The Impact of the Trade War: Divergence in Chinese and U.S. Innovations in the Post-Conflict Era

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Abstract

This paper investigates the impact of the US-China trade war on China's innovation activities and the link between Chinese new technology and the US. Employing textual analysis to gauge the resemblance of China's patents to the recent and past US patents, the paper finds that an increase in the firm-level exposure to US export tariffs results in a decrease in the similarity of China's patents to US patents, particularly the most recent ones. Innovations from different countries do not adhere to a single quality ladder but are multi-faceted, as evidenced by the fact that China's innovation similarities to other developed countries decline at heterogeneous magnitudes. Furthermore, this paper finds that the export tariff reduces both R&D investment and patent filings in China, while tariffs on imports from the US show no significant influence. We develop a model featuring firm-level export and innovation decisions on multiple products towards countries with heterogeneous preferences to elucidate the mechanism. The model predictions are consistent with the empirical findings, and we provide further evidence to illustrate the impact of innovation activities on firm performance.

JEL Code: F13, F14, O31, O34

Keywords: trade war, tariffs, patent applications, R&D spending, patent similarity.

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1 Introduction

The US-China trade war commenced in early 2018 when the Trump administration imposed tariffs on imported steel and aluminum. Subsequent actions included additional tariffs on Chinese goods and export sanctions directed at specific Chinese firms, notably those in the high technology and industrial sectors. The primary objective of the trade conflict was to address what the US considered unfair trade practices by China, such as intellectual property theft, forced technology transfer, and trade imbalances. Moreover, strategic objectives were intertwined with national security concerns, particularly regarding China's technological advancements and its perceived challenge to American technological supremacy. In response, China retaliated by imposing higher export tariffs on US products, particularly in the agricultural sector.

Considering that technology is a primary area 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 trade war have on the innovation intensity and trajectory of Chinese firms? How does the trade war shape the performance of Chinese firms through the innovation channel?

To address these two questions, we first construct a matched dataset containing comprehensive details on the operational activities, patent filings, and R&D expenditures of all Chinese publicly listed firms from 2000 to 2021. The number of patent applications and R&D investments are utilized as indicators of firms' innovation intensity. 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, with a focus on the frequency distribution of informative terms. Subsequently, we calculate the cosine similarity between 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.

Subsequently, we empirically investigate the effects of the trade war on firms' innovation intensity and technological trajectory using a Difference-in-Difference approach. The variation in innovation intensity and technological trajectory is assessed by comparing the average innovation characteristics before and after the trade war for each publicly listed firm. Specifically, we segment the sample period into a "pre" period (2014-2017) and a "post" period (2018-2021). The trade war is captured by the firm-level exposure to the changes in export tariffs to the US, import tariffs from the US, and a dummy variable indicating whether the firm faced sanctions imposed by the US government. To address potential endogeneity concerns stemming from the trade conflict's influence on trade volumes, we evaluate firms' exposure to export and import tariffs based on their trade composition during the pre-trade-war era (2014-2016), utilizing available customs data and the actual tariff rates for each product category after 2016. Additionally, we control for firms' operational characteristics and industry fixed effects in the empirical analysis.

We find that changes in export tariffs to the US lead to a substantial decrease in the innovation intensity of Chinese listed firms and drive a technological divergence from US patents. Specifically, a 10 percent increase in export tariffs results in a 7.07 percent decrease in firms' patent filings and a 15.4 percent decline in R&D expenditures. Additionally, it precipitates a decrease in the similarity between Chinese patents and US patents by 3.74 percent from its historical mean. The impact on patent applications manifests immediately after the onset of the trade war, while the effects on R&D spending and similarity become significant from 2019 onwards, amplifying over time. Particularly noteworthy is the more pronounced decrease in similarity concerning recent US patents, indicating a heightened effect on the competitive frontier. These findings suggest that the demand shock triggered by export tariffs undermines Chinese firms' incentives to gain a competitive edge in the US market. Conversely, alterations in import tariffs from the US and sanctions do not yield significant effects on China's innovation activities during the sample period. The subdued impact on the supply side may be attributed to the prevalence of tariffs targeting US exports in sectors with lower innovation intensity, notably in agriculture. Moreover, the effects of sanctions may require more time to materialize due to potential buffer periods.

Two competing yet not necessarily exclusive scenarios underlie the divergence in similarities between Chinese and US patents. On one hand, Chinese firms may lag behind in pursuing the US technology frontier on the same quality ladder. On the other hand, there may be a divergence in the direction of technological advancements between Chinese and US innovators. To disentangle these scenarios, we examine the impact of the increase in US export tariffs on the similarities between Chinese patents and patents originating from Europe, Japan, and South Korea while controlling for changes in export and import tariffs with these countries. The first scenario suggests that alterations in patent resemblance to other countries exhibit comparable magnitudes, whereas the latter scenario allows for varying magnitudes depending on the initial patent resemblance between the US and each of the other countries. Our findings reveal that the similarity to European patents declines more than to US patents, while the decline is of similar magnitude for Japanese patents and smaller for South Korean patents. These varying magnitudes suggest that innovations from different countries do not adhere to a single quality ladder but are multi-faceted. Upon controlling for changes in innovation resemblance between China and the US, the magnitude of the decrease in resemblance between China and other countries diminishes, although the reduction in resemblance with European patents remains significant. These results underscore the existence of common elements in innovation across different countries but also highlight their multidimensional nature.

To elucidate the mechanism by which export tariff shocks affect firms' innovation activities, we construct a partial equilibrium model focusing on multiple-product, multiple-destination firms with heterogeneous preferences across export markets. In our model, firms produce a continuum of products, each with its productivity contingent upon its level of innovation intensity. These firms make decisions on both the extent of investment in innovation and their participation in the export market for each product variety. Unlike conventional trade models that assume symmetry preferences across destination countries, our model integrates distinct country-specific tastes for each product variety. Consequently, changes in export 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 efforts across different product varieties. 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 preferences.

We further explore the impact of the trade war on the performance of Chinese firms through the innovation channel. Our investigation involves analyzing data from two sources. On the one hand, we utilize the data of publicly listed firms spanning from 2000 to 2021. On the other hand, our study uses the data of manufacturing firms in the Annual Survey of Industrial Firms data (ASIF) between 2000 and 2013, which was obtained from the National Bureau of Statistics (NBS), encompassing all firms in the industrial sector with sales above five million yuan. By examining the correlation between firms' performance metrics (such as revenue and exporting behavior) and their innovation activities (measured by the number of patent applications and the similarity of patents to those originating in the US), we uncover two major findings. First, we observe that a 10-percentage-point decrease in similarity to US innovations from its historical average corresponds to a 0.75% decrease in revenue, a 0.05% decrease in the probability of exporting, and a 0.25% decrease in export volume. Moreover, we find that the number of patent filings is correlated with firms' decisions to export but not their revenue. Specifically, a 10% decrease in patent applications is associated with a 0.33% decrease in the probability of exporting and a 1.52% decrease in export volume.

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., Fajgelbaum et al., 2019; Amiti, Redding and Weinstein, 2019; Fajgelbaum et al., 2023), especially from the perspective of Chinese firms (e.g., Benguria et al., 2022; Jiao et al., 2022). Most of the existing studies on the trade war primarily examine its impact on global trade patterns and welfare,[1]

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

typically assuming firms' productivity as given. On the contrary, our paper concentrates on the dynamic influence of the trade war on firms' productivity by altering the quantity and direction of inventions, leading to the potential prolongation of the trade war's impact.

By centering on innovation, our paper maintains a strong linkage to an extensive literature on trade and innovation. Extensive empirical evidence highlights the influence of changes in trade exposure on R&D expenditures and productivity, as demonstrated in studies such as Autor et al. (2020) for US firms, Lileeva and Trefler (2010) for Canadian firms and Bloom, Draca and Van Reenen (2015) and Aghion et al. (2018) for European firms. Additionally, empirical analysis has been conducted on how Chinese firms' innovation quantities respond to trade liberalization, as evidenced by studies like Liu and Qiu (2016), Bombardini, Li and Wang (2017), and Liu et al. (2021). This literature typically focuses on the impact of trade liberalization, whereas we study an era where trade became more extravagant. We also contribute to this literature by providing a comprehensive analysis of the impact of trade on both quantity (amount of inventions) and direction (the similarity of inventions with foreign countries' technology) of innovation.

Finally, our paper is associated with the comprehensive body of literature that utilizes patent data to quantify the nature of innovation, particularly in studies utilizing contextual analysis. Previous studies on patents predominantly focused on utilizing the structural information of patents, such as patent counts, citations, and technology classes (Hu and Jefferson, 2009; Lerner and Seru, 2017). However, knowledge diffusion and patent quality measured by patent citations are not accurate (Lampe, 2012). A vast amount of information is concealed within the unstructured data of patent texts. Some recent literature has developed new measures by leveraging the text similarity between patent text and product files, as well as the similarity between previous and subsequent patents, to gauge patents' scientific or commercial value (Comin and Hobijn, 2010; Hoberg and Phillips, 2016; Gentzkow, Kelly and Taddy, 2019; Bloom et al., 2021; Kelly et al., 2021). Though these studies employ patent text-based metrics to assess patent quality, which outperforms the citation-based metrics, they only focus on the patents filed in the US. Our paper extends the study by including patents from various patent offices, especially Chinese, Japanese, Korean, and European patent offices, and constructs a text-based metric to assess the technological similarities between patents from different countries.

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 an illustrative model to unveil the mechanisms in the empirical analysis. Section 5 further discusses how the performance of Chinese firms is influenced by the innovation channel. Section 6 concludes.

2 Context and Data

2.1 A Brief History of the US-China Trade War

The China–United States trade war began in January 2018 when then U.S. President Donald Trump started imposing tariffs and trade barriers on China. The main objectives were to address what it considered to be unfair trade practices by China, including intellectual property theft, forced transfer of American technology to Chinese companies, and imbalances in the U.S.-China trade relationship. Despite a phase one agreement reached in January 2020, the conflict continued throughout Trump's presidency. President Joe Biden has maintained the tariffs, and as of early 2024, Trump's campaign considered a 60% tariff on Chinese goods.

The United States imposed tariffs on a wide range of Chinese goods, starting with solar panels and washing machines in January 2018, and eventually 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. By July 2018, the U.S. began imposing tariffs on 34 billion worth of Chinese products, extending to 200 billion by September 2018 and eventually covering 250 billion worth of goods by May 2019. The tariffs targeted a broad spectrum of products, from consumer electronics to textiles and agriculture products, aiming to pressure China on trade practices the U.S. deemed unfair.

China retaliated by imposing tariffs on U.S. 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 U.S. industries, particularly those in states with significant political importance. China's tariffs were seen as a direct countermeasure to the U.S. tariffs, aiming to hurt the U.S. economy in areas where it could potentially influence political pressure on the U.S. administration to change its policies.

Table 1 reports the products that are affected by the tariff escalation the most. The products are defined by the Harmonized System (HS) codes, a standardized numerical method of classifying traded goods. We calculate the difference between the average tariff in 2018-2021 and the tariff in 2017 for each 8-digit HS code, then list the products with the most significant positive changes. The exercise is done 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 most significant increase in export tariff. Among US goods exported to China, agricultural products were imposed the highest tariffs.

Table 1: Products with the Highest Increase in Tariff

Export to the US		Export to China	
HS Product	Tariff Change (Percent)	HS Product	Tariff Change (Percent)
Generators	45.0	Meat, of swine	55.0
Electric accumulators	45.0	Offal, edible	55.0
Electrical apparatus	35.6	Aluminium	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 tariff due to the trade war. The left panel lists the exporting goods from China to the US and the corresponding percent increase in tariff; the right panel lists the exporting goods from the US to China and the corresponding percent increase in tariff.

In addition to tariffs, the U.S. government implemented export controls and sanctions on Chinese firms. These measures were designed to restrict Chinese companies' access to U.S. technology, especially those technologies that could have military applications or contribute to the enhancement of China's surveillance capabilities.

2.2 Data Sources

We begin our analysis by constructing 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 database, the China Stock Market & Accounting Research Database (CSMAR henceforth), provides financial reports of all firms listed in the Chinese stock market. We collect firm name, industry type, ownership, sales, employment, capital stock, R&D spending, and export destinations. We clean firms' basic information and financial reports in the CSMAR data following Tan et al. (2020).

The second source is the China Customs Trade Data (CCTD henceforth). This dataset offers detailed information about firm-level trade transactions from 2014 to 2016, including information on firms' names, trade destination countries (for exports) and origin countries (for imports), eight-digit HS product codes, and the value of their exports and imports in U.S. dollars. We merge the CCTD data with the listed firm data using consolidated firm names (He et al., 2018) to construct listed firms' exposure to tariff changes during the trade war period.

The third dataset consists of 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 Chinese patent data covers all the invention patent filings between 1985 and 2023, detailing an applicant's bibliography information, filing date, grant date, abstract, and references (patents) cited. It also provides the English translations of the abstracts, which are used to construct similarities with US patents. The USPTO provides records of patent grants from 1976 and patent filings since 2000. We collect the same indicators as for Chinese patent data. Moreover, we collect records of patent filings for European countries, Japan, and Korea from the PATSTAT Global 2023 Autumn Edition for supplementary analysis. We describe the data-cleaning process 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.

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 U.S. patents. In 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 USPTO to identify patents filed by U.S. domestic residents.

Next, we clean patent abstract data following standard procedures in 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 et al., 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 method to vectorize each piece of abstract. Before vectorization, we first calculate the document frequency of each word and remove the too-frequent words and too-infrequent words. The document frequency is the count of a word's appearance in different pieces of abstracts. 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 U.S. patents together and drop words with a document frequency larger than 100,000 and lower than 20 (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 point 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 represents the technical features of a patent by highlighting words of relatively high term frequency to document frequency. Thus, the text similarity between the two patents is a good indicator of the technical similarity between them.

Then, we construct the similarity measures between Chinese firms' patents and U.S. patents. We begin our analysis by calculating similarities between Chinese and U.S. patents at the aggregate level. For Chinese patents, we sum up the vectors of patents filed in the same year t and in the same technology class x at the 3-digit IPC level. As a result, each vector represents the technical features of patents filed in year t and in technology class x as a whole. We apply the same method to U.S. patents and construct the patent vectors at the year-IPC level. Then, we calculate the cosine similarity between Chinese patent vectors and U.S. patent vectors with Equation (1). We only compare patents within the same technology class since it is meaningless to compare the technical features between biological patents and semiconductor patents. As a result, we obtained a list of similarities of Chinese patents filed in each technology class x and in each year t to the U.S. patents filed in the same technology class x from 2000 to 2021.

$$\mathrm{Sim}_{x,t,\tau} = CosSim_{x,t,\tau}\{Vector_{CN,t,x}, Vector_{US,\tau,x}\} \tag{1}$$

Moreover, we calculate the patent similarities between patents of listed firms and U.S. patents.

On the one hand, for each firm, we add up the vectors of patents filed in the same year and within the same technology class at the 3-digit IPC level and construct firm-year-IPC patent vectors for all the Chinese listed firms from 2000 to 2021. On the other hand, we sum up the vectors of U.S. patents filed in the same year and the same technology class and construct year-IPC patent vectors for U.S. patents. For each firm, we calculate the cosine similarity of its patent vector of technology class x in year t to the U.S. patent vector of technology class x from 2000 to year t. The above procedures give a list of similarities for each firm's patents of all technology classes and years. We take the simple average of similarities for each firm in each year as the average technical similarity of its patents to U.S. patents, as shown in Equation (2).

$$\text{Sim}_{i,t,\tau} = \frac{1}{N} \sum_{x \in IPC} CosSim_{i,US,x,t,\tau}\{Vector_{i,t,x}, Vector_{US,\tau,x}\} \tag{2}$$

We construct the patent similarities between Chinese patents and European patents, Japanese patents, and Korean patents with the same method. The details are presented in the Appendix for brevity.

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 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 et al., 2017). Given that we consistently account for industry fixed effects in our regression analyses, any changes in competition within firms' output market are already captured. To evaluate 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:

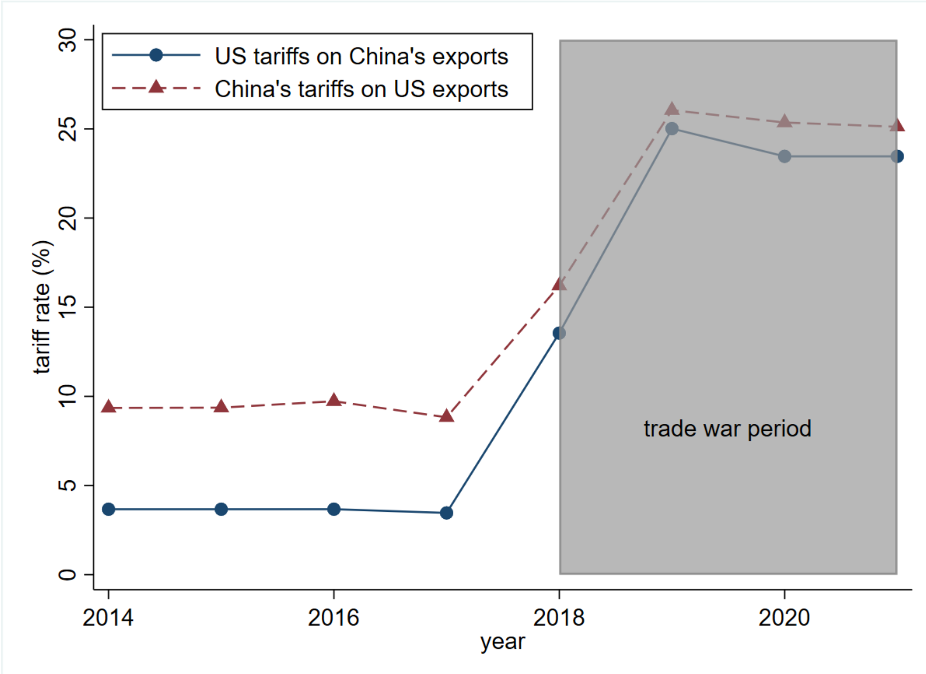
$$\text{exposure to China's tariff}_{i,t} = \sum_j \frac{\text{import}_{i,j,14-16}}{\sum_j \text{import}_{i,j,14-16}} \text{tariff}_{j,t}^{CHN} \tag{4}$$

where $import_{i,j,14-16}$ is the amount of imports for firm i regarding 6-digit HS product j between 2014 and 2016. $\text{tariff}_{j,t}^{CHN}$ 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 explore how the trade war affected Chinese firms' innovation. We start by describing the evidence on tariff changes and aggregate patent similarity changes between Chinese and US patents. Then, we provide a formal 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.

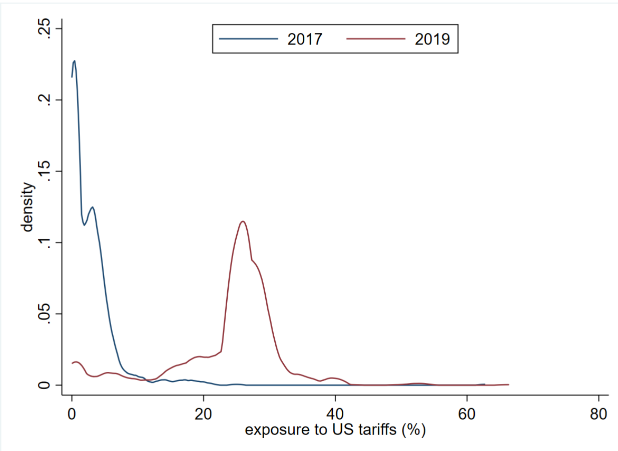
3.1 First Glance at Data

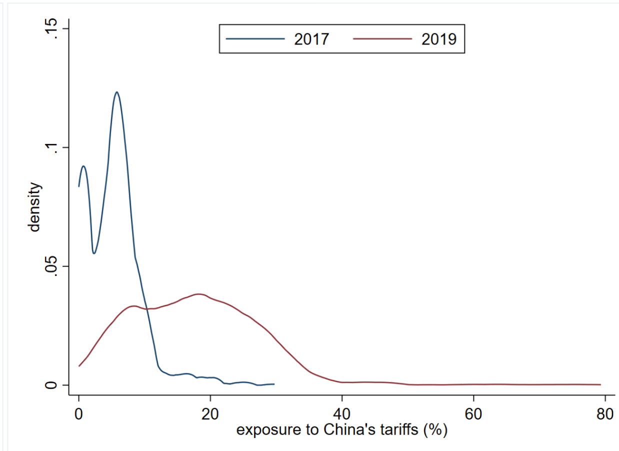
Figure 1 displays the overall patterns in tariff rates during the trade war period, in line with previous studies (Fajgelbaum et al., 2019; Amiti, Redding and Weinstein, 2019; Fajgelbaum et al., 2023). Specifically, the US imposed a tariff increase of approximately 20 percentage points (averaged across 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 by using Equations (3) and Equation (4). The data reveals a significant rise and substantial diversity in changes experienced during the trade war timeframe. This variability suggests the potential for varying impacts of the trade war on firms, a factor that will be explored in our empirical analysis.

Figure 3 displays the aggregate similarity between Chinese and US patents in the ICT and

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





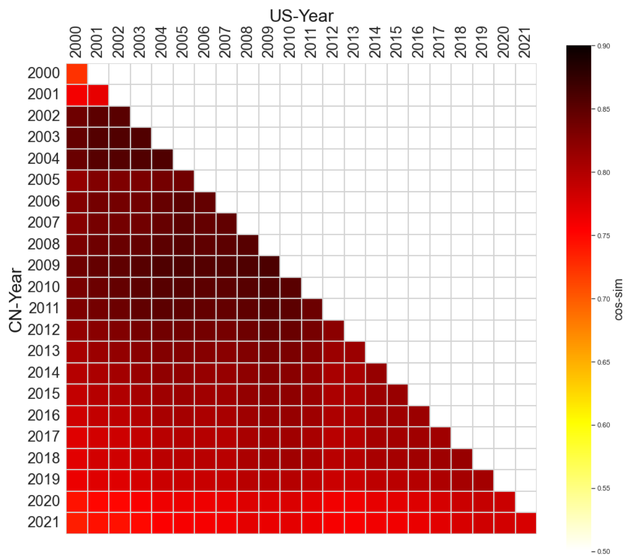
Notes: The figure shows the distribution of Chinese listed firms' exposure to tariffs on export to the US (Panel (a)) and tariffs on import from the US (Panel (b)). 2017 and 2019 are respective one year before and after the start of the trade war.

Electrical Computers and Digital Processing Systems industries. We first separately identify the ICT patents and the Electrical Computers and Digital Processing Systems patents filed by the Chinese and US patent offices and then calculate the similarities between them. [2] For instance, the left panel of Figure 3 shows the similarities between Chinese and US ICT patents from 2000 to 2021. Each pixel represents the similarity between Chinese patents filed in year t to US patents filed in year τ. Under the assumption that the US is the leading country in technology, we only visualize the similarity between Chinese patents that are filed in year t and the US patents that are filed before year t. Here, we sort the Chinese patents according to filing year in the rows and the US patents in the columns. The pixel in the southwest corner represents the similarity between Chinese patents filed in 2021 and US patents filed in 2000. The pixel in the southeast corner represents the similarity between Chinese patents filed in 2021 and US patents filed in 2021. The pixel in the diagonal represents the similarity between Chinese and US patents filed in the same year. Both panels depicted in Figure 3 demonstrate a decrease in the similarities between Chinese

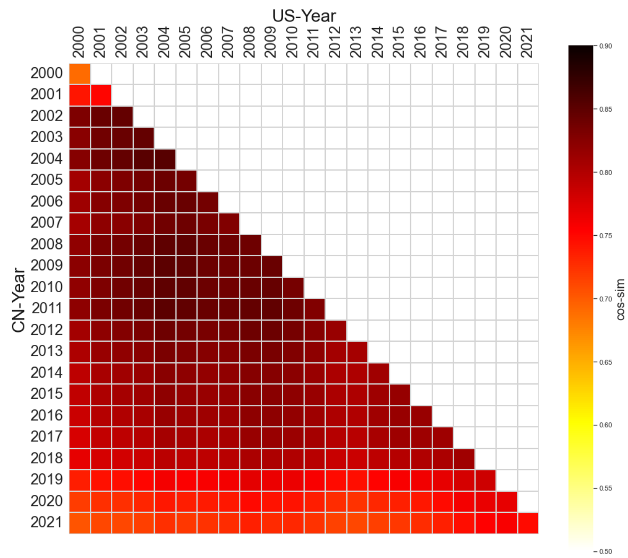
[2]The ICT sector includes four subfields: telecommunications, consumer electronics, computers, office machinery, and other ICTs (OECD, 2007). The definition of Electrical Computers and Digital Processing Systems can be found at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports.htm.

Figure 3: Similarity between Chinese and US Patents

(a) ICT



(b) Electrical Computers and 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.

and US patents during the post-trade war period.

3.2 Identification Strategy

As shown in the previous section, the trade war largely increased the tariff imposed on China's exports to the US and China's imports from the US. In the same period, the industry-level similarity between Chinese and US patents stopped its previous rising trends. To identify the impact of the export and import tariff on China's innovation activities, we start with the following regression,

$$Y_{ist} = \alpha_i + \beta_1 ln(1 + \text{tariff}_{it}^{E,US}) + \beta_2 ln(1 + \text{tariff}_{it}^{I,US}) + \beta_3 \text{sanction}_{it} + \gamma X_{it} + \mu_t + \theta_{st} + \epsilon_{ist}. \tag{5}$$

where i indexes firms, s indexes the firms' 3-digit industry code, and t indexes years. The dependent variable, Y_{ist}, includes measures of the intensity and the direction of China's innovation. The natural logarithm of the number of patents applied by the firm and the natural logarithm of the firm's R&D expenses are, respectively, proxies of the firm's innovation output and input. The firm-level similarity measure developed by this paper is a proxy for the firm's innovation direction. We use the demeaned average similarity to US patents granted in the recent 0-5 years (i.e., $\frac{1}{5}\sum_{\tau=t}^{t+5}\text{Sim}_{i,t,\tau}$) and assign value 0 to firms without any patent applications in the baseline regression. The regression results with similarity not demeaned and with similarity being missing if no patent applications are shown in the Appendix. The trade-war related independent variables include the firm-specific export tariff, $ln(1+\text{tariff}_{it}^{US})$, the firm-specific import tariff, $ln(1+\text{tariff}_{it}^{CHN})$, and a dummy variable, sanction_{it}, indicating whether the firm is sanctioned at year t. We control firm-level characteristics in X_{ist}, including the natural logarithm of firm sales, employment, assets, and the level of net profit in billion yuan. α_i controls the firm fixed effect that captures unobserved firm-level heterogeneity. μ_t denotes the year fixed effect that represents the time variation in the aggregate economy. θ_{st} denotes the industry by year fixed effect that captures the variations of industry-level characteristics across time.

The empirical strategy above is subject to two potential problems. First, the error term may have a serial correlation since the export and import tariffs after 2016 are constructed by the tariff between 2014 and 2016. Second, the innovation direction may not change very quickly after the yearly shock since it takes time to alter the target of the innovation process. This will lead to limited time variations of patent similarity across years within a firm and also contribute to the serial correlation in the error term. To address these problems, we adopt the correction method suggested by Bertrand, Duflo and Mullainathan (2004). We collapse the data into a "pre" period (2014-2017) and a "post" period (2018-2021) of the trade war. Then we take the first difference of the variables in Equation (5),

$$\Delta Y_{is} = \mu + \beta_1 \Delta ln(1+\text{tariff}_i^{E,US}) + \beta_2 \Delta ln(1+\text{tariff}_i^{I,US}) + \beta_3 \Delta\text{sanction}_i + \gamma X_{i,14-17} + \theta_s + \epsilon_{is}. \tag{6}$$

The dependent variable (ΔY_{is}) denotes the change in the innovation output, input, and similarity to US patents. $\Delta ln(1+\text{tariff}_i^{E,US})$ and $\Delta ln(1+\text{tariff}_i^{I,US})$ respectively represents the change in

Table 2: Summary Statistics

	2014-2017					2018-2021				
	count	mean	sd	min	max	count	mean	sd	min	max
Patent Application Number	3480	14.08295	136.9371	0	4413.5	3480	18.94339	175.1308	0	7413.25
R&D Spending (Yuan)	3480	1.26e+08	5.54e+08	0	1.23e+10	3480	2.59e+08	1.14e+09	0	2.68e+10
Similarity to US Patents (0-5 Years)	3476	.5325414	.6052511	0	4.643037	3477	.6062325	.5986431	0	4.435253
Export Tariff (China-US)	3480	.6700711	1.939411	0	20.4988	3480	5.247515	9.947808	0	64.56516
Import Tariff (China-US)	3480	1.331904	3.038335	0	29.76928	3480	3.869581	8.120883	0	67.51168
Sanctioned	3480	0	0	0	0	3480	.0238506	.1526054	0	1

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

the firm-level export and import tariff. $\Delta\text{sanction}_i$ is the change in the sanction status of the firm. Instead of putting in the difference in the firm-level characteristics, ΔX_{it}, we use the characteristics in the "pre" period, $X_{i,0}$, to reduce endogeneity. Besides the natural logarithm of firm sales, employment, assets, and the level of net profit in billion yuan, we add a dummy variable indicating whether the firm is state-owned. The constant term, μ, reflects the change in the aggregate economy in the two periods. The industry fixed effect, θ_s, is controlled to capture the industry-level change between periods.

The summary statistics of the variables related to the innovation intensity, direction, and trade war in the "pre" and "post" periods are displayed in Table 2. There are 3480 firms that exist in both periods. The average patent application number, R&D spending, and similarity to the US patents are larger in the "post" sample. Both the export and import tariffs between China and the US experienced a significant rise. Around 2.4% Chinese firms are sanctioned in the "post" period.

3.3 Impact of the Trade War on China's Innovation

The impact of the trade war on Chinese firms' innovation intensity and direction is reported in Table 3. Column (1) shows that when only the changes related to the trade war are controlled, a 10 percent increase in the export tariff on Chinese goods leads to a decrease in the number of patent applications of Chinese firms by 4.10 percent. This coefficient does not change much when firm characteristics are controlled (column (2)). When the industry fixed effect is added into the regression (column (3)-(4)), the effect of the export tariff becomes more negative and significant, indicating that industries with higher patent growth over time were imposed more export tariffs. The import tariff also has a negative effect on firms' patent applications, but the effect is not significant. This may be because the import tariff on US goods is mostly imposed on the agricultural industries that are not innovation-intensive. The sanction dummy is significantly positive without the firm or industry control but becomes insignificant with both controls. This implies that the US sanction was enforced on Chinese firms and industries with high growth potential in innovation activities. However, the sanction itself does not have a strong impact on firms' R&D output. The insignificant effect may be due to the limited time span of our observations, as the sanction mostly came with a buffer period. The sanction may have larger influences in the long run.

The effect of the trade war on Chinese firms' R&D spending has similar patterns to patent applications, but the magnitude is larger (columns (5)-(8)). A 10 percent increase in the export tariff on China's goods leads to a 15.41 percent decrease in Chinese firms' R&D expenses. The larger magnitude may be attributed to a convex R&D cost function, which is widely found in the literature (Blundell, Griffith and Windmeijer (2002), Hall and Ziedonis (2001), and Bloom, Griffith and Van Reenen (2002)). The effect of the import tariff is weaker, probably due to the same reason that the tariff is implemented most on industries with low innovation intensity. The sanction on Chinese firms has little impact on firms' innovation input in the observation periods.

Columns (9)-(12) report the change in the Chinese patents' similarity to US patents that were filed in the recent five years. Without controlling firm characteristics and the industry fixed effect, a 10 percent increase in the export tariff decreases the similarity by 4.08 percent of its historical average. The absolute magnitude of this coefficient decreases slightly to 3.74 when both the firm- and industry-level controls are included. Neither the import tariff nor the sanction has a significant effect on the similarity to US patents in the sample periods.

In summary, the results in Table 3 indicate that the export tariff imposed on Chinese goods by the US government significantly decreases the innovation intensity (both output and input) of firm-level innovation in China. Besides, the export tariff also causes a divergence of China's innovation activities from the US. The effect of the import tariff due to China's retaliation and the sanction does not significantly affect the intensity and direction of China's R&D activities.

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

	Patent Application Number				R&D Spending				Similarity to US Patent (0-5 Years)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Export Tariff	-0.410**	-0.483**	-0.615***	-0.707***	-3.165***	-3.182***	-1.386*	-1.541**	-0.408***	-0.393***	-0.373**	-0.374**
	(0.170)	(0.186)	(0.155)	(0.166)	(0.985)	(0.803)	(0.765)	(0.588)	(0.108)	(0.118)	(0.153)	(0.150)
Δ Import Tariff	-0.0744	-0.152	-0.107	-0.215	-2.578**	-2.256*	-1.431	-0.838	-0.249	-0.259	-0.253	-0.262
	(0.247)	(0.238)	(0.254)	(0.247)	(1.252)	(1.218)	(1.115)	(1.054)	(0.203)	(0.188)	(0.211)	(0.195)
Δ Sanction	0.232***	0.205***	0.154**	0.129	-0.412	-0.559	-0.306	-0.244	0.0620	0.0619	0.0792	0.0891
	(0.0742)	(0.0649)	(0.0745)	(0.0781)	(0.429)	(0.514)	(0.447)	(0.523)	(0.0624)	(0.0631)	(0.0698)	(0.0732)
Firm-level Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Industry Fixed Effect	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Observations	3,621	3,484	3,618	3,480	3,621	3,484	3,618	3,480	3,613	3,477	3,610	3,473
R-squared	0.004	0.025	0.055	0.073	0.005	0.018	0.079	0.100	0.005	0.005	0.032	0.034

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

The significant impact of the export tariff on China's innovation activities highlights the effect of the demand change. The weakened demand from the US market may decrease the incentive of Chinese firms to mimic US patents since the benefit of getting a cost advantage against US goods decreases. This effect is predicted to be more salient for similarity with recent US patents because the competitive fringe matters the most. To verify this conjecture, we calculate the similarity between Chinese patents and US patents by different vintages. Specifically, the demeaned similarity of a Chinese firm's patents filed in year t with all the US patents filed in year t and $t-1$, $\frac{1}{2}\sum_{\tau=t}^{t+2} \text{Sim}_{i,t,\tau}$, captures the closeness of the firm's innovation to the competitive fringe with other goods providers for the US market. US patents filed in year $t-2$ and $t-3$ are further away from the frontier, while patents filed in year $t-4$ and $t-5$ are even further. The similarity to these older vintages is less subject to competition for the market demand.

The effect of the trade war on patent similarity by US patent vintages is reported in Table 4. For all vintages, including the firm and industry controls, do not substantially alter the coefficient of the export tariff (columns (1)-(4), columns (5)-(8), and columns (9)-(12)). Comparison among different vintages shows that the export tariff has a larger influence on similarity to more recent US patents. A 10 percent increase in the export tariff decreases the similarity to US patents filed in the current and the previous one year by 4.01 percent of its historical average when firm- and industry-level controls are added, while the decrease is 3.46 percent for US patents filed in the previous four and five years. This result confirms that the demand shock is more salient for China's patent similarity with the most updated technology in the US.

Table 4: Impact of the Trade War on Chinese Patents' Similarity to US Patents (by Vintage)

	Similarity to US Patent											
	0-1 Years				2-3 Years				4-5 Years			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Export Tariff	-0.418***	-0.411***	-0.399***	-0.401***	-0.425***	-0.408***	-0.373**	-0.373**	-0.378***	-0.358***	-0.346**	-0.346**
	(0.106)	(0.113)	(0.148)	(0.144)	(0.110)	(0.121)	(0.151)	(0.149)	(0.117)	(0.127)	(0.160)	(0.157)
Δ Import Tariff	-0.245	-0.259	-0.240	-0.253	-0.258	-0.270	-0.261	-0.273	-0.229	-0.237	-0.248	-0.252
	(0.193)	(0.176)	(0.200)	(0.182)	(0.214)	(0.200)	(0.218)	(0.201)	(0.207)	(0.192)	(0.219)	(0.207)
Δ Sanction	0.0720	0.0717	0.0937	0.101	0.0662	0.0659	0.0846	0.0937	0.0499	0.0502	0.0630	0.0764
	(0.0638)	(0.0641)	(0.0724)	(0.0750)	(0.0625)	(0.0639)	(0.0702)	(0.0745)	(0.0622)	(0.0627)	(0.0691)	(0.0723)
Firm-level Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Industry Fixed Effect	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Observations	3,612	3,476	3,609	3,472	3,612	3,476	3,609	3,472	3,612	3,476	3,609	3,472
R-squared	0.005	0.006	0.033	0.036	0.005	0.005	0.033	0.036	0.004	0.004	0.030	0.034

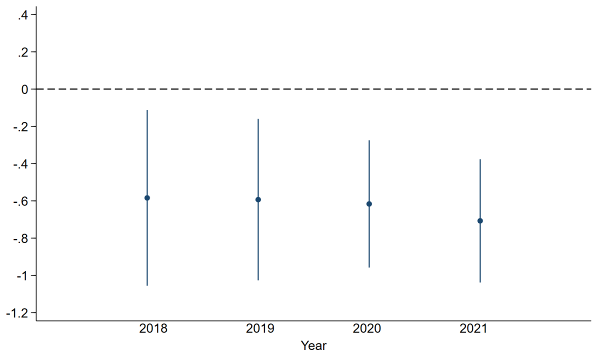
Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

3.4 The Gradual Impact of the Export Tariff

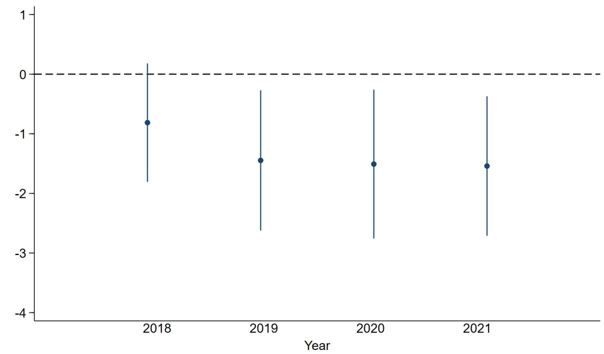
The impact of the export tariff may not be unleashed immediately since it often takes time to make adjustments to innovation activities. To observe the dynamics of the export tariff influence, we moderate the number of years contained in the "post" period while keeping the definition of the "pre" period the same. We include years beginning from 2018 up until year t in the "post" period to capture the impact up until year t. For example, if the "post" period includes year 2018 and 2019, the coefficient of the change in the export tariff represents its impact up until 2019. If the "post" period includes years from 2018 to 2021, the coefficient is the same as in the baseline regression. Figure 4 plot the coefficient and the 95 percent confidence interval of the Δ Export Tariff in regressions with the dependent variables respectively being the patent application number, R&D spending, similarity to US patents filed from five years ago and one year ago. All the controls are included in the regressions.

Figure 4: Effect on Innovation Intensity and Similarity to US Patents

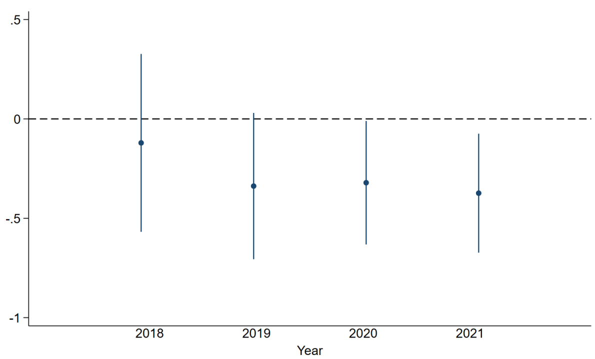
(a) Effect on Patent Application Number



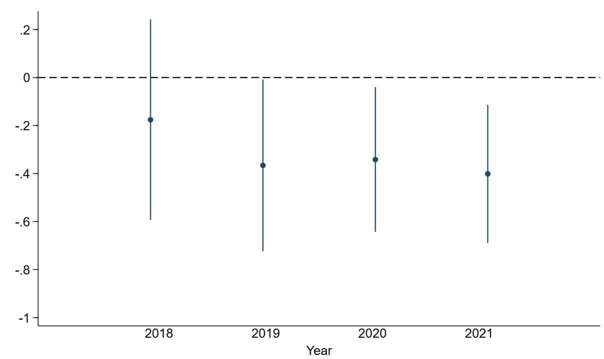
(b) Effect on R&D Spending



(c) Similarity to US in the past 0-5 Years



(d) Similarity to US in the past 0-1 Years



Notes: The figure shows the effect of the export tariff change on Chinese firms' innovation intensity and similarity to the US up until year t. Both the dot estimate and the 95 percent confidence interval are presented. Standard errors are clustered at the 3-digit industry level. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). The industry fixed effect is controlled at the 3-digit level.

Panel (a) of Figure 4 illustrates a rapid decline in Chinese firms' patent applications following the onset of the trade war, with the impact on R&D expenditure becoming significantly negative by 2019. This swift decrease in patent applications suggests a diminished motivation for securing intellectual property rights as market opportunities contract. Conversely, the more gradual adjustment in R&D investment (Panel B) highlights the delayed effect of market demand shocks on R&D commitments. Overall, the adverse consequences of the export tariff on the innovation intensity of Chinese firms have intensified over time. Panel (c) and (d) of Figure 4 demonstrates how the export tariff progressively influenced the alignment of Chinese firms' innovative activities with those in the US. The gradual implementation of the tariff underscores the time required to realign research priorities. The growing significance of this effect reflects an increasing divergence in the innovative endeavors between China and the US.

3.5 China's Innovation Similarity to Other Countries

The divergence between Chinese and US innovations may arise from two distinct scenarios: either China's emerging technologies increasingly lag behind those of the US within a single quality ladder, or China pursues innovation in varieties of goods that diverge significantly from US varieties. To ascertain the prevailing mechanism, our analysis examines the impact of the US-China trade war on the similarity of Chinese patents with those from other high-innovation-intensity economies. Notably, apart from the US and China, Europe, Japan, and South Korea stand out as regions with the highest volume of patent applications. Consequently, this study assesses the similarity of China's patent output with these areas through the execution of the following regression,

$$\begin{aligned}\Delta Y_{is}^{*} =& \mu + \beta_1 \Delta ln(1+\text{tariff}_i^{E,US}) + \beta_2 \Delta ln(1+\text{tariff}_i^{I,US}) + \beta_3 \Delta \text{sanction}_i + \\ & \beta_4 \Delta ln(1+\text{tariff}_i^{E,*}) + \beta_5 \Delta ln(1+\text{tariff}_i^{I,*}) + \eta \Delta sim\_US_i + \gamma X_{i,14-17} + \theta_s + \epsilon_{is}.\end{aligned} \tag{7}$$

where $* \in \{EU, JP, KR\}$. The dependent variable (ΔY_{is}^{*}) represents the variation in the similarity of China's patents to those in Europe, Japan, and South Korea across different patent vintages (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 6), this analysis incorporates changes in export and import tariffs with the respective regions.[3] Δsim_US_i quantifies the similarity between Chinese patents and US patents filed within the same vintage. Assuming a singular quality ladder exists, the disparity in patent similarities between China and other regions should align with the shifts observed between China and the US, given these regions experience little fluctuations in innovation quality. Consequently, the coefficient of the export tariff change is anticipated to resemble those

[3] The summary statistics of the export and import between China and other countries and the similarity of China's patents to those countries are reported in Table A-4 in the Appendix.

presented in column (12) of Table 3 and in columns of Table 4 with all controlled variables when Δsim_US_i is excluded. Conversely, when Δsim_US_i is included, the coefficient of the export tariff change is expected to approach zero. Should different countries innovate in diverse goods varieties, the alteration in patent similarity between China and other regions could differ based on the extent of common elements among the varieties of other countries and those of the US.

Table 5 displays the results on Chinese patents' similarity to European patents. Columns (1)-(4) exclude the similarity to US patents of the corresponding vintage, while columns (5)-(8) include it. The analysis reveals that a 10 percent increase in the US export tariff results in a 4.28 percent decrease from the historical average in the similarity of Chinese patents to European patents filed over the last five years, as shown in column (1). This effect is more pronounced than that on US patents, which stands at 3.74 percent. Even after adjusting for the similarity to US patents within the same timeframe, a significant reduction in similarity to European patents persists, with a magnitude of 0.8 percent. This reduction is primarily attributed to changes in similarity with European patents from the past two to five years. The findings in Table 5 indicate that the export tariffs imposed by the US lead to greater divergence between Chinese and European innovations, suggesting that innovation is multi-faceted rather than confined to a single quality ladder.

Table 6 and Table 7 respectively present the influence of the US-China trade war on Chinese innovation similarity to Japanese and South Korean patents. As shown in column (1) from the two tables, a 10 percent increase in the US export tariff results in a 3.62 percent decrease from the historical average in the similarity of Chinese patents to Japanese patents filed over the last five years, and a 2.48 percent decrease from the historical average for South Korean patents. The former is similar to that on US patents, while the latter is smaller. However, after adjusting for similarities to US patents, the influence on similarity to both Japanese and South Korean patents becomes negligible and statistically insignificant. These variations in the changes in patent similarity across different nations underscore the multifaceted nature of innovation, highlighting that, while there are shared elements, innovations from different countries exhibit distinct characteristics.

Table 5: Impact of the Trade War on Chinese Patents' Similarity to European Patents

VARIABLES	Similarity to European Patents							
	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)
Δ Export Tariff	-0.428**	-0.424**	-0.454***	-0.441***	-0.0846*	-0.0630	-0.119***	-0.136**
	(0.164)	(0.172)	(0.166)	(0.157)	(0.0480)	(0.0684)	(0.0446)	(0.0563)
Δ Import Tariff	-0.355	-0.376	-0.364	-0.324	-0.113	-0.135	-0.132	-0.113
	(0.264)	(0.254)	(0.269)	(0.271)	(0.127)	(0.128)	(0.132)	(0.125)
Δ Export Tariff (EU)	-0.268	-0.0289	-0.813	-0.126	-1.351*	-0.863	-1.837**	-1.563**
	(1.848)	(2.104)	(1.753)	(1.752)	(0.731)	(0.947)	(0.720)	(0.681)
Δ Import Tariff (EU)	-1.620	-1.588	-1.660	-1.792	-1.294*	-1.238	-1.318	-1.394**
	(1.082)	(1.011)	(1.185)	(1.144)	(0.743)	(0.784)	(0.966)	(0.567)
Δ Sanction	0.0272	0.0365	0.0260	0.0301	-0.0569	-0.0565	-0.0579	-0.0375
	(0.0753)	(0.0812)	(0.0788)	(0.0684)	(0.0547)	(0.0618)	(0.0594)	(0.0460)
Similarity to US	N	N	N	N	Y	Y	Y	Y
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,472	3,472	3,470	3,471	3,471	3,471	3,469	3,470
R-squared	0.032	0.032	0.031	0.034	0.804	0.784	0.772	0.782

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). In columns (5)-(8), we control similarity to US patents filed within the same period as the dependent variable. The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

3.6 Pre-existing Trends

One concern about the regression results in the previous sections is that firms that have a higher growth potential in innovation intensities and similarity to the US innovations may be more exposed to the trade shock. Those firms may be large exporters in the industries targeted by the US and, therefore, experienced a larger increase in the export tariff. To check whether there is a pre-existing trend in innovation intensity and direction before the trade war, we leverage the following placebo test,

$$\Delta Y_{is,placebo} = \mu + \beta_1 \Delta ln(1 + \text{tariff}_i^{E,US}) + \beta_2 \Delta ln(1 + \text{tariff}_i^{I,US}) + \beta_3 \Delta \text{sanction}_i + \gamma X_{i,12-15} + \theta_s + \epsilon_{is}. \tag{8}$$

We re-define the "pre" period to be 2012-2015 and the "post" period to be 2016-2017. Both periods are before the start of the trade war. The dependent variable, $\Delta Y_{is,placebo}$, represents the change

Table 6: Impact of the Trade War on Chinese Patents' Similarity to Japanese Patents

VARIABLES	Similarity to Japanese Patents							
	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)
Δ Export Tariff	-0.362**	-0.365**	-0.382**	-0.363**	-0.00519	0.0118	-0.0328	-0.0400
	(0.176)	(0.174)	(0.178)	(0.180)	(0.0785)	(0.0830)	(0.0829)	(0.0921)
Δ Import Tariff	-0.360*	-0.368*	-0.354*	-0.365*	-0.0963	-0.0979	-0.0840	-0.119
	(0.191)	(0.199)	(0.187)	(0.192)	(0.0959)	(0.0931)	(0.108)	(0.120)
Δ Export Tariff (JP)	-0.383	0.855	-1.043	-0.822	0.176	2.030	-1.019	-0.515
	(3.617)	(3.924)	(3.536)	(3.559)	(1.531)	(2.823)	(1.367)	(1.434)
Δ Import Tariff (JP)	-1.540	-1.898	-1.271	-1.054	0.450	0.134	0.764	0.731
	(1.623)	(1.677)	(1.724)	(1.644)	(0.767)	(0.850)	(0.883)	(0.845)
Δ Sanction	0.0141	0.0205	0.0118	0.00775	-0.0691*	-0.0746*	-0.0744**	-0.0616**
	(0.0563)	(0.0515)	(0.0599)	(0.0616)	(0.0351)	(0.0424)	(0.0351)	(0.0309)
Similarity to US	N	N	N	N	Y	Y	Y	Y
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,472	3,471	3,471	3,471	3,472	3,470	3,470	3,470
R-squared	0.033	0.033	0.032	0.033	0.752	0.738	0.734	0.725

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). In columns (5)-(8), we control similarity to US patents filed within the same period as the dependent variable. The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

in the innovation output, input, and similarity to US patents between the new "pre" and "post" periods. $\Delta ln(1+\text{tariff}_i^{E,US})$, $\Delta ln(1+\text{tariff}_i^{I,US})$ and $\Delta\text{sanction}_i$ are the original trade shock as in the baseline regression (Equation 3). Firms' characteristics in the new "pre" period as well as the industry fixed effect are controlled. The results are shown in Table 8. Columns (1)-(4) report the effect on innovation output and input; columns (5)-(7) report the effect on innovation similarity to US patents filed at different time frames. In all columns, the coefficient of $\Delta ln(1+\text{tariff}_i^{E,US})$ is not significant, demonstrating that there is not a pre-existing trend in the innovation activities.

Table 7: Impact of the Trade War on Chinese Patents' Similarity to South Korean Patents

VARIABLES	Similarity to South Korean Patents							
	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)
Δ Export Tariff	-0.254**	-0.261**	-0.266*	-0.248*	-0.0184	-0.000933	-0.0367	-0.0479
	(0.125)	(0.121)	(0.134)	(0.129)	(0.0669)	(0.0620)	(0.0924)	(0.0742)
Δ Import Tariff	-0.271	-0.242	-0.288	-0.242	-0.0902	-0.0599	-0.0958	-0.0801
	(0.211)	(0.207)	(0.202)	(0.233)	(0.0931)	(0.0987)	(0.0951)	(0.124)
Δ Export Tariff (KR)	1.781***	1.827***	1.797***	1.742***	-0.0582	-0.000483	0.0372	0.0151
	(0.626)	(0.633)	(0.662)	(0.654)	(0.322)	(0.302)	(0.405)	(0.449)
Δ Import Tariff (KR)	1.209	1.792	1.144	0.711	0.252	1.066	0.416	-0.635
	(1.070)	(1.145)	(1.158)	(1.015)	(0.812)	(0.868)	(0.950)	(0.826)
Δ Sanction	0.0510	0.0646	0.0421	0.0601	-0.0263	-0.0251	-0.0380	-0.00558
	(0.0484)	(0.0512)	(0.0456)	(0.0516)	(0.0386)	(0.0448)	(0.0403)	(0.0338)
Similarity to US	N	N	N	N	Y	Y	Y	Y
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,473	3,472	3,471	3,471	3,473	3,471	3,470	3,470
R-squared	0.041	0.039	0.042	0.042	0.754	0.741	0.729	0.710

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). In columns (5)-(8), we control similarity to US patents filed within the same period as the dependent variable. The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

Table 8: Placebo Tests

VARIABLES	Patent Application Number		R&D Spending		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)	(11)	(12)
Δ Export Tariff	-0.237	-0.232	0.0108	-0.0278	-0.136	-0.153	-0.191	-0.208	-0.0693	-0.0902	-0.151	-0.163
	(0.195)	(0.190)	(0.531)	(0.552)	(0.170)	(0.163)	(0.168)	(0.162)	(0.187)	(0.177)	(0.172)	(0.166)
Δ Import Tariff	0.0882	-0.0337	0.320	0.335	-0.412**	-0.361*	-0.396*	-0.341	-0.464**	-0.419**	-0.420*	-0.366*
	(0.320)	(0.336)	(1.011)	(1.007)	(0.201)	(0.195)	(0.208)	(0.207)	(0.204)	(0.197)	(0.215)	(0.206)
Δ Sanction	0.149	0.140	-0.262	-0.231	0.0531	0.0745	0.0517	0.0715	0.0526	0.0758	0.0550	0.0768
	(0.0985)	(0.0982)	(0.478)	(0.482)	(0.0662)	(0.0682)	(0.0661)	(0.0684)	(0.0713)	(0.0727)	(0.0626)	(0.0650)
Firm-level Controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,842	2,795	2,795	2,795	2,838	2,791	2,837	2,790	2,837	2,790	2,834	2,788
R-squared	0.024	0.031	0.036	0.036	0.027	0.026	0.028	0.026	0.028	0.027	0.027	0.025

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the new "pre" period (2012-2015). The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

4 Framework

We now develop a simple model to illustrate the mechanisms behind the impact of changes in tariff rates on firms' innovation in China.

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 may produce a product with different features (e.g., different car models, each produced by a firm), and we call 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 preference:

$$U^n = \prod_{i \in \mathcal{I}} (Q_i^n)^{\gamma_i^n} \tag{9}$$

$$Q_i^n = \left[\sum_{\omega} (q_i^n(\omega))^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad \text{where } q_i^n(\omega) = \left(\sum_{k \in \mathcal{K}_i} (\gamma_{ik}^n)^{\frac{1}{\epsilon}} q_{ik}^n(\omega)^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}} \tag{10}$$

where the upper-level preferences in equation (9) are Cobb-Douglas preferences over consumption level of product-level composite goods C_i^n, with γ_i^n governing the expenditure share and $\sum_i \gamma_i^n = 1$. Within each product, consumers have a nested CES preferences over different varieties with the elasticity of substitution $\sigma > 1$. The demand for a variety produced by firm ω is given by $q_i^n(\omega) = (p_i^n(\omega))^{-\sigma}(P_i^n)^{\sigma-1}\gamma_i^n E^n$, where $p_i^n(\omega)$ is the price charged by firm ω for each unit of $q_i^n(\omega)$. P_i^n is the aggregate price index of the composite good of product i in country n, and E_n is country n's total expenditure. Each firm's product is a bundle of different features, with variable $q_{ik}^n(\omega)$ 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.

Firms' Production and Trade Costs. If a firm is endowed with the technology for product $i \in \mathcal{I}(\omega)$, it produces different features of product i using the following equation:

$$q_{ik}(\omega) = z_{ik}(\omega) l_{ik}(\omega), \quad k \in \mathcal{K}_i$$

$z_{ik}(\omega)$ is feature-specific productivity level, and $l_{ik}(\omega)$ captures the amount of labor hired in producing feature k. Given the production function, the firm will minimize the cost of producing each unit of $q_i^n(\omega)$ (after accounting for consumers' preferences toward different features in market n), and thus we can compute the marginal cost of $q_i^n(\omega)$ as:

$$c_i^n(\omega) = \left[\sum_{k \in \mathcal{K}_i} \gamma_{ik}^n \left(\frac{w}{z_{ik}(\omega)} \right)^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} \tag{11}$$

To serve market n, a firm needs to pay iceberg costs $\tau^n \geq 1$. Moreover, exporting a certain product incurs fixed export costs f^n (Melitz, 2003) in units of labor, with the costs of the local market being $\tau^0 = 1$ and $f^0 = 0$.

Firms' Productivity and Innovation. We assume that firms' productivity levels on each product line are determined by two components: an inherent productivity and innovation increment.

$$\underbrace{z_{ik}(\omega)^{\epsilon-1}}_{\text{feature-specific productivity}} = \underbrace{z_{ik}^o(\omega)^{\epsilon-1}}_{\text{inherent productivity}} \times \underbrace{(1 + a_{ik}(\omega))}_{\text{increment from innovation}}$$

$z_{ik}^o(\omega)$ is the inherent productivity. $a_{ik}(\omega)$ reflects the productivity gains due to innovation outcomes on feature ω (i.e., the amount of patents). Incurring a productivity gain by a would cost $\psi a^\gamma,\ \gamma > 1$ units of labor.

Solving Firm's Problem. We first solve a firm ω's optimal prices given productivity levels and export status for each product i. The firm chooses the price to maximize variable profits for each market n:

$$\max_{p} \pi_i^n(\omega) = \left(p - \tau^n c_i^n(\omega)\right) p^{-\sigma} (P_i^n)^{\sigma-1} \gamma_i^n E^n$$

We can solve price $p_i^n(\omega) = \frac{\sigma}{\sigma-1} \tau^n c_i^n(\omega)$. The corresponding variable profits are given by:

$$\pi_i^n(\omega) = \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \tau^n c_i^n(\omega) \right)^{1-\sigma} (P_i^n)^{\sigma-1} \gamma_i^n E^n = \zeta_i^n c_i^n(\omega)^{1-\sigma}$$

where $\zeta_i^n = \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \tau^n \right)^{1-\sigma} (P_i^n)^{\sigma-1} \gamma_i^n E^n$ represents aggregate demand factor from market n for product i.

We can then solve the firm's innovation and export choices to maximize overall net profits for product i:

$$\begin{gathered} \max_{\{a_{ik}(\omega), \mathbf{1}_i^n(\omega)\}} \sum_{n=0}^{N} \mathbf{1}_i^n(\omega) (\zeta_i^n c_i^n(\omega)^{1-\sigma} - w f^n) - \sum_{k \in \mathcal{K}_i} \psi a_{ik}(\omega)^\gamma w \\ \text{s.t. } z_{ik}(\omega)^{\epsilon-1} = z_{ik}^o(\omega)^{\epsilon-1} \times (1 + a_{ik}(\omega)) \end{gathered} \tag{12}$$

where $\mathbf{1}_i^n(\omega)$ is a dummy variable indicating whether to export product i to market n (the firm always sells in the domestic market with $\mathbf{1}_i^0(\omega) = 1 \ \forall \ \omega$). Using the first-order condition, we can obtain the following solutions for the number of inventions:

$$a_{ik}(\omega) = \left(\frac{(\sigma-1) \sum_{n=0}^{N} \mathbf{1}_i^n(\omega) \zeta_i^n c_i^n(\omega)^{\epsilon-\sigma} \gamma_{ik}^n z_{ik}^o(\omega)^{\epsilon-1}}{(\epsilon-1) w^\epsilon \psi \gamma} \right)^{\frac{1}{\gamma-1}}$$

It is clear that investments $a_{ik}(\omega)$ depend on the export market, reflecting the interaction between trade and innovation. In particular, this interaction stems from market size effects (Schumpeter, 1942; Acemoglu and Linn, 2004), as supported by the extensive evidence in both China and other countries (e.g., Lileeva and Trefler, 2010; Bustos, 2011; Liu et al., 2021)

Our model implies a permutation problem for deciding the set of export destinations from all feasible combinations. In total, there are 2^N feasible combinations of destination markets $\mathbf{1}_i^n(\omega) \in \{0, 1\}$ for each market $n = 1, ..., N$. To solve the choice of export destinations, we first evaluate the benefit in equation (12) given each feasible combination of export destinations and then choose the optimal combination of export markets that delivers the highest profits.

In our model, the total quantity of innovation output for firm ω in product i is $\sum_{k\in\mathcal{K}_i} a_{ik}(\omega)$. Suppose that different features correspond to different words in the text. We can thus compute the similarity between firm ω's innovation and another vector of innovations characterized by amount b_{ik} in product i:

$$Sim = \frac{\sum_{k\in\mathcal{K}_i} a_{ik}(\omega) b_{ik}}{\left[\sum_{k\in\mathcal{K}_i}(a_{ik}(\omega))^2\right]^{1/2}\left[\sum_{k\in\mathcal{K}_i}(b_{ik})^2\right]^{1/2}} \tag{13}$$

Model Predictions on Tariff Changes. We now use our model to study a firm's response to changes in export market conditions. In particular, we study a scenario where there are higher ad valorem tariffs in market n, which implies higher iceberg trade τ_n. We have the following results.

- Higher tariff rates in market n increase iceberg costs τ_n, lowering export revenues ζ_i^n.
- Lower export revenues ζ_i^n reduce innovation quantity $\sum_{k\in\mathcal{K}_i} a_{ik}(\omega)$ if the firm is actively engaged in producing i and exporting to market n.
- Lower export revenues ζ_i^n will also move the direction of innovations in product i to be less driven by consumers' tastes in country, γ_{ik}^n.

Data Requirement If we treat product i as an IPC category and feature k as reflecting a cluster of words within the IPC category, we now need two moments:

- We need a mapping between HS products and IPC categories.
- We need to compute the frequency of each cluster of words within each IPC category for Chinese patents and the US patents.

Quantification. We treat each product as an IPC category. Each firm ω has a number k of products that it can potentially produce. We assume that $k \sim Pois(\lambda)$. Given the number k, the specific set of products that it produces is given by $\{i^1, ..., i^k\}$, each of which is randomly drawn among I products according to a distribution $G(i)$. As a starting point, we can think of $G(i)$ as a uniform distribution. Firms also draw initial productivity for each product and for each feature, $z \in F(z)$. As a starting point, we can think of $F(z)$ as Pareto distribution.

For each product i and feature k, market n's overall demand is given by $\gamma_{ik}^{n}\zeta_{i}^{n}$ (needs calibration). (As a starting point, we can consider home and foreign country) We also consider fixed cost of exporting to foreign country, f, as well as innovation costs ca^{γ}. (needs calibration)

5 The Impact of Similarity on Firms' Performance

The preceding sections highlight that the US-China trade war has led to a reduction in China's innovation endeavors and a decrease in the similarity between Chinese and US patents. However, what can we glean from the decline in Chinese patents that are less similar to those of the US? In this section, we aim to establish a connection between the similarity of Chinese patents to US patents and the performance of Chinese firms. We will explore the correlation between a firm's patent similarity with the US and its revenue and export behavior. To check these, we conduct the following regression model:

$$LnY_{ist} = \beta_0+\beta_1 Ln(acmapp_{ist}+1)+\beta_2 Avgsim_{ist}+\beta_3 Ln(capital_{ist})+\beta_4 Ln(labor_{ist})+\eta_i+\eta_{st}+\epsilon_{ist} \tag{14}$$

In Equation (14), LnY_{ist} represents the performance of firm i in industry s during year t. The variable $acmapp_{ist}$ denotes the cumulative number of patent applications for firm i up to year t. To address the issue of zero-value patents, we take the logarithm of the cumulative patent count, adding 1 to the value. Additionally, we calculate the average similarity of all patents filed by firm i up to year t with respect to US patents, denoted as $avgsim_{ist}$.[4] $Ln(capital_{ist})$ and $Ln(labor_{ist})$ represent the logarithm of firm i's fixed assets and employment levels in year t, respectively. These variables are included as controls in the regression to account for the possibility that firms with greater capital and labor resources may have more patents and exhibit better performance. In addition to capital and labor, we account for firm fixed effects η_i and industry-year fixed effects η_{st} in the regression to control for unobservable factors specific to each firm and industry-year combinations, respectively.

The regression results for Equation (14), which examines the firm's performance in terms of

[4] Note that in this calculation, same with the previous part, we first normalize the similarity by subtracting the average similarity across IPC 3-digit classes. This normalization allows us to compare the similarity of patents belonging to different technology classes and compute the average. For firms without patents, we set their similarity to US patents equal to zero.

Table 9: The Impact of Patents' Similarity on Firms' Revenue and Productivity

	Listed Firms: 2000-2021				NBS Firms: 2000-2008, 2011-2013			
	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)
Ln(acmapp+1)	-0.005	-0.005	-0.004	-0.004	-0.001	0.001	0.008**	0.006*
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Avgsim	0.075***	0.058***	0.061***	0.061***	0.006	0.009*	0.004	-0.002
	(0.018)	(0.017)	(0.017)	(0.017)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(capital)	0.197***	0.221***	0.212***	0.197***	0.242***	0.242***	0.245***	0.245***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.003)	(0.003)	(0.003)	(0.003)
Ln(labor)	0.536***	0.503***	0.514***	0.536***	0.255***	0.255***	0.281***	0.281***
	(0.015)	(0.013)	(0.014)	(0.015)	(0.006)	(0.006)	(0.006)	(0.006)
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Industry-year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	44,568	49,374	47,057	44,568	1,419,919	1,695,727	1,695,727	1,419,919
Adjusted R-squared	0.891	0.880	0.884	0.891	0.865	0.868	0.868	0.865

Notes: Standard errors are clustered at the 3-digit industry-year level. *** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

revenue, are presented in Table 9. We measure the firm's revenue by taking the logarithm of the prime operating income reported in the firm's accounting statement. We examine the correlation between firms' revenues and their accumulated patent numbers, as well as their average similarity to US patents. To maintain consistency with the previous similarity measurements used in Table 3 and 4, we construct the similarity to US patents for a Chinese patent filed in year t based on its similarity to patent texts of US patents filed from year $t-5$ to t. We also categorize these similarities into three groups: 0-1 year, 2-3 years, and 4-5 years. In columns (1) to (4), a significant positive correlation is observed between the similarity level with US patents and firms' revenue and productivity for all listed firms from 2000 to 2021. However, considering that listed firms represent a small portion of the total number of firms in China, we also conduct the same regression for manufacturing firms in columns (5) to (8). This allows for a larger sample size and increased representativeness. Consistent with the findings in columns (1) to (4), a higher similarity level of the patents owned by a firm is positively correlated with its revenue. Notably, this positive correlation is significant only for patents that are more similar to the most recent US patents.

Continuing with the regression model outlined in Equation (14), we proceed to examine firms' performance in terms of their export behavior. To obtain information about firms' export activities, we merge the manufacturing firms' data with Chinese customs data. For all manufacturing firms spanning from 2000 to 2008 and 2011 to 2013, We define firms' export behavior at the extensive margin by determining whether they export to foreign countries, to the US, and to foreign countries other than the US or not. At the intensive margin, we consider the export volume directed towards foreign countries, to the US, and to foreign countries other than the US, given a positive export volume. Table 10 and 11 present the results for the impact of patent similarity on firms' export behavior at the extensive and intensive margins, respectively.

Table 10: The Impact of Patents' Similarity on Firms' Export Behavior (Extensive Margin)

	Dummy(exp=1)				Dummy(exp to the US=1)				Dummy(exp to other countries=1)			
	0-5 years	0-1 years	2-3 years	4-5 years	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)	(9)	(10)	(11)	(12)
Ln(acmapp+1)	0.033***	0.034***	0.037***	0.038***	0.022***	0.022***	0.025***	0.026***	0.033***	0.033***	0.037***	0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Avgsim	0.005**	0.008***	0.010***	0.004*	-0.000	0.002	0.001	-0.001	0.006***	0.011***	0.009***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(capital)	0.008***	0.008***	0.010***	0.010***	0.004***	0.004***	0.005***	0.006***	0.008***	0.008***	0.010***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(labor)	0.013***	0.013***	0.014***	0.016***	0.009***	0.009***	0.011***	0.012***	0.013***	0.013***	0.015***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,755,289	2,406,951	2,145,682	1,755,289	1,755,289	2,406,951	2,145,682	1,755,289	1,755,289	2,406,951	2,145,682	1,755,289
Adjusted R-squared	0.807	0.785	0.791	0.807	0.712	0.679	0.691	0.712	0.800	0.779	0.785	0.800

Notes: Standard errors are clustered at the 3-digit industry-year level. *** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

The results in Table 10 demonstrate that considering the number of patents a firm holds, firms with higher average similarity to US patents are significantly more likely to be exporters to foreign countries other than the US. Furthermore, this correlation is stronger when examining the export behavior in relation to the average similarity of firms' patents to more recent US patents filed within 0-3 years, compared to patents filed within 4-5 years. However, there is a positive but not statistically significant correlation between a firm's exports to the US and the average similarity of its patents. This finding aligns with the results found in a study by Gong et al. (2023), which suggests that obtaining a patent grant in the US has a signaling effect rather than providing exclusive market rights. Consequently, it primarily increases the export of Chinese firms to regions other than the US (the rest of the world or ROW). Similarly, given the US's prominent position in global production and innovation, innovations that are closely aligned with those from the US can enhance the recognition of Chinese firms worldwide.

Table 11: The Impact of Patents' Similarity on Firms' Export Behavior (Intensive Margin)

	Quantity (exp to foreign countries)				Quantity(exp to the US)				Quantity(exp to other countries)			
	0-5 years	0-1 years	2-3 years	4-5 years	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)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Ln(acmapp+1)	0.152***	0.151***	0.155***	0.160***	0.099***	0.098***	0.105***	0.117***	0.143***	0.142***	0.149***	0.154***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.016)	(0.017)	(0.016)	(0.016)	(0.010)	(0.010)	(0.009)	(0.009)
Avgsim	0.025	0.035**	0.038***	0.027*	-0.006	-0.002	0.007	0.001	0.043**	0.047***	0.052***	0.044***
	(0.016)	(0.015)	(0.015)	(0.016)	(0.027)	(0.025)	(0.025)	(0.027)	(0.017)	(0.016)	(0.015)	(0.017)
Ln(capital)	0.178***	0.178***	0.196***	0.203***	0.177***	0.177***	0.194***	0.193***	0.179***	0.179***	0.196***	0.202***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)
Ln(labor)	0.270***	0.270***	0.311***	0.332***	0.267***	0.267***	0.307***	0.329***	0.260***	0.261***	0.302***	0.319***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)	(0.007)
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	342,196	444,008	411,591	342,196	161,444	205,435	192,779	161,444	334,747	434,316	402,687	334,747
Adjusted R-squared	0.767	0.756	0.761	0.767	0.742	0.725	0.732	0.742	0.756	0.742	0.748	0.756

Notes: Standard errors are clustered at the 3-digit industry-year level. *** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

Table 11 demonstrates the correlation between export behavior and the average similarity of firms' patents at the intensive margin. The results are similar to those observed at the extensive margin, with firms that have higher average similarity to US patents showing a higher volume of exports to foreign countries, particularly countries other than the US.

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 input and output among publicly listed Chinese firms, alongside a divergence in innovation patterns between China and the US.

This divergence does not occur solely along a single quality ladder, as evidenced by the varying degrees of similarity decline between China and other advanced economies, such as Europe, Japan, and South Korea. This suggests that innovation embodies elements of both Romer and Ricardo, as discussed in Hsieh, Klenow and Shimizu (2022). We develop a model incorporating heterogeneous preferences among destination countries to elucidate the potential mechanisms underlying the export shock. an escalation in export tariffs to a particular country diminishes the exporter's incentive to innovate in line with that country's demand. The departure from a symmetric destination setting has received scant attention in prior literature, yet our empirical results underscore its significant role in shaping the nexus between trade dynamics and innovation.

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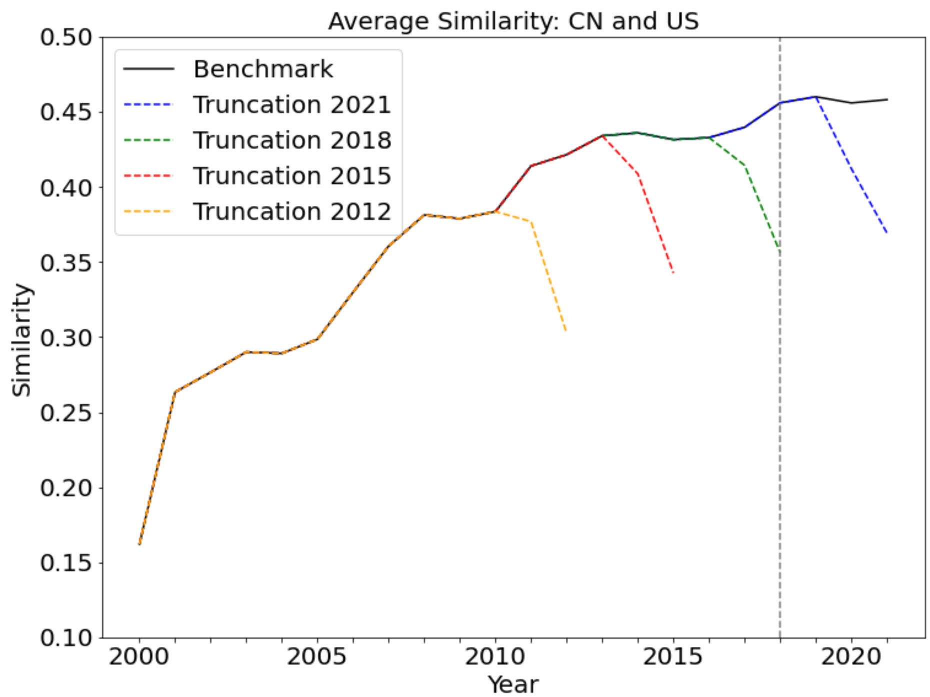
Appendix

A Various Issues of Patent Data

Data Truncation Problem. Although we have up-to-date patent data from the Chinese and U.S. patent offices, we only study the patents filed before 2021. The reason is that according to the patent laws in China and the U.S., a patent filing can be kept from the public for at most 18 months. After that, its filing materials, including abstract, claims, reference cited, description, and illustration graphs, should be open to the public. In this project, we collect patent data published till Sept. 2023, which covers all patent filings before 2021. Moreover, we conduct a robustness check by truncating patent data at different years and comparing the change of similarities. In Figure A-1, the dark line represents the average similarity between Chinese and U.S. 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. Moreover, we manipulate the sample by selecting patents according to their publication 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 are not all 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.

Similarity for 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, 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

Figure A-1: Robustness Check on Truncation of Publication Year

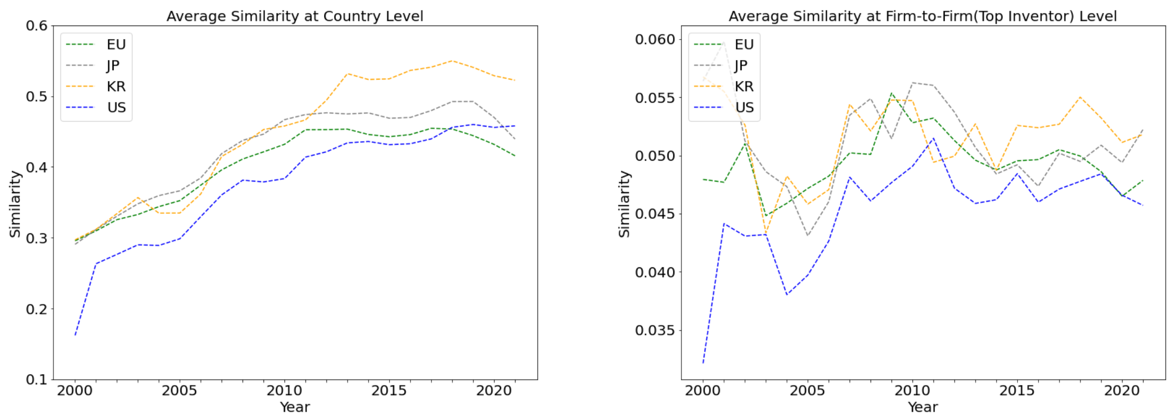


countries and the European Patent Office by the residents in these countries. For Japanese patents and Korean patents, we adopt the same criteria to identify domestic patents. Since the patent office does not always provide an English version of the patent abstract, we look for the patents with non-English abstracts in Google Patents and adopt the English version provided by Google. Only 10.61% of Japanese patents, 20.11% of Korean patents, and 23.21% of European patents 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-2. 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 class 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,

Figure A-2: Similarity between Chinese and Foreign Patents

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



which ceased thereafter. Similarly, we present the aggregate similarity between Chinese listed firms' patents and foreign patents in the right panel of Figure A-2. 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.

Alternative Methods in Constructing Similarities. There is an alternative way to construct vectors for firms and countries. We can first combine patent abstracts according to firm, filing year, and technology class for Chinese listed firms' patents and combine patent abstracts according to filing year and technology class for U.S. patents. Then, we vectorize the combined abstracts.

However, this method may return a biased document frequency while keeping term frequency accurate. Intuitively, the document frequency in this method is determined by the number of Chinese listed firms and technology class coverage of their patents.

B Additional Empirical Results

Tables A-1 through A-3 present regression outcomes employing diverse measures of patent similarity. In Table A-1, the dependent variable is the raw cosine similarity, without undergoing the demeaning process, thereby directly gauging the resemblance of informative terms within Chinese and US patents. The coefficients exhibit qualitative consistency with the baseline results documented in Tables 3 and 4, albeit with differing magnitudes attributable to distinct units of measurement. Specifically, a 10 percent increase in the export tariff corresponds to a 0.23 percent point reduction in similarity to US patents filed within the 0-5 year timeframe, with this effect primarily driven by the similarity to the most recent US patents (filed within the past 0-1 year). Furthermore, the impact of the import tariff increase is more significant than that observed in the baseline analysis.

Table A-1: Robustness Checks—Similarity without Demean

VARIABLES	Similarity to US Patents (Without Demean)							
	0-5 Years		0-1 Years		2-3 Years		4-5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Export Tariff	-0.0244*	-0.0232	-0.0293**	-0.0275**	-0.0242*	-0.0234	-0.0197	-0.0183
	(0.0141)	(0.0139)	(0.0139)	(0.0135)	(0.0141)	(0.0141)	(0.0142)	(0.0140)
Δ Import Tariff	-0.0329	-0.0361*	-0.0324	-0.0364*	-0.0340	-0.0379*	-0.0324	-0.0349*
	(0.0222)	(0.0201)	(0.0216)	(0.0195)	(0.0227)	(0.0207)	(0.0226)	(0.0208)
Δ Sanction	0.00716	0.00808	0.00773	0.00841	0.00795	0.00892	0.00641	0.00757
	(0.00650)	(0.00682)	(0.00655)	(0.00681)	(0.00664)	(0.00704)	(0.00649)	(0.00680)
Firm-level Controls	N	Y	N	Y	N	Y	N	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,610	3,473	3,609	3,472	3,609	3,472	3,609	3,472
R-squared	0.028	0.029	0.030	0.030	0.029	0.030	0.026	0.028

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, asset, the level of net-profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

Table A-2 exhibits the findings obtained after demeaning the similarity measure, wherein it is considered missing if a firm fails to file any patent during the period under consideration. Despite this adjustment, the impact of changes in export tariffs remains significantly negative on similarity to more recent US patents, albeit with a magnitude approximately two-thirds of the baseline value. This comparison suggests that the intensive margin accounts for two-thirds of the observed impact on similarity, while the remaining one-third stems from the extensive margin due to a decreased likelihood for firms to apply for patents.

Table A-2: Robustness Checks—Similarity is Missing when No Patent Application

VARIABLES	Similarity to US Patents (Missing Similarity if No Patents)							
	0-5 Years		0-1 Years		2-3 Years		4-5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Export Tariff	-0.245	-0.225	-0.286*	-0.269*	-0.262*	-0.244*	-0.192	-0.170
	(0.149)	(0.139)	(0.148)	(0.136)	(0.149)	(0.142)	(0.149)	(0.140)
Δ Import Tariff	-0.0184	-0.0349	-0.0184	-0.0337	-0.0277	-0.0487	0.0230	0.00814
	(0.235)	(0.214)	(0.217)	(0.195)	(0.244)	(0.223)	(0.254)	(0.238)
Δ Sanction	0.0102	0.00569	0.0213	0.0158	0.0156	0.00950	-0.000314	-0.000694
	(0.0824)	(0.0826)	(0.0869)	(0.0867)	(0.0863)	(0.0867)	(0.0784)	(0.0786)
Firm-level Controls	N	Y	N	Y	N	Y	N	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,025	1,940	2,024	1,939	2,024	1,939	2,024	1,939
R-squared	0.028	0.029	0.031	0.031	0.030	0.030	0.026	0.029

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

Table A-3 reports the impact of the trade war on the patent resemblance between publicly listed Chinese firms and a subset of US firms that represent the innovation frontier in the US. In this examination, we construct year-IPC-level patent vectors for US firms by selecting only those with an average number of patent applications ranking among the top 20 within each IPC classification from 2000 to 2021. The calculation of cosine similarity and the demeaning process adhere to the methodologies employed in the baseline analysis. Results in Table A-3 indicate that the impact of changes in export tariffs is notably more pronounced and negative compared to the baseline across all columns, suggesting that Chinese innovations deviate further away from the frontier of US innovations.

Table A-3: Robustness Checks—Similarity to US Top 20 Applications

VARIABLES	Similarity to US Patents (Top 20 Applications)							
	0-5 Years		0-1 Years		2-3 Years		4-5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Export Tariff	-0.506***	-0.534***	-0.542***	-0.586***	-0.509***	-0.531***	-0.435**	-0.443**
	(0.176)	(0.175)	(0.194)	(0.200)	(0.176)	(0.173)	(0.183)	(0.179)
Δ Import Tariff	-0.203	-0.177	-0.149	-0.116	-0.237	-0.220	-0.227	-0.188
	(0.227)	(0.211)	(0.230)	(0.213)	(0.239)	(0.227)	(0.239)	(0.227)
Δ Sanction	0.0295	0.0480	0.0177	0.0376	0.0450	0.0585	0.00703	0.0316
	(0.0926)	(0.0941)	(0.0895)	(0.0903)	(0.0980)	(0.0996)	(0.105)	(0.107)
Firm-level Controls	N	Y	N	Y	N	Y	N	Y
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,600	3,464	3,580	3,446	3,589	3,453	3,590	3,454
R-squared	0.029	0.032	0.026	0.029	0.032	0.035	0.028	0.032

Notes: Standard errors are clustered at the 3-digit industry level. Δ denotes a change in a variable between 2014-2017 and 2018-2021. Firm-level controls include the natural logarithm of firm sales, employment, assets, the level of net profit in billion yuan, and a dummy variable indicating whether the firm is state-owned, all measured by the average in the "pre" period (2014-2017). The industry fixed effect is controlled at the 3-digit level.
*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

Table A-4 displays the summary statistics of the patent similarity, export tariffs, and import tariffs between China and Europe, Japan, and South Korea, respectively, in the "pre" and "post" periods. There is an overall increase in patent similarity. The export and import tariffs between China and the aforementioned countries witnessed a marginal decline across the two periods.

Table A-4: Summary Statistics (Similarity and Tariff with Other Advanced Economies)

	2014-2017					2018-2021				
	count	mean	sd	min	max	count	mean	sd	min	max
Similarity to EU Patents (0-5 Years)	3475	.5365003	.6138304	0	6.535175	3477	.5917611	.5787756	0	4.170864
Similarity to JP Patents (0-5 Years)	3475	.5455509	.6229596	0	4.713557	3477	.6032444	.6016168	0	6.18047
Similarity to KR Patents (0-5 Years)	3476	.5381443	.6078777	0	4.8339	3477	.6105147	.5854554	0	6.537392
Export Tariff (China-EU)	3480	.9038183	2.097554	0	22.91203	3480	.8627115	2.099465	0	32.71944
Import Tariff (China-EU)	3480	1.982728	3.557735	0	26.47434	3480	1.757645	3.154867	0	24.81184
Export Tariff (China-JP)	3480	.29248	1.430111	0	23.9922	3480	.294556	1.427042	0	23.9618
Import Tariff (China-JP)	3480	1.295101	2.998806	0	25	3480	1.162472	2.666288	0	20.5
Export Tariff (China-KR)	3480	1.618819	8.572785	0	328	3480	1.188527	6.405991	0	246
Import Tariff (China-KR)	3480	.9514777	2.529741	0	31.15656	3480	.8480661	2.259769	0	15

Notes: This table reports the summary statistics of the main dependent and independent variables in the "pre" and "post" periods of the regression sample of Chinese patent similarity with other advanced economies.

In our model, the total quantity of innovation output for firm i is $\int_0^1 a_i(\omega)d\omega$. Denote $\mathbf{x}(\omega)$ as the vector of words used by innovations in product ω. Then for firm i, the vector of words by its innovations is given by $\int_0^1 a_i(\omega)\mathbf{x}(\omega)d\omega$, which depends on the amount of research carried out in each product and the corresponding vector of words. In particular, if the firm only sells to the domestic market, then the amount of product ω's innovation $a_i(\omega) \propto \zeta_0(\omega)^{1/(\gamma-1)}$ only relies on domestic demand. Thus, the vector $\int_0^1 a_i(\omega)\mathbf{x}(\omega)d\omega \propto \int_0^1 \zeta_0(\omega)^{1/(\gamma-1)}\mathbf{x}(\omega)d\omega$ is purely driven by domestic demand. Furthermore, we can also compute the similarity between firm i's innovation and another vector of innovations characterized by amount $b(\omega)$ in each product ω:

$$Sim = \frac{\int_0^1 \int_0^1 a_i(\omega)b(\omega')cov(\mathbf{x}(\omega), \mathbf{x}(\omega'))d\omega d\omega'}{\left(\int_0^1 \int_0^1 a_i(\omega)a_i(\omega')cov(\mathbf{x}(\omega), \mathbf{x}(\omega'))d\omega d\omega'\right)^{1/2} \left(\int_0^1 \int_0^1 b(\omega)b(\omega')cov(\mathbf{x}(\omega), \mathbf{x}(\omega'))d\omega d\omega'\right)^{1/2}}$$

Numerically, we can treat each product to correspond to a HS code and consider a finite number of products $\omega = 1, ..., N$. Then the similarity is:

$$Sim = \frac{\sum_{\omega=1}^N \sum_{\omega'=1}^N a_i(\omega)b(\omega')cov(\mathbf{x}(\omega), \mathbf{x}(\omega'))}{\left(\sum_{\omega=1}^N \sum_{\omega'=1}^N a_i(\omega)a_i(\omega')cov(\mathbf{x}(\omega), \mathbf{x}(\omega'))\right)^{1/2} \left(\sum_{\omega=1}^N \sum_{\omega'=1}^N b(\omega)b(\omega')cov(\mathbf{x}(\omega), \mathbf{x}(\omega'))\right)^{1/2}}$$

We need to compute the covariance matrix between two products, $cov(\mathbf{x}(\omega), \mathbf{x}(\omega'))$. We can construct $\mathbf{x}(\omega)$ as follows.

$$\mathbf{x}(\omega) = \frac{\sum_i \mathbf{v}_i \frac{ex_i(\omega)}{ex_i}}{\sum_i a_i \frac{ex_i(\omega)}{ex_i}}$$

where $\mathbf{v}_i$ is the vector of words shown in firm i's patents, a_i is the number of firm i's patents, and $\frac{ex_i(\omega)}{ex_i}$ is the share of exports in product ω relative to firm i's all exports.

C Quantitative Analysis

We consider a discrete number N of products, indexed by $n = 1, 2, 3....$ (N is the number of 6-digit HS products). Each firm i has a number k of products that it can potentially produce. We assume that $k \sim Pois(\lambda)$. Given the number k, the specific set of products that it produces is given by $\{n_i^1, ..., n_i^k\}$, each of which is randomly drawn among N products according to a distribution $G(n)$. As a starting point, we can think of $G(n)$ as a uniform distribution. Firms also draw initial productivity for each product, $z \in F(z)$. As a starting point, we can think of $F(z)$ as Pareto distribution.

For each product n, market j's overall demand is given by $P_j(n)^{\sigma-1}\gamma_j(n)E_j$ (needs calibration). (As a starting point, we can consider home and foreign country) We also consider fixed cost of exporting to foreign country, f, as well as innovation costs ca^γ. (needs calibration)