More Trade, Less Diffusion: Technology Transfers and the Dynamic Effects of Import Liberalization*

Gustavo de Souza[†] Ruben Gaetani[‡] Martí Mestieri[§]

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Abstract

We show that trade liberalization can reduce technology diffusion. Using Brazilian data, we document that tariff cuts lead to fewer technology transfers from foreign to Brazilian firms and a decline in Brazilian firms' citations of foreign patents. The most substantial drop in citations occurs among firms located near those receiving technology transfers, largely driven by a reduction in citations to firms that previously transferred technology to Brazil. These findings suggest that lowering import tariffs can slow the diffusion of foreign ideas by reducing technology transfers. In our quantitative model, when Brazilian tariffs fall, foreign firms opt to export their products directly rather than transfer their technology, weakening knowledge diffusion. An optimal subsidy for technology transfers amplifies the welfare gains from trade liberalization by a factor of four.

JEL Codes: O33, O40

Keywords: technology diffusion, growth, technology transfers, international trade

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[†]Federal Reserve Bank of Chicago, gustavo@microtomacro.net.

[‡]University of Toronto, ruben.gaetani@utoronto.ca.

[§]IAE-CSIC, CREI, BSE, and CEPR, marti.mestieri@iae.csic.es.

1 Introduction

A widely held view in economics is that international trade accelerates technology diffusion. Recent theories of economic growth suggest that as countries open to trade, domestic firms acquire knowledge from foreign competitors and imported inputs, increasing local productivity (e.g., Lucas, 2009, Alvarez et al., 2013, Buera and Oberfield, 2020). Yet, despite extensive theoretical work linking trade to knowledge flows, direct causal evidence on the impact of import liberalization on technology diffusion remains limited. This paper addresses this gap by identifying how import tariffs affect foreign firms' incentives to transfer their technologies, and how these transfers shape the overall diffusion of ideas.

Studying Brazil's trade liberalization, we find a surprising outcome: lower tariffs lead to a significant drop in technology diffusion. When tariffs fall, foreign firms choose to export their products directly to Brazil rather than engage in technology transfers with local firms, reducing the overall diffusion of foreign technology within the domestic economy. Using a quantitative model calibrated to match our empirical findings, we show that subsidizing technology transfers is essential to fully realize the benefits of trade liberalization.

To measure technology diffusion, we use data on technology transfers and patent citations. First, we collect comprehensive records on technology transfer contracts from the Brazilian patent office, capturing every instance in which foreign industrial knowledge—whether in the form of patents, technical assistance, or know-how—is licensed or sold to domestic Brazilian firms. These contracts are the primary channel through which foreign producers transfer cutting-edge technologies to local firms. Second, using PATSTAT, we track the citations that Brazilian patents make to foreign patents, measuring the extent to which Brazilian firms adopt or build upon foreign ideas.

We estimate gravity equations of knowledge flows on tariffs with a rich set of fixed effects, allowing us to isolate diffusion from other channels through which trade affects the local economy.[1] To address the endogeneity of tariff changes and identify the causal effect of tariffs on knowledge flows, we adopt the instrumental variable strategy proposed by Boehm et al. (2023). The key idea behind the instrument is that changes in Most Favored Nation (MFN) tariffs are primarily driven by factors related to large MFN trade partners, creating plausibly exogenous variation in tariffs for small MFN partners.

[1] Trade affects local productivity through several channels, including selection (Pavcnik, 2002, Melitz, 2003), access to inputs (Fieler et al., 2018, Kugler and Verhoogen, 2009), access to broader markets (Atkin et al., 2017, Bustos, 2011a), competition (Topalova, 2010), investment (Pierce and Schott, 2018), and innovation (Bloom et al., 2015).

We present robust evidence that trade liberalization reduces diffusion. First, we show that lower tariffs significantly decrease the number of technology transfers. Specifically, a 10-percentage-point decline in import tariffs leads to a 1.27% drop in transfers over the next three years. This effect is largely driven by contracts involving technological assistance and operates mainly through the extensive margin, as fewer firms engage in technology transfers. Second, we find that lower tariffs reduce Brazilian firms' citations of foreign patents, especially among firms with limited exposure to foreign markets (i.e., non-importers and non-exporters). Therefore, contrary to the common predictions of theories of trade and growth, our results indicate that more trade leads to less diffusion.

We further show that the declines in citations and technology transfers are interconnected. The drop in citations is most pronounced among firms located near recipients of technology transfers and is driven primarily by reduced citations to firms that previously transferred technology to Brazil. Using a causal forest approach (Wager and Athey, 2018), we show that country-sector pairs with stronger declines in technology transfers due to tariff changes also experience more significant drops in citations. Taken together, these findings suggest that the reduction in technology transfers leads to a lower overall diffusion of foreign technologies among domestic firms.

Additionally, we find that declining tariffs have no significant impact on the foreign ownership of Brazilian firms, ruling out foreign direct investment (FDI) as the primary driver of reduced knowledge diffusion. Similarly, firms' connections to foreign suppliers and changes in import tariffs in the countries where technology transfers originate also do not appear to play a role. These findings suggest that lower tariffs slow the diffusion of foreign knowledge within the local economy primarily by reducing technology transfers, rather than through changes in ownership structures, supplier relationships, or external trade policies.

To interpret these results and examine their welfare implications, we develop a multi-country, multi-sector growth model that explicitly accounts for technology transfers and their impact on knowledge diffusion.[2] The model features three countries: Brazil, a high-income foreign country, and a low-income foreign country. Firms in the high-income foreign country choose between transferring their technology to Brazil or exporting their final product directly. Firms in Brazil learn foreign knowledge either through exposure to imported goods or interaction with users of the transferred technology, with different weights on these two sources of learning. Therefore, the decision between exporting goods and transferring technology affects the speed at which fron-

[2]The model builds on Buera and Oberfield (2020).

tier ideas disseminate across borders, ultimately shaping the dynamic welfare gains from trade liberalization.

We calibrate the model parameters to match the elasticities identified in the data. To this end, we simulate in the model the same change in tariffs observed in Brazil during the trade liberalization. By running a regression on model-generated data, we adjust the parameters governing diffusion so that the model's predicted effects of tariffs on citations and technology transfers align with the empirical evidence.

Our quantitative results indicate that accounting for technology transfers reverses the prediction that welfare gains from trade are greater in the long run than in the short run. Tariff reductions weaken foreign producers' incentives to transfer technology, prompting them to favor exports instead. While this generates improved welfare in the short run, it slows diffusion and reduces productivity growth in the recipient country. In our baseline experiment, a full liberalization in Brazil generates overall welfare gains of 0.29% per period—relative to a status quo in which tariffs do not change—compared to short-run gains of 0.43%. By contrast, allowing diffusion to happen only via exposure to imported goods results in a significant over-estimate of the overall welfare gains, which reach 1.30% per period under this assumption. Thus, accounting for diffusion via technology transfers reduces the overall welfare gains from trade liberalization by more than three-fourths.

In our framework, subsidies for technology transfers are necessary to fully realize the benefits of trade liberalization, as the spillovers from technology transfers create a dynamic externality that justifies policy intervention. We analyze optimal subsidies for technology transfers, finding that while they distort the static allocation and reduce welfare in the short run, they significantly increase the number of technology transfers, accelerating diffusion and boosting long-term productivity growth. We compute the optimal subsidy, which balances these short-run losses and long-run gains. We find that implementing this optimal subsidy increases the overall welfare gains from trade liberalization by a factor of four.

Related Literature. We contribute to a large body of work investigating the implications of trade integration for long-term economic growth (Sachs et al., 1995; Lucas, 2009). Recent contributions in this literature have focused on how trade influences the accumulation and diffusion of knowledge, thus impacting productivity growth. Our work builds primarily on the framework of Buera and Oberfield (2020), which presents a quantitative theory where openness to trade influences the source distribution from which local producers derive their ideas. In addition, we incorporate insights from studies on technology diffusion in open economies (Rodriguez-Clare, 2007; Ramondo and Rodriguez-Clare, 2011; Lind et al., 2023; Hsieh et al., 2023), which highlight how trade barriers, geographic distance, and institutional factors influence the adoption of technology and innovation across countries. Other key areas examined in this literature include incentives for technology adoption or upgrading, selection effects on both local and foreign producers (e.g., Bustos, 2011b; Sampson, 2016; Farrokhi and Pellegrina, 2023; Perla et al., 2021; Bai et al., 2024), the reallocation of idea flows and innovation efforts across nations and sectors (e.g., Cai et al., 2022), the diffusion of technology embodied in traded inputs (Ayerst et al., 2023), and the interplay between labor market distortions and technology adoption (e.g., Farrokhi et al., 2024). Our study contributes to this literature by providing empirical evidence on the impact of import tariffs on international knowledge diffusion, focusing on the role of technology transfer contracts as a specific transmission mechanism. Furthermore, we show that accounting for the response of technology transfers can reverse the predictions of several existing models regarding the dynamic effects of import liberalization.

This paper also contributes to the broader literature on technology diffusion and adoption in economic development (e.g., Bustos et al., 2016; Comin and Mestieri, 2018; Juhász, 2018; Verhoogen, 2023; Cirera et al., 2024). Existing work in this area has explored how industrial policy shapes the diffusion of technology and impacts productivity growth. For example, Choi and Levchenko (2021) and Kim et al. (2021) examine the impact of industrial policy on firm productivity, sectoral innovation, and long-term growth in Korea. Other studies have focused on specific channels of diffusion, such as local development policies (e.g., Giorcelli, 2019; Giorcelli and Li, 2021) and technology transfer contracts (Santacreu, 2021; De Souza and Li, 2022), both of which are shaped by trade policy decisions.[3] By analyzing how trade policies, like tariffs and subsidies, affect firms' incentives for technology transfer, our work illustrates the broader implications these policies have on cross-border idea diffusion and ultimately economic development.

The remainder of the paper is organized as follows. Section 2 presents the data sources used in the analysis. Section 3 presents the empirical strategy and Section 4 the empirical results. Section 5 introduces the model, and Section 6 presents the calibration and quantitative experiments. Section 7 concludes.

[3]In recent work, Juhász et al. (2024) and Rodrik (2023) provide a nuanced view of how industrial policies are influenced by political and economic constraints, emphasizing the importance of context-specific factors such as governance structures.

2 Data

In this section, we describe our data on technology transfers, patent citations, foreign direct investment (FDI), and import tariffs in Brazil.

2.1 Technology Transfers

Our main dataset, collected by de Souza (2020), contains all technology transfers made to Brazilian firms since 1975. The dataset includes the transfer and licensing of patents, trademarks, know-how, and any other industrial knowledge transferred by foreign firms to firms located in Brazil. This dataset is collected from the Brazilian patent office records which, due to legacy regulation, requires firms to register all foreign transfers of industrial knowledge.

The government requires firms to register technology transfer. Brazilian firms are obliged to register their technology transfers at the patent office. According to a law dating back to 1962, firms making royalty payments for any intangible capital must register this transfer at the patent office for any royalty payment to a foreign entity to be allowed by the Central Bank. The requirement to register technology transactions at the patent office was created by law no. 4.131 in 1962, during a period of capital controls in Brazil. The goal of the requirement was to limit the payment of royalties and make it more difficult for firms to break the capital control regulation in place at the time. The requirement was maintained after the capital controls were lifted. Consequently, the Brazilian patent office keeps a record of all contracts of technology transfer to Brazilian firms since 1962. The dataset is constructed collecting information from all technology transfers at the patent office.

Coverage. The patent office lists the type of contracts that must be registered before any royalty payment is made. As a general principle, the requirement concerns contracts involving intellectual property transfers that lead to an improvement in the production process or the creation of a new product line. These contracts include the licensing or transfer of patents, trademarks, industrial designs, integrated circuit topography, know-how, or technical services, such as industrial or engineering consulting.

The patent office also clarifies that certain technical services do not classify as technology transfers and are therefore not eligible to be registered. These include financial, marketing, or legal consulting, the licensing or acquisition of software, maintenance services and services that do not generate a technical report.

Firms register technology transfer for legal protection. Because the Brazilian government requires the registration of all technology contracts, firms that do not register their contract lose the possibility of resolving judicial disputes in court. This creates strong incentives on the side of firms to comply with this requirement. According to a survey conducted by de Souza (2020) among experts in intellectual property, companies prefer to register their contracts with the patent office to receive legal protection in case of any dispute.

Variables. For each contract, the dataset contains the name of the foreign firm licensing the technology ("licensor"), its country of origin, the year in which the contract was signed, the name of the Brazilian firm receiving the technology transfer ("licensee"), its tax identifiers, and the type of technology being transferred. For contracts registered after 2010, we also observe a short description of the technology and its monetary value. Using data from the *Relação Anual de Informações Sociais*, an administrative matched employer-employee dataset, we assign a 4-digit sector code from the *Classificação Nacional de Atividades Econômicas 2.0* to each licensee.

Summary statistics and examples. Table 1 shows a breakdown of the contracts by category, as well as information on the number of unique buyers and sellers and the transaction value, when available. Transfer of know-how is the most common type of contract. The following know-how transfers exemplify how Brazilian firms rely on international technology transfers to improve their production processes or introduce new products. In 1983, Gerdau SA, a large Brazilian steel producer, received a technology transfer from Nippon Steel, a Japanese steel producer, to start its production of free cutting steel round bars.[4] In 2012, *Companhia Brasileira de Vidros Planos*, a Brazilian glass and concrete producer, received technological assistance from *Bottero S.p.A.*, an Italian glass producer, on the design of an assembly line for the production of float glass.

Appendix Figure A.1 shows that, on average, Brazil receives 600 technology transfers per year, with the majority coming from the USA and Germany. Despite the small number, technology transfers are important for large firms. About 18% of the wage bill in 2004 is concentrated among firms that received at least one technology transfer. Studying a 2001 reform that increased the cost for Brazilian firms to receive technology transfers from abroad, de Souza (2020) shows that

[4] This type of steel bar is called "S30VCTS2".

Table 1: **Summary statistics of technology transfers**

Variable	**N. Transfers**	**%**
Contract types		
Know-How Transf.	10,928	79.39
Trademark	2,208	16.04
Patent	564	4.10
All	13,765	100
Licensees and licensors		
Unique Licensees	5,484	
Unique Licensors	10,844	
HQ-Branch	401	3.31
Transaction value (in dollars)		
Mean	1,163,047	
Median	645,070	

Notes: The table contains summary statistics of contracts of technology transfer between 1995 and 2015. The top panel contains information on contracts by category, according to the definition used by the patent office. The middle panel contains information on licensees and licensors. The *HQ-Branch* row reports the share of transactions conducted between a headquarters and its branch, identified using information on firm ownership from the National Firm Registry dataset. The bottom panel contains information regarding the value of the transactions.

reduced access to technology transfers has a sizable negative effect on firms' growth.

2.2 Patents and Citations

Information on patents and citations comes from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT, Autumn 2018 version), which collects information from most patent offices around the world, covering both developed and developing countries. For each patent, PATSTAT records the year of the patent application, the country of the applicants, the technology classes, and the list of cited patents. We link citations to sectors using the crosswalk between International Patent Classification (IPC) fields and sectors created by Lybbert and Zolas (2014).

Summary statistics. Section A.2 shows statistics of Brazilian citations of patents outside of Brazil. Most of the citations are directed to patents in the United States. Chemicals and metallurgy are the most common sectors of the citing patents.

2.3 Firm Ownership and FDI

To measure FDI, we use the Firm Registry, an administrative dataset that contains ownership information for all firms that have ever been active in Brazil since 1990, including currently defunct firms. The dataset reports the list of owners and directors, their country of residence, and the date that they entered ownership of the firm.

Measuring FDI. Using the Firm Registry data we measure FDI as the opening of a new subsidiary, the total acquisition of an exiting firm, or the participation of foreigners in local Brazilian investment. If the foreign firm opens a new subsidiary, we observe the ownership by the parent firm, its country of origin, and the year the company was created. If a foreign firm acquires a Brazilian firm, we observe it entering the ownership of an already existing firm. Finally, if foreign firms or individuals make a partial acquisition of a firm, we also observe a foreign entity entering the ownership of the Brazilian firm.

Summary statistics. Appendix A.3 reports summary statistics on the FDI data. Most FDI is in machinery and chemicals, with the number of firms owned by foreigners growing throughout the sample period. The most common countries of origin of FDI are the United States, Germany, and Italy.

2.4 Other Data Sources

Tariff data come from the World Bank Trade Analysis Information System. Federal procurement data come from the *Controladoria-Geral da União* and cover all the federal procurement since 2000. Data on campaign contributions come from the *Superior Tribunal Eleitoral*, covering the presidential elections of 2002, 2006, and 2010.

3 Empirics

In this section, we describe our empirical strategy to identify the effect of tariffs on the flow of knowledge across countries.

3.1 Empirical Model

Isolating idea diffusion. International trade affects the economy through multiple channels. For example, it increases total factor productivity via selection (Pavcnik, 2002, Melitz, 2003), access to superior inputs (Fieler et al., 2018, Kugler and Verhoogen, 2009), and access to broader markets (Atkin et al., 2017, Bustos, 2011a). Trade also affects competition (Topalova, 2010), investment (Pierce and Schott, 2018), and innovation (Bloom et al., 2015). Idea diffusion—the focus of this paper—is only one of these possible channels. As a consequence, a regression of sector-level outcomes (even when using firm-level data) on tariff changes would capture the combined effects of all these channels (e.g., the effect of increased competition on firms' incentives to upgrade their technology).

To isolate idea diffusion from other mechanisms, we estimate a gravity equation with a rich set of fixed effects, allowing us to track learning within a particular sector from a specific country. The advantage of our gravity setting is that our dependent variable is indexed by sector, country-of-origin, and time. Therefore, we can control for common sector-time and country-time effects (among others) affecting all Brazilian firms in any given sector, as we discuss next.

Baseline empirical model. We use the following empirical model:

$$y_{c,s,t} = \beta \tau_{c,s,t} + \mu^1_{c,s} + \mu^2_{c,t} + \mu^3_{s,t} + X'_{c,s,t}\kappa + \epsilon_{c,s,t}, \tag{1}$$

where $y_{c,s,t}$ is an outcome, such as citations to country c from firms in sector s or technology transfers from country c to firms in sector s in year t, and $\tau_{c,s,t}$ is the average import tariff imposed by the Brazilian government against products in sector s originating from country c in year t. The specification includes a complete set of fixed effects, following the standard in the literature, e.g., Head and Mayer (2014) and Boehm et al. (2023). First, we include country-sector fixed effects, $\mu^1_{c,s}$, capturing systematic differences in the level of trade or technology licensing between countries and sectors. Second, we include country-year fixed effects, $\mu^2_{c,t}$, capturing time-varying country-specific shifters. Lastly, we include sector-year fixed effects, $\mu^3_{s,t}$, capturing time-varying sector-specific shifters, such as changes in sectoral demand or regulation affecting the incentives to adopt technology. The term $X_{c,s,t}$ denotes a set of controls.[5]

[5] As controls, we include a three year lag of the left-hand side variable and a dummy if that market is under MFN tariffs. As robustness checks, we also include tariffs on the inputs and tariffs that other countries impose on Brazilian goods.

Outcomes of interest: citation and technology transfer flows. The main outcomes of interest are the number of technology transfers received by Brazilian firms and citations of foreign patents made by Brazilian firms. Because technology takes time to adjust and has a lumpy response to shocks, we aggregate both variables over the following 3 years. Therefore, $y_{c,s,t}$ is the number of citations made by Brazilian firms in sector s to country c over the next 3 years starting at t. Three years is the window commonly used in the literature, e.g., Berkes et al. (2022), and the results are robust to alternative windows of aggregation.

Fixed effects control for various sources of bias. The rich set of fixed effects controls for a broad range of sectoral and country-level factors that could bias the estimates of Equation (1). The sector-year fixed effect, $\mu^3_{s,t}$, controls for sectoral shocks that might induce tariff changes, such as protection offered to fading industries or lobbying. It also captures the overall effect of tariffs on firms' incentives to upgrade technology due to increased market access (Bustos, 2011b; Atkin et al., 2017), changes in competition (Aghion et al., 2005) or access to superior inputs (Fieler et al., 2018; Kugler and Verhoogen, 2009). Because these forces are common within a sector, their effect is captured by $\mu^3_{s,t}$. The country-year fixed effect, $\mu^2_{c,t}$, captures country-level factors that could lead to more technology transfers. If, for instance, a trade agreement includes clauses on intellectual property transfer, that effect would be captured by the fixed effect $\mu^2_{c,t}$. Finally, the country-sector fixed effect $\mu^1_{c,s}$ captures the time-invariant characteristics that influence trade, such as language and geographical distance.

Instrument: Comparing small MFN partners to preferential partners (Boehm et al., 2023). Tariffs and trade flows are often influenced by similar factors, which can result in a biased estimate of β in Equation (1). For instance, industries facing heightened import competition may lobby for higher tariffs, prompting governments to adjust tariff policies in response to changes in trade patterns.

To address this endogeneity concern, we apply the instrumental variable approach proposed by Boehm et al. (2023), which leverages the MFN tariff system within the WTO. Under WTO rules, Brazil must impose uniform MFN tariffs on all member countries unless a preferential trade agreement is in place, regardless of each country's significance to Brazilian trade. Following Boehm et al. (2023), we identify the effect of a MFN tariff change by comparing the response of small trade partners to those not trading under MFN tariffs. The key identifying assumption is that changes to MFN tariffs are not influenced by trade flows among small trade partners.

The first stage is given by

$$\tau_{c,s,t} = \tilde{\theta}\, \mathbb{I}_{c,s,t}\{MFN\} \times \tau^{MFN}_{s,t} + \tilde{\mu}\, \mathbb{I}_{c,s,t}\{MFN\} + \tilde{\mu}^1_{c,s} + \tilde{\mu}^2_{c,t} + \tilde{\mu}^3_{s,t} + X'_{c,s,t}\tilde{\kappa} + \tilde{\epsilon}_{c,s,t}, \qquad (2)$$

where $\mathbb{I}_{c,s,t}\{MFN\}$ is a dummy variable equal to one if products in sector s from country c fall under an MFN trade agreement in year t,[6] and $\tau^{MFN}_{s,t}$ represents the MFN tariff applied by Brazil to products in sector s in year t. The fixed effect $\tilde{\mu}$ accounts for the impact of becoming a preferential trade partner. Since becoming a preferential trade partner is an endogenous decision made by the government, we control for this in the second-stage regression.

The instrument, $\mathbb{I}_{c,s,t}\{MFN\} \times \tau^{MFN}_{s,t}$, is used in conjunction with the sample selection dropping large trade partners that are under MFN tariffs. Observations are dropped if the following two conditions are satisfied:

$$\begin{aligned}
&\mathbb{I}_{c,s}\{\textit{MFN Partner at } t\} \times \mathbb{I}_{c,s}\{\textit{MFN Partner at } t-1\} = 1 \\
&\text{and} \\
&\mathbb{I}\{c \textit{ is a major partner in } t-1 \textit{ in aggregate}\} \\
+&\mathbb{I}\{c \textit{ is a major partner in } t-1 \textit{ in sector } s\} \\
+&\mathbb{I}\{c \textit{ is a major partner in } t \textit{ in aggregate}\} \\
+&\mathbb{I}\{c \textit{ is a major partner in } t \textit{ in sector } s\} > 0,
\end{aligned}$$

where, in period t, $\mathbb{I}\{c \textit{ is a major partner in } t \textit{ in aggregate}\}$ is a dummy equal to one if country c is among the top 10 Brazilian importers and $\mathbb{I}\{c \textit{ is a major partner in } t \textit{ in sector } s\}$ is a dummy equal to one if country c is among the top 10 Brazilian importers of sector s.

Identifying variation and identifying assumption. When using the instrument in Equation (2), the identification of the parameter of interest β in Equation (1) comes from comparing the change in the outcome of interest, e.g., technology transfers, between small MFN partners and preferential partners after an MFN tariff change. For example, Italy is a small trade partner with Brazil, trading on MFN terms, while Uruguay, with which Brazil has a preferential trade

[6] Most trade agreements cover all products from a particular country. However, a small subset of agreements applies only to specific products. We consider a sector s to trade under MFN if all its products from country c in sector s are under MFN tariffs. The results are robust to alternative assumptions.

agreement, is exempt from MFN tariffs. To isolate the causal effect of tariffs on technology transfers, we compare the change of technology flows from small MFN partners (e.g., Italy) to those from partners under preferential agreements (e.g., Uruguay) after Brazil reduced its MFN tariffs, which apply uniformly to all MFN partners.

The key identifying assumption is that the trends between small MFN partners and preferential agreement partners are parallel. In other words, absent the MFN tariff change, the outcome of interest from both groups would have followed the same trajectory. To validate this assumption, we document that the instrument is not correlated with other policies implemented during the period or with measures of the origin market's potential for technology transfers, and that the pre-period parallel trends holds.

Impulse response function. To implement the test for parallel trends discussed above and capture the dynamic effect of tariffs on the outcomes of interest, we also estimate the following impulse response function:

$$y_{c,s,t-3+j} = \beta_j \tau_{c,s,t} + \mu^1_{c,s} + \mu^2_{c,t} + \mu^3_{s,t} + X'_{c,s,t}\kappa + \epsilon_{c,s,t}, \tag{3}$$

where $y_{c,s,t-3+j}$ is the stock of citations to country c by firms in sector s or the stock of technology transfers from country c to firms in sector s over the next 3 years starting at $t-3+j$. If the identifying variation is valid, we expect that $\beta_j \approx 0$ for all $j < 0$. In estimating Equation (3), $\tau_{c,s,t}$ is instrumented as shown in Equation (2).

3.2 Validation of the Identification Strategy

There are two main concerns with the instrument's identification. First, changes in MFN tariffs might coincide with other sector-level policies that affect international technology transfers. Second, the Brazilian government could selectively adjust tariffs based on the target market's potential for technology transfer. We present evidence that these factors are unlikely to bias our results. To address these concerns, we show that neither the instrument nor the tariffs themselves correlate with variables predictive of sector-level policies—such as public procurement prevalence or campaign contributions—or with measures of innovation, productivity, and value added in the origin markets.

Table 2: **Instrument, political connections, and outcomes of the origin market**

Panel A: Tariffs and political connections				
	(1) *Shr Fed. Procurement*	(2) *Shr Donation*	(3) *log Procurement*	(4) *log Campaign Contribution*
Instrument	-0.0000262	-0.0000567	0.0154	-0.0247
	(0.000244)	(0.000200)	(0.0126)	(0.0357)
N	3,146	858	1,103	654
R^2	0.599	0.792	0.837	0.734

Panel B: Tariffs and outcomes of the origin market				
	(1) *log Employment*	(2) *Employment Share*	(3) *log Value Added*	(4) *Value Added Share*
Instrument	-1.885	-0.245	2.364	-0.0641
	(1.552)	(0.218)	(1.544)	(0.173)
N	3,902	3,902	3,902	3,902
R^2	0.994	0.991	0.996	0.959

Notes: Panel A shows the correlation between the instrument and sectoral outcomes in Brazil. The table displays the coefficient of the following regression: $y_{s,t} = \beta\tau^{inst}_{s,t} + \mu_s + \mu_t + \epsilon_{s,t}$, where $y_{s,t}$ is an outcome of sector s in Brazil in year t, $\tau^{inst}_{s,t}$ is the instrument averaged for products of sector s, μ_s is a sector fixed effect, and μ_t is an year fixed effect. The left-hand side variables are the share of firms that received federal procurement (column 1), the share of firms that made a campaign contributions (column 2), the log of total procurement contracts by the federal government (column 3), and the log of total campaign contribution (column 4). Panel B shows the correlation between import tariffs and outcomes of the country of origin using model 1. The left-hand side variables are log employment (column 1), sectoral employment share (column 2), log value added (column 3), and sectoral value added share (column 4) for the sector in the origin country. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The instrument does not correlate with other policies in Brazil. Panel A of Table 2 shows that the instrument does not predict a sector's connection to the government. The table reports the regression coefficients of the instrument, averaged at the sector level, on several indicators: the share of firms receiving federal procurement, the share of firms making campaign contributions, total government procurement expenditure, and total campaign contributions by sector. Additionally, Panel A of Appendix Table B.1 shows that tariffs themselves are not correlated with these same measures of government connection, further supporting the absence of political influence on tariff changes.

The instrument does not correlate with the origin market's potential for technology transfer. It is conceivable that the Brazilian government increased tariffs in fast-growing markets, which could bias our estimates since these markets are also more likely to engage in technology transfers globally. However, Panel B of Table 2 shows no significant correlation between the instrument and the key characteristics of the origin country's sectors. The instrument does not correlate with sectoral employment, value added, or their respective shares in the origin country's economy. Panel B of Appendix Table B.1 also shows that tariffs in Brazil themselves do not correlate with the characteristics of the destination country.

4 Empirical Results

In this section, we show that higher import tariffs lead to an increase in technology transfers to Brazil and a rise in patent citations from Brazilian firms to foreign firms.[7] The strongest response comes from firms located near technology licensees and is primarily directed at technology licensors. Moreover, country-sectors that send more technology transfers in response to tariffs also receive an increase in patent citations. Overall, these findings indicate that the adoption of ideas embedded in technology transfers promotes the diffusion of foreign knowledge within the local economy.

4.1 Tariffs Increase International Knowledge Diffusion

Strong and significant first stage. Appendix Table B.2 reports the estimates of the first-stage regression (Equation 2). There is a strong correlation between instrumented and actual import tariffs. In all specifications, the F-statistic exceeds 100, well above the threshold for weak instruments.

Tariffs increase technology transfers. Table 3 shows that tariffs increase the number of foreign technologies transferred to Brazil, with the effect driven by new licensors and new licensees entering the market. Column 1 shows the effect of tariffs on the inverse hyperbolic sine of the total number of technology transfers. A 100-percentage-point increase in import tariffs leads to a 12.7% increase in the number of transfers.[8] The effects on the number of unique licensees (column 2) and licensors (column 3) are similar in magnitude to the estimates in column 1, suggesting that tariffs primarily impact the extensive margin.

[7] Since the empirical model is linear, we describe the results in terms of tariff increases (as customary and for ease of interpretation) although import tariffs in Brazil decline on average over the sample period.

[8] We follow the standard practice of interpreting changes in the inverse hyperbolic sine as percentage changes, with caveats discussed by Chen and Roth (2022). We discuss alternative transformations of the outcome variables in Section 4.4.

Table 3: **Import tariffs and technology transfers**

	(1)	(2)	(3)	(4)	(5)	(6)
IHS	*N.Tech. Transfers*	*N.Unique Licensees*	*N.Unique Licensors*	*Patent Licenses*	*Trademark Licenses*	*Know-How*
Tariff	0.127***	0.108***	0.126***	0.000475	-0.0170*	0.143***
	(0.0472)	(0.0409)	(0.0469)	(0.000974)	(0.0101)	(0.0457)
N	1,178,000	1,178,000	1,178,000	1,178,000	1,178,000	1,178,000

Notes: This table reports the coefficients of regressing different measures of technology transfers to Brazil on tariffs, according to the model in Equation (1) using the first-stage regression in Equation (2). All specifications use the inverse hyperbolic sine transformation. The left-hand side variable is the number of technology transfers (column 1), the number of first-time technology licensees (column 2) and licensors (column 3), the number of technology transfers involving the licensing or reassignment of patents (column 4) and trademarks (column 5), the number of technology transfers involving the transfer of know-how (column 6), and the number of all other technology transfers (column 7). Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

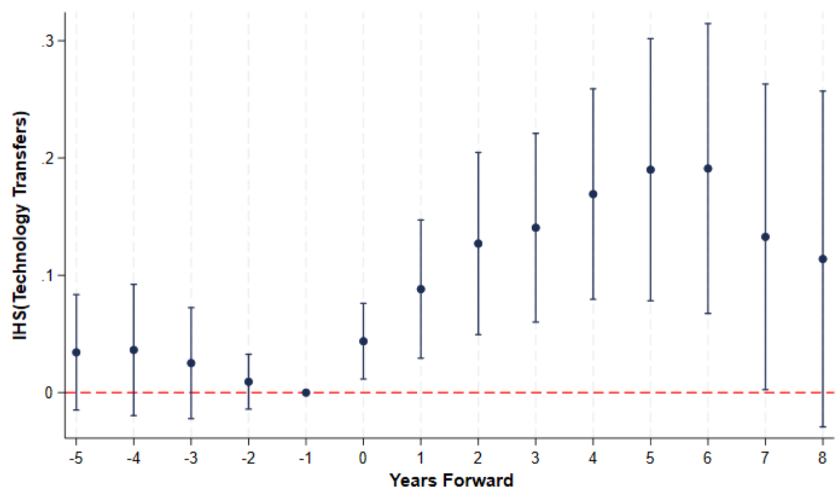
Tariffs only increase the number of know-how transfers, i.e., the transfer of knowledge not subject to intellectual property protection, such as technical consulting, technological assistance, or industrial secrets. This is shown in columns 5 to 7, which display the effect of tariffs on different categories of technology transfer. We find no effect on the licensing of patents (column 4) and a weak negative effect on trademarks (column 5). As shown in column 6, the effect is fully driven by transfers of know-how. This category includes the transfer of knowledge that is not covered by standard forms of intellectual property protection, such as technical consulting or technological assistance. Transfers of know-how are a common channel of technology diffusion across countries, which previous work has shown to generate large and persistent productivity gains for firms receiving it. For example, de Souza (2020), Giorcelli (2019), and Giorcelli and Li (2021) found that international transfers of know-how had sizable effects on productivity and firm growth in Brazil, Italy, and China, respectively.

Figure 1a shows that the effect of tariffs on technology transfers is temporary. The plot displays the effect of tariffs on technology transfers over different time horizons. Tariffs have no effect on the path of technology transfers in the years preceding the increase. After the increase, technology transfers gradually rise, but by seven to eight years later, the effect is no longer statistically significant.

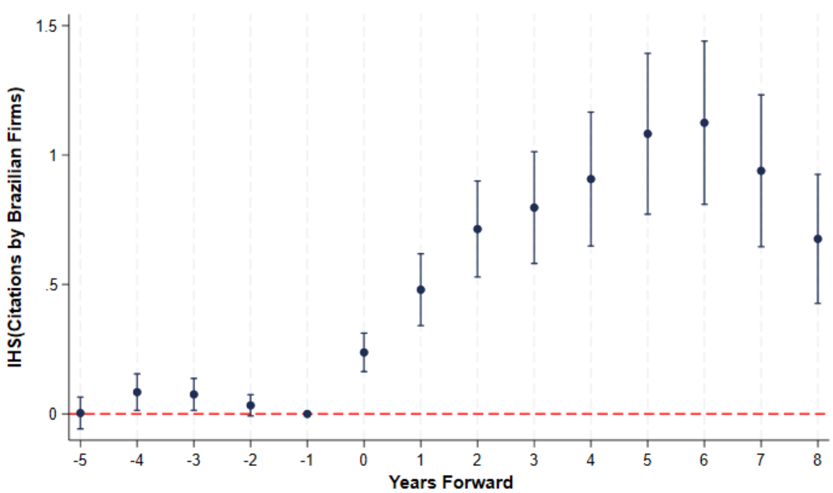
Import tariffs increase citations to foreign patents. Table 4 shows that tariffs increase Brazilian firms' citations of foreign patents. A 100-percentage-point increase in import tariffs raises citations by 71% (column 1) and the probability of observing at least one citation by 53

Figure 1: **Dynamic effect of tariffs on technology transfers and citations**

(a) Technology transfers



(b) Citations



Notes: This figure shows the effect of tariffs on technology transfers and citations over different time horizons, as described in Section 3. In the top panel, each dot represents the effect of tariffs on the cumulative sum of technology transfers from $t-2$ to t. The coefficient at $t=2$ corresponds to the result shown in column 1 of Table 3. The coefficient at $t=-1$ is omitted because all regressions control for the sum of technology transfers from $t-3$ to $t-1$. Similarly, in the bottom panel each dot represents the effect of tariffs on the cumulative sum of citations from $t-2$ to t, with the coefficient at $t=2$ matching that in column 1 of Table 4. Again, the coefficient at $t=-1$ is omitted due to the same control for the sum of citations between $t-3$ and $t-1$. The bandwidth represents the 90% confidence interval, and standard errors are clustered at the country-sector level.

Table 4: **Tariffs and citations**

	(1) *IHS Citations*	(2) *At Least One Cit.*	(3) *IHS. Cit. to Licensor*	(4) *IHS Cit. to Non-Licensor*	(5) *Technology Proximity*
Tariff	0.714***	0.537***	0.539***	0.232***	0.0570**
	(0.113)	(0.0836)	(0.0886)	(0.0769)	(0.0277)
N	1,178,000	1,178,000	1,178,000	1,259,775	901,284

Notes: This table reports the coefficients of regressing the number of citations of foreign patents made by Brazilian patents on tariffs using the model in Equation (1) and the first-stage regression in Equation (2). The left-hand side variable is the inverse hyperbolic sine of the number of citations of patents in the foreign country made by Brazilian patents in a given sector (column 1), an indicator equal to one if the sector in Brazil made at least one citation to the foreign country (column 2), the inverse hyperbolic sine of the number of citations made to technology licensors or patents cited by them (column 3), and the inverse hyperbolic sine of the number of citations to firms that have never made a technology transfer to Brazil or have not been cited by them (column 4). Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

percentage points (column 2). As we show below, this surprising result can be explained by the diffusion among Brazilian firms of foreign knowledge embedded in technology transfers.

Figure 1b shows the effect of tariffs on the dynamics of citations. The effect of tariffs on the path of technology transfers is close to zero in the years before the increase. After the increase, citations rise steadily until year seven and then start declining. The effect appears to be significantly persistent, and, as one would expect, more so than technology transfers since knowledge takes time to diffuse.

Import tariffs increase technological similarity to foreign patents. An alternative way of testing for the effect of import tariffs on the diffusion of foreign ideas is by measuring the technological proximity between patents filed by Brazilian firms and foreign patents in each country of origin. Following Bloom et al. (2013), we measure proximity as the cosine similarity between the stock of patents in Brazil and in the foreign country. Formally, technological proximity is defined as

$$Tech.\ Proximity_{s,c,t} = \frac{W_{s,t}.Y_{c,t}}{||W_{s,t}||||Y_{c,t}||}, \tag{4}$$

where $W_{s,t} = (W_{1,s,t}, ..., W_{P,s,t})$ denotes the vector with the share of Brazilian patents in sector s assigned to each technology class $p = 1, ..., P$ up to year t, and $Y_{c,t} = (Y_{1,c,t}, ..., Y_{P,c,t})$ denotes the corresponding vector for country c.

Column 3 of Table 4 shows the effect of tariffs on proximity. The point estimate implies that a 100 percentage point increase in import tariffs increases technological proximity by 5.7 percentage points, corresponding to 49% of a standard deviation.

More trade, less diffusion. These results suggest that import tariffs increase the diffusion of ideas across countries. This conclusion is surprising in light of the existing theoretical literature. Sampson (2016), Buera and Oberfield (2020), and Perla et al. (2021), among others, have proposed models in which openness to trade promotes diffusion by facilitating learning from foreign producers and input suppliers. In the next section, we show that the increase in citations to foreign firms is caused by the spread of knowledge embedded in technology transfers, highlighting a channel through which higher tariffs can lead to greater diffusion of foreign ideas.

4.2 Transferred Technology Diffuses Among Firms

Tariffs increase citations to technology licensors. Columns 3 and 4 of Table 4 show that the effect of tariffs on citations is mostly driven by citations to foreign technology licensors. The estimate in column 3, which only considers citations of patents of licensors or patents cited by them, is 2.3 times larger than the effect in column 4, which considers citations of patents that are *not* associated with licensors. These results suggest that tariffs lead Brazilian firms to learn and adopt knowledge that is embedded in technology transfers.[9]

The effect of tariffs on citations is stronger among firms not connected to foreign markets. In Table 5, we report the effect of tariffs on citations of foreign patents comparing different sub-samples of citing Brazilian firms. The first two columns compare the effect on citations of foreign patents given by licensees (column 1) and non-licensees (column 2). The following two columns split the sample between firms that import inputs (column 3) and those that do not import inputs (column 4). The last two columns look separately at the effect on exporters (column 5) and non-exporters (column 6). Consistently across these different sub-samples, we find that the effect on diffusion is about 3 to 4 times larger among firms that are *not* exposed to foreign markets.[10]

[9]Notice that, even in the case of transfers taking the form of a patent license, we do not observe the exact patents being licensed, so we cannot track citations of licensed patents directly. Moreover, as we discuss above, the most important type of transfer is know-how, which is industrial knowledge not covered by standard forms of intellectual property protection. Therefore, we interpret citation flows to licensors as measures of the overall diffusion of the knowledge transferred by foreign licensors to Brazilian firms, rather than as exact indicators of the adoption of ideas embedded in specific patents.

[10]A potential reason why licensees respond less than non-licensees is that, if available, the use of the foreign licensed technology is preferable to in-house innovation, since foreign technologies tend to be more productive (de Souza, 2020).

Table 5: **Tariffs, citations, and characteristics of the citing firm**

	(1)	(2)	(3)	(4)	(5)	(6)
	IHS Cit. by Tech. Licensees	*IHS Cit. by Non-Tech. Licensees*	*IHS Cit. by Importers*	*IHS Cit. by Non-Importers*	*IHS Cit. by Exporters*	*IHS Cit. by Non-Exporters*
Tariff	0.183***	0.582***	0.155***	0.600***	0.195***	0.584***
	(0.0431)	(0.107)	(0.0443)	(0.106)	(0.0487)	(0.105)
N	1,178,000	1,178,000	1,178,000	1,178,000	1,178,000	1,178,000

Notes: This table reports the coefficients of regressing the number of citations made by Brazilian patents to foreign patents on tariffs using the model in Equation (1) using the first-stage regression 2. The left-hand side variable is the inverse hyperbolic sine of the number of citations made to patents in the foreign country by Brazilian licensees (column 1) and non-licensees (column 2), by importers (column 3) and non-importers (column 4), by exporters (column 5) and non-exporters (column 6). Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The effect of tariffs on citations is stronger among firms located near technology licensees. The hypothesis that the effect of tariffs on citations is the result of the increase in international technology transfers has a simple testable implication: we should observe larger effects among firms near technology licensees. To verify this, we separately estimate the effect of tariffs on foreign citations among two groups of firms: those that are geographically close to licensees, and all the remaining firms. Column 1 of Table 6 shows the effect of import tariffs on citations to foreign patents made by firms in the same city of technology licensees (but excluding licensees themselves), while column 2 shows the corresponding effect on citations made by firms in different cities. Consistently with the existence of diffusion of foreign knowledge via technology transfers, we find that the effect among firms located in the same city as a licensee is almost twice as large as the effect among the remaining firms.

Markets providing more technology transfers receive more citations. To study the relation between technology transfers and citation flows, we calculate the conditional average treatment effect (CATE) of tariffs on technology transfers and citations, and we show that they are correlated. In other words, country-sectors that respond to tariffs by transferring more technology also experience larger increases in citations received. This result corroborates the spread of knowledge embedded in technology transfers as the primary mechanism driving the rise in citations following a tariff increase.

Table 6: **Tariffs, citations, and location of the citing firm**

	(1) *IHS Cit. Same City*	(2) *IHS Cit. Diff. City*
Tariff	0.443***	0.243***
	(0.0824)	(0.0697)
N	1,178,000	1,178,000

Notes: This table reports the coefficients of regressing different measures of citation on tariffs according to the location of the firm citing using the model in Equation (1) using the first-stage regression in Equation (2). In column 1, the left-hand side is the number of citations made by patents of firms on a city with at least one technology licensee during the sample period (excluding technology licensees themselves). In column 2, the left-hand side is the number of citations made by firms in cities that never had a technology licensee. Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

We re-write the reduced form version of the empirical model in Equation (1) in long differences:

$$\Delta y_{c,s} = \bar{\beta}\left(Z_{c,s}\right)\, \Delta\tau_{c,s}^{instr} + \tilde{\mu}_c^1 + \tilde{\mu}_s^2 + \epsilon_{c,s}, \tag{5}$$

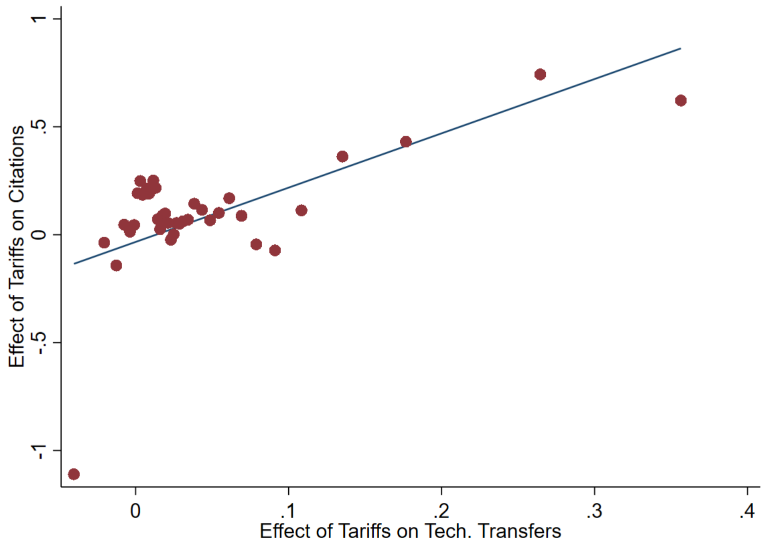
where $\Delta y_{c,s}$ is the change in outcome $y_{c,s}$ between 2000 and 2010 and $\Delta\tau_{c,s,t}^{instr}$ is the corresponding change in the instrument.[11] The term $\bar{\beta}\left(Z_{c,s}\right)$ denotes the CATE of import tariffs on citation or technology transfers to markets with characteristic $Z_{c,s}$. We estimate model (5) using the causal forest method proposed by Wager and Athey (2018). Appendix B.3 describes the procedure in detail.

Figure 2 plots the CATE of tariffs on technology transfers (horizontal axis) against the CATE of tariffs on citations (vertical axis) for each sector and country of origin. For clarity, observations are binned into 40 groups. The figure shows that markets with a stronger response of technology transfers to tariffs also display stronger responses in patent citations. This result indicates that the increase in citations in response to import tariffs is tightly connected to the increase in technology transfers.

Additional results in Appendix B.3 show a large degree of heterogeneity in the effect of tariffs. Tariffs increase citations and technology transfer from high-income countries with a larger stock of patents. These citations are coming from—and technology transfers are going to—Brazilian sectors with a significant history of innovation and technology transfers. The sectors that most benefit from diffusion are the extractive, chemical, and automobile manufacturing industries.

[11] We re-write the model in long differences because the standard methods to estimate CATE are not equipped to handle fixed effects. For the same reason, we use the reduced-form model instead of the two-stage least square.

Figure 2: **Correlation between the effect of tariffs on technology transfers and on citations**



Notes: This figure plots the correlation between the conditional average treatment effect (CATE) of the instrument on citations and on technology transfers. The CATE is calculated using causal forest. The treatment effect is conditioned on the stock of patents in the origin country in 1990, the per-capita GDP of the origin country in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from the origin country to sector s until 1990, and the number of citations made by sector s to the origin country c until 1990. Using these variables, we predict the treatment effect for each origin country-sector pair. For clarity, in the figure markets are binned into 40 groups. Appendix B.3 describes the procedure in detail.

Diffusion through technology transfers. These results indicate that higher tariffs lead foreign firms to transfer their technology to Brazil. Transferred technologies diffuse among Brazilian firms, leading to an increase in citations to technology licensors. This evidence suggests that higher tariffs, by influencing technology transfers, can lead to greater diffusion of technology across countries.

4.3 Alternative Explanations

In this section, we test alternative explanations for the effect of tariffs on technology diffusion. We start by showing that higher tariffs do not increase foreign ownership of Brazilian firms, ruling out FDI as the source of the increase in diffusion. We then show that connection to foreign input suppliers and access to larger foreign markets do not affect technology transfers or citations.

Higher tariffs do not increase FDI. A potential explanation for our findings is that technology transfers are a byproduct of FDI, and higher tariffs promote diffusion by increasing FDI, rather than directly through higher technology transfers. In Panel A of Table 7 we show that higher tariffs do not increase (and, if anything, decrease) measures of foreign ownership of Brazilian firms. Columns 1 to 3 display the effect of tariffs on the number of foreign firm owners, the number of firms owned by at least one foreigner, and an indicator that is equal to one if at least one firm is owned by a foreigner from the country of origin. Columns 4 to 6 display the corresponding estimates when the outcomes are measured in the three years following the tariff change. The absence of a positive impact of tariffs on FDI is consistent with the idea that local production by foreign-owned firms requires the import of intermediate inputs from the origin country, which is curtailed by higher tariffs (Ramondo and Rodríguez-Clare, 2013).

Connection to foreign suppliers does not increase citations. It could be the case that firms learn from foreigners not due to technology transfers but because they import foreign inputs. This may bias our results if tariffs on inputs are correlated with tariffs on outputs. To rule out this potential confounding factor, Panel B of Table 7 (columns 3 and 4) shows the main results, but adds as control the average import tariff on inputs.[12] Tariffs on inputs have no effect on technology transfers and a positive effect on citations. Introducing them as a control in our baseline regression leads to the same conclusions as in our main exercise.

Foreign market access does not affect licensing or diffusion. It could also be the case that the relevant margin is access to foreign markets, as in Bustos (2011b), rather than technology licensing. In particular, if import tariffs in Brazil are correlated with the tariffs that other countries impose on Brazilian goods, changes in tariffs can change firms' incentives to upgrade their technology to better serve foreign markets. To test this explanation, we augment the baseline model by adding as control the import tariff that the country of origin imposes on Brazilian goods in columns 5 and 6 of Panel B in Table 7. This tariff has no effect on technology transfers or citations to foreign patents.

4.4 Robustness

The previous sections have shown that an increase in import tariffs increases technology transfers and citations to foreign firms. In this sub-section, we show that these results are robust to using an Ordinary Least Squares (OLS) regression, changing the set of controls, limiting the sample to high-income countries, and using alternative functional forms to define the outcome variables.

OLS. Appendix Table B.5 presents the main empirical results without using the instrument by Boehm et al. (2023). Even without this instrument, we find that tariffs still lead to an increase in

[12]Input tariffs are constructed using the Brazilian input-output table from De Souza and Li (2022).

Table 7: **Testing for alternative explanations**

Panel A: Tariffs and FDI						
	(1)	(2)	(3)	(4)	(5)	(6)
	IHS N.For. Partners	*IHS N.Firms F.Owned*	$\mathbb{I}$*(At Least 1 Firm)*	*IHS N.For. Partners,3y*	*IHS N.Firms F.Owned,3y*	$\mathbb{I}$*(At Least 1 Firm,3y)*
Tariff	-0.00667	0.00373	0.00586	-0.0144	0.00304	0.0135
	(0.0204)	(0.0175)	(0.0177)	(0.0471)	(0.0423)	(0.0372)
N	1,010,757	1,010,757	1,010,757	1,010,757	1,010,757	1,010,757

Panel B: Tariffs and Diffusion						
	(1)	(2)	(3)	(4)	(5)	(6)
	IHS N.Tech. Licenses	*IHS Citations*	*IHS N.Tech. Licenses*	*IHS Citations*	*IHS N.Tech. Licenses*	*IHS Citations*
Tariff	0.127***	0.714***	0.205**	0.852***	0.0905**	0.709***
	(0.0472)	(0.113)	(0.0802)	(0.172)	(0.0379)	(0.119)
Input tariff			-0.110	-0.0406		
			(0.0829)	(0.189)		
Tariff on Brazil					-0.000429	-0.0124*
					(0.000562)	(0.00700)
N	1,178,000	1,178,000	976,976	976,976	599,293	599,293

Notes: Panel A of this table reports the coefficients of regressing different measures of foreign ownership of Brazilian firms on tariffs using the model in Equation (1) using the first-stage regression in Equation (2). The left-hand side is the number of foreign partners in firms of sector s from country c (column 1), the number of firms with at least one foreign partner from country c in sector s (column 2), an indicator equal to one if there is at least one firm with a foreign partner from country c in sector s (column 3), the sum of the number of foreign partners in firms of sector s from country c in the next 3 years (column 4), the number of firms with at least one foreign partner from country c in sector s in the next 3 years (column 5), and an indicator equal to one if there is at least one firm with a foreign partner from country c in sector s in the next 3 years (column 6). Panel B of this table shows the effect of tariffs on technology transfers augmenting the model in Equation (1) with different controls. Columns 1 and 2 display the baseline results. Columns 3 and 4 add as control the average import tariff in Brazil on inputs of each sector, columns 5 and 6 add as control the import tariff imposed against Brazilian products by foreign countries. Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

technology diffusion and in citations directed toward technology licensors.

Adding and removing controls. Appendix Table B.6 shows the results under different sets of controls. We still find that tariffs increase technology transfers and citations.

Sample selection. Not all countries or sectors are likely to transfer technology or receive citations from Brazilian firms. Appendix Table B.7 shows the results when limiting the sample to high-income countries. As expected, the effect of tariffs on technology transfers and citations are significantly larger in this sub-sample, although with a larger standard error.

Dealing with zeros. Appendix Table B.8 shows the results using alternative transformations of the outcome variables, following the suggestions by Chen and Roth (2023). Whether we use indicator variables, define the outcome variable as the percentile of technology transfers or citations, or use the raw levels of these variables, we consistently find that higher tariffs increase the diffusion of foreign technologies through technology transfers.

5 Model

In this section, we develop a model of trade, growth, and diffusion that rationalizes our empirical findings and allows us to explore their implications for welfare and policy. We extend the framework developed by Buera and Oberfield (2020) by explicitly modeling technology transfers as a channel of idea diffusion across countries. In the model, foreign firms face a tradeoff between exporting their goods or transferring their technology to Brazilian firms. This decision is shaped by trade policy: higher tariffs increase technology transfers by making them more profitable relative to exporting. The rate of diffusion of foreign technology depends on whether Brazilian producers come into contact with it through imported goods or technology transfers. This implies that trade policy, by influencing the tradeoff between exporting goods or transferring technology, determines the rate of diffusion of foreign ideas and productivity growth in the domestic economy.

Since many elements of the model are standard, in this section we briefly present the setting and equilibrium conditions, and leave the full derivations to Appendix D.

5.1 Environment

The world economy is composed of Brazil (B) and two sets of foreign countries: high-income (H) and low-income (D). Since we focus exclusively on domestic outcomes in Brazil, we assume that trade is frictionless within each set of foreign countries. To simplify the exposition, we refer to these sets simply as the high-income foreign country and the low-income foreign country, respectively.

Timing and sectors. Time is continuous and indexed by t. Each country i is populated by a mass N^i of workers, each of whom inelastically supplies one unit of labor to active producers within the country. There is a finite number of sectors, indexed by $k \in K$, each composed of a continuum of varieties, indexed by $s \in [0, 1]$. Labor is perfectly mobile across sectors and immobile across countries.

Representative consumer. A representative consumer in each country aggregates individual varieties into sectoral bundles, $C_t^{i,k}$, with a constant elasticity of substitution (CES) ϵ, and sectoral bundles into final consumption, $\mathcal{C}_t^i$, with a constant elasticity of substitution σ:

$$\mathcal{C}_t^i = \left[\sum_{k \in K} \left(\int_0^1 c_t^{i,k}(s)^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}s \right)^{\frac{\epsilon(\sigma-1)}{(\epsilon-1)\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \tag{6}$$

The representative consumer within each country values consumption over time according to a logarithmic utility function and a discount rate $r > 0$. Hence, discounted welfare at time 0 is equal to

$$W_0^i = \int_{t=0}^{\infty} e^{-rt} \log(\mathcal{C}_t^i) \, \mathrm{d}t. \tag{7}$$

The model has a static and a dynamic component that, for clarity, we present separately.

5.2 Static Equilibrium

Production. Each intermediate variety is produced with labor according to the linear technology

$$y_t^{i,k}(s) = q_t^{i,k}(s) l_t^{i,k}(s), \tag{8}$$

where $q_t^{i,k}(s)$ represents the productivity of the most efficient producer of variety s in country-sector (i, k) (which, in equilibrium, will be the only active producer), and $l_t^{i,k}(s)$ denotes the quantity of labor employed.

Iceberg trade cost. Exporting goods from country i to country j involves a time-varying iceberg trade cost $\tau_t^{i\to j,k} \geq 1$, whereby for each unit shipped a fraction $\frac{1}{\tau_t^{i\to j,k}}$ arrives at the destination. We assume that trade costs satisfy the triangular inequality, i.e. $\tau_t^{i\to j,k} < \tau_t^{i\to h,k}\tau_t^{h\to j,k}$, and we set $\tau_t^{i\to i,k} = 1$ for all i's. Notice that trade costs are sector-specific and hence are indexed by k.

Productivity in Brazil (B). In Brazil (B) there is a large mass of potential entrepreneurs. A subset of them controls a technology to produce variety $s \in [0,1]$ in sector k. The productivity of the most efficient among them is denoted by $q_t^{B,k}(s)$. As in Eaton and Kortum (2002) and Buera and Oberfield (2020), at time $t = 0$, the distribution of highest-productivity ideas in Brazil is Fréchet with scale parameter $\lambda_t^{B,k} > 0$ and shape parameter $\theta > 1$:

$$Pr\left(q_0^{B,k}(s) \leq q\right) = \exp\left(-\lambda_0^{B,k} q^{-\theta}\right). \tag{9}$$

As we show in Section 5.3, given our assumptions on the diffusion process, this distribution endogenously retains the same Fréchet structure over time, with a time-varying scale parameter $\lambda_t^{B,k}$ and a constant shape parameter θ. To simplify the exposition, we maintain this assumption in the description of the static equilibrium.

Productivity in the high-income foreign country (H): export or technology transfers. In the high-income foreign country (H), there is a mass one of firms for each sector k. Each firm controls a technology to produce a specific variety s with productivity $q_t^{X,k}(s)$. The output of this technology can be used for domestic consumption or export (hence the superscript X). When deciding to serve the Brazilian market, firms in H face a choice: they can either produce in-house and export their output to Brazil or transfer their knowledge to a Brazilian firm through a contract of technology transfer. In the latter case, the Brazilian firm gains access to the transferred technology, which must be operated locally in Brazil.

The productivity associated with the transferred technology, denoted by $q_t^{T,k}(s)$, is generally different from $q_t^{X,k}(s)$. Following Ramondo and Rodríguez-Clare (2013) and Lind and Ramondo (2023), we allow for an arbitrary degree of correlation between the two. In particular, we assume that the marginal distribution for the two technologies is Fréchet with scale parameters $\lambda_t^{X,k}$ and

$\lambda_t^{T,k}$, respectively, and shape parameter θ. The joint distribution is

$$Pr\left(q_t^{X,k}(s) \leq q_1, q_t^{T,k}(s) \leq q_2, \right) = \exp\left(-\left[(\lambda_t^{X,k} q_1^{-\theta})^{\frac{1}{1-\rho}} + (\lambda_t^{T,k} q_2^{-\theta})^{\frac{1}{1-\rho}}\right]^{1-\rho}\right), \tag{10}$$

with $\rho \in [0, 1]$. Setting $\rho = 0$ implies that the X and the T distributions are independent Fréchet, while setting $\rho = 1$ implies that the two distributions are perfectly correlated (i.e., the productivity of in-house production is proportional to the productivity of the technology transfer). The fact that the productivity distributions of exporting and transferring are distinct (albeit correlated) reflects that the applicability of foreign technologies to the local context ("appropriateness") can vary significantly due, among other factors, to environmental conditions (Moscona and Sastry, 2022) and the local supply of skills (de Souza, 2020).

Transferring technology involves a loss of efficiency that discounts the relevant productivity by a factor $d_t^k > 1$, reflecting transaction, communication, and coordination costs, such as language barriers and imperfect contract enforceability.

Productivity in the low-income foreign country (D). Similar to B and H, the low-income foreign country (D) has a mass one of firms for each sector k, each being assigned a variety s. Since the vast majority of technology transfers in the data originate from high-income countries, we assume that firms in D do not have the option to transfer their technology to foreign firms. Hence, firms in D are only endowed with one technology, which allows them to produce in-house (for domestic consumption or export) with productivity $q_t^{D,k}(s)$. The productivity term is drawn from a Fréchet distribution with shape parameter θ and scale parameter $\lambda_t^{D,k}$.

Two-stage pricing. Firms engage in two-stage pricing (see, e.g., Acemoglu et al., 2012), which guarantees that the varieties in each country are sold exclusively by the producer with the lowest marginal cost, charging the optimal markup. In the first stage, each firm has the option to pay a small fee to enter the second stage where price competition occurs. If more than one firm enters the second stage, Bertrand competition ensues, whereby the most productive firm sets the price equal to the marginal cost of the second best producer and captures the full market. Anticipating this outcome, no producer except for the most efficient one enters the second stage. Hence, the best producer sets its price as the optimal markup over its marginal cost.

Technology transfer fees. Each potential technology provider in the high-income foreign country is randomly matched to one potential entrepreneur in Brazil. The provider can then present a take-it-or-leave-it offer, granting a license to use the technology in exchange for a fixed licensing fee. The offer is accepted as long as the fee does not exceed the profits the entrepreneur can earn from using the technology. As a result, the provider will set the fee to capture the entirety of the profits generated through the transferred technology.

Domestic production, exporting, and technology transfers. The price faced by the Brazilian representative consumer for variety s in sector k is

$$p_t^{B,k}(s) = \frac{\epsilon}{\epsilon - 1} \times \min\left\{ \frac{w_t^B}{q_t^{B,k}(s)}, \frac{w_t^B d_t^k}{q_t^{T,k}(s)}, \frac{w_t^H \tau_t^{H\to B,k}}{q_t^{X,k}(s)}, \frac{w_t^D \tau_t^{D\to B,k}}{q_t^{D,k}(s)} \right\}, \tag{11}$$

where w_t^i is the wage paid to workers in country i. In words, the price consists of a constant markup over the lowest marginal cost among local production from domestic technology (first term) or technology transfers (second term), import from H (third term), and import from D (fourth term). The derivation of the equilibrium price index and expenditure shares is analogous to Lind and Ramondo (2023). We relegate the details to Appendix D.1.

The equilibrium conditions for the high- and low-income foreign countries are analogous to the ones for Brazil, with the exception that the varieties in those countries cannot be provided via technology transfers. As a consequence, the expressions for the equilibrium price index and expenditure shares are identical to the ones in the standard Eaton and Kortum (2002) framework, and we relegate them to Appendix D.1.

5.3 Dynamics of the Productivity Distribution

The dynamic component of the model pins down the evolution of the productivity distribution, as encapsulated in the parameters $\lambda_t^{i,k}$. For the technology controlled by foreign producers in H and D, we assume that these parameters grow at a constant and exogenous rate g_λ^*.[13] In what follows, we focus on the dynamics of the scale parameter for the distribution of local firms in Brazil, $\lambda_t^{B,k}$.

In modeling the process of idea diffusion, we build on the framework developed by Buera and Oberfield (2020). In their model, local firms adopt foreign technologies through interactions with exporters. We extend this framework by introducing an additional channel: local Brazilian firms

[13] In the remainder of the paper, upper-stars denote variables in their BGP values.

can also learn from other domestic firms that have received technology transfers from foreign firms. Furthermore, we allow the rate of diffusion among Brazilian producers to depend on how the technology enters the local market—whether through exports or direct technology transfers. We relegate all derivations of this section to Appendix D.2.

Contact rate with foreign ideas. Each potential entrepreneur in Brazil is exposed to ideas from foreign exporters at rate

$$a_t^{X\to B,k} = \alpha_t^k \pi_t^{X\to B,k},$$

and from local users of foreign technology at rate

$$a_t^{T\to B,k} = \alpha_t^k \omega_T \pi_t^{T\to B,k},$$

where $\pi_t^{i\to B,k}$ denotes the share of varieties sold in Brazil (B) that originate from exports ($i = X$) and foreign technology ($i = T$) in sector k. The parameter ω_T controls the efficiency of learning from technology transfers relative to learning from exporters: a value of ω_T greater than 1 (which will be the relevant case in our calibration; see Section 6.1) implies that learning foreign technologies is more efficient when it occurs through interaction with local users of the technology rather than through foreign exporters.

Personal insight. After obtaining an idea, this idea is combined with a personal insight, where the insight distribution is such that the Poisson arrival rate of insights larger than z is

$$A_t^{i\to B,k}(z) \equiv a_t^{i\to B,k} z^{-\theta}, \quad i \in \{X, L\}. \tag{12}$$

Learning from foreigners. As a result of this learning process, the entrepreneur develops a new idea, whose quality is given by

$$q = zq'^{\beta}, \tag{13}$$

where q' is the idea draw, z is the quality of the insight, and $\beta \in (0, 1)$ is a parameter that controls the weight of the learning component in the creation of the new idea.

Law of motion of productivity in Brazil. The productivity distribution of local producers in Brazil retains its Fréchet structure over time, with a constant shape parameter θ and with a scale parameter, $\lambda_t^{B,k}$, evolving according to the following law of motion:

$$\dot{\lambda}_t^{B,k} = \alpha_t^k \left[\pi_t^{X\to B,k} \mathbf{E}_t^{X\to B,k} \left(q_t^{X,k} \right)^{\theta\beta} + \omega_T \pi_t^{T\to B,k} \mathbf{E}_t^{T\to B,k} \left(q_t^{T,k} \right)^{\theta\beta} \right], \tag{14}$$

where $\mathbf{E}_t^{X\to B,k}$ and $\mathbf{E}_t^{T\to B,k}$ denote averages over the set of sector-k varieties provided in B via export and technology transfers from the high-income foreign country, respectively.

Equation (14) illustrates how productivity growth in Brazil is shaped by the diffusion of foreign technology. The first term inside the square brackets represents learning through contact with foreign exporters, the primary channel emphasized by Buera and Oberfield (2020). The second term captures learning from Brazilian receivers of technology transfers, reflecting the diffusion of transferred technologies to other local producers.

The equation also highlights how trade policy influences growth via technology transfers. When tariffs increase, the share of varieties imported directly from foreign producers, $\pi_t^{X\to B,k}$, declines, while the share of varieties entering through technology transfers, $\pi_t^{T\to B,k}$, rises. As a result, Brazilian firms shift from acquiring knowledge embedded in imported goods to learning from local firms that have adopted foreign technologies. The overall impact on productivity growth depends on the relative efficiency of learning from transferred technology, governed by the parameter ω_T. If this parameter is sufficiently high, stricter trade policies can enhance knowledge diffusion and accelerate productivity growth by increasing the role of technology transfers as a learning channel.

Balanced growth path. Since $\lambda_t^{X,k}$ and $\lambda_t^{T,k}$ grow at a constant exogenous rate g_λ^*, in order to have a BGP in which $\lambda_t^{B,k}$ grows at the same rate, α_t^k must grow at a rate $g_\alpha = (1-\beta)g_\lambda^*$. Notice that, given initial values for $\lambda_0^{i,k}$, we can solve for all the stationary objects and then back-out the value of α_0^k that is consistent with balanced growth. In other words, we can always initialize the model to be on a BGP by choice of α_0^k.

6 Quantitative Exploration

In this section, we calibrate our model and use it to explore quantitatively the implications of the wave of tariff reductions in Brazil in the early 1990s. We work with a version of the model in discrete time, which we calibrate to a yearly frequency.

6.1 Calibration

Our calibration proceeds in three steps. First, we calibrate a subset of parameters to common values from the literature. Second, using data on sectoral value added, trade flows, and income by country, we calibrate the BGP of the model in 1990, before the onset of the wave of trade liberalizations. Third, we simulate a once-and-for-all reduction in tariffs equal in magnitude to the one implemented in Brazil in the early 1990s. In this final step, we pin down the values of the key structural parameters by matching the empirical response of technology transfers and patent citations to changes in tariffs.

Data sources. Data on sectoral value added in 1990 is obtained from the long-run World Input Output Database (WIOD, Woltjer et al., 2021). This database uses ISIC-3 sector codes and comprises 21 industries, which we set as our level of sectoral disaggregation throughout the quantitative analysis. Data on value added by sector is only available for the majority of high-income countries and for a small subset of emerging economies (including Brazil). For this reason, we use this dataset to construct value added shares by sector for Brazil and high-income foreign countries, and we assume that the corresponding shares (but not average income) for low-income foreign countries are equal to the ones in Brazil. We use the CEPII gravity database (Conte et al., 2022) to compute the relative population and average income for Brazil and the sets of high- and low-income foreign countries. Data on tariffs and import values are from the World Bank Trade Analysis Information System.

Step 1: Externally assigned parameters. We assign standard values in the literature to a subset of the parameters. Following Buera and Oberfield (2020), we set $\theta = 4$ and $\beta = 0.6$. The elasticity of substitution of the outer aggregator, σ, is set to 4.4, as estimated in De Souza and Li (2022) for Brazil. The elasticity of substitution of the sectoral aggregators, ϵ, is set to 2.94, implying a labor share, $\frac{\epsilon-1}{\epsilon}$, of 66%. The yearly discount rate r is set to 5%, while the exogenous growth rate of productivity in foreign countries, g_λ^*, is set so that the growth rate of income per capita is 2% per year. The top panel of Table 8 summarizes this assignment of parameters.

Step 2: Initial balanced growth path. We initialize the model by assuming that the world economy is in a BGP in which productivity grows at the same rate in all countries and sectors and, as a result, relative prices, sectoral employment shares, and expenditure shares are constant. We assume that trade costs are symmetric in the initial BGP (i.e., $\tau_t^{i\to j,k} = \tau_t^{j\to i,k}$). We further assume that, on average, the quality of technologies controlled by foreign firms in high-income countries does not depend on whether it is used for export or technology transfer, i.e., $\lambda_t^{X,k} = \lambda_t^{T,k}$, although the productivity of individual varieties in general is different depending on whether they are used for exporting or technology transfer. The degree of correlation between the two is controlled by the parameter ρ. Given a value for ρ (determined in Step 3 below), we calibrate the initial BGP by setting the initial values of $\lambda_t^{i,k}$, $\tau_t^{i\to j,k}$, and d_t^k to exactly match relative average income by country, value-added shares by sector and country, as well as import shares and share of labor by sector employed in Brazilian firms that are receivers of technology transfers from foreign firms.

Step 3: Wave of trade liberalizations and calibration of ρ and ω_L. Starting from the initial BGP, we assume that in 1991 the economy is perturbed with a wave of tariff reductions matching the one implemented in Brazil in the early 1990s. We model this trade liberalization as a once-and-for-all change in tariffs that is fully realized in the first period of the shock.

To convert the changes in tariffs into changes in trade costs, we assume (as in Caliendo and Parro, 2015) that the trade costs calibrated in Step 2 have the following form:

$$\tau_t^{i\to B,k} = \bar{\tau}^{i\to B,k}(1 + T_t^{i\to B,k}), \tag{15}$$

where $\bar{\tau}^{i\to B,k}$ is a time-invariant component of the trade cost and $T_t^{i\to B,k}$ is a time-varying import tariff. Before the liberalization (i.e., in the initial BGP), we set tariffs for each sector to their respective averages in 1990. To calibrate the size of the liberalization, we set tariffs to their averages at the end of the sample.

Within this tariff reduction experiment, we still need to pin down the two time-invariant parameters that directly determine the relevance of technology transfers. To do so, we calibrate these two parameters by exactly matching the two main empirical results—the effect of tariff reductions on technology transfers and citations—with data generated from our model. First, we set ρ to match the semi-elasticity of technology transfers to tariff changes across sectors. Intuitively, a large value of ρ implies that the productivity distributions of exporting and providing transfers are highly correlated, so that a small increase in trade costs induces a large reallocation of resources towards technology transfers. By contrast, a small value of ρ implies that a small change in trade costs induces a small response in technology transfers. We target an empirical semi-elasticity of 0.489, corresponding to the effect of tariffs on the number of technology contracts from high-income countries in the three years following a change in tariffs (see column 1 of Table B.7). This yields a value of ρ equal to 0.138.[14] This relatively low value for ρ implies that productivity draws from H are weakly correlated, suggesting that the best technologies in the advanced economies are not necessarily the most productive in Brazil.

Second, we set ω_T to match the semi-elasticity of patent citations to foreign grants to tariff changes. In the model, we assume that total citations to foreign patents are proportional to the overall rate at which local entrepreneurs come into contact with foreign ideas, whether through interactions with foreign exporters or with local firms that have received technology transfers, i.e.:

$$Cit_t^{B\to H,k} \propto \pi_t^{X\to B,k} + \omega_T \pi_t^{T\to B,k}. \tag{16}$$

A large value of ω_T implies that, following an increase in tariffs and the resulting reallocation of expenditures from X to T, firms in Brazil will have a greater exposure to foreign technologies in the form of technology transfers, and hence their overall rate of learning from country H will be higher. We target an empirical semi-elasticity of 0.852, corresponding to the effect of tariffs on citations to high-income foreign countries in the 3 years following the change in tariffs (column 2 of Table B.7). This yields a value of ω_T equal to 99.1, implying a substantial learning advantage from technology transfers relative to imported goods.[15] The values and moment fit are summarized in the bottom panel of Table 8.

6.2 Quantitative Experiments

We now use the calibrated model to quantitatively assess the dynamic effects of trade liberalization. We first explore how accounting for technology transfers and their role in knowledge diffusion shapes the static and dynamic implications of tariff reductions. We then study the design and welfare effects of optimal subsidies to technology transfers.

[14]The top-left panel of Appendix Figure C.16 displays this correlation, with the regression line matching the empirical semi-elasticity by construction. As the model's counterpart of the number of technology contracts, we use the quantity of labor in Brazil using technologies transferred from abroad.

[15]The top-center panel of Appendix Figure C.16 displays this correlation where, once again, the regression line in the model is identical to the empirical one by construction. The bottom panels of Appendix Figure C.16 illustrate the identification by plotting the model-implied semi-elasticities for different values of ρ and ω. The plots show that the calibration strategy identifies unique values of the parameters that are consistent with the empirical moments.

Table 8: **Parameter values and targets**

Parameter	Value	Target	Model	Data
		Externally assigned parameters		
θ	4.0	Buera and Oberfield (2020)		
β	0.6	Buera and Oberfield (2020)		
σ	4.4	De Souza and Li (2022)		
ϵ	2.94	Labor share 66%		
g^*_λ	0.0824	Yearly income growth 2%		
r	0.05	Yearly discount rate		
		Internally calibrated parameters		
			Model	Data
ρ	0.1382	Semi-elasticity transfers to tariffs, 1-3 years	0.489	0.489
ω_T	99.1	Semi-elasticity citations to tariffs, 1-3 years	0.852	0.852

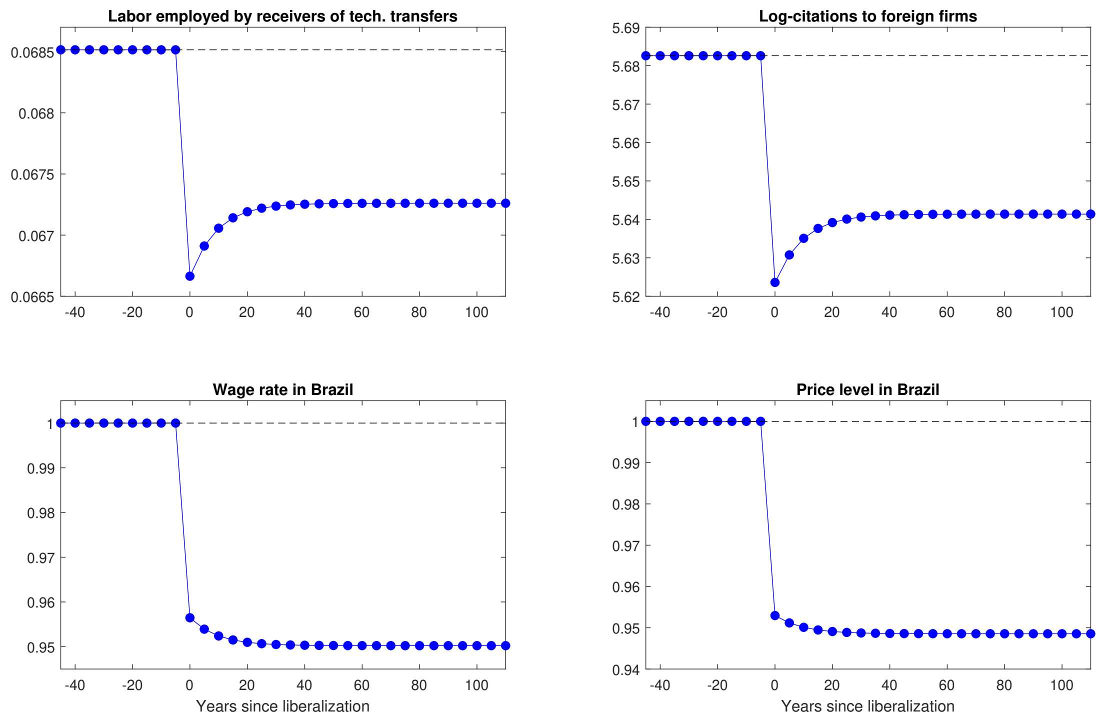
6.2.1 Dynamic effects of trade liberalization

In our model, trade liberalization affects the choice of foreign producers between exporting goods and transferring their technology, with implications for productivity growth and long-run welfare in the receiving country (Brazil, in our case). Specifically, tariff reductions make exporting more profitable relative to technology transfers, leading to a decrease in the number of technology transfers and slowing the diffusion of foreign technologies within the domestic economy.

The top panels of Figure 3 illustrate this effect. The top-left panel shows the dynamic impact of the tariff reductions implemented in Brazil since the early 1990s on the share of labor employed by transfer receivers, which drops significantly. Similarly, the top-right panel shows the dynamics of the number of citations to foreign patents—a proxy for the overall diffusion of foreign ideas among Brazilian firms—which display an analogous drop following the reduction in tariffs. The effect in the short run is more pronounced than the one in the long run. The reason is that, as the distance between the accumulated knowledge of Brazilian firms and the technology frontier in high-income foreign countries increases, the returns from technology transfers become larger, partially offsetting the short-run drop. Importantly, note that the magnitude of these responses is directly controlled by the parameters ρ and ω_T, which are calibrated to match the empirical semi-elasticity of transfers and citations to tariffs across sectors. Hence, in this experiment, the effects of tariff reductions are directly informed by the micro-level evidence.

The lower rate of technology transfer and the resulting drop in the rate of adoption of foreign

Figure 3: **Dynamic effects of the liberalization**

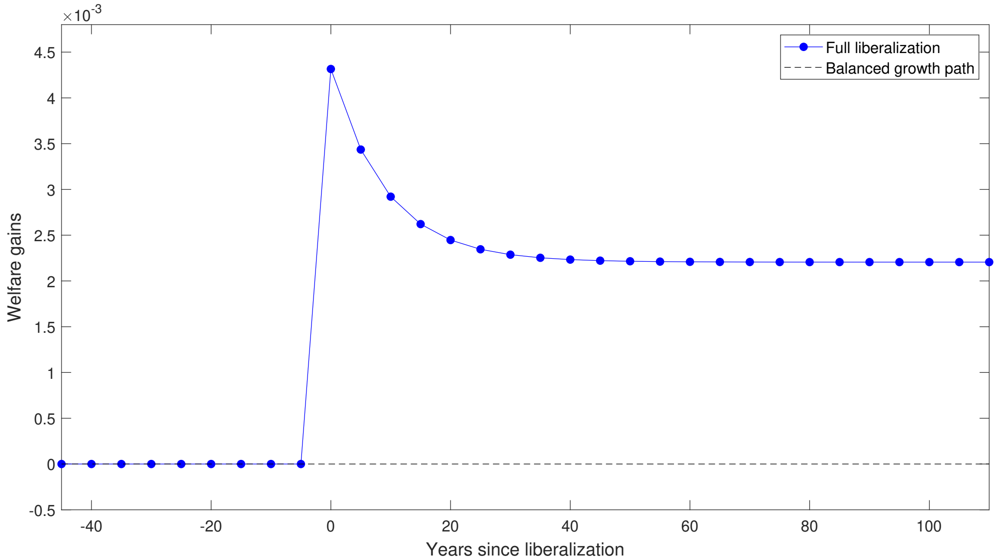


Notes: The marked blue lines show the share of labor in Brazil employed by transfer receivers (top-left panel), log-citations to foreign patents (computed as in Equation 16, top-right panel), the wage rate (bottom-left panel, relative to BGP), and the price level (bottom-right panel, relative to BGP) in Brazil.

technologies results in a persistent decline in productivity growth in Brazil. The bottom-left panel of Figure 3 displays the dynamics of the wage rate (relative to the BGP, which is normalized to one). On impact, the lower demand for local labor induces a drop in the wage rate. This drop is a common prediction of the Eaton-Kortum model, where the static welfare gains from trade originate from a more-than-proportional drop in the price of the final consumption bundle, displayed in the bottom-right panel. Over time, the lower rate of knowledge accumulation leads to a further decline in the wage rate. In the new BGP, the wage rate is 5.0% lower relative to the initial BGP. While this decline is partially compensated by a further drop in the price level, the wage rate falls relatively more, resulting in lower real consumption in the long run.

Figure 4 summarizes the impact of the trade liberalization on the welfare of the representative consumer. The dotted blue line shows the percentage deviation of real consumption under the full liberalization from a baseline scenario where the economy remains on its BGP without liberalization.

Figure 4: **Welfare gains from liberalization**



Notes: The marked blue line shows instantaneous consumption under the full liberalization scenario, in percentage deviation from the BGP.

On impact, the tariff reductions induce a 0.43% increase in consumption relative to the BGP. The magnitude of the short-run improvement in welfare is in line with the predictions of a wide range of models, as summarized by Arkolakis et al. (2012). In the years following the liberalization, the increase in welfare relative to the BGP is smaller than the short-run gains, in contrast to the predictions of a large class of existing models of trade and growth (e.g., Sampson, 2016, Buera and Oberfield, 2020, and Perla et al., 2021). While the overall welfare gains from the liberalization are positive (both along the transition and in the new BGP), these gains are highest in the short run and they become smaller over time. When the full dynamics of the liberalization are taken into account, the welfare gains are equivalent to an increase in consumption of 0.29% per period relative to the BGP. Following the initial increase in real consumption, the convergence of the economy to the new BGP is fast, with a half-life of about 7.5 years, which is comparable to that of the neoclassical growth model (King and Rebelo, 1993).[16]

The importance of idea diffusion. Table 9 highlights the role of idea diffusion in shaping the long-run outcomes after liberalization. The table reports average productivity (both unconditional and conditional on active producers in Brazil) and real consumption in the new BGP following tariff

[16] As shown in Appendix Figure C.17, while both drops in import tariffs with high-income and low-income foreign countries contribute significantly to the large short-run gains, the dynamic path is almost entirely driven by tariffs with high-income foreign countries.

Table 9: **Importance of idea diffusion in the Brazilian trade liberalization**

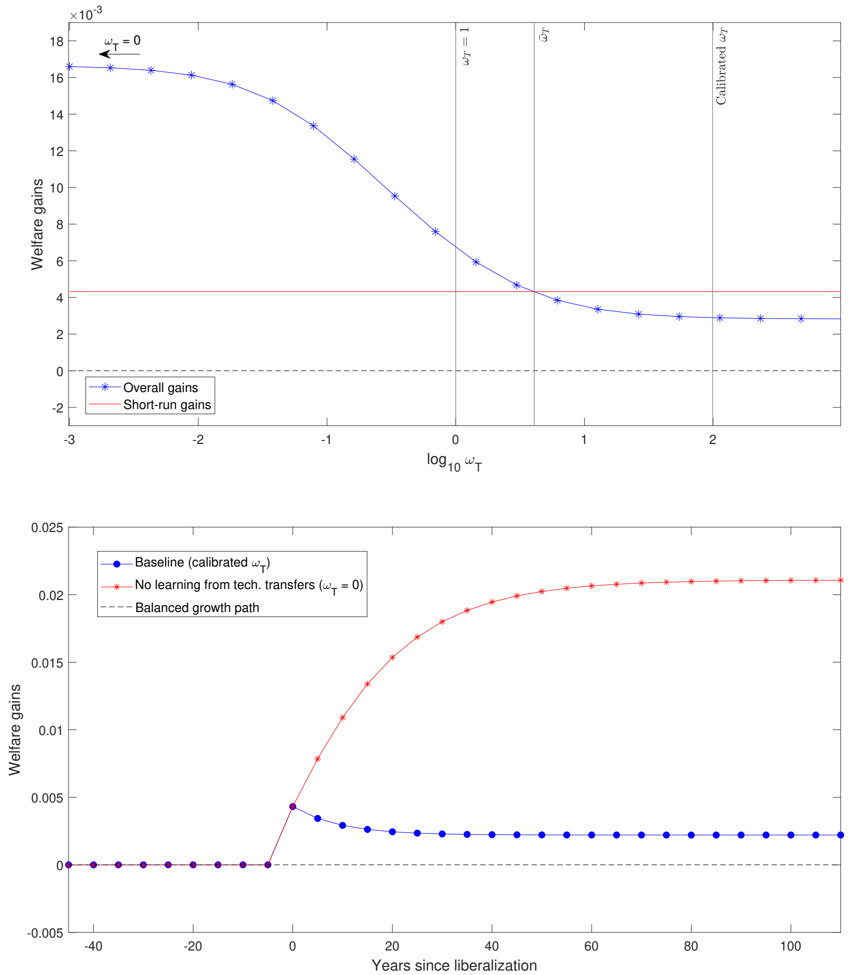
	Full model	No diffusion	Importance of diffusion
	(1)	(2)	$\frac{(1)-(2)}{(2)}$
Average productivity:			
$\Delta \log \mathbf{E}\left[q^B\right]$	-0.32%	0	-
Productivity active domestic firms:			
$\Delta \log \mathbf{E}^{B \to B}\left[q^B\right]$	+0.39%	+0.63%	-38.1%
Real Consumption in Brazil:			
$\Delta \log \mathcal{C}_t^B$	+0.22%	+0.43%	-48.8%

Notes: The table reports long-run outcomes (i.e., in the new BGP) in Brazil following the trade liberalization. $\mathbf{E}\left[q^B\right]$ denotes the average productivity of local producers, where each sector is weighted by the share of labor before the liberalization. $\mathbf{E}^{B \to B}\left[q^B\right]$ denotes the corresponding average across active producers only. Column 1 reports outcomes in the full model, where diffusion occurs through contact with exporters and with licensees. Column 2 reports outcomes in the model where productivity growth g_λ^B is exogenous.

reductions relative to the initial BGP. Column 1 presents results from the full model, while column 2 shows a version without the diffusion channel. In the full model, liberalization reduces average productivity due to lower learning by 0.32%. Conditional productivity rises in both models due to selection by 0.3 and 0.6%, respectively, but it increases more sharply when diffusion is absent. As a result, the rise in real consumption is about 50% lower in the full model compared to the model without diffusion (0.22% vs. 0.43%), where the welfare gain aligns with the estimates of Costinot and Rodríguez-Clare (2014).

Learning from technology transfers. The parameter ω_T (controlling the learning rate from licensing relative to that from importing) is key to generating the dynamic path for welfare displayed in Figure 4. This point is illustrated in the top panel of Figure 5, whose marked blue line plots the overall welfare gains from the liberalization for a range of values of ω_T (the short-run gains, represented by the solid red line, are constant with respect to ω_T). At the calibrated value of ω_T the overall gains are below the short-run gains. As we move towards lower values of ω_T, overall gains from openness become larger. To the left of a threshold value denoted by $\bar{\omega}_T$, the blue line is above the red line, indicating that the overall gains amplify the short-run ones. As ω_T approaches zero, all learning originates from exporters, and the dynamic amplification of the short-run gains is as large as it can be. The dynamics of welfare in this case are illustrated by the

Figure 5: **Welfare gains from liberalization for different degrees of diffusion via transfers**



Notes: The top panel displays short-run (solid red line) and overall (marked blue line) welfare gains from the liberalization for a range of values of ω_T (in $\log_{10}$ scale). The bottom panel shows instantaneous consumption under the full liberalization scenario, in percentage deviation from the BGP, in the full model (marked blue line) and in the model where we set $\omega_T = 0$ (starred red line).

starred red line in the bottom panel of Figure 5, which is plotted alongside the dynamics of welfare in the main calibration (in the marked blue line). When technology licensing does not affect the rate of learning, the liberalization generates overall welfare gains of 1.30% per period (more than twice as large as the short-run gains), compared to the 0.29% gains in the main calibration. In other words, accounting for learning from technology transfers reduces the overall gains from trade liberalization by more than three-fourths.

6.2.2 Optimal subsidy to technology transfers.

This diffusion process implies that technology transfers generate a dynamic effect on local productivity growth that is not internalized by the providers and receivers of the technology. This dynamic externality opens up room for policy intervention. In this section, we explore these policy implications by computing the optimal subsidies on technology transfers and evaluate their impact on welfare.

We introduce subsidies to technology transfers in the form of multiplicative discounts on the iceberg cost of transfers, financed via a lump-sum tax on the representative consumer in Brazil. Denoting by $\bar{d}_t^k$ the base iceberg cost in the absence of subsidies, the net iceberg cost d_t^k is defined as

$$d_t^k = \bar{d}_t^k (1 - \bar{S}_t),$$

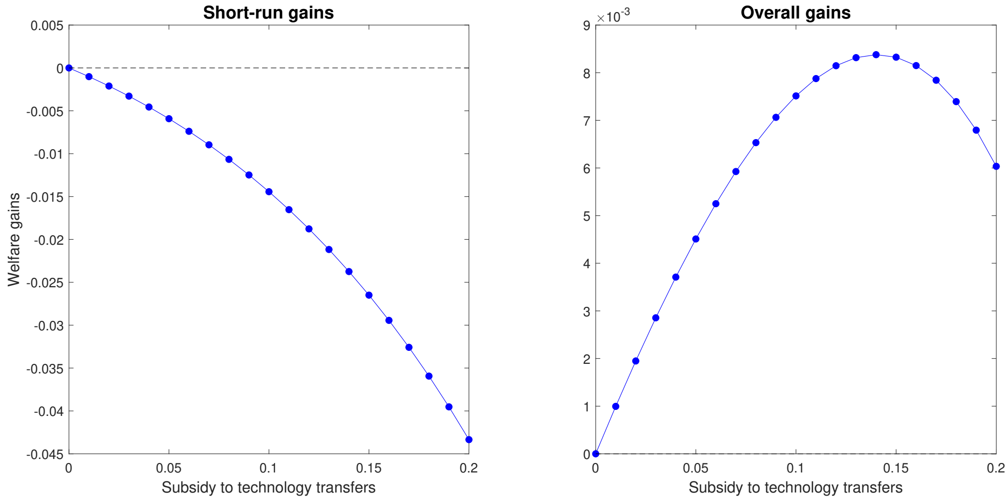
where $\bar{S}_t < 1$ denotes the subsidy rate. We assume that the subsidy introduction is permanent and it fully realizes in a single period.[17]

Other things being equal, a positive subsidy makes technology transfers more profitable, promoting a reallocation of local labor and local demand towards varieties produced locally using foreign technology. In the short run, this reallocation may generate static distortions that reduce social welfare. However, this negative impact may be compensated for by the effect of transfers on local learning and knowledge accumulation, generating positive dynamic welfare gains. The balance between static losses and dynamic gains defines an optimal level of subsidies.

Figure 6 illustrates this point. The left panel shows the short-run welfare effect (that is, the percentage change in consumption in the period in which the policy is introduced) induced by the range of subsidy rates on the horizontal axis. Subsidies to transfers generate substantial static losses that become progressively larger as the subsidy rate increases. The right panel depicts the overall gains, which account for the static distortion as well as the positive dynamic effect on learning and productivity growth. The overall gains display an inverted-u shape: Higher subsidy rates increase total discounted welfare up to an optimal subsidy rate, after which the static distortion dominates, and increasing the subsidy rate reduces total welfare. This combination of forces gives rise to an optimal subsidy rate, which we find to be equal to 14.1%. The corresponding welfare gains are equal to 0.84% of consumption per period.

[17] In other words, there is a period $\bar{t}$ such that $\bar{S}_t = 0$ for $t < \bar{t}$, and $\bar{S}_t = \bar{S} \geq 0$ for $t \geq \bar{t}$. We have numerically verified that optimizing the dynamic path of subsidies and their distribution across sectors does not generate substantial changes in welfare compared to a uniform and permanent subsidy. Therefore, we focus on this simpler subsidy scheme.

Figure 6: **Short-run and overall welfare gains from subsidizing technology transfers**



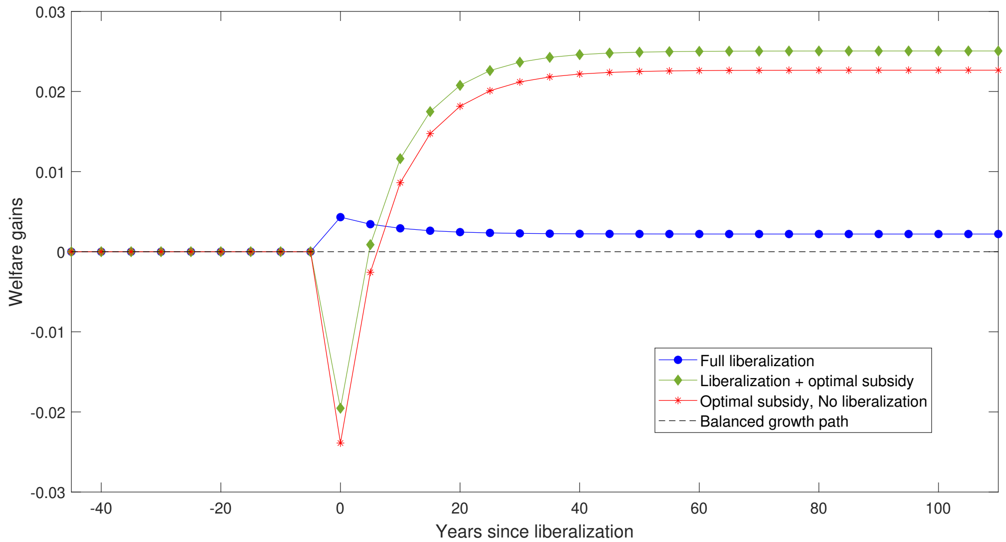
Notes: The left panel shows instantaneous consumption in the period in which the subsidy is introduced, in percentage deviation from the BGP. The right panel shows total discounted welfare in consumption-equivalent percentage deviation from the BGP.

Figure 7 displays the full dynamics of welfare when subsidies of technology transfers are introduced. The starred red line shows the dynamics with the optimal subsidy rate but no concurrent liberalization. Contrary to those induced by the liberalization (which are depicted in the marked blue line), these dynamics show a sharp drop in welfare on impact (-2.39%), followed by higher growth and large long-run gains that more than compensate for the short-run losses. In the long run, consumption is 2.27% higher compared to the initial BGP. Overall, the effect on total discounted welfare (+0.84%) is higher than the one obtained with the liberalization (+0.29%). The diamond-marked green line in the same graph shows the combined effect of the optimal subsidy and the liberalization being implemented at the same time. The effect of the two policies is nearly additive. Despite a 1.95% drop in welfare in the short run, the combined policies generate large long-run gains, with an overall effect on total discounted welfare of 1.14%.

7 Conclusions

Using a unique dataset on technology transfer contracts between foreign and Brazilian firms, we examined how trade policy affects technology diffusion. Our empirical findings show that higher tariffs significantly increase technology transfers and knowledge spillovers, as measured by patent citations, particularly among firms with limited foreign exposure and those near technology transfer

Figure 7: **Welfare gains from optimal subsidy to technology transfer**



Notes: The figure shows instantaneous consumption in each period under the full liberalization scenario (marked blue line), under the optimal subsidy to transfers and no liberalization (starred red line), and under the combined liberalization and subsidy scenario (diamond-marked green line), in percentage deviation from the BGP.

recipients. The rise in citations is concentrated among foreign firms that previously transferred technology to Brazil, suggesting that these transfers play a crucial role in facilitating knowledge diffusion within the domestic economy. Importantly, we rule out alternative explanations, such as foreign direct investment or supplier relationships, as the main drivers of this effect, reinforcing the conclusion that technology transfers are a key channel through which trade policy shapes knowledge diffusion.

These findings challenge the conventional view that trade liberalization always improves access to foreign ideas, showing instead that lower tariffs can reduce opportunities for domestic firms to absorb foreign knowledge. To explore the welfare implications of this result, we extended a trade and idea diffusion model to explicitly incorporate technology transfers and their role in knowledge diffusion. We calibrated the model to match the empirical responses of technology transfers and patent citations to changes in tariffs. Our quantitative results suggest that accounting for technology transfers significantly reduces the long-run welfare gains from trade liberalization, with long-term gains from openness shown to be lower than short-term gains. However, this result also highlights an opportunity for policy intervention due to the existence of a dynamic externality in technology transfers: combining trade liberalization with targeted subsidies for technology transfers can substantially enhance long-run welfare.

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Online Appendix
(for online publication only)

More Trade, Less Diffusion: Technology Transfers and the Dynamic Effects of Import Liberalization

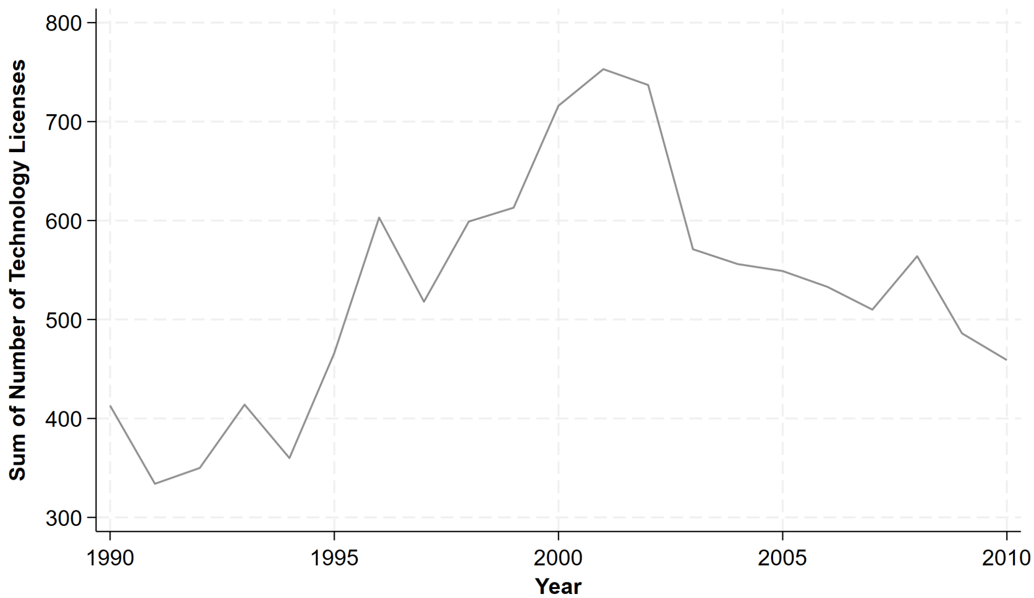
by Gustavo de Souza, Ruben Gaetani, and Martí Mestieri

March 2025

A Summary Statistics

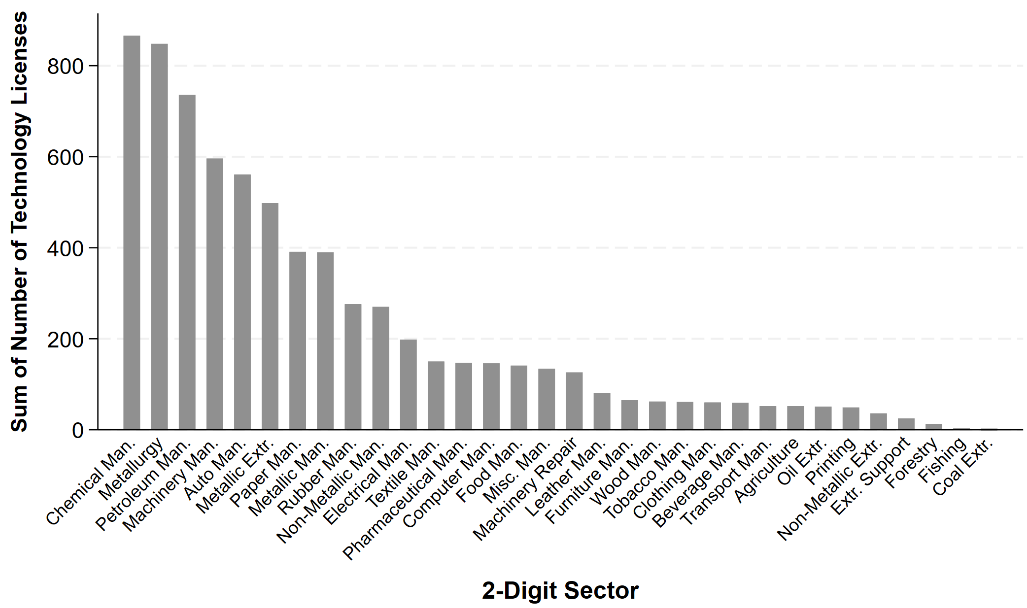
A.1 Summary Statistics of Technology Transfers

Figure A.1: **Number of technology transfers over time**



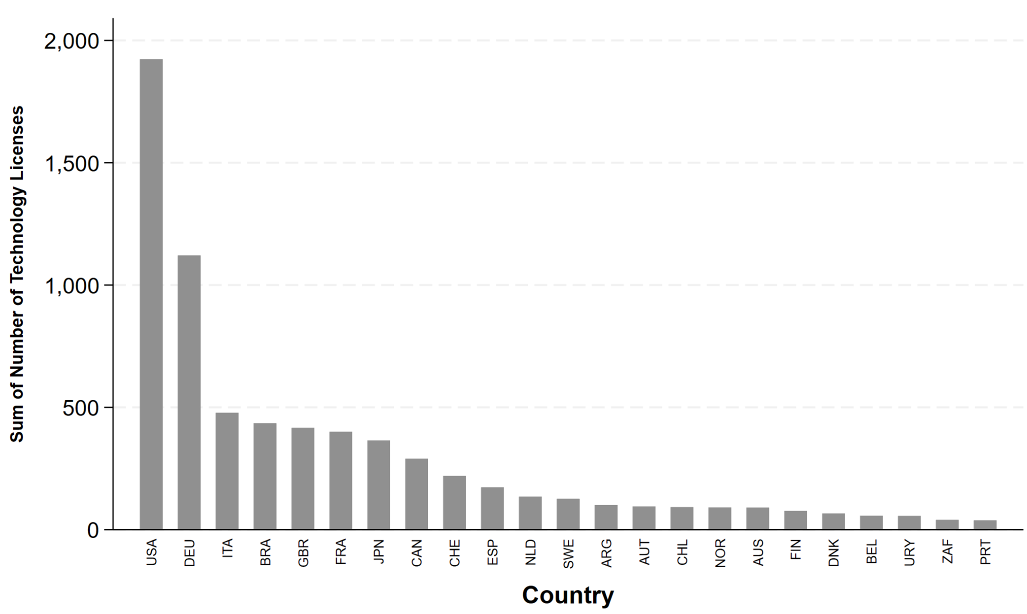
Notes: This figure displays the yearly number of technology transfers received by Brazilian firms.

Figure A.2: **Number of technology transfers by sector**



Notes: This figure shows the total number of technology transfers received by firms in different sectors.

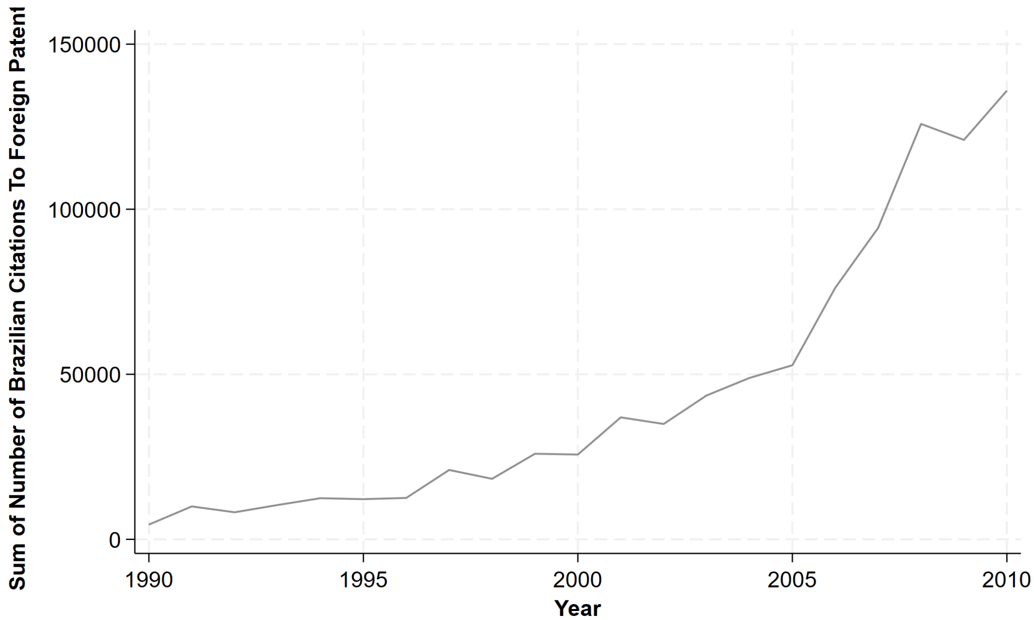
Figure A.3: **Number of technology transfers by country of origin**



Notes: This figure shows the number of technology transfers made according to the licensor's country of origin. The figure also includes technology transfers made between Brazilian firms.

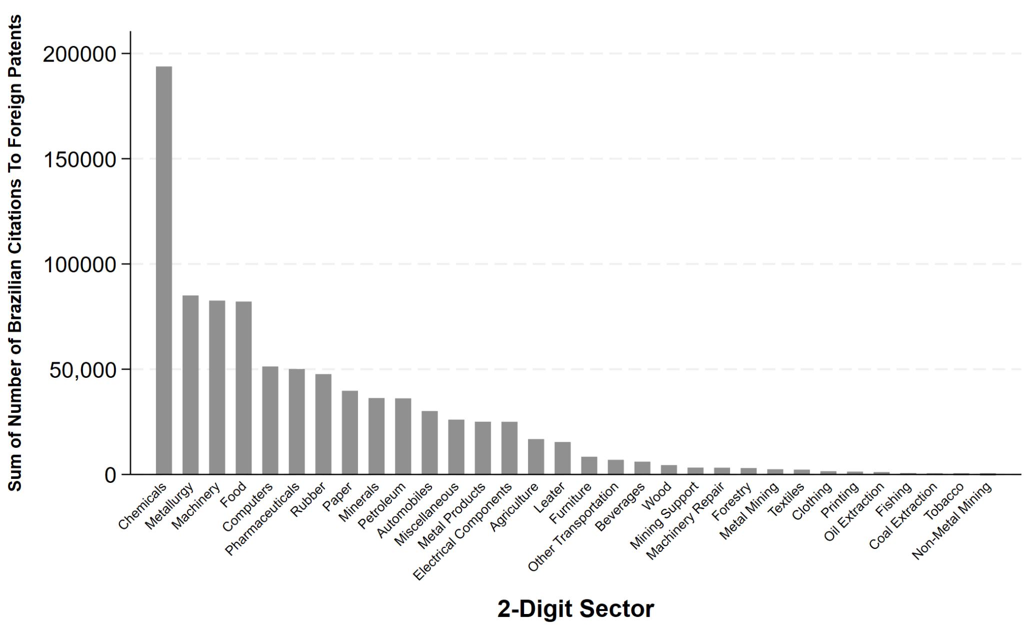
A.2 Summary Statistics of Patent Citations

Figure A.4: **Number of citations to foreign patents over time**



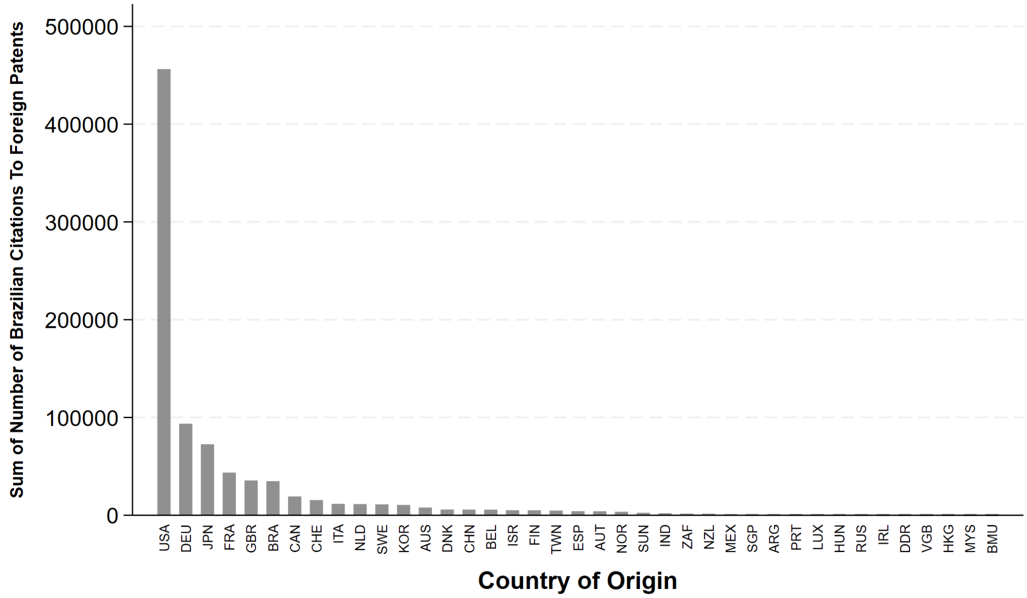
Notes: This figure displays the yearly number of citations made by Brazilian patents.

Figure A.5: **Total number of citations to foreign patents by sector**



Notes: This figure shows the total number of citations made by Brazilian patents according to the sector of the patent. We link citations to sectors using the crosswalk between International Patent Classification (IPC) fields and sectors created by Lybbert and Zolas (2014).

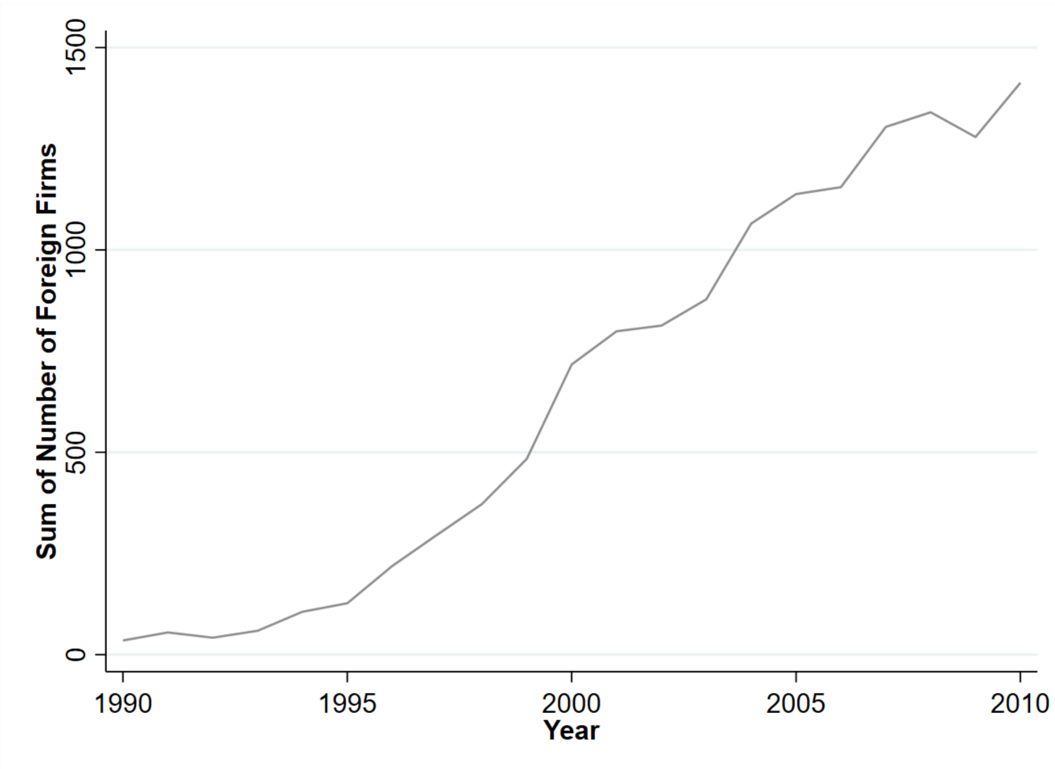
Figure A.6: **Total number of citations to foreign patents by country (most important countries)**



Notes: This figure shows the total number of citations made by Brazilian patents to patents in foreign countries.

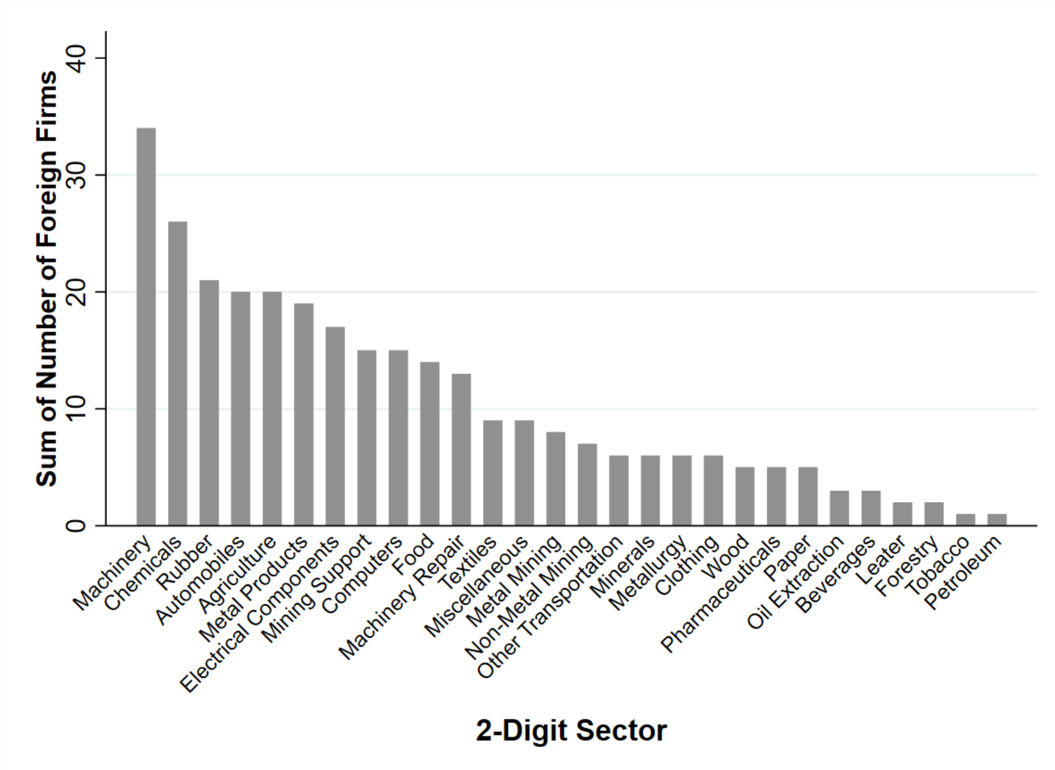
A.3 Summary Statistics of FDI

Figure A.7: **Number of firms owned by foreigners over time**



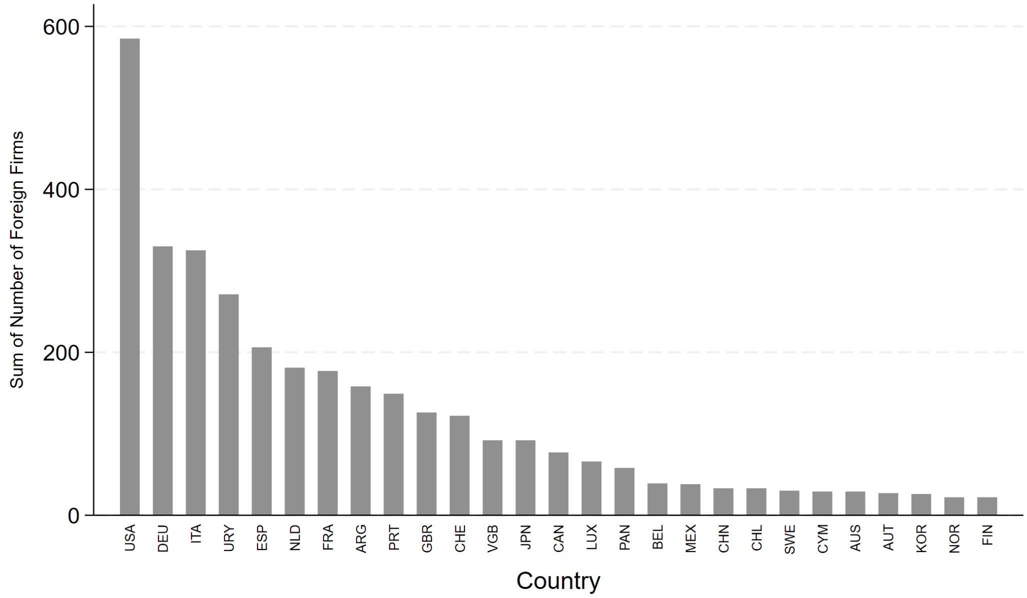
Notes: This figure shows the number of firms with at least one foreign partner per year.

Figure A.8: **Number of firms owned by foreigners by sector in 2010**



Notes: This figure shows the number of firms with at least one foreign partner per sector in 2010.

Figure A.9: **Number of firms owned by foreigners by country in 2010 (most important countries)**



Notes: This figure shows the number of firms with at least one foreign partner per country of the foreign partner in 2010.

B Empirics

B.1 Validation

Table B.1: **Tariff, political connections, and outcomes of the origin market**

Panel A: Tariffs and political connections				
	(1)	(2)	(3)	(4)
	Shr Fed. Procurement	*Shr Donation*	*log Procurement*	*log Campaign Contribution*
Tariff	-0.00310	-0.00374	1.478	-2.392
	(0.0235)	(0.0198)	(1.262)	(3.497)
N	3,146	858	1,103	654
R^2	0.599	0.792	0.837	0.734

Panel B: Tariffs and outcomes of the origin market				
	(1)	(2)	(3)	(4)
	log Employment	*Employment Share*	*log Value Added*	*Value Added Share*
Tariff	-0.673	-0.127	2.668	-0.0226
	(2.008)	(0.258)	(1.625)	(0.188)
N	4176	4176	4176	4176
R^2	0.994	0.990	0.996	0.958

Notes: Panel A shows the correlation between import tariffs and sectoral outcomes in Brazil. The table displays the coefficient of the following regression: $y_{s,t} = \beta\tau_{s,t} + \mu_s + \mu_t + \epsilon_{s,t}$, where $y_{s,t}$ is an outcome of sector s in Brazil in year t, $\tau_{s,t}$ is the average import tariff against products of sector s, μ_s is a sector fixed effect, and μ_t is an year fixed effect. The left-hand side variables are the share of firms that received a federal procurement (column 1), the share of firms that made a campaign contribution (column 2), the log of total procurement contracts by the federal government (column 3), and the log of total campaign contribution (column 4). Panel B shows the correlation between import tariffs and outcomes of the country of origin using model 1. The left-hand side variables are log employment (column 1), sectoral employment share (column 2), log value added (column 3), and sectoral value added share (column 4) for the sector in the origin country. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B.2 First Stage

Table B.2: **First Stage**

	(1)	(2)	(3)	(4)
	Tariff	*Tariff*	*Tariff*	*Tariff*
Instrument	0.994***	0.998***	0.687***	0.699***
	(0.000192)	(0.000125)	(0.0121)	(0.0123)
Country-Sector FE	N	Y	Y	Y
Country-Year FE	N	N	Y	Y
Sector-Year FE	N	N	Y	Y
Income-Region-Year FE	N	N	N	Y
N	1,392,641	1,392,527	1,392,523	1,148,854
R^2	0.996	0.998	0.999	0.999
F	26,751,637.6	64,037,226.0	3,213.7	3,243.0

Notes: This table presents the first-stage estimates, defined in Equation (2), using different sets of controls. In Column 1, there are no controls. Column 2 adds country-sector fixed effects. Column 3 includes country-year and sector-year fixed effects, while column 4 adds continent-income group-year fixed effects. Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B.3 Heterogeneous Treatment Effect

We use causal forest to identify the heterogeneity in treatment effects. The goal is to estimate the effect of the tariff conditional on a set of characteristics of the origin country or the home sector in Brazil. In technical terms, we estimate the Conditional Average Treatment Effect (CATE): $E\left[Y_{1,c,s} - Y_{0,c,s} | Z_{c,s} = z\right]$, where $Y_{1,c,s}$ and $Y_{0,c,s}$ denote the citations to or technology transfer from country c in sector s with and without a tariff increase, while X is a set of observable characteristics. Causal forest, as proposed by Wager and Athey, 2018 and Athey and Imbens, 2019, allows for a fully non-parametric relationship between the treatment effect and the set of controls $Z_{c,s}$.

We follow the implementation in Wager and Athey (2018). Because these methods are based in randomized control trials, first we re-write the model in Equation (1) in long-difference (as in Britto et al., 2022):

$$\Delta y_{c,s} = \beta\left(Z_{c,s}\right) \Delta \tau_{c,s}^{inst} + \mu_c + \mu_s + \epsilon_{c,s}, \tag{B.1}$$

where $\Delta y_{c,s}$ is the difference in citations or technology licenses between 2010 and 1990, $\Delta \tau_{c,s}$ is the change in tariffs, μ_c is a country fixed effect, and μ_s is a sector fixed effect. $\beta\left(Z_{c,s}\right)$ is the treatment effect conditional on variables $Z_{c,s}$. Using the Frisch–Waugh–Lovell theorem (Frisch and Waugh, 1933), we can re-write as:

$$\Delta \tilde{y}_{c,s} = \beta\left(Z_{c,s}\right) \Delta \tilde{\tau}_{c,s}^{inst} + \tilde{\epsilon}_{c,s}$$

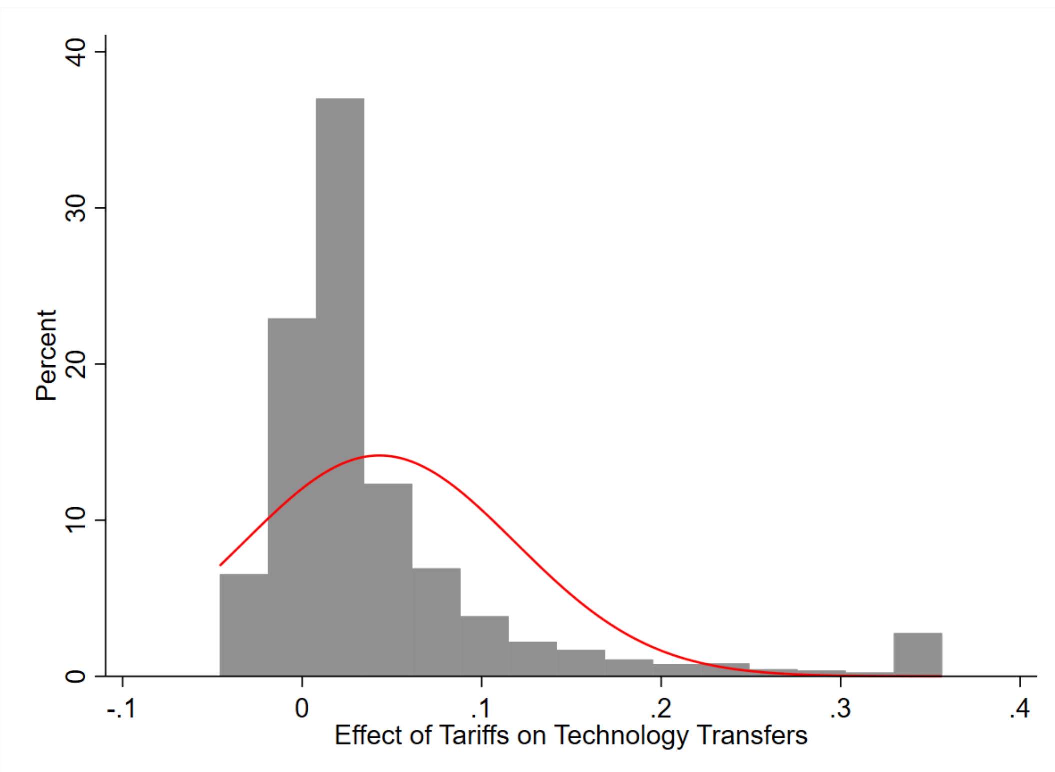
where $\Delta \tilde{y}_{c,s}$ is the residual of a regression of the fixed effects, μ_c and μ_s, on $\Delta y_{c,s}$.

The term $Z_{c,s}$ contains the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c until 1990.

As the name suggests, in a causal forest approach, $\beta(Z_{c,s})$ is calculated as the average of several causal trees. Each causal tree is calculated as follows. First, the sample is randomly divided into two groups: one is used to estimate the sample splits (leafs); the other, used for estimation of the CATE, which is curiously called "honest approach". Second, a random set of the covariates $Z_{c,s}$ is selected. Third, the algorithm searches for a split of the sample to maximize the difference in treatment effects in each of the sub-groups, ensuing that in each leaf there are treatments and controls. The more a variable is used to split the sample, larger is its importance to predict heterogeneity in the treatment effect. Forth, the process continues until the leaf or the heterogeneity in treatment effects between leafs is too small. This process is repeated 10,000 times and averaged out on the estimation sample.

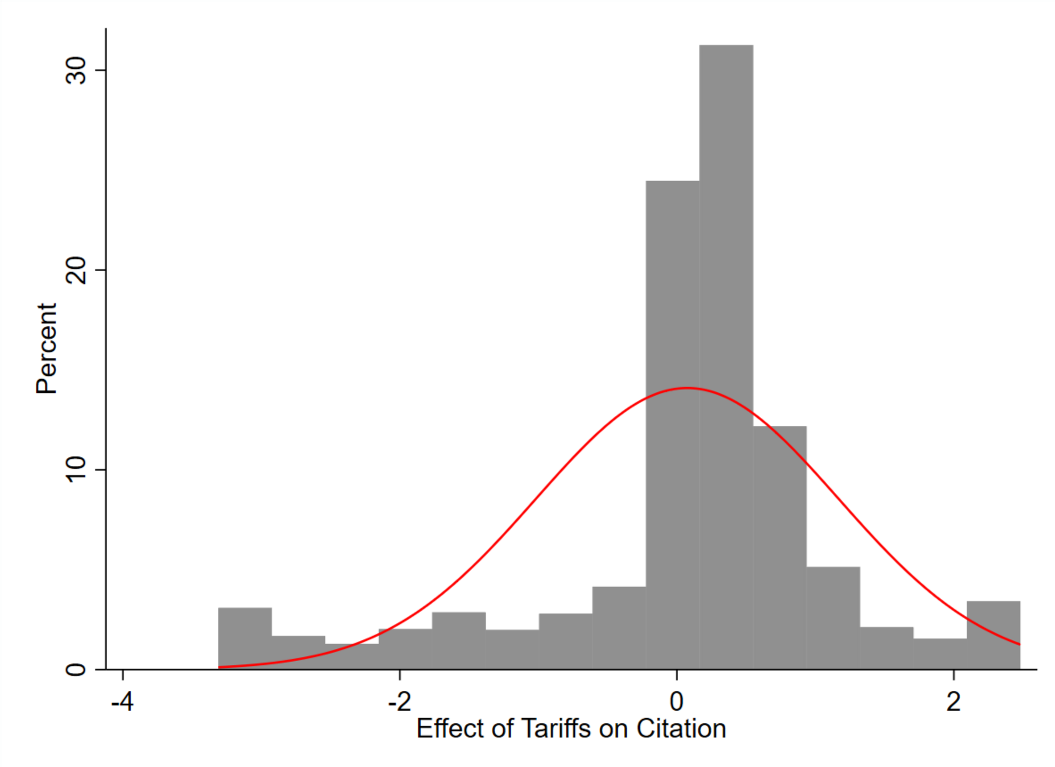
Distribution of treatment effect. Figure B.11 shows that there is a large degree of heterogeneity of the effect of tariffs on technology transfers and citations.

Figure B.10: **Distribution of the CATE of tariffs on technology transfers**



Notes: This figure shows the histogram of the conditional average treatment effect, $\beta(Z_{c,s})$, capturing how tariffs affect technology transfers. The covariates include the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c until 1990.

Figure B.11: **Distribution of the CATE of tariffs on citations**



Notes: This figure shows the histogram of the conditional average treatment effect, $\beta(Z_{c,s})$, capturing how tariffs affect citations. The covariates include the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c until 1990.

Correlation of treatment effects. Tables B.3 and B.4 show the correlation of different observables of the market of origin with the CATE of tariffs on technology transfer or citations. The effect of tariffs on technology transfer and citations is larger when the origin country has larger GDP and patent stock. The effect is also larger if the Brazilian sector is highly innovative or has a history of technology transfers.

Heterogeneity by sector. Figures B.12 and B.13 shows the average CATE by sector. The extractive sectors, chemicals, and automobile manufacturing are the ones most affected.

Heterogeneity by Country. Figure B.14 and B.15 shows the countries with largest CATE.

Table B.3: **Correlation between Effect of Tariff on Technology Transfers and Pre-Period Characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\beta_{tech.transf.}$	$\beta_{tech.transf.}$	$\beta_{tech.\ transf.}$	$\beta_{tech.transf.}$	$\beta_{tech.transf.}$	$\beta_{tech.transf.}$	$\beta_{tech.transf.}$
$\beta_{citation}$	0.0144***						
	(0.000415)						
log(GDP Per Capita)		0.0144***					0.0152***
		(0.000379)					(0.000433)
IHS(Patents Origin)			0.00208***				-0.00091***
			(0.000206)				(0.000280)
IHS(Patents BR)				-0.00430***			-0.00575***
				(0.000244)			(0.000290)
IHS(Citations)					0.0104***		-0.00780***
					(0.00239)		(0.00271)
IHS(Tech. Transf.)						0.0487***	0.0317***
						(0.00597)	(0.00616)
N	54,379	41,862	54,379	54,379	54,379	54,379	41,862
R^2	0.022	0.033	0.002	0.006	0.000	0.001	0.045

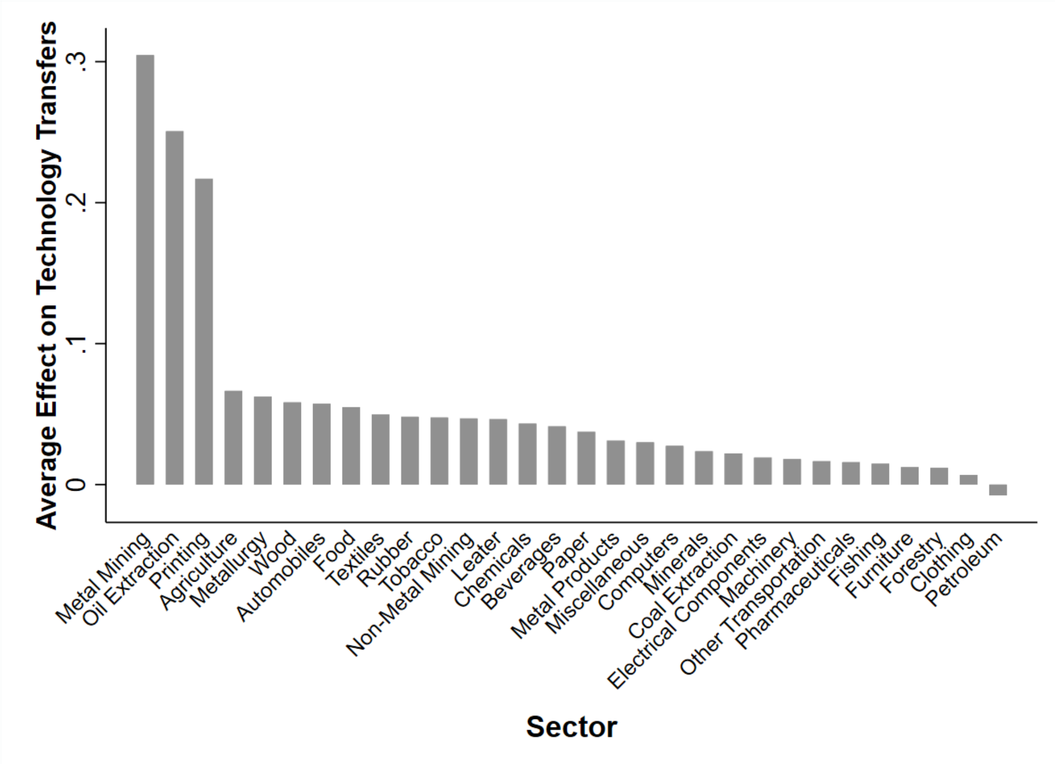
Notes: This table presents the correlation between the effect of tariff on technology transfers and pre-period characteristics. Each column represents a different specification where the dependent variable is the effect of tariffs on technology transfers. Standard errors are in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.4: **Correlation between Effect of Tariff on Citations and Pre-Period Characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$
$\beta_{tech.\ transf.}$	1.503***						
	(0.0434)						
log(GDP Per Capita)		-0.0690***					-0.0930***
		(0.00157)					(0.00170)
IHS(Patents Origin)			0.0286***				0.0336***
			(0.00211)				(0.00110)
IHS(Patents BR)				0.00942***			0.0582***
				(0.00250)			(0.00114)
IHS(Citations)					0.147***		-0.0640***
					(0.0244)		(0.0107)
IHS(Tech. Transf.)						0.0392	-0.0702***
						(0.0611)	(0.0243)
N	54,379	41,862	54,379	54,379	54,379	54,379	41,862
R^2	0.022	0.044	0.003	0.000	0.001	0.000	0.142

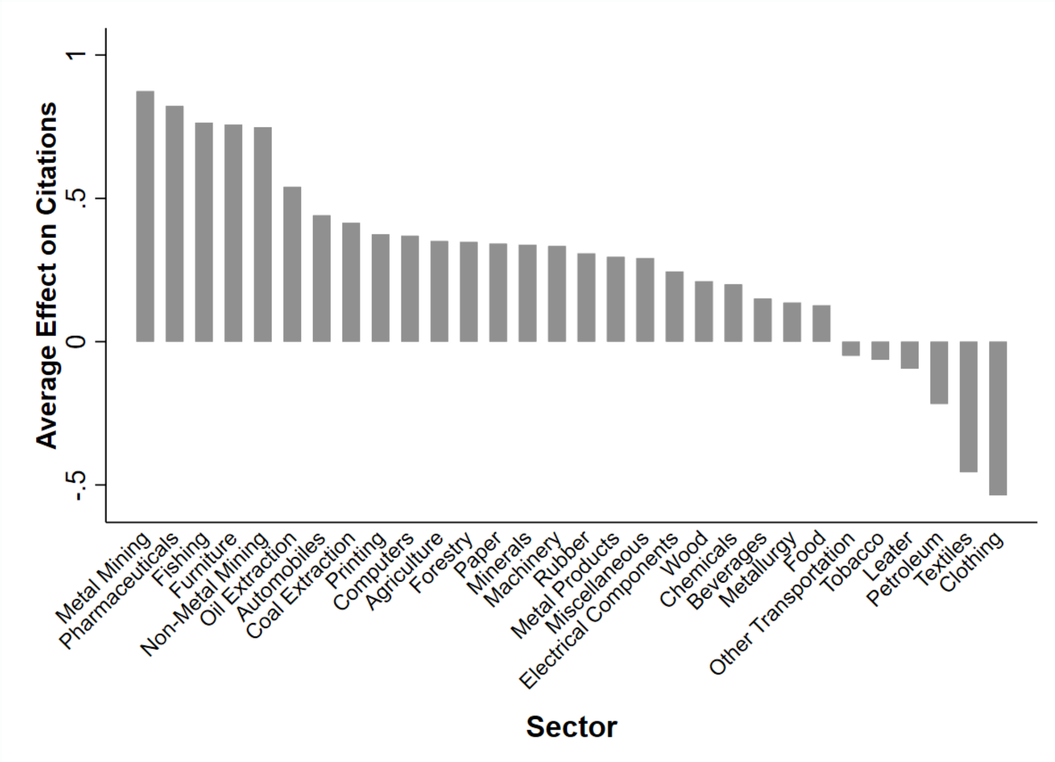
Notes: This table presents the correlation between the effect of tariff on citations and pre-period characteristics. Each column represents a different specification where the dependent variable is the effect of tariffs on citations. Standard errors are in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Figure B.12: **Effect of tariffs on technology transfers by sector**



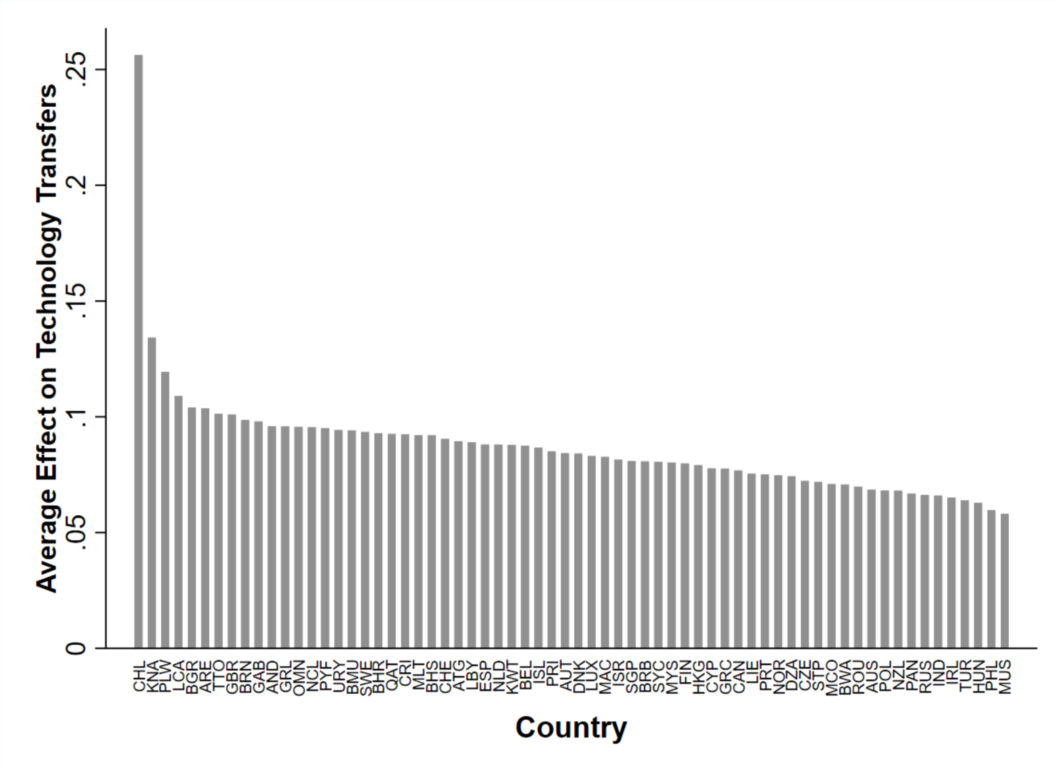
Notes: This figure shows the average of the conditional average treatment effect, $\beta(Z_{c,s})$, capturing how tariffs affect technology transfers by sector. For each sector we calculate $E_s\left[\beta(Z_{c,s})\right]$. The covariates include the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c until 1990.

Figure B.13: **Effect of tariffs on citations by sector**



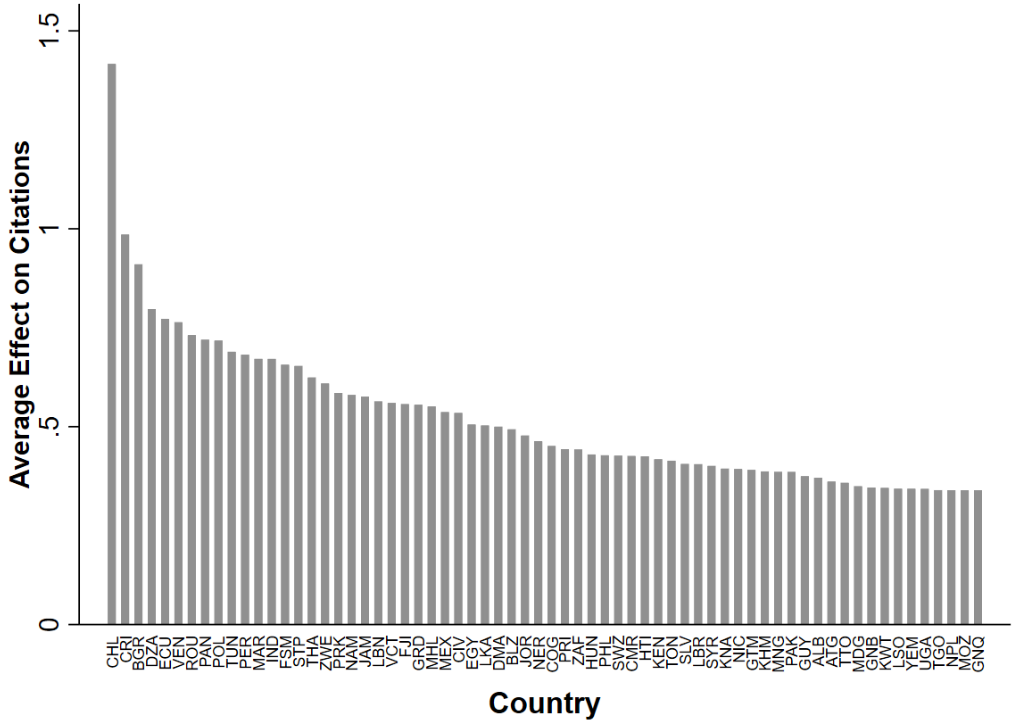
Notes: This figure shows the average of the conditional average treatment effect, $\beta(Z_{c,s})$, capturing how tariffs affect citations by sector. For each sector we calculate $E_s\left[\beta(Z_{c,s})\right]$. The covariates include the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c until 1990.

Figure B.14: **Effect of tariffs on technology transfers by country**



Notes: This figure shows the average of the conditional average treatment effect, $\beta(Z_{c,s})$, capturing how tariffs affect technology transfers by country. For each country we calculate $E_c\left[\beta(Z_{c,s})\right]$. The covariates include the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c until 1990.

Figure B.15: **Effect of tariffs on citation by country**



Notes: This figure shows the average of the conditional average treatment effect, $\beta(Z_{c,s})$, capturing how tariffs affect citation by country. For each country we calculate $E_c\left[\beta(Z_{c,s})\right]$. The covariates include the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c until 1990.

B.4 OLS Regressions

Table B.5: **Import tariffs and technology diffusion with OLS regressions**

	(1)	(2)	(3)	(4)
	IHS N. Tech. Transfers	*IHS Citations*	*IHS. Cit. to Non-Licensor*	*IHS Cit. to Licensor*
Tariff	0.0950**	0.416***	-0.0314	0.468***
	(0.0393)	(0.0673)	(0.0379)	(0.0594)
N	1,271,697	1,271,697	1,271,697	1,271,697
R^2	0.000	0.039	0.012	0.049

Notes: This table reports the coefficients of regressing different measures of technology transfers to Brazil on tariffs, according to the model in Equation (1) without using any instrument. All specifications use the inverse hyperbolic sine transformation. The left-hand side variable is the number of technology transfers (column 1), the number of citations (column 2), the number of citations to firms that never sent technology to Brazil (column 3), and the number of citations to patents of firms sending technology to Brazil or that are cited by them (column 4). Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B.5 Controls

Table B.6: **Import tariffs and technology diffusion under different controls**

	(1)	(2)	(3)	(4)	(5)	(6)
	IHS	*IHS*	*IHS*	*IHS*	*IHS*	*IHS*
	N.Tech.	*Citations*	*N.Tech.*	*Citations*	*N.Tech.*	*Citations*
Tariff	0.105**	0.651***	0.143**	0.781***	0.107**	0.610***
	(0.0483)	(0.118)	(0.0592)	(0.125)	(0.0486)	(0.108)
Income-Region FE	N	N	Y	Y	N	N
Lagged LHS	N	N	N	N	Y	Y
N	1,392,523	1,392,523	1,148,854	1,148,854	1,392,523	1,392,523

Notes: This table reports the coefficients of regressing different measures of technology diffusion on tariffs, according to the model in Equation (1) using the first-stage regression 2. All specifications use the inverse hyperbolic sine transformation. Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B.6 Sample Selection

Table B.7: **Import tariffs and technology diffusion constraining sample to high-income countries**

	(1)	(2)	(3)	(4)
	IHS Transfers	*IHS Citations*	*IHS Cit. to Non-Licensor*	*IHS Cit. to Licensor*
Tariffs	0.489**	0.852***	0.104**	0.739***
	(0.211)	(0.218)	(0.0466)	(0.219)
N	381,204	381,204	381,204	381,204

Notes: This table reports the coefficients of regressing different measures of technology diffusion on tariffs, according to the model in Equation (1) using the first-stage regression 2. All specifications use the inverse hyperbolic sine transformation. The sample is limited to high-income countries according to the world bank definition. Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B.7 Alternative Functional Forms

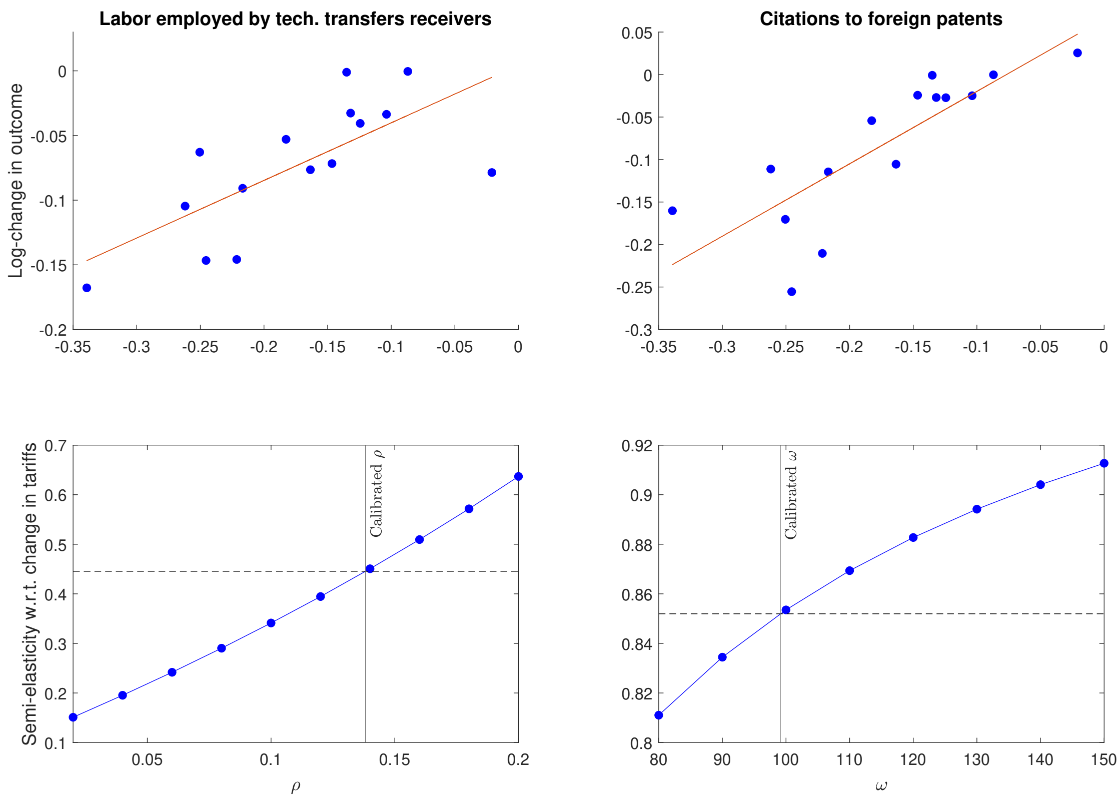
Table B.8: Effect of tariffs on international technology licensing

	(1) *At Least One Tech. Transf.*	(2) *At Least One Citation*	(3) *Percentile of N. Tech. Transf.*	(4) *Percentile of Citations*	(5) *N. Tech. Transf.*	(6) *Citations*
Tariffs	0.0847***	0.539***	8.382***	51.62***	0.229**	0.887***
	(0.0301)	(0.0838)	(2.976)	(8.011)	(0.0953)	(0.190)
N	1,178,000	1,178,000	1,178,000	1,178,000	1,178,000	1,178,000

Notes: This table reports the coefficients of regressing different measures of technology diffusion on tariffs, according to the model in Equation (1) using the first-stage regression 2. Column 1 shows the effect of tariffs on an indicator taking value of one for at least one technology transfer, column 2 on an indicator for at least one citation, column 3 on the percentile of technology transfer, column 4 on the percentile of citations, column 5 on the number of technology transfers, and column 6 on the number of citations. Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

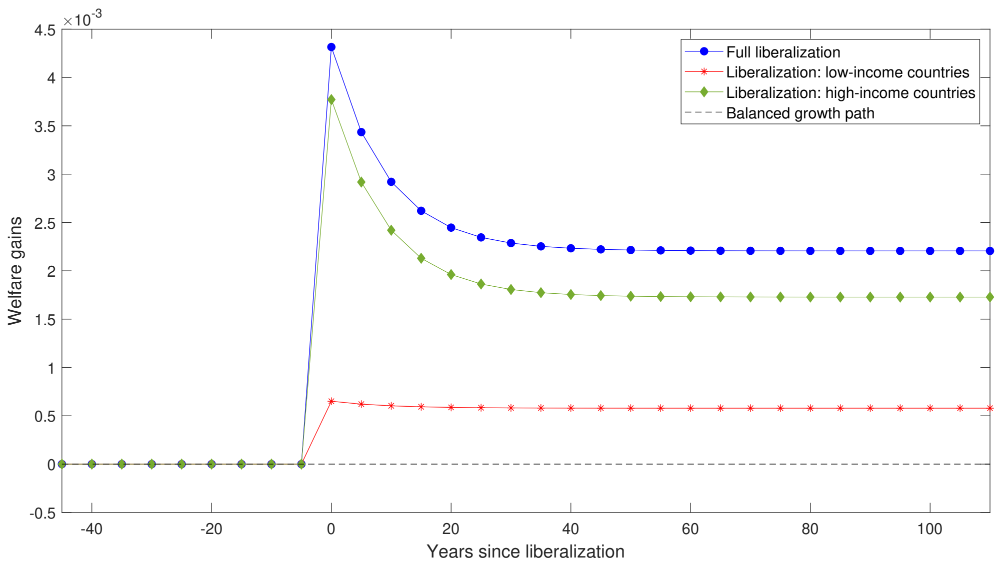
C Additional model figures

Figure C.16: **Identification of ρ and ω_L**



Notes: The top panels show the relationship between change in tariffs (horizontal axis) and % change in the outcome across ISIC-3 sectors in the model: Labor employed by licensees (top-left panel) and number of patent citations to foreign grants (top-right panel). The regression lines match the empirical semi-elasticities by construction. The bottom panels show the corresponding semi-elasticities for a range of values of rho (bottom-left panel) and ω_T (bottom-right panel).

Figure C.17: **Welfare gains from liberalization: Full vs. partial liberalization**



Notes: The figure shows instantaneous consumption in each period under the full liberalization scenario (marked blue line), under a liberalization that only involves low-income foreign countries (starred red line), and under a liberalization that only involves high-income foreign countries (diamond-marked green line), in percentage deviation from the BGP.

D Derivations

In this section, we provide details on the derivations of the equilibrium conditions and results of the model presented in Section 5.

D.1 Prices and Sectoral Demand

Letting $\mathcal{C}_t^i$ be final consumption in country i at time t, and letting $P_t^{i,k}$ be the price aggregator of sector k, total demand for sector k satisfies

$$C_t^{i,k} = \left(\frac{\mathcal{P}_t^i}{P_t^{i,k}}\right)^{\sigma} \mathcal{C}_t^i, \tag{D.2}$$

where $C_t^{i,k} = \left(\int_0^1 c_t^{i,k}(s)^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}s\right)^{\frac{\epsilon}{\epsilon-1}}$. The price aggregator of final consumption, $\mathcal{P}_t^i$, defined as $\mathcal{P}_t^i \mathcal{C}_t^i = \sum_k C_t^{i,k} P_t^{i,k}$, is equal to

$$\mathcal{P}_t^i = \left[\sum_k (P_t^{i,k})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{D.3}$$

Similarly, demand of variety s in sector k satisfies

$$c_t^{i,k}(s) = \left(\frac{P_t^{i,k}}{p_t^{i,k}(s)}\right)^{\epsilon} C_t^{i,k}, \tag{D.4}$$

while the sectoral price aggregator is equal to

$$P_t^{i,k} = \left(\int_0^1 (p_t^{i,k}(s))^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}. \tag{D.5}$$

The assumptions on two-stage pricing imply that each variety in each country will only be supplied by the producer with the lowest marginal cost, that will charge the optimal markup under monopolistic competition. Since the derivation of the price level and expenditure shares in H and D are otherwise identical to the standard Eaton-Kortum model, in what follows we focus on the derivations for B.

For each variety s, the price faced by consumers in country B is equal to

$$p_t^{B,k}(s) = \frac{\epsilon}{\epsilon-1} \times \min\left\{\frac{w_t^B}{q_t^{B,k}(s)}, \frac{w_t^B d_t^k}{q_t^{T,k}(s)}, \frac{w_t^H \tau_t^{H\to B,k}}{q_t^{X,k}(s)}, \frac{w_t^D \tau_t^{D\to B,k}}{q_t^{D,k}(s)}\right\}. \tag{D.6}$$

The cumulative distribution function of prices in sector k in country B is

$$Pr\left\{p_t^{B,k}(s) \le p\right\} = Pr\left\{\min\{p_t^{i\to B,k}(s) \le p\}\right\} = 1 - Pr\left\{\frac{\epsilon w_t^{i\to B}\tau_t^{i\to B,k}}{(\epsilon-1)q_t^{i,k}(s)} > p,\, \forall\, i\right\}, \tag{D.7}$$

where $w_t^{i\to B}$ denotes the relevant wage that applies to source i in Brazil, and $\tau_t^{i\to B,k}$ is equal to d_t^k whenever $i = T$. Rearranging:

$$Pr\left\{p_t^{B,k}(s) \le p\right\} = 1 - Pr\left\{\frac{(\epsilon-1)q_t^{i,k}(s)}{\epsilon w_t^{i\to B}\tau_t^{i\to B,k}} < \frac{1}{p},\, \forall\, i\right\} = 1 - \exp\left\{-p^{-\theta}\left(\frac{\epsilon}{\epsilon-1}\right)^{-\theta} G_t^{B,k}\right\}, \tag{D.8}$$

where $G_t^{B,k}$ is defined as:

$$G_t^{B,k} \equiv G^B\left(\lambda_t^{B,k}(w_t^B)^{-\theta}, \lambda_t^{T,k}(w_t^B d_t^k)^{-\theta}, \lambda_t^{X,k}(w_t^H \tau_{H\to B}^{k,t})^{-\theta}, \lambda_t^{D,k}(w_t^D \tau_{D\to B}^{k,t})^{-\theta}\right). \tag{D.9}$$

In Equation (D.9), $G^B(\cdot)$ denotes the correlation function across the four productivity distributions, which in this case is defined as

$$G^B(x_B, x_T, x_X, x_D) \equiv x_B + \left[x_T^{\frac{1}{1-\rho}} + x_X^{\frac{1}{1-\rho}}\right]^{1-\rho} + x_D. \tag{D.10}$$

Integrating over all prices with respect to the distribution in Equation (D.8), we obtain the price index for sector k:

$$P_t^{B,k} = \frac{\epsilon}{\epsilon-1}(G_t^{B,k})^{-\frac{1}{\theta}}\Gamma\left(\frac{1-\epsilon+\theta}{\theta}\right)^{\frac{1}{1-\epsilon}}, \tag{D.11}$$

where Γ denotes the Gamma function. This expression can then be plugged into Equation (D.3) to obtain the overall price index.

Finally, the share of varieties consumed in B that originate from i (which, due to the standard properties of the Eaton-Kortum model, also corresponds to the expenditure share from B to i) is equal to:

$$\pi_t^{i\to B,k} = \frac{\lambda_t^i(w_t^{i\to B}\tau_t^{i\to B,k})^{-\theta}\frac{\partial G_t^{B,k}}{\partial i}}{G_t^{B,k}}, \tag{D.12}$$

where $\frac{\partial G_t^{B,k}}{\partial i}$ denotes the partial derivative of $G_t^{B,k}$ with respect to $\lambda_t^{i,k}(w_t^{i\to B}\tau_t^{i\to B,k})^{-\theta}$.

The derivation for high- and low-income foreign countries is analogous to the one for Brazil, with the exception that varieties in those countries cannot be provided via a technology transfer. Hence, the price faced for variety s in sector k by the representative consumer in country $i \in \{H, D\}$

is given by

$$p_t^{i,k}(s) = \frac{\epsilon}{\epsilon - 1} \times \min\left\{ \frac{w_t^B \tau_t^{B\to i,k}}{q_t^{B,k}(s)}, \frac{w_t^H \tau_t^{H\to i,k}}{q_t^{X,k}(s)}, \frac{w_t^D \tau_t^{D\to i,k}}{q_t^{D,k}(s)} \right\}. \tag{D.13}$$

Since, in this case, all source distributions are independent, expenditure shares can be written as

$$\pi_t^{j\to i,k} = \frac{\lambda_t^j (w_t^j \tau_t^{j\to i,k})^{-\theta}}{G_t^{i,k}}, \tag{D.14}$$

where

$$G_t^{i,k} \equiv \sum_{j\in\{B,H,D\}} \lambda_t^{j,k} (w_t^j \tau_t^{j\to i,k})^{-\theta}.$$

Analogous expressions can be obtained for sectoral price indexes ($P_t^{i,k}$) and the overall price aggregator ($\mathcal{P}_t^i$).

D.2 Evolution of the productivity distribution in Brazil

The process described by Equations (12) and (13) gives rise to the following law of motion for the cumulative distribution function (CDF) of productivity of local entrepreneurs in Brazil, $F_t^{k,B}(q)$:

$$1 - F_{t+\Delta}^{B,k}(q) = [1 - F_t^{B,k}(q)] + \\ F_t^{B,k}(q) \int_t^{t+\Delta} \left[\int A_\tau^{X\to B,k}\left(\frac{q}{q'^\beta}\right) \mathrm{d}F_\tau^{X\to B,k}(q') + \int A_\tau^{T\to B,k}\left(\frac{q}{q'^\beta}\right) \mathrm{d}F_\tau^{T\to B,k}(q') \right] \mathrm{d}\tau,$$

where $F_t^{X\to B,k}$ and $F_t^{T\to B,k}$ are the distribution of productivity of *active* foreign exporters from high-income countries (X) and providers of technology (T), respectively, who sell their products in B.

Rearranging, taking the limit for $\Delta \to 0$, and using the definition of $A_t^{i\to B,k}(z)$ in Equation (12), we obtain the following differential equation describing the dynamics of the local CDF:

$$\frac{\mathrm{d} \ln F_t^{B,k}(q)}{\mathrm{d}t} = -q^{-\theta} \Lambda_t^{B,k}, \tag{D.15}$$

where

$$\Lambda_t^{B,k} \equiv \alpha_t^k \left[\pi_t^{X\to B,k} \int_0^\infty x^{\beta\theta} \mathrm{d}F_t^{X\to B,k}(x) + \omega_T \pi_t^{T\to B,k} \int_0^\infty x^{\beta\theta} \mathrm{d}F_t^{T\to B,k}(x) \right], \tag{D.16}$$

where the right-hand-side is equivalent to the right-hand-side of Equation (14).

Solving the differential equation in (D.15), we obtain

$$F_t^{B,k}(q) = F_0^{B,k}(q) \exp\left(-q^{-\theta} \int_0^t \Lambda_\tau^{B,k} \mathrm{d}\tau\right). \tag{D.17}$$

Using Equation (9) to replace $F_0^{B,k}(q)$ and letting $\lambda_t^{B,k} = \lambda_0^{B,k} + \int_0^t \Lambda_\tau^{B,k} \mathrm{d}\tau$ yields

$$F_t^{B,k}(q) = \exp\left(-\lambda_t^{B,k} q^{-\theta}\right). \tag{D.18}$$

This expression verifies that the CDF of best productivities among B producers is indeed Fréchet with shape parameter θ and with scale parameter $\lambda_t^{B,k}$, whose law of motion satisfies

$$\dot{\lambda}_t^{B,k} = \Lambda_t^{B,k}, \tag{D.19}$$

implying Equation (14).

It is straightforward to show that

$$\int_0^\infty x^{\beta\theta} \mathrm{d}F_{i\to B}^{k,t}(x) = \Gamma(1-\beta) \left(\frac{\lambda_t^{i,k} \frac{\partial G_t^{B,k}}{\partial i}}{\pi_{i\to B}^{k,t}}\right)^\beta. \tag{D.20}$$

Hence, the law of motion for $\lambda_t^{B,k}$ can be written as

$$\dot{\lambda}_t^{B,k} \propto \alpha_t^k \left[\pi_{X\to B}^{k,t} \left(\frac{\lambda_t^{X,k} \frac{\partial G_t^{B,k}}{\partial X}}{\pi_{X\to B}^{k,t}}\right)^\beta + \omega_T \pi_{T\to B}^{k,t} \left(\frac{\lambda_t^{T,k} \frac{\partial G_t^{B,k}}{\partial T}}{\pi_{T\to B}^{k,t}}\right)^\beta\right]. \tag{D.21}$$

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