6%	Aluminum	50.0%
Iron	32.5%	Nuts, edible	45.0%
Steel	32.5%	Fruit, edible	45.0%

Notes: This table shows the products (measured by the 8-digit HS code) that experienced the largest increase in tariffs due to the trade war. The left panel lists the exporting goods from China to the US and the corresponding percent increase in tariffs; and the right panel lists the exporting goods from the US to China and the corresponding percent increase in tariffs.

2.2 Data Sources

We construct a matched dataset with information on Chinese listed firms' operations, patents, and trade from 2000 to 2021. This dataset is compiled from four different sources, enabling us to conduct a comprehensive study on the effect of the trade war on Chinese listed firms.

The first dataset, the China Stock Market & Accounting Research Database (CSMAR), provides financial reports for all firms listed on Chinese stock exchanges. From this source, we collect information on firm name, industry classification, ownership type, sales, employment, capital stock, R&D expenditures, and export destinations. We follow the procedures outlined in Tan, Tian, Zhang and Zhao (2020) to clean firm-level characteristics and financial data from CSMAR.

The second source is the China Customs Trade Data (CCTD). This dataset offers detailed information about firm-level trade transactions from 2000 to 2016, including information on firms' names, trade destination countries (for exports) and origin countries (for imports), 8-digit HS product codes, and the value of their exports and imports in US dollars. We merge the CCTD data with the listed firm data using firm names (see Appendix B.1 for details), and the CCTD data will aid us in constructing the listed firms' exposure to tariff changes during the trade war period.

The third dataset comprises Chinese patent data from the China National Intellectual Property Administration (CNIPA) and US patent data from the United States Patent and Trademark Office (USPTO). The CNIPA data cover all invention patent filings from 1985 to 2023, including information on the applicant's bibliographic details, filing and grant dates, abstracts, and cited patent references. English translations of the abstracts are also provided and will be used to compute similarity with US patents. We merge the CNIPA data with the listed firm data using consolidated firm names. The USPTO dataset includes records of granted patents since 1976 and patent applications since 2000, from which we extract the same set of indicators as for the Chinese data. Additionally, for supplementary analysis, we collect patent filing records for European countries, Japan, and Korea from the PATSTAT Global 2023 Autumn Edition. The data-cleaning procedures are described in detail in the following section.

For our analysis, we utilize tariff data from Bown (2021) to construct the US tariff rates on imports from China and China's tariff rates on imports from the US during the trade war period between 2017 and 2021. The raw data is based on 10-digit Harmonized System (HS) products for the US and 8-digit HS products for China. To determine the tariff rate for each year, we calculate the tariff rate on December 31 of that year, taking into account all tariff changes throughout the year. In order to measure tariff rates prior to the trade war, we rely on reported tariff data from the World Integrated Trade Solution (WITS) between 2014 and 2016, which is based on 6-digit HS products. To ensure consistency in product classification across different data sets, we aggregate the tariff data from Bown (2021) into 6-digit HS products using trade volume as weights. Furthermore, we converted the 6-digit HS codes in 2017–2021 into the version used during 2014–2016 by employing the concordances provided by WITS.

To control for the effects of other potential non-tariff measures adopted by the US government during the trade war, we collect the information from the Entity List and Commercial Control List from the Bureau of Industry and Security (BIS) and assess firms' exposure to these restrictions. The Entity List is a trade restriction tool designed to prevent foreign entities from accessing sensitive US technologies that could threaten national security or foreign policy interests. Companies on the list face strict export controls, requiring US suppliers to obtain special licenses—often subject to a "presumption of denial"—before shipping regulated goods, software, or technology to them. For firms that are not restricted by the Entity List, they still face restrictions on importing certain products from the US, which are governed by the Commercial Control List. Each product on the list is assigned a five-character Export Control Classification Number (ECCN) that describes its nature and the reasons for control, such as anti-terrorism, nuclear non-proliferation, or regional stability. When a Chinese firm wants to import products on the list, it must file a license application with the BIS, specifying the destination, end-user, and end-use. We construct two measures to control for firms' exposure to non-tariff restrictions. On one hand, we determine whether a firm has been added to the Entity List. On the other hand, we identify the HS codes of products included in the Commercial Control List and construct a measure of each firm's exposure to US export controls. The details of exposure to non-tariff restrictions are presented in Appendix B.5.

2.3 Text-based Patent Similarity

In order to properly measure the similarities between Chinese patents and patents in foreign countries, we first define the scope of Chinese patents and US patents. In the USPTO and CNIPA, both domestic residents and foreigners can apply for patents. Simply treating the patents filed in CNIPA as the Chinese patents and patents filed in USPTO as the US patents is misleading. Thus, we define Chinese patents as those that are filed in CNIPA by Chinese domestic residents, including firms, individuals, universities, and research institutes. We apply a similar rule for patents filed in the USPTO to identify patents filed by US domestic residents.

We then clean patent abstract data following standard procedures in the literature (Bloom et al., 2021). We first remove symbols and numbers and only keep English letters in abstracts. Then, we lemmatize all nouns and verbs with Standard CoreNLP 4.5.4 (Manning, Surdeanu, Bauer, Finkel, Bethard and McClosky, 2014), which converts nouns from plural to singular and converts verbs to bare infinitives. These procedures turn each piece of patent abstract into a list of tokens, where each token is a lemmatized word.

With all patent abstracts cleaned, we adopt the TF-IDF algorithm to vectorize each piece of abstract. In Section 5, we demonstrate that the results of the TF-IDF algorithm can be interpreted using a quantitative model, offering an advantage over other textual analysis methods. This approach is also widely adopted in the literature (e.g., Acemoglu, Yang and Zhou, 2022; Kelly et al., 2021; Autor, Chin, Salomons and Seegmiller, 2024). Before vectorization, we calculate the document frequency of each word, which is the count of a word's appearance in different pieces of abstracts. We remove too-frequent words and too-infrequent words. If a word appears in too many patents, it means that this word is not informative in representing the technical features of patents. If a word only appears in a few patents, it is likely to be a typo or man-made word, which is also not informative in representing the technical features of patents. In this paper, we put Chinese and US patents together and drop words with a document frequency larger than 100,000 and lower than 20, following Bloom et al. (2021). Then, we apply the TF-IDF method to vectorize all patent abstracts. The size of the vector is the total number of unique tokens (words). Each element in the vector is the term frequency of a word, which is the count of the appearance of a word within a patent abstract divided by its document frequency. Intuitively, each vector captures the technical characteristics of a patent by emphasizing words with relatively high term frequency compared to their document frequency. Consequently, the textual similarity between two patents serves as a good proxy for their technical similarity.

Then, we construct similarity measures between Chinese and US patents. Specifically, we calculate the cosine similarity between each Chinese and US patent filed in the same technology class, defined at the 3-digit IPC level. We restrict comparisons to patents within the same technology class, as it is not meaningful to compare technical features across unrelated fields—such as biology and semiconductors. Within-class text similarity allows us to precisely capture differences in technological trajectories between Chinese and US patents. The cosine similarity between a Chinese patent p filed in year t and technology class x, and a US patent p' filed in year τ and the same class x, is defined by Equation (1):

$$\text{Sim}_{p,p',t,\tau,x} = Cos\left\{\mathbf{V}_{p,t,x}, \mathbf{V}_{p',\tau,x}\right\} = \frac{(\mathbf{V}_{p,t,x})^T \mathbf{V}_{p',\tau,x}}{\left[(\mathbf{V}_{p,t,x})^T \mathbf{V}_{p,t,x}\right]^{1/2} \left[(\mathbf{V}_{p',\tau,x})^T \mathbf{V}_{p',\tau,x}\right]^{1/2}}, \tag{1}$$

where $\mathbf{V}_{p,t,x}$ and $\mathbf{V}_{p',\tau,x}$ are corresponding vectors for two patents, and $\mathbf{V}^T$ represents the transpose of vector $\mathbf{V}$. We apply this procedure to obtain a set of similarity scores for each Chinese patent, comparing it to all US patents filed in the same technology class x between 2000 and 2021.

We derive firm-level and country-level similarity measures by aggregating patent-level similarities. Specifically, to compute the similarity between a Chinese listed firm i in year t and the US patents in year τ within technology class x, we average the pairwise cosine similarities between all patents filed by firm i in year t and class x, and all US patents filed in year τ and the same class x:

$$\text{Sim}_{i,t,\tau,x} = \frac{1}{N_{i,t,x}} \frac{1}{M_{US,\tau,x}} \sum_{p \in i} \sum_{p' \in US} Cos\{\mathbf{V}_{p,t,x}, \mathbf{V}_{p',\tau,x}\}. \tag{2}$$

In this equation, $N_{i,t,x}$ denotes the number of patents filed by firm i in technology class x in year t, while $M_{US,\tau,x}$ represents the number of US patents in class x in year τ.

The firm-level similarity of firm i to US patents is calculated as the weighted average of its patent similarities across technology classes x, with weights corresponding to the number of patents firm i holds in each class x. Similarly, the country-level similarity is computed as the weighted average of patent similarities across all technology classes for Chinese patents filed in year t, using patent counts as weights. To assess the representativeness of listed firms in our sample, we compare the average similarity to US patents over time for both listed and non-listed Chinese firms. As illustrated in Figure A-1, the similarities calculated for the two groups follow similar trends and are highly correlated, supporting the validity of using listed firms as a proxy for

China's overall innovation trajectory. Further details on how these measures are constructed can be found in Appendix B.

2.4 Exposure to Trade Shocks

To measure the extent to which Chinese listed firms were affected by tariffs during the trade war period, we utilize tariff and customs data. More specifically, for each firm i, we calculate its exposure to the US tariffs by relying on its export composition during the pre-trade-war period (2014-2016, based on available data). This calculation is performed using the following formula:

$$\text{exposure to US tariff}_{i,t} = \sum_j \frac{\text{export}_{i,j,14-16}}{\sum_j \text{export}_{i,j,14-16}} \text{tariff}^{US}_{j,t}. \tag{3}$$

Our firm-level customs data allows us to designate $export_{i,j,14-16}$ as the value of exports for firm i regarding 6-digit HS product j to the US between 2014 and 2016. $\text{tariff}^{US}_{j,t}$ indicates the tariff rate that the US imposed on the import of product j from China during year t. By this formula, we gauge the extent to which firm i is exposed to US tariffs, which portrays the average tariff rates faced by the firm when exporting to the US in year t based on its pre-trade-war export structure.

As a response to the deteriorating trade environment in the US, China implemented retaliatory measures by increasing tariffs on imports from the US. This escalation in import tariffs could potentially impact Chinese listed firms, particularly through changing the competition in firms' output market and the prices of imported inputs (Brandt, Van Biesebroeck, Wang and Zhang, 2017). Given that we consistently account for industry fixed effects in our regression analyses, any changes in competition within firms' industries are already captured. To control the impact of China's import tariffs imposed on the US on the listed firms, specifically through the prices of imported inputs, we rely on their import composition prior to the commencement of the trade war:

$$\text{exposure to China's tariff}_{i,t} = \sum_j \frac{\text{import}_{i,j,14-16}}{\sum_j \text{import}_{i,j,14-16}} \text{tariff}^{CN}_{j,t}, \tag{4}$$

where $import_{i,j,14-16}$ is the amount of imports for firm i regarding 6-digit HS product j from the US between 2014 and 2016. $\text{tariff}^{CN}_{j,t}$ indicates the tariff rate that China imposed on the import of product j from the US during year t. By this formula, we measure the average tariff rates faced by the firm when importing from the US in year t based on its pre-trade-war import structure.

3 Empirical Analysis

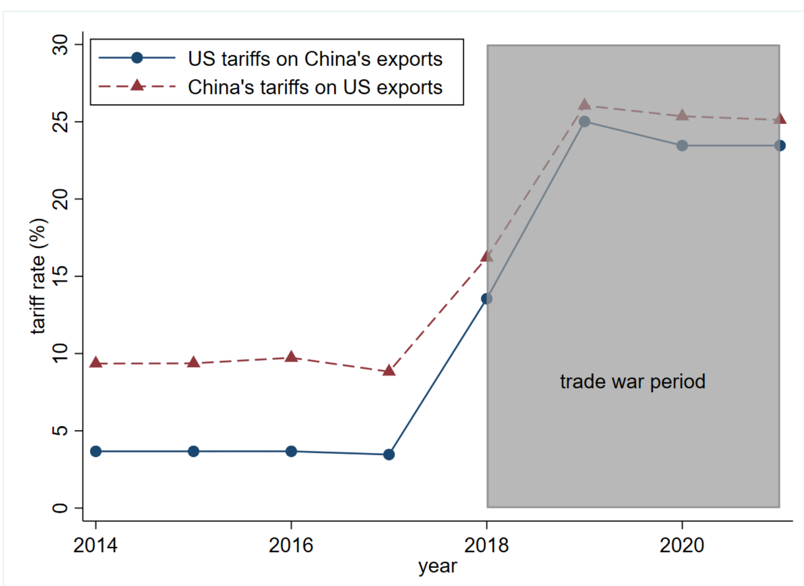
In this section, we examine the impact of US import tariff changes during the trade war on Chinese firms' innovation. We begin by presenting evidence on the tariff adjustments and the corresponding changes in aggregate patent similarity between Chinese and US patents. Then, we conduct a formal empirical analysis to assess these effects more rigorously.

3.1 First Glance at Data

Figure 1 presents the overall trends in tariff rates during the trade war period, consistent with the findings of previous studies (e.g., Chor and Li, 2024). Specifically, the US imposed a tariff increase of approximately 20 percentage points (averaged across 6-digit HS products) on China's exports, while China raised tariffs on US exports by around 15 percentage points.

Figure 2 illustrates the distribution of Chinese listed firms' exposure to tariffs imposed by the US and China, calculated using Equations (3) and Equation (4). The data reveals a significant rise and substantial diversity in changes experienced during the trade war. This variability allows for variation in firms' exposure to the trade war, a factor that will be explored in our empirical analysis.

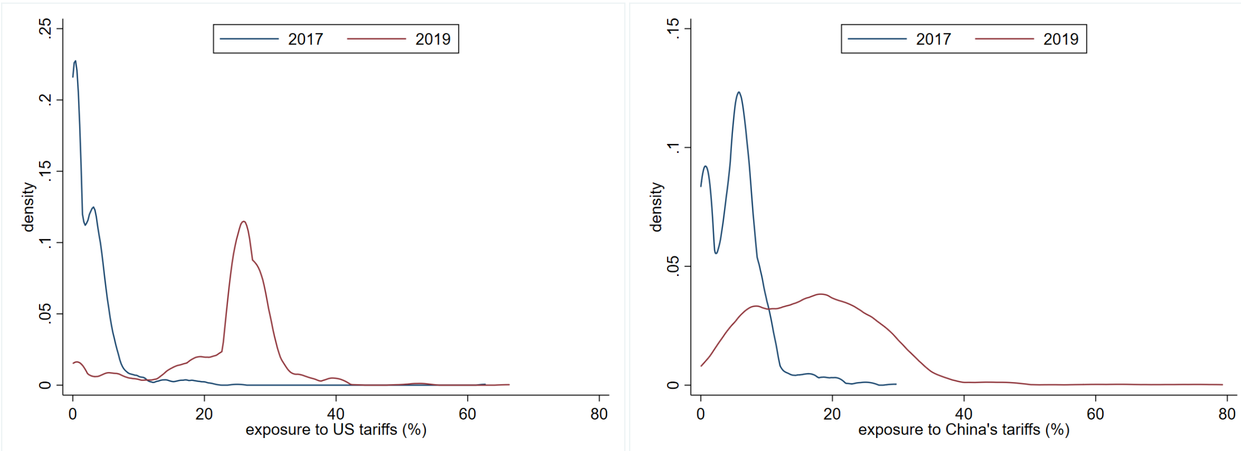
Figure 1: Average Tariff Rates across 6-digit HS Products



Notes: The figure displays the average US tariffs on China's export (solid blue curve) and the average China's tariff on US export (dashed red curve) from 2014 to 2021. Post-2016 data points are based upon the trading composition between 2014-2016 and the actual tariff rates across the 6-digit HS products. The shaded area is the trade-war period.

Figure 2: Distribution of Listed Firms' Exposure to US Tariffs

(a) Exposure to US Tariffs (b) Exposure to China's Tariffs



Notes: The figure shows the distribution of Chinese listed firms' exposure to tariffs on exports to the US (Panel (a)) and tariffs on imports from the US (Panel (b)). The years 2017 and 2019 represent the periods immediately before and after the onset of the trade war, respectively.

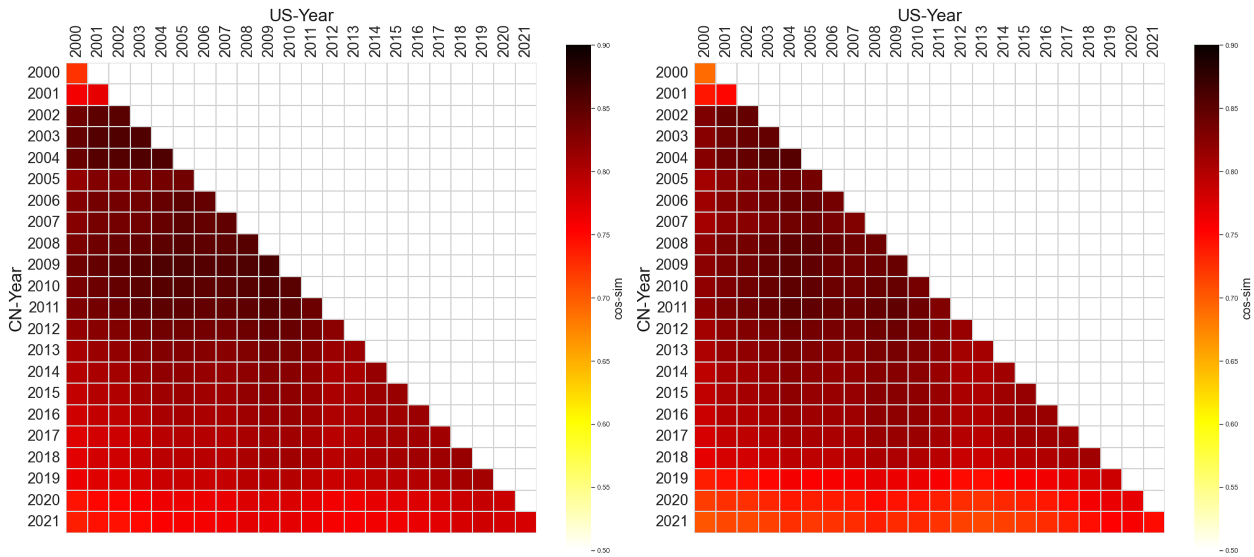
Figure 3 shows the aggregate similarity between Chinese and US patents in the "ICT" and "Electrical Computers and Digital Processing Systems" technology fields. Patents in each field are first identified separately from the Chinese and US patent offices, and pairwise similarities are then computed.[4] Each pixel of Figure 3 represents the similarity between Chinese patents filed in year t and US patents filed in year τ. Under the assumption that the US leads in technological advancement, for ease of description, we restrict the visualization to Chinese patents filed in year t and US patents filed in year $\tau \leq t$. In the heatmap, Chinese patents are sorted by filing year along the rows and US patents along the columns. The pixel in the southwest corner indicates the similarity between Chinese patents filed in 2021 and US patents filed in 2000, while the southeast corner reflects the similarity with US patents filed in 2021. The diagonal elements represent the similarity between patents filed in the same year. Both panels in Figure 3 reveal a marked decline in the similarity between Chinese and US patents after the onset of the trade war, reversing the earlier upward trend. This pattern suggests a potential shift in firms' innovation trajectories—an effect we examine more formally in the sections that follow.

[4] The "ICT" field includes four subfields: telecommunications, consumer electronics, computers, office machinery, and other ICTs. The definition of "Electrical Computers and Digital Processing Systems" field is available at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports.htm.

Figure 3: Similarity between Chinese and US Patents in Two Technology Fields

(a) ICT

(b) Electrical Computers-Digital Processing Systems



Notes: The figure visually presents the aggregate similarity between Chinese patents filed in a given year along the x-axis and corresponding US patents filed in the year along the y-axis. The degree of similarity is indicated by the darkness of each square, with darker shades denoting higher levels of similarity.

3.2 Identification Strategy

As shown in the previous section, the trade war led to a substantial increase in tariffs on Chinese exports to the United States. During the same period, the previously rising trend in industry-level similarities between Chinese and US patents came to a halt. To identify the effect of US import tariffs on Chinese innovation activity, we adopt the approach proposed by Bertrand, Duflo and Mullainathan (2004), which addresses the issue of serial correlation—particularly relevant here, as post-2016 tariffs are constructed based on data from 2014 to 2016. We collapse the data into a "pre" period (2014–2017) and a "post" period (2018–2021) of the trade war. Then, we estimate the following model using first differences of the average variable values in the two periods,

$$\begin{aligned}\Delta Y_{is} =& \beta_1 \Delta ln(1+\text{Tariff}_i^{US}) + \beta_2 \Delta ln(1+\text{Tariff}_i^{CN}) + \beta_3 \Delta \text{Export\_Control}_i^{US} + \\ & \beta_4 \Delta \text{Sanction}_i + \gamma X_{i,14-17} + \mu + \theta_s + \epsilon_{is}.\end{aligned} \tag{5}$$

In Equation (5), i indexes firms and s denotes the firm's 3-digit industry code. The dependent variable, ΔY_{is}, captures changes in both the quantity and direction of innovation at the firm level. Innovation intensity is proxied by the natural logarithm of one plus the number of patent applications filed by the firm. As a complementary measure, we also use the natural logarithm of one plus the firm's R&D expenditure in their annual report. Innovation direction is proxied by the firm-level similarity measure developed in this paper. Specifically, we use the demeaned average similarity to US patents granted within the most recent 0–5 years (i.e., $\frac{1}{5}\sum_{\tau=t}^{t+5}\text{Sim}_{i,t,\tau}$), assigning missing values to firms with no patent applications in the baseline regression.

The key independent variables related to the trade war include: the firm-specific change in exposure to US import tariffs, $\Delta\ln(1+\text{Tariff}_i^{US})$; the change in exposure to China's retaliatory import tariffs, $\Delta\ln(1+\text{Tariff}_i^{CN})$; the change in the number of HS codes in the firm's import basket that appear on the Commerce Control List, $\Delta\text{Export\_Control}_i$; and the change in a dummy variable indicating whether the firm was sanctioned via the Entity List, $\Delta\text{Sanction}_i$.

We control for pre-trade-war firm characteristics in $X_{i,14\text{–}17}$, which includes the natural logarithm of employment and total assets, as well as profit share (profit as a percentage of total revenue) measured in the pre-period (2014–2017). In the regressions focused on innovation direction, we also control for the change in the number of patent applications to ensure that any observed effect of the trade war on patent similarity is not driven by changes in patenting intensity. The constant term, μ, captures aggregate changes in the economy between the two periods, while the industry fixed effect, θ_s, accounts for time-varying differences across industries.

The sample used for the regression analysis consists of all publicly listed firms in China that applied for at least one patent between 2000 and 2021 and were active in both the pre- and post-trade-war periods. The requirement of having filed at least one patent ensures that the sample reflects innovating firms. Approximately 75% of Chinese listed firms meet this criterion. Summary statistics for the key variables are reported in Table 2, with exporting and non-exporting firms presented separately to highlight their distinct patterns. A firm is classified as an exporter if it reported a positive export value during the 2014–2017 period. On average, exporters saw a smaller rise in patent applications and generated patents that were less similar to those from other advanced economies compared to non-exporters following the trade war. After the trade war, non-exporters either showed an increase or only a modest decline in patent similarity to foreign technologies. During this period, import tariffs rose significantly in both China and the United States. However, the average number of HS codes subject to export controls in each firm's product portfolio increased only slightly. Additionally, approximately 2.4% of observations were subject to sanctions during the 2018–2021 period, compared to none in the pre-trade-war period.

Table 2: Summary Statistics

	2014–2017			2018–2021		
	mean	sd	count	mean	sd	count
Exporting Firms						
Patent Application Number	23.313	161.551	1328	31.722	256.551	1328
R&D Cost (Yuan)	1.64e+08	6.36e+08	1328	3.25e+08	1.31e+09	1328
Similarity to US Patents (0-5 Years)	.930	.463	1209	.917	.435	1209
Similarity to EU Patents (0-5 Years)	.980	.512	1209	.927	.438	1209
Similarity to JP Patents (0-5 Years)	.986	.500	1209	.930	.435	1209
Similarity to KR Patents (0-5 Years)	.947	.499	1209	.927	.419	1209
Non-exporting Firms						
Patent Application Number	13.717	152.781	1341	23.578	185.169	1341
R&D Cost (Yuan)	1.28e+08	5.59e+08	1341	2.64e+08	1.17e+09	1341
Similarity to US Patents (0-5 Years)	.934	.511	877	.942	.459	877
Similarity to EU Patents (0-5 Years)	.958	.539	877	.935	.434	877
Similarity to JP Patents (0-5 Years)	.960	.520	877	.935	.434	877
Similarity to KR Patents (0-5 Years)	.972	.537	877	.999	.441	877
Trade Shock						
Change in US Import Tariff	.831	2.042	2669	6.857	10.885	2669
Change in CN Import Tariff	1.714	3.304	2669	4.947	8.798	2669
US Export Controls	1.429	4.800	2669	1.439	4.812	2669
Sanctioned	0	0	2669	.024	.154	2669

Notes: This table reports the summary statistics of the main dependent and independent variables in the "pre" and "post" periods of the regression sample.

3.3 Impact of the US Import Tariff on China's Innovation

The effects of US import tariffs on Chinese firms' innovation intensity (Columns (1)–(4)) and innovation direction (Columns (5)–(8)) are reported in Table 3. Columns (1) and (5) include only trade-related shocks. Columns (2) and (6) add industry fixed effects, while Columns (3) and (7) further control for firm-level characteristics measured prior to the trade war. Column (4) replaces the patent count with firms' R&D expenditure as the dependent variable, and Column (8) includes the change in the number of patent applications as a control. The first four columns show that a 10-percentage-point increase in US import tariffs is associated with an approximately 10.88 percent reduction in the number of patent applications filed by Chinese firms. A similar effect is observed when using R&D expenditures as the dependent variable, with a decline of 9.51 percent. The last four columns indicate that a 10-percentage-point increase in US tariffs on Chinese exports reduces the similarity of Chinese patents to US patents by 2.58 percent of their historical average. The estimated coefficients remain stable across different model specifications.

Additional analyses are provided in the Appendix. Appendix Table A-1 reports results for (i) a subsample of exporting firms and (ii) the full sample with an interaction term between the US tariff

Table 3: Impact of the Trade War on Chinese Firms' Innovation Intensity and Direction

	Intensity				Direction			
	Δ Patent Number			Δ R&D Cost	Δ Similarity to US Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ US Import Tariff	-0.900***	-0.969***	-1.088***	-0.951*	-0.222**	-0.266**	-0.252**	-0.258**
	(0.203)	(0.187)	(0.189)	(0.534)	(0.0995)	(0.125)	(0.108)	(0.111)
Δ CN Import Tariff	-0.412	-0.228	-0.339	0.713	0.164	0.124	0.0830	0.0807
	(0.296)	(0.321)	(0.320)	(0.872)	(0.174)	(0.182)	(0.178)	(0.177)
Δ US Export Controls	-0.423**	-0.446**	-0.411*	-0.836*	-0.154	-0.0898	-0.0977	-0.100
	(0.192)	(0.210)	(0.213)	(0.499)	(0.101)	(0.128)	(0.121)	(0.121)
Δ US Sanctions	0.259**	0.202*	0.166	-0.298	-0.0670	-0.0317	-0.0365	-0.0359
	(0.117)	(0.106)	(0.100)	(0.276)	(0.0947)	(0.0998)	(0.101)	(0.102)
Δ Patent Number	/	/	/	/	N	N	N	Y
Firm Characteristics	N	N	Y	Y	N	N	Y	Y
Industry Fixed Effect	N	Y	Y	Y	N	Y	Y	Y
Observations	2,669	2,661	2,542	2,542	2,086	2,077	1,984	1,984
R-squared	0.014	0.068	0.090	0.158	0.002	0.027	0.029	0.029

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). Firm-level controls include the natural logarithm of employment, total assets, and the profit-to-revenue ratio before the trade war. Industries are defined at the 3-digit level.
*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

change and firms' pre-trade-war export share. Appendix Table A-2 presents results that account for the share of processing trade in firms' exposure to China's retaliatory import tariffs. Appendix Table A-3 shows results restricted to manufacturing firms. Appendix Table A-4 displays the trade-war effect on innovation direction, based on similarity between Chinese and US patents within the same 4-digit IPC class for finer granularity. Across all specifications, we consistently find negative impacts of US import tariffs on Chinese firms' innovation intensity and similarity with US patents.

Table 3 also shows that changes in Chinese import tariffs have no statistically significant impact on firms' patenting intensity or the direction of innovation. In contrast, US export controls are associated with a reduction in Chinese innovation intensity, while sanctions are occasionally positively correlated with innovation activity—possibly due to selection effects.

The significant impact of US import tariffs on China's innovation activity likely reflects the role of shifting demand. Reduced demand from the US market may lower Chinese firms' incentives to imitate US patents, as the returns to gaining a cost or quality advantage over US products decline. This effect is expected to be strongest for patents closely resembling recent US innovations, where competitive pressure is greatest at the technological frontier. To evaluate this hypothesis, we compute the similarity between Chinese patents filed in year t and US patents from three distinct filing windows: (i) the current and previous years (t and $t-1$); (ii) two to three years earlier ($t-2$ and $t-3$); and (iii) four to five years earlier ($t-4$ and $t-5$). For each window, firm-level similarities are demeaned to purge year fixed effects. The similarity to the most recent US patents therefore captures a firm's alignment with the cutting edge of technologies competing for US demand, whereas the similarity to older US patents should be less affected by demand-driven competitive pressures.

The impact of the trade war on the similarity of Chinese patents to US patents of different vintages is reported in Table 4. Divergence is most pronounced for new US technologies. A 10-percentage-point rise in US import tariffs lowers the similarity to US patents filed in the current or previous year by 2.69%, and to those filed two or three years earlier by 2.88%. By contrast, the decline in the similarity to older US patents is 2.11%. This pattern is robust across alternative regression specifications and indicates that the demand shock primarily weakens Chinese firms' alignment with recent US innovations.

Table 4: Impact of the Trade War on Chinese Patents' Similarity to US Patents by Filing Period

	Δ Similarity to US Patents											
	Recent 0-1 Years				Recent 2-3 Years				Recent 4-5 Years			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ US Import Tariff	-0.219**	-0.271**	-0.267**	-0.269**	-0.265**	-0.298**	-0.275**	-0.288**	-0.171*	-0.214*	-0.207**	-0.211**
	(0.106)	(0.129)	(0.112)	(0.116)	(0.108)	(0.132)	(0.116)	(0.119)	(0.0947)	(0.116)	(0.0989)	(0.102)
Δ CN Import Tariff	0.164	0.128	0.0694	0.0685	0.187	0.137	0.0915	0.0869	0.126	0.102	0.0820	0.0803
	(0.159)	(0.166)	(0.157)	(0.157)	(0.194)	(0.201)	(0.195)	(0.195)	(0.183)	(0.194)	(0.202)	(0.202)
Δ US Export Controls	-0.140	-0.0821	-0.0925	-0.0936	-0.119	-0.0528	-0.0562	-0.0620	-0.172*	-0.104	-0.111	-0.113
	(0.103)	(0.126)	(0.118)	(0.118)	(0.110)	(0.140)	(0.131)	(0.133)	(0.101)	(0.129)	(0.124)	(0.124)
Δ Sanctions	-0.0714	-0.0313	-0.0414	-0.0412	-0.0680	-0.0301	-0.0357	-0.0346	-0.0629	-0.0336	-0.0300	-0.0295
	(0.104)	(0.110)	(0.112)	(0.112)	(0.0963)	(0.101)	(0.102)	(0.103)	(0.0834)	(0.0880)	(0.0891)	(0.0897)
Δ Patent Number	N	N	N	Y	N	N	N	Y	N	N	N	Y
Firm Characteristics	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Industry Fixed Effect	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Observations	2,086	2,077	1,984	1,984	2,086	2,077	1,984	1,984	2,086	2,077	1,984	1,984
R-squared	0.002	0.028	0.029	0.029	0.003	0.030	0.031	0.032	0.002	0.025	0.029	0.029

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). Firm-level controls include the natural logarithm of employment, total assets, and the profit-to-revenue ratio before the trade war. Industries are defined at the 3-digit level.
*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

3.4 The Gradual Impact of the US Import Tariff

The effects of the tariff shocks may not materialize immediately, as firms typically require time to adjust their innovation activities. To examine the dynamics and persistence of these effects, separate treatment indicators are constructed for increases in US import tariffs and in Chinese import tariffs, with the associated coefficients allowed to vary over time. Each "Treated" dummy equals one for a firm whose applicable tariff rate rose after 2018 and zero otherwise. The analysis employs the following regression specification:

$$Y_{ist} = \sum_{\tau=2014}^{2021} \beta_{1\tau} \mathbb{1}(t = \tau)\text{Treated}_i^{US} + \sum_{\tau=2014}^{2021} \beta_{2\tau} \mathbb{1}(t = \tau)\text{Treated}_i^{CN} + \\ \beta_3 \text{Export\_Controls}_{ist} + \beta_4 \text{Sanction}_{ist} + \gamma X_{ist-1} + \alpha_i + \mu_t + \theta_{st} + \epsilon_{ist}, \tag{6}$$

where $\mathbb{1}(t = \tau)$ is an indicator function that equals one if year t is equal to τ, and zero otherwise.[5] Figure 4 below plots the coefficients $\beta_{1\tau}$ along with their 90 percent confidence intervals, illustrating the time-varying effects of US import tariffs. The dependent variables are, respectively, the logarithm of one plus the firm's patent application counts and the similarity to US patents filed in the past 5 years. The Poisson regression of patent application counts and the regression using the logarithm of firms' R&D spending yield similar results, as reported in Figure A-4. We control for firm-level characteristics in X_{it-1}, which includes the natural logarithm of the firm's employment and total assets, and the share of profits as a percentage of total revenue in year $t - 1$. In the regression on innovation direction, we add the logarithm of the number of patent applications as a control variable. The term α_i accounts for firm fixed effects, capturing unobserved firm-level heterogeneity. The term μ_t represents year fixed effects, reflecting time variation in the aggregate economy. The term θ_{st} denotes the industry-by-year fixed effects, capturing variations in industry-level characteristics over time. Therefore, the aggregate effect over years correspond to Columns (3) and (8) in Table 3 multiplied by the total increase in tariff rates.

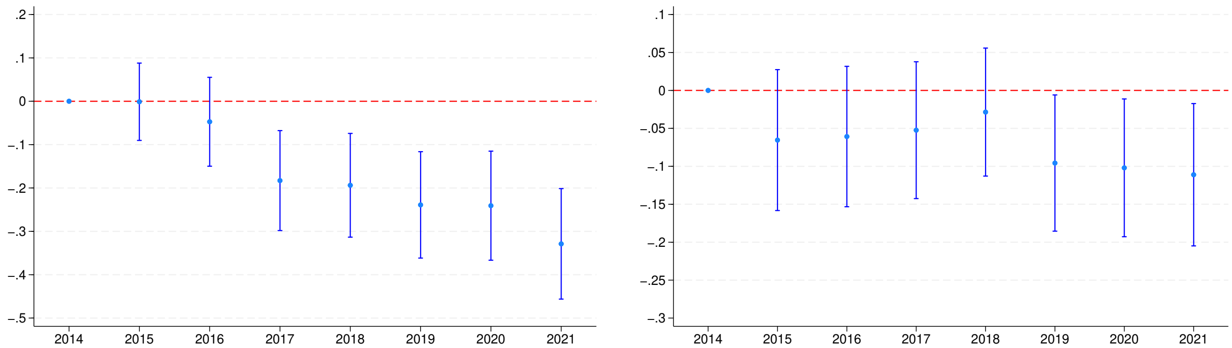
Figure 4 illustrates the gradual and persistent effects of US import tariff increases on both the intensity and direction of innovation in China. Panel (a) shows that the negative impact on Chinese firms' patenting activity has intensified over time. Panel (b) highlights a progressive decline in the alignment between Chinese innovation and US technological trajectories. The decline in patent applications began as early as 2017, suggesting that firms may have anticipated the tariff shock and strategically scaled back patent filings in advance.[6] Firms' R&D spending started to decline in 2018, as shown in Figure A-4. A noticeable drop in patent similarity emerged in 2019 and persisted thereafter, pointing to a sustained divergence in innovation trajectories between China and the United States.

[5] Among firms that experienced an increase in U.S. import tariffs, 97.2% of the increase occurred in 2018; the corresponding share for China's import tariffs is 98.5%. Therefore, the regression by calendar year yields results very similar to those from an event study.

[6] In August of 2017, the US Trade Representative launched a high-profile Section 301 investigation into Chinese intellectual property and technology practices—a clear signal of imminent policy escalation. Earlier in mid-2017, a proposed 100-day trade-deficit reduction plan between the US and China collapsed, further undermining expectations of a cooperative path forward. This backdrop of rising rhetoric, official scrutiny, and media coverage of a looming trade confrontation may have dampened firms' willingness to filing patents ahead of formal tariffs.

Figure 4: Effect of US Import Tariff over Years

(a) Effect on Patent Application Number **(b)** Similarity to US in Recent 5 Years



Notes: The figure illustrates the time-varying effects of US import tariffs on Chinese firms' innovation intensity and their similarity to US patents from 2014 onward. Both point estimates and 90 percent confidence intervals are shown, with standard errors clustered at the firm level. Firm-level controls include the natural logarithm of employment, total assets, and the profit-to-revenue ratio from the previous year. For the regressions on patent similarity, the number of patent applications is also controlled for. All regressions include firm fixed effects, year fixed effects, and industry-by-year fixed effects.

3.5 Robustness Checks

Two major concerns arise regarding the regression results presented in the previous sections. First, firms with higher growth potential in innovation intensity and greater similarity to US innovations may be more exposed to the US import tariff shock. In other words, there may be heterogeneous pre-existing trends that could lead to endogeneity. Second, the decrease in the similarity between Chinese and US patents might not indicate a divergence in innovation direction; instead, it could reflect strategic changes in the wording of patent abstracts to avoid tariff increases.

To address the first concern, we conduct placebo tests using data from 2012 to 2017, with 2012–2014 defined as the "pre" period and 2015–2017 as the "post" period. In this placebo setting, we apply the actual trade-related shocks—measured as the difference between the average values in 2018–2021 and 2014–2017—as counterfactual trade shocks. We then re-estimate regression Equation (5) using this placebo sample. The results, reported in Appendix Table A-5, show that the estimated effects of the counterfactual US import shocks on firms' innovation intensity and direction are statistically insignificant. This finding suggests that the baseline results are not driven by pre-existing trends and supports the identification strategy.

The second concern regarding the potential strategic wording of patent abstracts can be evaluated by focusing exclusively on patents without Patent Cooperation Treaty (PCT) applications. A PCT application allows an applicant to seek patent protection in multiple PCT member countries through a single international filing. Both China and the US are members of the PCT. Applicants who file under the PCT have the option of requesting an International Preliminary Examination, which provides an early indication of the patentability of the invention in certain member countries before their patent offices conduct their own examinations. This preliminary examination can help guide strategic decisions about where to pursue patent protection. Given the cost efficiency and additional guidance provided by the PCT application process, it is often the preferred option for applicants seeking protection outside their home country. Consequently, patents with PCT applications are more likely to be intended for international publication and are more inclined to strategically adjust their wording to align with the requirements of patent offices in other countries. By recalculating patent similarity using only a firm's patents that exclude PCT applications and re-estimating the regression in Equation (4), we can assess the impact of the trade war on patent similarity in a way that is less affected by strategic wording behavior than in the baseline setting. Appendix Table A-6 shows that the results remain highly consistent with the baseline, which helps mitigate the concern that our findings are merely driven by disclosure strategies.

3.6 China's Innovation Similarity to Other Countries

Has the similarity in innovation between China and other countries shifted following the rise in US import tariffs on Chinese goods? Furthermore, how does the similarity between Chinese patents and those of other countries relate to the level of similarity between China and the US? To address these questions, we examine the impact of the US-China trade war on the similarity between Chinese patents and those from other leading innovation economies. Besides the US and China, Europe, Japan, and South Korea are regions with substantial patenting activities. We assess the impact of the trade war on China's patent similarity with these regions with the following regression:

$$\begin{aligned}\Delta Y^{*}_{is} =& \beta_1 \Delta ln(1+\text{Tariff}^{US}_{i}) + \beta_2 \Delta ln(1+\text{Tariff}^{CN}_{i}) + \beta_3 \Delta \text{Export\_Control}^{US}_{i} + \beta_4 \Delta \text{Sanction}_i + \\ & \beta_5 \Delta ln(1+\text{Tariff}^{*}_{i}) + \beta_6 \Delta ln(1+\text{Tariff}^{CN,*}_{i}) + \gamma X_{i,14-17} + \mu + \theta_s + \epsilon_{is}.\end{aligned} \tag{7}$$

where $* \in \{EU, JP, KR\}$. The dependent variable (ΔY^{*}_{is}) represents the change in the similarity of Chinese firms' patents to those in Europe, Japan, and South Korea filed in different periods (namely, the past 0-5 years, 0-1 years, 2-3 years, and 4-5 years). In addition to the control variables specified in the baseline regression (Equation (5)), this analysis includes changes in import tariffs on Chinese goods imposed by the respective regions, $\Delta ln(1 + \text{Tariff}_i^*)$, and China's import tariffs on goods from the respective regions, $\Delta ln(1 + \text{Tariff}_i^{CN,*})$. The effect of increasing US import tariffs on Chinese firms is captured by the value of β_1. To further investigate whether the effect is driven by patent similarity between China and the US, we compare the estimates of β_1 from regressions that exclude and include changes in the similarity between Chinese firms' patents and US patents filed during the trade war period.

Table 5: Impact of the Export Tariff on Chinese Patents' Similarity to other Regions

VARIABLES	Δ Similarity to Patents in other Regions							
	0-5 Years	0-1 Years	2-3 Years	4-5 Years	0-5 Years	0-1 Years	2-3 Years	4-5 Years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Europe								
Δ US Import Tariff	-0.269*	-0.202	-0.293*	-0.295**	-0.0424	0.0237	-0.0630	-0.0699
	(0.145)	(0.152)	(0.149)	(0.142)	(0.0955)	(0.117)	(0.100)	(0.0858)
Δ Similarity to US					0.835***	0.832***	0.851***	0.831***
					(0.0311)	(0.0313)	(0.0322)	(0.0308)
Japan								
Δ US Import Tariff	-0.246**	-0.242**	-0.285**	-0.215*	-0.0426	-0.0391	-0.0792	-0.0142
	(0.110)	(0.114)	(0.109)	(0.114)	(0.0790)	(0.0841)	(0.0741)	(0.0874)
Δ Similarity to US					0.769***	0.768***	0.779***	0.759***
					(0.0319)	(0.0335)	(0.0314)	(0.0325)
South Korea								
Δ US Import Tariff	-0.149	-0.154	-0.182	-0.124	0.0160	0.0132	-0.0174	0.0389
	(0.0991)	(0.120)	(0.113)	(0.0819)	(0.0786)	(0.102)	(0.0872)	(0.0712)
Δ Similarity to US					0.749***	0.758***	0.747***	0.740***
					(0.0361)	(0.0329)	(0.0376)	(0.0410)
Δ Patent Number	Y	Y	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). Firm-level controls include the natural logarithm of the firm's employment, total assets, and the share of profits as a proportion of total revenue in the previous year. We also control for changes in the number of patent applications. Columns (1)–(4) do not control for the overall similarity between a firm's patents and US patents filed during the corresponding periods, whereas Columns (5)–(8) include this control. Industries are defined at the 3-digit level, and industry fixed effects are included in all specifications.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

Table 5 presents the results on patent similarity with the three other economies. Columns (1)–(4) do not control for the overall similarity between a firm's patents and US patents filed during the corresponding periods, whereas Columns (5)–(8) include this control. The results indicate that the similarity of Chinese patents to those from other regions decreases to varying extents. A 10-percentage-point increase in the US import tariff leads to a 2.69 percent decrease from the historical average in the similarity of Chinese patents to European patents filed over the past five years, as shown in Column (1). This effect is similar in magnitude to the decline observed in the similarity with US patents, which decreases by 2.58 percent. The negative impact on the similarity to Japanese patents is slightly smaller at 2.46 percent, while the effect on South Korean patents is even smaller and statistically insignificant. Columns (5)–(8) reveal that the impact of the export shock almost vanishes after controlling for the similarity to US patents, suggesting that the divergence in China's innovation activities from the US is the primary reason for the divergence from other regions. In other words, once the distance between Chinese and US patents is accounted for, Chinese patents do not exhibit further divergence from those of other regions. Moreover, the impact of US import tariffs on patent similarity with other regions is positively associated with the extent to which that similarity is explained by the degree of similarity to US patents.

The different changes in patent similarity across regions underscore the complex and multifaceted nature of innovation. While patent counts offer a basic measure of innovation output, a more nuanced understanding emerges from textual analysis of patent content, which reveals deeper insights into the specific directions of technological development.

3.7 Heterogeneity in Trade Shock Impact

Do Chinese firms' innovations diverge further from those of the most innovative US firms? Which types of Chinese firms are more sensitive to the increase in US import tariffs? In this subsection, we evaluate heterogeneity in the responses of firms' innovation to the trade war.

To answer the first question, we calculate the patent similarity between Chinese firms and the most innovative US firms in each IPC, which is defined as the top 20 firms with the highest number of patent applications in that IPC. The results are reported in Columns (1)–(4) of Table 6. Relative to the baseline coefficient estimates in Tables 3 and 4, the impact of US import tariff changes on patent similarity is now more pronounced, indicating that Chinese firms' innovation activities are diverging further from the technological frontier in the United States.

To answer the second question, we classify Chinese firms into two groups based on their average TFP from 2014 to 2017, the period before the trade war. High-TFP firms are defined as those with above-median TFP within their industry. Columns (5)–(10) of Table 6 illustrate the trade war's impact on innovation intensity and direction among these TFP groups. Columns (5) and (6) show that low-TFP firms experience a slightly larger decline in the number of patent applications in response to US import tariff shocks. Additionally, as shown in Columns (7) and (8), patent similarity with US patents decreases for both high- and low-TFP firms. Furthermore, Columns (9) and (10) indicate that innovation activities in low-TFP Chinese firms diverge even more from those of the most innovative US firms, suggesting that lower-productivity firms are more susceptible to trade-induced technological decoupling.

Table 6: Heterogeneous Impact of the Trade War by Innovativeness and TFP

	Innovation of Chinese Firms				Innovation by TFP of Chinese Firms					
	Δ Similarity to Top US Patents				Δ Patent Number		Δ Similarity to All US Patents		Δ Similarity to Top US Patents	
	0-5 Years	0-1 Years	2-3 Years	4-5 Years	High TFP	Low TFP	High TFP	Low TFP	High TFP	Low TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ US Import Tariff	-0.357**	-0.491**	-0.476***	-0.208*	-1.008***	-1.241***	-0.289*	-0.261	-0.299**	-0.468*
	(0.149)	(0.202)	(0.171)	(0.111)	(0.187)	(0.325)	(0.146)	(0.186)	(0.140)	(0.276)
Δ CN Import Tariff	-0.0726	0.0227	-0.0999	-0.0460	-0.260	-0.499	-0.0665	0.0992	-0.509*	0.263
	(0.235)	(0.209)	(0.275)	(0.277)	(0.357)	(0.466)	(0.204)	(0.304)	(0.280)	(0.367)
Δ US Export Controls	0.0432	0.0552	0.0532	0.0548	-0.463*	-0.504	0.183	-0.438***	0.358	-0.323
	(0.158)	(0.166)	(0.168)	(0.158)	(0.244)	(0.323)	(0.217)	(0.154)	(0.251)	(0.200)
Δ Sanctions	-0.136	-0.145	-0.0960	-0.152	0.119	0.293**	-0.0334	-0.0277	-0.134	-0.159
	(0.136)	(0.133)	(0.129)	(0.158)	(0.128)	(0.116)	(0.0920)	(0.224)	(0.108)	(0.287)
Δ Patent Number	Y	Y	Y	Y	/	/	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,980	1,981	1,981	1,981	1,247	1,277	998	975	996	973
R-squared	0.042	0.037	0.048	0.043	0.133	0.093	0.046	0.062	0.067	0.065

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). Columns (1)–(4) explores the impact of the trade war on patent similarity between Chinese firms and the most innovative US firms in each IPC, defined as the top 20 firms with the highest number of patent applications in that IPC. Columns (5)–(10) explore the impact of the trade war on Chinese firms' innovation intensity and directions by their average TFP level in 2014–2017. The dependent variables are, respectively, patent numbers in Columns (5)–(6), similarity to all US patents in Columns (7)–(8), and similarity to the most innovative US firms in each IPC in Columns (9)–(10). Firm-level controls include the natural logarithm of the firm's employment, total assets, and the share of profits as a proportion of total revenue before the trade war. Industries are defined at the 3-digit level, and industry fixed effects are included in all specifications.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

3.8 Equilibrium Effect of US Export Controls and China's Import Tariff

In addition to the direct demand shock induced by US import tariffs on Chinese goods, US export controls and China's import tariffs on US goods may also affect market demand through market-equilibrium channels. Specifically, increased difficulty in importing goods from the US may raise the prices of those goods in domestic markets, potentially encouraging firms innovating in the same technological fields to invest more in R&D.

To examine this effect, we compute each firm's technological exposure to China's import tariffs and US export controls using the distribution of the firm's patenting activity across technological fields prior to the trade war (2000–2017):

$$\text{Tech exposure to Import tariff}_{i,t} = \sum_j \frac{\text{patent number}_{i,j,00-17}}{\sum_j \text{patent number}_{i,j,00-17}} \text{Tariff}_{j,t}^{I,US} \tag{8}$$

$$\text{Tech exposure to Export Controls}_{i,t} = \sum_j \frac{\text{patent number}_{i,j,00-17}}{\sum_j \text{patent number}_{i,j,00-17}} \text{Export Control}_{j,t} \tag{9}$$

where i indexes firms and j represents 3-digit IPC technology fields. We aggregate HS-product-level tariffs and export controls into IPC-level measures using the concordance between IPC and HS products based on customs and patent data.[7]

The changes in these exposure measures between the pre– and post–trade war periods are incorporated into the regression model specified in Equation (5), with the results presented in Table 7. Technological exposure to China's import tariffs on US goods is associated with an increase in the number of patent applications by Chinese firms. However, no significant effect is observed on patent similarity, suggesting that China's import tariffs and US export controls may not significantly alter the direction of innovation among Chinese firms. Since market equilibrium may influence innovation outcomes, we will account for its effects in the quantitative analysis.

Table 7: Market-Equilibrium Effect of US Export Controls and China's Import Tariff

	Δ Patent Number		Δ Similarity to US Patents							
			0-5 Years		0-1 Years		2-3 Years		4-5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ US Import Tariff	-1.023***	-1.148***	-0.250*	-0.245**	-0.258*	-0.258**	-0.281*	-0.275**	-0.196	-0.195*
	(0.182)	(0.189)	(0.132)	(0.116)	(0.135)	(0.120)	(0.141)	(0.126)	(0.122)	(0.105)
Δ CN Import Tariff	-0.238	-0.353	0.126	0.0815	0.128	0.0694	0.139	0.0876	0.104	0.0811
	(0.317)	(0.312)	(0.182)	(0.177)	(0.167)	(0.157)	(0.201)	(0.195)	(0.194)	(0.201)
Δ US Export Controls	-0.454**	-0.420**	-0.0862	-0.0981	-0.0802	-0.0924	-0.0486	-0.0592	-0.0992	-0.110
	(0.207)	(0.209)	(0.125)	(0.118)	(0.123)	(0.115)	(0.135)	(0.129)	(0.125)	(0.120)
Δ Import Tariff (Tech Exp.)	1.503**	1.704**	-0.480	-0.362	-0.381	-0.289	-0.516	-0.361	-0.569	-0.471
	(0.654)	(0.669)	(0.573)	(0.620)	(0.536)	(0.597)	(0.620)	(0.660)	(0.624)	(0.659)
Δ US Export Controls (Tech Exp.)	-0.129	-0.125	-0.0926	0.0262	0.0537	0.146	-0.148	-0.0268	-0.167	-0.0301
	(0.461)	(0.420)	(0.338)	(0.374)	(0.367)	(0.420)	(0.381)	(0.404)	(0.292)	(0.326)
Δ Patent Number	/	/	N	Y	N	Y	N	Y	N	Y
Firm Characteristics	N	Y	N	Y	N	Y	N	Y	N	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,546	2,539	1,994	1,984	1,994	1,984	1,994	1,984	1,994	1,984
R-squared	0.040	0.092	0.004	0.029	0.004	0.029	0.004	0.032	0.004	0.029

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). Firm-level controls include the natural logarithm of employment, total assets, and the profit-to-revenue ratio before the trade war. Industries are defined at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

[7] The detailed procedure for calculating IPC-level trade conflicts is presented in Appendix D.3.

4 Quantitative Model

While the empirical analysis provides robust evidence that US import tariffs are associated with declines in both innovation intensity and similarity to US patents, the findings cannot fully rule out the possibility of strategic patenting or wording behavior. To address it, we complement the reduced-form evidence with a quantitative model that explicitly captures the role of the demand channel. This model enables us to quantify the extent to which the observed decline in innovation intensity and the divergence in patent similarity are driven by shifts in market demand, and to assess how these reallocations of innovation affect firms' export performance. Specifically, the model incorporates the TF-IDF algorithm and focuses on the joint decision-making of Chinese listed firms (hereafter "domestic firms") regarding innovation and exporting.

4.1 Model Setup

4.1.1 Preferences and Market Demand

We consider a world with many destination markets indexed by $n = 0, 1, 2, .., N$, where $n = 0$ represents the domestic market. There are a set of $\mathcal{I}$ products that can be potentially produced, and each firm ω can produce a subset of products $\mathcal{I}(\omega) \subset \mathcal{I}$. Each product i has a set of features $\mathcal{K}_i$ (e.g., engines and air-conditioning for a car). Firms producing the same product can differ in the product's features (e.g., distinct car models), and we treat each firm's product as a variety. We assume that within a product market, different varieties are engaged in monopolistic competition.

Consumers in each destination n have the following preferences:

$$U_t^n = \prod_{i \in \mathcal{I}} (Q_{it}^n)^{\gamma_i^n},$$

$$Q_{it}^n = \left[\sum_{\omega} (q_{it}^n(\omega))^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad \text{where } q_{it}^n(\omega) = \left(\sum_{k \in \mathcal{K}_i} (\gamma_{ik}^n)^{\frac{1}{\epsilon}} q_{ikt}^n(\omega)^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}},$$

where the upper-level preferences are Cobb-Douglas preferences over product-level composite goods Q_{it}^n, with γ_i^n governing the expenditure share and $\sum_i \gamma_i^n = 1$. Within each product, consumers have a nested CES preference over different varieties with the elasticity of substitution $\sigma > 1$. Under monopolistic competition, we compute the demand for a variety produced by firm ω as given by $q_{it}^n(\omega) = (p_{it}^n(\omega))^{-\sigma} (P_{it}^n)^{\sigma-1} \gamma_i^n E_t^n$, where $p_{it}^n(\omega)$ is the price charged by firm ω for each unit of $q_{it}^n(\omega)$. P_{it}^n is the aggregate price index of the composite good of product i in country n, and E_t^n is country n's total expenditure. Each firm's product is a bundle of different features, with variable $q_{ikt}^n(\omega)$ denoting the quantity level of feature k offered by firm ω. Parameter γ_{ik}^n captures the taste of consumers from country n for feature k of product i: for example, US consumers usually prefer SUVs to sedans, while the opposite is true for Chinese consumers. The parameter $\epsilon > 1$ is the elasticity of substitution between different features of a variety.

4.1.2 Domestic Firms' Production and Trade Costs

There is a total of M_t domestic firms. If a domestic firm is endowed with the technology for product $i \in \mathcal{I}(\omega)$, it produces different features of product i using the following equation:

$$q_{ikt}(\omega) = z_{ikt}(\omega)^{\frac{1}{\epsilon-1}} l_{ikt}(\omega), \quad k \in \mathcal{K}_i.$$

$z_{ikt}(\omega)$ is feature-specific productivity level, and $l_{ikt}(\omega)$ captures the amount of labor hired in producing feature k. We introduce the exponent $\frac{1}{\epsilon-1}$ on $z_{ikt}(\omega)$ to simplify the derivation. Additionally, it is noteworthy that in the special case where there is only one feature ($\#M_i = 1$) with elasticity $\epsilon = \sigma$, revenue becomes proportional to productivity, $p_{it}^n q_{it}^n \propto z_{it}^n$, which aligns with a common assumption in the growth literature (e.g., Akcigit, Celik and Greenwood, 2016).[8]

Given the production function, the firm will minimize the cost of producing each unit of $q_{it}^n(\omega)$ (after accounting for consumers' preferences toward different features in market n), and thus we can compute the marginal cost of $q_{it}^n(\omega)$ as:

$$c_{it}^n(\omega) = \left[\sum_{k \in \mathcal{K}_i} \gamma_{ik}^n z_{ikt}(\omega) \right]^{\frac{1}{1-\epsilon}} w_t^0,$$

where w_t^0 is the wage rate in the home country.

To serve market n, a firm must incur iceberg costs (inclusive of tariff costs) denoted by $\tau_{it}^n \geq 1$.[9] We allow τ_{it}^n to vary over time to account for changes in tariff policies. Moreover, exporting a certain product incurs fixed export costs f_i^n (Melitz, 2003) in units of labor, with the costs of the local market being $\tau_{it}^0 = 1$ and $f_i^0 = 0$.

---

[8] In the following derivation, we assume that innovation enhances the level of $z_{ikt}(\omega)$. If, instead, we assume that innovation directly improves the level of $z_{ikt}(\omega)^{\frac{1}{\epsilon-1}}$, this would result in excessively high innovation returns (since revenues are elastic with respect to $z_{ikt}(\omega)^{\frac{1}{\epsilon-1}}$) and could lead to the risk of explosive solutions.

[9] In this model, we do not explicitly account for tariff revenues or the government budget constraint.

4.1.3 Innovation and Evolution of Domestic Firms' Productivity

We assume that firms' productivity levels evolve over time as follows:

$$\underbrace{z_{ik,t+1}(\omega)}_{\text{next-period feature-specific productivity}} = \underbrace{(1-\delta)z_{ikt}(\omega)}_{\text{current-period productivity}} + \underbrace{[s_{ikt}(\omega)a_{it}(\omega)]^{\phi}}_{\text{increment from innovation}}. \tag{10}$$

The term $a_{it}(\omega)$ represents the number of inventions by firm ω related to product i at time t, while $s_{ikt}(\omega)$ denotes the share of innovation directed towards feature k, with the condition that $\sum_{k\in\mathcal{K}_i} s_{ikt}(\omega) = 1$. The existing literature on directed technology change, such as the works by Acemoglu (2010) and Acemoglu, Aghion, Bursztyn and Hemous (2012), examines factor-biased or sector-biased technological change. Our study broadens this scope by exploring how firms can allocate their innovation efforts across various features of a product. We follow the literature (e.g., Bloom, Romer, Terry and Van Reenen, 2020) to assume that innovation efforts exhibit diminishing returns, with $0 < \phi < 1$. Incurring an invention would cost ψ units of labor.[10]

4.1.4 Market Equilibrium

To close the model, we must also consider the sales of foreign firms in each market. Given the lack of data and the fact that China represented only a small portion of foreign demand, we assume that the behavior of foreign firms is not influenced by Chinese firms.[11] Specifically, for each product, we follow Krugman (1991) to assume that there is a unit measure of firms that produce differentiated varieties in each foreign country $m \in \{1, ..., N\}$, and all these firms are exporters. The firm's unit cost of production to serve market n is $c_{it}^{n,m}$. Let $\tau_{it}^{n,m}$ be the iceberg costs from foreign country $m \in \{1, ..., N\}$ to destination n, then the market equilibrium in destination n is:

$$M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega (P_{it}^n)^{\sigma-1}\gamma_i^n E_t^n + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}(P_{it}^n)^{\sigma-1}\gamma_i^n E_t^n = \gamma_i^n E_t^n, \tag{11}$$

where export choice $\mathbf{1}_{it}^n(\omega) \in \{0, 1\}$ and domestic firms' price $p_{it}^n(\omega)$ will be solved below. Due to monopolistic competition, the foreign firm's price is $\tilde{\sigma} = \frac{\sigma}{\sigma-1}$ over the marginal costs. The

[10] Assuming diminishing returns to innovation and linear innovation costs is analogous to assuming linear returns to innovation and convex innovation costs (e.g., Acemoglu, Akcigit, Bloom and Kerr, 2018).

[11] Although China is often seen as the "world factory," the proportion of foreign manufacturing expenditures spent on Chinese goods was only about 5% in 2015, according to the OECD Inter-Country Input-Output Table, reflecting cross-border trade barriers. Therefore, we assume that changes in China have minimal effects on firm behavior in other countries, while still considering the impact of Chinese firms' export activities on foreign aggregate price indices as shown in Equation (12).

left-hand side of Equation (11) is the supply of product i to market n (aggregated across origins), while the right-hand side represents the total demand for product i in market n. Canceling out the common terms, we obtain:

$$M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma} = (P_{it}^n)^{1-\sigma}. \tag{12}$$

By Equation (12), we consider the market equilibrium in each product market, taking into account the impact of trade war on aggregate price indices, following a similar practice by Handley and Limão (2017), with computation details provided in Appendix D.3.1.[12]

We follow the literature (e.g., Costinot, Donaldson and Smith, 2016; Antràs, Fort and Tintelnot, 2017) to assume that there is an outside sector, which absorbs labor and produces goods that are freely tradable across countries, leading to exogenously determined wage rates in all countries. We also assume that expenditures are exogenously given in all countries.[13]

4.2 Solving Domestic Firms' Problem

4.2.1 Static Problem: Choosing Export Price and Status.

Given productivity levels, we first solve a domestic firm ω's optimal prices and export status at each time t. As the production function exhibits constant returns to scale, the export decisions are independent across destinations. The firm chooses the price to maximize variable profits for each market n:

$$\max_{\{\mathbf{1}_{it}^n(\omega), p\}} \pi_{it}^n(\omega) = \mathbf{1}_{it}^n(\omega) \left[\left(p - \tau_{it}^n c_{it}^n(\omega)\right) p^{-\sigma} (P_{it}^n)^{\sigma-1} \gamma_i^n E_t^n - w_t^0 f_i^n \right].$$

From the first-order condition regarding the price, we can solve price $p_{it}^n(\omega) = \tilde{\sigma} \tau_{it}^n c_{it}^n(\omega)$ if the firm exports to market n. The corresponding profits are given by:

$$\pi_{it}^n(\omega) = \mathbf{1}_{it}^n(\omega) \left[\frac{1}{\sigma} \left(\tilde{\sigma} \tau_{it}^n c_{it}^n(\omega)\right)^{1-\sigma} (P_{it}^n)^{\sigma-1} \gamma_i^n E_t^n - w_t^0 f_i^n \right] = \mathbf{1}_{it}^n(\omega) \left[\zeta_{it}^n c_{it}^n(\omega)^{1-\sigma} - w_t^0 f_i^n \right], \tag{13}$$

[12] Handley and Limão (2017) consider heterogeneity in foreign firms' productivity and the fixed costs of entering markets, which can lead to changes in the export entry cutoff in response to economic shocks. However, due to the absence of data on the export behavior of foreign firms and the computational complexity of calibrating the multi-dimensional productivity distribution across foreign countries, we abstract from firm heterogeneity and assume that all foreign firms are homogeneous and exporters (Krugman, 1991).

[13] One way to derive exogenous expenditures is to assume that workers allocate a fixed proportion of their income to spending on the heterogeneous-good sector.

where $\zeta_{it}^n = \frac{1}{\sigma}\left(\tilde{\sigma}\tau_{it}^n\right)^{1-\sigma}\left(P_{it}^n\right)^{\sigma-1}\gamma_i^n E_t^n$ represents aggregate demand factor from market n for product i. The firm exports to destination n ($\mathbf{1}_{it}^n(\omega) = 1$) if and only if $\zeta_{it}^n c_{it}^n(\omega)^{1-\sigma} \geq w_t f_i^n$.

4.2.2 Dynamic Problem: Innovation Choices.

We can then solve the firm's innovation choices to maximize the value for product i:

$$
\begin{aligned}
V_{it}(\mathbf{z}_{it}(\omega)) = \max_{\{s_{ikt}(\omega), a_{it}(\omega)\}} & \sum_{n=0}^{N} \pi_{it}^n(\omega) - \psi w_t^0 a_{it}(\omega) + \frac{1}{1+r} V_{it+1}(\mathbf{z}_{it+1}(\omega)) \\
\text{s.t. } & z_{ik,t+1}(\omega) = (1-\delta) z_{ikt}(\omega) + [s_{ikt}(\omega) a_{it}(\omega)]^{\phi} \\
& \sum_{k \in \mathcal{K}_i} s_{ikt}(\omega) = 1.
\end{aligned}
$$

The first-order conditions regarding the share of inventions devoted to feature k, $s_{ikt}(\omega)$, imply:

$$
\frac{s_{ik't}(\omega)}{s_{ikt}(\omega)} = \left[\frac{\partial V_{it}(\mathbf{z}_{it}(\omega))/\partial z_{ik't+1}(\omega)}{\partial V_{it}(\mathbf{z}_{it}(\omega))/\partial z_{ikt+1}(\omega)}\right]^{\frac{1}{1-\phi}}. \tag{14}
$$

Here, $\partial V_{it}(\mathbf{z}_{it}(\omega))/\partial z_{ik't+1}(\omega)$ captures the marginal return from improving the productivity of feature k:

$$
\frac{\partial V_{it}(\mathbf{z}_{it}(\omega))}{\partial z_{ikt+1}(\omega)} = \sum_{x=t+1}^{\infty} \left(\frac{1-\delta}{1+r}\right)^{x-t} \frac{1-\sigma}{(1-\epsilon)(1-\delta)} (w_x^0)^{1-\sigma} \sum_{n=0}^{N} \mathbf{1}_{ix}^n(\omega) \zeta_{ix}^n (c_{ix}^n(\omega))^{\epsilon-\sigma} \gamma_{ik}^n.
$$

The reliance of marginal benefits on $\sum_{n=0}^{N} \mathbf{1}_{ix}^n(\omega)\zeta_{ix}^n(c_{ix}^n(\omega))^{\epsilon-\sigma}\gamma_{ik}^n$ indicates that demand for a particular feature k, as captured by the weighted average destination's taste for a certain feature γ_{ik}^n, would affect the firm's proportion of innovation devoted to that feature. Consequently, if foreign consumers prefer feature k and the firm serve these consumers (higher γ_{ik}^n for some foreign market n with $\mathbf{1}_{ix}^n(\omega) = 1$), this optimal scenario suggests that the firm would allocate more effort toward feature k across all its innovations.

Using the first-order condition with regard to innovation quantity $a_{it}(\omega)$, we can also obtain the following solutions for the number of inventions:

$$
a_{it}(\omega) = \left(\frac{\sum_{k \in \mathcal{K}_i} \phi (s_{ikt}(\omega))^{\phi} \partial V_{it}(\mathbf{z}_{it})/\partial z_{ikt+1}}{w_t^0 \psi}\right)^{\frac{1}{1-\phi}}. \tag{15}
$$

Now, consider the impact of permanently higher tariff rates in market n, which raise iceberg costs τ_{it}^{n}, thereby reducing export revenues ζ_{ix}^{n} $(x \geq t)$ for all future periods. According to Equation (14), if the firm is actively producing good i and exporting to market n, the decline in export revenues ζ_{ix}^{n} will shift the focus of innovations in product i away from the preferences of consumers in country n (γ_{ik}^{n}). Additionally, Equation (15) suggests that the lower export revenues ζ_{ix}^{n} will also decrease the total quantity of innovation, $a_{it}(\omega)$, assuming that the firm exports to market n.

Finally, suppose that distinct product features correspond to different words in the patent text (we provide empirical support for this assumption in Section 5.1.1). We can thus compute the similarity between firm ω's innovation vector $\mathbf{a}_{it}(\omega) = [a_{ikt}]$ and another vector of innovations characterized by the vector $\mathbf{b}_{it} = [b_{ikt}]$ in product i across features:

$$Sim(\mathbf{a}_{it}(\omega), \mathbf{b}_{it}) = \frac{\sum_{k\in\mathcal{K}_i} a_{ikt}(\omega) b_{ikt}}{\left[\sum_{k\in\mathcal{K}_i}(a_{ikt}(\omega))^2\right]^{1/2}\left[\sum_{k\in\mathcal{K}_i}(b_{ikt})^2\right]^{1/2}}. \tag{16}$$

5 Quantitative Analysis

To assess the significance of accounting for both the intensity and direction of innovation when evaluating the impact of trade shocks on firm performance, we conduct a quantitative analysis using the US-China trade war as a case study. In this section, we first calibrate the model using data from 2016, and then simulate the effects of the trade war that unfolded after 2018.

Since our primary objective is to examine how trade shocks influence firms' innovation choices and their aggregate effects, we focus on innovative listed firms—specifically, those that filed at least one patent between 2000 and 2016 and were active both before and after the trade war. This results in a sample of 2,057 innovative firms, which we will simulate in our quantitative analysis. Given that this subset represents a relatively small share of the overall labor market, we abstract from general equilibrium effects on wages and aggregate demand. However, we do account for market equilibrium in each product market, which leads to product-level price adjustments, following the approach of Handley and Limão (2017).

5.1 Calibration

We now describe how we calibrate the model to the data. The calibration includes three countries: China, the US, and a constructed Rest of the World (ROW), which aggregates all other countries. Accordingly, we define the country index as $n \in \{0, 1, 2\}$, where $n = 0$ corresponds to China, $n = 1$ to the United States, and $n = 2$ to the ROW.

5.1.1 Mapping Patent Words to Product Features

In the quantitative analysis, we focus on 120 products, each corresponding to a three-digit IPC category. In our earlier empirical work, similarity was measured using word-level information. To map the data to the model and compute similarity according to Equation (16), we interpret each patent word as a product feature in the model. To support this interpretation, Figure 5 presents word clouds constructed from Chinese and U.S. self-driving patents filed during 2014–2017 and 2018–2021. The keywords extracted from patent texts align closely with the actual functional features of self-driving vehicles. Specifically, Chinese patents often emphasize parking and navigation technologies, reflecting a focus on urban mobility and driver-assistance functions suited to China's dense traffic conditions and complex parking environments. In contrast, U.S. patents more frequently highlight lidar (Light Detection and Ranging) and autonomous control systems. Appendix D.1 provides additional details and discussions, illustrating the divergence between Chinese and U.S. self-driving patents by visualizing their trajectories of change.

A key challenge in conducting the quantitative analysis lies in the high dimensionality of patent words—exceeding 10,000 due to the richness of patent texts—which poses substantial computational burdens and requires estimating a large number of parameters. To address this issue, we apply Non-negative Matrix Factorization (NMF) to reduce dimensionality by clustering semantically related words into 256 features, with details of the NMF method in Appendix D.2.[14]

5.1.2 Calibration Procedure

We classify the model parameters into three groups. The first group is calibrated using aggregate statistics or values from the existing literature. The second group is directly estimated from the micro-level data. The third group is jointly calibrated using the simulated model.

Panel A of Table 8 reports the parameters in the first group, $\{\mathcal{I}, \mathcal{K}, \sigma, \epsilon, \delta, \phi\}$. As discussed earlier, we consider $\mathcal{I} = 120$ products and $\#\mathcal{K} = 256$ features. The elasticity of substitution between different varieties, σ, and the elasticity of substitution between different features, ϵ, both take the value of 5, following Head and Mayer (2014).[15] The depreciation rate of technology, δ, is 0.08, consistent with Holmes, McGrattan and Prescott (2015). The elasticity of innovation output

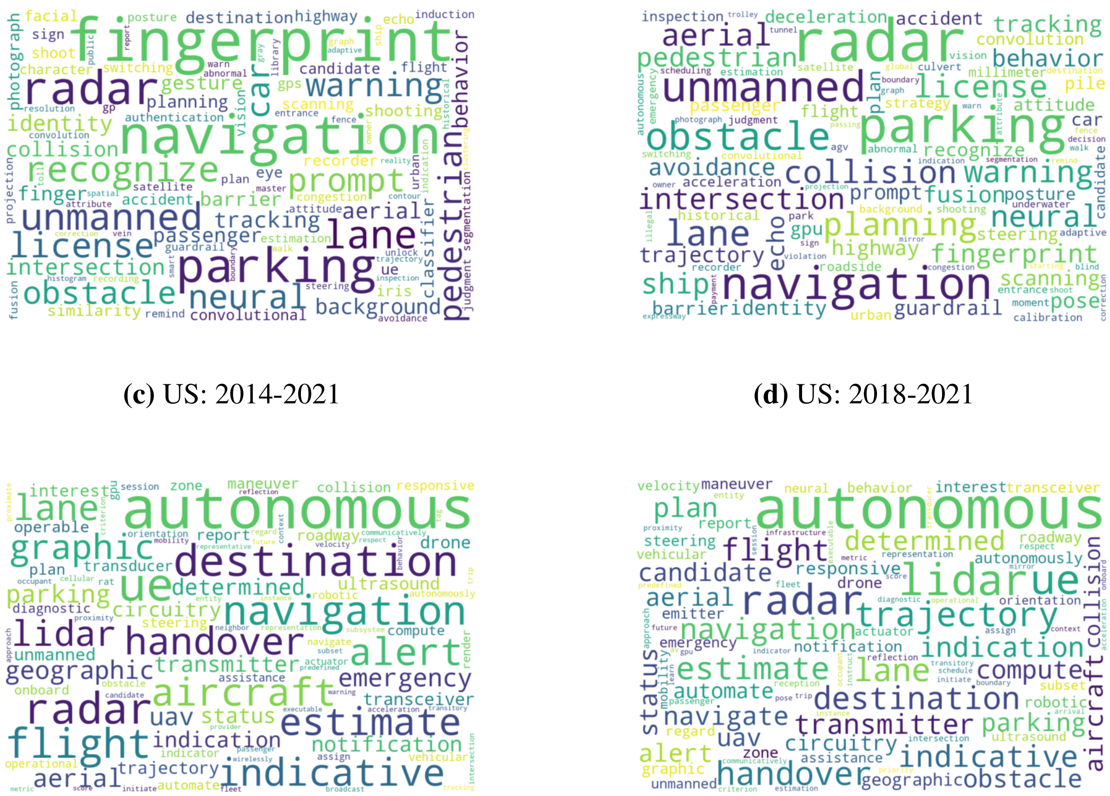
[14]Regressing patent similarity on trade shocks (Equation 5) using these low-dimensional embeddings yields results that closely match those reported in Tables 3 and 4.

[15]In our model, $\sigma - 1$ represents the trade elasticity. Accordingly, we set $\sigma = 5$, following common estimates of trade elasticity in the literature (e.g., Head and Mayer, 2014; Simonovska and Waugh, 2014). Due to limited empirical evidence on the elasticity of substitution ϵ between different features, we assume it to be equal to the elasticity of substitution across varieties. We perform robustness checks regarding the value of ϵ in Section 5.2.2.

Figure 5: Word Cloud of Self-Driving Vehicle Patents: CN vs. US

(a) CN: 2014-2017 **(b)** CN: 2018-2021

(c) US: 2014-2021 **(d)** US: 2018-2021



This figure presents word cloud visualizations of keywords from Chinese and U.S. self-driving patents. Panels (a) and (b) display the word clouds for Chinese patents filed during 2014–2017 and 2018–2021, respectively, while panels (c) and (d) present the corresponding word clouds for U.S. patents over the same periods.

with regard to cost, ϕ, is set to be 0.5, which is commonly used by the growth literature and based on empirical findings (see Acemoglu et al., 2018, for a review).

The parameters in the second group, $\{\gamma_{ik}^n, z_{ik,2016}(\omega)\}$, are directly estimated from the data. Since γ_{ik}^n reflects the preference of consumers in country n for feature k of product i, we calibrate γ_{ik}^n using each country's share of patent text devoted to each feature within each IPC category from 2000 to 2016—a period unaffected by the trade war.[16] $z_{ik,2016}(\omega)$ represents firm ω's initial productivity in feature k of product i. It is determined by the firm's accumulated number of patents from 2000 to 2016, weighted by the share of patent text devoted to feature k, and calculated using

[16]Specifically, for each country, the majority of firm sales occurred in the domestic market. From Equation (14), we observe that for firms selling exclusively in their home market, $s_{ik} \propto (\gamma_{ik}^n)^{1/(1-\phi)}$. Therefore, we use each country's IPC-feature share between 2000 and 2016, s_{ik}, to infer γ_{ik}^n, imposing the normalization $\sum_k \gamma_{ik}^n = 1$.

Table 8: Parameter Values

Notation	Definition	Value	Source
	Panel A: Parameters Set from Aggregate Data and Literature		
$\mathcal{I}$	Number of products	120	Data
$\mathcal{K}_i$	Number of features	256	Data
σ	Elasticity of substitution over different varieties	5	Head and Mayer (2014)
ϵ	Elasticity of substitution over different features	5	Head and Mayer (2014)
δ	Depreciation rate of technology	0.08	Holmes et al. (2015)
ϕ	Decreasing return rate of innovation	0.5	Bloom et al.(2020)
	Panel B: Parameters Set from Micro-level Data		
$\gamma_{ik}^{n=0}$	Domestic product-feature-specific preferences	0.004 (3.66e-5)	
$\gamma_{ik}^{n=1}$	US product-feature-specific preferences	0.004 (6.35e-5)	
$\gamma_{ik}^{n=2}$	ROW product-feature-specific preferences	0.004 (6.07e-5)	
$z_{ik,2016}(\omega)$	Firm-feature-specific initial productivity	0.20 (0.05)	
	Panel C: Parameters Set Using Method of Moments		
$\zeta_i^{n=0}$	Aggregate demand factor from domestic market for each product	62.19 (82.35)	
$\zeta_i^{n=1}$	Aggregate demand factor from US market for each product	3.34 (3.93)	
$\zeta_i^{n=2}$	Aggregate demand factor from ROW market for each product	12.38 (10.59)	
$f_i^{n=1}$	Fixed export costs to the US for each product	8.93 (11.07)	
$f_i^{n=2}$	Fixed export costs to the ROW for each product	25.76 (24.28)	
ψ	Innovation costs	225.29	
ξ	Initial productivity multiplier	2.12	

Notes: For the moments with multiple values, we report the average value, with the standard deviation in parentheses.

the evolution Equation (10).

The third group of parameters, $\{\zeta_i^n, f_i^n, \phi, \xi\}$, is jointly calibrated within the model by minimizing the distance between moments in the model and the data. While the estimation is conducted jointly, we can link specific parameters to particular moments to guide our choice of moment conditions. The parameter ζ_i^n captures aggregate demand from market n for product i by Chinese firms. Since it affects firms' sales in market n, we discipline ζ_i^n using Chinese firms' exports of product i to market n in 2016, resulting in $N \times \mathcal{K} = 360$ moments. The fixed export costs f_i^n $(n = 1, 2)$ shape the extensive margin of exporting to the US or ROW and are primarily identified from the share of product-i firms exporting to each destination in 2016. The parameter ψ, which governs average innovation costs, is informed by the average number of patent applications filed between 2016 and 2021. Finally, motivated by evidence that much of China's early productivity growth was driven by imitation (Wei, Xie and Zhang, 2017), we introduce a productivity multiplier ξ to scale firms' initial productivity $z_{ik,2016}$. This adjustment helps the model match the observed sales growth rate and avoids overstating the contribution of R&D to productivity gains.

Panel C of Table 8 reports the estimation results for all internally estimated parameters from the third parameter group. Notably, we find that domestic demand for Chinese firms exceeds demand from both the US and ROW, consistent with the presence of trade barriers that limit Chinese firms' access to foreign markets. As shown in Table 9, the estimated parameters allow the model to closely match the targeted data moments on sales and innovation.

Finally, although market equilibrium for each product depends on production and iceberg costs faced by foreign producers, we demonstrate in Appendix D.3.1 that counterfactual product-level price indices can be derived using Exact-Hat Algebra and observable data moments, without the need to explicitly identify these parameters for foreign producers, following the approach in Dekle, Eaton and Kortum (2008).

Table 9: Targeted Moments Generated by Data and Model

Description	Data	Model
Domestic sales for each product (billion)	536.67 (267.81)	536.87 (267.71)
Exports to US for each product (billion)	29.73 (13.05)	29.73 (13.05)
Exports to ROW for each product (billion)	111.83 (48.18)	111.77 (48.20)
Share of exporters (US) among all firms producing each product	0.64 (0.12)	0.64 (0.13)
Share of exporters (ROW) among all firms producing each product	0.79 (0.11)	0.79 (0.11)
Average number of patent applications for each firm	35.6	35.6
Growth rate of total sales of listed firms between 2016 and 2017	0.17	0.17

5.2 Understanding the Quantitative Impact of the Trade War

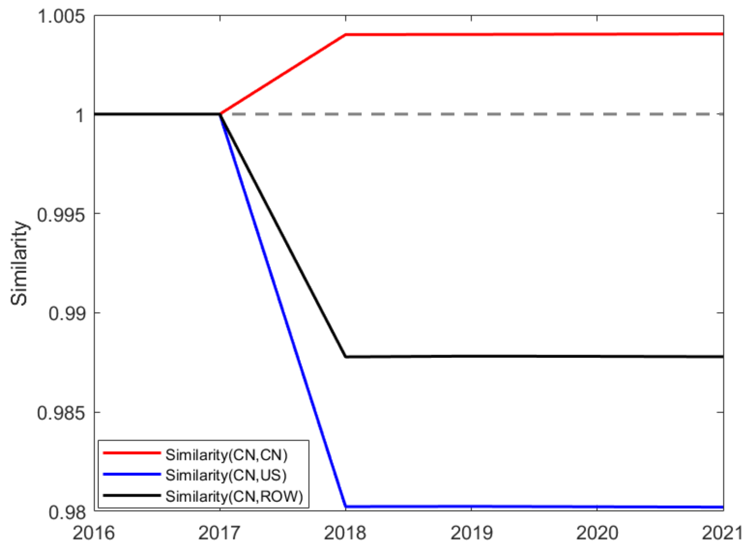
We now apply our calibrated model to examine the impact of the trade war, focusing in particular on how it influences export sales to the US through shifting innovation decisions by Chinese firms.

5.2.1 The Effect of 2018 Trade War

To assess the impact of the US–China trade war during the 2018–2019 period, we simulate the calibrated model over the 2016–2021 horizon. We proceed in two steps. First, we simulate the model without any tariff shocks to generate a baseline trajectory of firms' decisions, using the calibrated aggregate demand ζ_i^n for all years. Second, we introduce unexpected tariff increases during the 2018–2021 trade war period, including US tariffs imposed on China and China's retaliatory tariffs, as well as observed tariff changes in the ROW.[17] In this scenario, we adjust aggregate demand for

[17] In response to the trade war, the Chinese government reduced import tariffs on goods from the ROW.

Figure 6: Patent Similarity to Domestic and US Innovations



Notes: The figure illustrates the similarity of Chinese patents to domestic innovations (red line), US innovations (blue line) and ROW innovations (black line), using 2016 as the base year. The dashed curve represents the simulation results without unexpected export tariff shocks, while the solid curve represents the results with the shocks.

Chinese firms to $\hat{\zeta}_i^n = \zeta_i^n \left(\frac{\tau_{it}^n}{\tau_{ipre}^n}\right)^{1-\sigma} \left(\frac{\hat{P}_{it}^n}{P_{it}^n}\right)^{\sigma-1}$. Here, $\widehat{x}$ denotes the counterfactual value of variable x. The term $\left(\frac{\tau_{it}^n}{\tau_{ipre}^n}\right)$ captures tariff changes attributable to the trade war, while $\left(\frac{\hat{P}_{it}^n}{P_{it}^n}\right)$ reflects the endogenous adjustment in product-level price indices, computed by applying the Exact-Hat algebra to the product-level market equilibrium detailed in Appendix D.3.1. Finally, we compare the outcomes from the two simulations to quantify the trade war's effects.

It is important to note that firms' innovation choices—$a_{it}(\omega)$ and $s_{ikt}(\omega)$—depend on their expected future export status, $\mathbf{1}_{ix}^n(\omega)$ for $x = t+1, t+2, \ldots$ (see Equations 14 and 15). Conversely, export decisions are influenced by past innovation choices through their effect on firm productivity (see Equation 13). As a result, we iteratively solve for the time paths of innovation and export decisions for each firm until convergence is achieved. When analyzing the impact of the 2018–2019 trade war, we assume that tariff rates remain constant at their 2021 levels from 2022 onward.[18] Although we report results for the 2016–2021 period, the model is simulated through 2030 to account for firms' forward-looking innovation decisions, which depend on expected future profits.[19]

Figure 6 depicts the evolution of patent similarity between Chinese firms and domestic, US,

[18]The second phase of the trade war was unexpected and not anticipated before 2024.
[19]Beyond 2030, firm profits are assumed to remain constant at their 2030 levels.

and ROW innovations over time. The similarity measures in the scenario of no trade shocks are normalized to 1, so that the solid lines indicate relative changes in similarity with trade shocks, respectively. The simulations show rising similarity with domestic innovations, accompanied by declining similarity with US and ROW innovations, consistent with our empirical results.

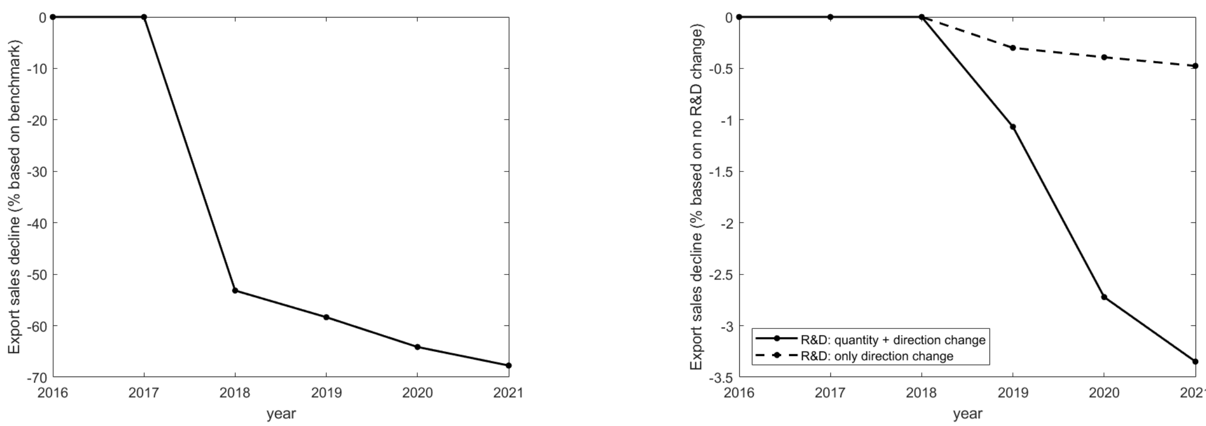
The simulation shows that in the presence of the trade war, export sales to the US declined by 68% through 2021, as illustrated in the left panel of Figure 7. This finding aligns with empirical estimates from Jiao et al. (2022), who indicate that a 1-percentage-point increase in US tariffs led to a 4% decline in Chinese exports to the U.S. (as noted in Section 3.1, US tariffs on Chinese goods rose by about 20 percentage points between 2018 and 2019). According to WTO data, China's share of total US imports gradually fell from 22% in 2016 to 13% in 2024. This decline is smaller than what our model predicts, potentially due to mitigating factors such as tariff exemptions (Cen, Cohen, Wu and Zhang, 2024), tariff evasion (Che, Lin and Zhang, 2025), and trade rerouting.

To assess the role of innovation in shaping the aggregate impact, we conduct two counterfactual exercises. In the first, we hold both firms' innovation intensity ($a_{it}(\omega)$) and direction ($s_{ikt},\ k \in \mathcal{K}(\omega)$) fixed at their levels in the calibrated model without trade shocks, and then introduce tariff shocks. Comparing this outcome to the simulation result that incorporates innovation adjustments allows us to isolate the impact of changes in R&D decisions induced by the trade war. In the second exercise, we decompose this effect into contributions from changes in innovation intensity versus changes in innovation direction. The basic idea is to alternately hold one dimension fixed while allowing the other to adjust, so that we can separate their respective roles.[20] The results are shown in the right panel of Figure 7.

We find that, relative to a scenario in which firms maintain their R&D behavior—both in quantity and direction—throughout the trade war, changes in R&D lead to a 3.3% decline in export sales to the US by 2021. Of this decline, 14% (approximately 0.5 percentage points) is attributable to changes in R&D direction. This indicates that trade-war-induced shifts in innovation direction have a meaningful impact on firm performance.

[20]To be specific, we implement this by two complementary approaches. First, we fix innovation intensity at its no-shock level while allowing direction and tariffs to vary, and compare the outcome to both the no-shock model and the model with trade shocks and innovation adjustments along both dimensions; this isolates the effect of direction. Second, we fix direction at its no-shock level while allowing intensity and tariffs to vary; the difference then isolates the effect of intensity, with the residual explained by direction. We take the average of the two approaches.

Figure 7: Changes in Export Sales due to Innovation Decisions



Notes: The figure shows the change in Chinese firms' export sales to the US due to export tariff shocks (the left panel) and the impact of firms' innovation choices (the right panel). In the right panel, the solid curve represents the combined contribution of both innovation intensity and direction, while the dashed curve isolates the contribution of innovation direction alone.

5.2.2 Model Fit and Robustness Check

We demonstrate the reliability of our model's estimation and prediction from two perspectives. First, we show its fit by replicating several empirical regularities identified in our analysis that were not explicitly targeted during calibration. Second, we test the sensitivity of the results to changes in key model parameters.

Model Fit First, the baseline regression results in Table 3 indicate that a 10-percentage-point increase in US import tariffs reduces Chinese firms' patent applications by 10.88% and patent similarity by 2.58% relative to the historical averages. Columns (2) and (4) of Table 10 report coefficients by simulating the impact of the same tariff changes in our model, which captures 6.5% of the estimated decline in innovation intensity and 21% of the estimated drop in similarity to US patents. Columns (5)–(8) further incorporate firms' technological exposure to China's import tariffs, which could influence product-level competition in the domestic market. The coefficients on US import tariffs remain largely unchanged, suggesting that our model reproduces the direction of the empirical patterns: higher US tariffs reduce both the intensity of Chinese innovation and its similarity to US patents. The simulated effects are smaller than the empirical estimates, indicating that additional factors beyond the demand channel are at play. Examples include knowledge diffusion through global R&D networks (Liu and Ma, 2021), strategic notching at specific sales thresholds (Chen, Liu, Serrato and Xu, 2021), and strategic patenting or wording of abstracts in response to geopolitical considerations.[21] These mechanisms, too, may be shaped by trade tensions.

Table 10: Non-targeted Moments: Trade Shock and Innovation

	Δ Patent Number		Δ Similarity to US Patents		Δ Patent Number		Δ Similarity to US Patents	
	(1) data	(2) model	(3) data	(4) model	(5) data	(6) model	(7) data	(8) model
Δ US Import Tariff	-1.088***	-0.071***	-0.258**	-0.055***	-1.148***	-0.085***	-0.245**	-0.044***
	(0.189)	(0.017)	(0.111)	(0.005)	(0.189)	(0.023)	(0.116)	(0.008)
Δ Tech Exposure (Import Tariff)					1.704**	0.032	-0.362	-0.026**
					(0.669)	(0.039)	(0.620)	(0.012)

Notes: This table replicates Table 3 using the model-generated data, along with the original empirical results from Table 3.

Second, Table 5 indicates that the decline in the similarity between Chinese patents and those from the ROW can be largely attributed to a reduction in their similarity with US patents. Consistently, our calibrated model reproduces a similar pattern: as shown in Columns (1) to (4) of Table 11, when similarity to the US is additionally included in the regression on Chinese patent similarity to the ROW, the estimated coefficient on the US import tariff declines substantially.

Table 11: Non-targeted Moments: Trade Shock and Innovation Direction (Other Countries)

	Δ Similarity to ROW Patents			
	(1) data	(2) data	(3) model	(4) model
Δ US Import Tariff	-0.222*	-0.023	-0.040***	-0.007***
	(0.123)	(0.064)	(0.004)	(0.002)
Δ Similarity to US		0.784***		0.601***
		(0.021)		(0.007)

Notes: This table replicates Table 5 using the model-generated data, along with the original empirical results from Table 5.

Robustness Check In our simulation, we account for both changes in US import tariffs and China's retaliatory tariffs. It is likely that innovation among Chinese firms is influenced by China's retaliatory tariffs: higher Chinese import tariffs increase the cost of foreign goods, shifting demand toward domestic alternatives. This shift boosts domestic firms' incentives to innovate, partially mitigating the negative impact of higher US tariffs. To isolate this effect, we conduct a counterfactual analysis holding Chinese tariffs constant. The results, shown in the second row of Table 12, indicate that without the change in Chinese tariffs, the predicted decline in export sales to the US—as well as the declines linked to changes in R&D intensity and direction—is only slightly larger. This supports the conclusion that the increase in US tariffs is the primary driver of the overall export contraction, consistent with Table 1, which shows that China's retaliatory tariffs were largely concentrated in agricultural products and might have little impact on innovation.

[21] Some Chinese firms may deliberately scale back innovation to avoid drawing scrutiny from US authorities.

Table 12: Changes in Export Sales
(No Import Tariff Change, Varying Elasticity of Substitution over Features and R&D costs)

	Export decline to the US (%)		
	Total (2021)	Due to innovation (2021)	Due to innovation direction (2021)
Baseline	-67.740	-3.349	-0.476
Without import tariff change	-67.741	-3.351	-0.476
$\epsilon = 4$	-42.894	-2.348	-0.494
$\epsilon = 6$	-72.779	-2.350	-0.283
R&D costs change (5%)	-68.377	-5.267	-0.367
R&D costs change (10%)	-69.198	-7.803	-0.440
R&D costs change (25%)	-70.793	-12.600	-0.413
R&D costs change (50%)	-72.761	-18.536	-0.571

Notes: "Total (2021)" reports the decline in the predicted export sales to the US relative to a no–trade-war counterfactual. "Due to Innovation" compares outcomes with and without firms' endogenous R&D responses. The last column isolates the contribution of changes in innovation direction in 2021. The definitions of these three variables are the same as those in Figure 7.

An additional concern is the limited empirical evidence on the elasticity of substitution across features. We assume it equals the elasticity of substitution across varieties in our baseline estimation. However, consumers may be more sensitive to within-product features, implying that feature-level elasticity could be higher. To test this, Rows (3) and (4) report results using smaller and larger values of ϵ, respectively. The outcomes show only small changes, suggesting robustness to alternative assumptions about ϵ.

Lastly, following the trade war, China may learn less from the United States, thereby making innovation more difficult. Incorporating the global knowledge-flow network directly into the model would require a substantially more complex structure, and thus instead we examine the sensitivity of our predictions to higher R&D costs. Rows (5) through (8) of Table 12 increase the R&D cost parameter ψ by 5%, 10%, 25%, and 50% after 2018, and report the resulting predicted decline in export sales to the US. As expected, higher R&D costs amplify the overall export decline and magnify the effect of R&D adjustments.

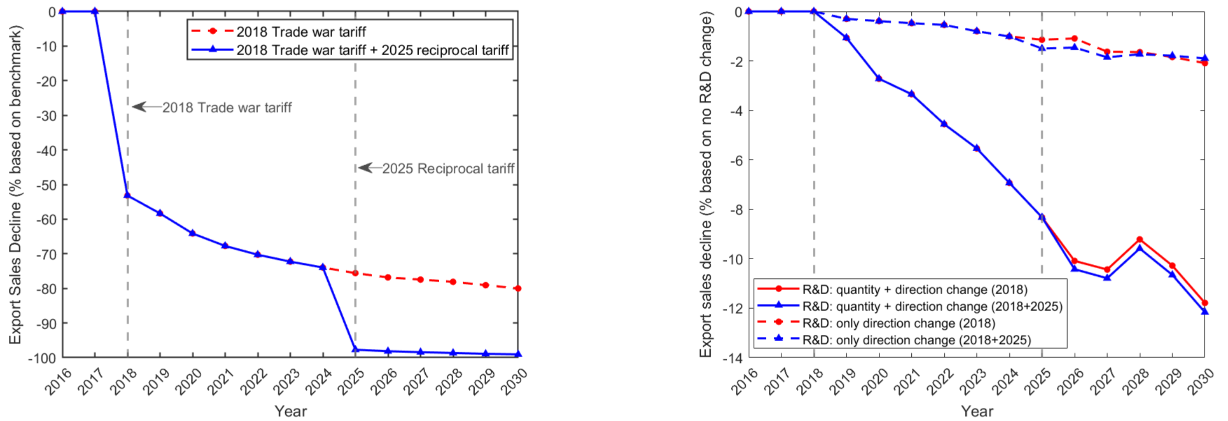
5.2.3 The Effect of New US Import tariff in 2025

In 2025, Trump's return to office sparked a renewed wave of tariff disputes—this time marked by reciprocal trade measures. As documented in Chad Bown's "Trade War Timeline 2.0," a 30% import tariff had already been imposed on China by August 18, 2025.[22] We therefore apply our

[22] https://www.piie.com/blogs/realtime-economics/2025/trumps-trade-war-timeline\protect\penalty\z@-20-date-guide

framework to assess the potential economic impact of these new reciprocal tariffs.

Figure 8: Changes in Export Sales due to Innovation Decisions (Plus Reciprocal Tariff)



Notes: The figure illustrates the change in Chinese firms' export sales to the US resulting from tariff shocks in 2018 alone versus in both 2018 and 2025 (left panel), and the impact of firms' innovation choices on export sales (right panel). The definitions of the variables are the same as those in Figure 7.

The red dashed line in the left panel of Figure 8 represents the decline in export sales to the US due to the 2018 trade war, consistent with the left panel of Figure 7, extended here through 2030. Without the reciprocal tariff introduced in 2025, the export decline follows a smooth downward trend, reflecting the accumulated effects of productivity slowdown due to less innovation. By contrast, the blue solid line depicts the predicted decline in exports to the US when reciprocal tariffs are imposed in addition to the 2018 US tariff increase. In this case, export sales to the US are projected to fall sharply—by 97% in 2025 and 99% in 2030. Because we do not account for other macroeconomic adjustments such as exchange rate movements, tariff exemptions, export subsidies, or trade rerouting, these results may overstate the magnitude of the trade war's impact on export volumes, as they purely isolate the effect of the decline in the aggregate demand due to tariff increases. The right panel decomposes the contributions of changes in R&D intensity and R&D direction. Analogous to the left panel, the red lines correspond to the 2018 trade conflict alone (as in Figure 7), while the blue lines capture the additional effect of a 30% reciprocal tariff in 2025.[23] The contributions of both R&D change and direction change only alter slightly relative to considering the 2018 trade war alone.[24] This likely reflects the fact that the initial round of tariffs

[23]To ensure comparability between the red and blue lines, the blue lines incorporate only the endogenous change in firms' R&D decisions under the reciprocal tariff in 2025, while firms' export decisions are held fixed at the levels observed under the 2018 trade war alone.

[24]There are two reasons for the peak in exports to the US due to R&D changes in 2028. First, the persistent decline in innovation caused by the trade war raises the marginal return to R&D. Second, as firms' productivity increases, more firms become exporters. Together, these factors mitigate the decline in export sales resulting from reduced innovation in each period.

in 2018 had already substantially reduced exports to the US, leaving subsequent tariff increases with only a limited additional impact on Chinese firms' R&D decisions.

6 Conclusion

This paper delves into the impact of the US-China trade war on the innovation strategies of Chinese firms. Given that China's technological progress was one of the primary catalysts for the initiation of the trade conflict by the Trump administration, this study aims to ascertain whether the conflict has influenced the trajectory of China's innovation efforts. Leveraging natural language processing on patent abstracts, we develop a novel metric for measuring patent similarity between China and the US, complementing the citation-based metrics commonly utilized in the literature (e.g., Han, Jiang and Mei, 2021). Our findings reveal that a reduction in export tariffs leads to diminished R&D intensity among publicly listed Chinese firms, alongside a divergence in innovation patterns between China and the US. To interpret this finding, we develop a model featuring heterogeneous consumers' preferences toward product features among destination markets, in which an escalation in export tariffs to a particular country diminishes the exporter's incentive to innovate in line with that country's consumers' preferences. Quantitatively, we find that changes in innovation amplify the damage of the trade war, leading to an additional 3.3% decline in export sales to the US by 2021. Of this decline, 14% is attributable to changes in innovation direction, highlighting the importance of accounting for innovation direction.

Leveraging natural language models, our study highlights the multi-dimensional nature of innovation in shaping the dynamic effects of reduced foreign demand in the aftermath of the trade war. Trade conflicts may influence innovation through various channels—such as diminished cross-country knowledge spillovers and geopolitical concerns about sanctions—that extend beyond direct economic impacts. A promising direction for future research is to quantify the significance of these alternative channels, which will ultimately enhance our understanding and evaluation of the long-term consequences of trade disputes.

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Online Appendix

A A Brief History of the US-China Trade War

The China–United States trade war began in January 2018 when US President Donald Trump initiated tariffs and trade barriers against China. The primary goals were to combat what the US deemed unfair trade practices by China, such as intellectual property theft, the forced transfer of American technology to Chinese companies, and trade imbalances between the two nations. Although a phase one agreement was reached in January 2020, the conflict persisted throughout President Trump's term. President Joe Biden kept the tariffs in place, and as of 2025, President Trump has raised tariffs on Chinese exports even further.

The United States imposed tariffs on a wide range of Chinese goods, starting with solar panels and washing machines in January 2018, and soon extending to various other products including steel, aluminum, and a variety of other goods across different sectors. The list expanded to cover technological and industrial goods, particularly focusing on products related to China's "Made in China 2025" initiative, which aims to make China dominant in global high-tech industries (Ju et al., 2024). By July 2018, the US began imposing tariffs on $34 billion worth of Chinese products, extending to additional $200 billion of imports by September 2018, and eventually covering $250 billion worth of goods by May 2019. In September 2019, the US imposed tariffs on additional $100 billion worth of goods. The tariffs targeted a broad spectrum of products, from consumer electronics to textiles and agriculture products.

China retaliated by imposing tariffs on US goods in several rounds, affecting a wide array of products, including agricultural products, automobiles, and seafood. The Chinese government's response was strategically targeted to impact key US industries, particularly those in states with significant political importance (Fajgelbaum et al., 2020). China's tariffs were seen as a direct countermeasure to the US tariffs, aiming to hurt the US economy in areas where it could potentially influence political pressure on the US administration to change its policies.

B Data

B.1 Data Preparation

In order to study the effect of the trade war on innovations of Chinese listed firms, we construct a matched dataset with information on Chinese listed firms' operations, patents, and trade from 2000 to 2021.

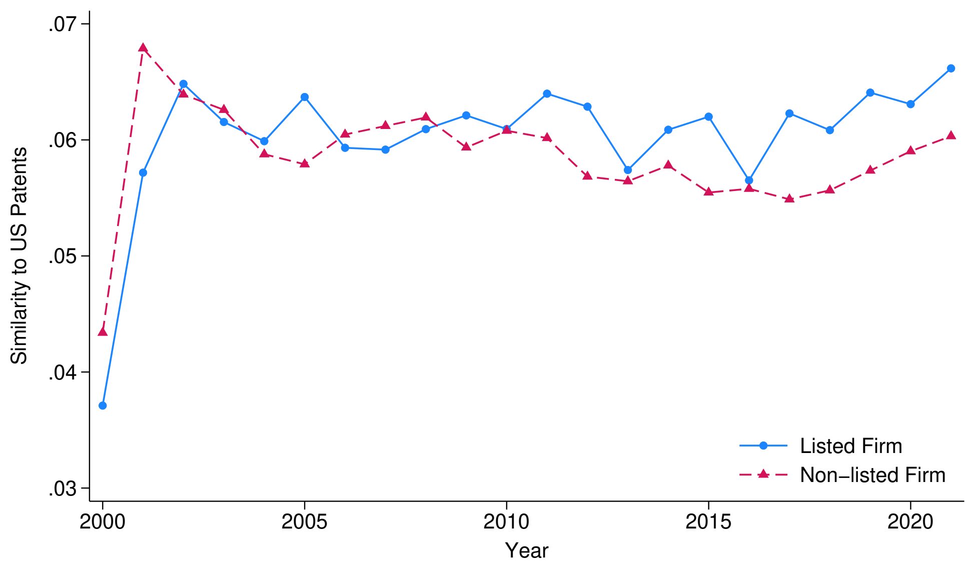
The dataset contains data from several sources. The financial reports of listed firms are collected from the China Stock Market & Accounting Research Database (CSMAR). We collect information on firm name, industry classification, ownership type, sales, employment, capital stock, R&D expenditures, and export destinations. The trade transactions are collected from the China Customs Trade Data (CCTD). It offers detailed information about firm-level trade transactions from 2000 to 2016, including information on firms' names, trade destination countries (for exports) and origin countries (for imports), 8-digit HS product codes, and the value of their exports and imports in US dollars. The patent data of Chinese listed firms is collected from the Chinese patent data from the China National Intellectual Property Administration (CNIPA). The CNIPA data cover all invention patent filings from 1985 to 2023, including information on the applicant's bibliographic details, filing and grant dates, abstracts, and cited patent references.

Then, we merge the three datasets through the Chinese Firm Registration Data (CFRD), which is provided by the State Administration for Industry and Commerce. It provides up-to-date information on all firms registered in China from 1978 to 2024, including firm names, industry classifications, year of establishment, and the year of exit, if applicable. Moreover, it offers a comprehensive change log for every firm, including changes in firm name, registered address, and industry classification. Therefore, we merge the patent data, listed firm data, and custom trade data with the firm registration data separately, using the current name and the historical names. As a result, we obtain a matched data set with operations, patents, and trade information of Chinese listed firms.

B.2 Sample Representativeness

Comparison between Listed and Non-listed Firms in Patent Similarity. To assess whether the listed firms in our sample are representative of the broader population of Chinese firms, we compare the average similarity to US patents over time for both listed and non-listed firms. Specifically, we compute firm-level similarity for each firm in both groups and then take simple averages across firms by year. As shown in Figure A-1, the two groups exhibit closely aligned trends, indicating that the innovation patterns of listed firms broadly reflect those of non-listed firms. The correlation between the two time series is 0.65, supporting the validity of using listed firms as a proxy for the overall landscape of Chinese innovation in our analysis.

Figure A-1: Comparison of Patent Similarity for Chinese Listed and Non-listed Firms

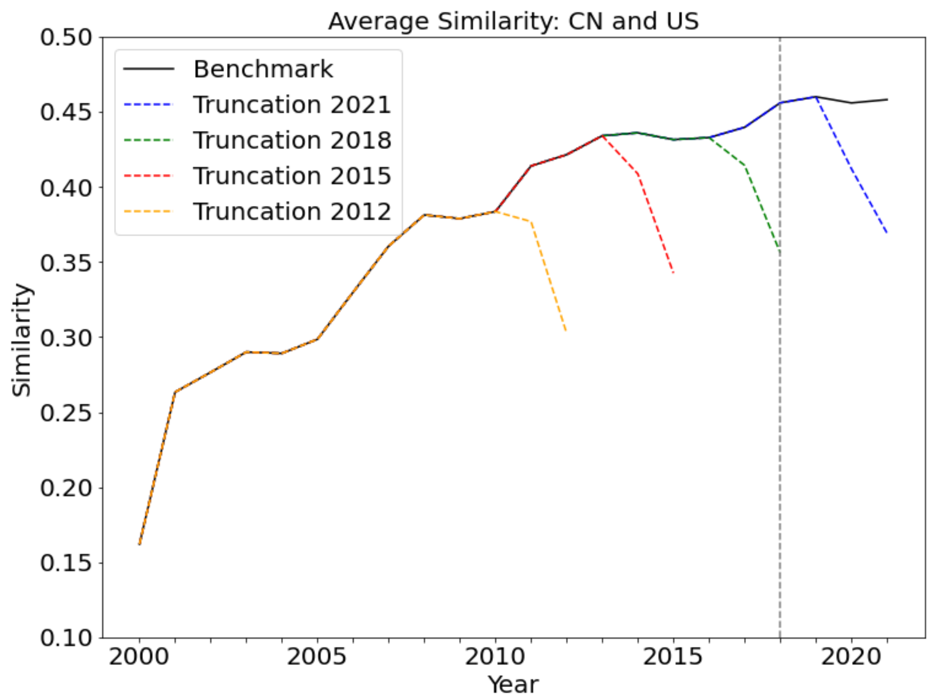


B.3 Patent Data Coverage

Although we have up-to-date patent data from the Chinese and US patent offices, we only study the patents filed before 2021. The reason is that, according to the patent laws in China and the US, a patent filing can be kept from the public for at most 18 months. After that, the filing materials, including abstract, claims, reference cited, description, and illustration graphs, should be open to the public. In this project, we collect patent data from the Patstat Global 2023 Autumn edition, which covers all patent filings until 2021.

Moreover, we conduct a robustness check by truncating patent data in different publication years and comparing the changes in aggregate similarities. In Figure A-2, the dark line represents the average similarity between Chinese and US patents from 2000 to 2021. The data used in the calculation are the patent filings that were published before Sept. 2023, and it is the benchmark case in our paper. Then, we manipulate the sample by selecting patents according to their publica-

Figure A-2: Robustness Check on Truncation of Publication Year



tion year. We selected patent filings that were published before 2021, 2018, 2015, and 2012 and calculated the similarities between Chinese and US patents with the same methods.

The blue dashed line represents the sample with publication year before 2021, and patents that were filed in 2020 and 2021 may not be totally included in the sample. Clearly, compared with the benchmark sample, the similarities in 2020 and 2021 in this truncated sample are substantially lower due to the missing data. Similarly, we observe under-estimated similarities for the years around the truncation year in other truncated samples.

Since our patent data includes all patents published before Sept. 2023, the change of similarity between Chinese and US patents after 2018 is not derived by the data truncation issue.

B.4 Similarity to Other Countries

In this paper, we study the patents of 16 European countries that had joined the European Patent Convention, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, Switzerland, and the United Kingdom before 2000. Their patent filings account for almost all of the total patent filings in Europe.

We define the EU domestic patents as those filed in these countries and the European Patent Office by residents in these countries. For Japanese patents and Korean patents, we adopt the same criteria to identify domestic patents. Since the patent office does not always provide an English version of the patent abstract, we look for the patents with non-English abstracts in Google Patents and adopt the English version provided by Google. For only 10.61% of Japanese patents, 20.11% of Korean patents, and 23.21% of European patents, we need to obtain English abstracts from Google Patents.

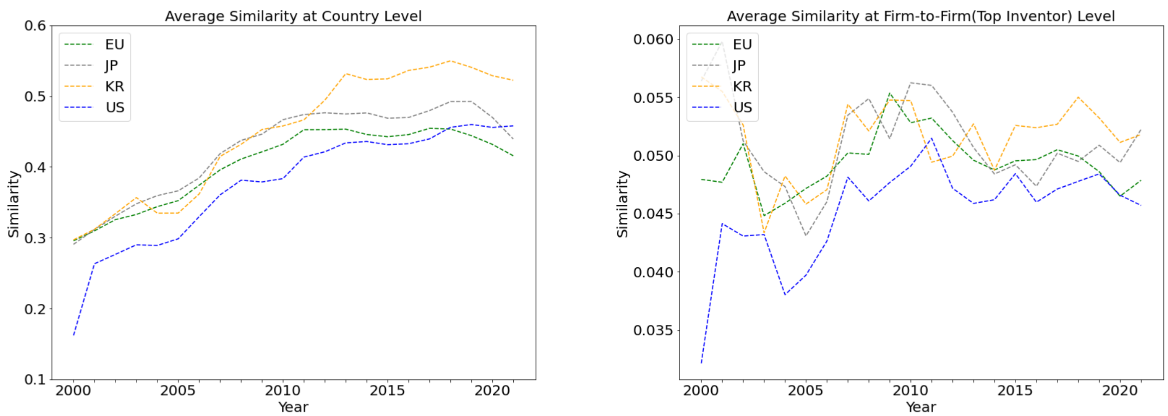
We present the aggregate similarity between Chinese patents and foreign patents in the left panel of Figure A-3. The statistics are calculated as follows. We first sum up vectors of Chinese patents by filing year t and three-digit IPC x and construct year-IPC-level patent vectors $V_{t,x,CN}$. Then, we calculate the similarity between the Chinese patent vector $V_{t,x,CN}$ and foreign patent vector $V_{t,x,F}$ for all technology classes x from 2000 to 2021. The average similarity in each year is measured as the simple average of the similarities across technology classes. Before 2018, despite a disparity in levels, both Chinese and foreign patents exhibited a comparable upward trajectory, which ceased thereafter. Similarly, we present the aggregate similarity between Chinese listed firms' patents and foreign patents in the right panel of Figure A-3. The statistics are calculated as follows. We first sum up vectors of Chinese listed firms' patents by filing year t and three-digit IPC x and construct year-IPC-level patent vectors $V_{t,x,CN\ List}$. The construction of patent vectors of foreign patents is a bit different. In order to make both sides comparable, we identify the patents filed by top inventors in each technology class and sum up their patent vectors to represent the country-IPC-level patent vector, denoted by $V_{t,x,F\ Top}$. The top inventors in each country and technology class are defined as the twenty applicants with the highest annual average filing activity in each three-digit IPC in each country. Despite being considerably more volatile and lacking a distinct upward trend prior to the trade war, the resemblances between patents held by Chinese listed firms and those of top inventors from foreign nations demonstrate a downward trajectory for most countries post-2018.

B.5 Exposure to the US Export Controls

The US export control system regulates the export of commercial and dual-use items (those with both civilian and military applications) to protect national security and foreign policy interests. A key component of this system is the Commerce Control List (CCL), maintained by the Bureau of Industry and Security (BIS) under the Department of Commerce. The CCL is divided into

Figure A-3: Similarity between Chinese and Foreign Patents

(a) Country-Level Similarity **(b)** Firm-Level Similarity



10 categories (e.g., nuclear materials, electronics, aerospace) and further into 5 product groups (e.g., equipment, instrument, materials, software, technology). Each item is assigned an Export Control Classification Number (ECCN), a 5-character code describing its nature and the reasons for control.

To assess firms' exposure to export control, we collect the annual Commerce Control List between 2014 and 2021 from the BIS and identify the 6-digit HS code for restricted products under each ECCN code (e.g., Li, Liang, Pan and Tao, 2025). There are multiple restricted products under each ECCN code, and a product could be restricted due to reasons listed in multiple ECCN codes. We construct the firm-level measure of exposure to export control with Equation (17):

$$\text{Exposure to US Export Control}_{i,t} = \sum_j \frac{\text{import}_{i,j,14-16}}{\sum_j \text{import}_{i,j,14-16}} \text{ECCN Number}_{j,t}. \tag{17}$$

Here, ECCN $\text{Number}_{j,t}$ represents the number of ECCN codes that put restrictions on product j under the 6-digit HS code in year t. This measure captures both the intensive margin and the extensive margin of US export control on product j in each year. We then use the import share between 2014 and 2016 for each firm i as weights in the aggregation to the firm-level measure of exposure.

C Additional Empirical Results

C.1 Sample of Only Exporters and Inclusion of Exporting Intensity

The baseline results in Table 3 are based on a sample of listed firms that includes both exporters and non-exporters. To assess whether the findings are driven by underlying differences between these two groups, we conduct two complementary analyses. First, we restrict the sample to exporters and re-estimate the regression specified in Equation (5); the results are reported in Columns (1)–(4) of Table A-1. Second, using the full sample, we construct an adjusted measure of tariff exposure by replacing the denominator of Equation (3) with the total sales of each firm in 2014-2016. This approach allows for variation in shock intensity related to firms' export-to-sales ratio, with the results shown in Columns (5)–(8). In both exercises, the negative effects on innovation intensity and the divergence of Chinese innovation from US technologies remain robust.

Table A-1: Impact of the Trade War on Chinese Firms' Innovation Intensity and Direction

	Only Exporters				All Sample			
	Δ Patent Number	Δ R&D Cost	Δ Similarity		Δ Patent Number	Δ R&D Cost	Δ Similarity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ US Import Tariff	-0.533*	-0.998**	-0.141	-0.143				
	(0.270)	(0.493)	(0.113)	(0.111)				
Δ US Import Tariff (Adjusted)					-2.018	-1.870	-2.204*	-2.210*
					(1.721)	(1.530)	(1.252)	(1.247)
Δ CN Import Tariff	0.190	0.888	-0.0589	-0.0584	-0.830**	-0.0958	-0.00707	-0.0113
	(0.374)	(0.700)	(0.226)	(0.226)	(0.323)	(0.739)	(0.182)	(0.183)
Δ US Export Controls	-0.315	-0.666**	-0.106	-0.108	-0.384*	-0.897*	-0.112	-0.114
	(0.249)	(0.306)	(0.122)	(0.123)	(0.228)	(0.531)	(0.131)	(0.131)
Δ US Sanctions	0.202	-0.108	-0.0193	-0.0189	0.203*	-0.308	-0.0263	-0.0256
	(0.180)	(0.138)	(0.141)	(0.142)	(0.115)	(0.294)	(0.107)	(0.108)
Δ Patent Number	/	/	N	Y	/	/	N	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,270	1,270	1,158	1,158	2,402	2,402	1,850	1,850
R-squared	0.065	0.170	0.050	0.050	0.092	0.158	0.032	0.032

Notes: Standard errors are clustered at the firm level. Δ denotes the difference between the tariff rates in a given year to the average rates in 2014–2017. Firm-level controls include the natural logarithm of the firm's employment, total assets, and the share of profits as a proportion of total revenue in the previous year. For the regressions on patent similarity, patent application number is controlled. Industries are defined at the 3-digit level. *** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

C.2 Accounting for Processing Trade

Since Chinese firms engaged in processing trade are not subject to China's import tariffs, firms' exposure to China's retaliatory import tariff shock is recalculated by adjusting the baseline measure. Specifically, the baseline exposure is multiplied by one minus the firm's share of processing trade during 2014–2016, as follows:

$$\text{Exposure to Import tariff}_{i,t} = \sum_j \frac{\text{import}_{i,j,14-16}}{\sum_j \text{import}_{i,j,14-16}}(1 - \text{process share}_{i,j,14-16})\text{Tariff}^{CN}_{j,t}$$

Table A-2 presents the results using the adjusted measure. Excluding processing trade from the regression does not alter the estimated impact of changes in US import tariffs.

Table A-2: Impact of the Trade War on Chinese Firms' Innovation Intensity and Direction

	Intensity				Direction			
	Δ Patent Number			Δ R&D Cost		Δ Similarity to US Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ US Import Tariff	-0.928***	-0.982***	-1.104***	-1.027*	-0.229**	-0.270**	-0.260**	-0.266**
	(0.194)	(0.174)	(0.179)	(0.534)	(0.0991)	(0.123)	(0.107)	(0.110)
Δ CN Import Tariff	-0.333	-0.193	-0.303	1.366	0.239	0.183	0.154	0.151
(Accounting for Processing Trade)	(0.310)	(0.326)	(0.333)	(1.036)	(0.162)	(0.159)	(0.159)	(0.158)
Δ US Export Controls	-0.433**	-0.450**	-0.416*	-0.920*	-0.164*	-0.0976	-0.107	-0.110
	(0.194)	(0.211)	(0.213)	(0.511)	(0.0966)	(0.123)	(0.116)	(0.117)
Δ US Sanctions	0.260**	0.203*	0.167	-0.301	-0.0676	-0.0324	-0.0369	-0.0363
	(0.117)	(0.106)	(0.100)	(0.276)	(0.0947)	(0.1000)	(0.101)	(0.102)
Δ Patent Number	/	/	/	/	N	N	N	Y
Firm Characteristics	N	N	Y	Y	N	N	Y	Y
Industry Fixed Effect	N	Y	Y	Y	N	Y	Y	Y
Observations	2,669	2,661	2,542	2,542	2,086	2,077	1,984	1,984
R-squared	0.014	0.068	0.090	0.158	0.002	0.027	0.029	0.029

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). Firm-level controls include the natural logarithm of employment, total assets, and the profit-to-revenue ratio before the trade war. Industries are defined at the 3-digit level.
*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

C.3 Results in the Manufacturing Sector

The manufacturing sector is the primary target of US import tariffs on China. To examine the trade war's impact on this sector, the sample is restricted to manufacturing firms. The corresponding results are reported in Table A-3. The coefficients are consistent with the baseline results.

C.4 Cosine Similarity at the 4-digit IPC Level

In the baseline regressions (Tables 3 and 4), cosine similarity is measured between Chinese and US patents within the same 3-digit IPC technology class. To test robustness to the level of techno-

Table A-3: Impact of the Trade War on Chinese Firms' Innovation Intensity and Direction (Manufacturing Industry)

	Intensity				Direction			
	Δ Patent Number			Δ R&D Cost		Δ Similarity to US Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
US Import Tariff	-0.666***	-0.826***	-0.933***	-0.559	-0.251**	-0.265**	-0.263**	-0.274**
	(0.203)	(0.173)	(0.166)	(0.484)	(0.111)	(0.128)	(0.112)	(0.115)
CN Import Tariff	-0.395	-0.398	-0.545	0.537	0.0648	0.0292	-0.0209	-0.0271
	(0.322)	(0.337)	(0.329)	(0.490)	(0.179)	(0.183)	(0.178)	(0.177)
US Export Controls	-0.518**	-0.478*	-0.473*	-0.118	-0.239	-0.241	-0.238*	-0.245*
	(0.245)	(0.244)	(0.249)	(0.209)	(0.142)	(0.150)	(0.135)	(0.139)
US Sanctions	0.336**	0.284***	0.266***	0.0227	-0.133	-0.0912	-0.0929	-0.0911
	(0.129)	(0.0803)	(0.0793)	(0.0810)	(0.110)	(0.114)	(0.113)	(0.115)
Patent Number	/	/	/	/	N	N	N	Y
Firm Characteristics	N	N	Y	Y	N	N	Y	Y
Industry Fixed Effect	N	Y	Y	Y	N	Y	Y	Y
Observations	1,952	1,952	1,857	1,857	1,646	1,646	1,567	1,567
R-squared	0.013	0.038	0.060	0.033	0.005	0.024	0.026	0.026

Notes: Standard errors are clustered at the firm level. Δ denotes the difference between the tariff rates in a given year and the average rates in 2014–2017. The sample is restricted to the manufacturing sector. Firm-level controls include the natural logarithm of the firm's employment, total assets, and the share of profits as a proportion of total revenue in the previous year. For the regressions on patent similarity, patent application number is controlled. Industries are defined at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

logical granularity, we recalculate similarity within the 4-digit IPC class. The estimated impact of the trade war on Chinese firms' patent similarity is close to the baseline, as reported in Table A-4.

C.5 Alternative Measures of Innovation Intensity

We employ two alternative measures of innovation intensity when estimating Equation (6). The left panel of Figure A-4 presents Poisson estimates based on the raw count of patent applications, while the right panel uses the logarithm of one plus firms' R&D spending as the dependent variable. Both panels indicate a persistent effect of the US import tariff change. Relative to patent counts, the effect on R&D spending emerges later but is larger in absolute magnitude.

C.6 Checking Pre-existing Trends

To assess whether there were any pre-existing heterogeneous trends among firms prior to the trade war, we use data from 2012 to 2017, defining 2012–2014 as the "pre" period and 2015–2017 as

Table A-4: Impact of the Trade War on Patents' Similarity (IPC4)

	Similarity based on similarity between patents within the same IPC4							
	0-5 Years		0-1 Years		2-3 Years		4-5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ US Import Tariff	-0.226*	-0.218	-0.256*	-0.230	-0.200	-0.201	-0.221*	-0.221*
	(0.125)	(0.131)	(0.138)	(0.142)	(0.135)	(0.143)	(0.121)	(0.125)
Δ China Import Tariff	0.0867	0.0896	0.109	0.118	0.112	0.112	0.0770	0.0767
	(0.230)	(0.229)	(0.218)	(0.217)	(0.250)	(0.249)	(0.249)	(0.249)
Δ US Export Controls	0.0248	0.0284	0.0441	0.0559	0.0522	0.0515	-0.0141	-0.0144
	(0.125)	(0.124)	(0.132)	(0.129)	(0.131)	(0.130)	(0.131)	(0.132)
Δ Sanctions	-0.0416	-0.0425	-0.0477	-0.0507	-0.0503	-0.0501	-0.0202	-0.0201
	(0.0730)	(0.0734)	(0.0766)	(0.0764)	(0.0844)	(0.0850)	(0.0650)	(0.0659)
Patent Number	N	Y	N	Y	N	Y	N	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,981	1,981	1,981	1,981	1,981	1,981	1,981	1,981
R-squared	0.029	0.029	0.032	0.034	0.029	0.029	0.033	0.033

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). The similarity measure is the weighted average of cosine similarity of patents in the same 4-digit IPC class. Firm-level controls include the natural logarithm of the firm's employment, total assets, and the share of profits as a proportion of total revenue in the previous year. Industries are defined at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

the "post" period. A corresponding placebo test is then conducted as follows,

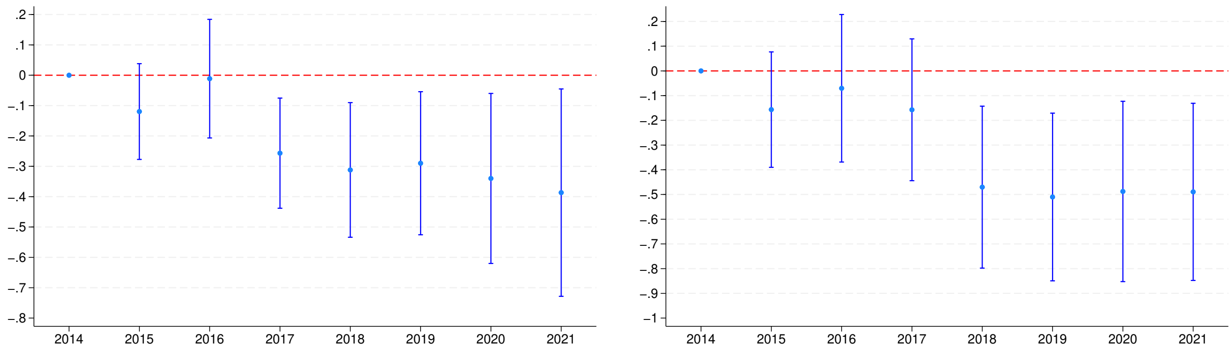
$$\begin{aligned}\Delta Y_{is}^{placebo} =& \beta_1 \Delta ln(1+\text{Tariff}_i^{US,placebo}) + \beta_2 \Delta ln(1+\text{Tariff}_i^{CN,placebo}) + \\ & \beta_3 \Delta \text{Export\_Control}_i^{US,placebo} + \beta_4 \Delta \text{Sanction}_i^{placebo} + \gamma X_{i,12-14} + \mu + \theta_s + \epsilon_{is}.\end{aligned} \tag{18}$$

The dependent variables include changes between the "pre" and "post" periods in the number of firms' patent applications, R&D expenditures in firms' annual report, and the similarity of their patents to US patents filed within the past five years. The placebo values for US import tariffs, $\Delta\ln(1+\text{tariff}_i^{US,\text{placebo}})$, China's retaliatory import tariffs, $\Delta\ln(1+\text{tariff}_i^{CN,\text{placebo}})$, US export controls, $\Delta\text{Export\_Control}_i^{\text{placebo}}$, and sanctions, $\Delta\text{Sanction}_i^{\text{placebo}}$, are defined as the actual changes in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). The results, reported in Table A-5, show no statistically significant differences in firms' innovation activities prior to the trade war, suggesting that the estimated effects of US import tariffs are not driven by pre-existing trends.

Figure A-4: Effect of US Import Tariff over Years

(a) Effect on Patent Application Number

(b) Effect on R&D spending



Notes: The figure illustrates the time-varying effects of US import tariffs on Chinese firms' innovation intensity from 2014 onward. Both point estimates and 90 percent confidence intervals are shown, with standard errors clustered at the firm level. Firm-level controls include the natural logarithm of employment, total assets, and the profit-to-revenue ratio from the previous year. All regressions include firm fixed effects, year fixed effects, and industry-by-year fixed effects.

C.7 Strategic Patenting

Patents without the Patent Cooperation Treaty (PCT) applications are less prone to strategic adjustment of their abstract to cater to foreign patent offices. We measure patent similarity based only on patents without PCT applications and rerun the baseline regressions. The results are presented in the first four columns of Table A-6. The effects of changes in export and import tariffs on the similarity of Chinese patents to US patents filed in different periods remain significant and are very close to the baseline results.

Table A-5: Placebo Test of the Trade-War Effect on Chinese Firms' Innovation Intensity and Direction

	Intensity				Direction			
	Δ Patent Number			Δ R&D Cost	Δ Similarity to US Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ US Import Tariff	-0.0375	-0.258	-0.273	-0.427	-0.0792	-0.102	-0.197	-0.193
	(0.181)	(0.201)	(0.202)	(0.485)	(0.0935)	(0.101)	(0.144)	(0.144)
Δ CN Import Tariff	-0.991***	-1.032***	-1.084***	1.906	0.203	0.254	0.0768	0.0828
	(0.271)	(0.297)	(0.316)	(1.349)	(0.190)	(0.217)	(0.256)	(0.255)
Δ US Export Controls	0.164	0.127	0.157	-0.252	-0.0327	-0.0452	-0.165	-0.167
	(0.226)	(0.227)	(0.229)	(1.118)	(0.160)	(0.172)	(0.140)	(0.140)
Δ US Sanctions	0.190*	0.165	0.138	0.582	0.0501	0.0124	0.0515	0.0495
	(0.104)	(0.106)	(0.106)	(0.397)	(0.0819)	(0.0825)	(0.0938)	(0.0959)
Δ Patent Number	/	/	/	/	N	N	N	Y
Firm Characteristics	N	N	Y	Y	N	N	Y	Y
Industry Fixed Effect	N	Y	Y	Y	N	Y	Y	Y
Observations	2,669	2,661	2,542	2,542	2,086	2,077	1,984	1,984
R-squared	0.014	0.068	0.090	0.158	0.002	0.027	0.029	0.029

Notes: Standard errors are clustered at the firm level. The dependent variables represent changes in firms' innovation intensity and direction between the 2012–2014 and 2015–2017 periods. The independent variables are based on trade-related shocks, measured as changes in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). Firm-level controls include the natural logarithm of employment, total assets, and the profit-to-revenue ratio averaged over 2012–2014. Industries are defined at the 3-digit level. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table A-6: Impact of the Trade War on Patents' Similarity (Non-PCT Applications)

	Similarity based on non-PCT Applications							
	0-5 Years		0-1 Years		2-3 Years		4-5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ US Import Tariff	-0.253**	-0.266**	-0.267**	-0.278**	-0.273**	-0.293**	-0.210**	-0.220**
	(0.112)	(0.115)	(0.115)	(0.119)	(0.119)	(0.121)	(0.104)	(0.106)
Δ CN Import Tariff	0.0190	0.0142	0.00638	0.00239	0.0263	0.0189	0.0235	0.0198
	(0.180)	(0.180)	(0.160)	(0.161)	(0.198)	(0.198)	(0.204)	(0.204)
Δ US Export Controls	-0.0826	-0.0884	-0.0779	-0.0827	-0.0391	-0.0479	-0.0948	-0.0993
	(0.122)	(0.124)	(0.119)	(0.121)	(0.134)	(0.136)	(0.127)	(0.127)
Δ Sanctions	-0.0278	-0.0265	-0.0277	-0.0267	-0.0277	-0.0258	-0.0244	-0.0234
	(0.107)	(0.108)	(0.120)	(0.121)	(0.108)	(0.110)	(0.0929)	(0.0940)
Patent Number	N	Y	N	Y	N	Y	N	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,070	1,978	2,070	1,978	2,070	1,978	2,070	1,978
R-squared	0.024	0.025	0.024	0.024	0.027	0.028	0.024	0.026

Notes: Standard errors are clustered at the firm level. Δ denotes the change in variable values between the pre-trade-war period (2014–2017) and the post-trade-war period (2018–2021). The similarity measure is based on patents without PCT applications. Firm-level controls include the natural logarithm of the firm's employment, total assets, and the share of profits as a proportion of total revenue in the previous year. Industries are defined at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

D Additional Results for Quantitative Analysis

D.1 Additional Supporting Evidence

In this section, we illustrate examples of word content and their trajectories of change in Chinese and U.S. patent abstracts.

First, we provide evidence supporting the mapping between patent vectors and product features. For each Chinese and U.S. self-driving patent, we extract five keywords with the highest TF–IDF scores. The TF–IDF metric identifies words that are both frequent within a specific document and relatively rare across the entire corpus, which is commonly used in the literature (Yao, Pengzhou and Chi, 2019; Wang and Ning, 2020). In other words, it highlights terms that are distinctive to a given patent rather than common across all patents, making them effective indicators of the patent's core technological content.

We present the results in Figure 5, which visualizes keywords from Chinese and U.S. self-driving patents using word clouds. Panels (a) and (b) display the word clouds for Chinese patents filed during the 2014–2017 and 2018–2021 periods, respectively, while panels (c) and (d) show the corresponding visualizations for U.S. patents over the same periods. The keywords in Chinese patents evolved gradually over time, with several core terms appearing consistently across both periods. A similar pattern is observed in the U.S. patents. Another notable observation is the difference in keyword emphasis between the two countries: Chinese patents frequently feature terms such as "parking" and "navigation", whereas U.S. patents emphasize "lidar" (Light Detection and Ranging) and "autonomous", reflecting distinct technological focuses in their self-driving innovation trajectories.

Moreover, the keywords extracted from patent texts exhibit a strong correspondence with the actual functional features of self-driving vehicles. Specifically, Chinese self-driving patents frequently emphasize parking and navigation technologies, reflecting a focus on urban mobility and driver-assistance functions suited to China's dense traffic environments and complex parking scenarios. In contrast, U.S. patents tend to highlight lidar and autonomous control systems, underscoring the industry's emphasis on high-precision sensing and full autonomy. These technological priorities are mirrored in the product features of commercially available vehicles in the two markets. In China, many domestically produced smart vehicles prioritize automated parking, low-speed navigation, and integration with urban infrastructure. Meanwhile, U.S. models often incorporate advanced perception systems, such as lidar-based environmental mapping and autonomous high-way driving capabilities. This alignment suggests that patent keywords not only capture firms' technological directions but also reflect their strategic adaptation to local consumer preferences, regulatory environments, and infrastructural conditions.

Second, we visualize the trajectories of Chinese and U.S. self-driving patents filed over different time periods using a two-dimensional projection based on the t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm. The t-SNE algorithm is a nonlinear dimensionality reduction technique that maps high-dimensional text embeddings into a low-dimensional space while preserving their local structure (Arora, Hu and Kothari, 2018; Linderman and Steinerberger, 2019). Intuitively, patents that share similar technological content or focus on related innovation themes are positioned closer together in the t-SNE map, whereas dissimilar patents are placed farther apart. This visualization helps reveal clusters of technological specialization. By comparing the t-SNE projections for China and the U.S., we can identify how each country's patenting activities are concentrated around distinct technological domains and how these patterns evolve over time.

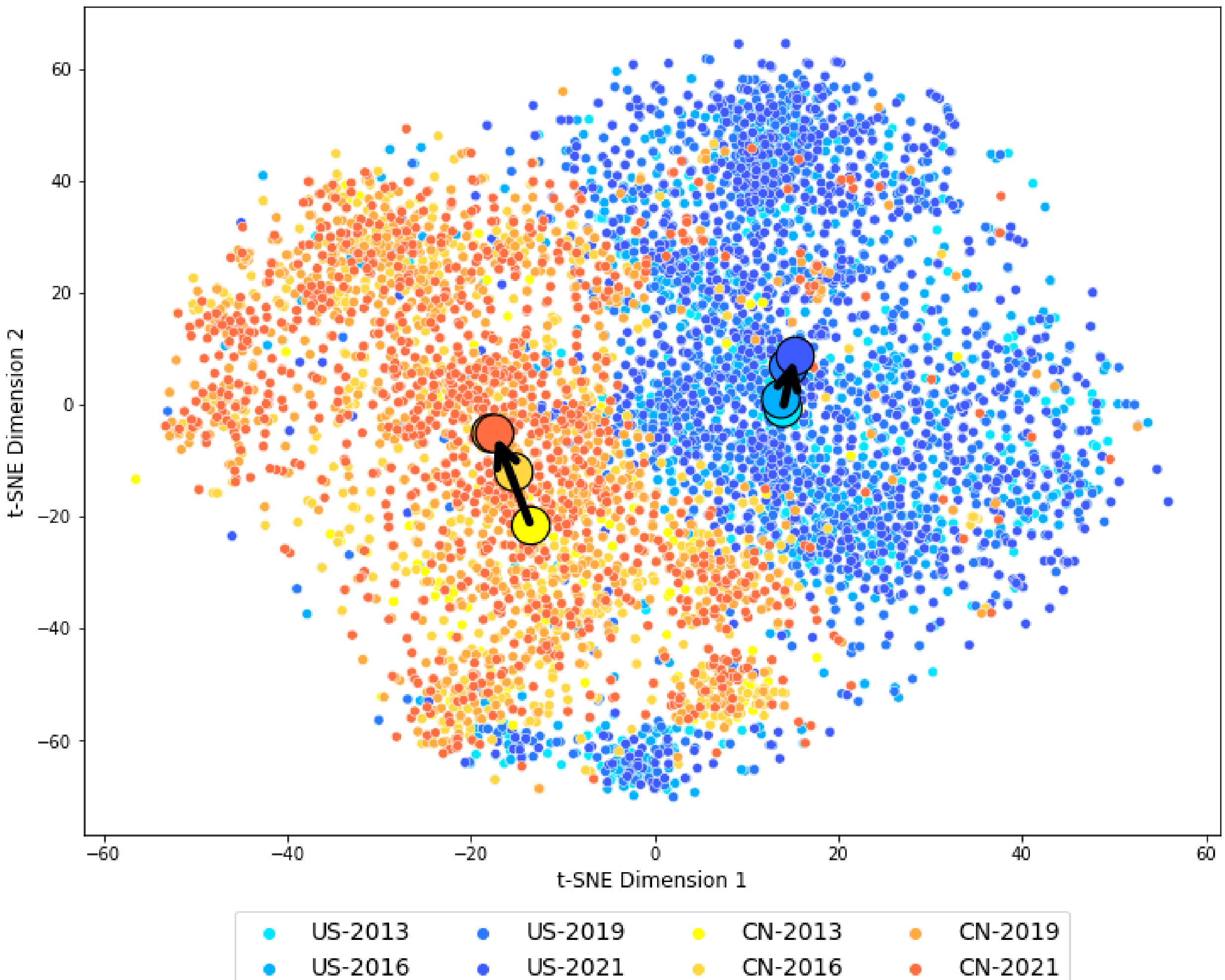
We adopt the t-SNE algorithm to project high-dimensional patent vectors into a two-dimensional space and show the results in Figure A-5. The small blue dots represent U.S. patents filed in 2013, 2016, 2019, and 2021, while the larger circles indicate the centroid of the patent distribution for each corresponding year. The black arrow traces the directional shift of these centroids from 2013 to 2021. Similarly, the yellow and orange dots represent Chinese self-driving patents. Two key insights emerge from this figure. First, Chinese and U.S. self-driving patents form distinct clusters, with only limited overlap between the blue and orange dots. This pattern suggests that Chinese and U.S. innovators are focusing on different technological domains within the self-driving field. Second, the centroids of Chinese and U.S. patents diverged progressively over time, indicating that their technological trajectories have been increasingly differentiated.

D.2 The NMF Method

In order to generate low-dimensional vector representation for parameter estimation in the quantitative model, we adopt the Non-negative Matrix Factorization (NMF) method to reduce the dimension of vectors generated by the TF-IDF method.

There have been long-lasting interests in transforming texts into low-dimensional dense embeddings. Early works, such as Latent Semantic Indexing (LSA), Latent Dirichlet Allocation (LDA), and Principal Component Analysis (PCA), have been widely used in computational science and natural language processing. However, the low-dimensional matrix generated by these methods

Figure A-5: Visualization of Self-Driving Vehicle Patents: CN vs. US



Notes: This figure visualizes Chinese and U.S. self-driving patents filed in selected years using a two-dimensional t-SNE projection. The small blue dots represent U.S. patents filed in 2013, 2016, 2019, and 2021, while the larger circles denote the centroid of the patent distribution in each corresponding year. For visualization purposes, we only randomly select 1000 patents in each year. The black arrow indicates the directional shift of these centroids from 2013 to 2021. Similarly, the yellow and orange dots represent the Chinese self-driving patents.

contains negative values, which may cause trouble in model estimation. As a result, we adopt the NMF method to lower the dimension of the original TF-IDF matrix, which only returns non-negative values in the low-dimensional matrix.

The NMF method has been widely used in image processing and natural language processing. For instance, in order to do facial recognition quickly, the NMF method can lower the pixels of the original graphs while still keeping the important features, which reduces the time and resource cost in computation. In text mining, the NMF method can reconstruct the original high-dimensional bag-of-words matrix to a low-dimensional topic matrix. Therefore, given a set of documents, the NMF method identifies topics and simultaneously classifies the documents among these different topics. We briefly present the technical features of the NMF method, and please refer to Paatero and Tapper (1994) and Lee and Seung (1999) for technical details.

$$A_{m\times n} = W_{m\times k} H_{k\times n} \tag{19}$$

For a matrix A of dimensions m by n generated by the TF-IDF method, where each element is larger or equal to zero, it can be factorized into two matrices, W and H, as defined in Equation (19). W matrix is usually labeled as the feature matrix, where k is the number of features. H matrix is usually labeled as the coefficient matrix, which serves as the bridge between the original high-dimensional bag of words and the new low-dimensional features. Intuitively, each element of the new low-dimensional vector is a linear combination of elements of the original high-dimensional vector with the coefficients in the H matrix.

In our paper, we adopt the NMF method to identify the technical features of each patent, where we set $k = 256$. As a result, we transform the original $m \times n$ dimensional TF-IDF matrix into a $m \times k$ matrix where m is the number of patents, and n is the count of unique words in the patent abstracts. The coefficient matrix H obtained here can be used to transform any high-dimensional bag-of-words vector to a low-dimensional topic vector.

D.3 Computing IPC-level Trade Frictions

The original tariff rates are provided at the HS product level, as we discussed in Section 2. To derive tariff rates for each IPC category, we utilize patent and export data from listed firms. Specifically, the tariff rate for IPC category x is constructed as follows:

$$\text{exposure to US tariff}_{x,t} = \sum_j \frac{\sum_i \frac{N_{i,x}}{N_i}\text{export}_{i,j,14-16}}{\sum_i \sum_j \frac{N_{i,x}}{N_i}\text{export}_{i,j,14-16}} \text{tariff}^{US}_{j,t}. \tag{20}$$

$\frac{N_{i,x}}{N_i}\text{export}_{i,j,14-16}$ represents firm i's export volume of product j during the 2014–2016 period, weighted by the share of the firm's patents in IPC category x among all its patent holdings up to 2016 $\left(\frac{N_{i,x}}{N_i}\right)$. Since firms may hold multiple patents that each contribute to sales, this adjustment allows $\frac{N_{i,x}}{N_i}\text{export}_{i,j,14-16}$ to better reflect the portion of sales attributable to firm i's patent holdings in IPC category x. Using this measure, we aggregate across all exporters to obtain the total export value associated with IPC x, $\sum_i \frac{N_{i,x}}{N_i}\text{export}_{i,j,14-16}$, and apply these weights to convert HS product-level tariff rates into IPC-level tariff rates. The underlying intuition is that patent holdings reflect a firm's technological capabilities, while exports stem from its production activities—allowing us to use export patterns to link IPC categories with corresponding HS products.

Using the weights $\sum_i \frac{N_{i,x}}{N_i}\text{export}_{i,j,14-16}$, we aggregate various product-level US trade barriers (e.g., export controls) into IPC-level measures. Similarly, we use these weights to convert China's product-level tariffs on US imports into IPC-level tariff rates.[25]

D.3.1 Endogenous Price Effects

Following Handley and Limão (2017), we account for the possibility that changes in tariffs may endogenously influence aggregate prices. Note that from the market equilibrium from our model:

$$\underbrace{M_t \int \mathbf{1}^n_{it}(\omega) p^n_{it}(\omega)^{1-\sigma} d\omega (P^n_{it})^{\sigma-1}\gamma^n_i E^n_t}_{\text{calibrated to match sales by Chinese firms to destination } n} + \sum_{m=1}^{N} (\tilde{\sigma}\tau^{n,m}_{it} c^{n,m}_{it})^{1-\sigma} (P^n_{it})^{\sigma-1}\gamma^n_i E^n_t = \underbrace{\gamma^n_i E^n_t}_{\text{calibrated using expenditures in each destination}}. \tag{21}$$

After matching sales by Chinese firms to destination n and total expenditures in destination n for product i, we can compute (divide both sides by $\gamma^n_i E^n_t$):

$$\sum_{m=1}^{N} (\tilde{\sigma}\tau^{n,m}_{it} c^{n,m}_{it})^{1-\sigma} (P^n_{it})^{\sigma-1} = 1 - \frac{M_t \int \mathbf{1}^n_{it}(\omega) p^n_{it}(\omega)^{1-\sigma} d\omega (P^n_{it})^{\sigma-1}\gamma^n_i E^n_t}{\gamma^n_i E^n_t}, \tag{22}$$

which is the share of sales from non-Chinese firms.

[25] In calculating China's IPC-level tariffs on US imports, we continue to use the concordance based on patent and export data, rather than import composition, since imports primarily reflect input purchases rather than firms' production activities.

We note that aggregate prices satisfy the following condition in the baseline model:

$$(P_{it}^n)^{1-\sigma} = M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma} \tag{23}$$

Given this price index, the share of sales from non-Chinese firms in destination n becomes:

$$\sum_{m=1}^{N} (\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma} (P_{it}^n)^{\sigma-1} = \frac{\sum_{m=1}^{N} (\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}{M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}} \tag{24}$$

Now we consider counterfactual changes in price indices. For clarity, we denote $\widehat{x}$ as the counterfactual value for variable x. In the counterfactual scenario, the condition for price indices becomes:

$$(\widehat{P}_{it}^n)^{1-\sigma} = M_t \int \widehat{\mathbf{1}}_{it}^n(\omega) \widehat{p}_{it}^n(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma} \widehat{\tau}_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}. \tag{25}$$

Dividing Equation (25) by Equation (23), we obtain the general situation:

$$\begin{aligned}\left(\frac{\widehat{P}_{it}^n}{P_{it}^n}\right)^{1-\sigma} = & \underbrace{\frac{M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{share of Chinese firms' sales in destination } n \text{ in baseline}} \times \underbrace{\frac{M_t \int \widehat{\mathbf{1}}_{it}^n(\omega) \widehat{p}_{it}^n(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega}}_{\text{proportional change in Chinese firm sales, teasing out agg price effec}} \\ & + \sum_{m}^{N} \underbrace{\frac{(\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}{M_t \int \mathbf{1}_{it}^n(\omega) p_{it}^n(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma} \tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{sales share of firms from } m \text{ in destination } n \text{ in baseline}} \times \underbrace{\left(\frac{\widehat{\tau}_{it}^{n,m}}{\tau_{it}^{n,m}}\right)^{1-\sigma}}_{\text{proportional change in tariffs}}.\end{aligned} \tag{26}$$

We consider three markets separately:

1. Chinese domestic market: $n = 0$. In the Chinese market, two components of Equation (26) change: (1) Chinese firms' part (even though all Chinese firms sell in domestic markets, their productivity may evolve differently in counterfactual scenarios); (2) tariff rates on US firms

change. Therefore, we have (for $n=0$):

$$\left(\frac{\widehat{P}_{it}^{n}}{P_{it}^{n}}\right)^{1-\sigma} = \underbrace{\frac{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{share of Chinese firms' sales in destination } n \text{ in baseline}} \times \underbrace{\frac{M_t \int \widehat{\mathbf{1}}_{it}^{n}(\omega) \widehat{p}_{it}^{n}(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega}}_{\text{proportional change in Chinese firm sales, teasing out agg price}}$$
$$+ \underbrace{\frac{(\tilde{\sigma}\tau_{it}^{n,US} c_{it}^{n,US})^{1-\sigma}}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{sales share of firms from US in destination } n \text{ in baseline}} \times \underbrace{\left(\frac{\widehat{\tau}_{it}^{n,US}}{\tau_{it}^{n,US}}\right)^{1-\sigma}}_{\text{proportional change in tariffs from China on US}}$$
$$+ \underbrace{\sum_{m \neq US, m \neq 0} \frac{(\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{sales share of firms from non-US and non-Chinese firms in destination } n \text{ in baseline}}. \tag{27}$$

We compute the last term by deducting sales share of firms from non-Chinese firms in China (computed from Equation (24)) from sales share of US firms in China. In this way, we take into account retalitory tariffs by China and US potential export restrictions to China.

2. US market. In the US market, one component of Equation (26) changes: (1) Chinese firms' part due to tariffs and different productivity evolution, which change $p_{it}^{n}(\omega)$, and different exporting decisions, which change $\mathbf{1}_{it}^{n}(\omega)$. We have (when $n = US$):

$$\left(\frac{\widehat{P}_{it}^{n}}{P_{it}^{n}}\right)^{1-\sigma} = \underbrace{\frac{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{share of Chinese firms' sales in destination } n \text{ in baseline}} \times \underbrace{\frac{M_t \int \widehat{\mathbf{1}}_{it}^{n}(\omega) \widehat{p}_{it}^{n}(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega}}_{\text{proportional change in Chinese firm sales, teasing out agg price}}$$
$$+ \underbrace{\sum_{m}^{N} \frac{(\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{sales share of non-Chinese firms in destination } n \text{ in baseline}}. \tag{28}$$

3. ROW market. In the ROW market, one component of Equation (26) changes: (1) Chinese firms' part due to different productivity evolution, which change $p_{it}^{n}(\omega)$, and different exporting

decisions, which change $\mathbf{1}_{it}^{n}(\omega)$. We have (when $n = ROW$):

$$\left(\frac{\widehat{P}_{it}^{n}}{P_{it}^{n}}\right)^{1-\sigma} = \underbrace{\frac{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{share of Chinese firms' sales in destination } n \text{ in baseline}} \times \underbrace{\frac{M_t \int \widehat{\mathbf{1}}_{it}^{n}(\omega) \widehat{p}_{it}^{n}(\omega)^{1-\sigma} d\omega}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega}}_{\text{proportional change in Chinese firm sales, teasing out agg price}}$$
$$+ \underbrace{\sum_{m}^{N} \frac{(\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}{M_t \int \mathbf{1}_{it}^{n}(\omega) p_{it}^{n}(\omega)^{1-\sigma} d\omega + \sum_{m=1}^{N} (\tilde{\sigma}\tau_{it}^{n,m} c_{it}^{n,m})^{1-\sigma}}}_{\text{sales share of non-Chinese firms in destination } n \text{ in baseline}}. \tag{29}$$

We use equations (27)–(29) to calculate endogenous aggregate price adjustments in each product market and destination during the counterfactual exercises.