

Trademarks and Gains from Variety: The Role of Multinational Enterprises

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Abstract: The availability of novel differentiated products, or varieties, constitutes a significant portion of the welfare gains from globalization, yet attempts to empirically quantify these gains suffer from a number of shortcomings. This paper uses data on trademarks registered in the United States to overcome one major shortcoming: the inability to disentangle production from design origin of new goods using trade data. First, I quantify the variety gains from trade, obtaining 2-3 times larger variety gains for the years 1995-2014 compared to using standard measures. Second, I study the effect of import competition from China on the introduction of new products. Combining trademarks with detailed Chinese customs data, I show that not all imports are equal from the perspective of variety growth. Only imports from Chinese-owned firms located in China have a detrimental effect on the introduction of new American products in the US market. Instead, imports from multinational enterprises located in China increase the availability of American products for US buyers. This paper suggests that existing estimates of welfare gains from new varieties might be biased in the presence of multinational enterprises and provides a new perspective on the effects of import competition on product innovation.

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“A trademark is any word, name, symbol, or device, or any combination thereof used by a person to identify and distinguish a good or service from those of others [...].”

15 U.S. Code §1127

1 Introduction

The availability of novel differentiated products, or varieties, plays a crucial role within the umbrella of economic innovation. International trade has long been considered a source of new varieties: as trade costs decrease, consumers benefit from both lower prices and increased access to foreign varieties.¹

Quantifying the welfare gains from new varieties, however, remains challenging. While recent access to granular customs data, and therefore detailed trade flow data, has allowed for progress (Feenstra, 1994; Broda and Weinstein, 2006; Amiti et al., 2019; Flaaen et al., 2020), three substantial challenges remain. First, trade flows can only capture foreign varieties, forcing researchers to seek complementary measures of domestic varieties elsewhere (Hsieh and Ossa, 2016; Feenstra and Weinstein, 2017; Amiti et al., 2020; Hsieh et al., 2020). Second, even very disaggregated sectoral classifications are relatively coarse compared to the theoretical notion of a variety as a firm-specific product (Melitz, 2003).² Third, trade flows treat the country of production as an intrinsic characteristic of a variety. While potentially valid for cheese or wine, this assumption may be restrictive in the case of goods manufactured by multinational enterprises (MNEs), which often produce the same product in a number of different source countries.³

These limitations raise important concerns. Consider an Apple smartphone produced in China and sold to American consumers. Does it constitute a “Chinese” or an “American” variety of smartphone? Do its competitors view Apple’s China-produced smartphones as belonging to a Chinese firm? Apple has recently moved the assembly line of some

¹The theoretical literature positing variety gains from trade is well established (Krugman, 1979, 1980; Helpman, 1981; Romer, 1990, 1994; Melitz, 2003), but quantitative applications continue to be relevant to this day (Akcigit and Melitz, 2022; Akcigit and Van Reenen, 2023; Melitz and Redding, 2023).

²For example, the Harmonized System 6-digits code for small SUVs (code 870323 – spark-ignition motor cars with 1,500-3,000 cc) is coarse compared to the number of car models with those specifications. In 2002, there were eighteen models shipped from Japan to the US: Honda CR-V, Isuzu Bighorn, Isuzu VehiCROSS, Infiniti QX4, Mitsubishi Airtrek, Mitsubishi Challenger, Mitsubishi Parejo Wagon, Nissan Murano, Nissan Terrano, Subaru Forester, Suzuki Escudo, Lexus GX, Lexus LX, Lexus RX, Toyota Hilux Surf, Toyota Kluger V, Toyota Land Cruiser 100, Toyota RAV4 (data source: Head and Mayer (2019)).

³This is especially problematic, considering that MNEs account for half of global imports and exports (OECD, 2018).

iPhones to India.⁴ These phones will have the same designs and use the same components as their Chinese-made counterparts. As of yet, there remains remarkably little work accounting for the fact that an iPhone produced in China or India is still an American design.

This paper addresses the question of how to measure the set of available varieties in a country. I propose a new measure using trademarks. Trademarks are a relatively understudied type of intellectual property that protects any word, name, or symbol distinguishing the good or service of a firm from those of its competitors.⁵ They can be seen as the legal counterpart to brands (Griffiths, 2011), thus providing an intuitive link from our theoretical notion of variety to its measurement.

I use data on the universe of federal trademarks registered between 1982 and 2014 at the United States Patents and Trademarks Office (USPTO). I leverage information on the text protected in each trademark, grouping together those referring to the same product. This new measure improves upon those used so far in a number of ways: (i) it covers all sectors, including intermediate goods; (ii) it reports the origin country of the design of varieties, without tracking the location of production; and (iii) it encompasses both domestic and foreign varieties in a market.

The trademark-based measure of varieties suggests that distinguishing the location of design from the location(s) of manufacture is important. It provides two novel empirical facts. First, I show that the share of varieties supplied by manufacturing countries like China, Mexico, and the Philippines is larger when measuring varieties using sectoral US import data than when using trademarks. More specifically, China was the fourth provider of varieties for US consumers when ranked according to sectoral trade flows in 2001, compared to being the twentieth provider of trademarks. That is, China was a major producer and exporter of goods to the United States, but these goods were designed elsewhere.

Second, I complement trademark data with detailed Chinese customs data, reporting the country of ownership of exporters located in China.⁶ I show that Chinese-owned trademarks registered in the United States are correlated with increased imports from Chinese-owned

⁴In August 2023, Apple started manufacturing the iPhone15 in Sriperumbudur, India. Source: [Bloomberg](#).

⁵Section 1127 of text 15 of the U.S. Code provides the following definition of trademark: “any word, name, symbol, or device, or any combination thereof, (1) used by a person, or (2) which a person has a bona fide intention to use in commerce and applies to register on the principal register established by this chapter, to identify and distinguish his or her goods, including a unique product, from those manufactured or sold by others and to indicate the source of the goods, even if that source is unknown”.

⁶The Chinese customs data indicate whether a firm is Chinese-owned or foreign-owned.

firms, but these firms only constitute 40 percent of all US imports from China during the period 2000-2009. The remaining 60 percent is associated with non-Chinese MNEs, and this MNE-led trade has no effect on the number of Chinese trademarks established in the US. This is the first paper establishing a direct and credible connection between customs data and varieties while providing a cautionary result: not all trade is equal from the perspective of variety growth.

This evidence highlights the importance of distinguishing between the country of production and the country of design of a variety. To show this formally, I extend a two-countries heterogeneous-firms [Melitz \(2003\)](#) model of trade to feature export platforms. Firms in the high-wage country pay a fixed cost to produce abroad and enjoy lower wages, but then ship the final products back to be sold in the domestic market. I refer to this multinational activity as re-sourcing. The existence of re-sourcing creates a difference between theory and empirics. In the model, re-sourcing does not create new varieties, as these products are the same regardless of where the production happens. In other words, the model accounts for the fact that an iPhone produced in China is still an American product, while a Huawei smartphone produced in China is a Chinese product. In the empirics, we often only observe sectoral-level trade flows between countries, without information on the nationality of the design behind the products being shipped. In other words, an iPhone produced in China and a Huawei smartphone are both Chinese varieties, simply because we can only observe their production location.

Attributing the correct nationality is important for welfare. To quantify changes in consumer welfare, I decompose the price index into three components: the average unit price of all varieties, the market concentration of firms, and the number of available varieties. This paper focuses on the last component, the change in the set of available varieties, which I will refer to as variety gains from trade. I quantify variety gains from trade using, in turn, two different approaches: first, pairs of country of origin and sectoral Harmonized System 6-digit codes; second, trademarks. These two approaches differ in two main dimensions: (i) sectoral codes are coarse, understating the creation of new varieties within the same category; (ii) sectoral codes treat the country of production as an attribute of a variety, overstating the creation of new varieties due to MNEs activity across multiple countries. I find that variety gains from trade in 1995-2014 are two to three times larger when using trademarks compared to sectoral trade codes. This result suggests that sectoral trade flows ignore some of the relevant variation and fail to capture a large extent of the product

innovation happening within sectoral categories.

The notion that not all trade is equivalent from a variety perspective has potential implications for our understanding of major trade policies, like China opening up to trade and joining the World Trade Organization. This work is the first to illustrate the influence of Chinese import competition on product innovation in the US, disentangling the effect of *direct* import competition and imports from MNEs located abroad. Similarly to the findings of [Autor et al. \(2020\)](#) for patenting activity of large productive firms, I find that overall Chinese import competition has no effect on the entry rate of US varieties. However, by leveraging ownership information of firms located in China, my analysis disentangles two opposing forces at work. I show that an increase in US imports from non-Chinese multinational companies located in China positively affects the introduction of non-Chinese varieties in the US market. On the contrary, US imports from Chinese-owned firms located in China deter product innovation of non-Chinese firms: a 1 standard deviation increase corresponds to a 5-8 percent decrease in domestic varieties offered by new firms in the United States. The deterrent effect on entry is stronger for other foreign varieties, with an effect of up to 13 percent, consistent with Chinese varieties being closer substitutes with other foreign varieties than domestic ones. In order to isolate the supply shock coming from China and allow a causal interpretation of my results, I instrument trade flows from China to the United States with trade flows from China to the rest of the world ([Costa et al., 2016](#); [Hummels et al., 2014](#)).

The heterogeneous effect of US imports from China based on the ownership of exporters is in line with the predictions of the model and highlights the importance of distinguishing between the country of production and the country of design of a variety.

Trademarks come with their own set of limitations. For example, the lack of detailed information on prices and quantities of individual trademarks makes them less suitable to answer questions about the change in the overall price index for American consumers or to estimate the elasticity of substitution across products. Those are questions that this paper does not attempt to answer. Instead, the focus of this paper is on the change in the set of varieties available to consumers. Its goal is to address the mismatch between the theory on variety gains from trade and the empirics on globalization and product innovation.

This paper contributes to the debate on varieties along two different dimensions. The

first dimension is methodological. I propose a new measure that is anchored on product features that matter for consumers, that spans all sectors of the economy, and that captures both domestic and foreign varieties without conflating the country of origin of the design with the country of production. This measure is essential to better quantify welfare gains from varieties. It provides a novel perspective on the benefits consumers derive from more products and is a good complement to existing measures capturing price changes, using trade product classifications (Feenstra, 1994; Broda and Weinstein, 2006; Bernard et al., 2010, 2011; Hsieh et al., 2020, 2022; Mayer et al., 2021) or barcodes (Broda and Weinstein, 2010; Hottman et al., 2016; Ghai and Hottman, 2019).

The second contribution relates to the effect of import competition on product innovation. I show that not all imports are equal from a varieties standpoint. Only trade flows from Chinese-owned firms located in China deter the entry of new products in the US market. Disentangling US imports from China according to the ownership status of exporters complements the approach used in the literature so far, which has relied on overall flows from China and has mainly used patents or expenditure in Research & Development as a proxy for innovation activity at large (Bloom et al., 2016, 2021; Xu and Gong, 2017; Impullitti and Licandro, 2018; Autor et al., 2020; Chakravorty et al., 2022).⁷

This project also speaks to the limited but growing literature related to trademarks (Mangani, 2007; Alfaro et al., 2022; Dinlersoz et al., 2023; Pearce and Wu, 2024).⁸ To the best of my knowledge, this is the first paper to harness the information in the text protected by trademarks and use it to study the change in varieties over time.

The rest of the paper is organized as follows. [Section 2](#) provides more information on trademarks and their use as measure of varieties. [Section 3](#) introduces the data. [Section 4](#) describes the empirical facts. [Section 5](#) contains the model and its predictions about the effect of import competition on product innovation through some comparative statics. [Section 6](#) tests whether the predictions of the model hold in the data. [Section 7](#) quantifies the welfare gains from trade using trademarks and compares them with what can be obtained using standard measures. Finally, [Section 8](#) concludes.

⁷See [Akcigit and Van Reenen \(2023\)](#) and [Melitz and Redding \(2023\)](#) for a literature review on innovation.

⁸See [Schautschick and Greenhalgh \(2016\)](#) for a literature review of all empirical studies on trademarks.

2 Measuring varieties

Any empirical study concerning varieties must first tackle the challenge of defining the term “variety” itself. I define a variety as any good of a firm that is distinct from those of its competitors, *as perceived by buyers*. Ideally, we would like a metric capable of capturing the uniqueness of varieties across all sectors, regardless of their country of production. Traditional measures may fall short of capturing the essence of this intuitive definition. Though useful in answering other research questions, they may not be suitable for studying changes in the mass of available varieties over time.

2.1 Customs codes, barcodes, and patents

An important research stream in trade economics relies on custom trade product classifications.⁹ Despite their great influence and common use, there are four main limitations to the insights provided by custom code and country of origin pairs. First, this approach assumes the country of production is the only determinant of differentiation in varieties. Second, this classification groups products based on physical characteristics and applicable tariff schemes. Third, the Harmonized Systems (HS) codes – the most used standardized classification – are updated every five years, making it problematic to conduct analysis spanning longer time periods.¹⁰ Fourth, it implicitly assumes an upper limit on the number of available varieties for consumers, determined by the number of possible trading partners multiplied by the total number of categories in the most recent customs data classification. With 5,000 distinct HS codes and 180 trading partners, there would be a ceiling of 900,000 varieties available to US consumers.

A more recent strand of the literature relies on the uniqueness of barcodes attached to products.¹¹ Similarly to custom codes, this measure has limited applicability to time series analysis of varieties due to two reasons. First, changes in available varieties may reflect a change in packaging rather than the creation of products with actual distinctive features.¹²

⁹Among the numerous papers using customs trade product classifications to measure varieties, see: Mayer et al. (2021); Amity et al. (2020); Hottman and Monarch (2020); Hsieh et al. (2020); Feenstra and Romalis (2014); Bernard et al. (2011); Bernard et al. (2010); Goldberg et al. (2010); Broda and Weinstein (2006).

¹⁰There is considerable attrition in the use of the old system when the new classification system comes into place, as seen in the descriptive statistics provided for the BACI dataset (Gaulier and Zignago, 2010).

¹¹A non-exhaustive list of papers using barcode data to measure varieties include McCully et al. (2024); Argente et al. (2021); Ghai and Hottman (2019); Jaravel (2019); Hottman et al. (2016); Broda and Weinstein (2010).

¹²For example, a 36-pack of 355 ml cans of Budweiser has code 00062067335297, while the same pack giving the chance of winning a smoker has code 00062067385124 (source: <https://www.bcliquorstores.com/>).

Second, barcode data cover only consumer product goods sold in physical retail stores, representing 14% of total consumption of goods in the US (Argente et al., 2021).

Contribution to the research on new varieties has also come from the literature on innovation through the use of patent data (Akcigit and Kerr, 2018). However, patents are better suited to capture process rather than product innovation: only 38% of patents can be associated with a new product and firms that never patent account for 65% of product innovation (Argente et al., 2021). They primarily reflect lower marginal costs in production rather than an increase in the stock of available varieties.¹³

2.2 Trademarks in the United States

Unlike customs codes, barcodes, and patents, trademarks offer a more direct measure of varieties due to their focus on consumer perception and market presence. Trademarks are an ancient type of intellectual property, as producers have used distinctive marks to differentiate their products at least since medieval Europe (Richardson, 2008). In the United States, the modern concept of trademarks was established in 1946 with the Lanham Act. The Lanham Act defines a trademark as “any word, name, symbol, or device, or any combination thereof” that is used “to identify and distinguish” the markholder’s goods “from those manufactured or sold by others and to indicate the source of the goods” (15 U.S.C. §1127). Trademarks have been described as the legal counterpart of brands (Griffiths, 2011). This project proposes trademarks as a measure of varieties, primarily driven by two compelling reasons. First, trademarks are fundamental in ensuring that consumers can confidently identify specific goods or services, making consumer protection their primary goal (Grynberg, 2022; Schautschick and Greenhalgh, 2016; Landes and Posner, 1987).¹⁴ Such protection is granted for any type of good, both final and intermediates: for example, *SuperElso500* is a trademark identifying a specific type of steel produced by Arcelormittal, one of the largest steel manufacturers in the world. Second, trademarks are often filed in proximity to new product introduction (Flikkema et al., 2014).

¹³Perhaps due to the paucity of good measures of product innovation, Garcia-Macia et al. (2019) infer the creation of new varieties by examining the shifts in the labor market through the lense of a general equilibrium model. While providing an invaluable first step in advancing the literature, they do not use any direct data on varieties and require restrictive simplifying assumptions.

¹⁴An applied-for trademark can be refused as not registrable if it is generic or merely descriptive, geographic, a surname, deceptive, a municipal, state, national, or foreign flag or insignia, or the name, likeness, or signature of a living person used without their consent. Examining attorneys search existing registrations and pending applications for similar trademarks and assess whether use of the applicant’s trademark on the identified goods or services is likely to cause confusion among consumers (15 U.S.C §1052).

Trademarks protected at the federal level enjoy additional features that make them a valuable measure of varieties. First of all, the United States Patents and Trademarks Office requires low barriers to registration and renewal, favoring the inclusion of small and medium enterprises (Mendonça et al., 2004; Dinlersoz et al., 2018) and leading to entrepreneurs considering trademarks as a key tool for Intellectual Property protection (Mezzanotti and Simcoe, 2023).¹⁵ Secondly, this federal protection extends equally to trademarks registered by domestic and foreign firms. Crucially for this project, the nationality of the owner of a trademark captures the country of origin of the design, rather than the country of production.¹⁶ Lastly, a so-called “dual system of protection” is in effect, where trademarks are safeguarded only when actively used in the marketplace, impacting international or interstate commerce. In practice, goods should display the feature protected by the trademark, thus creating a clear link with the consumer market.

3 Data

3.1 Trademark data

Trademark-level data is the primary data used in this project. I rely on two datasets provided by the United States Patents and Trademarks Office (USPTO). First, the Trademark Case Files dataset (Graham et al., 2013), which includes the universe of trademarks filed in the USPTO between 1982 and 2020. It includes information on a trademark’s color, its shape, its text, its sector – called NICE class – as well as the name and nationality of its owner. I use this dataset to construct a measure of varieties based on the number of trademarks filed by each firm. Second, the Trademark Assignment dataset (Graham et al., 2018). Like any other asset, trademarks can change ownership over time, either as part of a Merger and Acquisitions or as a direct transaction across firms. The Trademark Assignment dataset includes information on the transfer of ownership of trademarks between firms, which I use to distinguish firms between incumbents and entrants.

¹⁵The cost of registering a trademark ranges between \$250 to \$350 for each class of goods or services pertaining to it. The same fees apply for the renewal process, happening every ten years. For more information on the application, registration, and renewal process, see Cain (2021).

¹⁶Using trademarks may raise concerns linked to profit shifting: MNEs transferring intellectual property in order to maximize their profits net of taxes (Dischinger and Riedel, 2011; Karkinsky and Riedel, 2012; Griffith et al., 2014). However, if firms transfer ownership, it follows that the owner location at the time of *registration* was not optimal in terms of corporate taxation. By focusing on the location at the time of the registration, I minimize the risk of using locations chosen for tax incentives. Moreover, I exclude tax havens from my analysis. The full list of countries included in my dataset can be found in Appendix B.

As a result of the Trademark Law Revision Act of 1988, firms can file intent-to-use applications at the USPTO: firms are granted a period of six years to actually use the trademark in commerce, otherwise the application is treated as abandoned. In order to keep only trademarks used in the market, I exclude those that have been canceled, abandoned, or filed after 2014. To group trademarks into products, I define a variety as one unique pair of protected text and product or service class per firm.¹⁷ This grouping gives a baseline dataset of 3.4 million varieties owned by 1 million firms from 1982 to 2014. Most varieties are goods and are owned by US companies. Although foreign companies represent only 20 percent of firms in the dataset, they account for 24 percent of the varieties available in the US market (Table 1), indicating that they tend to have more varieties per firm on average. The distribution of varieties per firm is highly skewed. Each firm owns 3.4 varieties on average, but half the firms own 1 variety until 2006 and 2 varieties in the subsequent years (Figure 1.1).¹⁸ The conditional distribution of new varieties per firm is similarly skewed, with an average of 2 new varieties per innovating firm and a median of 1 new variety per innovating firm (Figure 1.2).¹⁹ The rest of the paper will focus on goods only.²⁰

One may be concerned that not all products are trademarked. Pearce and Wu (2024) combines trademark data with Nielsen barcode data to show that over 80 percent of sales-weighted brands in the years 2006-2018 have an associated trademark. I further validate the data by comparing trademarks with the number of car models owned by Ford, Volkswagen, and Toyota. Trademarks cover at least 89 percent of sales-weighted car models sold in the US (Table B1 in Appendix B).

A running assumption in this paper is that the number of trademarks is proportional to the number of varieties, and this proportionality remains constant over time.²¹ To adhere

¹⁷More details on this grouping and on the data cleaning process can be found in Appendix B.

¹⁸This distribution is less skewed than the one inferred by Garcia-Macia et al. (2019) using shifts in the labor market, where the estimated number of firms with only one product is 92% in 1983-1993, 84% in 1993-2003, and 90% in 2003-2013. The average number of varieties per firm is in line with the findings of Broda and Weinstein (2010) on the average number of brands per firm using barcode data, which ranges from 2.9 in 1994 to 4.2 in 2003.

¹⁹Foreign firms are larger than domestic ones, both in terms of varieties and new varieties (Figure A2 in Appendix A). This is in line with exporters being larger than the average firm.

²⁰Summary statistics for goods can be seen in Table A1 and Figure A1 in Appendix A.

²¹Pearce and Wu (2024) find that one brand in Nielsen barcode data is matched with 2.15 trademarks on average. However, thoroughly validating this assumption further requires defining what a variety in real life is. That is particularly challenging because many goods we interact with are composite goods: think for example of a laptop, which is made by several branded chips and hardware.

Table 1: Summary statistics

	Varieties		Firms	
	Count	Percentage	Count	Percentage
Overall	3,381,845		962,735	
Goods	2,189,939	65%	643,645	67%
Services	1,191,906	35%	470,063	49%
Final	1,594,400	47%	569,502	59%
Intermediate	1,787,445	53%	590,850	61%
Domestic	2,614,616	76%	776,078	80%
Foreign	767,229	24%	186,657	20%

Notes: Count of varieties and firms, overall or split by sector and nationality. Final and intermediate sectors are defined based on the share of consumer expenditure of the corresponding ISIC code using the US Input-Output table: varieties in sectors for which at least 70% of final consumption is done by consumers are classified as final. Note that percentages for firms do not always sum up to 100% because firms can own both goods and services trademarks, or both final and intermediate varieties. The concordance from the trademarks sectoral classification to the ISIC classification is taken from [Batacharyya et al. \(2017\)](#).

Figure 1: Varieties and new varieties per firm are highly skewed

Figure 1.1: Varieties

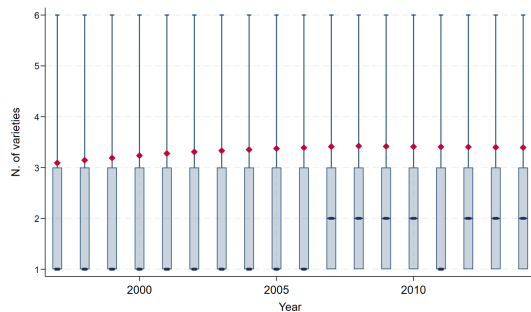
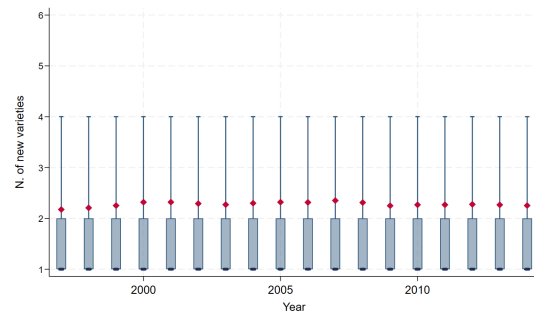


Figure 1.2: New varieties



Notes: The figures show the distribution of varieties and new varieties per firm over time. The bars show the 25th and 75th percentile of the distribution, the darker blue line shows the median, while the upper spike shows the 90th percentile of the distribution. The red diamond shows the average number of varieties or new varieties per firm.

to this assumption, I focus on interpreting the results in terms of elasticities and changes over time, rather than the number of trademarks. Moreover, this assumption is more likely to hold at a high level of aggregation, such as the sectoral level. As a consequence, I focus mostly on sectoral-level results, rather than firm-level ones.

3.2 Other data

Chinese customs data. I complement trademark data with a transactions-level dataset of Chinese exports collected by the Customs Administration of China over the years 1997-2014. Crucially for this project, the data contains information on firm ownership type (state-owned, Chinese-owned, and foreign-owned), destination country, and sector at the HS 8-digits level.

Trade flows data. I use information on bilateral trade flows at the HS 6-digits level across countries from UNCOMTRADE ([United Nations Statistics Division, 2022](#)) and from the CEPII BACI dataset ([Gaulier and Zignago, 2010](#)). Information on bilateral distance, common language, and GDP per capita is obtained from the CEPII Gravity dataset ([Conte et al., 2022](#)).

Other. To cross-walk from the NICE sector classification to other standard classifications, like SITC and HS, I use the probabilistic matching provided in [Battacharyya et al. \(2017\)](#). Information on real GDP in the United States is sourced from the [U.S. Bureau of Economic Analysis \(2023\)](#).

4 Stylized facts

Using this novel measure for varieties, this paper provides two new stylized facts. First, it documents which countries provide the most varieties to US consumers and contrasts its results with the ranking obtained using HS codes and country of origin pairs. Second, it focuses on China and on the composition of its exports to the United States.

4.1 Which countries provide the most varieties to US consumers?

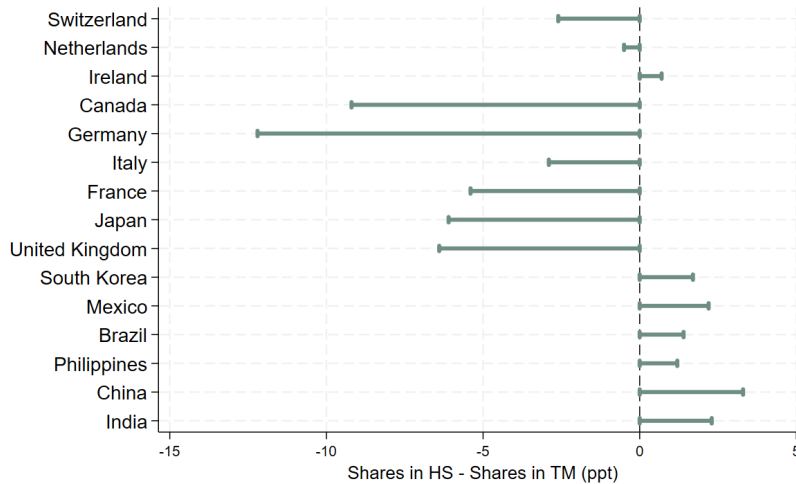
Ideally, a researcher could use detailed customs data for all US trading partners and apply the analysis done for Chinese varieties to all foreign varieties available in the US. As this data is not available, I compare US trading partners in terms of varieties measured with

the two metrics for the year 2001. Specifically, I compute the following difference:

$$\frac{\text{HS-var from } c}{\text{Total HS-var}} - \frac{\text{TM-var from } c}{\text{Total TM-var}} \quad (1)$$

where “HS-var from c ” is the number of HS 10-digits codes for which the US imports a non zero value of imports from country c , while “TM-var from c ” is the number of trademarks-based varieties with c -nationality available in the US.²² Both are measured as shares over foreign varieties.

Figure 2: Comparison of variety shares



Notes: The figure compares the varieties share of selected countries in 2001 as measured using HS 10-digits codes and using trademarks. It shows the percentage points lost or gained when using trademarks compared to the shares obtained through 10-digits HS codes and country of origin pairs, as defined in Equation 1. Countries are ranked based on their GDP per capita in 2001.

Figure 2 shows the difference in shares for the major US trading partners when using trademarks compared to custom codes for the year 2001. There is substantial variation across countries, mainly due to the fact that customs codes are entirely related to trade flows and therefore affected by MNE activity. Lower-GDP countries that are hosts of export platforms and that export large volumes of processing trade to the US lose substantial shares when using trademarks. Most notably, Mexico, China, India, and the Philippines lose 3 or 4 percentage points when assessed using trademarks rather than custom codes, which is equivalent to roughly halving their varieties share (Figure A7 in Appendix A).

²²I use US import data at the 10-digits HS level provided by The Center for International Data.

Conversely, high-GDP countries that are hosts of MNEs headquarters gain between 6 and 12 percentage points, which corresponds to tripling the share of Canadian varieties or quadrupling the share of German varieties (Figure A7 in Appendix A).²³ In terms of ranking of varieties providers, China is the fourth provider of HS 10-digits varieties but only the twentieth provider of trademark varieties (Figure A9 in Appendix A). The change in ranking position suggests that China may have indeed been the fourth *producer* of foreign varieties for US consumers, but it was likely only the twentieth *designer* of foreign varieties for US consumers in 2001. This empirical fact pushes the idea that decoupling varieties from trade flows can lead to new results on varieties gains from trade, as the country of production is not necessarily equal to the country of design.²⁴ Building on this finding, I now turn to the specific case of China to explore whether its exports truly represent Chinese varieties.

4.2 Does China export Chinese varieties?

The early 2000s were characterized by the surge of China as the world manufacturer. World imports from China have more than tripled in the years 1989-2014 and many economists have studied the impact of what has been known as the “China shock” on various outcomes, ranging from employment to patenting activity.²⁵ But what do Chinese imports contain and who exports from China? Trade flows from China could include cheap, low-quality goods, whose presence in the US market undermines the sales of domestic firms. However, we know

²³Figure A4 in Appendix A extends the analysis to the top thirty trading partners. Similar results are obtained using the more aggregate HS 8-digits and HS 6-digits levels (Figure A5 in Appendix A). Using data for the year 2014 brings similar results, with the exception of China and South Korea, which are now providers of larger shares of trademarks than HS 6-digits codes (Figure A6 in Appendix A). More comparisons with HS codes for the year 2014 are shown in Figure A10 and Figure A11 in Appendix A.

²⁴This idea is further supported by the fact that the ranking of US trading partners based on custom codes exhibits a stronger correlation with exports to the United States than the ranking based on trademarks (Figure A8 in Appendix A). Additionally, varieties measured using trademarks or custom codes both satisfy the gravity equation but exhibit different distance and GDP elasticities, offering further validation that not all trade flows are the same from a variety standpoint (Appendix C).

²⁵The literature on the “China shock” brings evidence of lower prices (Feenstra and Weinstein, 2017; Amiti et al., 2020), but also of lower earnings in the US and, to a lesser extent, in Germany, Spain, Norway, and France (Autor et al., 2013; Dauth et al., 2014; Donoso et al., 2015; Balsvik et al., 2015; Malgouyres, 2017). These negative labor market effects are smaller or absent when looked at a more aggregate level (Hsieh and Ossa, 2016; Galle et al., 2017; Adao et al., 2019; Caliendo et al., 2019). With respect to innovation, there is conflicting evidence on the role of Chinese competition: it has a positive (Bloom et al., 2016; Xu and Gong, 2017; Impullitti and Licandro, 2018), neutral or somewhat negative (Autor et al., 2020), or inverted-U (Chakravorty et al., 2022) effect on innovation as measured by patenting activity and/or R&D expenditure. Finally, Yang et al. (2021) find that the effect of Chinese competition on Canadian firms depends on the type of the innovation itself: while product innovation incentives are stimulated by an increase in competition from China, process innovation incentives decline.

that multinationals account for half of the world trade (OECD, 2018), so it is possible that there are big multinationals owning subsidiaries in China whose manufacturing activity has benefitted from lower tariffs after China’s entry in the World Trade Organization. Consider, for example, Nike owning several shoe production facilities in China. If Nike shoes are part of US imports from China, then interpreting a surge in imports from China as a surge in Chinese varieties becomes problematic. In short, not all “made in China” goods are Chinese varieties.²⁶ This distinction is crucial for accurately assessing the impact of Chinese exports on the US market.

Complementing trademarks data with Chinese custom data, I can directly test whether or not trade flows from China correspond to Chinese varieties. Chinese custom data categorizes trade flows as originating from either Chinese-owned firms or foreign-owned firms located in China, hence MNEs.²⁷ Approximately 60% of US imports from China are attributed to MNEs operating in China, as shown in Figure 3.²⁸ Interestingly, trade flows from Chinese firms located in China seem to comove with the number of Chinese varieties available in the US market as measured through trademarks.

This comovement is more rigorously tested regressing Chinese varieties available in the US on the different types of US imports from China. Specifically, I estimate the following specification:

$$\text{Var}_{st} = \beta \text{CN-import}_{st} + \gamma \text{MNE-import}_{st} + \boldsymbol{\delta} + \varepsilon_{st} \quad (2)$$

where Var_{st} is the number of Chinese-owned trademarks as a share of all foreign-owned trademarks in sector s and year t , CN-import_{st} are US imports from Chinese-owned firms located in China as a share of total US imports, and MNE-import_{st} are US imports from foreign-owned firms located in China as a share of total US imports. $\boldsymbol{\delta}$ is a vector of sector and year Fixed Effects, and errors ε_{st} are clustered at the sector level.

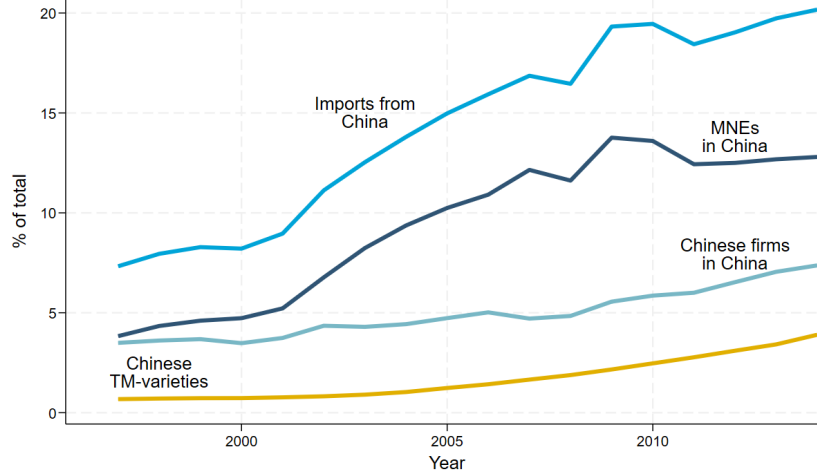
Table 2 shows that a one percentage point increase in trade flows from Chinese-owned

²⁶This argument is in line with the work of Jakubik and Stolzenburg (2021) which removes US value added in Chinese exports from the exposure measure of US local labor market used in Autor et al. (2013). Jakubik and Stolzenburg (2021) find that this decoupling reduces the volume of the shock as well as the size of the negative effect on local labor markets.

²⁷The Customs Administration of China distinguishes between private-owned firms, state-owned firms, and foreign-owned firms. In this paper, I refer to both private-owned firms and state-owned firms as Chinese-owned firms.

²⁸Brandt and Lim (2023) provide a detailed analysis of Chinese export dynamics by firm ownership type, production locations, destinations, and sectors over the years 2000-2013.

Figure 3: Trade flows and varieties from China



Notes: The figure compares different types of US imports from China with Chinese-owned varieties in the US market. “Imports from China” is US overall imports from China as a percentage of total US imports. “MNEs in China” is US imports from non-Chinese-owned firms located in China as a percentage of total US imports. “Chinese firms in China” is US imports from Chinese-owned firms located in China as a percentage of total US imports. “Chinese TM-varieties” is trademarks registered in the US and owned by Chinese firms as a percentage of all foreign-owned trademarks registered in the US.

Table 2: Trade flows from MNEs in China do not explain Chinese varieties

	(1) Chinese varieties (% of foreign)	(2) Chinese varieties (% of foreign)
Total imports (%)	0.101*** (0.030)	
Chinese firms (%)		0.209*** (0.051)
MNEs (%)		0.024 (0.027)
Obs.	612	612
R ²	0.816	0.830

Notes: The observations are at the sector-year level. The dependent variable is Chinese varieties, measured as Chinese-owned trademarks as a percentage of all foreign-owned trademarks registered in the US. The explanatory variables are different types of trade flows from China to the US as percentage of total US imports: total imports from China; imports from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China. Column (2) shows estimates of Equation 2. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

firms corresponds to a 0.21 percentage points increase in Chinese varieties, while trade flows from MNEs have no effect on Chinese varieties. This result is the first compelling evidence linking imports with imported varieties, without relying on uniquely on trade data. The same pattern emerges when disaggregating trade flows from Chinese firms by final and intermediate goods (Figure A13 and Table A2 in Appendix A) and retains statistical significance when bootstrapping the standard errors (Table A3 in Appendix A). In terms of varieties elasticity to trade flows, a 1% increase in US imports of final goods from Chinese-owned firms located in China corresponds to a 0.4% increase in Chinese-owned trademarks available in the US market (Table A4 and Table A5 in Appendix A). In terms of value, this relationship implies that an additional billion dollars exported by Chinese-owned firms to the US corresponds to 45 new Chinese-owned varieties sold in the US market (Table A6 in Appendix A). Conversely, only exports from MNEs in China – and especially of intermediate inputs – have explanatory power over varieties when measured by HS-codes (Figure A12, Table A7, and Table A8 in Appendix A).

These results confirm that not all trade flows are equal in terms of variety: trade flows due to the activity of multinational companies need to be taken into account and may lead to mismeasurements in the trends of foreign varieties.

5 Theoretical framework

The previous section shows that trade is not equal from a variety perspective. This suggests that there may have been substantial mismeasurements in the gains from trade predicted by the theory. To highlight the wedge between theory and empirics created by the existence of MNEs, I extend the model built by Helpman et al. (2004) to feature export platforms that domestic firms can use to produce cheaply and ship final goods back home.²⁹ In doing so, I maintain a simple two-country structure. In a nutshell, firms have the option of paying a fixed cost to produce abroad and enjoy lower wages, but then have to pay iceberg trade costs when shipping the final products back to be sold in the domestic market. A decrease in tariffs allows more firms to offshore their production, while granting consumers access to additional foreign goods. In this model, the gains from variety can then be decoupled into gains in terms of new foreign goods being directly imported, as well as gains from

²⁹This is by all means a simplification of existing models with export platforms, which focus on location choice and on the structure of multinational activity, while this paper focuses on quantifying variety gains from trade (Tintelnot, 2017; Arkolakis et al., 2018; Head and Mayer, 2019).

domestic goods being offshored. While this model is not novel, it allows me to highlight the precautions necessary when using customs data to quantify variety gains from trade. I start with the model set-up, describe both autarky and trade equilibrium, and then provide some comparative statics to inform the value of decoupling imports based on the country of design rather than the country of origin.³⁰

5.1 Set-up

There are two countries labelled by $i \in \{U, C\}$ – the United States and China for illustrative purposes, but the model could be generalized to North and South of the world. Each country is characterized by a mass of workers L_i .

Consumption Consumers in country i have Cobb-Douglas preferences over an homogeneous good, which they consume in quantity q_{Hi} , and a composite good over a mass of varieties Ω_i under Constant Elasticity of Substitution with parameter $\sigma > 1$. Consumers of country i consume a quantity $q_{kji}(\omega)$ of variety ω owned by a firm of country k , produced in country j , and sold in country i . Therefore, consumers in i have the following utility:

$$U_i = (q_{Hi})^{1-\alpha} \left[\int_{\omega \in \Omega_i} q_{kji}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}\alpha}$$

where α is the Cobb-Douglas preference weight for the differentiated composite good. Consumers maximize their utility under the budget constraint $I_i = p_{Hi}q_{Hi} + \int_{\omega \in \Omega_i} p_{kji}(\omega)q_{kji}(\omega)d\omega$, where I_i is the total income in country i and $p_{kji}(\omega)$ is the price of a variety ω owned by a firm in country k , produced in country j , and sold in country i .

Homogeneous good The homogeneous good is freely traded across both countries at a price equal to 1. This will be the numeraire. When α is sufficiently low, both countries produce some of the homogeneous good under Constant Returns to Scale technology. In each country, 1 unit of labor produces w_i quantity of the homogeneous good under Perfect Competition. As a consequence, different wages across countries represent different productivity levels, in a manner not dissimilar from [Chaney \(2008\)](#): higher wages imply higher productivity at the country level.

³⁰Details on the derivations of the model can be found in [Appendix D](#).

Differentiated good The varieties ω are produced by firms which are heterogeneous in their productivity $\varphi \sim G$, only use labor, are monopolistically competitive, and face a per-period probability of exit equal to δ . Each firm produces only one good.

I assume productivity to be distributed according to a Pareto with support $[b, +\infty)$: $\varphi \sim G(\varphi) = 1 - (\frac{b}{\varphi})^k$.³¹ There is an endogenous mass of entrant firms M_i^E . To know its productivity, a firm pays a fixed cost f_i^E in terms of labor in country i . Upon observing its productivity, the firm can choose whether to produce or not. If the firm produces domestically, it only pays variable costs, that is labor. This is a small departure from Melitz (2003), as I assume that firms do not pay a fixed cost for producing domestically. This assumption implies that there is not an endogenous cutoff productivity for producing domestically: once they pay the fixed cost of entering f_i^E , all firms can produce. Therefore, the average productivity of firms producing domestically is not endogenous and the adjustment in comparative statics does not happen through a change in cutoff productivity of entry but through a change in the mass of firms entering the market.

If the firm offshores production to country j , it pays a fixed cost of value f_{ij}^{FDI} . The fixed cost of offshoring is expressed in terms of labor in the country of production: f_{ij}^{FDI} is paid in terms of labor in country j . This assumption is intuitive if we think that fixed costs of offshoring include the cost of creating a new establishment abroad or setting up new contracts with foreign suppliers.³²

If country i firm produces in country i and ships to country j , it pays a fixed cost f_{ij}^X in terms of the labor of country i .³³ Once it has produced its differentiated good, the firm can either serve the same market where it has produced the good, or it can pay an iceberg trade cost $\tau_{ij} \geq 1$ to serve the other market j .

In summary, a firm of country i has two options for selling to country i and country j consumers, respectively: produce in country i and sell domestically without paying any additional costs; produce in country j and sell to country i , paying fixed costs of offshoring f_{ij}^{FDI} and variable iceberg trade costs τ_{ij} ; produce in country i and sell to country j , paying fixed costs of exporting f_{ij}^X and variable iceberg trade costs τ_{ij} ; produce in country j and sell to country j paying only fixed costs of offshoring f_{ij}^{FDI} .

³¹The results shown hold for any distribution that is continuous over its support.

³²Assuming that the fixed cost of offshoring is paid in terms of labor in the headquarter country would change the labor market clearing conditions but would not affect the results shown.

³³If a firm of country i produces in country j and then ships the final good back to country i , I am assuming it does not have to pay the fixed cost of exporting. This simplification does not affect the results shown.

Since my goal is to isolate the variety gains from trade in the US market when there is MNE activity, I make the following simplifying assumptions. First, I assume that the fixed cost of offshoring production to country j are larger than the fixed cost of exporting to country j : $f_{ij}^{FDI} > f_{ij}^X$. Such ordering of fixed costs is plausible, as it characterizes the additional costs of monitoring a subsidiary or establishing a contract abroad, as well as the costs of complying with foreign standards and regulations. Second, I assume that $f_{CU}^{FDI} = +\infty$ and that wages in the two countries are different. Specifically, wages in the US are larger than wages in China: $w_C < w_U$. Since what matters are relative wages, I normalize wages in the US to be equal to one. These assumptions imply that US firms may offshore production to China, but Chinese firms do not offshore production to the US. This assumption is driven by the data, as the US is the largest source of foreign direct investments (FDI) in China, while China is not a large source of FDI in the US (OECD, 2017). Third, I assume that US goods are not sold in China. While not necessary for the results stated below, this assumption is driven by data limitations. I do not observe varieties available in China, so I am not able to say anything about them. Under this assumption, US firms merely see offshoring as a technology: they pay fixed and variable costs in exchange for lower wages.

5.2 Autarky equilibrium in the US

In autarky, firms cannot export and cannot offshore production. Since everything is specific to country $i = U$, I drop the country indices for readability for the time being.

A firm with productivity φ sets the optimal price equal to $p(\varphi) = \frac{\sigma}{\sigma-1} \frac{w}{\varphi}$. The optimal demand of consumers for the good produced by a firm with productivity φ is

$$q(\varphi) = p(\varphi)^{-\sigma} \mathbb{P}_{\Omega}^{\sigma-1} \alpha E$$

where E is overall consumers expenditure and $\mathbb{P}_{\Omega} \equiv \left[\int_{\omega \in \Omega} (p(\omega))^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}}$ is the exact price index of the composite differentiated good.

The profits of US firms are

$$\pi(\varphi) = p(\varphi)q(\varphi) - \frac{w}{\varphi}q(\varphi) = \frac{1}{\sigma}r(\varphi)$$

where $r(\varphi)$ is the revenues of a firm with productivity φ . Since there are no fixed costs of production, all firms who enter are also able to produce. Therefore, the average productivity is not endogenous. On the contrary, the mass of firms paying the sunk cost of entry is

endogenous and determined by the labor market clearing condition and by the Free Entry condition, stating that the net value of entry should be zero. The mass of available varieties is equal to the mass of operating firms.

Welfare is given by the real wage. In [Appendix D](#), I show that the price index for the composite differentiated good can be rewritten as

$$\mathbb{P} = \mathbb{P}_\Omega^\alpha = \tilde{p}M^{\frac{\alpha}{1-\sigma}} \quad (3)$$

where \tilde{p} is the price of the average productivity firm.

5.3 Trade equilibrium

When countries open up to trade, they can choose where to produce and where to sell. I will use the following notation: x_{ijl} represents variable x of country i firms producing in country j and selling to country l . Therefore, the profits of a country i firm producing domestically and selling to country i are:

$$\pi_{iii}(\varphi) = p_{iii}(\varphi)q_{iii}(\varphi) - \frac{w_i}{\varphi}q_{iii}(\varphi) = \frac{1}{\sigma}r_{iii}(\varphi)$$

where $r_{iii}(\varphi)$ are the revenues made by country i firms producing and selling domestically. The profits of a country i firm producing in country j and selling to country i are:

$$\pi_{iji}(\varphi) = p_{iji}(\varphi)q_{iji}(\varphi) - \frac{w_j\tau_{ji}}{\varphi}q_{iji}(\varphi) - f_{ij}^{FDI}w_j = \frac{1}{\sigma}r_{iji}(\varphi) - f_{ij}^{FDI}w_j$$

where $r_{iji}(\varphi)$ are the revenues made by country i firms producing in country j and selling to i . Finally, the profits of a country i firm producing domestically and exporting to country j are

$$\pi_{ijj}(\varphi) = p_{ijj}(\varphi)q_{ijj}(\varphi) - \frac{w_i\tau_{ij}}{\varphi}q_{ijj}(\varphi) - f_{ij}^X w_i = \frac{1}{\sigma}r_{ijj}(\varphi) - f_{ij}^X w_i$$

where $r_{ijj}(\varphi)$ are the revenues made by country i firms producing in i and exporting to country j .

US firms US firms sell only to US consumers. They can choose whether to produce domestically or offshore production to China. US firms will produce in China if and only if

$$\pi_{UCU}(\varphi) \geq \pi_{UUU}(\varphi).$$

Since profits are an increasing function of φ , there is a unique cutoff productivity φ_{UC}^{FDI} such that firms with productivity above it will offshore production to China, and firms with productivity below it will produce domestically. The cutoff productivity φ_{UC}^{FDI} is implicitly defined by the Zero Cutoff Profit condition for offshoring production:

$$\pi_{UCU}(\varphi_{UC}^{FDI}) = \pi_{UUU}(\varphi_{UC}^{FDI}). \quad (4)$$

Notice that the fixed costs need to be large enough to guarantee that φ_{UC}^{FDI} is greater than b , the lower bound of the support.

I define two (harmonic) average productivities that will be helpful in the equilibrium equations later on. First, the average productivity of US firms producing domestically:

$$\tilde{\varphi}_{UUU} = \left[\int_b^{\varphi_{UC}^{FDI}} \varphi^{\sigma-1} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi \right]^{\frac{1}{\sigma-1}} \quad (5)$$

where $g(\varphi)$ is the probability density function of the Pareto distribution. Second, the average productivity of US firms offshoring production to China:

$$\tilde{\varphi}_{UCU} = \left[\int_{\varphi_{UC}^{FDI}}^{\infty} \varphi^{\sigma-1} \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi \right]^{\frac{1}{\sigma-1}}. \quad (6)$$

[Appendix D](#) shows the expression for both average productivities.

Chinese firms Chinese firms cannot offshore production. They can sell domestically and, on top of that, they have the option to export to the US market. Chinese firms export to the US if and only if

$$\pi_{CCU}(\varphi) \geq 0.$$

Since profits are an increasing function of φ , there is a unique cutoff productivity φ_{CCU}^X such that firms with productivity above it export to the US, and firms with productivity below it do not export. The cutoff productivity φ_{CCU}^X is implicitly defined by the Zero

Cutoff Profit condition for exporting:

$$\pi_{CCU}(\varphi_{CCU}^X) = 0 . \quad (7)$$

Notice that the fixed costs need to be large enough to guarantee that φ_{CCU}^X is greater than b , the lower bound of the support.

Similarly, I define two (harmonic) average productivities for China. First, the average productivity of all Chinese firms, which is exogeneous:

$$\tilde{\varphi}_C = \left[\int_b^{\varphi_{UC}^\infty} \varphi^{\sigma-1} g(\varphi) d\varphi \right]^{\frac{1}{\sigma-1}} = \left[\frac{k}{k+1-\sigma} \right]^{\frac{1}{\sigma-1}} b . \quad (8)$$

Second, the average productivity of Chinese firms exporting to the United States:

$$\tilde{\varphi}_{CCU} = \left[\int_{\varphi_{CCU}^X}^{\infty} \varphi^{\sigma-1} \frac{g(\varphi)}{1-G(\varphi_{CCU}^X)} d\varphi \right]^{\frac{1}{\sigma-1}} . \quad (9)$$

[Appendix D](#) shows the expression for both.

Equilibrium In each period, firms face an exogenous probability δ of incurring a negative shock and having to exit the market. The present discounted value of their expected profit flow is

$$\bar{v} = \sum_{t=0}^{+\infty} (1-\delta)^t \bar{\pi} = \frac{\bar{\pi}}{\delta} .$$

The Free Entry condition requires that expected profits equal entry costs, making the net value of entry zero:

$$\bar{\pi}_i = \delta f_i^E w_i . \quad (10)$$

In equilibrium, the following Aggregate Stability Condition must hold, where the mass of firms entering the market in each period is equal to the mass of firms exiting the market:

$$M_i^E = \delta M_i .$$

In this model, some quantity L_{Hi} of labor in each country is used to produce the homogeneous good. In each country, workers are also used to pay the fixed costs of entry. On top of that, US workers are employed by US firms producing domestically. Therefore, the US labor

market clearing condition is:

$$L_U = L_{HU} + \frac{q_{UUU}(\tilde{\varphi}_{UUU})}{\tilde{\varphi}_{UUU}} M_{UUU} + M_U^E f_U^E \quad (11)$$

where $\tilde{\varphi}_{UUU}$ is the average productivity of US firms producing domestically as defined in [Equation 5](#). Notice that the mass of US firms producing domestically is a portion $G(\varphi_{UC}^{FDI})$ of the total mass of US firms M_U : $M_{UUU} = G(\varphi_{UC}^{FDI})M_U$.

Similarly, workers in China are employed to produce the homogeneous good; to pay the fixed costs of entry, exporting, and offshoring; to produce all the differentiated goods made by Chinese firms; and to produce the differentiated goods offshored by US firms. Therefore, the Chinese labor market clearing condition is:

$$\begin{aligned} L_C = & L_{HC} + \frac{q_{CCC}(\tilde{\varphi}_{CCC})}{\tilde{\varphi}_{CCC}} M_{CCC} + M_C^E f_C^E + M_{CCU} f_{CU}^X + M_{UCU} f_{UC}^{FDI} + \\ & + \frac{\tau_{CU} q_{CCU}(\tilde{\varphi}_{CCU})}{\tilde{\varphi}_{CCU}} M_{CCU} + \frac{\tau_{CU} q_{UCU}(\tilde{\varphi}_{UCU})}{\tilde{\varphi}_{UCU}} M_{UCU} \end{aligned} \quad (12)$$

where $M_{CCU} = [1 - G(\varphi_{CU}^X)] M_C$ is the mass of Chinese exporters, $M_{UCU} = [1 - G(\varphi_{UC}^{FDI})] M_U$ is the mass of US firms offshoring production to China, and $\tilde{\varphi}_C$, $\tilde{\varphi}_{CCU}$, and $\tilde{\varphi}_{UCU}$ are the average productivities defined in [Equation 8](#), [Equation 9](#), and [Equation 6](#), respectively.

In this model, US workers receive income from labor and from the net profits of US firms, but have to pay the fixed costs of entry.³⁴ Therefore, the income of US workers is:

$$\begin{aligned} I_U = & w_U L_U - w_U f_U^E M_U^E + \\ & + \left[r_{UUU}(\tilde{\varphi}_{UUU}) - w_U \frac{q_{UUU}(\tilde{\varphi}_{UUU})}{\tilde{\varphi}_{UUU}} \right] M_{UUU} + \\ & + \left[r_{UCU}(\tilde{\varphi}_{UCU}) - w_C \tau_{CU} \frac{q_{UCU}(\tilde{\varphi}_{UCU})}{\tilde{\varphi}_{UCU}} - w_C f_{UC}^{FDI} \right] M_{UCU} . \end{aligned}$$

³⁴Notice that the labor income of workers includes all the fixed costs paid by the firms. However, workers in this model also own the firms, so that they have to pay the fixed costs back. Moreover, workers' income includes the net profits made in the homogeneous sector, which are equal to zero.

Similarly, the income of Chinese workers is:

$$\begin{aligned}
I_C &= w_C L_C - w_C f_C^E M_C^E + \\
&+ \left[r_{CCC}(\tilde{\varphi}_{CCC}) - w_C \frac{q_{CCC}(\tilde{\varphi}_{CCC})}{\tilde{\varphi}_{CCC}} \right] M_{CCC} + \\
&+ \left[r_{CCU}(\tilde{\varphi}_{CCU}) - w_C \tau_{CU} \frac{q_{CCU}(\tilde{\varphi}_{CCU})}{\tilde{\varphi}_{CCU}} - w_C f_{CU}^X \right] M_{CCU}.
\end{aligned}$$

In equilibrium, the income of workers is equal to the total expenditure in each country:

$$I_U = E_U = p_{HU} q_{HU} + r_{UUU}(\tilde{\varphi}_{UUU}) M_{UUU} + \quad (13)$$

$$+ r_{UCU}(\tilde{\varphi}_{UCU}) M_{UCU} + r_{CCU}(\tilde{\varphi}_{CCU}) M_{CCU}$$

$$I_C = E_C = p_{HC} q_{HC} + r_{CCC}(\tilde{\varphi}_{CCC}) M_{CCC} \quad (14)$$

where $q_{Hi} = (1 - \alpha) E_i$ is the optimal demand for the homogeneous good in country i .

The equilibrium is given by the cutoff productivities $\{\varphi_{UC}^{FDI}, \varphi_{CU}^X\}$, the mass of entrant firms $\{M_U^E, M_C^E\}$, the expenditures $\{E_U, E_C\}$, and the mass of labor used in the homogeneous sector $\{L_{HU}, L_{HC}\}$ such that the Zero Cutoff Profit conditions hold (Equation 4 and Equation 7), the Free Entry condition of each country holds (Equation 10), the labor market clearing conditions hold (Equation 11 and Equation 12), and there is expenditure-income balance in each country (Equation 13 and Equation 14), for a given set of wages $\{w_U, w_C\}$ and price indices $\{\mathbb{P}_{\Omega U}, \mathbb{P}_U, \mathbb{P}_{\Omega C}, \mathbb{P}_C\}$ defined as follows:

$$\mathbb{P}_{\Omega U} = \left[M_{UUU} p_{UUU} (\tilde{\varphi}_{UUU})^{1-\sigma} + M_{UCU} p_{UCU} (\tilde{\varphi}_{UCU})^{1-\sigma} + M_{CCU} p_{CCU} (\tilde{\varphi}_{CCU})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

$$\mathbb{P}_{\Omega C} = \left[M_{CCC} p_{CCC} (\tilde{\varphi}_{CCC})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

and $\mathbb{P}_U = \mathbb{P}_{\Omega U}^\alpha$ and $\mathbb{P}_C = \mathbb{P}_{\Omega C}^\alpha$.

5.4 Foreign varieties in theory and in the data

Since each firm produces only one variety, the mass of varieties available in the United States is equal to the sum of the mass of US firms producing domestically (M_{UUU}), the mass of US firms offshoring production (M_{UCU}), and the mass of Chinese firms exporting

to the US (M_{CCU}):

$$\Omega_U = M_{UUU} + M_{UCU} + M_{CCU} .$$

Welfare in the United States is given by the real wage. The price index of the composite good can be rewritten as:³⁵

$$\mathbb{P}_{\Omega U} = \left[M_{UUU} \tilde{p}_{UUU}^{1-\sigma} + M_{UCU} \tilde{p}_{UCU}^{1-\sigma} + M_{CCU} \tilde{p}_{CCU}^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \quad (15)$$

where \tilde{p}_{UUU} is the price of the average productivity firm producing domestically, \tilde{p}_{UCU} is the price of the average productivity firm offshoring production to China, and \tilde{p}_{CCU} is the price of the average productivity firm exporting to the US. The overall price index in the US is $\mathbb{P}_{\Omega U}^\alpha$. Therefore, the real wage in the US is given by

$$\frac{w_U}{\mathbb{P}_U} = \frac{w_U}{\left[M_{UUU} \tilde{p}_{UUU}^{1-\sigma} + M_{UCU} \tilde{p}_{UCU}^{1-\sigma} + M_{CCU} \tilde{p}_{CCU}^{1-\sigma} \right]^{\frac{\alpha}{1-\sigma}}} . \quad (16)$$

Notice that the mass of foreign varieties implied by the model is M_{CCU} . However, using data on trade flows would conflate M_{CCU} and M_{UCU} as foreign varieties, thus overstating variety gains from foreign varieties in [Equation 16](#). Without making a distinction between the Chinese and the American designs contained in US imports from China, we would implicitly assume that all Chinese trade flows are the same from a variety standpoint. Re-sourcing from the United States to China would artificially inflate the number of foreign varieties available in the US market if we erroneously attributed all Chinese trade flows to Chinese designs. Attributing the correct design country of imported goods goes beyond a mere reshuffle of welfare; it also has implications for the effect of trade policy on product innovation. These will be explored in the next subsection.

5.5 Comparative statics

In 2001, China's accession to the World Trade Organization marked a significant shift in its economic integration with the global market. This development implied that China would become a more interconnected participant in the world economy, and that Chinese exports would be subject to more predictable tariff regimes ([Pierce and Schott, 2016](#)). The practical implications of this shift were twofold. First, it boosted imports of Chinese goods by other countries. Second, it enabled greater foreign direct investment (FDI) in China,

³⁵See [Appendix D](#) for details on the derivations.

allowing firms to leverage it as a production hub.

These two channels – Chinese firms exporting and US firms offshoring to China – likely have distinctive impacts on the US market. While both imply greater imports from China, they differ in the type of goods they bring to US consumers: Chinese firms exporting to the US bring Chinese varieties, but US firms producing in China bring US varieties. In this model, I explore each channel by examining the effects of a reduction in fixed costs associated with exporting and offshoring, respectively.³⁶

First, I look at the effect of a decrease in fixed costs of exporting for Chinese firms. By making it easier for these firms to export to the US, more Chinese firms export to the US and more Chinese varieties are available to US consumers. These foreign varieties compete with domestic ones, driving some US firms out of the market.

Figure 4 shows the effect of decreasing fixed costs of exporting for Chinese firms. The fixed costs of exporting f_{CU}^X enters directly only the profits of Chinese firms exporting to the US. For each productivity level, Chinese firms get larger profits from exporting. This directly affects the cutoff productivity for Chinese exporters implicitly defined by the Zero Cutoff Profit condition in Equation 7. With lower fixed costs of exporting, the cutoff productivity for Chinese firms to start exporting to the US decreases (the red line in Figure 4.1), more Chinese firms export, and there are more Chinese goods being imported in the US (the red line in Figure 4.2). Note that in this case, Chinese goods make for the vast majority of US imports, which is what we can observe in the data (the purple line in Figure 4.2). As more Chinese goods enter the US market, US firms face tougher competition on the product space. Prices in the US decrease and so does the demand for US-owned varieties. This lessens the sales of US firms in the domestic market, and some of them are forced to exit: the share of US-owned varieties decreases (*Domestic design* in Figure 4.3). Since the vast majority of US firms produce domestically, also US-owned varieties produced domestically decrease (*Domestic production* in Figure 4.3). A similar pattern is visible for the overall market share of US-owned varieties (*Domestic design* in Figure 4.4) and for the market share of the subset of US-owned varieties produced domestically (*Domestic production* in Figure 4.4). The more marked difference between the two lines in the last panel is due to the fact that there are very few, very productive, and therefore very large, US firms offshoring production to China. Overall, this comparative static exercise shows

³⁶This section shows comparative statics obtained for a change in the fixed costs of exporting for Chinese firms and the fixed costs of offshoring for US firms. The comparative statics for a change in iceberg trade costs are shown in Appendix D and are similar to those obtained for a change in fixed costs of exporting.

Figure 4: Change in fixed costs of exporting

Figure 4.1: Cutoffs

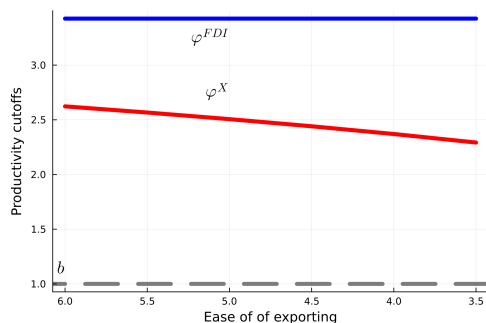


Figure 4.2: Imported varieties

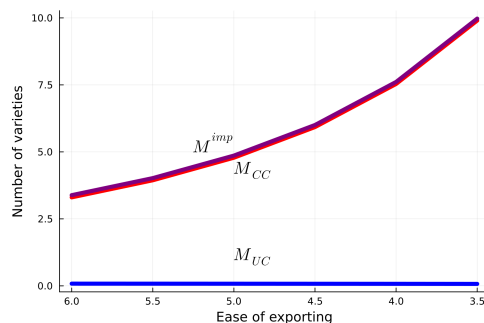


Figure 4.3: Variety share

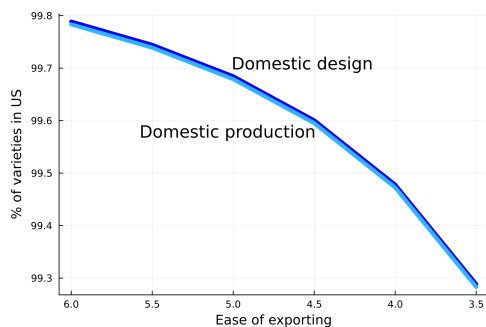
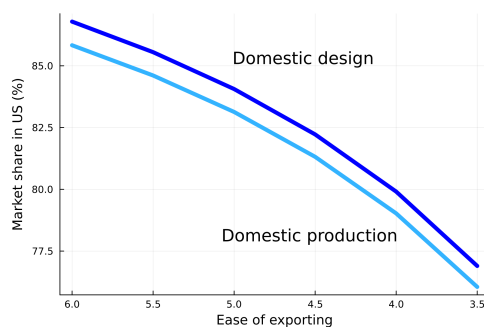


Figure 4.4: Market share



Note: Comparative statics for different values of fixed costs of exporting f_{CU}^X on the inverted x-axis. The top-left panel shows the cutoff productivity for Chinese firms to start exporting to the US (φ^X , red line), for US firms to start offshoring production to China (φ^{FDI} , blue line), and the lower bound of the productivity distribution in both countries (b , dashed gray line). The top-right panel shows the mass of Chinese-owned varieties imported by the US (M_{CC} , red line), the mass of US-owned varieties produced in China (M_{UC} , blue line), and their sum – the total mass of varieties imported by the US (M^{imp} , purple line). The bottom-left panel shows all US-owned varieties regardless of their production location (*Domestic design*, dark blue line) and US-owned varieties produced domestically (*Domestic production*, light blue line) as a percentage of all varieties sold in the US market. The bottom-right panel shows the US market share of all US-owned varieties regardless of their production location (*Domestic design*, dark blue line) and US-owned varieties produced domestically (*Domestic production*, light blue line).

that facilitating Chinese exports to the US has a negative effect on US firms, as they face more competition from Chinese goods.

In the second comparative statics exercise, I look at the effect of a decrease in fixed costs of offshoring for US firms. By making it easier for US firms to produce in China, more US firms offshore production and more US varieties are produced in China and are now part of US imports from China. Expected profits of US firms rise, allowing more US firms, and consequently more US varieties, to enter the market. This trade policy is similar to giving US firms access to a cheaper production technology.

Figure 5 shows the effect of decreasing fixed costs of offshoring for US firms. The fixed costs of offshoring f_{UC}^{FDI} enters directly only the profits of US firms offshoring production to China. For each productivity level, US firms get larger profits from offshoring production to China. The cutoff productivity implicitly defined by the Zero Cutoff Profit condition in Equation 4 is directly affected by the fixed costs of offshoring: the lower the fixed costs of offshoring, the lower the cutoff productivity for US firms to start offshoring (the blue line in Figure 5.1). As a consequence, more US firms offshore production to China, and there are more US varieties produced abroad being imported in the US (the blue line in Figure 5.2). With more US firms producing in China and shipping those goods back to the US, overall US imports from China increase (the purple line in Figure 5.2). These overall imports are what we usually observe in the data, but mask the fact that most of the increase comes from the import of US-owned varieties (the red and the blue line in Figure 5.2, respectively). As US imports from China increase, US exports to China must also increase to maintain balanced trade. The United States export the homogeneous good sector, so the demand for labor to be employed in the homogeneous good sector increases. With more US varieties being produced in China, fewer US varieties are produced domestically (*Domestic production* in Figure 5.3) and so their market share decreases as well (*Domestic production* in Figure 5.4). As the largest, more productive US firms move their production activities to China, and as their sales increase with lower fixed costs of offshoring, the market share of all US-owned varieties increases (*Domestic design* in Figure 5.4).

The comparative statics show that the effect of an increase in imports from China on the mass of US-owned varieties, whether produced domestically or not, depends on the type of the shock, and consequently on the composition of these imports. In the data we rarely observe such composition: we can only observe overall exports from China, not whether

Figure 5: Change in fixed costs of offshoring

Figure 5.1: Cutoffs

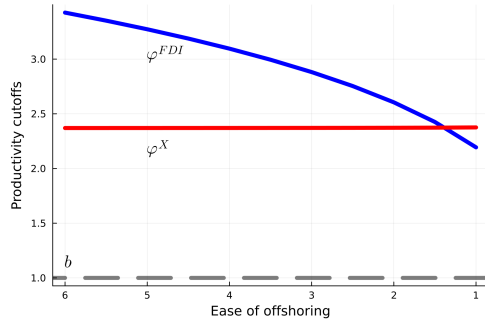


Figure 5.2: Imported varieties

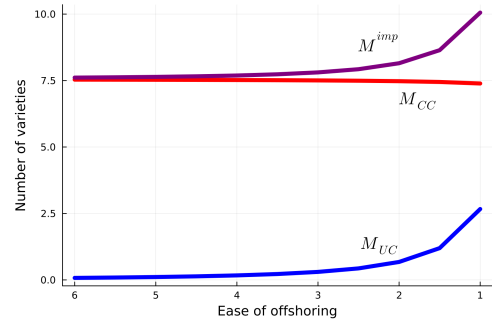


Figure 5.3: Variety share

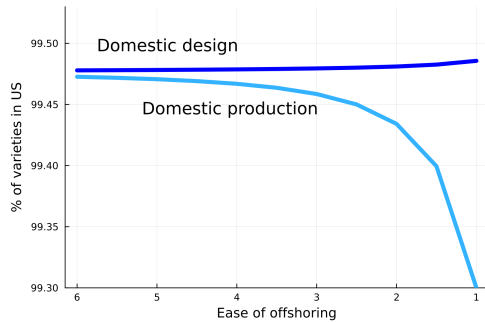
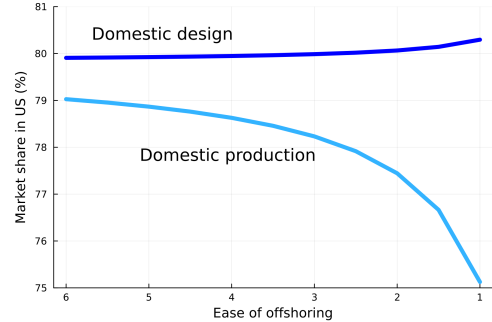


Figure 5.4: Market share



Note: Comparative statics for different values of fixed costs of offshoring f_{UC}^{FDI} on the inverted x-axis. The top-left panel shows the cutoff productivity for Chinese firms to start exporting to the US (φ^X , red line), for US firms to start offshoring production to China (φ^{FDI} , blue line), and the lower bound of the productivity distribution in both countries (b , dashed gray line). The top-right panel shows the mass of Chinese-owned varieties imported by the US (M_{CC} , red line), the mass of US-owned varieties produced in China (M_{UC} , blue line), and their sum – the total mass of varieties imported by the US (M^{imp} , purple line). The bottom-left panel shows all US-owned varieties regardless of their production location (*Domestic design*, dark blue line) and US-owned varieties produced domestically (*Domestic production*, light blue line) as a percentage of all varieties sold in the US market. The bottom-right panel shows the US market share of all US-owned varieties regardless of their production location (*Domestic design*, dark blue line) and US-owned varieties produced domestically (*Domestic production*, light blue line).

they are made by Chinese-owned firms or foreign-owned firms. This project provides the necessary framework for empirically testing the predictions of this model, which I will explore in detail in the next section.

6 Chinese competition and product innovation

The early 2000s were characterized by the surge of China as the world manufacturer. Between 1989 and 2014, US imports from China as a share of total imports have grown by six times, leading many economists to study the impact of what has been known as the “China shock” on various outcomes, ranging from employment to patenting activity.³⁷ However, what do US imports from China consist of? Most of these studies posit that these flows are composed of many cheap goods manufactured in China, whose presence in the US market undermines the sales of domestic firms. However, among US firms there are big multinationals whose manufacturing activity has benefitted from lower wages in the Chinese market and from lower tariffs after China’s entry in the World Trade Organization. As discussed in [Section 4](#), US imports from China largely consist of imports from MNEs located in China. Interpreting a surge in trade flows as a surge in varieties becomes problematic, as it creates a discrepancy with the theory described in [Section 5](#): trade flows from China include both Chinese designs and US designs manufactured in China; the latter are not new varieties for American consumers. In summary, not all “made-in-China” goods are genuinely Chinese varieties.³⁸

³⁷The literature on the “China shock” brings evidence of lower prices ([Feenstra and Weinstein, 2017](#); [Amiti et al., 2020](#)), but also of lower earnings to labor markets in the US, and, to a lesser extent, in Germany, Spain, Norway, and France ([Autor et al., 2013](#); [Dauth et al., 2014](#); [Donoso et al., 2015](#); [Balsvik et al., 2015](#); [Malgouyres, 2017](#)). With respect to innovation, the literature finds conflicting evidence on the role of Chinese competition: it has a positive ([Bloom et al., 2016](#); [Xu and Gong, 2017](#); [Impullitti and Licandro, 2018](#)), negative ([Autor et al., 2020](#)), or inverted-U effect on innovation ([Chakravorty et al., 2022](#)). Finally, [Yang et al. \(2021\)](#) find that the effect of Chinese competition depends on the type of the innovation itself: while product innovation incentives of Canadian firms are stimulated by an increase in competition from China, process innovation incentives decline. Negative labor market effects are smaller or not present on aggregate at the national level ([Hsieh and Ossa, 2016](#); [Galle et al., 2017](#); [Caliendo et al., 2019](#); [Adao et al., 2019](#)).

³⁸This argument is in line with the work of [Jakubik and Stolzenburg \(2021\)](#) which removes US value added in Chinese exports from the exposure measure used in [Autor et al. \(2013\)](#). They find that this decoupling reduces the volume of the shock as well as the size of the negative effect on local labor markets.

6.1 Import competition

Given that not all imports from China represent the same varieties, it is crucial to distinguish between trade flows from Chinese firms and those from MNEs when examining the impact of Chinese import competition on product innovation. I define two explanatory variables for a sector s over an h -years time window before year τ . The first one is the Davis-Haltiwanger growth rate (Davis and Haltiwanger, 1992) of US imports from MNEs in China:

$$\text{MNE}_{s,\tau} = \frac{\left(\frac{M_{s,\tau}^{\text{MNE},US}}{M_{s,\tau}^{US}} - \frac{M_{s,\tau-h+1}^{\text{MNE},US}}{M_{s,\tau-h+1}^{US}} \right)}{0.5 \times \left(\frac{M_{s,\tau}^{\text{MNE},US}}{M_{s,\tau}^{US}} + \frac{M_{s,\tau-h+1}^{\text{MNE},US}}{M_{s,\tau-h+1}^{US}} \right)} \times 100 \quad (17)$$

where $M_{s,\tau}^{\text{MNE},US}$ is US imports of sector s goods coming from MNEs located in China in year τ and $M_{s,\tau}^{US}$ is overall imports of sector s goods in the US in year τ . The second explanatory variable is the Davis-Haltiwanger growth rate of US imports from Chinese-owned firms:

$$\text{CN}_{s,\tau} = \frac{\left(\frac{M_{s,\tau}^{\text{CN},US}}{M_{s,\tau}^{US}} - \frac{M_{s,\tau-h+1}^{\text{CN},US}}{M_{s,\tau-h+1}^{US}} \right)}{0.5 \times \left(\frac{M_{s,\tau}^{\text{CN},US}}{M_{s,\tau}^{US}} + \frac{M_{s,\tau-h+1}^{\text{CN},US}}{M_{s,\tau-h+1}^{US}} \right)} \times 100 \quad (18)$$

where $M_{s,\tau}^{\text{CN},US}$ is US imports of sector s goods coming from Chinese firms located in China. It is possible that the effect of import competition on product innovation is heterogeneous across firms. I split trademarking firms in two categories: incumbent firms, which have owned a trademark for at least 5 years or have purchased a trademark from another firm, and entrant firms, which have owned a trademark for less than 5 years. Motivated by the difference in entry rates between entrant and incumbent firms shown in Figure A3 in Appendix A, I test for a heterogeneous impact of import competition on firms based on their status as either entrant or incumbent. Empirically, I aggregate the data at the sector, year, and status level to estimate the following fully saturated specification:

$$Y_{sit} = \beta_{\text{MNE}}^{\text{E}} \text{MNE}_{sit}^{\text{E}} + \beta_{\text{MNE}}^{\text{I}} \text{MNE}_{sit}^{\text{I}} + \beta_{\text{CN}}^{\text{E}} \text{CN}_{sit}^{\text{E}} + \beta_{\text{CN}}^{\text{I}} \text{CN}_{sit}^{\text{I}} + \boldsymbol{\delta}' + \varepsilon_{sit} \quad (19)$$

where index s represents a sector, index t represents a year, and index i represents the status of entrant or incumbent. The dependent variable Y_{ist} is either the h -years growth rate of varieties in sector s over all firms of status i or the logarithm of the number of firms with status i and varieties in sector s operating in the last h years. $\text{MNE}_{st}^{\text{E}}$ is trade flows

from MNEs as defined in [Equation 17](#) and interacted with an indicator variable for entrant firms, while MNE_{st}^I is the same variable interacted with an indicator variable for incumbent firms. The other two sets of explanatory variables are CN_{st}^E and CN_{st}^I , which are the trade flows from Chinese firms as defined in [Equation 18](#) interacted with an indicator variable for entrant firms and for incumbent firms, respectively. Finally, I control for a battery of fixed effects δ , including year, sector, and status fixed effects. The error term ε_{sit} is clustered at the sector-year level. My baseline specification uses time intervals of five years, but results are robust to using time intervals of three years.³⁹

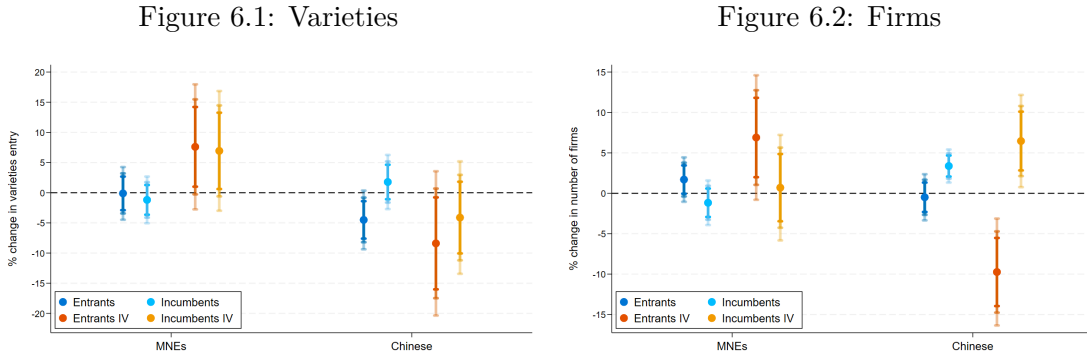
This specification may be subject to omitted variable bias. There may be an unobservable variable causing both trade flows from China and American-owned varieties to change. For example, a positive demand shock in the United States could cause both imports from China and domestic varieties to rise. To account for that, I instrument both MNEs and Chinese exports to the US with the corresponding trade flows to the rest of the world. In other words, I instrument trade flows from foreign-owned firms located in China to the US with trade flows from foreign-owned firms located in China to any other country in the world. Similarly, I instrument trade flows from Chinese-owned firms located in China to the US with trade flows from Chinese-owned firms located in China to the rest of the world.⁴⁰ In doing so, I am able to exclude the effect of potential unobservable shocks specific to the United States. However, note that the exclusion restriction of this instrument holds only if the unobservable shocks of the United States are not correlated with the unobservable shocks of all other countries.

I am interested in the coefficients β_{MNE}^E and β_{MNE}^I for the effect of trade flows from MNEs, and in the coefficients β_{CN}^E and β_{CN}^I for the effect of trade flows from Chinese-owned firms. A one standard deviation increase in the growth of trade flows from MNEs leads to more US-owned varieties, as displayed in [Figure 6.1](#): a one standard deviation increase in the growth of trade flows from MNEs located in China leads to a 7-8% increase in variety entry rate of both incumbent and entrant firms. In contrast, a one standard deviation increase in the growth of trade flows from Chinese-owned firms leads to an 8% decrease in the entry rate of varieties of newly established American firms. This result suggests a deterrance effect of *direct* import competition from China on new US products. The magnitude of

³⁹Results for three-years time intervals are displayed in [Figure A14](#) and [Figure A15](#) in [Appendix A](#).

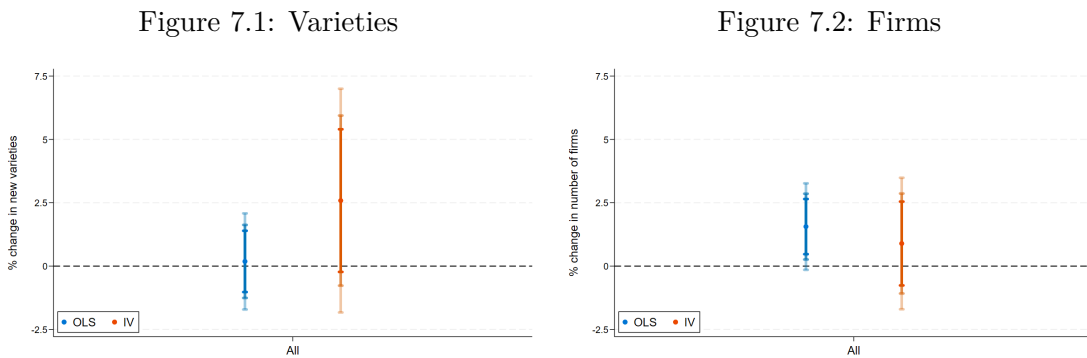
⁴⁰This instrument is not dissimilar from those used by [Costa et al. \(2016\)](#) and [Hummels et al. \(2014\)](#) for Brazil and Denmark, respectively. The first stage is shown in [Table A11](#) in [Appendix A](#).

Figure 6: The effect of import competition on domestic product innovation



Notes: The figure shows the estimated coefficients for entrant and incumbent firms of the effect of import competition on the entry rate of US-owned varieties and on the number of US firms (Equation 19). Import competition is computed using only trade flows of foreign-owned firms located in China (“MNEs”), or only trade flows of Chinese-owned firms located in China (“Chinese”). 90%, 95%, and 99% confidence intervals are shown. The dark and light blue coefficients report OLS estimates, while the red and yellow coefficients report 2SLS estimates. Coefficients in terms of percentage of the average value of the dependent variable are taken from Table A12 and Table A13 in Appendix A.

Figure 7: The effect of aggregate import competition on domestic product innovation



Notes: The figure shows the estimated coefficients of the effect of aggregate imports from China on the entry rate of US-owned varieties and on the number of US firms. 90%, 95%, and 99% confidence intervals are shown. The dark blue coefficients report OLS estimates, while the red coefficients report 2SLS estimates.

such effect is sizeable: doubling the growth in imports from Chinese firms leads to a 10% decrease in the entry rate of US-owned varieties in the American market.⁴¹

The effect on the number of firms offering these products is similar. A one standard deviation increase in the growth of trade flows from Chinese-owned firms corresponds to a 10% decrease in the number of newly established US firms (Figure 6.2).

Taken together, Figure 6.1 and Figure 6.2 provide evidence that increased trade flows from Chinese firms hinder the entry of new firms in the US market and the introduction of new varieties. In other words, competition from China reduces the profit margins that firms expect to make once entering the market, and thus dissuades them from doing so.

The notion that intense competition is responsible for the decreased entry of firms is supported by Figure A16 in Appendix A which further splits direct Chinese import competition into trade flows of final and intermediate goods. The negative effect of import competition comes exclusively from imports of final goods departing from Chinese-owned firms.

On the contrary, trade flows from MNEs located in China lead to an increase in new US firms producing differentiated products and on product entry. The intuition here is that some US firms may create a new product – hence a US variety – but benefit from low manufacturing costs in China and ship their made-in-China goods to the US. For example, a new model of Nike shoes (a US company) could be manufactured and shipped to the US by Nike’s subsidiary in Suzhou (a foreign-owned company in China).⁴² The differential effect of US imports from Chinese-owned firms and MNEs matches the predictions made by the model in Section 5: an influx of Chinese varieties has pro-competitive effects on the US market and prevents the entry of more firms, while an increase in trade flows from MNEs allows more firms to enter and introduce products.

This is in line with the findings of Fort et al. (2020), suggesting that in the years 2007-2011 some US firms have shifted manufacturing to China but have kept patenting in the US. It

⁴¹The OLS estimates for the growth of imports from Chinese-owned firms and the growth of imports from MNEs are biased in different directions. As formalized by Levinsohn and Petrin (2003), this can happen if the two types of imports are positively correlated and one of the two responds to the unobservable shock more than the other. The two trade flows are positively correlated, as seen in Figure 3. The unobservable shock could be a positive demand shock in the US market, making it plausible that US imports from Chinese-owned firms located in China respond more to it than US imports from MNEs located in China.

⁴²While the actual manufacture of shoes may also happen through third-party contract suppliers (Fort, 2023), some of these subsidiaries are responsible for import and export activities in China. For example, of the four Nike’s subsidiaries reported for China in 2013, three operate in import/export. The full list of subsidiaries can be accessed on exhibit 21 of their annual report (10-K) filed with the US Securities and Exchange Commission: <https://www.sec.gov/>.

is also in line with more direct evidence on the product innovation activity of offshoring firms: [Branstetter et al. \(2021\)](#) find that Taiwanese firms offshoring some production to China introduce new products in other parts of their portfolio.

The results shown in [Figure 6](#) provide a more nuanced insight than what could be obtained from merely looking at aggregate US imports from China, which pool trade flows from Chinese-owned and foreign-owned firms together. [Figure 7](#) shows that aggregate import competition has a zero effect on product innovation. This result is somewhat in line with [Autor et al. \(2020\)](#), finding a negative effect of Chinese import competition on patenting activity of small firms, but no effect on the patenting activity of above-median firms. Patenting activity is likely to conflate both product and process innovation, as many products are not associated with patents ([Argente et al., 2021](#)). From [Yang et al. \(2021\)](#) we should expect product and process innovation to respond differently to import competition. If we split firms into entrants and incumbents, we can see that aggregate import competition has no effect on new products brought by entrant firms but a positive effect on new products brought by incumbent firms (column (1) in [Table A12](#) in [Appendix A](#)). However, distinguishing trade flows from China based on the ownership of the exporting firms is crucial for uncovering novel results: the increase in variety entry rate is explained only by the increase in trade flows from MNEs located in China, suggesting that the introduction of new varieties was possible because of access to cheaper manufacturing costs abroad.

It is natural to ask what would have been obtained by using a more standard measure of varieties, such as HS codes and country of origin pairs. The answer is that it is not possible to measure domestic varieties using HS codes and country of origin pairs. To construct a proxy for domestic US varieties using sectoral trade flows, I assume that HS 6-digits sectors exported by the United States are sectors where US firms are active and equivalent to domestic varieties for US consumers. This is possibly a lower bound of the actual domestic varieties, if US consumers have access to varieties as measured by HS codes that are never expored. I then compute the growth rate of US exported varieties to the rest of the world and use it as a proxy for the growth rate of US varieties. [Table A14](#) in [Appendix A](#) shows the results with this alternative measure. Note that my previous Instrumental Variable is not valid in this specification.⁴³ Contrary to the results obtained with trademarks, imports

⁴³Since US varieties are now measured as the number of sectors with a positive value of US exports, there may be an unobservable shock, like a demand shock in some foreign countries, affecting both imports

from Chinese-owned firms located in China have no effect on the entry rate of US varieties when using HS codes. On the other hand, [Table A14](#) in [Appendix A](#) shows a negative effect of US imports from foreign-owned firms located in China on the entry rate of US varieties. While at first counterintuitive, these results can be rationalized once we realize that the measure of domestic varieties is based on US exporting activity, which is diverted by the US offshoring activity to China. If the United States offshore production to China, they can access the Chinese market or any other market from there, no longer having to ship goods from the US.⁴⁴

6.2 Export competition

I then turn to foreign product innovation in the US market, as US imports from China may have effects on the introduction of new products by third countries. An increase in US imports from China may, for example, sway a German or French firm from selling a brand new product to American consumers. This is usually referred to as export competition, as it is competition happening in a common export market.

To study the effect of increased US imports from China on product innovation of other foreign firms, I use a similar specification to [Equation 19](#):

$$Y_{sit} = \beta_{MNE}^E MNE_{sit}^E + \beta_{MNE}^I MNE_{sit}^I + \beta_{CN}^E CN_{sit}^E + \beta_{CN}^I CN_{sit}^I + \boldsymbol{\delta}' + \varepsilon_{sit} \quad (20)$$

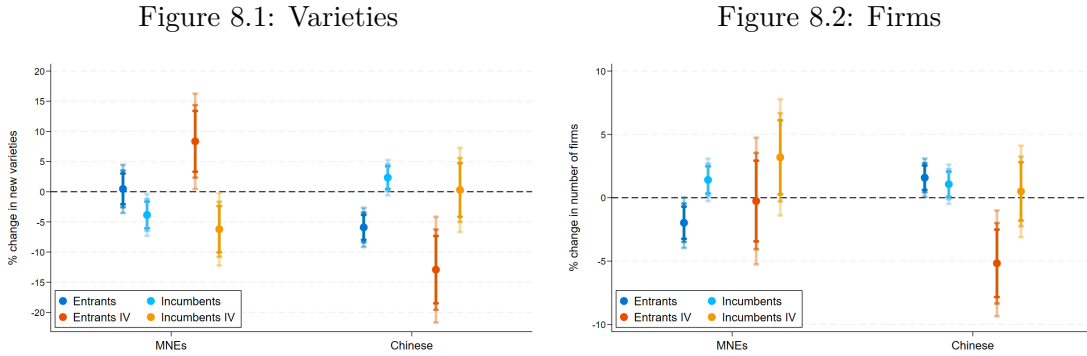
where index s represents a sector, index t represents a year, and index i represents the status of entrant or incumbent. The dependent variable Y_{sit} is now either the h -years growth rate of varieties over all firms of non-US and non-Chinese nationality and status i in sector s or the logarithm of the number of firms with non-US and non-Chinese nationality, status i , and varieties in sector s operating in the last h years. MNE_{st}^E is trade flows from MNEs as defined in [Equation 17](#) and interacted with an indicator variable for entrant firms, while MNE_{st}^I is the same variable interacted with an indicator variable for incumbent firms. The other two sets of explanatory variables are CN_{st}^E and CN_{st}^I , which are the trade flows from Chinese firms as defined in [Equation 18](#) interacted with an indicator variable for entrant

from China (the instrument for US imports from China) and the range of sectors imported from the US (the dependent variable).

⁴⁴Note that the negative effect of US imports from MNEs located in China is not driven by the sectors that are only exported by the United States to China, as the estimated coefficients do not substantially change when excluding those HS codes ([Table A15](#) in [Appendix A](#)).

firms and for incumbent firms, respectively. Finally, I control for year, sector, and status fixed effects in δ . The error term ε_{sit} is clustered at the sector-year level.

Figure 8: The effect of export competition on foreign product innovation



Notes: The figure shows the estimated coefficients for entrant and incumbent firms of the effect of export competition on the entry rate of non-US-owned and non-Chinese-owned varieties in the US market and on the number of those firms (Equation 20). Export competition is computed using only trade flows of foreign-owned firms located in China (“MNEs”), or only trade flows of Chinese-owned firms located in China (“Chinese”). 90%, 95%, and 99% confidence intervals are shown. The dark and light blue coefficients report OLS estimates, while the red and yellow coefficients report 2SLS estimates. Coefficients in terms of percentage of the average value of the dependent variable are taken from Table A16 and Table A17 in Appendix A.

When looking at non-US and non-Chinese firms, I observe similar results both in terms of direction and magnitude. A one standard deviation increase in trade flows from Chinese firms to the US market corresponds to almost a 15% decrease in new foreign-owned varieties from newly established firms (Figure 8.1). Once again, import competition from Chinese firms deters entry and product innovation of newly established non-Chinese firms.

Such entry prevention is larger than those observed for US firms. Intuitively, we can expect entry deterrence to be stronger between goods that are closer substitutes. Feenstra et al. (2018) show that the elasticity of substitution between alternative import sources is larger than the elasticity between domestic and foreign sources. Chinese varieties have a higher elasticity of substitution with domestic varieties than with foreign ones, thus making it harder for consumers to substitute a US variety with a Chinese one. The greater difficulty in switching products may explain why entry prevention is less pronounced for domestic firms than for foreign ones.

A main distinction compared to the previous results comes from incumbent firms. Trade flows from MNEs lead to almost a 10% decrease in the product innovation activities of

foreign incumbent firms. As much of offshoring activity in China is made by US firms, it is possible that the negative effect of MNE trade flows simply indicates US firms being more competitive at the expenses of non-Chinese foreign firms who do not get the chance to offshore production to China. Unfortunately, Chinese customs data does not have information on the precise nationality of foreign-owned firms in China, which would help uncover whether this effect comes from American MNEs in China or not.⁴⁵

Once again, we may ask what would have been obtained by using the more standard measure relying on sectoral trade classifications. I estimate again [Equation 20](#) measuring foreign varieties as unique pairs of HS 6-digits codes and country of origin for which the United States have positive imports. [Table A18](#) in [Appendix A](#) shows that no measure of US imports from China has an effect on the growth rate of foreign varieties in the US market when using HS codes.

7 Variety gains from trade

Ultimately, economists are interested in changes in the mass of varieties because they reflect on consumer welfare. [Section 5](#) introduced a model with CES preferences. In such a setting, the price index for any mass of varieties M can be decomposed into three components:

$$\ln \mathbb{P} = \overline{\ln p} - \frac{1}{\sigma - 1} \frac{1}{M} \sum_{m=1}^M \ln \left(\frac{\bar{R}}{R_m} \right) - \frac{1}{\sigma - 1} \ln M \quad (21)$$

where R represents revenues and \bar{x} is the average of variable x over all varieties.⁴⁶ The first component, $\overline{\ln p}$, is the average log unit price. This component is positively correlated with the overall price index: if on average there are goods with higher unit prices, then the overall price index increases. The second component shown in [Equation 21](#) is the Theil

⁴⁵The effect on Chinese product innovation reflects the findings of [Table 2](#): trade flows from MNEs partially deter the entry of newly established firms, while trade flows from Chinese firms foster both innovation and entry ([Figure A17](#) in [Appendix A](#)).

⁴⁶[Equation 21](#) is obtained from the result that revenue shares are proportional to the price shares: $\frac{R_m}{\sum_m R_m} = \left(\frac{p_m}{\mathbb{P}} \right)^{1-\sigma}$. Taking logs and averaging over the whole set of varieties, it holds that:

$$\frac{1}{M} \sum_{m=1}^M \ln R_m - \ln \sum_{m=1}^M R_m = (1 - \sigma) \left(\frac{1}{M} \sum_{m=1}^M \ln p_m - \ln \mathbb{P} \right).$$

Adding and subtracting $\ln(M\bar{R})$ and rearranging terms, we obtain [Equation 21](#).

index, a measure of market concentration. This component directly affects the overall price index: with a more concentrated market in terms of revenues, $\frac{1}{\sigma-1} \frac{1}{M} \sum_{m=1}^M \ln \left(\frac{\bar{R}}{R_m} \right)$ decreases and the overall price index increases. If the product market is highly concentrated, consumers tend to pay higher prices. The last component shown in [Equation 21](#) relates to the mass of varieties available in the market. As the mass of varieties increases, the price index decreases, reflecting the fact that consumers enjoy a higher level of welfare by consuming a wider set of goods.

Using the decomposition shown in [Equation 21](#), I can rewrite changes in welfare over a time window h as the first difference of log price indices:

$$\begin{aligned} \ln \left(\frac{w_{t+h}}{\mathbb{P}_{t+h}} \right) - \ln \left(\frac{w_t}{\mathbb{P}_t} \right) &= \ln \left(\frac{w_{t+h}}{w_t} \right) + \overline{\ln p_t} - \overline{\ln p_{t+h}} + \\ &+ \frac{1}{\sigma-1} \left[\frac{1}{M_{t+h}} \sum_{m=1}^{M_{t+h}} \ln \left(\frac{\overline{R_{t+h}}}{R_{m,t+h}} \right) - \frac{1}{M_t} \sum_{m=1}^{M_t} \ln \left(\frac{\overline{R_t}}{R_{m,t}} \right) \right] + \\ &+ \frac{1}{\sigma-1} (\ln M_{t+h} - \ln M_t) \end{aligned} \quad (22)$$

This paper quantifies the welfare change resulting from an increase in the mass of available varieties, referred to as variety gains from trade; specifically, the last term of [Equation 22](#).⁴⁷ Since trademarks lack information on prices and revenues at the product level, they are not suitable for computing the other components of the price index decomposition in [Equation 21](#). However, using data on US imports and measuring varieties as HS-country pairs, the mass of varieties appears to contribute between 40 to 45 percent of the price index of imported goods ([Table A10](#) in [Appendix A](#)). Therefore, any insights on the variety gains from trade gives us a better understanding of almost half of the price index.

[Table 3](#) shows the variety gains from trade obtained by US consumers over the period 1995 to 2014 using two different definitions of variety: pairs of HS codes and country of origin, or trademarks. This is the change in welfare obtained by a change in the mass of available varieties, keeping constant US wages, unit prices, and market concentration.⁴⁸ In addition

⁴⁷The literature has shown that the contribution of variety gains from trade on the price index is quite large: the increase in mass of available Chinese varieties in the years 2000-2006 corresponds to two-thirds of the decrease in price index for US consumers ([Amiti et al., 2020](#)). However, notice that [Amiti et al. \(2020\)](#) use a different kind of decomposition, where variety gains include the market share of new varieties.

⁴⁸A constant market concentration is plausible: [Amiti and Heise \(2024\)](#) shows that market concentration of all firms selling to the US market has not changed in the years 1992-2012, whether measured as the

to changes in the number of varieties, welfare is determined by the elasticity of substitution σ . When using HS codes, the literature has commonly used an elasticity of substitution of 5. For trademarks, I estimate the elasticity of substitution implied by monopolistic competition markups of Compustat firms that own only one trademark throughout the sample period. Depending on the fraction of selling, general, and administrative expenses attributed to variable costs, I obtain an elasticity of substitution of 5 or 10 (see [Table A9](#) in [Appendix A](#)).

Depending on the elasticity used, the welfare gains implied by trademarks are between two and five times larger than those implied by 6-digit HS codes. The two approaches differ conceptually in two dimensions. On one hand, HS codes may undercount the number of varieties because they are coarse groupings, so they fail to capture the creation of new varieties within one sector. For example, they would not capture the creation of different brands of compact SUVs, as they would all fall within the same HS 6-digit category 870323. On the other hand, HS codes may overstate the number of varieties because they treat the country of shipment as an intrinsic characteristic of a good. Going back to the compact SUVs example, HS codes would count a Honda CR-V imported from Japan and a Honda CR-V imported from Mexico as two different varieties. The larger welfare gains observed with trademarks in [Table 3](#) suggest that the first source of bias is more significant than the second.

One could be concerned that the US price index for foreign varieties obtained using HS codes and trademarks are conceptually different. Indeed they are conceptually different: both include foreign varieties produced abroad, but the HS-based price index contains also US varieties produced abroad, while the trademarks-based price index also contains foreign varieties produced in the US. For example, the HS-based price index contains Nike shoes manufactured in Suzhou, while the trademark-based price index contains Honda cars assembled in Ohio. To make the two price indices comparable, I compute them over all varieties available in the US, both domestic and foreign ones. However, HS codes cannot be used to measure domestic varieties because they only track shipments across borders. To construct the overall HS-based price index, I assume that the number of HS codes exported by the US is also consumed domestically, using that as a proxy for domestic US varieties. [Table 4](#) shows that trademarks still imply larger welfare gains than HS 6-digit codes, but the difference is smaller in magnitude: variety gains implied by trademarks are between

market share of the top 20 firms or as the Herfindahl-Hirschman Index.

Table 3: Variety gains from trade

Time interval	HS 6-digit	Trademarks	
	$\sigma = 5$	$\sigma = 5$	$\sigma = 10$
1995-1999	2.47%	11.95%	5.15%
2000-2004	1.62%	9.40%	4.07%
2005-2009	-1.47%	7.56%	3.29%
2010-2014	0.84%	5.51%	2.41%

Notes: The table shows the welfare gains for US consumers due to an expansion in the mass of foreign varieties available in four time periods. The first column defines varieties as pairs of HS 6-digits codes and country of origin. The second and third column use varieties as measured by trademarks, but differ in the elasticity of substitution σ being used, which is obtained from computing markups of firms in Compustat (Table A9 in Appendix A).

Table 4: Variety gains from trade including domestic varieties

Time interval	HS 6-digit	Trademarks	
	$\sigma = 5$	$\sigma = 5$	$\sigma = 10$
1995-1999	2.63%	7.91%	3.44%
2000-2004	1.46%	7.22%	3.15%
2005-2009	-1.43%	3.76%	1.66%
2010-2014	0.73%	3.96%	1.74%

Notes: The table shows the welfare gains for US consumers due to an expansion in the mass of overall varieties available in four time periods. The first column defines varieties as combinations of HS 6-digits codes and country of origin. The second and third column uses varieties as measured by trademarks, but differ in the elasticity of substitution σ being used, which is obtained from computing markups of firms in Compustat (Table A9 in Appendix A). Domestic trademark-based varieties are trademarks registered by US firms. Domestic HS-based varieties are the number of HS 6-digits codes for which the US has non zero value of exports to any other country.

two to three times larger than variety gains implied by HS codes.

8 Conclusion

The relationship between globalization and the availability of new products is a key theoretical channel for welfare. However, quantifying these welfare gains is challenging, as it requires a measure of the change in the range of varieties available in a market. In this paper, I propose a new measure of varieties that does not use production location as a characteristic and that allows to capture both domestic and foreign products.

This measure is based on trademarks registered in the United States between 1982 and 2020. Combining them with detailed Chinese customs data, I show that not all imports are equal from a variety standpoint: disentangling country of *design* with country of *production* of a product is key to fully assess variety gains from trade.

Overall, this paper sheds light on two key issues. First, it quantifies variety gains from trade. Trademarks deliver 2-3 times larger variety gains for the years 1995-2014 compared to what can be obtained using standard measures. This result suggests that sectoral trade flows do not capture a large extent of the product innovation happening within sectoral categories. Second, it studies the effect of import competition from China on the introduction of new products in the American market. I find that only imports from Chinese-owned firms located in China have a detrimental effect on the introduction of new US products.

This is the first paper establishing a direct and credible connection between customs data and varieties while providing a cautionary, if not intuitive, result: not all trade is equal from the perspective of variety growth. Correctly measuring varieties matters for broader questions in international trade with relevant policy implications. Extending the data coverage beyond 2014 could allow to study the reallocation of brands due to the US-China Trade War. My new measure does not treat re-sourcing as a new variety, allowing to more accurately assess the effect of the trade war on the availability of new products in the American market.

References

- Adao, R., C. Arkolakis, and F. Esposito. 2019.** “Spatial Linkages, Global Shocks, and Local Labor Markets: Theory and Evidence.” Cowles Foundation for Research in Economics, Yale University Cowles Foundation Discussion Papers 2163.
- Akcigit, U., and J. Van Reenen. 2023.** *The Economics of Creative Destruction: New Research on Themes from Aghion and Howitt.*
- Akcigit, U., and M. J. Melitz. 2022.** “International Trade and Innovation.” *Handbook of International Economics* Vol. 5, 377–404. Elsevier.
- Akcigit, U., and W. Kerr. 2018.** “Growth through Heterogeneous Innovations.” *Journal of Political Economy*, 126(4): 1374–1443.
- Alfaro, L., C. G. Bao, M. X. Chen, J. Hong, and C. Steinwender. 2022.** “Omnia Juncta in Uno: Foreign Powers and Trademark Protection in Shanghai’s Concession Era.” NBER Working Papers.
- Amiti, M., and S. Heise. 2024.** “Market Concentration and Import Competition.” *Review of Economic Studies*.
- Amiti, M., M. Dai, R. Feenstra, and J. Romalis. 2020.** “How did China’s WTO entry affect U.S. prices?” *Journal of International Economics*, 126: 1–24.
- Amiti, M., S. J. Redding, and D. E. Weinstein. 2019.** “The Impact of the 2018 Tariffs on Prices and Welfare.” *Journal of Economic Perspectives*, 33(4): 187–210.
- Argente, D., S. Baslandze, D. Hanley, and S. Moreira. 2021.** “Patents to Products: Product Innovation and Firm Dynamics.” Federal Reserve Bank of Atlanta FRB Atlanta Working Paper.
- Arkolakis, C., N. Ramondo, A. Rodríguez-Clare, and S. Yeaple. 2018.** “Innovation and Production in the Global Economy.” *American Economic Review*, 108(8): 2128–73.
- Autor, D., D. Dorn, and G. H. Hanson. 2013.** “The China Syndrome: Local Labor Market Effects of Import Competition in the United States.” *American Economic Review*, 103(6): 2121–68.

- Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu. 2020.** “Foreign Competition and Domestic Innovation: Evidence from US Patents.” *American Economic Review: Insights*, 2(3): 357–74.
- Balsvik, R., S. Jensen, and K. G. Salvanes. 2015.** “Made in China, sold in Norway: Local labor market effects of an import shock.” *Journal of Public Economics*, 127(C): 137–144.
- Battacharyya, P., T. Lybbert, and N. Zolas. 2017.** “An ‘Algorithmic Links with Probabilities’ Concordance for Trademarks wit an Application Towards Bilateral IP Flows.” *The World Economy*, 40(6): 1184–1213.
- Bernard, A. B., S. J. Redding, and P. K. Schott. 2010.** “Multiple-Product Firms and Product Switching.” *American Economic Review*, 100(1): 70–97.
- Bernard, A. B., S. J. Redding, and P. K. Schott. 2011.** “Multiproduct firms and trade liberalization.” *The Quarterly Journal of Economics*, 126(3): 1271–1318.
- Bloom, N., M. Draca, and J. Van Reenen. 2016.** “Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity.” *The Review of Economic Studies*, 83(1): 87–117.
- Bloom, N., P. Romer, S. Terry, and J. V. Reenen. 2021.** “Trapped Factors and China’s Impact on Global Growth.” *The Economic Journal*, 131(633): 156–191.
- Brandt, L., and K. Lim. 2023.** “Opening Up in the 21st Century: A Quantitative Accounting of Chinese Export Growth.”
- Branstetter, L., J.-R. Chen, B. Glennon, and N. Zolas. 2021.** “Does Offshoring Manufacturing Harm Innovation? Evidence from Taiwan and China.” NBER Working Papers 29117.
- Broda, C., and D. E. Weinstein. 2006.** “Globalization and the Gains from Variety.” *The Quarterly Journal of Economics*, 121(2): 541–585.
- Broda, C., and D. E. Weinstein. 2010.** “Product creation and destruction: Evidence and price implications.” *American Economic Review*, 100(3): 691–723.
- Cain, C. P. 2021.** *Trademark Manual of Examining Procedures*. USPTO.

- Caliendo, L., M. Dvorkin, and F. Parro. 2019.** “Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock.” *Econometrica*, 87(3): 741–835.
- Chakravorty, U., R. Liu, R. Tang, and L. Zhao. 2022.** “Firm innovation under import competition from low-wage countries.” Working Paper.
- Chaney, T. 2008.** “Distorted Gravity: The Intensive and Extensive Margins of International Trade.” *American Economic Review*, 98(4): 1707–21.
- Conte, M., P. Cotterlaz, and T. Mayer. 2022.** “The CEPII Gravity database.” CEPII Working Paper 2022-05.
- Costa, F., J. Garred, and J. P. Pessoa. 2016.** “Winners and losers from a commodities-for-manufactures trade boom.” *Journal of International Economics*, 102(C): 50–69.
- Dauth, W., S. Findeisen, and J. Suedekum. 2014.** “The Rise of the East and the Far East: German Labor Markets and Trade Integration.” *Journal of the European Economic Association*, 12(6): 1643–1675.
- Davis, S., and J. Haltiwanger. 1992.** “Gross Job Creation, Gross Job Destruction, and Employment Reallocation.” *Quarterly Journal of Economics*, 107(3): 819–63.
- Dinlersoz, E. M., N. Goldschlag, A. Fila, and N. Zolas. 2018.** “An anatomy of US firms seeking trademark registration.” USPTO Economic Working Paper Working Papers.
- Dinlersoz, E. M., N. Goldschlag, M. Yorukoglu, and N. Zolas. 2023.** “On The Role of Trademarks: From Micro Evidence to Macro Outcomes.” CES Working Paper.
- Dischinger, M., and N. Riedel. 2011.** “Corporate taxes and the location of intangible assets within multinational firms.” *Journal of Public Economics*, 95(7-8): 691–707.
- Doherr, T. 2016.** “Inventor mobility index: A method to disambiguate inventor careers.” *ZEW-Centre for European Economic Research Discussion Paper*, , (17-018).
- Donoso, V., V. Martin, and A. Minondo. 2015.** “Do Differences in the Exposure to Chinese Imports Lead to Differences in Local Labour Market Outcomes? An Analysis for Spanish Provinces.” *Regional Studies*, 49(10): 1746–1764.
- Feenstra, R. C. 1994.** “New Product Varieties and the Measurement of International

- Prices.” *American Economic Review*, 84(1): 157–177.
- Feenstra, R. C., and D. E. Weinstein. 2017.** “Globalization, Markups, and US Welfare.” *Journal of Political Economy*, 125(4): 1040–1074.
- Feenstra, R. C., and J. Romalis. 2014.** “International Prices and Endogenous Quality.” *The Quarterly Journal of Economics*, 129(2): 477–527.
- Feenstra, R. C., P. Luck, M. Obstfeld, and K. N. Russ. 2018.** “In Search of the Armington Elasticity.” *The Review of Economics and Statistics*, 100(1): 135–150.
- Flaen, A., A. Hortaçsu, and F. Tintelnot. 2020.** “The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines.” *American Economic Review*, 110(7): 2103–27.
- Flikkema, M., A.-P. de Man, and C. Castaldi. 2014.** “Are Trademark Counts a Valid Indicator of Innovation? Results of an In-Depth Study of New Benelux Trademarks Filed by SMEs.” *Industry and Innovation*, 21(4): 310–331.
- Fort, T. C. 2023.** “The Changing Firm and Country Boundaries of US Manufacturers in Global Value Chains.” *Journal of Economic Perspectives*, 37(3): 31–58.
- Fort, T., W. Keller, P. Schott, S. Yeaple, and N. Zolas. 2020.** “Colocation of Production and Innovation: Evidence from the United States.”
- Galle, S., A. Rodriguez-Clare, and M. Yi. 2017.** “Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade.” National Bureau of Economic Research, Inc NBER Working Papers 23737.
- Garcia-Macia, D., C.-T. Hsieh, and P. J. Klenow. 2019.** “How destructive is innovation?” *Econometrica*, 87(5): 1507–1541.
- Gaulier, G., and S. Zignago. 2010.** “BACI: International Trade Database at the Product-Level. The 1994-2007 Version.” CEPII Working Papers 2010-23.
- Ghai, S., and C. Hottman. 2019.** “Exchange Rates, Product Variety, and Substitution in U.S. Scanner Data.” Society for Economic Dynamics 2019 Meeting Papers.
- Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova. 2010.** “Imported Intermediate Inputs and Domestic Product Growth: Evidence from India.” *The Quarterly*

Journal of Economics, 125(4): 1727–1767.

- Graham, S. J. H., A. C. Marco, and A. F. Myers. 2018.** “Monetizing marks: Insights from the USPTO trademark assignment dataset.” *Journal of Economics & Management Strategy*, 27(3): 403–432.
- Graham, S. J. H., G. Hancock, A. C. Marco, and A. F. Myers. 2013.** “The USPTO trademark case files dataset: Descriptions, lessons, and insights.” *Journal of Economics & Management Strategy*, 22(4): 669–705.
- Griffith, R., H. Miller, and M. O’Connell. 2014.** “Ownership of intellectual property and corporate taxation.” *Journal of Public Economics*, 112(C): 12–23.
- Griffiths, A. 2011.** *An economic perspective on trade mark law*. Edward Elgar Publishing.
- Grynberg, M. 2022.** *Trademark Law*.
- Head, K., and T. Mayer. 2019.** “Brands in Motion: How Frictions Shape Multinational Production.” *American Economic Review*, 109(9): 3073–3124.
- Helpman, E. 1981.** “International trade in the presence of product differentiation, economies of scale and monopolistic competition: A Chamberlin-Heckscher-Ohlin approach.” *Journal of International Economics*, 11(3): 305–340.
- Helpman, E., M. J. Melitz, and S. R. Yeaple. 2004.** “Export versus FDI with Heterogeneous Firms.” *American Economic Review*, 94(1): 300–316.
- Hottman, C. J., and R. Monarch. 2020.** “A matter of taste: Estimating import price inflation across U.S. income groups.” *Journal of International Economics*, 127(C).
- Hottman, C. J., S. J. Redding, and D. E. Weinstein. 2016.** “Quantifying the sources of firm heterogeneity.” *The Quarterly Journal of Economics*, 131(3): 1291–1364.
- Hsieh, C.-T., and R. Ossa. 2016.** “A global view of productivity growth in China.” *Journal of International Economics*, 102(C): 209–224.
- Hsieh, C.-T., N. Li, R. Ossa, and M.-J. Yang. 2020.** “Accounting for the New Gains from Trade Liberalization.” *Journal of International Economics*, 127.
- Hsieh, C.-T., P. Klenow, and K. Shimizu. 2022.** “Romer or Ricardo?”

- Hummels, D., R. Jørgensen, J. Munch, and C. Xiang. 2014.** “The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data.” *American Economic Review*, 104(6): 1597–1629.
- Impullitti, G., and O. Licandro. 2018.** “Trade, Firm Selection and Innovation: The Competition Channel.” *Economic Journal*, 128(608): 189–229.
- Jakubik, A., and V. Stolzenburg. 2021.** “The ‘China Shock’ revisited: insights from value added trade flows.” *Journal of Economic Geography*, 21(1): 67–95.
- Jaravel, X. 2019.** “The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector.” *The Quarterly Journal of Economics*, 134(2): 715–783.
- Karkinsky, T., and N. Riedel. 2012.** “Corporate taxation and the choice of patent location within multinational firms.” *Journal of International Economics*, 88(1): 176–185.
- Krugman, P. 1979.** “Increasing Returns, Monopolistic Competition, and International Trade.” *Journal of International Economics*, 9(4): 469–479.
- Krugman, P. 1980.** “Scale Economies, Product Differentiation, and the Pattern of Trade.” *The American Economic Review*, 70(5): 950–959.
- Landes, W., and R. Posner. 1987.** “Trademark Law: An Economic Perspective.” *Journal of Law and Economics*, 30(2): 265–309.
- Levinsohn, J., and A. Petrin. 2003.** “Estimating Production Functions Using Inputs to Control for Unobservables.” *The Review of Economic Studies*, 70(2): 317–341.
- Malgouyres, C. 2017.** “The Impact of Chinese Import Competition on the Local Structure of Employment and Wages: Evidence from France.” *Journal of Regional Science*, 57: 411–441.
- Mangani, A. 2007.** “Measuring Variety and Quality of Products with Trademarks.” *International Economic Journal*, 21(4): 613–631.
- Mayer, T., M. J. Melitz, and G. I. Ottaviano. 2021.** “Product Mix and Firm Productivity Responses to Trade Competition.” *The Review of Economics and Statistics*, 103(5): 874–891.
- McCully, B. A., T. Jaccard, and C. Albert. 2024.** “Immigrants, Imports, and Welfare:

Evidence from Household Purchase Data.” Working Papers.

Melitz, M. J. 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica*, 71(6): 1695–1725.

Melitz, M. J., and S. J. Redding. 2023. *Trade and Innovation*. The Economics of Creative Destruction. Harvard University Press.

Mendonça, S., T. S. Pereira, and M. M. Godinho. 2004. “Trademarks as an indicator of innovation and industrial change.” *Research policy*, 33(9): 1385–1404.

Mezzanotti, F., and T. Simcoe. 2023. “Innovation and Appropriability: Revisiting the Role of Intellectual Property.” National Bureau of Economic Research Working Paper 31428.

OECD. 2017. AMNE, Activity of Multinational Enterprises.

OECD. 2018. “Multinational enterprises in the global economy.” OECD Policy note.

Pearce, J., and L. Wu. 2024. “Brand Reallocation and Market Concentration.” Working Paper.

Pierce, J. R., and P. K. Schott. 2016. “The Surprisingly Swift Decline of US Manufacturing Employment.” *American Economic Review*, 106(7): 1632–62.

Raffo, J. 2015. “MATCHIT: Stata module to match two datasets based on similar text patterns.” *Statistical Software Components, Boston College Department of Economics*.

Raffo, J., and S. Lhuillery. 2009. “How to play the “Names Game”: Patent retrieval comparing different heuristics.” *Research Policy*, 38(10): 1617–1627.

Richardson, G. 2008. “Brand Names Before the Industrial Revolution .” NBER Working Papers 13930.

Romer, P. M. 1990. “Endogenous Technological Change.” *Journal of Political Economy*, 98(5): S71–S102.

Romer, P. M. 1994. “New Goods, Old Theory, and the Welfare Costs of Trade Restrictions.” *Journal of Development Economics*, 43(1): 5–38.

- Schautschick, P., and C. Greenhalgh. 2016.** “Empirical Studies of Trade Marks: The Existing Economic Literature.” *Economics of Innovation and New Technology*, 25(4): 358–390.
- Tintelnot, F. 2017.** “Global Production with Export Platforms.” *The Quarterly Journal of Economics*, 132(1): 157–209.
- Trajtenberg, M., G. Shiff, and R. Melamed. 2006.** “The “names game”: Harnessing inventors’ patent data for economic research.”
- United Nations Statistics Division. 2022.** “UN COMTRADE.” International Merchandise Trade Statistics, United Nations Statistics Division, New York, USA.
- U.S. Bureau of Economic Analysis. 2023.** FRED, Federal Reserve Bank of St. Louis.
- Xu, R., and K. Gong. 2017.** “Does Import Competition Induce R&D Reallocation? Evidence from the U.S.” International Monetary Fund IMF Working Papers 2017/253.
- Yang, M.-J., N. Li, and K. Lorenz. 2021.** “The impact of emerging market competition on innovation and business strategy: Evidence from Canada.” *Journal of Economic Behavior and Organization*, 181: 117–134.

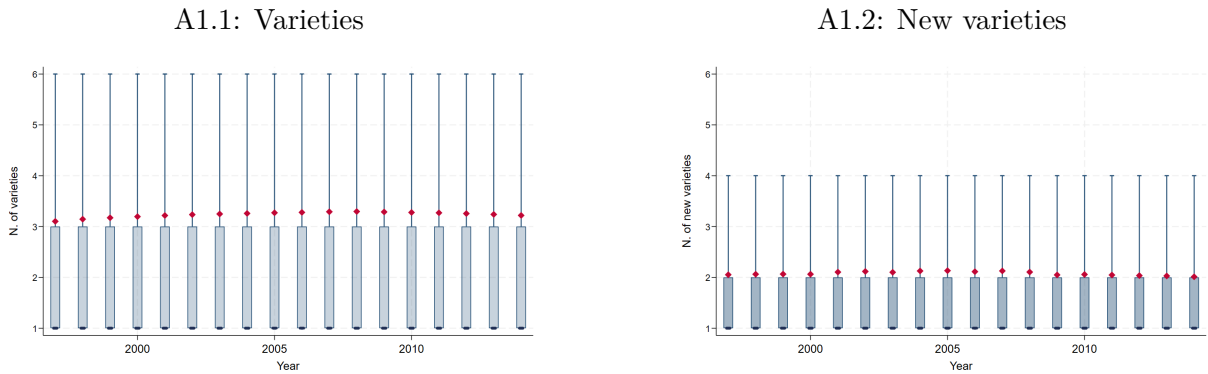
A Other tables and figures

Table A1: Summary statistics for goods

	Varieties		Firms	
	Count	Percentage	Count	Percentage
Overall	2,189,939		643,645	
Final	1,020,348	47%	334,616	52%
Intermediate	1,169,591	53%	401,232	62%
Domestic	1,611,724	73%	476,844	74%
Foreign	578,215	27%	166,801	26%

Notes: Count of varieties and firms, overall or split by sector and nationality. Final and intermediate sectors are defined based on the share of consumer expenditure of the corresponding ISIC code using the US Input-Output table: varieties in sectors for which at least 70% of final consumption is done by consumers are classified as final. Note that percentages for firms do not always sum up to 100% because firms can own both final and intermediate varieties. The concordance from the trademarks sectoral classification to the ISIC classification is taken from [Battacharyya et al. \(2017\)](#).

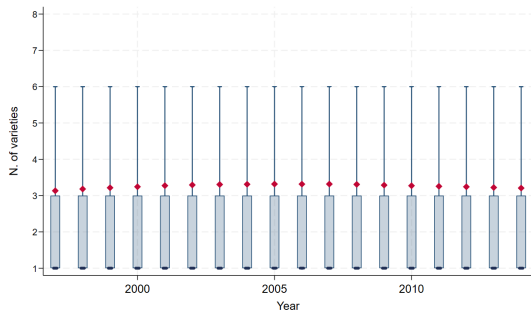
Figure A1: Goods and new goods per firm



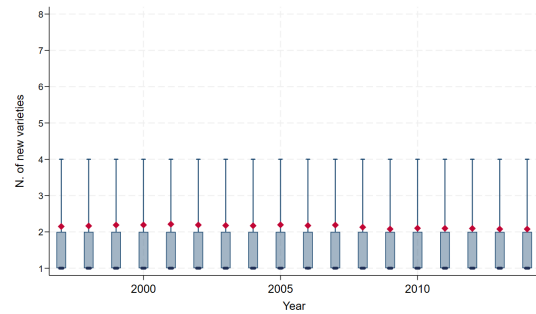
Notes: The figures show the distribution of varieties and new varieties per firm over time. Only varieties in the goods sector are considered. The bars show the 25th and 75th percentile of the distribution, the darker blue line shows the median, while the upper spike shows the 90th percentile of the distribution. The red diamond shows the average number of varieties or new varieties per firm.

Figure A2: Varieties and new varieties per firm

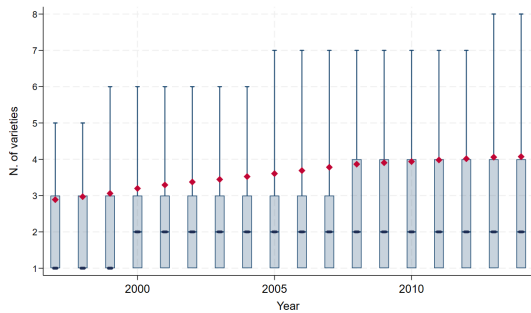
A2.1: Varieties of domestic firms



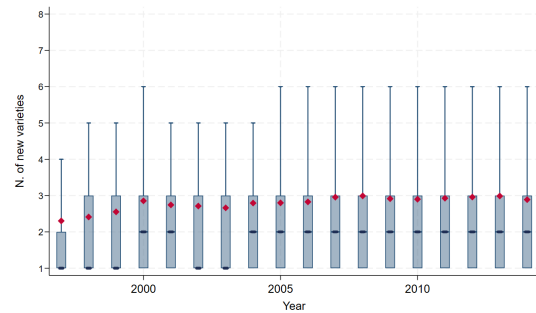
A2.2: New varieties of domestic firms



A2.3: Varieties of foreign firms

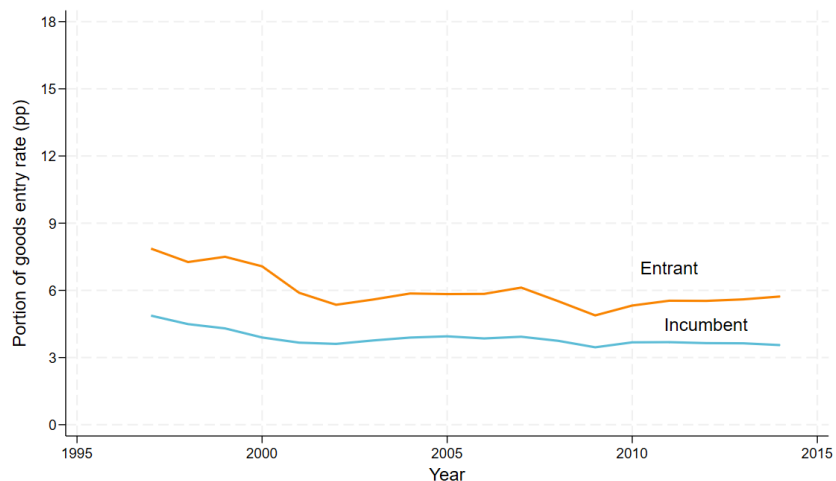


A2.4: New varieties of foreign firms



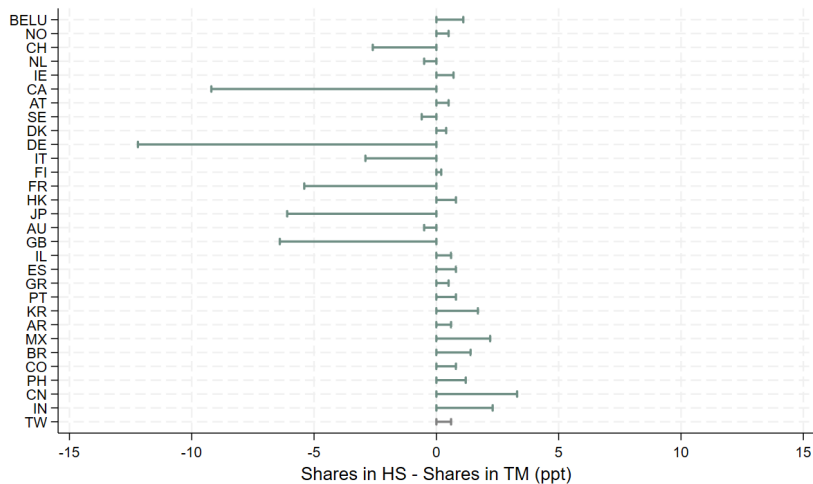
Notes: The figures show the distribution of varieties and new varieties per firm over time. The upper panels show the distribution of varieties and new varieties for domestic firms, the bottom panels show the distribution for foreign firms. The bars show the 25th and 75th percentile of the distribution, the darker blue line shows the median, while the upper spike shows the 90th percentile of the distribution. The red diamond shows the average number of varieties or new varieties per firm.

Figure A3: Fewer new varieties from entrant firms



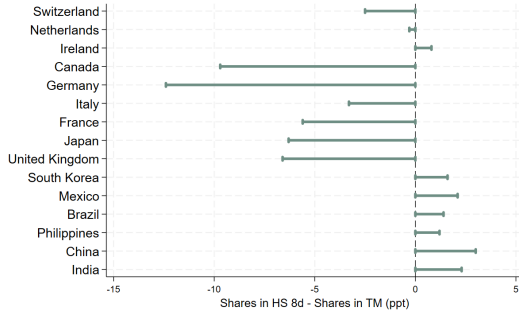
Notes: The figure shows the variety entry rate of new firms (*Entrant*) and the variety entry rate of incumbent firms (*Incumbent*). Incumbent firms are defined as firms owning a trademark for at least five years or purchasing an existing trademark.

Figure A4: Comparison of variety shares of top 30 partners

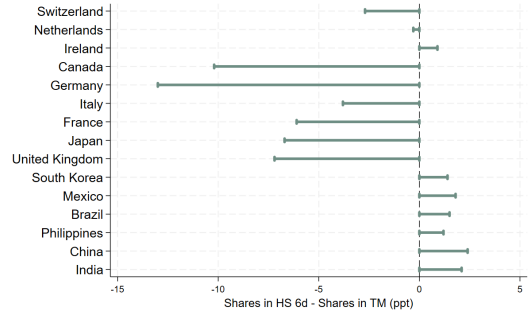


Notes: The figure compares the varieties share of selected countries in 2001 as measured using HS 10-digits codes and using trademarks. It shows the percentage points lost or gained when using trademarks compared to the ranking obtained through 10-digits HS codes and country of origin pairs, as defined in [Equation 1](#). Countries are ranked based on their GDP per capita in 2001. GDP per capita is not available for Taiwan, which is displayed in gray on the bottom.

Figure A5: Comparison of variety shares – different HS digits



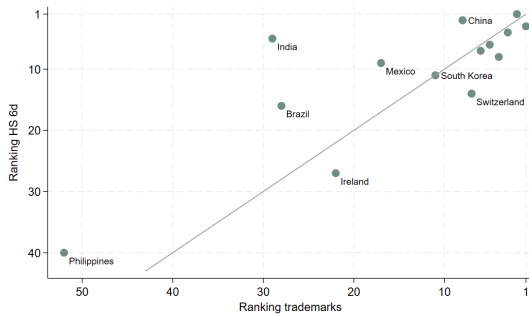
A5.1: HS 8-digit



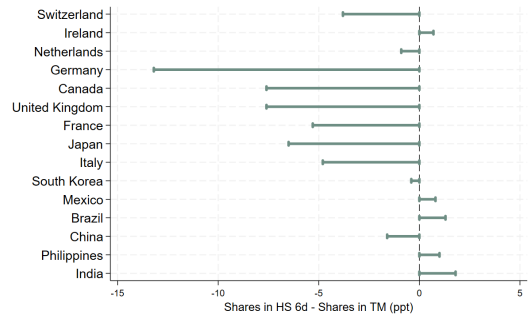
A5.2: HS 6-digit

Notes: The figure compares the varieties share of selected countries in 2001 as measured using trademarks and HS 8-digits codes on the left panel, or HS 6-digits codes on the right panel. It shows the percentage points lost or gained when using trademarks compared to the ranking obtained through 8-digits or 6-digits HS codes and country of origin pairs, as defined in Equation 1. Countries are ranked based on their GDP per capita in 2001.

Figure A6: Comparison of ranking and variety shares in 2014



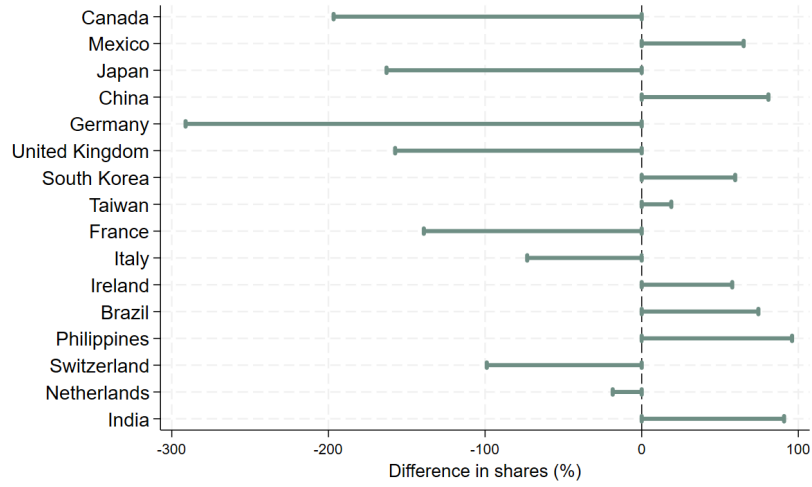
A6.1: Ranking



A6.2: Shares difference

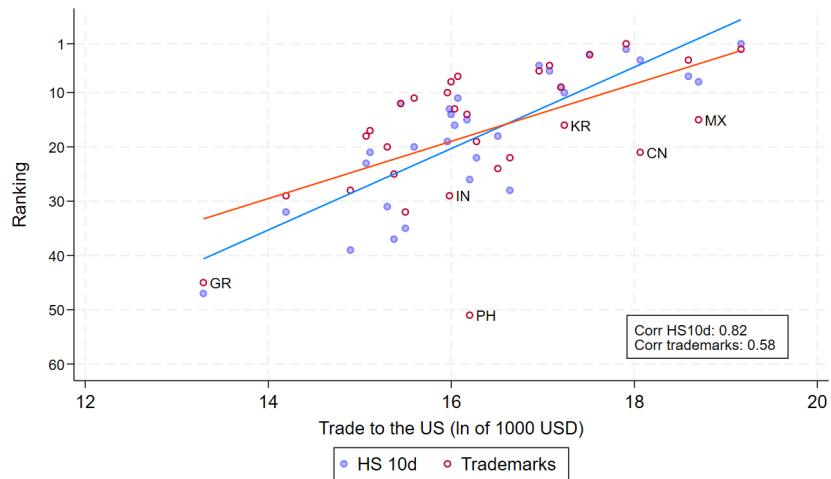
Notes: The figure compares the varieties share of selected countries in 2014 as measured using trademarks and HS 6-digits codes. The left panel shows the ranking of each trading partner using trademarks on the horizontal axis and using HS 6-digits codes on the vertical axis. The right panel shows the percentage points lost or gained when using trademarks compared to the ranking obtained through 6-digits HS codes and country of origin pairs, as defined in Equation 1. On the right panel, countries are ranked based on their GDP per capita in 2014.

Figure A7: Percentage change in share of trade partners



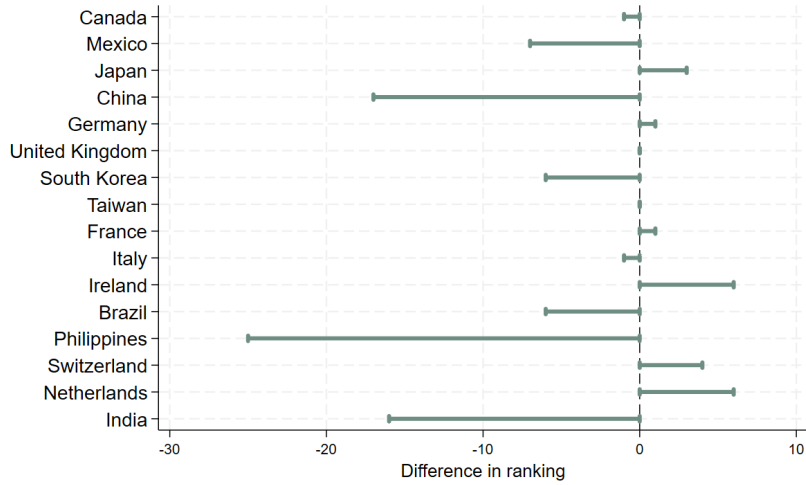
Notes: The figure shows the object defined in Equation 1 – the difference between the share of varieties provided by each country c in terms of HS 10-digits codes and the share in terms of trademarks – as a percentage of the share of HS 10-digits codes. Countries are sorted based on the number of HS 10-digits varieties provided to the US in 2001.

Figure A8: Variety ranking and trade flows



Notes: The figure compares trade flows of selected countries in 2001 (horizontal axis) and their ranking in terms of foreign varieties brought to the US in the same year, as measured using 10-digits HS codes and using trademarks (vertical axis).

Figure A9: Change in ranking of trade partners



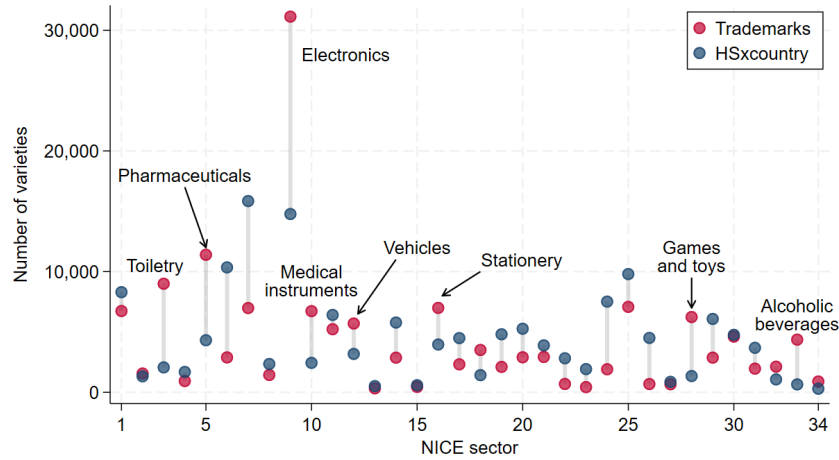
Notes: “Difference in ranking” is computed as the difference in the ranking of country c as variety provider calculated using HS 10-digits codes and using trademarks. Countries are sorted based on the number of HS 10-digits varieties provided to the US in 2001.

Figure A10: Number of varieties in the two measures



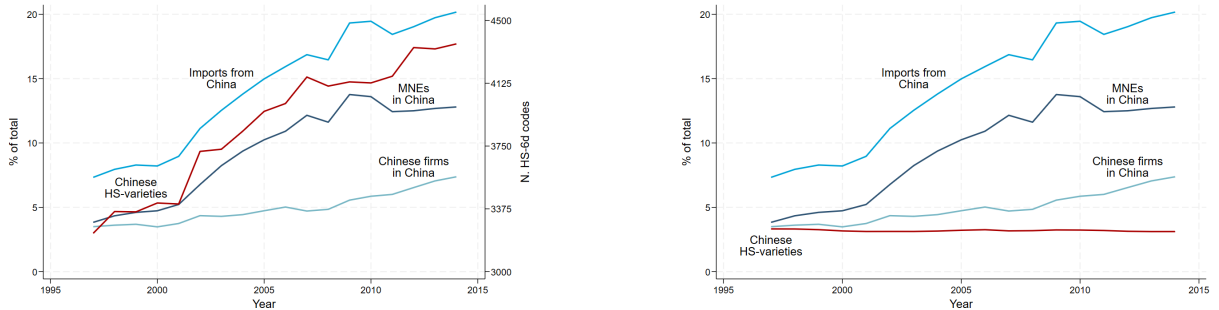
Notes: The figure shows the number of varieties measured by HS 6-digits codes (x-axis) and trademarks (y-axis) for each trading partner of the United States in the year 2014. Both axis are in log-scale. The red line is a 45-degree line.

Figure A11: Number of varieties in the two measures by sector



Notes: The figure shows the number of varieties measured by HS 6-digits codes and country of origin (blue) and trademarks (red) for each sector in the year 2014.

Figure A12: US imports from China and HS codes from China do not correlate

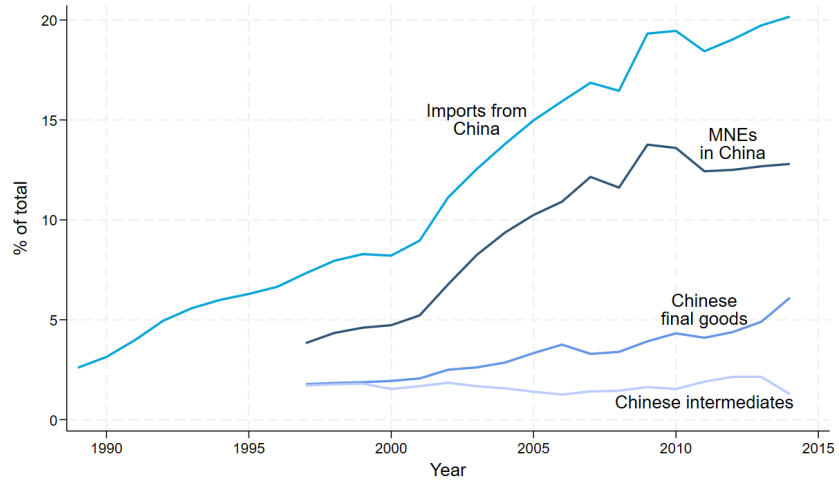


A12.1: HS-codes counts

A12.2: HS-codes shares

Note: The figure compares different types of US imports from China with Chinese-owned varieties located in the United States. “Imports from China”, “MNEs in China”, and “Chinese firms in China” are overall US imports from China, US imports from non-Chinese-owned firms located in China, and US imports from Chinese-owned firms located in China as a percentage of total US imports, respectively. “Chinese HS-varieties” is the number of 6-digits HS codes exported by China, either as count (left panel) or as a percentage of HS 6-digits codes and country of origin pairs (right panel).

Figure A13: Detailed US imports from China



Note: The figure compares different types of US imports from China. “Imports from China” is US overall imports from China as a percentage of total US imports. “MNEs in China” is US imports from non-Chinese-owned firms located in China as a percentage of total US imports. “Chinese final goods” is US imports of final goods produced by Chinese-owned firms located in China as a percentage of total US imports. “Chinese intermediates” is US imports of intermediate goods produced by Chinese-owned firms located in China as a percentage of total US imports.

Table A2: Trade flows from Chinese firms in China explain Chinese varieties

	(1)	(2)
	Chinese varieties (% of foreign)	Chinese varieties (% of foreign)
Chinese final goods (%)	0.228*** (0.058)	0.207*** (0.059)
Chinese intermediates (%)	0.111 (0.068)	0.128* (0.068)
MNEs (%)	0.022 (0.025)	
MNEs final goods (%)		0.056 (0.036)
MNEs intermediates (%)		0.006 (0.025)
Obs.	612	612
R ²	0.832	0.833

Notes: The observations are at the sector-year level. The dependent variable is Chinese varieties, measured as Chinese-owned trademarks as a percentage of all foreign-owned trademarks registered in the US. The explanatory variables are different types of trade flows from China to the US as percentage of total US imports: imports of final goods from Chinese-owned firms located in China; imports of intermediate goods from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China; imports of final goods from MNEs located in China; imports of intermediate goods from MNEs located in China. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A3: Trade flows from Chinese firms in China explain Chinese varieties

	(1)	(2)	(3)	(4)
	Chinese varieties (% of foreign)	Chinese varieties (% of foreign)	Chinese varieties (% of foreign)	Chinese varieties (% of foreign)
Total imports (%)	0.101*** (0.029)			
Chinese firms (%)		0.209*** (0.051)		
MNEs (%)		0.024 (0.032)	0.022 (0.031)	
Chinese final goods (%)			0.228*** (0.063)	0.207*** (0.057)
Chinese intermediates (%)			0.111* (0.064)	0.128* (0.067)
MNEs final goods (%)				0.056 (0.043)
MNEs intermediates (%)				0.006 (0.028)
Obs.	612	612	612	612
R ²	0.816	0.830	0.832	0.833

Notes: The observations are at the sector-year level. The dependent variable is Chinese varieties, measured as Chinese-owned trademarks as a percentage of all foreign-owned trademarks registered in the US. The explanatory variables are different types of trade flows from China to the US as percentage of total US imports: total imports from China; imports from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China; imports of final goods from Chinese-owned firms located in China; imports of intermediate goods from Chinese-owned firms located in China; imports of final goods from MNEs located in China; imports of intermediate goods from MNEs located in China. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level and bootstrapped using 100 iterations in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A4: Trade flows from Chinese firms in China explain Chinese varieties

	(1)	(2)	(3)
	Chinese varieties	Chinese varieties	Chinese varieties
	(ln)	(ln)	(ln)
Total imports (ln)	0.133 (0.137)		
Chinese firms (ln)		0.317** (0.143)	
MNEs (ln)		-0.286** (0.119)	
Chinese final goods (ln)			0.387*** (0.122)
Chinese intermediates (ln)			-0.075 (0.056)
MNEs final goods (ln)			-0.137* (0.078)
MNEs intermediates (ln)			-0.061 (0.054)
Obs.	612	612	610
R ²	0.938	0.947	0.951

Notes: The observations are at the sector-year level. The dependent variable is Chinese varieties, measured as the (log) number of Chinese-owned trademarks in the US. The explanatory variables are the (log) values of different types of trade flows from China to the US: total imports from China; imports from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China; imports of final goods from Chinese-owned firms located in China; imports of intermediate goods from Chinese-owned firms located in China; imports of final goods from MNEs located in China; imports of intermediate goods from MNEs located in China. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A5: Trade flows from Chinese firms in China explain Chinese varieties

	(1)	(2)	(3)
	Chinese varieties	Chinese varieties	Chinese varieties
	(ln)	(ln)	(ln)
Total imports (ln)	0.133 (0.145)		
Chinese firms (ln)		0.317** (0.152)	
MNEs (ln)		-0.286*** (0.103)	
Chinese final goods (ln)			0.387*** (0.115)
Chinese intermediates (ln)			-0.075 (0.054)
MNEs final goods (ln)			-0.137** (0.067)
MNEs intermediates (ln)			-0.061 (0.061)
Obs.	612	612	610
R ²	0.938	0.947	0.951

Notes: The observations are at the sector-year level. The dependent variable is Chinese varieties, measured as the (log) number of Chinese-owned trademarks in the US. The explanatory variables are the (log) values of different types of trade flows from China to the US: total imports from China; imports from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China; imports of final goods from Chinese-owned firms located in China; imports of intermediate goods from Chinese-owned firms located in China; imports of final goods from MNEs located in China; imports of intermediate goods from MNEs located in China. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level and bootstrapped using 100 iterations in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A6: Trade flows value from Chinese firms in China explain Chinese varieties

	(1)	(2)	(3)	(4)
	Chinese varieties (number)	Chinese varieties (number)	Chinese varieties (number)	Chinese varieties (number)
Total imports (B \$)	13.340*** (0.937)			
Chinese firms (B \$)		44.906*** (12.076)		
MNEs (B \$)		9.453*** (1.208)	9.514*** (1.187)	
Chinese final goods (B \$)			47.613*** (13.555)	45.492*** (13.952)
Chinese intermediates (B \$)			32.337*** (7.982)	39.286*** (9.800)
MNEs final goods (B \$)				10.249*** (1.720)
MNEs intermediates (B \$)				8.968*** (0.865)
Obs.	612	612	612	612
R ²	0.852	0.883	0.884	0.884

Notes: The observations are at the sector-year level. The dependent variable is Chinese varieties, measured as number of Chinese-owned trademarks registered in the US. The explanatory variables are different types of trade flows from China to the US as percentage of total US imports: total imports from China; imports from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China; imports of final goods from Chinese-owned firms located in China; imports of intermediate goods from Chinese-owned firms located in China; imports of final goods from MNEs located in China; imports of intermediate goods from MNEs located in China. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A7: HS 6-digits codes do not correlate with trade flows from China

	(1)	(2)	(3)	(4)
	HS-6d (%)	HS-6d (%)	HS-6d (%)	HS-6d (%)
Total imports (%)	0.009 (0.012)			
Chinese firms (%)		0.009 (0.018)		
MNEs (%)		0.009 (0.011)	0.011 (0.011)	
Chinese final goods (%)			-0.001 (0.015)	0.002 (0.018)
Chinese intermediates (%)			0.060 (0.039)	0.058 (0.035)
MNEs final goods (%)				0.006 (0.011)
MNEs intermediates (%)				0.013 (0.015)
Obs.	612	612	612	612
R ²	0.825	0.825	0.830	0.830

Notes: The observations are at the sector-year level. The dependent variable is the number of HS 6-digits codes for which China has non-zero exports to the United States, as a percentage of all HS 6-digits codes and country of origin pairs that the United States import. The explanatory variables are different types of trade flows from China to the US as percentage of total US imports: total imports from China; imports from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China; imports of final goods from Chinese-owned firms located in China; imports of intermediate goods from Chinese-owned firms located in China; imports of final goods from MNEs located in China; imports of intermediate goods from MNEs located in China. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A8: HS codes correlate with imports from MNEs in China

	(1)	(2)	(3)	(4)	(5)	(6)
	HS-6d	HS-6d	HS-6d	HS-8d	HS-8d	HS-8d
	(ln)	(ln)	(ln)	(ln)	(ln)	(ln)
Total imports (ln)	0.022			0.026		
	(0.021)			(0.018)		
Chinese firms (ln)		-0.032**			-0.017	
		(0.012)			(0.015)	
MNEs (ln)		0.069***			0.049*	
		(0.023)			(0.024)	
Chinese final goods (ln)			-0.035**			-0.017
			(0.014)			(0.015)
Chinese intermediates (ln)			0.007			0.005
			(0.009)			(0.007)
MNEs final goods (ln)			0.026**			0.021*
			(0.010)			(0.011)
MNEs intermediates (ln)			0.025**			0.018
			(0.012)			(0.011)
Obs.	612	612	610	612	612	610
R ²	0.993	0.994	0.994	0.994	0.994	0.994

Notes: The observations are at the sector-year level. The dependent variable in columns (1)-(3) is the (log) number of HS 6-digits codes for which China has non-zero exports to the United States. The dependent variable in columns (4)-(6) is the (log) number of HS 8-digits codes for which China has non-zero exports to the United States. The explanatory variables are the (log) values of different types of trade flows from China to the US: total imports from China; imports from Chinese-owned firms located in China; imports from foreign-owned firms (MNEs) located in China; imports of final goods from Chinese-owned firms located in China; imports of intermediate goods from Chinese-owned firms located in China; imports of final goods from MNEs located in China; imports of intermediate goods from MNEs located in China. All columns include fixed effects for 34 sectors and 18 years. OLS estimates with standard errors clustered at the sector level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A9: Elasticity of substitution

	Conservative ($\theta = 1$)	Semi-conservative ($\theta = 0.5$)	Liberal ($\theta = 0$)
All firms	11.1	5.3	3.8
Firms with one variety	12.4	5.4	3.9
Firms with always one variety	9.6	5.2	3.6

Notes: This table shows the elasticity of substitution computed from the estimated markups of roughly 10,000 firms matched on Compustat data. θ is the fraction of selling, general, and administrative expenses attributed to variable costs. In the *Conservative* definition, all of them are variable costs; in the *Semi-conservative* definition, half of them are variable costs; in the *Liberal* definition, none of them are variable costs. Each row represents a different sample of firms. “Firms with one variety” are firms owning one variety as measured through trademarks, while “Firms with always one variety” are firms owning one variety as measured by trademarks throughout the whole sample period.

Table A10: Price index decomposition

Year	Unit prices	Theil index value	Variety gains	Unit prices	Theil index %	Variety gains
1995	2.47	1.00	2.91	38.69	15.70	45.61
1996	2.52	1.02	2.92	39.06	15.76	45.18
1997	2.53	1.03	2.93	38.98	15.91	45.11
1998	2.53	1.03	2.94	38.92	15.87	45.21
1999	2.47	1.05	2.95	38.41	16.78	45.56
2000	2.40	1.20	2.99	36.41	18.10	45.41
2001	2.39	1.20	3.00	36.32	18.25	45.44
2002	2.41	1.20	3.00	36.44	18.18	45.37
2003	2.48	1.21	3.00	37.08	18.09	44.83
2004	2.54	1.24	3.01	37.45	18.21	44.34
2005	2.61	1.26	3.01	37.89	18.35	43.76
2006	2.71	1.29	3.02	38.54	18.40	43.05
2007	2.80	1.29	3.01	39.16	18.34	42.36
2008	2.82	1.30	3.00	39.59	18.26	42.15
2009	2.89	1.28	3.00	40.30	17.88	41.82
2010	2.91	1.32	3.00	40.19	18.28	41.54
2011	2.96	1.34	3.01	40.55	18.30	41.20
2012	2.99	1.34	3.01	40.69	18.30	41.00
2013	3.01	1.34	3.01	40.85	18.24	40.92
2014	3.01	1.34	3.01	40.86	18.24	40.92

Notes: The table shows the decomposition of the price index into the average log unit price, the Theil index of revenues, and the variety gains for the US market as shown in [Equation 21](#). The last three columns show the percentage of each component in the price index. The price index decomposition has been obtained using data on US imports and defining varieties as unique pairs of HS 6-digit codes and country of origin with positive import value. 138,077 varieties have been dropped because they did not reported information on unit prices.

Table A11: First stage

	(1)	(2)	(3)	(4)
	MNE_{st}^I	MNE_{st}^E	CN_{st}^I	CN_{st}^E
non-US MNE_{st}^I	0.880*** (0.063)	-0.123*** (0.042)	0.131* (0.077)	0.033 (0.053)
non-US MNE_{st}^E	-0.123*** (0.042)	0.880*** (0.063)	0.033 (0.053)	0.131* (0.077)
non-US CN_{st}^I	0.129** (0.053)	0.171*** (0.032)	0.595*** (0.065)	-0.011 (0.031)
non-US CN_{st}^E	0.171*** (0.032)	0.129** (0.053)	-0.011 (0.031)	0.595*** (0.065)
Obs.	884	884	884	884
R ²	0.723	0.723	0.514	0.514
F-stat	112.86	112.86	24.37	24.37

Notes: The observations are at the sector-status-year level. The dependent variable in columns (1) and (2) is the 5-year growth of US imports from MNEs located in China, as defined in Equation 17, and interacted with an indicator for incumbent and entrant firms, respectively. The dependent variable in columns (3) and (4) is the 5-year growth of US imports from Chinese-owned firms located in China, as defined in Equation 18, and interacted with an indicator for incumbent and entrant firms, respectively. The explanatory variables are the 5-year growth of non-US imports from MNEs located in China and the growth of non-US imports from Chinese-owned firms located in China, interacted for entrant and incumbent firms. All columns include fixed effects for sectors, years, and status. OLS estimates with standard errors clustered at the sector-year level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A12: New US varieties on import competition – $h = 5$

	(1)	(2)	(3)	(4)	(5)	(6)
	New Var.	New Var.	New Var.	New Var.	New Var.	New Var.
All_{st}^E	-0.026*** (0.009)	-0.012 (0.016)				
All_{st}^I	0.019*** (0.006)	0.053*** (0.016)				
MNE_{st}^E			-0.001 (0.008)	0.036* (0.019)	-0.002 (0.008)	0.022 (0.016)
MNE_{st}^I			-0.006 (0.007)	0.033* (0.018)	-0.008 (0.007)	0.018 (0.016)
CN_{st}^E			-0.028** (0.012)	-0.052* (0.029)		
CN_{st}^I			0.011 (0.011)	-0.026 (0.022)		
Chinese Final $_{st}^E$					-0.024** (0.011)	-0.027 (0.020)
Chinese Final $_{st}^I$					0.020* (0.010)	0.007 (0.015)
Chinese Intermediate $_{st}^E$					0.003 (0.005)	0.016 (0.012)
Chinese Intermediate $_{st}^I$					-0.001 (0.004)	-0.011 (0.013)
Obs.	1,428	1,428	884	884	884	884
R ²	0.682		0.711		0.713	
F-stat All		136				
F-stat MNE				113		76
F-stat CN all				24		
F-stat CN final						32
F-stat CN intermediates						24

Notes: Observations at the sector-status-year level, where status can be either incumbent or entrant. The dependent variable is the 5-year variety entry rate of US firms. The explanatory variables are the 5-year growth of aggregate US imports from China, the 5-year growth of US imports from MNEs located in China, the 5-year growth of US imports from Chinese-owned firms located in China, the 5-year growth of US imports of final goods from Chinese-owned firms located in China, and the 5-year growth of US imports of intermediate goods from Chinese-owned firms located in China. Fully saturated specification with each explanatory variable interacted by an indicator variable for status of incumbent or entrant. All specification include fixed effects for sectors, years, and status. Standard errors clustered at the sector-year level. Columns (1), (3), and (5) report OLS estimates. Columns (2), (4), and (6) report 2SLS estimates. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A13: Number of US firms on import competition – $h = 5$

	(1)	(2)	(3)	(4)	(5)	(6)
	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)
All _{st} ^E	0.114*** (0.027)	0.250*** (0.044)				
All _{st} ^I	-0.044* (0.025)	-0.250*** (0.046)				
MNE _{st} ^E			0.032 (0.020)	0.131** (0.057)	0.025 (0.021)	0.083* (0.044)
MNE _{st} ^I			-0.022 (0.020)	0.013 (0.048)	-0.019 (0.020)	-0.013 (0.043)
CN _{st} ^E			-0.012 (0.028)	-0.245*** (0.064)		
CN _{st} ^I			0.085*** (0.020)	0.162*** (0.055)		
Chinese Final _{st} ^E					0.022 (0.023)	-0.142*** (0.042)
Chinese Final _{st} ^I					0.027 (0.017)	0.071 (0.045)
Chinese Intermediate _{st} ^E					-0.019 (0.012)	-0.021 (0.035)
Chinese Intermediate _{st} ^I					0.044*** (0.010)	0.127*** (0.026)
Obs.	1,428	1,428	884	884	884	884
R ²	0.971		0.986		0.987	
F-stat All		136				
F-stat MNE				113		76
F-stat CN				24		
F-stat CN final						32
F-stat CN intermediate						24

Notes: Observations at the sector-status-year level, where status can be either incumbent or entrant. The dependent variable is the (log) number of US firms over a 5-year period. The explanatory variables are the 5-year growth of aggregate US imports from China, the 5-year growth of US imports from MNEs located in China, the 5-year growth of US imports from Chinese-owned firms located in China, the 5-year growth of US imports of final goods from Chinese-owned firms located in China, and the 5-year growth of US imports of intermediate goods from Chinese-owned firms located in China. Fully saturated specification with each explanatory variable interacted by an indicator variable for status of incumbent or entrant. All specification include fixed effects for sectors, years, and status. Standard errors clustered at the sector-year level. Columns (1), (3), and (5) report OLS estimates. Columns (2), (4), and (6) report 2SLS estimates. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A14: New HS domestic varieties on import competition

	(1)	(2)	(3)	(4)	(5)	(6)
	New HS6d	New HS6d	New HS6d	New HS6d	New HS6d	New HS6d
All	-0.108 (0.119)	0.141 (0.370)				
MNEs			-0.449** (0.209)	-0.185 (0.426)	-0.467** (0.223)	-0.117 (0.398)
Chinese			0.139 (0.232)	0.118 (0.626)		
Chinese Final					0.019 (0.174)	0.020 (0.440)
Chinese Intermediate					0.124 (0.137)	-0.038 (0.304)
Obs.	646	646	442	442	442	442
R ²	0.196		0.181		0.180	
F-stat All		71				
F-stat MNE				44		26
F-stat CN				31		
F-stat CN final						22
F-stat CN intermediate						17

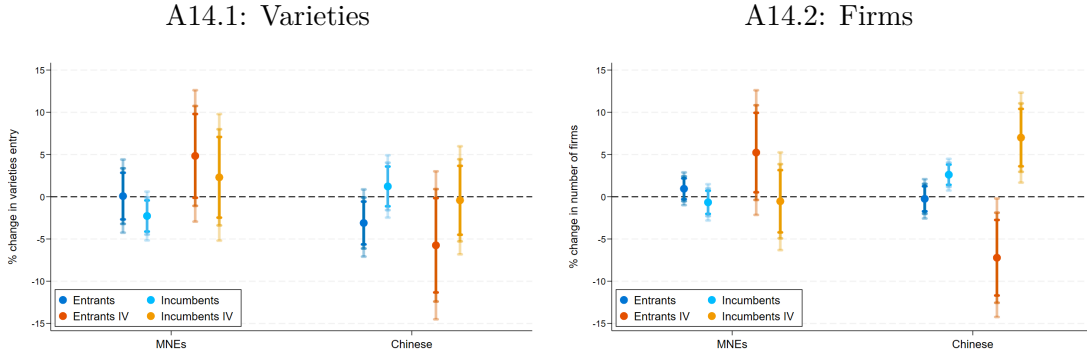
Notes: Observations at the sector-year level. The dependent variable is the 5-year entry rate of US domestic varieties measured as unique pairs of HS 1992 6-digits codes and destination country. The explanatory variables are the 5-year growth of aggregate US imports from China, the 5-year growth of US imports from MNEs located in China, the 5-year growth of US imports from Chinese-owned firms located in China, the 5-year growth of US imports of final goods from Chinese-owned firms located in China, and the 5-year growth of US imports of intermediate goods from Chinese-owned firms located in China. All specification include fixed effects for sectors and years. Robust standard errors in parenthesis. Columns (1), (3), and (5) report OLS estimates. Columns (2), (4), and (6) report 2SLS estimates. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A15: New HS domestic varieties on import competition – China excluded

	(1)	(2)	(3)	(4)	(5)	(6)
	New HS6d	New HS6d	New HS6d	New HS6d	New HS6d	New HS6d
All	-0.109 (0.119)	0.142 (0.370)				
MNEs			-0.449** (0.209)	-0.186 (0.426)	-0.467** (0.223)	-0.117 (0.398)
Chinese			0.138 (0.232)	0.119 (0.626)		
Chinese Final					0.019 (0.174)	0.022 (0.440)
Chinese Intermediate					0.123 (0.137)	-0.040 (0.304)
Obs.	646	646	442	442	442	442
R ²	0.196		0.180		0.180	
F-stat All		71				
F-stat MNE				44		26
F-stat CN				31		
F-stat CN final						22
F-stat CN intermediate						17

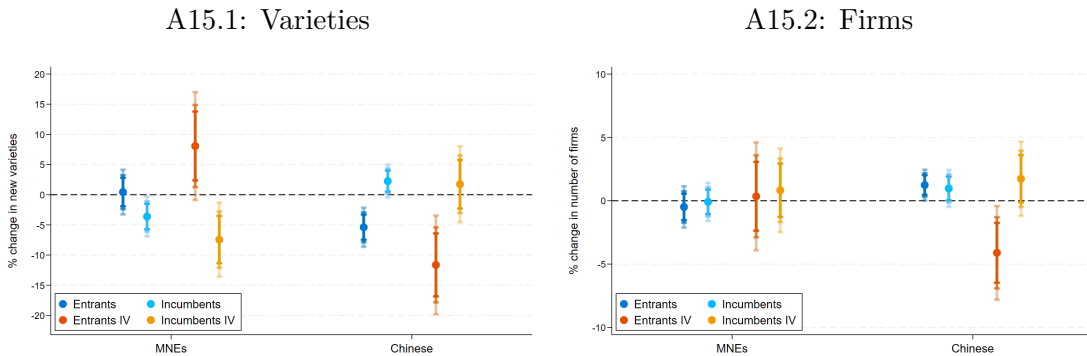
Notes: Observations at the sector-year level. The dependent variable is the 5-year entry rate of US domestic varieties measured as unique pairs of HS 1992 6-digits codes and destination country, excluding exports to China. The explanatory variables are the 5-year growth of aggregate US imports from China, the 5-year growth of US imports from MNEs located in China, the 5-year growth of US imports from Chinese-owned firms located in China, the 5-year growth of US imports of final goods from Chinese-owned firms located in China, and the 5-year growth of US imports of intermediate goods from Chinese-owned firms located in China. All specification include fixed effects for sectors and years. Robust standard errors in parenthesis. Columns (1), (3), and (5) report OLS estimates. Columns (2), (4), and (6) report 2SLS estimates. *** significant at 1%, ** significant at 5%, * significant at 10%.

Figure A14: Domestic product innovation – $h = 3$



Notes: Notes: The figure shows the estimated coefficients for entrant and incumbent firms of the effect of import competition on the entry rate of US-owned varieties in the US market and on the number of those firms over a three-years period (Equation 19). Export competition is computed using only trade flows of foreign-owned firms located in China (“MNEs”), or only trade flows of Chinese-owned firms located in China (“Chinese”). 90%, 95%, and 99% confidence intervals are shown. The dark and light blue coefficients report OLS estimates, while the red and yellow coefficients report 2SLS estimates.

Figure A15: Foreign product innovation – $h = 3$



Notes: Notes: The figure shows the estimated coefficients for entrant and incumbent firms of the effect of export competition on the entry rate of non-US-owned and non-Chinese-owned varieties in the US market and on the number of those firms over a three-years period (Equation 20). Export competition is computed using only trade flows of foreign-owned firms located in China (“MNEs”), or only trade flows of Chinese-owned firms located in China (“Chinese”). 90%, 95%, and 99% confidence intervals are shown. The dark and light blue coefficients report OLS estimates, while the red and yellow coefficients report 2SLS estimates.

Table A16: New foreign varieties on export competition – $h = 5$

	(1)	(2)	(3)	(4)	(5)	(6)
	New Var.	New Var.	New Var.	New Var.	New Var.	New Var.
All×I(Entrant)	-0.027*** (0.006)	-0.054*** (0.012)				
All×I(Incumbent)	0.020*** (0.007)	0.012 (0.013)				
MNEs×I(Entrant)			0.002 (0.007)	0.038*** (0.014)	0.003 (0.007)	0.030* (0.017)
MNEs×I(Incumbent)			-0.017*** (0.006)	-0.028*** (0.011)	-0.018*** (0.006)	-0.041*** (0.012)
Chinese×I(Entrant)			-0.035*** (0.007)	-0.077*** (0.020)		
Chinese×I(Incumbent)			0.014** (0.007)	0.002 (0.016)		
Chinese Final×I(Entrant)					-0.037*** (0.007)	-0.079*** (0.017)
Chinese Final×I(Incumbent)					0.011* (0.006)	0.005 (0.013)
Chinese Intermediate×I(Entrant)					-0.004 (0.004)	0.015 (0.011)
Chinese Intermediate×I(Incumbent)					0.006* (0.004)	0.015 (0.009)
Obs.	1,428	1,428	884	884	884	884
R ²	0.603		0.680		0.685	
F-stat All		136				
F-stat MNE				113		76
F-stat CN				24		
F-stat CN final						32
F-stat CN intermediate						24

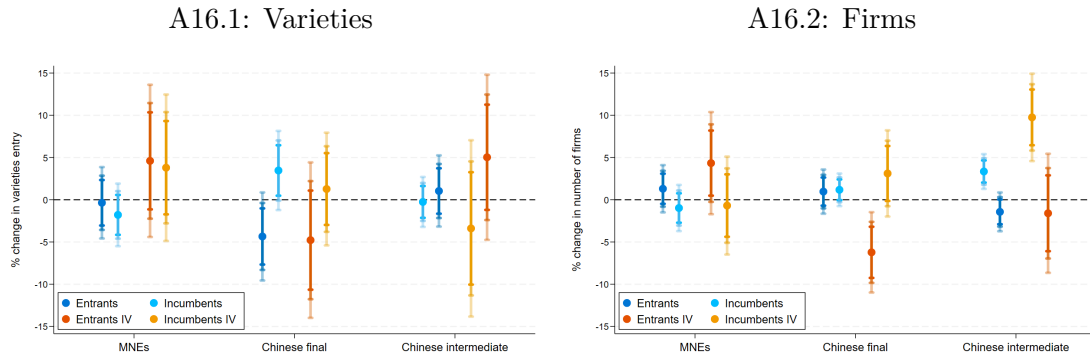
Notes: Observations at the sector-status-year level, where status can be either incumbent or entrant. The dependent variable is the 5-year variety entry rate of non-US and non-Chinese firms. The explanatory variables are the 5-year growth of aggregate US imports from China, the 5-year growth of US imports from MNEs located in China, the 5-year growth of US imports from Chinese-owned firms located in China, the 5-year growth of US imports of final goods from Chinese-owned firms located in China, and the 5-year growth of US imports of intermediate goods from Chinese-owned firms located in China. Fully saturated specification with each explanatory variable interacted by an indicator variable for status of incumbent or entrant. All specification include fixed effects for sectors, years, and status. Standard errors clustered at the sector-year level. Columns (1), (3), and (5) report OLS estimates. Columns (2), (4), and (6) report 2SLS estimates. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A17: Number of non-US and non-Chinese firms on export competition – $h = 5$

	(1)	(2)	(3)	(4)	(5)	(6)
	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)
All×I(Entrant)	0.091*** (0.021)	0.266*** (0.040)				
All×I(Incumbent)	-0.081*** (0.022)	-0.282*** (0.049)				
MNEs×I(Entrant)			-0.038** (0.015)	-0.005 (0.037)	-0.039*** (0.015)	-0.026 (0.030)
MNEs×I(Incumbent)			0.027** (0.012)	0.061* (0.034)	0.031** (0.012)	0.044 (0.027)
Chinese×I(Entrant)			0.040*** (0.015)	-0.130*** (0.041)		
Chinese×I(Incumbent)			0.027* (0.015)	0.013 (0.035)		
Chinese Final×I(Entrant)					0.046*** (0.014)	-0.081*** (0.030)
Chinese Final×I(Incumbent)					0.007 (0.014)	0.004 (0.028)
Chinese Intermediate×I(Entrant)					-0.002 (0.008)	-0.012 (0.023)
Chinese Intermediate×I(Incumbent)					0.003 (0.006)	0.044** (0.022)
Obs.	1,428	1,428	884	884	884	884
R ²	0.971		0.991		0.991	
F-stat All		136				
F-stat MNE				113		76
F-stat CN				24		
F-stat CN final						32
F-stat CN intermediate						24

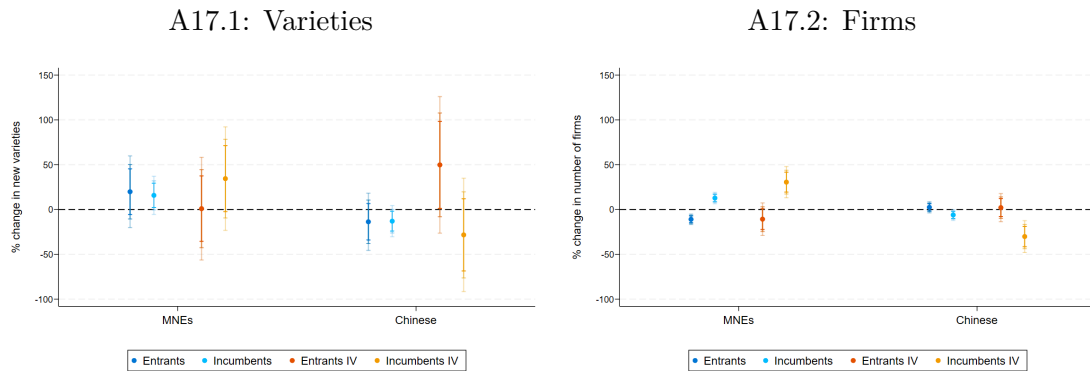
Notes: Observations at the sector-status-year level, where status can be either incumbent or entrant. The dependent variable is the (log) number of non-US and non-Chinese firms over a 5-year period. The explanatory variables are the 5-year growth of aggregate US imports from China, the 5-year growth of US imports from MNEs located in China, the 5-year growth of US imports from Chinese-owned firms located in China, the 5-year growth of US imports of final goods from Chinese-owned firms located in China, and the 5-year growth of US imports of intermediate goods from Chinese-owned firms located in China. Fully saturated specification with each explanatory variable interacted by an indicator variable for status of incumbent or entrant. All specification include fixed effects for sectors, years, and status. Standard errors clustered at the sector-year level. Columns (1), (3), and (5) report OLS estimates. Columns (2), (4), and (6) report 2SLS estimates. *** significant at 1%, ** significant at 5%, * significant at 10%.

Figure A16: The effect of Chinese import competition in final and intermediates



Notes: The figure shows the estimated coefficients for entrant and incumbent firms of the effect of import competition on the 5-year entry rate of US-owned varieties and on the number of US firms over a 5-year period (Equation 19). Import competition is computed using only trade flows of foreign-owned firms located in China (“MNEs”), only trade flows of final goods from Chinese-owned firms located in China (“Chinese final”), or only trade flows of intermediate goods from Chinese-owned firms located in China (“Chinese intermediate”). 90%, 95%, and 99% confidence intervals are shown. The dark and light blue coefficients report OLS estimates, while the red and yellow coefficients report 2SLS estimates. Coefficients in terms of percentage of the average value of the dependent variable are taken from Table A12 and Table A13 in Appendix A.

Figure A17: The effect of import competition on Chinese product innovation



Notes: Notes: The figure shows the estimated coefficients for entrant and incumbent firms of the effect of import competition on the 5-year entry rate of Chinese-owned varieties and on the number of Chinese firms over a 5-year period. Import competition is computed using only trade flows of foreign-owned firms located in China (“MNEs”), or only trade flows of Chinese-owned firms located in China (“Chinese”). 90%, 95%, and 99% confidence intervals are shown. The dark and light blue coefficients report OLS estimates, while the red and yellow coefficients report 2SLS estimates.

Table A18: New HS foreign varieties on export competition

	(1)	(2)	(3)	(4)	(5)	(6)
	New HS6d	New HS6d	New HS6d	New HS6d	New HS6d	New HS6d
All	0.006 (0.300)	0.005 (0.678)				
MNEs			0.285 (0.356)	-0.287 (0.975)	0.241 (0.356)	0.096 (0.963)
Chinese			-0.206 (0.362)	0.546 (1.263)		
Chinese Final					0.086 (0.412)	0.226 (1.021)
Chinese Intermediate					-0.080 (0.216)	-0.367 (0.598)
Obs.	646	646	442	442	442	442
R ²	0.506		0.292		0.290	
F-stat All		71				
F-stat MNE				44		26
F-stat CN				31		
F-stat CN final						22
F-stat CN intermediate						17

Notes: Observations at the sector-year level. The dependent variable is the 5-year entry rate of foreign varieties measured as unique pairs of HS 1992 6-digits codes and country of origin in US imports. The explanatory variables are the 5-year growth of aggregate US imports from China, the 5-year growth of US imports from MNEs located in China, the 5-year growth of US imports from Chinese-owned firms located in China, the 5-year growth of US imports of final goods from Chinese-owned firms located in China, and the 5-year growth of US imports of intermediate goods from Chinese-owned firms located in China. All specification include fixed effects for sectors and years. Robust standard errors in parenthesis. Columns (1), (3), and (5) report OLS estimates. Columns (2), (4), and (6) report 2SLS estimates. *** significant at 1%, ** significant at 5%, * significant at 10%.

B Data

From trademarks to products

The first challenge in mapping trademarks to varieties is that trademarks include slogans, jingles, and symbols, which may not be an appropriate indicator for a variety. In order to exclude these categories, I do not consider in my analysis trademarks that cannot be graphically represented (i.e., jingles), trademarks that do not have any text (i.e., symbols), and trademarks that have been abandoned or cancelled within six years from filing. The last criteria deals with trademarks that do not appear in the real consumer market and with potential slogans in the data, since they tend to have a shorter life span.⁴⁹

The second challenge in mapping trademarks to varieties is that multiple trademarks are registered for different features of the same protected text. As an illustrative example, consider the water brand “Dasani” owned by The Coca-Cola Company. A trademark featuring the word “Dasani” was first filed by The Coca-Cola Company in 1998, while another one was filed in 2014, featuring the same word but in stylized font with a slightly curved “S”.⁵⁰ A naive count of trademarks would end up overstating the number of varieties, as the two trademarks above would be counted as two different varieties of water. Since I am interested in uncovering the number of products, I measure a variety as a unique pair of protected text and class per firm. This process filters out roughly 14 percent of trademarks in my data. In doing so, the two trademarks above both protect the same word “Dasani” and both belong to the same NICE class number 32, and hence are counted as one single variety.⁵¹ The year of entry of such variety is the earliest year of registration of all trademarks belonging to that variety, and the year of exit (if any) is the latest year of expiration of all trademarks belonging to that variety.

Finally, to keep only products sold by profit-maximizing firms, I exclude trademarks filed by individuals, trusts, estates, foundations, state or federal agencies, and unknown legal entities.

⁴⁹As a result of the Trademark Law Revision Act of 1988, firms can file intent-to-use applications at the USPTO. According to Congress, the intent to use must be in the ordinary course of trade and not merely to reserve a right in a mark, and there must be a bona fide intent to use the mark on each of the goods or services listed in the application. Firms are granted a period of six years to actually use the trademark in commerce. If the owner fails to establish use of the mark, the application is treated as abandoned.

⁵⁰The trademark filed in 1998 has serial number 75551076; the trademark filed in 2014 has serial number 86209498.

⁵¹NICE class 32 includes beers, non-alcoholic beverages, mineral and aerated waters, fruit beverages and fruit juices, syrups and other preparations for making non-alcoholic beverages.

To validate the data, I compare the number of varieties obtained using this definition with the number of varieties owned by three car manufacturers: Ford, Volkswagen, and Toyota (Table B1). Varieties measured using trademarks cover between 75 and 100 percent of all car models sold in the United States and first introduced by the car manufacturer; that is, car models not acquired from other manufacturers through mergers or acquisitions. Coverage increases to at least 89 percent when car models are weighted by sales in the United States.⁵²

Table B1: Car models sold in the US

	Car models		Trademarked car models	
	Number	Number	% of models	% of sales
<i>Ford</i>				
Ford models	33	30	91%	89%
<i>Volkswagen</i>				
Volkswagen models	18	14	78%	93%
<i>Toyota</i>				
Toyota models	32	24	75%	90%
Lexus models	16	15	94%	100%
Scion models	5	5	100%	100%

Notes: For three different manufacturers, this table show the number of car models sold in the United States, and the number, share, and sales-weighted share of car models with a trademark associated to them. Information on the names and sales of car models is sourced from [Head and Mayer \(2019\)](#).

Firm identifiers

The USPTO Trademarks Case File dataset does not provide firm identifiers, but only the name and location of each firm owning a trademark. This is a common challenge in intellectual property data. The patent literature has overcome this challenge by grouping

⁵²Usually, the car models that do not have a trademark associated to them are improvements on existing car models (for example, Volkswagen Golf is trademarked, but Volkswagen Golf SportWagen is not). The car models that do not have a trademark associated to them in my data are: Ford Expedition Max, Ford Freestar, Ford F-150 SuperCrew, Volkswagen Beetle Convertible, Volkswagen New Beetle Convertible, Volkswagen Golf SportWagen, Volkswagen Jetta SportWagen, Toyota Estima, Toyota MR-S, Toyota Land Cruiser 200, Toyota Vitz, Toyota Prius Alpha, Toyota Belta, Toyota Kluger V, Toyota Hilux Surf.

inventors or firms names using homonymy or quasi-homonymy ([Trajtenberg et al., 2006](#); [Raffo and Lhuillery, 2009](#); [Doherr, 2016](#)). I rely on a similar approach. Specifically, I strip firm names of punctuation characters and common non-informative words (e.g., “the”, “company”, “and”), apply a probabilistic matching at the bigram level within country (within state for the United States), and keep as successful matches only those with a Jaccard probability score above 90 percent.⁵³ I validate this matching using the algorithm developed by [Autor et al. \(2020\)](#) to link firms appearing in the USPTO Patent and Inventor database and in Compustat. I focus on a subset of 250 firms: I search their name on Bing.com, retain the top five URL results, and match firm names that return the same URLs. Comparing the two methodologies, the algorithm by [Autor et al. \(2020\)](#) provides more matches than the bigrams-based matching process. However, none of the bigrams-based matches was not included in the URLs-based matches. This means that the bigram-based algorithm does not give false positive matches, therefore it may overstate the number of entrant firms.

List of countries

The sixty-one countries included in my analysis are: Argentina, Australia, Austria, Belgium, Brazil, Cambodia, Canada, Chile, China, Colombia, Czechia, Denmark, Dominican Republic, Ecuador, Estonia, Finland, France, Germany, Greece, Guatemala, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Korea, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Netherlands, New Zealand, Norway, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Taiwan, United Kingdom, United States, Uruguay, Venezuela, Viet Nam.

⁵³I use the “matchit” Stata command developed by [Raffo \(2015\)](#) for patents’ inventors.

C Gravity

Varieties share similarities with some trade flows. One empirical pattern that trade flows are famous for is the gravity equation. Here, I test whether varieties share the same empirical pattern and if so, whether they exhibit notable differences in the estimated elasticities. To do so, I estimate the following specification of a gravity projection:

$$\ln(V_{c,s,t}) = \beta_1 \ln(\text{dist}_c) + \beta_2 \ln(\text{pop}_{c,t}) + \beta_3 \ln(\text{GDPcap}_{c,t}) + \beta_4 \mathbb{I}(\text{Lang}_c) + \alpha_s + \alpha_t + \varepsilon_{c,s,t} \quad (\text{C1})$$

where $V_{c,s,t}$ is the number of varieties in sector s available at time t from country c . The specification includes sector and year fixed effects (α_s and α_t , respectively) as well as standard gravity regressors: the distance between country c and the US (dist_c), population of country c in year t ($\text{pop}_{c,t}$), GDP per capita in country c in year t ($\text{GDPcap}_{c,t}$), and the indicator variable $\mathbb{I}(\text{Lang}_c)$ equal to one if country c and the US share the same official language. Standard errors are clustered at the sector and year level.

Table C1: Varieties obey gravity

	(1)	(2)	(3)	(4)
	N. varieties	N. varieties	Trade flow	Trade flow
Distance (ln)	-0.567*** (0.039)	-0.344*** (0.026)	-0.604*** (0.093)	-0.852*** (0.161)
Population (ln)	0.889*** (0.026)	1.040*** (0.035)	1.331*** (0.032)	1.010*** (0.084)
GDP per capita (ln)	2.304*** (0.107)	3.024*** (0.150)	1.761*** (0.157)	1.026*** (0.219)
$\mathbb{I}(\text{Lang}_c)$	0.447*** (0.051)	0.120 (0.095)	0.693*** (0.091)	-0.142 (0.171)
Estimator	OLS	PPML	OLS	PPML
Obs.	29,897	38,318	37,780	38,318
R^2 (Adj. or Pseudo)	0.709	0.863	0.620	0.710

Notes: The observations are at the country-sector-year level. The dependent variable for specifications in columns (1) and (2) is the (log) number of varieties available in the United States from country c in sector s and in year t . The dependent variable in columns (3) and (4) is the (log) value of trade flows from country c to the United States in sector s and year t . The explanatory variables are (log) distance to the United States, (log) population, (log) GDP per capita, and an indicator variable equal to one if country c and the United States share the same official language. All specifications include sector and year fixed effects. OLS estimates in parentheses in columns (1) and (3); Poisson Pseudo-Maximum Likelihood estimates in columns (2) and (4). Standard errors clustered at the sector and year level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Columns (1) and (2) of [Table C1](#) shows the estimated coefficients for [Equation C1](#), obtained either through an OLS estimator or a Poisson Pseudo-Maximum Likelihood estimator to account for zeros. Using both estimation methods, varieties satisfy the gravity equation and the coefficients exhibit the expected signs: a negative distance elasticity, and positive elasticities for population, GDP per capita, as well as common language. The estimated coefficients retain their sign when controlling for trade flows ([Table C2](#)), something that does not hold true for the distance elasticity when varieties are counted using custom codes ([Table C3](#)). Once again, this difference speaks to the fact that varieties measured through customs codes are fully captured by trade flows data. Therefore, measuring varieties through custom codes can be swayed by offshoring because it erroneously relies on the assumption that all trade flows are varieties flows. Comparing the coefficients for varieties in columns (1) and (2) with those obtained for trade flows in columns (3) and (4) reflects the notion that not all trade flows are varieties flows. Crucial dissimilarities can be observed for distance and GDP per capita elasticities estimated with the Poisson Pseudo-Maximum Likelihood estimator: varieties are less elastic to distance and more elastic to GDP per capita than imports. The first elasticity highlights the importance of multinational activity and foreign direct investment. Since firms do not have to ship goods from the country where they were devised, they can produce goods in countries that are closer to the market of consumption. Trademarks keep track of the country where the blueprint has been devised, not the country where the good has ultimately been produced. Therefore, the lower distance elasticity exhibited by trademarks is not surprising: the origin of the blueprint can be further away than the country of assembly of the good itself. The second elasticity concerns GDP per capita. While trade flows can capture both flows of differentiated and generic goods, my measure of varieties only captures differentiated goods available in the US market. Higher productivity is needed for firms to produce differentiated goods, while generic goods can be produced by all types of firms. Therefore, countries with higher GDP per capita are expected to produce more differentiated varieties than countries with lower GDP per capita.

Table C2: Varieties obey gravity even controlling for trade flows

	(1)	(2)
	N. varieties	N. varieties
Distance (ln)	-0.410*** (0.032)	-0.183*** (0.036)
Population (ln)	0.600*** (0.035)	0.748*** (0.060)
GDP per capita (ln)	1.981*** (0.098)	2.656*** (0.152)
I(Lang _c)	0.287*** (0.055)	-0.018 (0.099)
Trade flow (ln)	0.249*** (0.020)	0.267*** (0.038)
Estimator	OLS	PPML
Obs.	29,822	37,780
R ² (Adj. or Pseudo)	0.759	0.892

Notes: The observations are at the country-sector-year level. The dependent variable is the (log) number of varieties available in the United States from country c in sector s and in year t as measured through trademarks. The explanatory variables are (log) distance to the United States, (log) population, (log) GDP per capita, an indicator variable equal to one if country c and the United States share the same official language, and (log) imports of the US from country c . All specifications include sector and year fixed effects. OLS estimates in parentheses in column (1); Poisson Pseudo-Maximum Likelihood estimates in column (2). Standard errors clustered at the sector and year level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table C3: Varieties as measured by HS codes

	(1)	(2)	(3)	(4)
	N. varieties	N. varieties	N. varieties	N. varieties
	(HS codes)	(HS codes)	(HS codes)	(HS codes)
Distance (ln)	-0.121*** (0.021)	-0.025 (0.023)	-0.063*** (0.017)	0.012 (0.015)
Population (ln)	0.407*** (0.020)	0.253*** (0.016)	0.303*** (0.021)	0.182*** (0.018)
GDP per capita (ln)	0.612*** (0.048)	0.432*** (0.040)	0.480*** (0.042)	0.331*** (0.038)
I(Lang _c)	0.245*** (0.021)	0.142*** (0.019)	0.173*** (0.013)	0.107*** (0.011)
Trade flow		0.150*** (0.014)		0.121*** (0.006)
Estimator	OLS	OLS	PPML	PPML
Obs.	37,780	37,780	38,318	38,318
R ² (Adj. or Pseudo)	0.813	0.824	0.814	0.824

Notes: The observations are at the country-sector-year level. The dependent variable is the (log) number of varieties available in the United States from country c in sector s and in year t as measured through unique HS 6-digits codes with positive trade flows. The explanatory variables are (log) distance to the United States, (log) population, (log) GDP per capita, an indicator variable equal to one if country c and the United States share the same official language, and (log) imports of the US from country c . All specifications include sector and year fixed effects. OLS estimates in columns (1) and (2); Poisson Pseudo-Maximum Likelihood estimates in columns (3) and (4). Standard errors clustered at the sector and year level in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

D Model

D.1 Autarky equilibrium

The average realized productivity is the harmonic mean of φ over the entire support:

$$\begin{aligned}\tilde{\varphi} &= \left[\int_b^\infty \varphi^{\sigma-1} g(\varphi) d\varphi \right]^{\frac{1}{\sigma-1}} = \left[\int_b^\infty \varphi^{\sigma-1} \frac{kb^k}{\varphi^{k+1}} d\varphi \right]^{\frac{1}{\sigma-1}} = \\ &= \left[\frac{k}{k+1-\sigma} b^{\sigma-1} \int_b^\infty \frac{(k+1-\sigma)b^{k+1-\sigma}}{\varphi^{k+1-\sigma+1}} d\varphi \right]^{\frac{1}{\sigma-1}} = \\ &= \left(\frac{k}{k+1-\sigma} \right)^{\frac{1}{\sigma-1}} b\end{aligned}$$

where $g(\varphi)$ is the probability density function of a Pareto distribution with scale parameter b and shape parameter k .

The expected profits are

$$\begin{aligned}\bar{\pi} &= \int_b^\infty \pi(\varphi) g(\varphi) d\varphi = \int_b^\infty \frac{1}{\sigma} r(\varphi) \frac{kb^k}{\varphi^{k+1}} d\varphi = \\ &= \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} w \right)^{1-\sigma} \mathbb{P}_\Omega^{\sigma-1} \alpha E \int_b^\infty \frac{kb^k}{\varphi^{k+1-\sigma+1}} d\varphi = \\ &= \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} w \right)^{1-\sigma} \mathbb{P}_\Omega^{\sigma-1} \alpha E \frac{k}{k+1-\sigma} b^{\sigma-1} \int_b^\infty \frac{(k+1-\sigma)b^{k+1-\sigma}}{\varphi^{k+1-\sigma+1}} d\varphi = \\ &= \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} w \right)^{1-\sigma} \mathbb{P}_\Omega^{\sigma-1} \alpha E \frac{k}{k+1-\sigma} b^{\sigma-1} = \pi(\tilde{\varphi}).\end{aligned}$$

The exact price index over differentiated goods can be rewritten as

$$\begin{aligned}\mathbb{P}_\Omega &= \left[\int_b^\infty p(\varphi)^{1-\sigma} M g(\varphi) d\varphi \right]^{\frac{1}{1-\sigma}} = \\ &= \left[\int_b^\infty \left(\frac{\sigma}{\sigma-1} \frac{w}{\varphi} \right)^{1-\sigma} M \frac{kb^k}{\varphi^{k+1}} d\varphi \right]^{\frac{1}{1-\sigma}} = \\ &= \left[\left(\frac{\sigma}{\sigma-1} \frac{w}{\varphi} \right)^{1-\sigma} M \frac{kb^{\sigma-1}}{k-\sigma+1} \right]^{\frac{1}{1-\sigma}} = \left[M p(\tilde{\varphi})^{1-\sigma} \right]^{\frac{1}{1-\sigma}} = p(\tilde{\varphi}) M^{\frac{1}{1-\sigma}} = \tilde{p} M^{\frac{1}{1-\sigma}}\end{aligned}$$

where $\tilde{p} = p(\tilde{\varphi})$ for brevity.

The labor market clearing condition is

$$\begin{aligned} L &= L_H + \int_b^\infty l(\varphi) M g(\varphi) d\varphi = L_H + M l(\tilde{\varphi}) = L_H + M \frac{1}{\tilde{\varphi}} q(\tilde{\varphi}) = \\ &= L_H + \left(\frac{\sigma}{\sigma-1} w \right)^{-\sigma} \mathbb{P}_\Omega^{\sigma-1} \alpha E M \frac{k}{k+1-\sigma} b^{\sigma-1}. \end{aligned} \quad (D1)$$

The income of consumers is equal to the sum of labor income and the total profits made by firms, net of the fixed costs of entry:

$$I = wL + \bar{\pi}M - f^E M^E. \quad (D2)$$

In each period, firms face an exogenous probability δ of incurring a bad shock and having to exit the market. The present discounted value of their expected profit flow is

$$\bar{v} = \sum_{t=0}^{+\infty} (1-\delta)^t \bar{\pi} = \frac{\bar{\pi}}{\delta}.$$

The Free Entry condition states that the net value of entry should be zero; that is, expected profits should equal entry costs: $\bar{\pi} = \delta f^E$. Replacing the expression for the average profit gives:

$$\frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} w \right)^{1-\sigma} \left(p(\tilde{\varphi})^{1-\sigma} M^{\frac{1}{1-\sigma}} \right)^{\sigma-1} \alpha E \frac{k}{k+1-\sigma} b^{\sigma-1}. \quad (D3)$$

D.2 US firms in open economy

I will use the following notation: x_{ijl} represents variable x of country i firms producing in country j and selling to country l . US firms do not pay fixed costs for producing and selling domestically. Therefore, they make profits

$$\pi_{UUU}(\varphi) = p_{UUU}(\varphi) q_{UUU}(\varphi) - \frac{1}{\varphi} q_{UUU}(\varphi) w_U = \frac{1}{\sigma} p_{UUU}(\varphi) q_{UUU}(\varphi).$$

US firms pay fixed cost of value f_{UC}^{FDI} to offshore production to China, and also variable costs τ_{CU} for each unit of goods they have to ship back to the United States. Their profits are

$$\pi_{UCU}(\varphi) = p_{UCU}(\varphi) \tau_{CU} q_{UCU}(\varphi) - \frac{\tau_{CU}}{\varphi} q_{UCU}(\varphi) w_C - f_{UC}^{FDI} w_C = \frac{1}{\sigma} r_{UCU}(\varphi) - f_{UC}^{FDI} w_C.$$

US firms sell only to US consumers. They can choose whether to produce domestically or to offshore production to China. US firms will produce in China if and only if

$$\pi_{UCU}(\varphi) \geq \pi_{UUU}(\varphi).$$

Since profits are an increasing function of φ , there is a unique cutoff productivity φ_{UC}^{FDI} such that firms with productivity above it will offshore production to China, and firms with productivity below it will produce domestically. The Zero Cutoff Profit condition for offshoring production is:

$$\pi_{UCU}(\varphi_{UC}^{FDI}) = \pi_{UUU}(\varphi_{UC}^{FDI})$$

which implies

$$\begin{aligned} \pi_{UCU}(\varphi_{UC}^{FDI}) - \pi_{UUU}(\varphi_{UC}^{FDI}) &= \frac{1}{\sigma} r_{UCU}(\varphi) - f_{UC}^{FDI} w_C - \frac{1}{\sigma} r_{UUU}(\varphi) = \\ &= \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \frac{1}{\varphi_{UC}^{FDI}} \right)^{1-\sigma} \mathbb{P}_{\Omega U}^{\sigma-1} \alpha E_U \left[(\tau_{CU} w_C)^{1-\sigma} - w_U^{1-\sigma} \right] - f_{UC}^{FDI} w_C = 0 \\ \Rightarrow \varphi_{UC}^{FDI} &= \left(\frac{\sigma}{\sigma-1} \right) \left(\frac{\sigma f_{UC}^{FDI} w_C}{\alpha E_U} \right)^{\frac{1}{\sigma-1}} \frac{1}{\mathbb{P}_{\Omega U}} \left[(\tau_{CU} w_C)^{1-\sigma} - w_U^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \end{aligned}$$

Notice that the fixed costs need to be large enough to guarantee that φ_{UC}^{FDI} is greater than b , the lower bound of the support. Otherwise, all US firms would offshore production abroad, and there would be no employment for US workers.

Define $\tilde{\varphi}_{UUU}$ the harmonic average productivity of US firms producing domestically, and $\tilde{\varphi}_{UCU}$ the harmonic average productivity of US firms offshoring production.

$\tilde{\varphi}_{UUU}$ can be rewritten as

$$\begin{aligned} \tilde{\varphi}_{UUU} &= \left[\int_b^{\varphi_{UC}^{FDI}} \varphi^{\sigma-1} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi \right]^{\frac{1}{\sigma-1}} = \\ &= \left[\frac{k}{k+1-\sigma} \frac{1}{1 - \left(\frac{b}{\varphi_{UC}^{FDI}} \right)^k} \left(b^{\sigma-1} - \frac{b^k}{(\varphi_{UC}^{FDI})^{k+1-\sigma}} \right) \right]^{\frac{1}{\sigma-1}}. \end{aligned}$$

Similarly, $\tilde{\varphi}_{UCU}$ can be rewritten as:

$$\begin{aligned}\tilde{\varphi}_{UCU} &= \left[\int_{\varphi_{UC}^{FDI}}^{\infty} \varphi^{\sigma-1} \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi \right]^{\frac{1}{\sigma-1}} = \\ &= \left[\frac{k}{k+1-\sigma} \right]^{\frac{1}{\sigma-1}} \varphi_{UC}^{FDI}.\end{aligned}$$

D.3 Chinese firms in open economy

I will use the following notation: x_{ijl} represents variable x of country i firms producing in country j and selling to country l . Chinese firms do not pay fixed costs for producing and selling domestically. Therefore, they make profits

$$\pi_{CCC}(\varphi) = p_{CCC}(\varphi)q_{CCC}(\varphi) - \frac{1}{\varphi}q_{CCC}(\varphi)w_C = \frac{1}{\sigma}p_{CCC}(\varphi)q_{CCC}(\varphi).$$

Chinese firms that want to export pay a fixed cost of value f_{CU}^X and variable iceberg trade costs τ_{CU} for each unit of goods exported. Therefore, their profits are

$$\pi_{CCU}(\varphi) = p_{CCU}(\varphi)\tau_{CU}q_{CCU}(\varphi) - \frac{\tau_{CU}}{\varphi}q_{CCU}(\varphi)w_C - f_{CU}^X = \frac{1}{\sigma}p_{CCU}(\varphi)q_{CCU}(\varphi) - f_{CU}^X w_C.$$

Notice that $\pi_{CCU}(\varphi)$ are an increasing function of φ . Then, there is a cutoff productivity φ_{CCU}^X such that firms with productivity above it will export to the US, and firms with productivity below it will not export. The Zero Cutoff Profit condition for exporting is:

$$\pi_{CCU}(\varphi_{CCU}^X) = 0$$

which implies

$$\begin{aligned}\pi_{CCU}(\varphi_{CCU}^X) &= \frac{1}{\sigma}p_{CCU}(\varphi_{CCU}^X)q_{CCU}(\varphi_{CCU}^X) - f_{CU}^X w_C = \\ &= \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \tau_{CU} \frac{w_C}{\varphi_{CCU}^X} \right)^{1-\sigma} \mathbb{P}_{\Omega U}^{\sigma-1} \alpha E_U - f_{CU}^X w_C = 0 \\ \Rightarrow \varphi_{CCU}^X &= \frac{\sigma}{\sigma-1} \left(\frac{\sigma f_{CU}^X w_C}{\alpha E_U} \right)^{\frac{1}{\sigma-1}} \frac{\tau_{CU} w_C}{\mathbb{P}_{\Omega U}}.\end{aligned}$$

Notice that fixed costs should be high enough to guarantee $\varphi_{CCU}^X > b$, otherwise all Chinese firms would export and no firm would sell to the Chinese market.

Define $\tilde{\varphi}_{CCU}$ as the harmonic average productivity of Chinese firms exporting to the US:

$$\begin{aligned}\tilde{\varphi}_{CCU} &= \left[\int_{\varphi_{CCU}^X}^{\infty} \varphi^{\sigma-1} \frac{g(\varphi)}{1 - G(\varphi_{CCU}^X)} d\varphi \right]^{\frac{1}{\sigma-1}} = \\ &= \left[\frac{k}{k + 1 - \sigma} \right]^{\frac{1}{\sigma-1}} \varphi_{CCU}^X.\end{aligned}$$

Recall that, as in autarky, the harmonic average productivity of all Chinese firms is exogenous:

$$\tilde{\varphi}_C = \left[\int_b^{\infty} \varphi^{\sigma-1} g(\varphi) d\varphi \right]^{\frac{1}{\sigma-1}} = \left(\frac{k}{k + 1 - \sigma} \right)^{\frac{1}{\sigma-1}} b.$$

D.4 Equilibrium conditions

In each period, firms face an exogenous probability δ of incurring a bad shock and having to exit the market. The present discounted value of their expected profit flow is

$$\bar{v} = \sum_{t=0}^{+\infty} (1 - \delta)^t \bar{\pi} = \frac{\bar{\pi}}{\delta}.$$

Firms have to pay a sunk cost f_i^E to know their productivity. The Free Entry condition states that the net value of entry should be zero; that is, expected profits should equal entry costs:

$$\bar{\pi}_i = \delta f_i^E.$$

In equilibrium, the mass of firms entering the market each year must be equal to the mass of firms exiting the market. The following Aggregate Stability Condition must hold:

$$M_i^E = \delta M_i$$

where M_i^E is the mass of entrant firms in country i and δM_i is the mass of exiting firms in country i .

The mass of US workers used in the differentiated good sector is

$$\begin{aligned}
L_{\Omega U} &= \int_b^{\varphi_{UC}^{FDI}} l_{UUU}(\varphi) M_{UUU} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi = \int_b^{\varphi_{UC}^{FDI}} \frac{q_{UUU}(\varphi)}{\varphi} M_{UUU} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi = \\
&= \left(\frac{\sigma}{\sigma-1} w_U \right)^{-\sigma} \mathbb{P}_U^{\sigma-1} \alpha X_U M_{UUU} \left[\int_b^{\varphi_{UC}^{FDI}} \varphi^{\sigma-1} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi \right]^{\frac{1}{\sigma-1}} = \\
&= \left(\frac{\sigma}{\sigma-1} w_U \right)^{-\sigma} \mathbb{P}_U^{\sigma-1} \alpha X_U M_{UUU} (\tilde{\varphi}_{UUU})^{\sigma-1} = l_{UUU}(\tilde{\varphi}_{UUU}) M_{UUU}
\end{aligned}$$

where $g(\varphi)$ is the probability density function of the Pareto distribution and M_{UUU} is the mass of US firms producing domestically. Notice that the mass of US firms producing domestically is a portion $G(\varphi_{UC}^{FDI})$ of the total mass of US firms M_U : $M_{UUU} = G(\varphi_{UC}^{FDI}) M_U$. Moreover, some quantity L_{HU} of labor is used to produce the homogeneous good. Finally, US labor is used to pay the fixed costs of entry. Therefore, the US labor market clearing condition is:

$$L_U = L_{HU} + L_{\Omega U} + M_U^E f_U^E .$$

The mass of Chinese workers used in the differentiated good sector comprises workers employed by all Chinese firms and by US firms offshoring production to China:

$$\begin{aligned}
L_{\Omega C} &= \int_b^{\infty} l_{CCC}(\varphi) M_C g(\varphi) d\varphi + \int_{\varphi_{CU}^X}^{\infty} l_{CCU}(\varphi) M_{CCU} \frac{g(\varphi)}{1 - G(\varphi_{CU}^X)} d\varphi + \\
&\quad + \int_{\varphi_{UC}^{FDI}}^{\infty} l_{UCU}(\varphi) M_{UCU} \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi = \\
&= \int_b^{\infty} \frac{q_{CCC}(\varphi)}{\varphi} M_C g(\varphi) d\varphi + \int_{\varphi_{CU}^X}^{\infty} \frac{\tau_{CU} q_{CCU}(\varphi)}{\varphi} M_{CCU} \frac{g(\varphi)}{1 - G(\varphi_{CU}^X)} d\varphi + \\
&\quad + \int_{\varphi_{UC}^{FDI}}^{\infty} \frac{\tau_{CU} q_{UCU}(\varphi)}{\varphi} M_{UCU} \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi = \\
&= l_{CCC}(\tilde{\varphi}_C) M_C + l_{CCU}(\tilde{\varphi}_{CCU}) M_{CCU} + l_{UCU}(\tilde{\varphi}_{UCU}) M_{UCU}
\end{aligned}$$

where $g(\varphi)$ is the probability density function of a Pareto distribution, M_C is the total mass of Chinese firms, M_{CCU} is the mass of Chinese exporters, and M_{UCU} is the mass of US firms offshoring production to China. Notice that the mass of Chinese exporters is a proportion $1 - G(\varphi_{CU}^X)$ of the total mass of Chinese firms, and the mass of US firms offshoring production is a proportion $1 - G(\varphi_{UC}^{FDI})$ of the total mass of US firms: $M_{CCU} = [1 - G(\varphi_{CU}^X)] M_C$ and $M_{UCU} = [1 - G(\varphi_{UC}^{FDI})] M_U$.

Moreover, some quantity L_{HC} of labor is used to produce the homogeneous good. Finally,

labor in China is used to pay the fixed costs of entry, the fixed costs of exporting, and the fixed costs of offshoring. Therefore, the labor market clearing condition for China is:

$$L_C = L_{HC} + L_{\Omega C} + M_C^E f_C^E + M_{CCU} f_{CU}^X * M_{UCU} f_{UC}^{FDI} .$$

The expenditure of Chinese workers for the homogeneous and the differentiated goods is equal to the revenues made by firms selling to the Chinese market:

$$\begin{aligned} E_C &= p_{HC} q_{HC} + \int_b^\infty r_{CCC}(\varphi) M_C g(\varphi) d\varphi = q_{HC} + \int_b^\infty p_{CCC}(\varphi) q_{CCC}(\varphi) M_C g(\varphi) d\varphi = \\ &= q_{HC} + \left(\frac{\sigma}{\sigma - 1} w_C \right)^{1-\sigma} \mathbb{P}_{\Omega C}^{\sigma-1} \alpha X_C M_{CCC} \int_b^\infty \varphi^{1-\sigma} g(\varphi) d\varphi = q_{HC} + r_{CCC}(\tilde{\varphi}_C) M_C \end{aligned}$$

where $p_{HC} = 1$ and $q_{HC} = (1 - \alpha)E_C$.

Similarly, the expenditure of US workers on the homogeneous and differentiated goods is equal to the revenues made by firms selling to the US market:

$$\begin{aligned} E_U &= \int_b^{\varphi_{UC}^{FDI}} r_{UUU}(\varphi) M_{UUU} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi + \int_{\varphi_{UC}^{FDI}}^\infty r_{UCU}(\varphi) M_{UCU} \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi + \\ &+ \int_{\varphi_{CU}^X}^\infty r_{CCU}(\varphi) M_{CCU} \frac{g(\varphi)}{1 - G(\varphi_{CU}^X)} d\varphi + p_{HU} q_{HU} = \\ &= r_{UUU}(\tilde{\varphi}_{UUU}) M_{UUU} + r_{UCU}(\tilde{\varphi}_{UCU}) M_{UCU} + r_{CCU}(\tilde{\varphi}_{CCU}) M_{CCU} + q_{HU} \end{aligned}$$

where $p_{HU} = 1$ and $q_{HU} = (1 - \alpha)E_U$.

In this model, workers receive income from labor and from the net profits of US firms, but have to pay the fixed costs of entry.⁵⁴ Therefore, the income of US workers is

$$\begin{aligned} I_U &= w_U L_U - w_U f_U^E M_U^E + \\ &+ \left[r_{UUU}(\tilde{\varphi}_{UUU}) - w_U \frac{q_{UUU}(\tilde{\varphi}_{UUU})}{\tilde{\varphi}_{UUU}} \right] M_{UUU} + \\ &+ \left[r_{UCU}(\tilde{\varphi}_{UCU}) - w_C \tau_{CU} \frac{q_{UCU}(\tilde{\varphi}_{UCU})}{\tilde{\varphi}_{UCU}} - w_C f_{UC}^{FDI} \right] M_{UCU} . \end{aligned}$$

⁵⁴Notice that the labor income of workers includes all the fixed costs paid by the firms. However, workers in this model also own the firms, so that they have to pay the fixed costs back.

Similarly, the income of Chinese workers is

$$\begin{aligned}
I_C &= w_C L_C - w_C f_C^E M_C^E + \\
&+ \left[r_{CCC}(\tilde{\varphi}_{CCC}) - w_C \frac{q_{CCC}(\tilde{\varphi}_{CCC})}{\tilde{\varphi}_{CCC}} \right] M_{CCC} + \\
&+ \left[r_{CCU}(\tilde{\varphi}_{CCU}) - w_C \tau_{CU} \frac{q_{CCU}(\tilde{\varphi}_{CCU})}{\tilde{\varphi}_{CCU}} - w_C f_{CU}^X \right] M_{CCU}.
\end{aligned}$$

Notice that the income of workers also includes the net profits made in the homogeneous sector, which are equal to zero.

In equilibrium, the income of workers must be equal to their total expenditure: $I_i = E_i$.

The expected profit of US firms is $\bar{\pi}_U = G(\varphi_{UC}^{FDI})\bar{\pi}_{UUU} + [1 - G(\varphi_{UC}^{FDI})]\bar{\pi}_{UCU}$, where $\bar{\pi}_{UUU}$ is the expected profit of US firms who produce domestically and $\bar{\pi}_{UCU}$ is the expected profit of US firms who offshore production to China:

$$\bar{\pi}_{UUU} = \int_b^{\varphi_{UC}^{FDI}} \pi_{UUU}(\varphi) \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi = \pi_{UUU}(\tilde{\varphi}_{UUU})$$

and

$$\begin{aligned}
\bar{\pi}_{UCU} &= \int_{\varphi_{UC}^{FDI}}^{\infty} \pi_{UCU}(\varphi) \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi = \\
&= \int_{\varphi_{UC}^{FDI}}^{\infty} \left(\frac{1}{\sigma} r_{UCU}(\varphi) - f_{UC}^{FDI} w_C \right) \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi = \\
&= \frac{1}{\sigma} r_{UCU}(\tilde{\varphi}_{UCU}) - f_{UC}^{FDI} w_C = \pi_{UCU}(\tilde{\varphi}_{UCU})
\end{aligned}$$

where $G(\cdot)$ is the CDF of a Pareto distribution with size parameter b and shape parameter k .

The expected profit of Chinese firms is: $\bar{\pi}_C = \bar{\pi}_{CCC} + [1 - G(\varphi_{CU}^X)]\bar{\pi}_{CCU}$, where $\bar{\pi}_{CCC}$ is the expected profit of Chinese firms selling domestically and $\bar{\pi}_{CCU}$ is the expected profits of Chinese firms exporting to the United States:

$$\bar{\pi}_{CCC} = \int_b^{\infty} \pi_{CCC}(\varphi) g(\varphi) d\varphi = \pi_{CCC}(\tilde{\varphi}_C)$$

and

$$\begin{aligned}
\bar{\pi}_{CCU} &= \int_{\varphi_{CU}^X}^{\infty} \pi_{CCU}(\varphi) \frac{g(\varphi)}{1 - G(\varphi_{CU}^X)} d\varphi = \\
&= \int_{\varphi_{CU}^X}^{\infty} \left(\frac{1}{\sigma} r_{CCU}(\varphi) - f_{CU}^X w_C \right) \frac{g(\varphi)}{1 - G(\varphi_{CU}^X)} d\varphi = \\
&= \frac{1}{\sigma} r_{CCU}(\tilde{\varphi}_{CCU}) - f_{CU}^X w_C = \pi_{CCU}(\tilde{\varphi}_{CCU}) .
\end{aligned}$$

Label M_{UUU} the mass of US firms producing and selling domestically and M_{UCU} as the mass of US firms producing in China and selling domestically. Notice that $M_{UUU} = (1 - G(\varphi_{UC}^{FDI}))M_U$ and $M_{UCU} = G(\varphi_{UC}^{FDI})M_U$, where M_U is the total mass of US firms. Similarly, define $M_{CCU} = (1 - G(\varphi_{CU}^X))M_C$ the mass of Chinese firms exporting to the United States, where M_C is the total mass of Chinese firms, which is equivalent to the mass of Chinese firms selling in the Chinese market. The exact price index for the composite differentiated good in the United States is

$$\begin{aligned}
\mathbb{P}_{\Omega U} &= \left[\int_{\omega \in \Omega_U} (p(\omega))^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} = \\
&= \left[\int_b^{\varphi_{UC}^{FDI}} (p_{UUU}(\varphi))^{1-\sigma} M_{UUU} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi + \int_{\varphi_{UC}^{FDI}}^{\infty} (p_{UCU}(\varphi))^{1-\sigma} M_{UCU} \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi + \right. \\
&\quad \left. + \int_{\varphi_{CU}^X}^{\infty} (p_{CCU}(\varphi))^{1-\sigma} M_{CCU} \frac{g(\varphi)}{1 - G(\varphi_{CU}^X)} d\varphi \right]^{\frac{1}{1-\sigma}} = \\
&= \left[\left(\frac{\sigma}{\sigma - 1} w_U \right)^{1-\sigma} M_{UUU} \int_b^{\varphi_{UC}^{FDI}} \varphi^{\sigma-1} \frac{g(\varphi)}{G(\varphi_{UC}^{FDI})} d\varphi + \right. \\
&\quad \left. + \left(\frac{\sigma}{\sigma - 1} \tau_{CU} w_C \right)^{1-\sigma} M_{UCU} \int_{\varphi_{UC}^{FDI}}^{\infty} \varphi^{\sigma-1} \frac{g(\varphi)}{1 - G(\varphi_{UC}^{FDI})} d\varphi + \right. \\
&\quad \left. + \left(\frac{\sigma}{\sigma - 1} \tau_{CU} w_C \right)^{1-\sigma} M_{CCU} \int_{\varphi_{CU}^X}^{\infty} \varphi^{\sigma-1} \frac{g(\varphi)}{G(\varphi_{CU}^X)} d\varphi \right]^{\frac{1}{1-\sigma}} .
\end{aligned}$$

Then, the price index of the differentiated goods in the US can be rewritten as

$$\mathbb{P}_{\Omega U} = \left[M_{UUU} \tilde{p}_{UUU}^{1-\sigma} + M_{UCU} \tilde{p}_{UCU}^{1-\sigma} + M_{CCU} \tilde{p}_{CCU}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

where $p(\tilde{\varphi}_{UUU})$ has been rewritten as \tilde{p}_{UUU} , $p(\tilde{\varphi}_{UCU})$ has been rewritten as \tilde{p}_{UCU} , and $p(\tilde{\varphi}_{CCU})$ has been rewritten as \tilde{p}_{CCU} , for brevity. The exact price index for the composite differentiated and homogeneous good is $\mathbb{P}_U = \mathbb{P}_{\Omega U}^{\alpha}$.

The exact price index of the differentiated goods in China can be rewritten as

$$\begin{aligned}
\mathbb{P}_{\Omega_C} &= \left[\int_{\omega \in \Omega_C} (p(\omega))^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} = \\
&= \left[\int_b^\infty (p_{CCC}(\varphi))^{1-\sigma} M_C g(\varphi) d\varphi \right]^{\frac{1}{1-\sigma}} = \\
&= \left[M_C \left(\frac{\sigma}{\sigma-1} w_C \right)^{1-\sigma} \frac{k}{k+1-\sigma} b^{\sigma-1} \right]^{\frac{1}{1-\sigma}} = \\
&= \left[M_C p_{CCC}(\tilde{\varphi}_C)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} = \tilde{p}_{CCC} M_C^{\frac{1}{1-\sigma}}
\end{aligned}$$

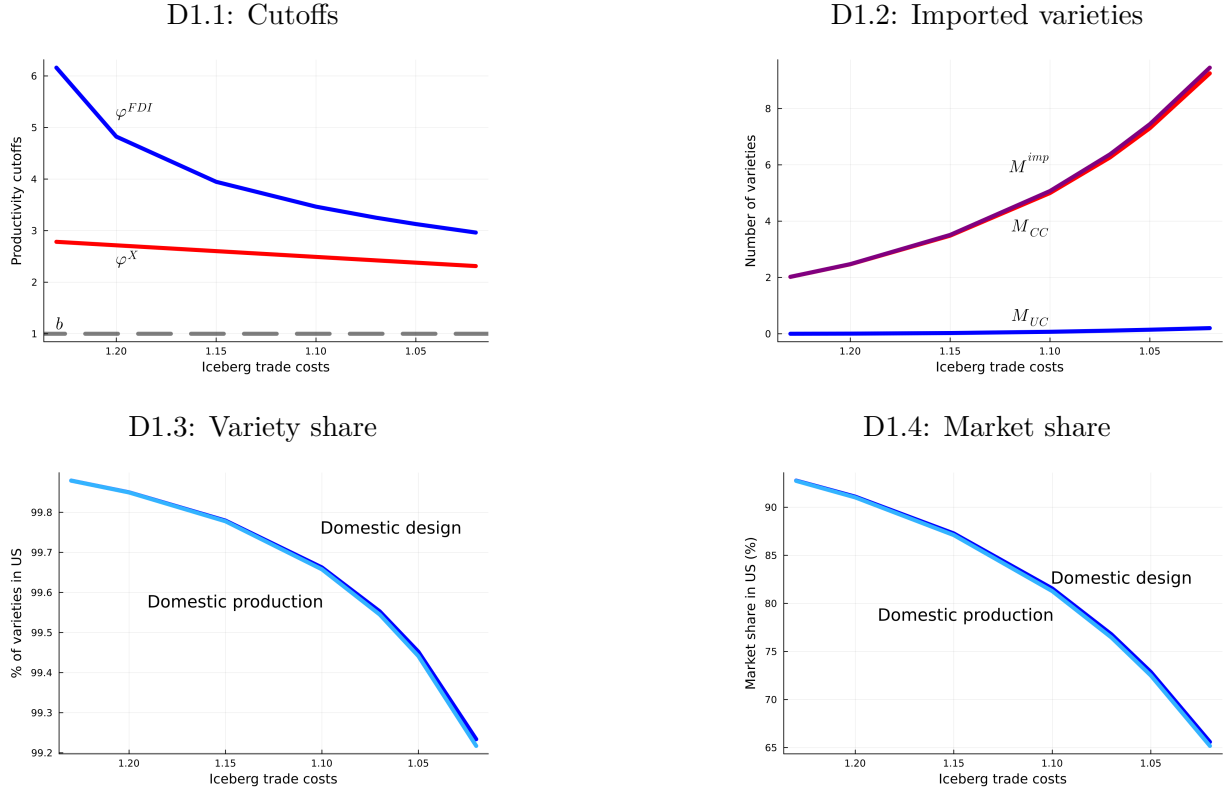
where $p_{CCC}(\tilde{\varphi}_C)$ is the price of the average productivity Chinese firm, renamed \tilde{p}_{CCC} for brevity. The exact price index for the composite differentiated and homogeneous good is $\mathbb{P}_C = \mathbb{P}_{\Omega_C}^\alpha$.

The equilibrium is given by the cutoff productivities $\{\varphi_{UC}^{FDI}, \varphi_{CU}^X\}$, the mass of entrant firms $\{M_U^E, M_C^E\}$, the expenditures $\{E_U, E_C\}$, and the mass of labor used in the homogeneous sector $\{L_{HU}, L_{HC}\}$ such that the Zero Cutoff Profit conditions hold, the Free Entry condition of each country holds, the labor market clearing conditions hold, and there is expenditure-income balance in each country, for a given set of wages $\{w_U, w_C\}$ and price indices $\{\mathbb{P}_{\Omega_U}, \mathbb{P}_U, \mathbb{P}_{\Omega_C}, \mathbb{P}_C\}$ defined above.

D.5 Comparative statics

Figure D1 shows the effect of decreasing iceberg trade costs for all firms. A decrease in iceberg trade costs lowers the productivity cutoff necessary to both Chinese firms to export (red line) and US firms to offshore production (blue line in D1.1). Still, the cutoff for US firms to offshore is quite high, so that only a few US firms start offshoring production to China (blue line) and the bulk of US imports from China (what we usually observe in the data, the purple line) still consists of Chinese-owned varieties (the red line in D1.2). Both the share of US-owned varieties and the share of US-owned varieties produced domestically in the US market decrease (the dark blue and the light blue lines in D1.3, respectively), but they tend to diverge as shipping becomes cheaper. The same pattern is visible for the market share of US-owned varieties and US-owned varieties produced domestically in the US market (the dark blue and the light blue lines in D1.4, respectively).

Figure D1: Change in iceberg trade costs



Note: Comparative statics for different values of τ_{CU} on the x-axis. The top-left panel shows the cutoff productivity for Chinese firms to start exporting to the US (red line), for US firms to start offshoring production to China (blue line), and the lower bound of the productivity distribution in both countries (in gray). The top-right panel shows the mass of Chinese-owned varieties imported by the US (red line), the mass of US-owned varieties produced in China (blue line), and the total mass of varieties imported by the US (purple line). The bottom-left panel shows US-owned varieties (dark blue line) and US-owned varieties produced domestically (light blue line) as a percentage of all varieties sold in the US market. The bottom-right panel shows the market share of US-owned varieties (dark blue line) and US-owned varieties produced domestically (light blue line) in the US market.