Trademarks and Gains from Variety: The Role of Multinational Enterprises

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PRELIMINARY AND INCOMPLETE

Abstract

This paper investigates the role of multinational enterprises on variety growth. I introduce a new measurement of varieties based on trademarks, which is able to encompass all sectors of the economy and offer a unique perspective on the country of origin of varieties. Using data on federal trademarks registered in the United States between 1989 and 2014, I uncover a surprising trend of declining variety entry rates, despite a contemporaneous increase in imports. Detailed Chinese customs data show that the entry of Chinese firms into exporting is associated with Chinese variety gains but non-Chinese variety losses for US consumers, while multinational activity from China has a mildly positive effect on non-Chinese varieties. Therefore, this research contributes to a more nuanced understanding of the relationship between Chinese import competition and product innovation in the United States, challenging the assumption that all trade flows result in equal gains from variety.

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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 and to indicate their source."

15 U.S. Code §1127

1 Introduction

Innovation is widely held to be one of the core contributors to growth in living standards. Product innovation – the creation of novel and differentiated products or varieties – holds a crucial role within the wider spectrum of innovation. International trade is often credited with playing a significant role in the process of variety expansion: Broda and Weinstein (2006) estimate that the expansion of imported varieties between 1972 and 2001 benefited US consumers by as much as 2.6 percent of US GDP. In addition, the increased competition associated with trade may spur even greater innovation and variety creation by domestic firms (Akcigit and Melitz, 2022; Akcigit and Van Reenen, 2023; Melitz and Redding, 2023).[1]

Despite focusing on the role of international trade, the literature on gains from varieties has not dealt with the core players of the globalization process: multinational enterprises (MNEs).[2] The activity of multinational companies raises important concerns when one tries to attribute a specific nationality to product varieties. For instance, consider the case of a multinational giant like Apple. When Apple exports smartphones from a subsidiary in China, is it exporting "Chinese" or "American" varieties of smartphones? What are the implications of Apple's MNE activity abroad on the product innovation process of its competitors in America and abroad? As of yet, there remains remarkably little work accounting for the fact that an Apple smartphone produced in China is still an American smartphone.

This is an empirical issue requiring an empirical solution. Numerous studies have tackled the challenge of measuring new varieties. Broda and Weinstein (2006) led the way with their pioneering use of diads of customs trade product classifications and country of origin.[3] While offering an invaluable first step in the quantification of variety gains from trade, the reliance of this measure on country of origin of shipments makes it vulnerable to the very same concerns described above in the context of multinational activities. An alternative method relies on the uniqueness of barcodes attached to products.[4] Although barcode data offers detailed insights into product characteristics,

[1] Differences in the amount of varieties can explain up to 45% of the variation in comparative advantage across countries, according to Redding and Weinstein (2023).

[2] Multinational companies are responsible for more than half of world exports and half of world imports in 2014 (OECD, 2018).

[3] Among the numerous papers using customs trade product classifications to measure varieties, see: Mayer et al. (2021); Amiti 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).

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

its availability is narrowly circumscribed to consumer product goods sold in physical stores. This limitation makes barcode data impractical for assessing the overall economic impact of trade.

This paper introduces a new measure of varieties that relies on an understudied type of intellectual property – trademarks – which protects any word, name, or symbol distinguishing the good or service of a firm from those of its competitors.[5] This new methodology improves upon those used so far in a number of ways: (i) it covers all sectors; (ii) it reports the origin country of the blueprint of varieties, without tracking the location of production; and (iii) as I show later on, it corroborates variety counts in Chinese customs data once multinational activity is accounted for. Empirically, I use data on the universe of federal trademarks registered between 1989 and 2014 at the United States Patents and Trademarks Office (USPTO). After discarding jingles, logos, and slogans, I use simple text analysis to create a mapping from trademarks to domestic and foreign varieties spanning both good and service sectors. Using this trademark-based measure of varieties, I document that the rate of variety growth has been declining, ranging from 15 percent in 1989 to 10 percent in 2014. This finding represents an intriguing puzzle, especially when juxtaposed with the simultaneous increase in total US imports as a percentage of GDP by over 50 percent. Since US imports from China have more than quadrupled over the same time period, I leverage detailed customs data from China to estimate sector-level correlations in Chinese export growth and variety growth in the US. I find that trademarks established in the US by Chinese firms are positively correlated with trade flows to the US by Chinese domestic firms, however exports to the US from China by non-Chinese MNEs are completely uncorrelated with Chinese trademark growth.[6] This finding is particularly striking given that over the period 2000-2009, almost 60 percent of exports to the US from China were attributable to non-Chinese MNEs. This is the first paper establishing a direct and credible connection between customs data and variety counts while providing a cautionary, if not intuitive, result: not all trade is equal from the perspective of variety growth.

If trade is not equal from a variety perspective, then there may have been substantial mismeasurements in the gains from trade predicted by the theory. To quantify them and to highlight the mechanism set in place by the existence of MNEs, I develop a toy model featuring Dixit-Stiglitz competition and firm-level heterogeneity in productivity. Firms have the option of paying a fixed cost to produce abroad and enjoy lower wages, but then have to ship the final products back to be

[5] Section 1127 of text 15 of the U.S. Code displays 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”.

[6] Redding and Weinstein (2023) find that most of the increase in China’s share of aggregate US imports over the years 1997-2011 occurs through increases in the number of varieties, average firm appeal, and the dispersion in appeal-adjusted prices.

sold in the domestic market. A decrease in tariffs allows more firms to offshore their production, while granting consumers further access to foreign goods. The gains from variety can be splitted into gains in terms of new foreign goods being directly exported, but also gains in terms of new foreign and domestic goods being offshored. (Work in Progress)

Motivated by the theoretical competition results as well as the relevance of MNEs in US imports from China, I explore the relationship between import competition from China and varieties available in the United States. I show that an increase in US imports from non-Chinese multinational companies located in China has no effect on non-Chinese new varieties nor on the number of firms offering varieties in the US market. On the contrary, US imports from Chinese firms located in China deters innovation of non-Chinese firms: a 1 standard deviation increase corresponds to a 2.5-6 percent decrease in domestic varieties offered by new firms in the US and a 6 percent decrease in the number of domestic entrant firms. Entry prevention is stronger for other foreign varieties, with an effect of up to 10 percent. Intuitively, entry deterrence is stronger between close substitues, and it is likely that Chinese varieties have a lower elasticity of substitution with other foreign varieties than with domestic US varieties. This result is the first attempt at illustrating the effect of Chinese import competition on product innovation in the US.[7] My findings are in line with those of Yang et al. (2021) for Canadian firms selling in the Canadian market. Using self-reported data over the years 1999-2005, they find that firms facing stronger import competition from China adopt more product innovation strategies and perform better if they survive. My research can shed light on both domestic and foreign firms response to Chinese import competition, and does so in a broader market such as the United States.

The goal of this paper is to address the mismatch between the theory on international trade as driver in expanding the set of products available to consumers, and the empirics on globalization and product innovation. To this end, I consider the contributions of this paper as twofold. The first one is a methodological contribution. 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 products without conflating the country of origin of their blueprint with the country of their production. The reliability of this measure is validated by the fact that it speaks directly to Chinese custom data: Chinese varieties measured through trademarks comove with trade flows from Chinese firms located in China. The second contribution relates to Chinese import competition and product innovation. I show that trade flows from multinational companies do not matter for changes in varieties in the US market, while trade flows from Chinese firms

[7] Hombert and Matray (2018) show that US firms who have invested in differentiating their product were shielded more successfully from Chinese import competition, but do not show whether their differentiation activity changed due to import competition.

located in China deter the entry of new firms and new products in the US market.

The results put forward in this paper provide an important caveat for a common assumption made in the literature: trade flows are not all the same from a varieties standpoint. In a world where MNEs account for half of worldwide trade flows (OECD, 2018), counting all custom codes by country of origin pairs as varieties may lead to substantial mismeasurements of the gains from trade predicted by the theory.

Related Literature. This paper relates to the previous studies that have attempted to address the challenge of measuring new varieties or product innovation. While the literature has relied on custom trade product classifications (Feenstra, 1994; Broda and Weinstein, 2006; Bernard et al., 2010, 2011; Hsieh et al., 2020; Mayer et al., 2021), barcodes (Broda and Weinstein, 2010; Hottman et al., 2016; Ghai and Hottman, 2019), patents (Akcigit and Kerr, 2018), or inference from shifts in the labor market (Garcia-Macia et al., 2019), this paper proposes the use of trademarks to gauge the availability of varieties in the US market.

When focusing on trade flows from China, this project has strong ties with those documenting the effect of foreign competition on the innovation activity of domestic firms. While most papers have used patents or expenditure in Research & Development as a proxy for broad innovation activity (Bloom et al., 2016; Xu and Gong, 2017; Impullitti and Licandro, 2018; Autor et al., 2020; Chakravorty et al., 2022), this project looks at trademarks as a proxy for product innovation.[8]

Finally, this paper joins a recent strand of the literature that has been focusing on trademarks.[9] There is a particularly strong connection with the work by Mangani (2007) on a cross-country comparison of products quality. However, this research departs from Mangani (2007) in several key ways. First, I use a 25-years dataset of trademark registrations in the US rather than trademark applications in European market for 2003. Second, I employ detailed information at the trademark level, enabling me to map trademarks to product varieties in a way that is not feasible with a simple count of trademarks.

The rest of the paper is organized as follows. Section 2 explains why there is a need for an alternative measure of varieties if we want to take into account MNEs activity and why US trademarks satisfy this need. Section 3 describes the data and the definition of varieties used in this paper. Section 4 illustrates the novel empirical results obtained with this new measure of varieties. Section 5 introduces the model and quantifies the bias in gains from variety obtained

[8] Hombert and Matray (2018) find that firms with more diverse products were shielded from Chinese import competition, but do not show whether Chinese import competition has affected their product innovation activity. See Griffith and Van Reenen (2021); Akcigit and Melitz (2022); Akcigit and Van Reenen (2023); Melitz and Redding (2023) for a literature review on product market competition and innovation.

[9] Recent Economics papers using trademarks include Alfaro et al. (2022); Pearce and Wu (2022). See Schautschick and Greenhalgh (2016) for a comprehensive literature review of the empirical studies on trademarks.

when not accounting for MNEs (Work in Progress). Section 6 explores the relationship between Chinese import competition and product innovation. Finally, Section 7 concludes.

2 The need for an alternative measure of varieties

Any empirical study concerning varieties has to face the initial challenge of finding a meaningful definition of the term "variety" itself. In this paper, I define a variety as any good or service 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 and encompassing all sectors of the economy. Below, I explain why traditional measures of varieties may not fully encompass the essence of this intuitive definition, and why trademarks provide a more comprehensive insight.

2.1 Customs codes, barcodes, and patents

An important research stream in trade economics relies on custom trade product classifications.[10] Despite their great influence and common use, there are four main limitations to what one can learn from varieties defined by custom codes or custom code and country of origin pairs. First, this approach places significant emphasis on the country of origin of shipments, even though it may have little direct relevance in terms of consumers' perception of distinct varieties.[11] Second, this classification groups products based on physical characteristics and tariff values, which may not always accurately reflect the true distinctions between varieties from a consumer's perspective.[12] Third, it implicitly assumes an upper limit on the number of available varieties for consumers, which is determined by the number of possible trading partners multiplied by the total number of categories in the most recent customs data classification.[13] Fourth, the Harmonized Systems (HS) codes, the most used standardized numerical method of classifying traded products among all countries, is updated every five years. This continued change in classification makes it problematic to conduct analysis spanning longer time periods as there is considerable attrition in the use of the old system when the new classification system comes into place.[14]

A more recent strand of the literature utilizes the uniqueness of barcodes attached to products.[15]

[10] Among the numerous papers using customs trade product classifications to measure varieties, see: Mayer et al. (2021); Amiti 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).

[11] For example, consider a US firm that starts offshoring to Mexico. The re-import of the product produced by the Mexican subsidiary would be counted as a new variety using custom codes, even though the same product produced in plants in two different countries hardly constitutes two different varieties in the eyes of consumers.

[12] For example, all sparkling wine from Italy would be grouped in one single variety (code 220421 in the HS 2012 revision), with much discontent from Spumante and Prosecco producers.

[13] There are roughly 5,000 distinct product codes and 180 trading partners for the United States, thus imposing a ceiling of 900,000 varieties available to US consumers.

[14] The attrition can be seen in the descriptive statistics provided for the BACI dataset: BACI website.

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

Similarly to custom codes, this measure has limited applicability to time series analysis of varieties in the broad economy due to two reasons. First, changes in available varieties captured through this measure may reflect a change in packaging rather than the creation of products with actual distinctive features.[16] Second, barcode data cover only consumer product goods sold in physical retail stores, representing only a small fraction of consumer consumption.[17]

Contribution to the research on new varieties has also come from the literature on innovation using patent data (Akcigit and Kerr, 2018). However, patents conflate product and process innovation.[18] Therefore they also translate into lower marginal costs in the production of a specific variety rather than an increase in the stock of available varieties.[19]

2.2 Trademarks in the United States

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 primary federal trademark statute of law, 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). This project proposes trademarks as a measure of varieties, primarily driven by two compelling reasons. Firstly, trademarks are fundamental in ensuring that consumers can confidently identify specific goods or services, making consumer protection a central goal of trademark law that spans across all sectors of the economy (Grynberg, 2022; Schautschick and Greenhalgh, 2016; Landes and Posner, 1987).[20] Secondly, trademarks have a

[16]For example, a single can of beer and a pack of cans of beer have two different barcodes, and a pack of cans of beer giving the chance of winning a prize has yet another barcode: the barcode of a single 740 ml can of Budweiser is 00062067335709; the barcode of a 36-pack of 355 ml cans of Budweiser is 00062067335297; the barcode of a 36-pack of 355 ml cans of Budweiser giving the chance of winning a smoker is 00062067385124 (BC Liquor website).

[17]The most comprehensive and commonly-used barcode data is provided by the Kilts-Nielsen Data Center and covers about 40% of the consumer product goods sector sales for the years 2006-2015. The consumer product goods sector accounts for 14% of the total consumption of goods in the US in the same time period. In terms of sales, the transactions recorded in the data are worth approximately $300 billion per year and represent 53% of all sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores (Argente et al., 2021), which itself covers around 8% of total GDP consumption (Pearce and Wu, 2022).

[18]Only 38% of patents lead to product innovation and 54% of product innovation comes from firms that do not patent. When accounting for quality improvements of new products, firms that never patent account for 65% of product innovaion (Argente et al., 2021).

[19]Perhaps 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. This paper has provided an invaluable first step in advancing the literature, but it does not use any direct data on varieties and requires restrictive simplifying assumptions.

[20]An 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

unique capacity to capture product innovation, often being filed in close proximity to new product introduction (Flikkema et al., 2014).[21]

Trademarks protected at the federal level in the United States 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).[22] Secondly, this federal protection extends equally to trademarks registered by domestic and foreign firms, allowing for the observation of both domestic and foreign product varieties within the US market. 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, this means that goods, containers, tags, or advertising of services should display the feature protected by the trademark. This clear link between intellectual property and the real consumer market prevents firms from registering trademarks solely to reserve rights in specific features.[23]

3 Data

3.1 Trademark data and mapping to varieties

The main data used in this project comes from the Trademark Case Files dataset provided by the United States Patents and Trademarks Office (USPTO).[24] It has information on the universe of trademarks filed at the office, including the feature being protected, its color, its shape, its text, and the good or sector classification it is applied to, called NICE class.[25] I focus on the subsample of trademarks filed between 1989 and 2014. All firms that seek trademark protection at the federal level for goods or services sold in the US market must register their trademarks at the USPTO. Therefore, this dataset contains information on both domestic and foreign firms, as long as their sales affect interstate or international commerce.[26] As any other asset, trademarks

services is likely to cause confusion among consumers (15 U.S.C §1052).

[21] 60% of trademark applications done by 660 surveyed companies in Benelux between 2007 and 2008 refer directly to a broad range of innovation activities. Moreover, most trademarks are filed close to the market introduction of products, thus making trademarks useful to measure product innovations in the late stages of their development.

[22] The 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, which happens every ten years (USPTO website). Moreover, entrepreneurs consider them as a key tool for Intellectual Property protection (Mezzanotti and Simcoe, 2023).

[23] For more information on the application, registration, and renewal process of trademarks at the United States Patents and Trademarks Office, please refer to Cain (2021).

[24] See Graham et al. (2013) for a description of the USPTO Trademark Case File dataset.

[25] The U.S. adopted the International Classification of Goods and Services under the Nice Agreement in 1973.

[26] Using trademarks raises the question of whether nationality of trademark owners is affected by corporate tax incentives. The literature on corporate taxation shows that multinational companies transfer intellectual property ownership to subsidiaries in other countries 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 of intellectual property due to profit-shifting motives, it follows that the location of the owner at the time of *registration* was not optimal in terms of corporate taxation. Therefore, by focusing on the location of the owner at the time of the

can change ownership over time, either as part of a Merger and Acquisitions process or as a direct transaction across firms. Information on these exchanges is stored in the USPTO Trademark Assignment dataset, which I use to better distinguish between incumbent and entrant firms.[27]

The main 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 potential slogans in the data, since they tend to have a shorter life span, as well as with trademarks filed without already being used in commerce.[28] I further exclude trademarks filed by individuals, trusts, estates, foundations, state or federal agencies, and unknown legal entities. The last step in translating trademarks into varieties consists in finding the unique pairs of text and product or service class per firm. Since multiple trademarks may protect different features of the same text, like fonts or colors, not considering the textual content of trademarks would end up overstating the number of varieties. As an 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".[29] Since I measure a variety as a unique pair of text and class per firm, the two trademarks count as one single variety. Failing to do so, would overstate the number of varieties, as these two trademarks would be counted as two different varieties of water.

All the steps above result in a baseline dataset of 3.4 million varieties owned by 1 million firms from 1989 to 2014.[30] Most varieties are goods and are owned by US companies. Foreign companies tend to have on average more varieties per firm: despite representing only 20 percent of the firms

registration, I minimize the risk of using locations chosen for tax incentives. A manual check of notable famous trademarks shows that they are owned by firms with the nationality we would expect: iPhone has US nationality, Fiat 500 has Italian nationality, and Dyson has UK nationality. Lastly, I exclude from my analysis countries that are known for being destination of transfers of assets for profit shifting motives: among others, American Samoa, Anguilla, Bahamas, Liechtenstein, Saint Lucia, St. Vincent and the Granadines, US Virgin Islands, and Vanuatu. The full list of countries included in my dataset can be found in Appendix B.

[27] See Graham et al. (2018) for more details on the USPTO Trademark Assignment dataset.

[28] As 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.

[29] The trademark filed in 1998 has serial number 75551076; the trademark filed in 2014 has serial number 86209498.

[30] I validate the data by comparing the number of varieties obtained using this definition with the number of varieties owned by three car manufacturers. Varieties measured using USPTO trademarks cover between 75 and 100 percent of all varieties sold in the US and first introduced by the car manufacturer (not acquired from other manufacturers through mergers or acquisitions). Coverage increases to at least 89 percent when car models are weighted by sales (Table 4 in Appendix A).

in the dataset, they account for 24 percent of the varieties available in the US market (Table 1). The distribution of varieties per firm is highly skewed. Each firm owns 3.4 varieties on average, but half the firms own 1 variety up until 2006 and 2 varieties in the subsequent years (Figure 1.1).[31] The conditional distribution of new varieties per firm is equally skewed, with an average of 2 new varieties per innovating firm and a median of 1 new variety per innovating firm (Figure 1.2).[32]

The empirical facts highlighted in Section 4 deal with trade flows and comparisons to statistics obtained using customs data. For their nature, they concern tradable varieties. Therefore, I will focus on goods only from this moment onwards.[33]

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: There are firms owning both goods and services, or both final and intermediates. Varieties are classified as final or intermediate based on the share of consumer expenditure of the corresponding ISIC code: varieties in sectors for which at least 70% of final consumption is done by consumers are classified as final.

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 contain information on firm ownership type, destination country, and sector at the HS eight-digits classification.

[31] This distribution is less skewed than the one inferred by Garcia-Macia et al. (2019), 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 range from 2.9 in 1994 to 4.2 in 2003.

[32] Foreign firms are larger than domestic ones, both in terms of varieties and new varieties. This can be explained by the fact that foreign firms are more selected: they are exporters by definition, and exporters are known for being larger than the average firm (Figure 9 in Appendix A).

[33] Summary statistics for goods can be seen in Table 5 and Figure 8 in Appendix A.

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

Figure 1.1: Varieties

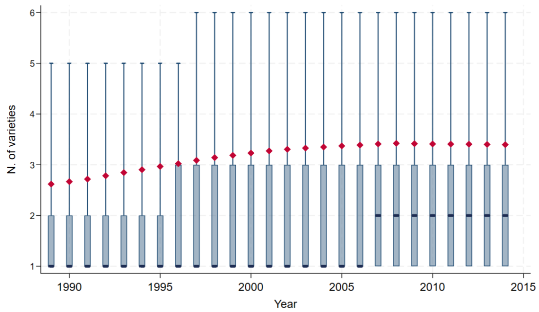
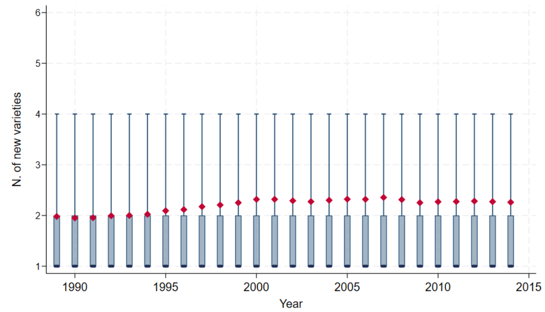


Figure 1.2: New varieties



Notes: The bars show the 25th and 75th percentile of the distribution of the number of varieties or new varieties per firm. 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.

Trade flows data. Furthermore, I use information on bilateral trade flow across countries over the time period spanning from 1989 to 2014 sourced from UNCOMTRADE (United Nations Statistics Division, 2022). Information on bilateral distance, common language, and GDP per capita is obtained from the Gravity dataset of CEPII (Conte et al., 2022).

Concordances. To cross walk from NICE to other standard sector classifications, like SITC and HS, I use the probabilistic matching provided in Battacharyya et al. (2017).

4 Empirical facts

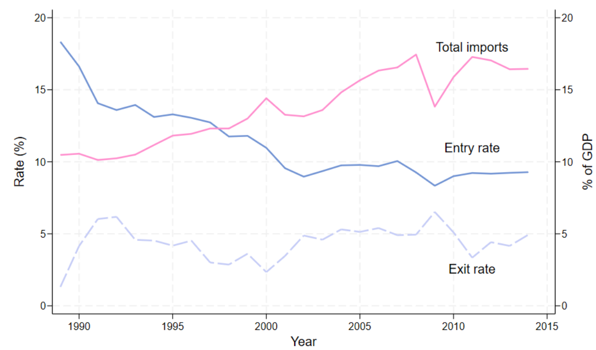
4.1 Fewer new varieties are available

The years between 1989 and 2014 have been characterized by increased globalization. One of the core channels of international trade in improving welfare is its ability to bring new varieties to consumers. This paper can directly test such prediction for the US market.

I define the entry rate of varieties as the number of new varieties available in a year divided by the number of varieties available in the previous year. Operationally, the entry rate is $\frac{\tilde{V}_t}{V_{t-1}}$, where $\tilde{V}$ is the flow of new varieties in year t and V_{t-1} is the stock of varieties in year $t-1$. Similarly, I define the exit rate of varieties as the number of exiting varieties in a year divided by the number of varieties available in the previous year: $\frac{X_t}{V_{t-1}}$, where X_t is the number of varieties that were available in year $t-1$ but not in year t.

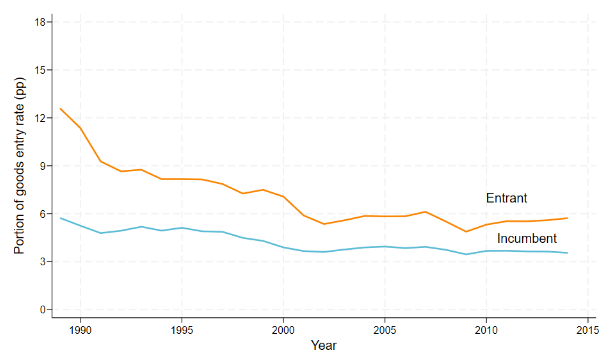
Figure 2 plots these two measures for the years 1989 to 2014. Varieties available in the US market have been increasing over time, but at a decreasing pace: there are fewer new varieties each year. This trend is visible across consumption, capital, and intermediate goods (Figure 12 in Appendix A).

Figure 2: Fewer new varieties



Notes: The blue solid line represents the entry rate of new varieties each year. The dashed lighter line represents the exit rate of varieties each year. The pink line represents total US imports as a percentage of GDP.

Figure 3: Fewer new varieties from entrant firms



Notes: The graph represents the portion, in percentage points, of new varieties entry rate accounted for by incumbent firms and entrant firms. Incumbent firms are defined as firms with at least one variety older than five years or who have purchased a trademark from another firm.

The decreasing trend may differ depending on the status of the firms: whether they are incumbent firms or newly established firms. To distinguish the two, I define incumbents as firms with at least one variety older than five years, or firms who have acquired ownership of a trademark from another firm. All other firms are considered entrants from a differentiated variety point of view: they may have exhisted before in the market, but they are introducing a new variety for the first time. Plotting the entry rate of varieties for the two types of firms, the decrease in entry rate seems to be more pronounced for varieties introduced by new firms (Figure 3).[34]

The evidence of decreased pace of produt innovation raises two questions. First, is it a reasonable

[34] The decrease seems to be more pronounced for domestic firms rather than foreign ones (Figure 13 in Appendix A). I do not have data on market shares, therefore I cannot tackle market concentration directly. However, a decrease in new varieties owned by entrant firms seems in line with the evidence of increased market concentration in various sectors.

assumption to expect varieties to increase with *any* trade flows? In other words, should we take into account the fact that many trade flows are due to MNEs activity, and how does that translate into varieties? Second, has the increased in competition brought by globalization decelerated the product innovation activity of newly established firms? The next subsection will show that both these questions deserve our attention and can be answered through trademarks.

4.2 Chinese varieties and the heterogeneous impact of import competition

The early 2000s have been 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.[35]

But what do Chinese import contain and who exports from China? Most of these studies posit that trade flows from China are composed of many cheap low-quality goods, whose presence in the US market undermines the sales of domestic firms. However, among US firms 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. If those goods are part of imports from China, then interpreting a surge in trade flows from China as a surge in Chinese varieties becomes problematic. In short, not all "made in China" goods are Chinese varieties.[36]

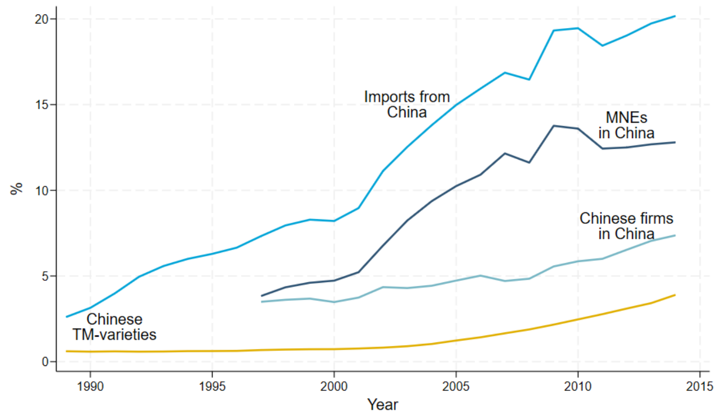
Complementing trademarks data with Chinese custom data, I can directly show whether or not all trade flows from China are the same in terms of Chinese varieties. Chinese custom data splits trade flows between those occurring from Chinese firms and those occurring from foreign firms located in China, hence MNEs. Figure 4 shows that most of the increase in US imports from China is due to an increase in imports from MNEs located in China. Interestingly, trade flows from Chinese firms located in China seem to comove with the number of Chinese varieties available in the US market.[37] This comovement is shown more formally in Table 2, which shows the estimates

[35] The 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 (Chakravorty et al., 2022) effect on innovation as measured by patenting activity and R&D expenditure. 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).

[36] This 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.

[37] There is no comovement between trade flows from China and Chinese varieties measured using HS 6-digits codes

Figure 4: Trade flows and varieties from China



Notes: "Imports from China", "MNEs in China", and "Chinese firms in China" are overall imports from China, imports from non-Chinese firms in China, and imports from Chinese firms in China as a percentage of total US imports, respectively. "Chinese varieties" is varieties owned by Chinese firms as a percentage of all foreign varieties.

for a regression of the different types of US imports from China on Chinese varieties available in the US. Specifically, a one percentage points increase in trade flows from Chinese firms located in China corresponds to a 0.21 percentage points increase in Chinese varieties, while trade flows from MNEs in China have no effect on Chinese varieties.[38] These results confirm that not all trade flows are the same for a varieties point of view: trade flows due to the offshoring activity of multinational companies need to be taken into account and may lead to mismeasurements in the trends of foreign varieties.

Overall, these findings shed light on the link between varieties and trade flows. When counting varieties, it is important to disentangle trade flows due to offshoring from trade flows originating from local firms. Despite having shown it so far only for the Chinese context, the following section will demonstrate that it holds more broadly across the spectrum of US trading partners. Moreover, it will highlight the substantial disparities that may arise when opting for customs codes as the metric for assessing the spectrum of available product variations.

4.3 Varieties satisfy gravity when controlling for trade flows

The previous subsection has shown that 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

(Figure 15 in Appendix A).

[38] These results hold also when splitting trade flows from Chinese firms by final and intermediate goods: Figure 16 and Table 6 in Appendix A.

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

	(1) Chinese varieties (% of foreign)	(2) Chinese varieties (% of foreign)
Total imports (%)	0.074***	
	(0.023)	
Chinese firms (%)		0.209***
		(0.051)
MNEs (%)		0.024
		(0.027)
Obs.	884	612
R^2	0.801	0.830

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All specifications include fixed effects for 34 sectors and 25 years. Standard errors clustered at the sector level.

the estimated elasticities. To do so, I estimate the following specification of a gravity projection:

$$\ln\left(V_{c,s,t}\right) = \beta_1 \ln\left(\text{dist}_c\right) + \beta_2 \ln\left(\text{pop}_{c,t}\right) + \beta_3 \ln\left(\text{GDPcap}_{c,t}\right) + \beta_4 \mathbb{I}\left(\text{Lang}_c\right) + \alpha_s + \alpha_t + \varepsilon_{c,s,t} \quad (1)$$

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 $\mathbb{I}\left(\text{Lang}_c\right)$ equal to one if country c and the US share the same official language. Standard errors are clustered at the sector and year level.

Columns (1) and (2) of Table 3 shows the estimated coefficients for Equation 1, 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 11 in Appendix A), something that does not hold true for the distance elasticity when varieties are counted using custom codes (Table 12 in Appendix A). 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.

Table 3: Varieties obey gravity

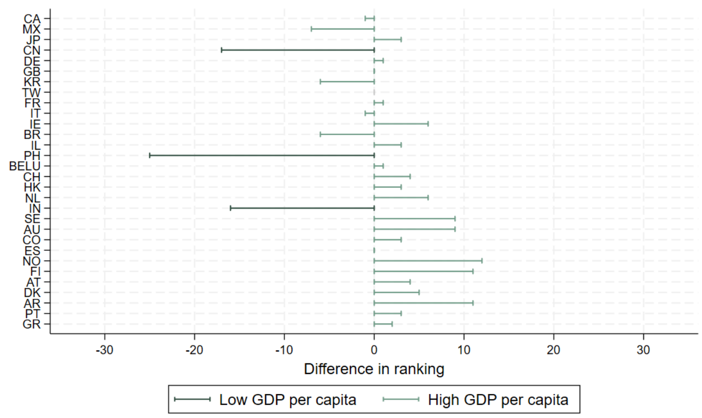
	(1) N. varieties	(2) N. varieties	(3) Trade flow	(4) Trade flow
Distance (ln)	-0.567***	-0.344***	-0.604***	-0.852***
	(0.039)	(0.026)	(0.093)	(0.161)
Population (ln)	0.889***	1.040***	1.331***	1.010***
	(0.026)	(0.035)	(0.032)	(0.084)
GDP per capita (ln)	2.304***	3.024***	1.761***	1.026***
	(0.107)	(0.150)	(0.157)	(0.219)
$\mathbf{I}(\text{Lang}_c)$	0.447***	0.120	0.693***	-0.142
	(0.051)	(0.095)	(0.091)	(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: Standard errors clustered at the sector and year level in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable for specifications in columns (1) and (2) is the 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 value of trade flows from country c to the United States in sector s and year t. All specifications include sector and year fixed effects.

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.

To further illustrate the different results obtained through trademarks and custom codes, I rank US trading partners in terms of varieties measured with the two metrics. Figure 5 shows the number of positions lost or gained by each trading partner when using trademarks compared to the ranking obtained when using custom codes as in Broda and Weinstein (2006). The two rankings differ substantially, mainly due to the fact that custom codes are entirely related to trade flows and therefore affected by offshoring. Countries that are hosts of subsidiaries owned by multinational companies lose several positions when using trademarks. Most notably, China, India, and the Philippines lose between 15 and 30 positions when ranked using trademarks rather than custom codes.[39] This empirical fact pushes the idea that there is something more to trademarks, while varieties as measured through custom codes are perfectly explained by trade flows.[40] Therefore, it is more likely that varieties measured through custom codes may mismeasure the actual gains from varieties in the presence of Foreign Direct Investments and multinational companies.

Figure 5: Change in ranking of trade partners



Notes: The figure compares the ranking of selected countries in terms of foreign varieties brought to the US in 2001 as measured in Broda and Weinstein (2006) and using trademarks. It shows the number of positions lost or gained when using trademarks compared to the ranking obtained through custom codes in Broda and Weinstein (2006).

5 Model (Work in Progress)

6 Chinese competition and product innovation

The early 2000s have been characterized by the surge of China as the world manufacturer. US imports from China as a share of total imports have grown by six times over 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.[41]

[39]A similar result is obtained when looking at the difference in the shares of trademark-based varieties and HS-based varieties for each country (Figure 18 in Appendix A).

[40]This idea is further supported by the fact that the ranking based on custom codes exhibit a stronger correlation with exports to the United States than the ranking based on trademarks (Figure 19 in Appendix A).

[41]The 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

But what do Chinese import contain? Most of these studies posit that these flows are composed of many cheap low-quality 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 seen in Section 4, if those goods are part of imports from China, then interpreting a surge in trade flows as a surge in varieties becomes problematic. In short, not all "made in China" goods are Chinese varieties.[42]

If imports from China are not the same in terms of varieties, then we need to distinguish between trade flows from Chinese firms and trade flows from MNEs when looking at the effect 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-Haltinwanger growth rate of US imports from MNEs in China:

$$\text{MNE}_{s,\tau} = \frac{\left(\frac{M_{s,\tau}^{MNE,US}}{M_{s,\tau}^{US}} - \frac{M_{s,\tau-h+1}^{MNE,US}}{M_{s,\tau-h+1}^{US}}\right)}{0.5 \times \left(\frac{M_{s,\tau}^{MNE,US}}{M_{s,\tau}^{US}} + \frac{M_{s,\tau-h+1}^{MNE,US}}{M_{s,\tau-h+1}^{US}}\right)} \times 100 \tag{2}$$

where $M_{s,\tau}^{MNE,US}$ 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-Haltinwanger growth rate of US imports from Chinese firms in China:

$$\text{CN}_{s,\tau} = \frac{\left(\frac{M_{s,\tau}^{CN,US}}{M_{s,\tau}^{US}} - \frac{M_{s,\tau-h+1}^{CN,US}}{M_{s,\tau-h+1}^{US}}\right)}{0.5 \times \left(\frac{M_{s,\tau}^{CN,US}}{M_{s,\tau}^{US}} + \frac{M_{s,\tau-h+1}^{CN,US}}{M_{s,\tau-h+1}^{US}}\right)} \times 100 \tag{3}$$

where $M_{s,\tau}^{CN,US}$ is US imports of sector s goods coming from Chinese firms located in China. Motivated by the difference in entry rate between entrant and incumbent firms show in Figure 3, I look for heterogeneous impact of such import competition on firms based on their status of entrant or incumbent. Formally, I aggregate the data at the sector, year, and status level to estimate the

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).

[42] This 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.

following specification:

$$Y_{ist} = \beta_{MNE}\,\text{MNE}_{st} + \gamma_{MNE}(\text{MNE}_{st} \times \mathbb{I}_i) + \beta_{CN}\,\text{CN}_{st} + \gamma_{CN}(\text{CN}_{st} \times \mathbb{I}_i) + \boldsymbol{\delta}' + \varepsilon_{ist} \quad (4)$$

where index s represents a sector, index t represents a year, and index i represents the status. The dependent variable $Y_{i,s,t}$ is either the h-years growth rate of varieties 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. MNE_{st} is trade flows from MNEs as defined in Equation 2 and CN_{st} is the trade flows from Chinese firms as definde in Equation 3. $\mathbb{I}_i$ is a status fixed effect, while $\boldsymbol{\delta}$ is a vector of sector and year fixed effects. Finally, $\varepsilon_{i,s,t}$ are errors clustered at the sector-year level.
This specification suffers from omitted variable bias: there may be an unobservable variable causing both trade flows from China and US varieties to increase (for example, a demand shock). To account for that, I instrument each type of trade flow from China to the US with trade flows from China to the rest of the world, so that only the supply shock from China is captured.

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

Figure 6.1: Varieties

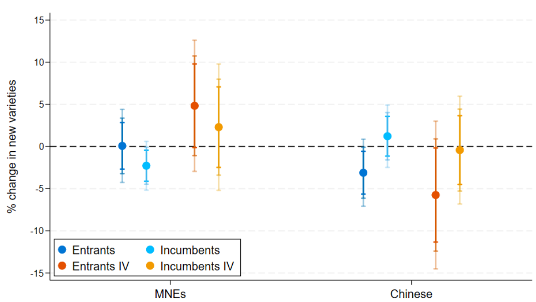
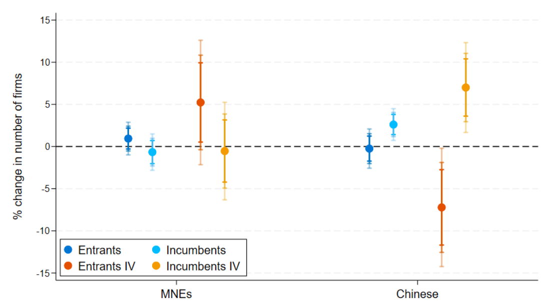


Figure 6.2: Firms

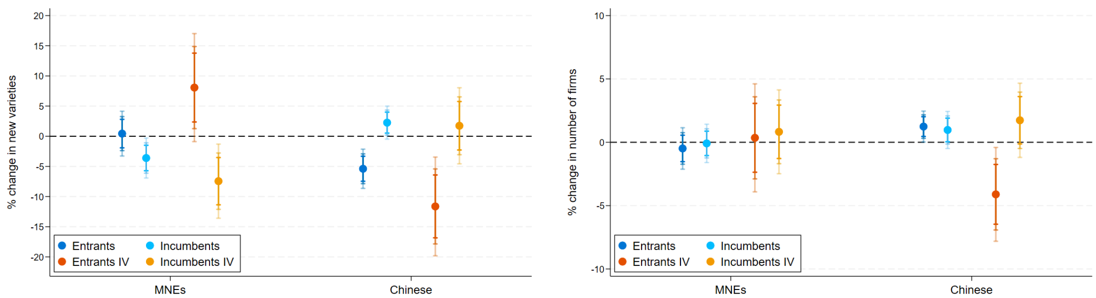


Notes: The figure shows the estimated coefficients for entrants and incumbents of the effect of import competition on US varieties growth and number of US firms. Import competition is computed using only trade flows of foreign firms in China ("MNEs"), or only trade flows of Chinese firms in China ("Chinese"). 90%, 95%, and 99% confidence intervals shown. "IV" stands for 2SLS estimator. Coefficients from Table 9 and Table 10 in Appendix A.

Essentially, I am interested in the coefficient β_{MNE} and its sum with γ_{MNE} for trade flows from multinational companies, and in the coefficient β_{CN} and its sum with γ_{CN} for trade flows from Chinese firms. One standard deviation increase in the growth of trade flows from MNEs in China has no effect on the growth of US varieties, as displayed in Figure 6.1 (a 5% increase in new varieties by entrants is barely not statistically significant). On the contrary, one standard deviation increase in the growth of trade flows from Chinese firms in China corresponds to a 5% decrease in the entry rate of US varieties by entrants. Similar results hold for the number of firms: one standard deviation increase in the growth of trade flows from Chinese firms in China corresponds to an 8% increase in the number of incumbent firms and an equal decrease in the number of entrant firms (Figure 6.2). Taken together, Figure 6.1 and Figure 6.2 are evidence that an increase in trade flows from Chinese firms located in China prevents the entry of new firms in the US market and, similarly, the introduction of new varieties from these firms. On the contrary, trade flows from MNEs located in China seem to have a slightly positive effect on the number of new US firms producing differentiated products, but no substantial effect on product innovation.

Figure 7: The effect of MNEs and Chinese import competition on foreign product innovation

Figure 7.1: Varieties | Figure 7.2: Firms



Notes: The figure shows the estimated coefficients for entrants and incumbents of the effect of import competition on foreign varieties growth and number of foreign firms. Import competition is computed using only trade flows of foreign firms in China ("MNEs"), or only trade flows of Chinese firms in China ("Chinese"). 90%, 95%, and 99% confidence intervals shown. "IV" stands for 2SLS estimator.

I then turn to foreign product innovation in the US market. A one standard deviation increase in trade flows from Chinese firms corresponds to almost a 15% decrease in new foreign varieties from newly established firms (Figure 7.1). Moreover, trade flows from MNEs lead to almost a 10% decrease in the product innovation activities of incumbent firms. Once again, import competition from Chinese firms in China seems to deter the entry and product innovation activities of newly established non-Chinese firms. Such entry prevention is stronger than those obtained for US firms. Intuitively, we can expect entry deterrence to be stronger between goods that are close substitutes. It is likely that Chinese varieties have a higher elasticity of substitution with domestic varieties than with foreign varieties, thus making it harder for consumers to substitute a US variety with a Chinese one. The higher difficulty in switching products may explain why entry prevention is weaker for domestic firms than for foreign ones.[43]

[43] The effect on Chinese product innovation reflects the findings of Table 2: trade flows from MNEs located in China have no effect on Chinese varieties and partially deter the entry of newly established firms, while trade flows from Chinese firms have a foster product innovation as well as entry (Figure 17 in Appendix A). Specifically, a one standard deviation increase in import competition from Chinese firms corresponds to a 50% increase in varieties from entrant Chinese firms and a 25% decrease in the number of incumbent Chinese firms. Import competition occurring from MNEs located in China does not have an effect on Chinese varieties, but seems to prevent entry of

7 Conclusion

The relationship between globalization and the availability of new products is a key theoretical channel for welfare. When this relationship is explored in the data, the lack of a suitable measure for varieties imposes a key assumption: all trade flows contribute equally to new products. By using trademarks to measure varieties available in a market, this paper obtains several new findings that challenge and ultimately reject such assumption in the data. First, varieties available in the US market have been increasing over time, but at a decreasing pace. This decrease happens during a time where US imports increase by more than 50 percent. Second, only exports of Chinese firms located in China has explanatory power over Chinese varieties available in the US market. This insight is relevant in the debate over the impact of import competition on product innovation. In fact, it is the increase in US imports from Chinese firms located in China – and not the increase in US imports from MNEs located in China – that prevents non-Chinese product innovation activities: a one standard deviation increase in imports corresponds to a decrease in product innovation of 5 to 10 percent. Finally, a direct comparison between using custom codes and trademarks to measure varieties shows that the former approach is fully captured by trade flows. This finding represents a caution against the indiscriminate use of trade flows as varieties flows in calibrating trade models, as custom data may be swayed by offshoring and other types of Foreign Direct Investment.

newly established Chinese firms, as it corresponds to an increase in the number of incumbent firms by almost 25%.

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., 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.

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.

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.

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.

Conte, M., P. Cotterlaz, and T. Mayer. 2022. "The CEPII Gravity database." CEPII Working Paper 2022-05.

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.

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.

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.

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.

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.

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.

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., and J. Van Reenen. 2021. “Product market competition, creative destruction and innovation.” CEPR Discussion Paper No. DP16763 Working Papers.

Griffith, R., H. Miller, and M. O’Connell. 2014. “Ownership of intellectual property and corporate taxation.” *Journal of Public Economics*, 112(C): 12–23.

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.

Hombert, J., and A. Matray. 2018. "Can Innovation Help U.S. Manufacturing Firms Escape Import Competition from China?" *The Journal of Finance*, 73(5): 2003–2039.

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.

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.

Landes, W., and R. Posner. 1987. "Trademark Law: An Economic Perspective." *Journal of Law and Economics*, 30(2): 265–309.

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.

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. 2018. "Multinational enterprises in the global economy." OECD Policy note.

Pearce, J., and L. Wu. 2022. "Brand Reallocation, Concentration, and Growth." Working Paper.

Redding, S. J., and D. E. Weinstein. 2023. "Accounting for Trade Patterns." Princeton University. Economics Department. Working Papers.

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

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.

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 results

Table 4: Car varieties sold in the US

	Car data HM (2019)	Trademarked	Coverage Models	Coverage Sales
Ford				
Ford brand models	33	30	91%	89%
Volkswagen				
Volkswagen brand models	18	14	78%	93%
Toyota				
Toyota brand models	32	24	75%	90%
Lexus brand models	16	15	94%	100%
Scion brand models	5	5	100%	100%

Notes: Names and sales of car models come from Head and Mayer (2019).

Table 5: 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: Percentages for firms do not always sum up to 100% because there are firms owning both goods and services, or both final and intermediates. Varieties are classified as final or intermediate based on the share of consumer expenditure of the corresponding ISIC code: varieties in sectors for which at least 70% of final consumption is done by consumers are classified as final. For the concordance from the USPTO sector classification to the ISIC classification I have used the probabilistic matching developed by Battacharyya et al. (2017).

Figure 8: Goods and new goods per firm

Figure 8.1: Varieties

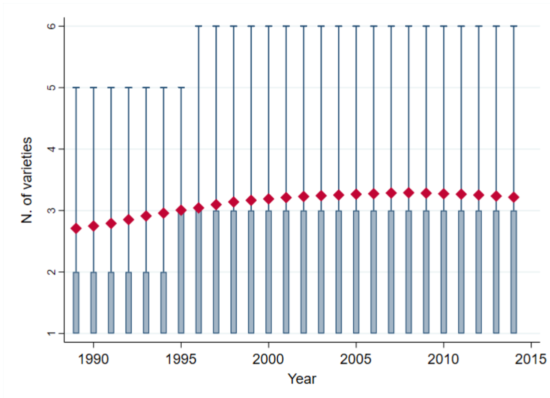
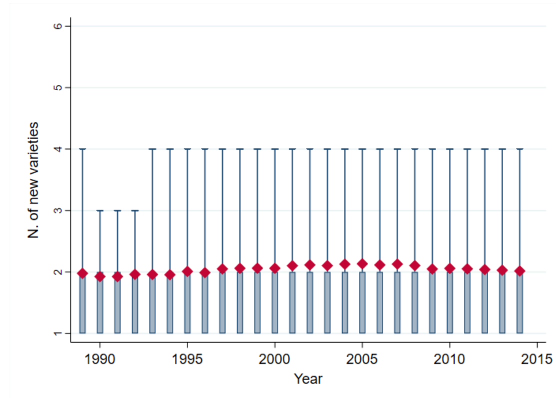


Figure 8.2: New varieties



Notes: The bars show the 25th and 75th percentile of the distribution of the number of varieties or new varieties per firm. 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 9: Varieties and new varieties per firm

Figure 9.1: Varieties of domestic firms

Figure 9.2: New varieties of domestic firms

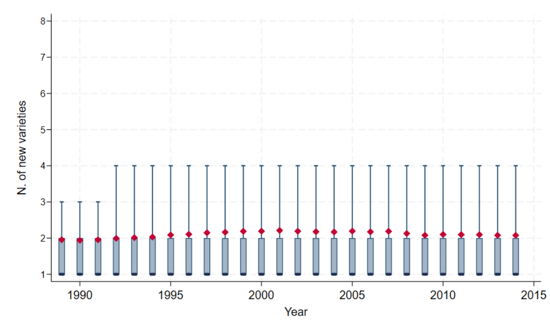
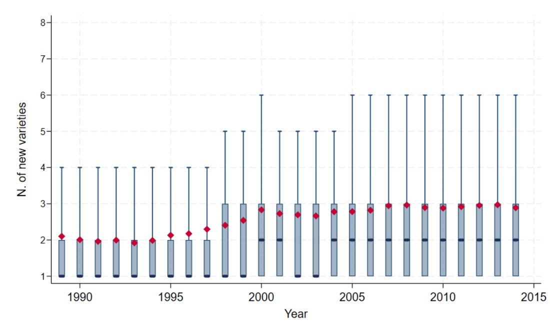


Figure 9.3: Varieties of foreign firms

Figure 9.4: New varieties of foreign firms



Notes: The bars show the 25th and 75th percentile of the distribution of the number of varieties or new varieties per firm. 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 10: Fewer new varieties

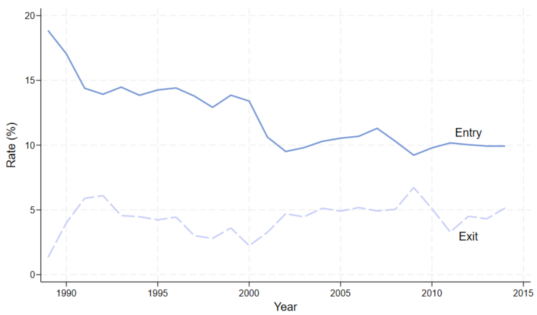


Figure 10.1: All

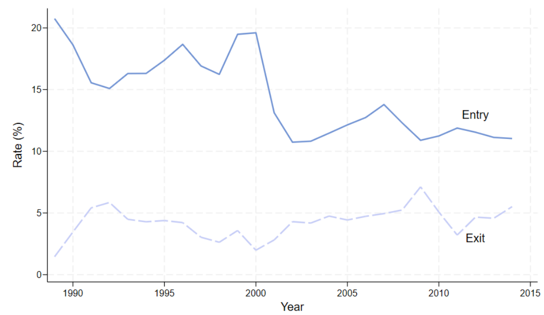
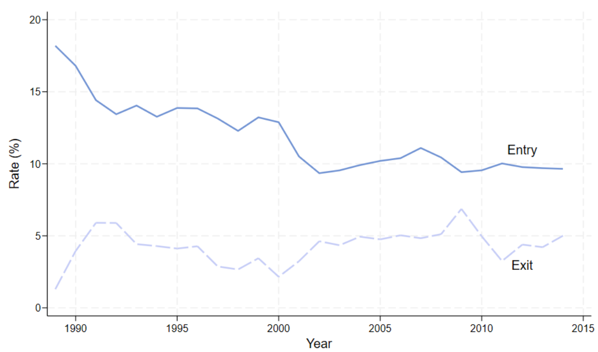


Figure 10.2: Services

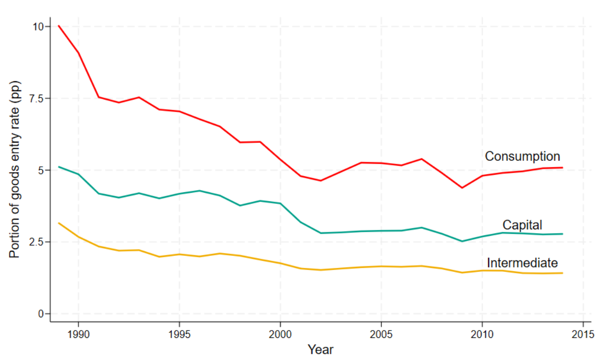
Notes: The solid line represents the entry rate of new varieties each year. The dashed lighter line represents the exit rate of varieties each year. Panel (a) shows analysis done on all varieties; panel (b) shows analysis on services.

Figure 11: Fewer new varieties – GDP adjusted



Notes: The solid line represents the entry rate of new varieties each year. The dashed lighter line represents the exit rate of varieties each year. Both statistics are normalized by real expenditure-side Gross Domestic Product with reference year 2017 (U.S. Bureau of Economic Analysis, 2023).

Figure 12: Fewer new varieties – System of National Accounts



Notes: The graph represents entry rate of new varieties by each of the three categories in the System of National Accounts.

Figure 13: Fewer new varieties from domestic entrants

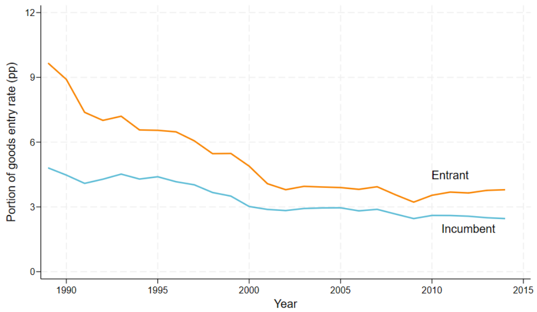


Figure 13.1: Domestic

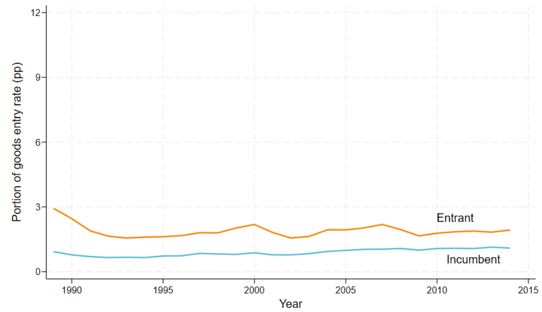


Figure 13.2: Foreign

Notes: The graph represents the portion, in percentage points, of new varieties entry rate accounted for by incumbent firms and entrant firms. Incumbent firms are defined as firms with at least one variety older than five years or who have purchased a trademark from another firm. Panel (a) shows analysis done on US firms; panel (b) shows analysis on foreign firms.

Figure 14: Fewer new varieties from entrants

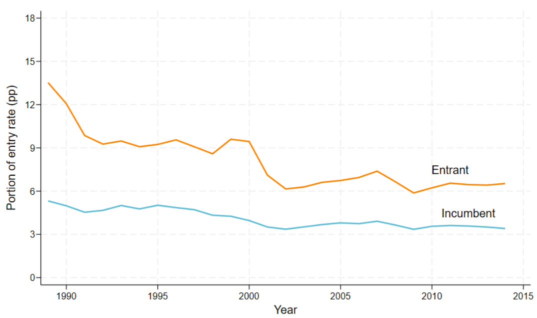


Figure 14.1: All

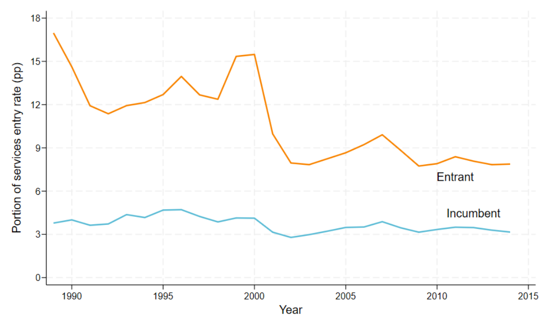
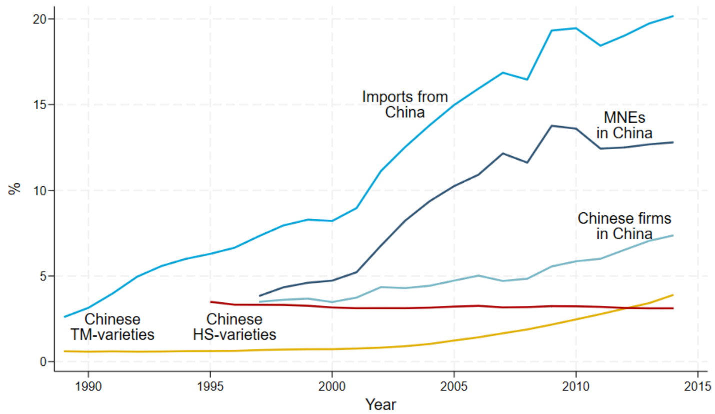


Figure 14.2: Services

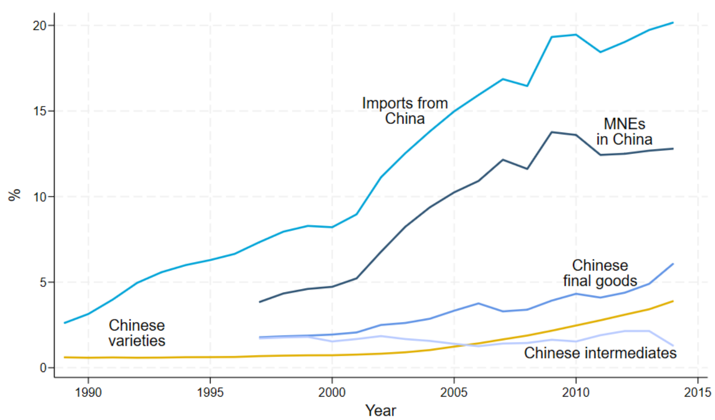
Notes: The graph represents the portion, in percentage points, of new varieties entry rate accounted for by incumbent firms and entrant firms. Incumbent firms are defined as firms with at least one variety older than five years or who have purchased a trademark from another firm. Panel (a) shows analysis done on all varieties; panel (b) shows analysis on services.

Figure 15: Trade flows and varieties from China



Note: "Imports from China", "MNEs in China", "Chinese firms in China" are overall imports from China, imports from non-Chinese firms in China, and imports from Chinese firms in China as a percentage of total US imports, respectively. "Chinese varieties" is the number of trademark-based varieties owned by Chinese firms as a percentage of all foreign varieties. "Chinese HS codes" is the number of 6-digits HS codes by country of origin diads originating from China as a percentage of all diads.

Figure 16: Trade flows and varieties from China – detailed



Note: "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 firms located in China as a percentage of total US imports. "Chinese final goods" is US imports of final goods produced by Chinese firms located in China as a percentage of total US imports. "Chinese intermediates" is US imports of intermediate goods produced by Chinese firms located in China as a percentage of total US imports. "Chinese varieties" is varieties owned by Chinese firms and available in the US market as a percentage of total foreign varieties available in the US market.

Table 6: Trade flows from Chinese firms in China explain Chinese varieties

	(1) Chinese varieties (% of foreign)	(2) Chinese varieties (% of foreign)
Chinese final goods (%)	0.228***	0.207***
	(0.058)	(0.059)
Chinese intermediates (%)	0.111	0.128*
	(0.068)	(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: *** p < 0.01, ** p < 0.05, * p < 0.1. All specifications include fixed effects for 34 sectors and 25 years. Standard errors clustered at the sector level.

Table 7: Overall imports from China on new varieties

	(1) New Var.	(2) New Var.	(3) New Var.	(4) New Var.
All	-0.023***	-0.026**	0.013**	0.042***
	(0.006)	(0.011)	(0.005)	(0.011)
All×$\mathbb{I}$(Incumbent)	0.036***	0.068***		
	(0.007)	(0.013)		
All×$\mathbb{I}$(Entrant)			-0.035***	-0.068***
			(0.007)	(0.013)
Obs.	1,564	1,564	1,564	1,564
R^2	0.665		0.665	
F-stat		34		34

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. All specification include fixed effects from sectors, years, and status. Standard errors clustered at the sector-year level.

Table 8: Overall imports from China on number of firms

	(1)	(2)	(3)	(4)
	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)
All	0.206***	0.457***	-0.124***	-0.486***
	(0.035)	(0.060)	(0.034)	(0.070)
All×$\mathbb{I}$(Incumbent)	-0.329***	-0.937***		
	(0.058)	(0.114)		
All×$\mathbb{I}$(Entrant)			0.329***	0.937***
			(0.058)	(0.114)
Obs.	1,564	1,564	1,564	1,564
R^2	0.965		0.965	
F-stat		34		34

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All specification include fixed effects from sectors, years, and status. Standard errors clustered at the sector-year level.

Table 9: Trade flows from MNEs and Chinese firms on new varieties

	(1)	(2)	(3)	(4)
	New Var.	New Var.	New Var.	New Var.
MNEs	0.000	0.018	-0.008**	0.008
	(0.006)	(0.011)	(0.004)	(0.011)
MNEs×𝕀(Incumbent)	-0.009	-0.009		
	(0.006)	(0.007)		
Chinese	-0.015**	-0.028*	0.006	-0.002
	(0.008)	(0.017)	(0.007)	(0.012)
Chinese×𝕀(Incumbent)	0.021**	0.026*		
	(0.009)	(0.015)		
MNEs×𝕀(Entrant)			0.009	0.009
			(0.006)	(0.007)
Chinese×𝕀(Entrant)			-0.021**	-0.026*
			(0.009)	(0.015)
Obs.	1,020	1,020	1,020	1,020
R^2	0.718		0.718	
F-stat		6		6

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All specification include fixed effects from sectors, years, and status. Standard errors clustered at the sector-year level.

Table 10: Trade flows from MNEs and Chinese firms on number of firms

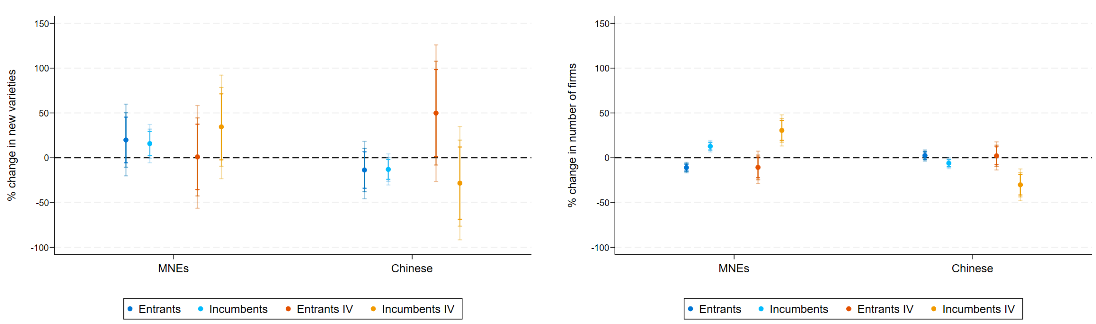
	(1)	(2)	(3)	(4)
	N. firms (ln)	N. firms (ln)	N. firms (ln)	N. firms (ln)
MNEs	0.023	0.129*	-0.016	-0.013
	(0.018)	(0.070)	(0.021)	(0.055)
MNEs×𝕀(Incumbent)	-0.040	-0.142***		
	(0.024)	(0.049)		
Chinese	-0.008	-0.240***	0.087***	0.233***
	(0.030)	(0.090)	(0.024)	(0.069)
Chinese×𝕀(Incumbent)	0.095**	0.474***		
	(0.038)	(0.100)		
MNEs×𝕀(Entrant)			0.040	0.142***
			(0.024)	(0.049)
Chinese×𝕀(Entrant)			-0.095**	-0.474***
			(0.038)	(0.100)
Obs.	1,020	1,020	1,020	1,020
R^2	0.985		0.985	
F-stat		6		6

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. All specification include fixed effects from sectors, years, and status. Standard errors clustered at the sector-year level.

Figure 17: The effect of MNEs and Chinese import competition on Chinese product innovation

Figure 17.1: Varieties

Figure 17.2: Firms



Notes: The figure shows the estimated coefficients for entrants and incumbents of the effect of import competition on Chinese varieties growth and number of Chinese firms. Import competition is computed using only trade flows of foreign firms in China (“MNEs”), or only trade flows of Chinese firms in China (“Chinese”). 90%, 95%, and 99% confidence intervals shown. “IV” stands for 2SLS estimator.

Table 11: Varieties obey gravity even controlling for trade flows

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

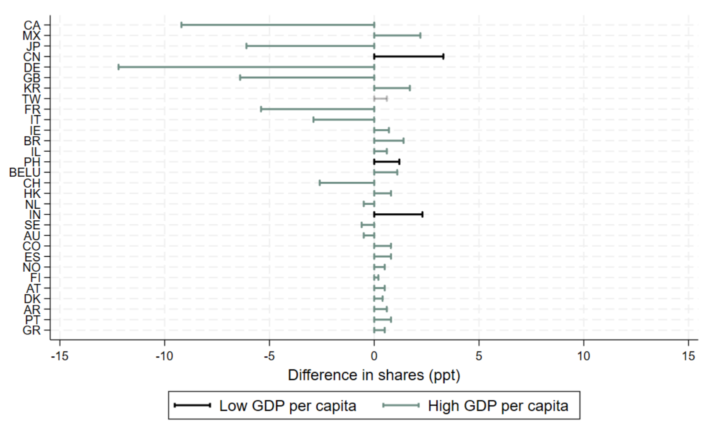
Notes: Standard errors clustered at the sector and year level in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable in all specifications is the number of varieties available in the United States from country c in sector s at year t. All specifications include sector and year fixed effects.

Table 12: Varieties as measured by HS codes

	(1) N. varieties (HS codes)	(2) N. varieties (HS codes)	(3) N. varieties (HS codes)	(4) N. varieties (HS codes)
Distance (ln)	-0.121***	-0.025	-0.063***	0.012
	(0.021)	(0.023)	(0.017)	(0.015)
Population (ln)	0.407***	0.253***	0.303***	0.182***
	(0.020)	(0.016)	(0.021)	(0.018)
GDP per capita (ln)	0.612***	0.432***	0.480***	0.331***
	(0.048)	(0.040)	(0.042)	(0.038)
$\mathbf{I}(\text{Lang}_c)$	0.245***	0.142***	0.173***	0.107***
	(0.021)	(0.019)	(0.013)	(0.011)
Trade flow		0.150***		0.121***
		(0.014)		(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

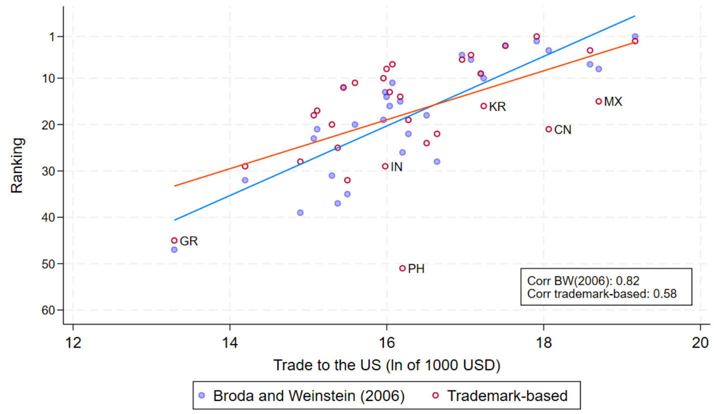
Notes: Standard errors clustered at the sector and year level in parenthese. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable in all specifications is the number of varieties in sector s available from country c in a specific year, computed as the number of unique HS codes with positive trade values. All specifications include sector and year fixed effects.

Figure 18: Change in share of trade partners



Notes: "change in shares" is computed as fraction of varieties from country c calculated using trademarks minus fraction calculated using HS 10 digits codes.

Figure 19: 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 United States in the same year, as measured in Broda and Weinstein (2006) and using trademarks (vertical axis).

B Data

List of countries: 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.