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

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September 2024

Abstract

How does international trade affect technology diffusion? We show that tariff increases in Brazil lead to more international technology transfers to Brazilian firms and more citations to foreign patents. The highest increase in citations occurs among firms located near those receiving technology transfers, and it is driven largely by citations to firms transferring technology to Brazil. These findings suggest that import tariffs can facilitate the diffusion of foreign technology by promoting technology transfers. We quantify this effect in a growth model that incorporates trade, technology transfers, and their effect on diffusion. When tariffs in Brazil rise, foreign firms transfer their technology rather than export their products, boosting the diffusion of foreign knowledge. An optimal subsidy to technology transfers significantly amplifies the welfare gains from trade liberalization.

JEL Codes: O33, O40

Key Words: technology diffusion, growth, technology transfers, international trade

*The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Chicago or the Federal Reserve System. Gaetani gratefully acknowledges financial support from the Institute of Management and Innovation Research Grant. All errors are our own.

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1 Introduction

Dynamic gains from trade can surpass static gains, as exposure to foreign ideas through trade enhances domestic productivity (e.g., Lucas, 2009, Alvarez et al., 2013, Sampson, 2016; Buera and Oberfield, 2020; Perla et al., 2021). However, despite the well-recognized role of trade in driving innovation and knowledge diffusion, direct evidence of how these channels operate remains limited.

This paper takes a first step in addressing this gap by formalizing a novel channel for dynamic gains from trade through technology diffusion and providing micro-level measurements to quantify its impact. We focus on technology transfer contracts, a form of technology diffusion that is particularly relevant for emerging economies. These contracts, such as technology licensing or technical assistance agreements, involve intentional knowledge transfers between firms across borders. This paper investigates how trade policy, particularly import tariffs, affects these technology transfers and international knowledge diffusion, and how this channel contributes to dynamic welfare gains from trade liberalization.

Our empirical findings reveal a perhaps surprising outcome: higher tariffs lead to a significant increase in technology transfers from foreign to domestic firms, along with substantial knowledge spillovers, boosting the diffusion of foreign ideas within the local economy. Using a quantitative model calibrated to match the empirical responses, we show that incorporating technology transfers challenges the predictions from traditional trade and growth theories, resulting in dynamic gains from openness that are *compressed* relative to static gains. Subsidies to technology transfers emerge as an effective policy remedy: setting subsidies to the optimal level increases dynamic gains from trade liberalization by a factor of three.

Our analysis leverages a unique and comprehensive dataset that covers all technology transfer contracts between Brazilian and foreign firms (de Souza, 2020), combined with detailed information on patent citations and tariffs across countries and sectors. We examine the impact of trade policy—particularly changes in import tariffs in the context of Brazil's trade liberalization since the early 1990s—on the number of technology transfers and the diffusion of foreign knowledge. To achieve identification, we follow the strategy proposed by Boehm et al. (2023), exploiting the plausibly exogenous variation in import tariffs on minor trade partners under Most-Favored Nation (MFN) status.

We present robust evidence that tariffs significantly increase the number of technology transfers, with this effect being primarily driven by contracts related to technological assistance. We also find that higher tariffs result in more citations of foreign patents by Brazilian firms, particularly patents owned or cited by technology transfer providers. The increase in diffusion is most pronounced among firms located geographically near the recipients of technology transfers and among firms with limited exposure to foreign markets (i.e., non-importers and non-exporters). Moreover, using a causal forest approach, we show that country-sectors which experience a greater increase in technology transfers in response to tariffs also see a larger rise in the number of citations received. Overall, these findings suggest that higher tariffs, through their effect on technology transfers, enhance the diffusion of foreign knowledge within the local economy.

We formalize this mechanism and examine its welfare implications by developing a multi-country, multi-sector growth model that explicitly accounts for technology transfers and their impact on knowledge diffusion. We extend the framework proposed by Buera and Oberfield (2020) to allow technological leaders to choose between producing locally for export or licensing their technology to foreign firms through technology transfer contracts. Firms in the recipient country absorb foreign knowledge either through exposure to imported goods or interaction with users of the transferred technology. The learning rate varies depending on whether the technology is embedded in an imported good or is used locally by transfer receivers. Hence, the decision between exporting goods and transferring technology influences the speed at which frontier ideas disseminate across borders, ultimately shaping the dynamic welfare gains from trade liberalization.

We quantify this mechanism in the context of Brazil's wave of tariff reductions in the early 1990s. Our calibration exercise has a recursive structure that allows us to draw a transparent mapping between the model's objects and their corresponding data moments. We initialize the model to match the value added, the stock of technology transfers, and the trade flows by sector in Brazil before 1990. We then simulate a once-and-for-all reduction in tariffs of the same magnitude as the one implemented in Brazil in the early 1990s. By matching the empirical response of technology transfers and patent citations to changes in tariffs, we pin down the key parameters controlling the channels of idea diffusion.

Our quantitative results indicate that accounting for technology transfers reverses the prediction that the dynamic gains from trade amplify static ones. Tariff reductions reduce foreign producers' incentives to transfer technology, favoring exports instead. While this generates a static improvement in welfare, it slows down diffusion and negatively affects productivity growth in the recipient country. In our baseline experiment, a full liberalization generates dynamic welfare gains of 0.34% per period in Brazil—relative to status quo in which tariffs do not change—compared to static welfare gains of 0.41%. By contrast, the dynamic gains in a version of the model in which diffusion occurs only through contact with imported goods generates dynamic welfare gains of 1.07% per period. Thus, accounting for diffusion via technology transfers reduces the dynamic welfare gains from the liberalization by more than two-thirds.

In our framework, subsidies to 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. This boost in transfers accelerates diffusion, driving long-term productivity growth and welfare improvements. The optimal subsidy level 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 three.

Related Literature. We contribute to two main strands of the literature. First, we contribute to a large body of work that investigates the channels that shape the implications of trade integration for long-term economic growth (Sachs et al., 1995; Lucas, 2009). Recent work in this literature has focused on how trade shapes the accumulation and diffusion of knowledge, and hence affects productivity growth. We mostly build on the framework by Buera and Oberfield (2020), who developed a quantitatively-oriented theory in which openness to trade shapes the source distribution from which local producers draw their ideas. Other channels studied in this literature include incentives to adopt or upgrade technology and selection effects on local and foreign producers (e.g., among others, Bustos, 2011; Sampson, 2016; Farrokhi and Pellegrina, 2023; Perla et al., 2021; Bai et al., 2024), the reallocation of idea flows and innovation activities across countries and sectors (e.g., Cai et al., 2022), and the interaction between labor market distortions and technology adoption (e.g., Farrokhi et al., 2024). We contribute to this literature by empirically studying the effects of import tariffs on knowledge diffusion across countries, and by providing direct evidence on a specific channel (i.e., contracts of technology transfers) that mediates such effect. We also show quantitatively that accounting for the response of technology transfers can reverse the predictions of that large class of models on the dynamic effects of import liberalization. We also contribute to the large literature on the determinants and implications of technology diffusion and adoption in the process of economic development (e.g., among others, Bustos et al., 2016; Comin and Mestieri, 2018; Juhász, 2018; Verhoogen, 2023; Cirera et al., 2024). In particular, a recent literature has studied specific channels of diffusion, such as policies of local development (e.g., Giorcelli, 2019;

Giorcelli and Li, 2021) and contracts of technology transfers (Santacreu, 2021; De Souza and Li, 2022). We contribute to this literature by showing how trade policy affects firms' incentives to transfer their technology to foreign producers, thereby affecting adoption and diffusion of ideas across countries.

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

2 Data

In this section, we describe our data on technology transfers, patent citations, foreign direct investment (FDI), and import tariffs in Brazil. In Section 3, we will use this data to study the effect of import tariffs on knowledge diffusion.

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 a foreign firm to a firm 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.

How the data was collected. Brazilian firms are required 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 control 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 that was in place at the time. The requirement was kept in place after capital control was lifted. As a consequence, 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 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, license or acquisition of software, services of maintenance, and services that do not generate a technical report.

Validation. Because the Brazilian government requires registration of all technology contracts, firms that do not register their contract lose the possibility of resolving any judicial dispute in court. This creates strong incentives on the side of the firm to comply with this requirement. According to a survey ran by de Souza (2020) among intellectual property experts, firms favor registering their contract in 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 RAIS, an administrative matched employer-employee dataset, we assign a 4-digit sector 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 on the transaction value, when available. Transfer of know-how is the most common type of contract. A few concrete examples of know-how transfers can illustrate 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 up its production of free cutting steel round bars.[1] In 2012, the *Companhia Brasileira de Vidros Planos*, a Brazilian glass and concrete producer, received technological as-

[1]These type of bars are called "S30VCTS2".

Table 1: **Summary statistics of technology transfer contracts**

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
Buyers and sellers		
Unique Buyers	5,484	
Unique Sellers	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 buyers and sellers. The row *HQ-Branch* reports the share of transactions realized between an headquarter 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.

sistance 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 most 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 lower access to technology transfers had a sizeable 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). PATSTAT collects information from most patent offices around the world, including 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 to 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 Firms Ownership and FDI

To measure FDI, we use the Firm Registry, an administrative dataset which 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 can 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 agent 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 comes from the *Controladoria-Geral da União* and covers all the federal procurement since 2000. Data on campaign contribution comes from the *Superior Tribunal Eleitoral (TSE)*, 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

Baseline empirical model. Throughout our analysis, 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 or the number of technology transfers, from country c, by 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.[2] The term $X_{c,s,t}$ denotes a set of controls.[3]

Outcomes of interest: citation and technology transfer flows. The main outcomes of interest are the number of citations made by Brazilian firms and technology transfers received by Brazilian firms. Because technology takes time to adjust and have 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), but we show in the robustness section that results are robust to alternative windows of aggregation.

[2]Openness to trade can affect the incentives of firms to upgrade their technology due to changes in competition or market size. Because these forces affect the incentive of firms to license technologies from all countries, it should be loaded on the fixed effects $\mu^3_{s,t}$.

[3]As controls, we include the lagged left-hand size variable and its lagged cumulative sum to account for persistence in the trends. As robustness checks, we also include tariffs on the inputs and tariffs that other countries impose on Brazilian goods.

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). For example, the sector-year fixed effect, $\mu^3_{s,t}$, controls for sectoral shocks that might induce tariff changes, such as protection to fading industries or lobbying. It also captures the overall effect of tariffs on firms' incentives to upgrade technology. When tariffs change, firms have incentives to upgrade their technology due to increased market access (Bustos, 2011) or change in competition (Aghion et al., 2005). Because these forces affect the incentives to adopt technology from all destinations for a given 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 $\mu^2_{c,t}$.

Instrument: Comparing small MFN partners to preferential partners (Boehm et al., 2023). Tariffs and trade flows are often affected by the same factors, leading to a biased estimate of β in our baseline specification, Equation (1). For instance, industries facing increased import competition may lobby for higher tariffs, prompting governments to adjust tariffs in response to evolving trade patterns.

To address this endogeneity concern and identify the causal effect of tariffs, we use the instrumental variable approach proposed by Boehm et al. (2023), which exploits the WTO's Most-Favored Nation (MFN) tariff system. According to WTO rules, unless a preferential trade agreement exists, Brazil must apply uniform MFN tariffs to all WTO members, regardless of their significance to Brazilian trade. Following the methodology of Boehm et al. (2023), we identify the tariff effect by comparing the behavior of smaller trade partners—who are subject to the MFN tariffs—to that of countries trading under different agreements. The key identification assumption is that tariff changes are exogenous to trade flows among small trade partners, ensuring that the instrument captures variations in tariffs unrelated to endogenous shifts in trade patterns.

We construct the instrument at the product level and average it up to the sector level. The product-level instrument is given by

$$\tau^{instr}_{c,p,t} = \mathbb{I}_c \left\{\text{MFN Partner at } t\right\} \times \mathbb{I}_c \left\{\text{MFN Partner at } t-1\right\} \times \tau^{'}_{p,t} \tag{2}$$

where $\mathbb{I}_c \left\{\text{MFN Partner at } t\right\}$ is an indicator that takes value one if country c is a MFN trade partner to Brazil in year t and $\tau^{MFN}_{p,t}$ is the MFN tariff that the Brazilian government imposes on product p.

The instrument described in Equation (2) is used alongside a sample selection that excludes large trade partners subject to MFN tariffs. Observations are removed if the following two conditions are met:

$$\mathbb{I}_c \{\text{MFN Partner at } t\} \times \mathbb{I}_c \{\text{MFN Partner at } t-1\} = 1 \tag{3}$$

and

$$\begin{aligned}
\mathbb{I}\{c \text{ is a major trading partner at } t-1 \text{ in aggregate}\}+\\
\mathbb{I}\{c \text{ is a major trading partner at } t-1 \text{ in product } p\}+\\
\mathbb{I}\{c \text{ is a major trading partner at } t \text{ in aggregate}\}+\\
\mathbb{I}\{c \text{ is a major trading partner at } t \text{ in product } p\} > 0,
\end{aligned}$$

where, in any given year t, country c is considered to be a major trading partner if it is among the top 10 exporters to Brazil, either in the aggregate or for product p.[4]

The instrument for tariffs on sector s and country c at year t, denoted by $\tau^{instr}_{c,s,t}$, is then obtained by averaging instrumented product-level tariffs, $\tau^{instr}_{c,p,t}$, within each sector. Therefore, the first stage of our instrumental variable approach is

$$\tau_{c,s,t} = \theta\tau^{instr}_{c,s,t} + \tilde{\mu}^1_{c,s} + \tilde{\mu}^2_{c,t} + \tilde{\mu}^3_{s,t} + X'_{c,s,t}\tilde{\kappa} + \tilde{\epsilon}_{c,s,t}. \tag{4}$$

Identifying variation and identifying assumption. When using the instrument in Equation (4), the identification of the parameter of interest β in Equation (1), comes from comparing the growth rate of the outcome of interest, e.g., technology transfer, between small MFN partners and preferential partners after an MFN tariff change. For example, Italy is a small trade partner to Brazil, trading on MFN terms, while Uruguay, with which Brazil has a preferential trade agreement, is exempt from MFN tariffs. To isolate the causal effect of tariffs on technology transfers, we compare the growth rate of technology flows from small MFN partners (e.g., Italy) to those from partners under preferential agreements (e.g., Uruguay) after Brazil reduces its MFN tariffs, which

[4]One potential concern with this approach is that countries go in and out of MFN status selectively across sectors. This is extremely rare. To account for this, we have augmented our baseline regression to include country-spell-out-of-MFN fixed effect. We find that the estimates are the same up to the fourth decimal point.

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 growth rates of the outcome of interest from both groups, e.g. technology transfers, 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, does not correlate with the growth rate in the origin country, and that 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:

$$y_{c,s,t-3+j} = \beta_j \tau_{c,s,t} + \mu^1_{c,s} + \mu^2_{c,t} + \mu^3_{s,t} + X'_{c,s,t}\kappa + \epsilon_{c,s,t}, \tag{5}$$

where $y_{c,s,t-3+j}$ is the stock of citations to or technology transfers from country c by 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 (5), $\tau_{c,s,t}$ is instrumented as shown in Equation (4).

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 influence 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 the first concern, we show that the instrument and tariffs do not correlate with variables predictive of sector-level policies, such as public procurement prevalence or campaign contributions. To address the second concern, we show that tariff changes are not correlated with measures of innovation, productivity, or value added in the origin countries.

The instrument does not correlate with other policies in Brazil. Panel A of Table 2 shows that the instrument does not predict connection to the government. The table reports the 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,

Table 2: **Instrument, 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*
Instrument	-0.0000371	-0.0000398	0.00982	-0.0252
	(0.000231)	(0.000181)	(0.0129)	(0.0375)
N	3,146	858	1,103	654
R^2	0.599	0.792	0.892	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*
Instrument	-0.404	-0.197	1.117	-0.00813
	(1.168)	(0.160)	(0.941)	(0.0305)
N	3,915	3,915	3,915	3,915
R^2	0.995	0.994	0.999	0.976

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 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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Panel A of Table B.1 in the Appendix shows that tariffs themselves are not correlated with other policy measures in Brazil, further supporting the absence of political influence in tariff changes.

The instrument does not correlate with 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 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 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. We provide evidence that the increase in diffusion is the result of the spreading among Brazilian firms of the knowledge embedded in technology transfers. Specifically, we find that tariffs result in more patent citations, particularly from firms located near technology licensees, and primarily directed towards technology licensors. Moreover, country-sectors that experience greater technology transfers in response to tariffs also see 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 Import Tariffs Increase International Knowledge Diffusion

Strong and significant first stage. Appendix Table B.2 reports the first stage, Equation (4). There is a strong correlation between the instrumented and actual import tariffs. In all specifications, the F-statistic exceeds 100, 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 15.7% increase in the number of transfers.[5] The effects on the number of unique licensees (column 2) and licensors (column 3) are similar in magnitude to the estimate in column 1, suggesting that tariffs primarily impact the extensive margin.

Tariffs only increase the number of know-how transfers to Brazilian companies, i.e., the transfer of knowledge not subject to intellectual property protection, such as technical consulting, technological assistance, or industrial secretes. Columns 5 to 7 display the effect of tariffs on different categories of technology transfer. We find no effect on the licensing of patents (column 4) and trademarks (column 5), and on transfers in the residual category, such as industrial design or franchises (column 7). As shown in column 6, the effect is fully driven by transfers of know-how. This category includes the transfer of knowledge, such as technical consulting or technological

[5]We follow the standard practice of interpreting changes in the inverse hyperbolic sine as percentage changes, with caveats discussed by Chen and Roth (2022).

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

IHS	(1) *N.Tech. Transfers*	(2) *N.Unique Licensees*	(3) *N.Unique Licensors*	(4) *Patent Licenses*	(5) *Trademark Licenses*	(6) *Know-How*	(7) *Other Transfers*
Tariff	0.157**	0.131**	0.154**	-0.00100	-0.0327	0.182***	0.00479
	(0.0712)	(0.0643)	(0.0707)	(0.0107)	(0.0217)	(0.0686)	(0.00328)
N	1,229,689	1,229,689	1,229,689	1,229,689	1,229,689	1,229,689	1,229,689

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 (4). 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 containing the licensing or reassignment of patents (column 4) and trademarks (column 5), the number of technology transfers containing 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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

assistance, that is not covered by standard forms of intellectual property protection. Transfers of know-how are a common channel of technology diffusion across countries, which previous work has shown to generate large and persistent productivity gain for firms receiving it. For example, de Souza (2020), Giorcelli (2019), and Giorcelli and Li (2021) found that international transfers of know-how had sizeable effects on productivity and firm growth in Brazil, Italy, and China, respectively.

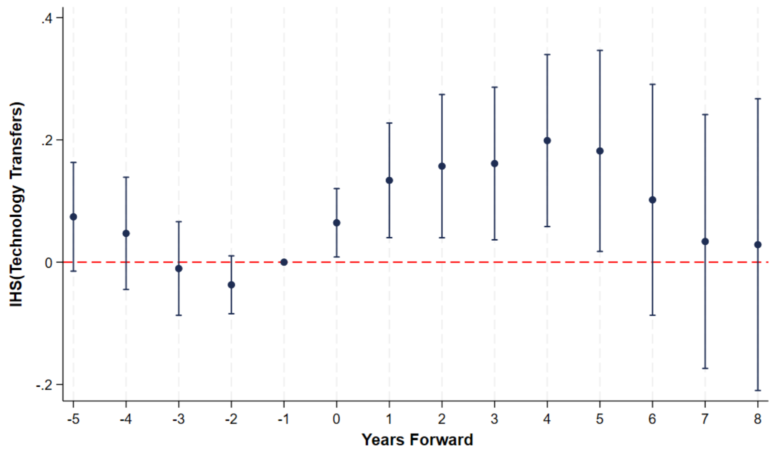
Figure 1a shows that the effect of tariffs on technology transfers is temporary. It displays the effect of tariffs on technology transfers over different time horizons. Before the tariff increase, there is no correlation between tariff changes and technology transfers. After the increase, technology 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 the number of citations that Brazilian firms make to foreign patents, which suggests that foreign ideas are diffusing to Brazil. Column 1 shows that a a 100 percentage point increase in import tariffs increases citations by 57%, and column 2 shows that it increases the probability of at least one citation by 41 percentage points.

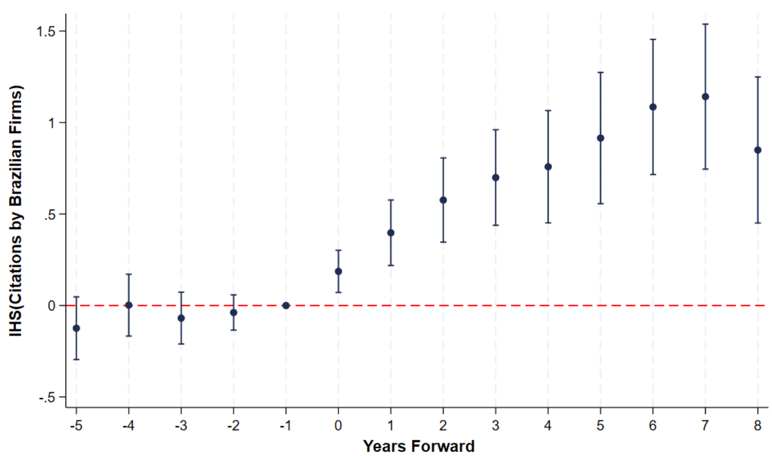
Figure 1b shows the effect of tariffs on the dynamics of citations. Before a tariff increase, the estimated effect of tariff changes on citations is zero. After the increase, citations rise steadily up to year seven and start declining subsequently. The effect appears to be significantly persistent, and, as one would expect, more so than technology transfers since knowledge takes time to diffuse.

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 5. 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.

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), 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 knowledge embedded in technology transfers

Table 4: **Tariffs, citations, and technological similarity**

	(1) *IHS Citations*	(2) *At Least One Cit.*	(3) *IHS. Cit. to Licensor*	(4) *IHS Cit. to Non-Licensor*
Tariff	0.577***	0.411***	0.565***	0.206
	(0.140)	(0.0825)	(0.132)	(0.126)
N	1,229,689	1,229,689	1,229,689	1,229,689

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 in Equation (4). The left-hand side variable is the inverse hyperbolic sine of the number of citations made by Brazilian patents in a given sector to patents in the foreign country (column 1), an indicator taking value 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 patents of firms that have never made a technology transfer to Brazil or have not being cited by them (column 4). Standard errors are clustered at the country-sector level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

spreads among Brazilian firms, leading to an increase in diffusion.

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 driven by citations to foreign technology licensors. The estimate in column 3, which only considers citations to patents of licensors or patents cited by them, is 2.7 times larger than the effect in column 4, which considers citations to patents that are *not* associated to licensors. These results suggest that tariffs lead Brazilian firms to learn and adopt knowledge that is embedded in technology transfers.[6]

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 to foreign patents comparing different sub-samples of citing Brazilian firms. The first two columns compare the effect on citations to 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

[6] 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 to licensed patents directly. Moreover, as we discussed 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 that foreign licensors transfer to Brazilian firms, rather than as exact indicators of the adoption of ideas embedded in specific patents.

Table 5: **Tariffs and citations by characteristics of 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	0.164	0.452***	0.179	0.461***	0.173	0.460***
	(0.106)	(0.133)	(0.110)	(0.133)	(0.110)	(0.133)
N	1,229,689	1,229,689	1,229,689	1,229,689	1,229,689	1,229,689

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 4. 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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

non-exporters (column 6). Consistently across these different sub-samples, we find that the effect on diffusion is about 4 times larger among firms that are *not* exposed to foreign markets.[7]

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 that are more closely exposed to the transferred knowledge. 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. Columns 1 and 3 of Table 6 show the effect of import tariffs on citations to foreign patents made by firms in the same ZIP code and city, respectively, of technology licensees (but excluding licensees themselves), while columns 2 and 4 show the corresponding effect on citations made by firms in different ZIP codes and cities. Consistently with the existence of diffusion of foreign knowledge via technology transfers, we find that the effect among firms located in the same ZIP code or city as a licensees is more than 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 affect (CATE) of tariffs on technology transfers and citations and we show that they are

[7]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 6: **Tariffs and citations according to location of citing firm**

	(1)	(2)	(3)	(4)
	IHS. Cit. Same Zip	*IHS. Cit. Diff. Zip*	*IHS Cit. Same City*	*IHS Cit. Diff. City*
tariff	0.312***	0.206*	0.351***	0.136
	(0.120)	(0.121)	(0.122)	(0.120)
N	1,229,689	1,229,689	1,229,689	1,229,689

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 (4). In column 1, the left-hand side is the number of citations made by patents of firms on a ZIP code 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 ZIP codes that never had a technology licensee. In column 3, the left-hand side is the number of citations made by firms in cities that have at least one technology licensee (excluding technology licensees themselves). In column 4, 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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

correlated. In other words, country-sectors that transfer more technology in response to tariffs, also receive more citations in response to tariffs. This result corroborates the idea that the increase in technology transfers is the primary mechanism driving the rise in citations following a tariff increase.

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

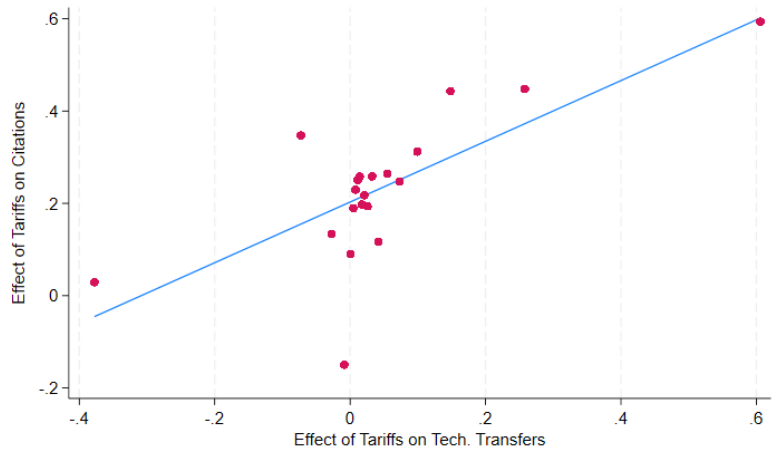
$$\Delta y_{c,s} = \bar{\beta}\left(Z_{c,s}\right)\,\Delta\tau^{instr}_{c,s} + \tilde{\mu}^{1}_{c} + \tilde{\mu}^{2}_{s} + \epsilon_{c,s}, \tag{6}$$

where $\Delta y_{c,s}$ is the change in outcome $y_{c,s}$ between 2000 and 2010 and $\Delta\tau^{instr}_{c,s,t}$ is the corresponding change in the instrument.[8] 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 (6) 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 20 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.

[8]We re-write the model in long-difference because the standard methods to estimate CATE is not equipped to handle fixed effects. For the same reason we use the reduced form model instead of the two-stages 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 20 groups. Appendix B.3 describes the procedure in detail.

Additional results in Appendix B.3 show that there is 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, with technology transfers coming mostly from the United States, Germany, and Britain.

Summary. These results suggest that higher tariffs lead foreign firms to transfer their technology to Brazil. Transferred technologies diffuse among Brazilian firms neighboring technology licensees, inducing an increase in citations to technology licensors.

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 import of intermediate inputs from the origin country, which is curtailed by higher tariffs (Ramondo and Rodríguez-Clare, 2013).

Connection to foreign supplier 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 the output. To rule out this potential confounding factor, Panel B of Table 7 (columns 3 and 4) shows the main results but adding as control the average import tariff on inputs.[9] 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 (2011), 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.

[9]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	-0.0436	-0.0249	-0.0236	-0.0495	-0.0284	0.00282
	(0.0287)	(0.0239)	(0.0227)	(0.0636)	(0.0542)	(0.0476)
N	1,053,236	1,053,236	1,053,236	1,053,236	1,053,236	1,053,236
R^2	0.000	0.000	0.001	0.007	0.008	0.014

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	0.157**	0.577***	0.314**	0.777***	0.0843*	0.714***
	(0.0712)	(0.140)	(0.133)	(0.253)	(0.0507)	(0.134)
Input tariff			-0.202*	0.0327		
			(0.119)	(0.241)		
Tariff on Brazil					0.000107	-0.00344
					(0.000845)	(0.00638)
N	1,229,689	1,229,689	1,019,616	1,019,616	620,469	620,469
R^2	0.000	0.868	0.000	0.026	0.000	0.014

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 (4). 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 that has value 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 that has value 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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

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 technology diffusion and a rise in citations directed toward technology licensors.

Adding and removing controls. Appendix Table B.6 shows the results under different sets of controls. Changing the set of controls delivers consistent estimates of the impact of tariffs on technology transfers and diffusion.

Sample selection. Not all countries or sectors are likely to transfer technology or receive citation from Brazilian firms. Appendix Table B.7 displays 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 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 allows us to rationalize our empirical findings and explore their implications for welfare and policy.

We extend the framework developed by Buera and Oberfield (2020) by explicitly modeling technology transfers. We focus on a domestic economy (Brazil) whose interactions with the rest of the world lead to diffusion of foreign technologies among local producers, driving productivity growth. 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 what follows we briefly present the setting and equilibrium conditions, and relegate 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 will 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 them inelastically supplying 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. The representative consumer 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:

$$\mathcal{C}_t^i = \left[\sum_{k \in K} \left(\int_0^1 c_t^{i,k}(s)^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}s \right)^{\frac{\epsilon(\sigma-1)}{(\epsilon-1)\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \tag{7}$$

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

$$W_0^i = \int_{t=0}^{\infty} e^{-rt} \log(\mathcal{C}_t^i) \, \mathrm{d}t. \tag{8}$$

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

$$y_t^{i,k}(s) = q_t^{i,k}(s) l_t^{i,k}(s), \tag{9}$$

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 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, although not all of them are necessarily active at any given point in time. A subset of them controls a technology to produce variety $s \in [0,1]$ in sector k, with the productivity of the most efficient among them being 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 $\theta > 1$:

$$Pr\left(q_0^{B,k}(s) \leq q\right) = \exp\left(-\lambda_0^{B,k} q^{-\theta}\right). \tag{10}$$

To simplify the exposition of the static equilibrium, in the description that follows we assume that the distribution of the highest-productivity technologies in (B,k) retains the same Fréchet structure over time, with a time-varying scale parameter $\lambda_t^{B,k}$ and a constant shape parameter θ. As we show in Section 5.3 below, this fact results endogenously from the assumptions on the diffusion process.

Productivity in the high-income foreign country (H): export or technology transfer. In the high-income foreign country (H), there is a mass 1 of firms for each sector k, each being assigned a given variety s. Each firm is endowed with two distinct technologies to produce the same variety. The first technology, whose productivity is denoted by $q_t^{X,k}(s)$, can be used by the firm to produce in-house for the domestic market or for export (hence the superscript X). The second technology, whose productivity is denoted by $q_t^{T,k}(s)$, can be provided by the firm to a Brazilian producer via a contract of technology transfer (hence the superscript T). Transferring 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. For simplicity, we do not allow firms in H to transfer their technology to firms in the low-income foreign country (D), and we assume that goods produced with transferred technology cannot be exported.

The technologies for in-house production and transfer can be different, but, as in Ramondo and Rodríguez-Clare (2013) and Lind and Ramondo (2023), we allow the two to be correlated. 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

$$Pr\left(q_t^{X,k}(s) \leq q_1, q_t^{T,k}(s) \leq q_2,\right) = \exp\left(-\left[(\lambda_t^{X,k} q_1^{-\theta})^{\frac{1}{1-\rho}} + (\lambda_t^{T,k} q_2^{-\theta})^{\frac{1}{1-\rho}}\right]^{1-\rho}\right), \tag{11}$$

with $\rho \in [0,1]$. In this formulation, setting $\rho = 0$ implies that the X and the T distributions are two independent Fréchet distributions, 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 degree of applicability and effectiveness of foreign technologies to the local context (i.e., the degree of "appropriateness") can vary significantly due, among the other factors, to environmental conditions (Moscona and Sastry, 2022) and the local supply of skills (de Souza, 2020).

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 a 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 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 producers 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. Since technology transfers only involve goods produced and consumed in Brazil, the equilibrium conditions vary slightly between Brazil and the rest of the world.

In Brazil, the price faced by the representative consumer for variety s in sector k is given by

$$p_t^{B,k}(s) = \frac{\epsilon}{\epsilon - 1} \times \min\left\{ \frac{w_t^B}{q_t^{B,k}(s)}, \frac{w_t^B d_t^k}{q_t^{T,k}(s)}, \frac{w_t^H \tau_t^{H\to B,k}}{q_t^{X,k}(s)}, \frac{w_t^D \tau_t^{D\to B,k}}{q_t^{D,k}(s)} \right\}, \tag{12}$$

where w_t^i is the wage paid to workers in country i. In words, the price consists of a constant markup times the lowest marginal cost between domestic production in Brazil from domestic insights (first term) or technology transfers, exports from H and exports from D.

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 price index for sector k is equal to

$$P_t^{B,k} = \frac{\epsilon}{\epsilon - 1}(G_t^{B,k})^{-\frac{1}{\theta}} \Gamma\left(\frac{1-\epsilon+\theta}{\theta}\right)^{\frac{1}{1-\epsilon}}, \tag{13}$$

where Γ denotes the Gamma function and

$$G_t^{B,k} \equiv \sum_{i=B,D} \lambda_t^{i,k}(w_t^i \tau_t^{i\to B,k})^{-\theta} + \left[\sum_{i=T,X} \left(\lambda_t^{i,k}(w_t^{i\to B}\tau_t^{i\to B,k})^{-\theta}\right)^{\frac{1}{1-\rho}}\right]^{1-\rho}. \tag{14}$$

In Equation (14), with a slight abuse of notation, we denote by $w_t^{i\to B}$ the relevant wage (which is w_t^B if $i = T$ and w_t^H if $i = X$), and we let $\tau_t^{i\to B,k} = d_t^k$ whenever $i = T$. Sectoral indexes can then be combined into an overall price level, which we denote by $\mathcal{P}_t^B$, via the usual CES price aggregator.

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:

$$\pi_t^{i\to B,k} = \frac{\lambda_t^i(w_t^{i\to B}\tau_t^{i\to B,k})^{-\theta}\frac{\partial G_t^{B,k}}{\partial i}}{G_t^{B,k}}, \tag{15}$$

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

$$p_t^{i,k}(s) = \frac{\epsilon}{\epsilon - 1} \times \min\left\{\frac{w_t^B \tau_t^{B\to i,k}}{q_t^{B,k}(s)}, \frac{w_t^H \tau_t^{H\to i,k}}{q_t^{X,k}(s)}, \frac{w_t^D \tau_t^{D\to i,k}}{q_t^{D,k}(s)}\right\}. \tag{16}$$

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

$$\pi_t^{j\to i,k} = \frac{\lambda_t^j(w_t^j \tau_t^{j\to i,k})^{-\theta}}{G_t^{i,k}}, \tag{17}$$

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 ($\mathcal{P}_t^i$).

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.[10] In what follows, we focus on the dynamics of the parameter for the distribution of local entrepreneurs in Brazil, $\lambda_t^{B,k}$.

In modeling the process of idea diffusion, we extend the framework of Buera and Oberfield (2020)'s in which local entrepreneurs learn via their exposure to varieties sold in B and produced using technologies from H. In our model, these technologies enter the Brazilian market either through exports or technology transfer contracts, with both channels contributing to diffusion. However, crucially for our purposes, we allow the rate of diffusion among Brazilian producers to vary depending on whether the technology arrives via export or through direct technology transfer.

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

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

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. The idea is combined with a personal insight, so that the Poisson rate of arrival of insights larger z is

$$A_t^{i\to B,k}(z) \equiv a_t^{i\to B,k} z^{-\theta}, \quad i \in \{X, L\}. \tag{18}$$

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

$$q = z q'^{\beta}, \tag{19}$$

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.

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

Law of motion of productivity in Brazil. This framework extends Buera and Oberfield (2020) by allowing learning to happen, with different efficiency, from both foreign exporters of goods and providers of technology. We show in Appendix D.2 that the productivity distribution of local producers in Brazil retains a Fréchet structure over time:

$$F_t^{B,k}(q) = \exp\left(-\lambda_t^{B,k} q^{-\theta}\right), \tag{20}$$

where the scale parameter, $\lambda_t^{B,k}$, evolves according to the following law of motion:

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

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 first calibrate our model and then use it to explore quantitatively the welfare implications of the wave of tariff reductions in Brazil in the early 1990s. For this quantitative exploration, 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 relative population and average income for Brazil and the sets of low- and high-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 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 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 the average 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 and the degree of correlation is controlled by the parameter ρ. Given a value for ρ (the value of ρ is determined in the third step), 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 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 that matches 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, although in reality the change was more gradual and it unfolded over multiple years.

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:

$$\tau_t^{i\to B,k} = \bar{\tau}^{i\to B,k}(1 + T_t^{i\to B,k}), \tag{22}$$

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 experiment, we pin down the two remaining time-invariant parameters.

First, we set ρ to match the cross-sector semi-elasticity of workers employed by transfer receivers with respect to tariff changes. Intuitively, a large value of ρ implies that the distribution of productivity of exporters and transfer providers is highly correlated, so that a small change 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 0.157, corresponding to the effect of tariffs on the number of technology contracts in the three years following a change in tariffs documented column (1) of Table 3 in Section 3. As the model's counterpart of the number of technology contracts, we use the quantity of labor in Brazil using technologies transferred from abroad. This yields a value of ρ equal to 0.0232. The top-left panel of Appendix Figure C.13 displays this correlation, with the regression line matching the empirical semi-elasticity by construction. This relatively low value for ρ implies that the correlation in the productivity draws from H is also low, 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 cross-sector semi-elasticity of the number of patent citations to foreign grants with respect to tariff changes, where, in the model, total citations to foreign patents are defined as

$$Cit_t^{B\to H,k} = \pi_t^{X\to B,k} + \omega_T \pi_t^{T\to B,k}. \tag{23}$$

Table 8: **Parameter values and targets**

Parameter	Value	Target	Model	Data
		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		
		Calibrated parameters		
ρ	0.0232	Semi-elasticity transfers to tariffs, 1-3 years	0.157	0.157
ω_T	110.5	Semi-elasticity citations to tariffs, 1-3 years	0.577	0.577

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 larger 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 0.577, corresponding to the effect of tariffs on citations to foreign countries in the 3 years following the change in tariffs. This yields a value of ω_T equal to 110.5. The top-center panel of Appendix Figure C.13 displays this correlation where, again, the regression line is by construction equal between the model and the data.

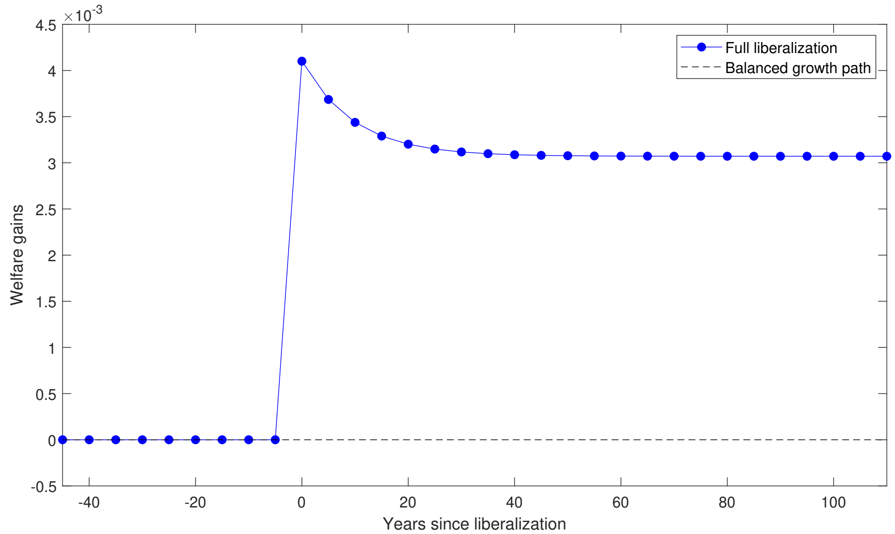
The bottom panels of Appendix Figure C.13 illustrate the identification by plotting the model-implied semi-elasticities for different values of ρ and ω. The plots show that the calibration strategy identifies unique values of the parameters that are consistent with the empirical moments. The values and 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 liberalizations. 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.

Welfare effects of the trade liberalization. Figure 3 shows the effect of the tariff reductions implemented in Brazil since the early 1990s on the welfare of the representative consumer. The blue

Figure 3: **Welfare gains from liberalization: Full model**



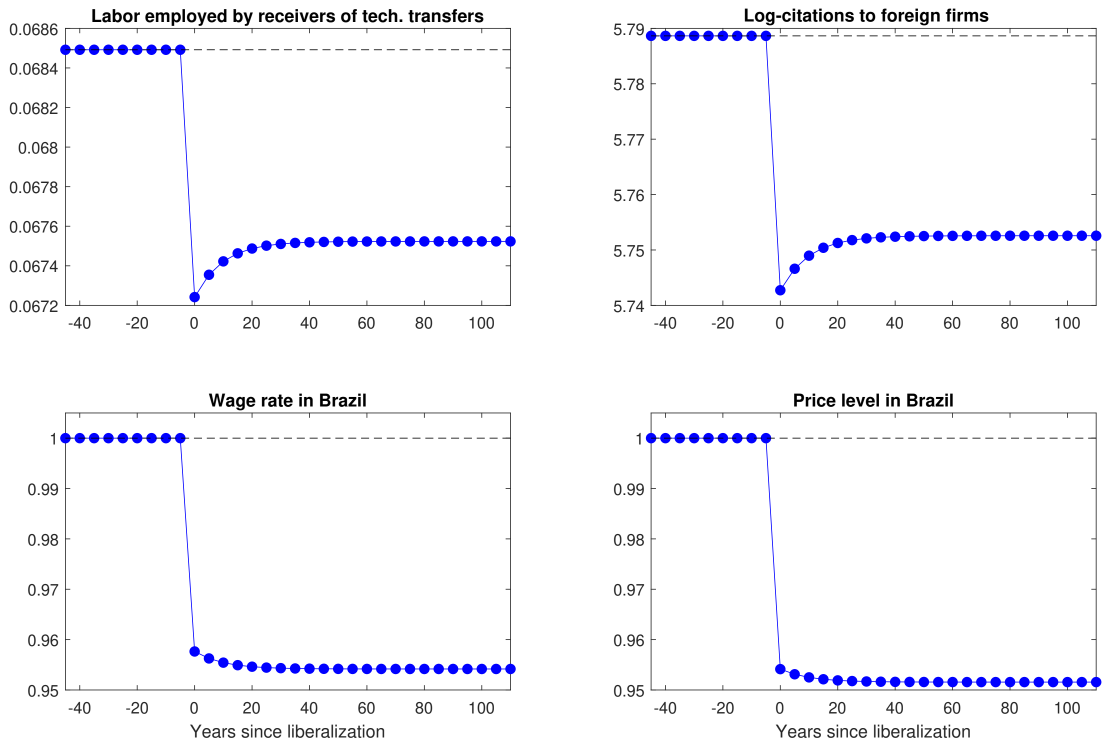
Notes: The marked blue line shows instantaneous consumption under the full liberalization scenario, in percentage deviation from the BGP.

line represents consumption under the full liberalization in percentage deviation from a baseline scenario in which the liberalization does not occur, and the economy remains on its BGP.

On impact, the liberalization induces a 0.41% increase in consumption relative to the BGP. The magnitude of the static improvement in welfare is consistent 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 static gains. 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 0.34% per period relative to the BGP. As shown in Appendix Figure C.14, while both drops in import tariffs with high-income and low-income foreign countries contribute significantly to the large static gains, the dynamic path is almost entirely driven by tariffs with high-income foreign countries.

The fact that the dynamic gains are compressed relative to the static gains is in contrast with 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). The reason for this discrepancy lies in the effect of the tariff reduction on the choice of foreign producers between exporting goods and transferring their technology, and in the implications of this choice for the path of productivity growth in the

Figure 4: **Effect of the liberalization on technology transfers, citations, and wage rate**



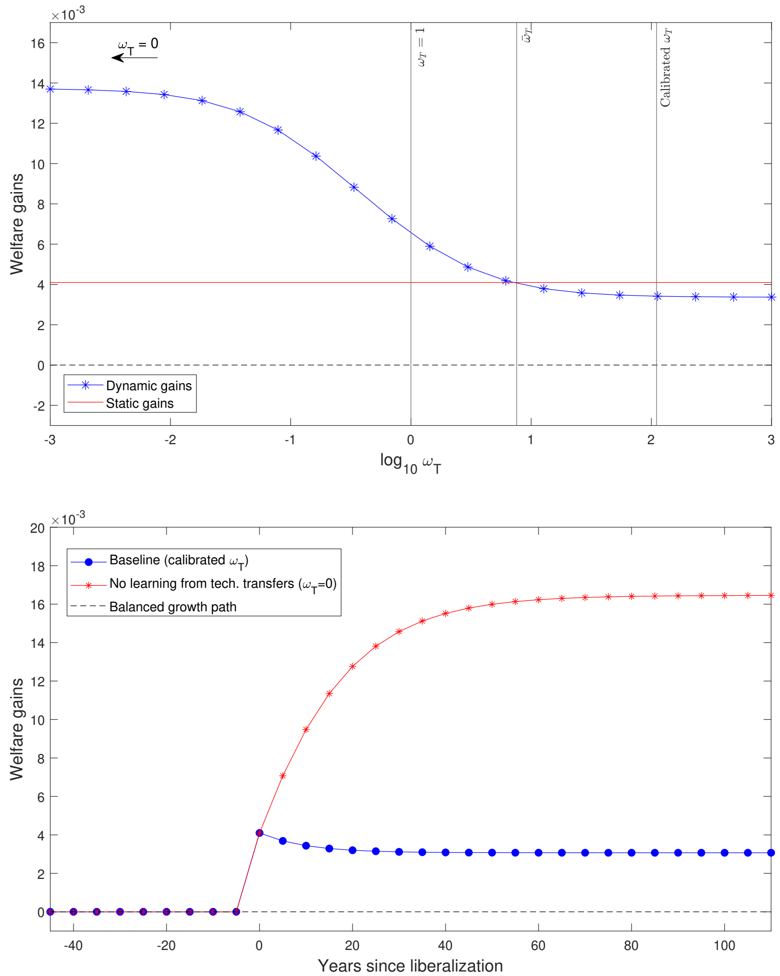
Notes: The marked blue lines show the share of labor in Brazil employed by transfer receivers (top-left panel), log-citations to foreign patents (computed as in Equation 23, top-right panel), the wage rate (bottom-left panel), and the price level (bottom-right panel) in Brazil, in deviation from the BGP.

receiving country (Brazil, in our case).

The top-left panel of Figure 4 shows the dynamic effect of the liberalization on the share of labor employed by transfer receivers in Brazil, which drops significantly on impact. 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. 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. Note that the magnitude of these responses is 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 drivers of the welfare effect of the liberalization 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 5: **Welfare gains from liberalization for different degrees of diffusion via transfers**



Notes: The top panel displays static (solid red line) and dynamic (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).

technologies results in a persistent decline in productivity growth in Brazil. The bottom-left panel of Figure 4 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 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. In the new BGP, the wage rate is 4.6% 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 consumption in the long run.

The parameter ω_T (controlling the learning rate from licensing relative to that from importing) is key in generating the dynamic path for welfare displayed in Figure 3. This point is illustrated in the top panel of Figure 5, whose marked blue line plots the dynamic welfare gains from the liberalization for a range of values of ω_T (the static gains, represented by the solid red line, are constant with respect to ω_T). At the calibrated value of ω_T the dynamic gains are below the static gains. As we move towards lower values of ω_T, dynamic 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 dynamic gains amplify the static ones. As ω_T approaches zero, all learning originates from exporters, and the dynamic amplification of the static gains is as large as it can be. The dynamics of welfare in this case are illustrated by the 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 dynamic welfare gains of 1.07% per period (more than twice as large as the static gains), compared to the 0.34% dynamic gains in the main calibration. In other words, accounting for learning from technology transfers reduces the dynamic gains from the liberalization by more than two thirds.

Optimal subsidies 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

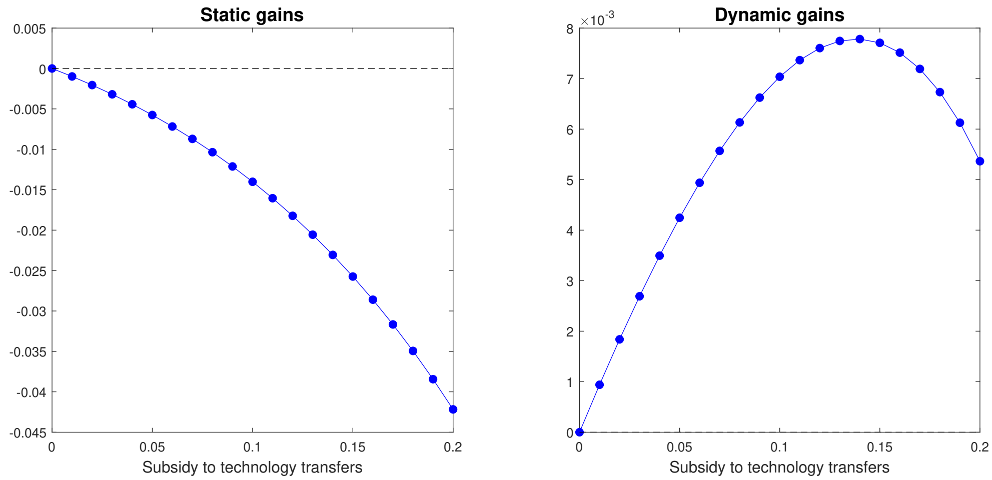
$$d_t^k = \bar{d}_t^k (1 - S_t^k),$$

where $S_t^k < 1$ denotes the subsidy rate. We assume that subsidies are uniform across sectors (i.e., $S_t^k = \bar{S}_t$), and their introduction is permanent and fully realizes in a single period.[11]

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

[11]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 $t \geq \bar{t}$. Optimizing the dynamic path of subsidies and their distribution across sectors does not generate visible changes in welfare compared to a uniform and permanent subsidy.

Figure 6: **Static and dynamic welfare gains from subsidizing technology transfers**



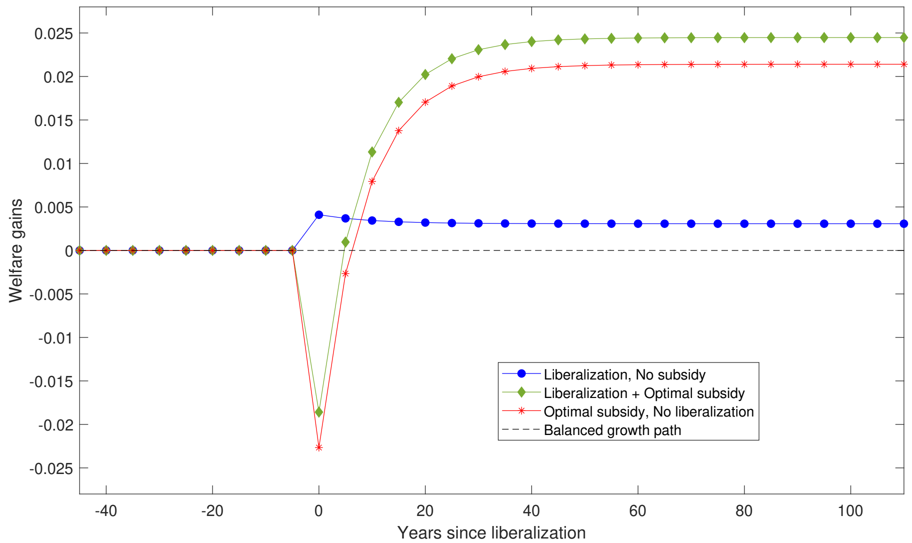
Notes: The left panel shows instantaneous consumption in the period in which the subsidy is introduced, in percentage deviation from the BGP. The right panel shows total discounted welfare in consumption-equivalent percentage deviation from the BGP.

foreign technology. In the short-run, this reallocation may generate static distortions that reduce social welfare. However, this negative impact may be compensated 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 static 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 full dynamic gains, which account for the static distortion as well as the positive effect on learning and productivity growth. The full dynamic 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 13.8%. The corresponding welfare gains are equal to 0.78% of consumption per period.

Figure 7 displays the full dynamics of welfare when subsidies to 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 static drop in welfare on impact (-2.27%), followed by higher growth and large dynamic gains that more than compensate for the static losses. In the

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.

long run, consumption is 2.14% higher compared to the initial BGP. Overall, the effect on total discounted welfare (+0.78%) is higher than the one obtained with the liberalization (+0.34%). 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 1.86% drop in welfare in the short run, the combined policies generate large dynamic gains, with an overall effect on total discounted welfare of 1.12%.

7 Conclusions

We used a unique dataset on contracts of technology transfers from foreign to Brazilian firms to study the effects of trade policy on the patterns of technology diffusion across countries. Empirically, we showed that higher tariffs lead to a large increase in the quantity of technology transfers from foreign to Brazilian firms, as well as an increase in the associated knowledge spillovers measured via patent citations.

To understand the welfare implications of this finding, we augmented a model of trade and idea diffusion to explicitly account for technology transfers and their effect on knowledge diffusion. We calibrated the model to match the empirical responses of contracts and patent citations to changes in tariffs. Our quantitative results suggest that accounting for technology transfers significantly compresses the dynamic welfare gains from trade liberalization: contrary to common predictions of theories of trade and diffusion, dynamic gains from openness are *lower* than static gains. The existence of a dynamic externality in technology transfers opens up room for policy. Trade liberalization combined with subsidies to technology transfers produces large long-run welfare gains.

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Online Appendix
(for online publication only)

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

by Gustavo de Souza, Ruben Gaetani, and Martí Mestieri

September 2024

A Summary Statistics

A.1 Summary Statistics of Technology Transfers

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

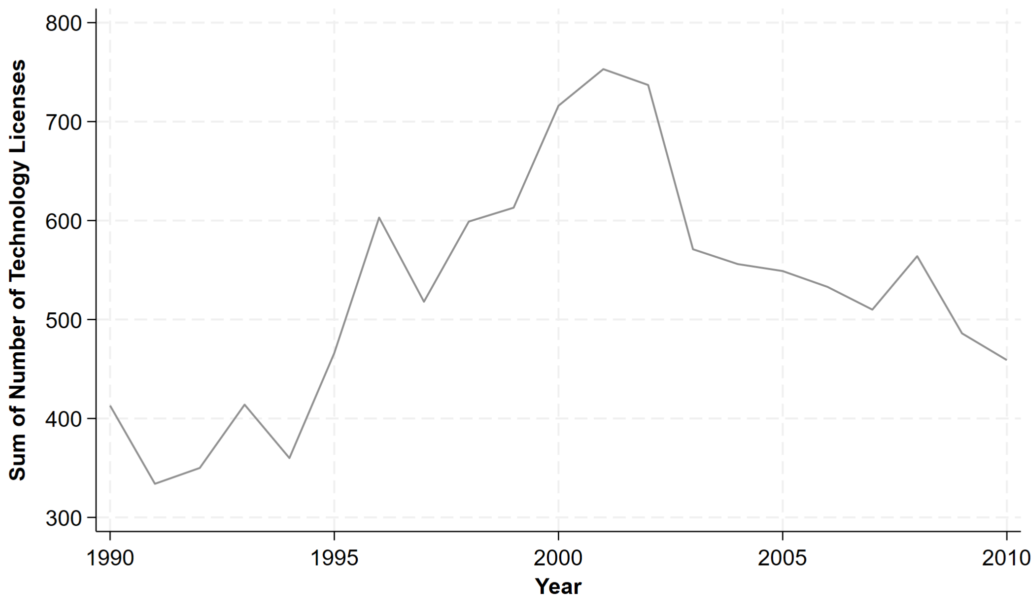


Figure A.2: **Number of technology transfers by sector**

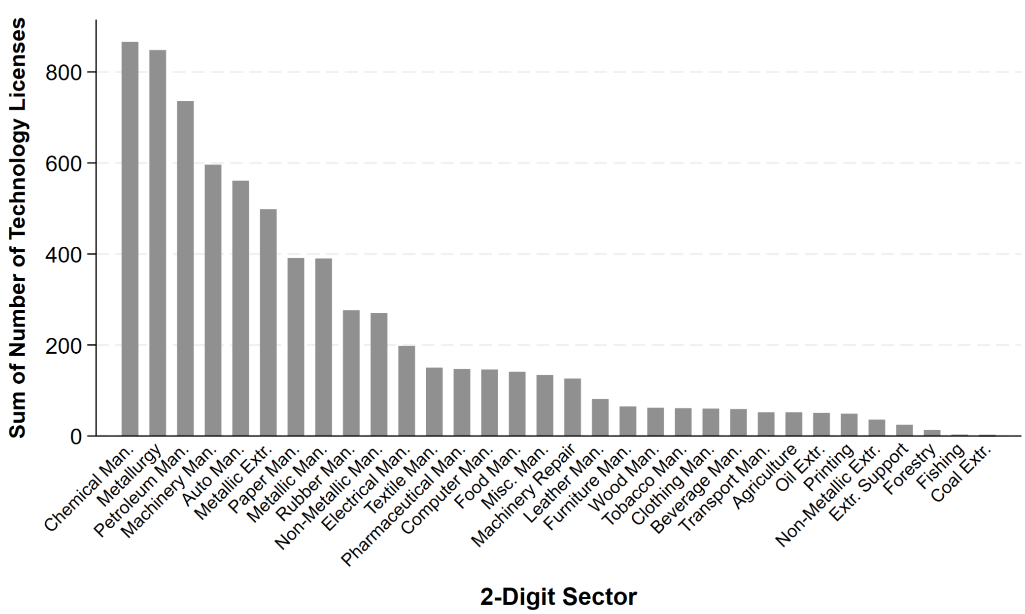
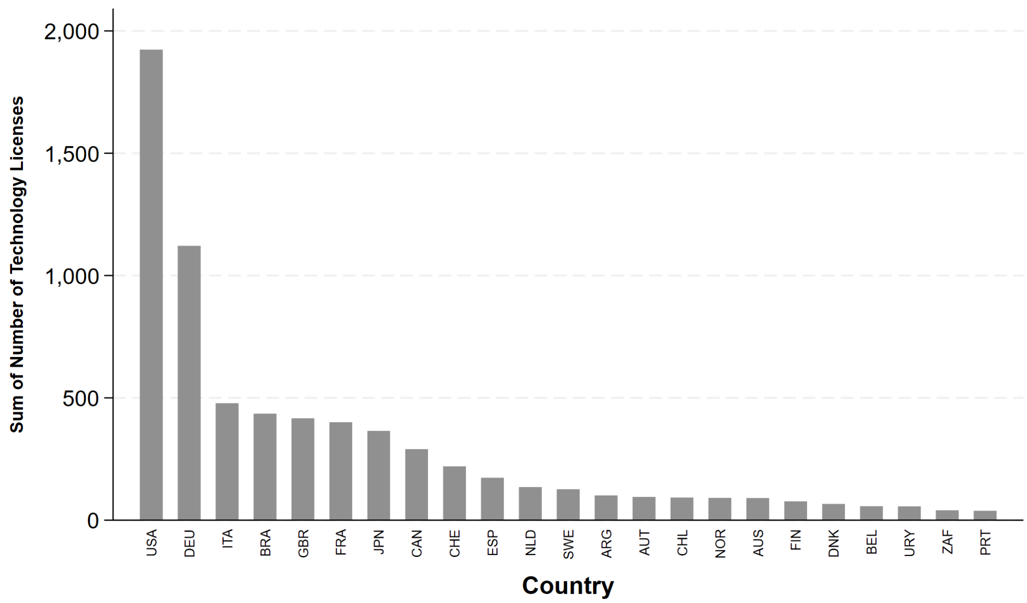


Figure A.3: **Number of technology transfers by country of origin**



A.2 Summary Statistics of Patent Citations

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

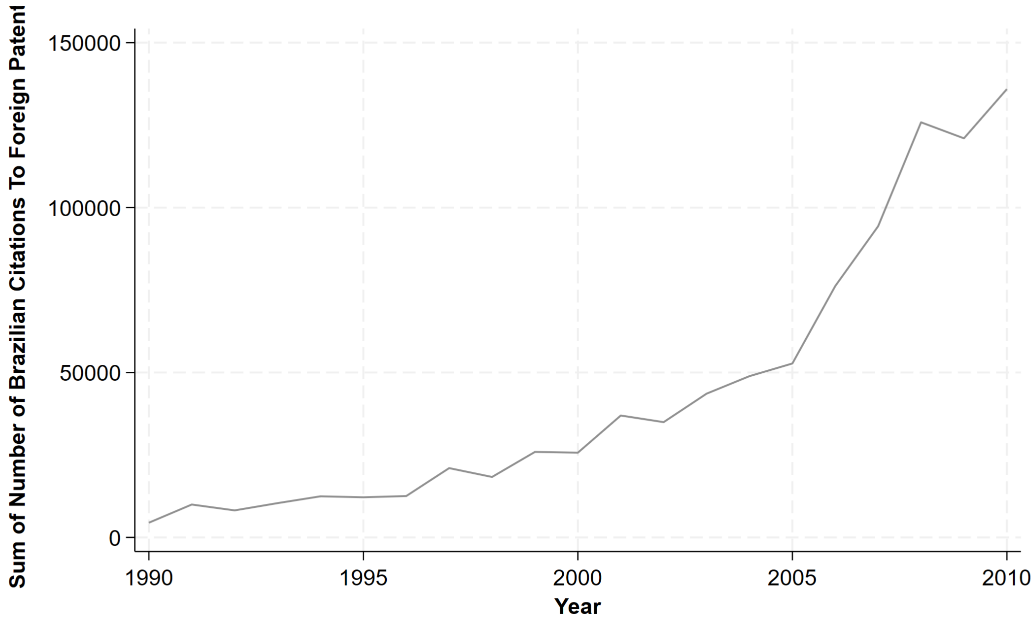


Figure A.5: **Total number of citations to foreign patents by sector**

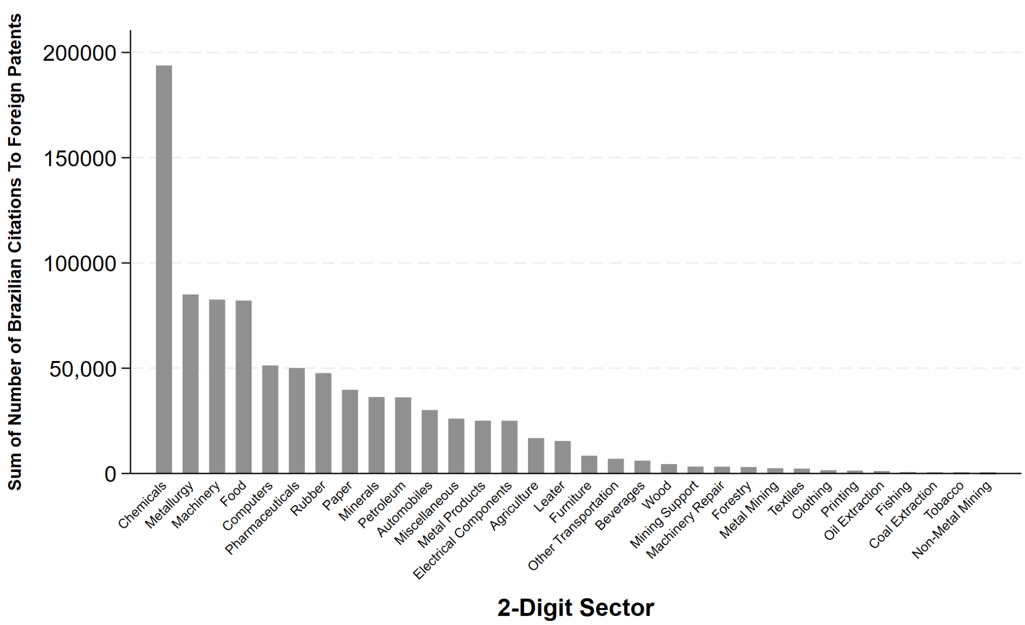
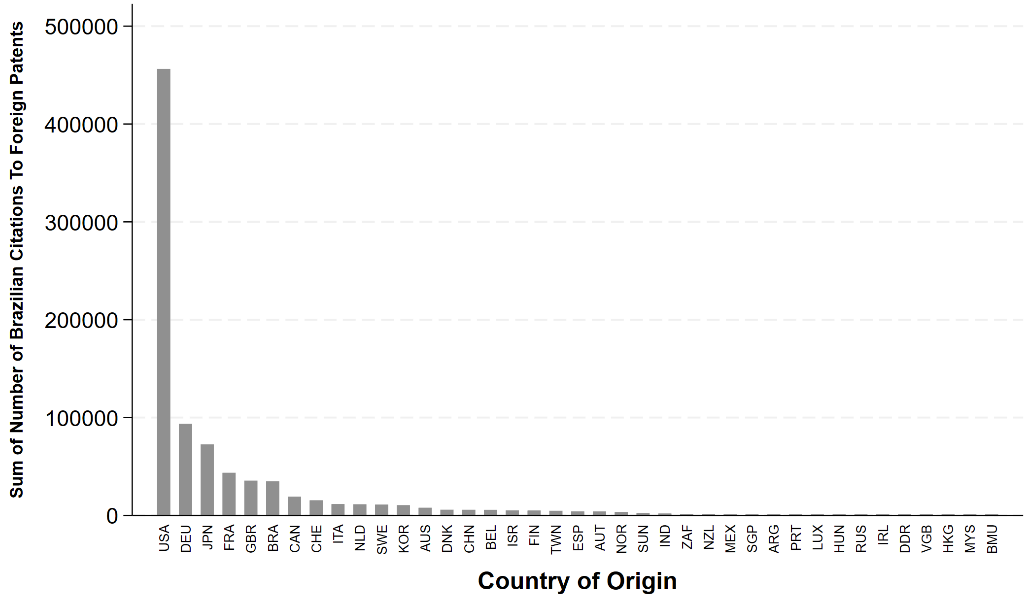


Figure A.6: **Total number of citations to foreign patents by country (most important countries)**



A.3 Summary Statistics of FDI

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

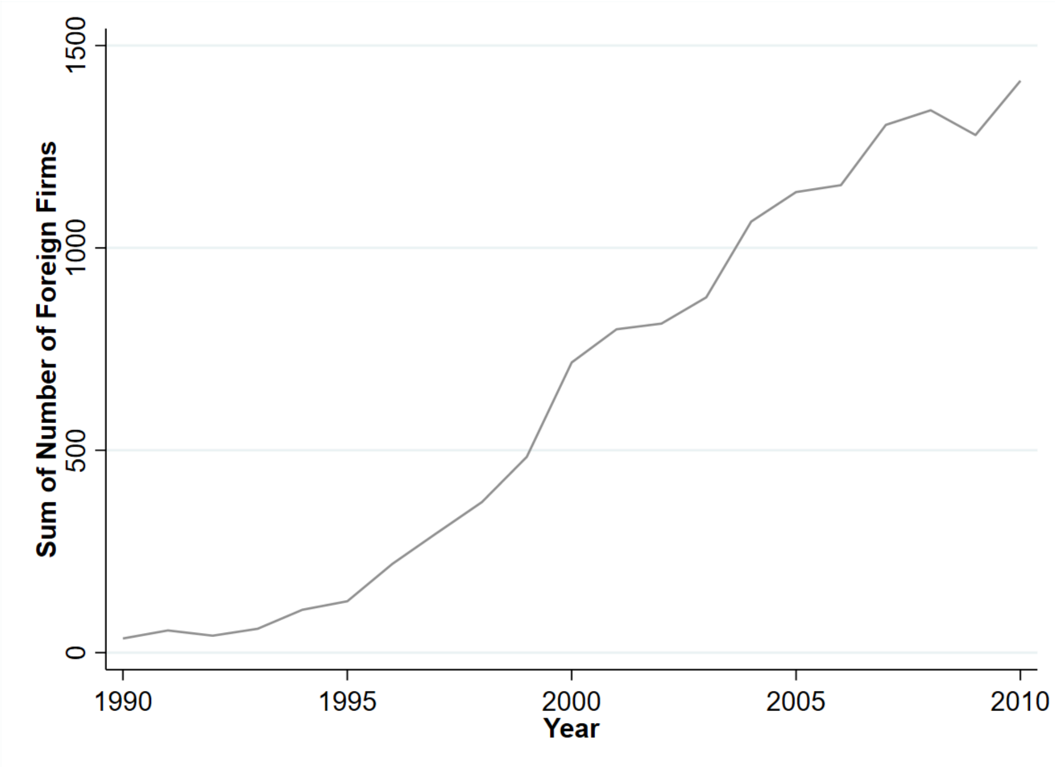


Figure A.8: **Number of firms owned by foreigners by sector in 2010**

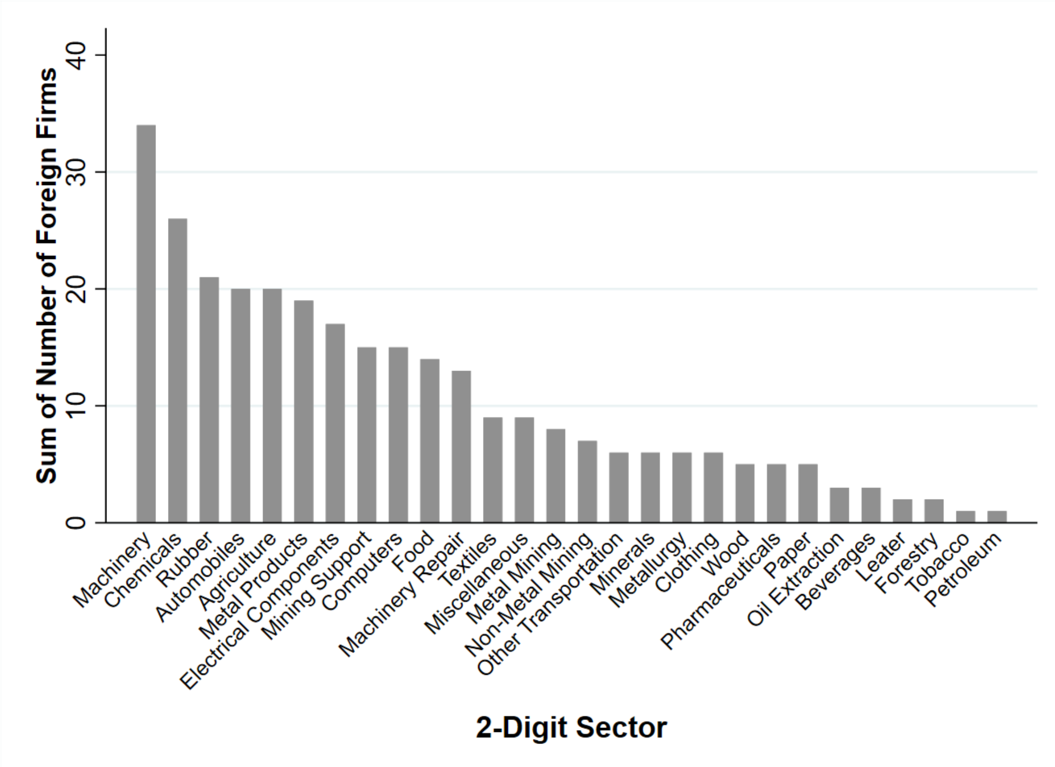
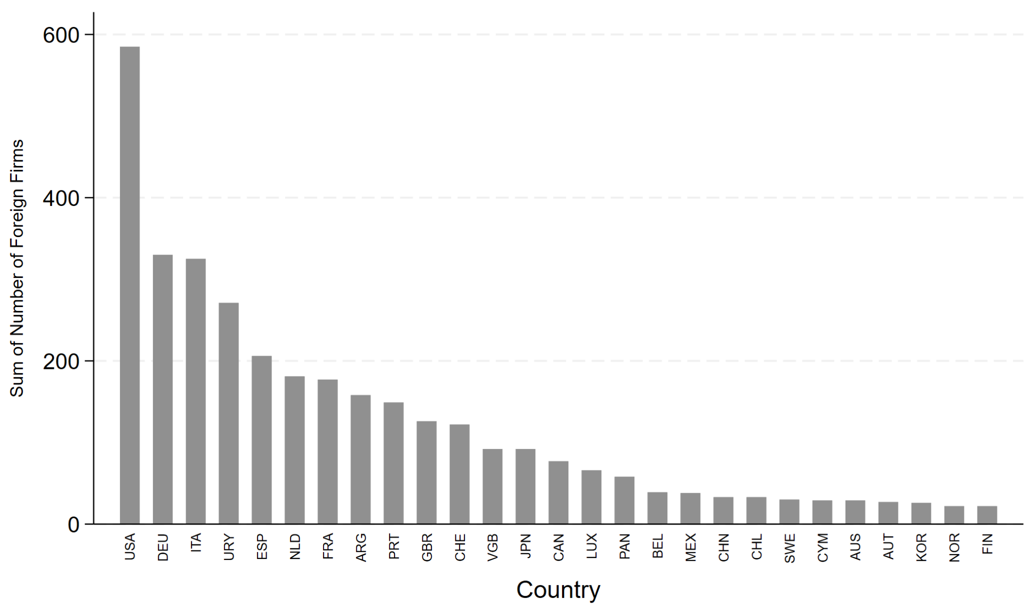


Figure A.9: **Number of firms owned by foreigners by country in 2010 (most important countries)**



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	-0.00427	-0.00226	0.952	-2.436
	(0.0229)	(0.0177)	(1.275)	(3.714)
N	3,146	858	1,103	654
R^2	0.599	0.792	0.892	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	2.655	-0.298	1.999	-0.133
	(4.136)	(0.195)	(1.736)	(0.185)
N	2,025	2,025	2,025	2,025
R^2	0.997	0.996	0.999	0.983

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	0.990***	0.983***	0.533***	0.517***
	(0.000240)	(0.000449)	(0.00994)	(0.00967)
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	1,470,974	1,470,948	1,470,948	1,259,775
R^2	0.993	0.995	0.999	0.999
F	16,975,266.8	4,805,138.6	2,880.0	2,856.2

Notes: This table presents the first-stage estimates, defined in Equation (4), 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:

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

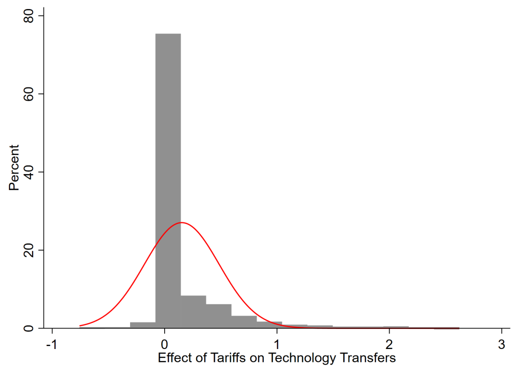
where $\Delta\tilde{y}_{c,s}$ is the residual of a regression of the fixed effects, μ_c and μ_s, on $\Delta y_{c,s}$.

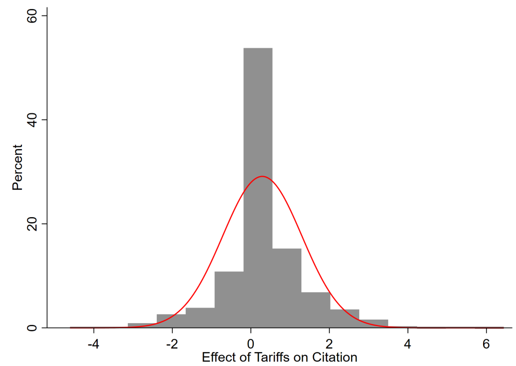
The term $Z_{c,s}$ contains the number of patents issued by country c until 1990, per-capita GDP in 1990, the number of patents issued by sector s in Brazil until 1990, the number of technology transfers from country c by sector s until 1990, and the number of citations made by sector s to country c 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.10 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 and citations**





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. Figure B.11 averages the CATE by sector. The extractive sectors, chemicals, and automobile manufacturing are the ones most affected.

Heterogeneity by Country. Figure B.12 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)
	$\beta_{tech.\ transf.}$	$\beta_{tech.\ transf.}$	$\beta_{tech.\ transf.}$	$\beta_{tech.\ transf.}$	$\beta_{tech.\ transf.}$	$\beta_{tech.\ transf.}$	$\beta_{tech.\ transf.}$
$\beta_{citation}$	0.0893***						
	(0.00130)						
log(GDP Per Capita)		0.0955***					0.0178***
		(0.000899)					(0.000741)
IHS(Stock of Patents in the Origin)			0.0714***				0.0570***
			(0.000341)				(0.000431)
IHS(Stock of Patents in Brazil)				0.00990***			-0.00953***
				(0.000652)			(0.000499)
IHS(Stock of Citations)					0.328***		0.0230***
					(0.00235)		(0.00233)
IHS(Stock of Technology Transfers)						0.833***	0.537***
						(0.00562)	(0.00489)
N	59122	46781	59122	59122	59122	59122	46781
R^2	0.074	0.195	0.426	0.004	0.247	0.271	0.616

Description:

Table B.4: **Correlation between effect of tariff on citations and pre-period characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$	$\beta_{citation}$
$\beta_{tech.\ transf.}$	0.823***						
	(0.0120)						
log(GDP Per Capita)		0.0413***					-0.0462***
		(0.00233)					(0.00253)
IHS(Stock of Patents in the Origin)			0.0986***				0.0838***
			(0.00131)				(0.00147)
IHS(Stock of Patents in Brazil)				0.0881***			0.0950***
				(0.00195)			(0.00170)
IHS(Stock of Citations)					0.303***		0.00901
					(0.00815)		(0.00793)
IHS(Stock of Technology Transfers)						0.272***	-0.124***
						(0.0200)	(0.0167)
N	59122	46781	59122	59122	59122	59122	46781
R^2	0.074	0.007	0.088	0.033	0.023	0.003	0.183

Description:

Figure B.11: **Effect of tariffs on technology transfer and citations by sector**

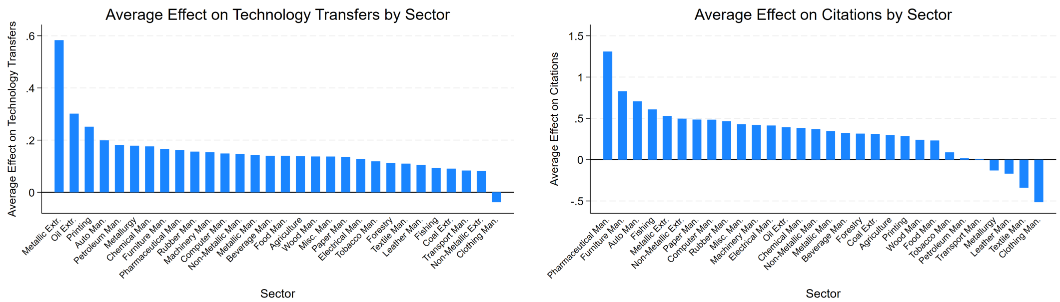
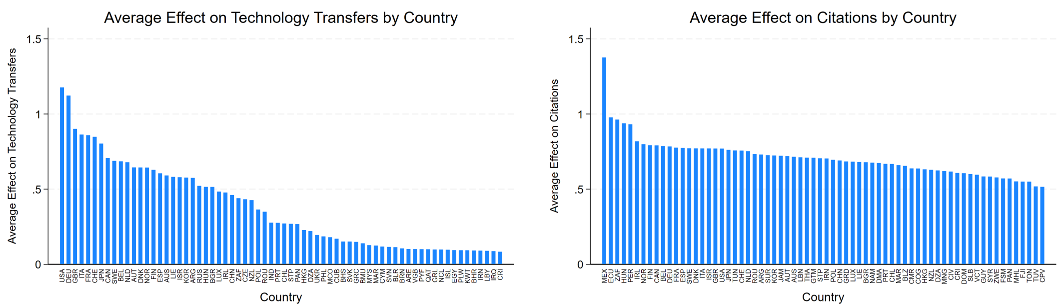


Figure B.12: **Effect of tariffs on technology transfers and citations by country**



B.4 OLS Regressions

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

	(1)	(2)	(3)	(4)	(5)	(6)
	IHS N. Tech. Transfers	*IHS Citations*	*IHS. Cit. to Non-Licensor*	*IHS Cit. to Licensor*	textitIHS. Cit. Same Zip	*IHS. Cit. Diff. Zip*
Tariff	0.101**	0.409***	0.00858	0.423***	0.281***	0.131***
	(0.0446)	(0.0679)	(0.0350)	(0.0609)	(0.0433)	(0.0395)
N	1241562	1241562	1241562	1241562	1241562	1241562
R^2	0.000	0.032	0.008	0.040	0.022	0.019

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	0.113*	0.369**	0.157**	0.613***	0.113*	0.373***
	(0.0606)	(0.145)	(0.0711)	(0.154)	(0.0605)	(0.126)
Income-Region FE	N	N	Y	Y	N	N
Lagged LHS	N	N	N	N	Y	Y
N	1,470,948	1,470,948	1,229,689	1,229,689	1,470,948	1,470,948

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 4. 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	0.425*	0.803**	-0.271	0.968**
	(0.241)	(0.379)	(0.303)	(0.404)
N	442347	442347	442347	442347

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 4. 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

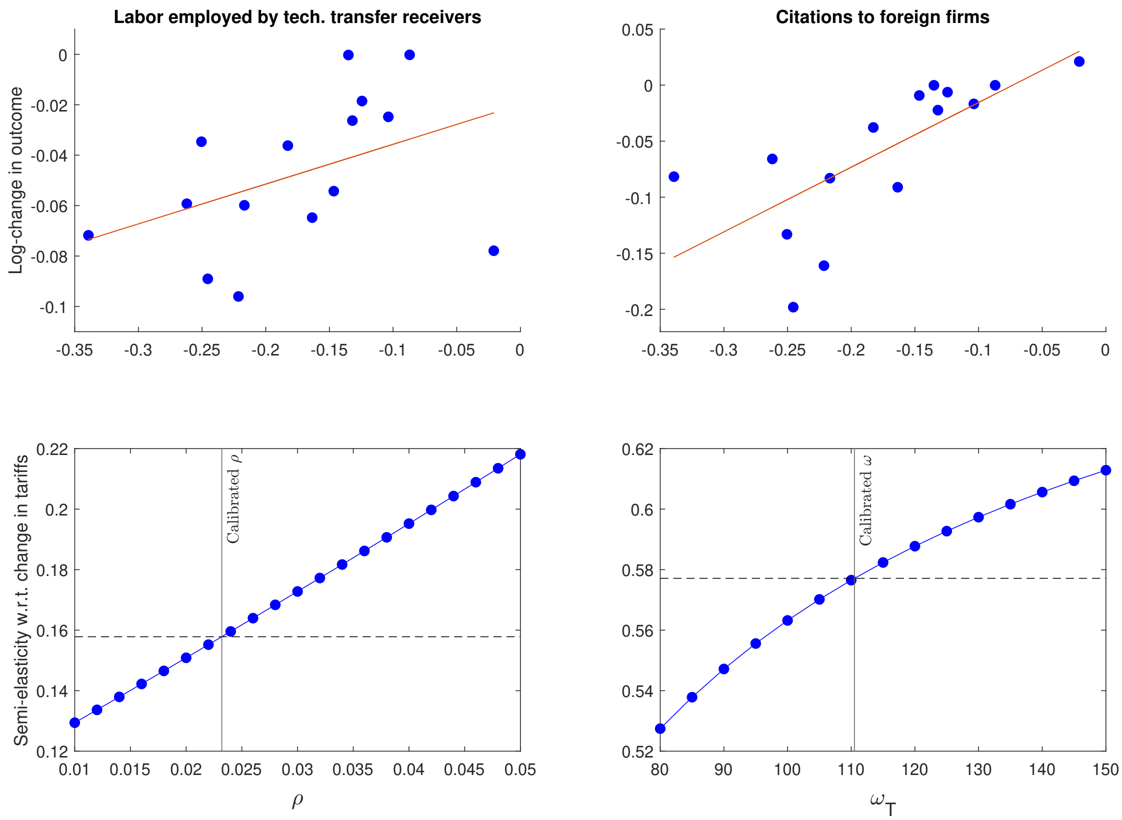
Table B.8: Effect of tariffs on international technology licensing

	(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	0.0982*	0.416***	9.724*	39.80***	0.316**	3.855
	(0.0536)	(0.0839)	(5.307)	(8.038)	(0.145)	(9.315)
N	1229689	1229689	1229689	1229689	1229689	1229689

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 4. 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. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

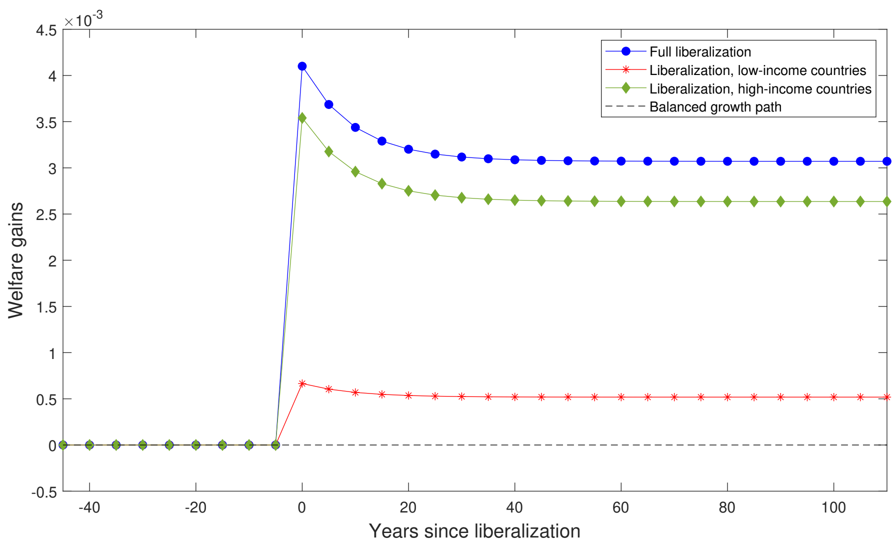
C Additional model figures

Figure C.13: **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.14: **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

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

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:

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

where $G_t^{B,k}$ is defined as in Equation (14).

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

$$P_t^{B,k} = \frac{\epsilon}{\epsilon-1}(G_t^{B,k})^{-\frac{1}{\theta}}\Gamma\left(\frac{1-\epsilon+\theta}{\theta}\right)^{\frac{1}{1-\epsilon}}, \tag{D.9}$$

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:

$$\pi_t^{i\to B,k} = \frac{\lambda_t^i(w_t^{i\to B}\tau_t^{i\to B,k})^{-\theta}\frac{\partial G_t^{B,k}}{\partial i}}{G_t^{B,k}}, \tag{D.10}$$

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

D.2 Evolution of the productivity distribution in Brazil

The process described by Equations (18) and (19) gives rise to the following law of motion for the cumulative distribution function (CDF) of productivity of local entrepreneurs in Brazil, $F_t^{k,B}(q)$:

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

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 (18), we obtain the following differential equation describing the dynamics of the local CDF:

$$\frac{\mathrm{d}\ln F_t^{B,k}(q)}{\mathrm{d}t} = -q^{-\theta}\Lambda_t^{B,k}, \tag{D.11}$$

where

$$\Lambda_t^{B,k} \equiv \alpha_t^k \left[\pi_t^{X\to B,k}\int_0^\infty x^{\beta\theta}\mathrm{d}F_t^{X\to B,k}(x) + \omega_T \pi_t^{T\to B,k}\int_0^\infty x^{\beta\theta}\mathrm{d}F_t^{T\to B,k}(x)\right]. \tag{D.12}$$

Solving the differential equation in (D.11), we obtain

$$F_t^{B,k}(q) = F_0^{B,k}(q)\exp\left(-q^{-\theta}\int_0^t \Lambda_\tau^{B,k}\mathrm{d}\tau\right). \tag{D.13}$$

Using Equation (10) 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

$$F_t^{B,k}(q) = \exp\left(-\lambda_t^{B,k} q^{-\theta}\right). \tag{D.14}$$

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

$$\dot{\lambda}_t^{B,k} = \Lambda_t^{B,k}. \tag{D.15}$$

It is straightforward to show that

$$\int_0^\infty x^{\beta\theta}\mathrm{d}F_{i\to B}^{k,t}(x) = \Gamma(1-\beta)\left(\frac{\lambda_t^{i,k}\frac{\partial G_t^{B,k}}{\partial i}}{\pi_{i\to B}^{k,t}}\right)^\beta. \tag{D.16}$$

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

$$\dot{\lambda}_t^{B,k} \propto \alpha_t^k \left[\pi_{X\to B}^{k,t}\left(\frac{\lambda_t^{X,k}\frac{\partial G_t^{B,k}}{\partial X}}{\pi_{X\to B}^{k,t}}\right)^\beta + \omega_T \pi_{T\to B}^{k,t}\left(\frac{\lambda_t^{T,k}\frac{\partial G_t^{B,k}}{\partial T}}{\pi_{T\to B}^{k,t}}\right)^\beta\right]. \tag{D.17}$$

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