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Abstract

Developing countries rely on technology created by developed countries. I show that such reliance increases wage inequality but leads to greater production in developing countries. I study a Brazilian innovation program that taxed the transfer of international technology, such as patent licenses or technical consulting, to subsidize national innovation. The program induced firms to replace technology transferred from developed countries with in-house innovations, which led to a decline in both employment and the share of high-skilled workers. Using a model of directed technological change and technology transfer, I find that closing Brazil to international technology transfers would decrease the skilled wage premium by 1% and GDP by 28%.

Keywords: technology transfers, appropriate technology, macroeconomic development, innovation

JEL Codes: O11, O33, O38

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1 Introduction

Developing countries rely on technology created by developed countries. Because of the abundance of skilled workers in developed countries, these adopted technologies are typically biased towards high-skilled workers.[1] But developing countries often have a much lower supply of high-skilled workers than the developed countries that produce these technologies. Economists have expressed concern that the resulting mismatch between the skill bias of technology and factor supply is a source of low productivity in developing countries.[2] Due to this factor mismatch, they argue that technologies from developed countries are inappropriate for developing countries. Guided by this view, several developing countries have implemented ambitious innovation programs to induce innovation and discourage the adoption of technologies from developed countries.

However, some argue that technologies from developed countries offer greater productivity and, regardless of factor mismatch, lead to greater output.[3] According to this view, developing countries should introduce policies that foster the diffusion of technologies from developed countries.

In this paper, I ask: In a developing country, what is the effect of replacing technology transferred from developed countries with domestic innovations? I tackle this question using a novel firm-level dataset for Brazil containing information on international technology transfers, such as patent licenses, technical consulting, or trade secrets. I use this unique dataset to study a reform that taxed international technology transfers and subsidized innovation in Brazil. I show that firms switching from international technology to national innovations slightly increased the share of low-skill workers in their wage bill and significantly decreased employment. Calibrating a model to reproduce these results, I find that technologies from developed countries have higher productivity and a slightly higher skill-bias compared to technologies created in Brazil. Therefore, the Brazilian program taxing international technology transfers reduced output by inducing firms to adopt technologies of

[1] Okoye (2016), Hendricks and Schoellman (2023), Rossi (2022).

[2] Schumacher (1973), Stewart (1977), Stewart (1987), Basu and Weil (1998), Acemoglu and Zilibotti (2001), Gancia and Zilibotti (2009), Kaplinsky (2011), and Gancia et al. (2013). See Ely and Bell (2009) for a discussion on innovation policy and on appropriate technology.

[3] Giorcelli and Li (2021), Giorcelli (2019), Comin and Hobijn (2010), Comin and Hobijn (2004), and Keller (2004). For a review of the literature, see Comin and Mestieri (2014).

lower productivity without a significant change in factor mismatch.

I begin by creating a novel dataset containing information on innovation, employment, and international technology transfers by Brazilian firms. Data on patents, trademarks, and industrial design applications was collected from the Brazilian patent office through web scraping. This data was then merged with employment data from RAIS, an administrative matched employer-employee dataset that includes information on the universe of formal firms in Brazil. RAIS also enables the measurement of firms' innovation efforts through the hiring of PhDs and scientists.

I constructed a dataset of all international technology transfers that Brazilian firms have received since 1985. Due to regulations dating back to the capital control era, Brazilian firms are required to register any technology transfer contract at the patent office, which includes agreements on the transfer of a patent, industrial design, trademark, know-how, trade secrets, or any other industrial knowledge. The dataset is constructed by scraping information from all technology transfer contracts registered with the patent office.

Firms that do not register their technology transfer at the patent office are not allowed to make royalty payments to foreigners by the central bank, cannot solve contractual disputes in the judiciary system, and cannot appeal to the patent office in case of intellectual property infringements, which makes it likely that all international technology transfers are covered in the database. The central bank, which oversees international transfers, will only allow payment for technology transfers to flow abroad with proof of registration of the contract with the patent office. Moreover, according to a survey of intellectual property lawyers, registering their contracts with the patent office provides firms with stronger intellectual property claims and allows settling disputes through the judiciary system. Therefore, firms not registering their contract with the patent office cannot go to a court to protect their intellectual property or to request the agreed payment. According to intellectual property lawyers, these features makes it common practice for firms to register their technology contract with the patent office.

Using this novel dataset, I show three new facts about technology adoption in Brazil that will guide the empirical analysis and the model. First, technology adoption is a large and long-lasting investment for firms. Technology transfers last 4 years on average and cost 1.1

million dollars, which is 3 times the average firm's yearly wage bill. In 1990, 36% of the Brazilian wage bill came from firms receiving international technology transfers. Second, 87% of technology transfers come from developed countries, mostly the USA and Europe. Third, firms receiving foreign technologies are bigger and have more skilled workers than firms innovating in Brazil. A potential explanation for the third fact is a difference in bias and productivity between local and foreign technologies. But, to make a definitive claim on the difference between the two technologies one needs exogenous variation in the adoption of foreign versus local technologies, which I discuss next.

I study a Brazilian innovation program that taxed the transfer of foreign technology to subsidize local Brazilian innovations, which I call *Technology Substitution Program* (TSP), that encouraged firms to adopt local over foreign technologies. In 2001 the Brazilian government created a 10% marginal tax rate on the royalty payments for foreign technology and used the revenue to subsidize innovation projects by firms in targeted sectors. Firms with innovations in fields related to biotechnology, aviation, health, or agriculture could apply for a subsidy from the federal government, which is, on average, three times the firm's yearly wage bill. The program thus encourages firms to substitute international technology with national innovations.

To evaluate the impact of the TSP, I use a difference-in-difference strategy. The treatment group is the set of firms in sectors that are eligible for the subsidy and that licensed foreign technology before 2001, and the control group is the set of all other firms in Brazil. After 2001, relative to the control group, treatment firms experienced an increase to the cost of their current technology transfers and, simultaneously, a decline to the cost of innovating. Thus, a comparison between firms in the treatment and control groups demonstrates how firm-level outcomes respond to a replacement of international technology with national innovations.

Exogeneity tests combined with institutional facts support the identifying assumption of parallel trends. First, all variables of interest show pre-period parallel trends. Second, the program introduction surprised the private sector as it was fast-tracked and approved by the federal government in under 6 months, which is too fast to affect technology adoption.[4] Third, TSP exposure does not correlate with tariffs, government loans, procurement

[4] The federal government draw the bill at closed doors. It was subsequently sent to the congress in

contracts, labor taxes, and subsidies. In other words, it is exogenous to some of the most prominent policies. Moreover, TSP exposure does not correlate with campaign contributions, suggesting that the government didn't favor the treatment group through other policies. Fourth, TSP exposure does not correlate with changes in international prices. Therefore, TSP exposure is orthogonal to the commodity boom that affected the Brazilian economy in the 00's. Fifth, I show that firms did not increase foreign direct investment (FDI) in response to the TSP, indicating that they are not using FDI to skip the tax on technology transfers. Finally, I also show that the TSP did not affect firm entry and exit, thus not biasing the estimates.

In response to the TSP, firms changed technology, factor shares, and total employment. They increased the probability of having at least one patent by 4.4 percentage points, i.e., they were almost three times more likely to issue patents than the average firm in Brazil. They also hired more scientists and PhD workers, indicating increased innovation efforts. Moreover, they decreased the licensing of technologies from developed countries. Therefore, they replaced foreign technology with local innovations. The TSP also led firms to change the composition of workers and their size. As a response to the TSP, firms increased the expenditure share with high-school dropouts by 5.1% and decreased the average education of their labor force by 4%, despite hiring more scientists. Moreover, in the 10 years following the program, firms reduced their wage bill by 19%.

The TSP had no impact on innovation quality, new product introduction, adoption of labor-saving machines, or productivity spillovers. Using text analysis to infer patent quality, I show that firms didn't increase the textual complexity of their patents, suggesting limited learning-by-doing.[5] Firms also didn't increase the average education of their scientists or the share of them with a PhD. These results suggest limited effect of the TSP in innovation quality. Using trademark data, I show that firms haven't changed the class of products that they produce, which suggests that they didn't introduce new products. Additionally, I found that firms decreased their imports of capital, imports of labor-saving machines, and the hiring of workers operating machines, suggesting that firms are also using less capital.

regiment of urgency, meaning that it was fast tracked through the Congress and Senate.

[5] As Packalen and Bhattacharya (2012) notes, the text complexity of patents is correlated with their number of citations.

Finally, I don't find evidence for positive spillovers. To test this, I reproduced the main regressions at the sector level and still found a large drop in employment.

These results are robust to additional controls, a matched difference-in-difference strategy, and alternative exposure measures. First, controlling for firm-level trends, pre-period growth, or exposure to international markets does not change the results, indicating that they are not driven by pre-period trends or aggregate shocks to the foreign market, such as the commodity boom or exchange rate fluctuation. Second, a matched difference-in-difference strategy, in which treatment and control firms are matched based on pre-treatment characteristics, delivers the same set of results. Third, the results are robust to several alternative exposure measures, including using only firms receiving technology transfers in the past or exploiting variation on the probability of firms receiving the subsidy. Finally, the results remain consistent when using sector-level exposure measures, indicating that survivor bias or changes in the composition of firms do not drive results.

To understand these effects and create policy counterfactuals, I develop a model of endogenous technology bias and international technology transfers. In the model, there are two countries, the United States and Brazil, and each has an inelastic supply of high- and low-skilled workers. All firms in the United States innovate and are homogeneous. Brazilian firms, on the other hand, choose between innovating or paying a fixed cost to license technology from the U.S. . Brazilian firms are heterogeneous in productivity and licensing costs. When a firm innovates, it can choose the skill bias of its technology, constrained by the efficiency of its R&D sector; higher efficiency leads to more productive innovations. If a firm licenses U.S. technology, the bias was chosen by the U.S. firm, but it has U.S. productivity. Therefore, firms in Brazil are trading off the bias and the productivity of their technology.

The model rationalizes the empirical findings. Because Brazil is skill-poor, Brazilian firms licensing international technology are more intensive on high-skilled workers than innovating firms. If the productivity of the US R&D sector is sufficiently larger than its Brazilian counterpart, firms licensing international technology outsize innovating firms because they use better technology. When the government introduces a tax on international technology licensing, firms switch from international technology, which is high-skilled biased and high productivity, to national innovations, which are low-skilled biased and low productivity.

As a consequence of the technology change, firms increase their expenditure shares with low-skilled workers and decrease overall employment, matching the empirical findings. In aggregate, output and skilled wage premia decrease.

The model delivers closed-form solutions linking the effect of the TSP to model parameters. The effect of the TSP on low-skill expenditure shares informs about the skill-bias of the two technologies while its effect on firm size informs about technologies' productivities. Because there is a small effect of the TSP on factor shares and a large negative effect of it on firm size, the model predicts US technologies to have 67% higher productivity than Brazilian technologies and only 6% higher high-skill bias.

Due to the large differences in productivity between Brazilian and US technologies, programs inducing the replacement of foreign technology with local innovation have a negative effect on output. An innovation program that shifts 1 percentage point of firms from foreign technologies to local innovations decreases output by 0.2% and the skilled wage premium by 0.02%. Therefore, despite a factor–technology mismatch, Brazil's reliance on technology transferred from developed countries thus increases output.

The main result is that technologies from developed countries have higher productivity but a similar skill-bias to technologies from developing countries. Therefore, the TSP reduced output by inducing firms to adopt technologies of lower productivity. This conclusion is robust to a battery of tests and model extensions. First, changing the calibration strategy or parametrization of the model does not change the conclusion. Second, using as a measure of innovation the number of scientists hired, workers with PhD, industrial design applications, or any intellectual property applications delivers the same result, which shows that results are not driven by the way innovation is measured. Third, adding a labor market for scientists or an elastic labor supply for workers also leads to the same conclusions. Fourth, adding to the model the ability for firms to adopt outdated technology also leads to the same result. Finally, a model that includes an externality on innovation still predicts the TSP to decrease output under a reasonable calibration of the externality parameter.

I contribute to the literature on appropriate technology by quantifying the mismatch between factor supply and technology bias. Atkinson and Stiglitz (1969), Stewart (1977), and Schumacher (1973) were the first to propose that developed countries create technologies biased towards high-skill workers. Because these technologies later diffuse to developing countries, which are skill poor, there is a mismatch between factor supply and technology bias in developing countries. Building on this intuition, Basu and Weil (1998), Gancia et al. (2013), Acemoglu and Zilibotti (2001), and Gancia and Zilibotti (2009) use a model to show that the mismatch between factor supply and technology bias can lead to persistent lower growth in developing countries. Okoye (2016), using cross-country comparisons, doesn't find evidence that developing countries are using technologies biased towards high-skill workers. Moscona and Sastry (2022), studying the use of pesticides in agriculture, find that ecological mismatches with developed countries leads to lower productivity in developing countries.

I contribute to this literature on measurement and identification. This is the first paper to collect an administrative dataset with firm-level information on technologies created in-house and those adopted from developed countries. Therefore, differently from previous papers, I can observe what happens to firms moving from foreign to local technologies. My second contribution to this literature is on the identification. I isolate the effect of replacing foreign technologies with local innovations by studying a policy reform that affected the relative price of these two technologies.

I also contribute to the literature on technology diffusion by studying a policy that created barriers to the diffusion of technologies.[6] Giorcelli and Li (2021) and Giorcelli (2019) study the effect of know-how transfers in Italy and China finding that they had a significant and persistent effect on firm growth. Comin and Hobijn (2010, 2004) and Comin and Mestieri (2018) study the diffusion of technologies across countries, arguing that technology adoption accounts for at least a quarter of per capita income differences. I contribute to this literature by studying a unique policy that, instead of inducing the adoption of foreign technologies, created barriers to it.

This paper also contributes to the literature studying drivers of the relative efficiency of skilled labor by isolating the contribution of technology. Caselli and Coleman (2006) shows that low-skill workers are relatively more productive in developing countries, which suggests the adoption of low-skill biased technology. Okoye (2016), Hendricks and Schoellman (2023),

[6] Griffith et al. (2006), Coe et al. (2009), and Glitz and Meyersson (2020) discuss the diffusion of knowledge across countries through R&D or espionage. Comin and Mestieri (2014) and Keller (2004) discuss the literature.

and Rossi (2022), using variation from the wage of migrants in the US, argue that differences in relative efficiency of skilled labor across countries cannot be explained by human capital. Malmberg (2022) suggests that differences in organizational capital accumulation across countries can explain the difference in skill bias.

This paper sheds light on the drivers of the relative efficiency of skilled labor across countries. Most of the literature estimates the contribution of technology to the relative efficiency of skilled labor by comparing differences across countries in skill-premium which is not explained by human capital. Therefore, they load on the technology factor differences in regulation, infrastructure, and any other factors varying across countries that could affect the relative efficiency of skilled labor. I isolate the contribution of technology to the relative efficiency of skilled labor by looking at factor share change within firms before and after they replace foreign technologies with local innovations. My findings that there is little skill bias difference between foreign and local technology supports the interpretation of Malmberg (2022) that organizational capital drives differences in the relative productivity of skilled labor across countries.

2 Data

I collected firm-level data on employment, imports, and applications for R&D subsidies from various administrative sources. I extracted data on patents, industrial designs, trademarks, and technology transfers from the Brazilian Patent Office's webpage. To validate the dataset on technology transfers, I conducted a survey among intellectual property lawyers. From the Ministry of Science's webpage, I extracted data from inventors' CVs. I use this dataset in section 4 to understand how a program subsidizing local innovations and taxing foreign technology transfers affected firm growth and innovation.

2.1 Technology Transfers

Brazilian firms that receive intellectual property transfers, such as patents, licenses, or know-how, from any firm outside of Brazil must register their contracts with the Brazilian Patent Office. This paper uses data extracted from all technology-transfer contracts registered at the patent office to assess how innovation and international technology transfers affect the macro-economy.

Institutions. Firms are required to register their technology contracts at the patent office, a feature that guarantees a representative sample of all technology transfers. If a contract is signed with a firm outside of Brazil, firms must register the contract at the patent office for the international transfer of payments to be allowed by the central bank. This requirement dates back to 1962, a period of capital controls in Brazil.[7] 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. After capital control was lifted, the government maintained the requirement. Section A.1 discusses all regulations regarding technology transfers in Brazil.

The patent office does not play a passive role; it can either accept, reject, or demand changes to a technology contract application, a feature that ensures each contract captures real technology transfers between firms. A contract is rejected if a board of technicians concludes that no significant transfer of technology or know-how is part of the transaction.[8] More information is required when the documentation provided is uninformative about the ownership of the technology or does not prove the transfer of know-how or intellectual property. About 70.5% of contracts had extra information required, and 3.2% were denied. In Appendix A.4, I discuss the process of registration and inspection of technology contracts.

Coverage and Examples. Brazilian firms are required to register any intellectual property transfer that leads to an increase in productivity or the creation of a new product line. According to the patent office, those 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 a technology transfer and are therefore not able to be registered. Those include financial, marketing, or legal consulting, license or acquisition of software, services of maintenance, and services that do not generate a technical report.

[7] The requirement to register technology transfers at the patent office was created by law no. 4.131 in 1962.

[8] For instance, firms attempting to register accounting services or management consulting have their contract rejected because those are not considered a transfer of technology.

Data Collection. By scraping information from the patent office's webpage, I construct a dataset using information on all technology transfers registered with the office. For transparency, the patent office allows the public to consult its contract database. By scraping information from technology transfer contracts, I construct a dataset that includes the name of the firms involved, a description of the contract or service offered, its value, the buyer's sector, the country of origin, and the type of the contract.[9] A full set of statistics on technology transfers is provided in Appendix A.2.

Validation. This is the first dataset that registers technology transfers at the firm level. To evaluate its extension and ability to measure technology transfers across firms, I administered a survey among intellectual property lawyers who specialize in writing and registering technology transfers. The survey suggests that registering technology transfers is costly, bureaucratic, and requires technical documentation. The population of international technology transfers are registered in the Brazilian patent office, and firms are unlikely to fraudulently register technology transfers for tax purposes. Details on the survey and further statistics appear in Appendix A.5.

Summary Statistics. Table 1 shows basic statistics on technology transfers in Brazil, suggesting that such transfers are over know-how (i.e., transfer of expertise or technical assistance to production improvement not protected by property rights) and represent a large investment for the firm.[10] Appendix A.2 describes other statistics of technology transfers in Brazil.

2.2 Patent, Trademark and Industrial Design Applications

To measure a firm's innovation efforts, I create a dataset using information on patents, trademarks, and industrial design applications submitted to the Brazilian Patent Office. Using this large set of intellectual property objects, I construct various measures of firm-level

[9] A description of the technology transferred and the value of the contract was not observed for all contracts.

[10] For example, in 2009 Tegron Industrial Automation, a U.S. based firm, implemented improvements on the Doritos production line of Pepsico Brazil. Patent, trademarks, and industrial design do not fall into this class.

Table 1: **Statistics on Technology Transfers**

Variable	**N. Contracts**	**%**
Contract Types		
Know How	10,928	79.39
Trademark	2,208	16.04
Patent	564	4.10
All	13,765	100
Licensee and Licensor		
Unique Licensee	5,484	
Unique Licensor	10,844	
HQ-Branch	401	3.31
Transaction Value (in dollars)		
Mean	1,163,047	
Median	645,070	
Contract Duration (in years)		
Mean	3.77	

Description: This table contains statistics of technology transfers applications made to the Brazilian Patent Office between 1995 and 2015. The first panel contains information from technology contracts by type, according to the definition from the patent office. The second panel contains information from technology sellers and buyers. Line *HQ-Branch* reports the share of transfers realized between an HQ and branch, identified using information from firm ownership in the National Firm Registry dataset. The last panel contains information regarding the value of technology transfers.

innovation.[11] The dataset with information on patents, trademarks and industrial designs was constructed by scraping information from the Brazilian Patent Office. It contains the population of patents, trademarks, and industrial designs submitted to the office between 1995 and 2015.[12]

Summary Statistics. Table 2 shows a set of baseline statistics for patents, trademarks, and industrial designs in Brazil. Appendix A.6, A.7 and A.8 reports a full set of statistics on this database.

[11] Patents, trademarks, and industrial designs are created to protect different types of intellectual property. Patents protect inventions, industrial designs protect a new design of an invention already patented, and a trademark protects company names, logos, products, and brands. For example, if a firm creates and sells a new type of sunglasses in different shapes, the sunglasses are protected by a patent, each shape of the sunglasses is protected by an industrial design, and the brand is protected by a trademark.

[12] Appendix A.9 discuss the matching of patents to firms.

Table 2: **Statistics on Patents, Industrial Designs, and Trademarks**

	Patents	**Trademarks**	**Industrial Design**
Patent/Trademark/ID	198.727	2.326.586	79.745
Number of Applicants	13.372	859.384	22.085
Number Scientists	176.960	-	35.051

Description: This table shows statistics for patents, trademarks, and industrial design applications submitted by Brazilian firms and inventors to the Brazilian Patent Office. The first line shows the number of various patents, trademarks, and industrial designs. The second line contains the number of unique applicants who submitted applications for each form of property right. An applicant can be a firm or an individual inventor. The third line contains the overall number of authors in each dataset. No author identifier appeared in the trademark database

2.3 Matched Employer–Employee Data

The primary source of labor force information is the administrative dataset RAIS - *Relação Anual de Informações Sociais*, collected by the Brazilian Ministry of Labor and covering the population of formal firms. Its use has been widespread in various areas of economics in recent years.[13] In RAIS, each observation contains yearly information on a worker, where a firm's and a worker's tax IDs are observable. With this information, I link workers and firms over time within RAIS and across databases.

Using RAIS to Measure Innovation Effort. I also use RAIS to measure the innovation effort of firms. Using occupational and educational codes, I can identify PhD workers and scientists, which according to Goolsbee (1998) corresponds to most of the R&D cost.

2.4 Other Datasets

R&D Subsidy Applications and Recipiency. I use an administrative dataset on applications for R&D subsidies to identify exposure to the innovation policy. R&D subsidy application data is from the Funding Authority for Studies and Projects (*Financiadora de Estudos e Projetos*), FINEP, which selects innovation projects according to predetermined technical criteria. I observe information on all subsidies for R&D given by FINEP since 2000, including the subsidy's value, a description of the project, the sector of the project, and the type of subsidy. Appendix A.10 describes the application and selection process of firms for federal subsidies, and includes statistics on R&D subsidies in Brazil.

[13] Rafael Dix-Carneiro (2019), Dix-Carneiro and Kovak (2017), Colonnelli and Prem (2019a) and Colonnelli and Prem (2019b) are some.

CV of Inventors. To measure invention quality, I create a dataset using information extracted from the CVs of inventors of patents and industrial designs. The CVs were gathered from the Lattes Platform, an administrative database of academic CVs in Brazil. Having an updated CV hosted on the platform is required for scientists, academics, and PhD students receiving federal support or associated to institutions receiving federal support. Section A.14 describes the dataset and present summary statistics.

Imports of Materials and Machines. To identify how innovation and technology adoption affects the use of inputs other than labor, I construct a dataset that contains information on imports of machines and materials by firms. For each firm, I observe a probability of it importing a four-digit product code. The procedure to construct the dataset is described in appendix A.11.

Revenue, Profit, Capital and Other Financial Outcomes. Revenue and capital is gathered for public Brazilian firms. The data includes historical records on all companies that issued bonds and all companies with equity traded on the Stock Exchange.

2.5 Facts on Innovation and Technology Transfers

In this section, I show three new facts on innovation and technology transfers that motivates the empirical analysis and the model. First, Brazilian firms mostly receive technologies from developed countries. Second, firms receiving technology are larger than firms innovating. Third, firms receiving technology are more intensive in high-skill workers than firms innovating. In the following sections, I show that the difference in size and factor share between firms receiving technology and firms innovating is explained by differences in productivity and bias between local and foreign technologies.

Fact 1: Brazilian firms receive technologies from developed countries. Table 3 displays the number of technology transfers by country.[14] 86% of technology licenses are signed with firms in developed countries, with the US and Germany leading the table.

[14] Table 13 on appendix A.2 replicates Table 3 using technology value.

Table 3: **Country of Origin of Technology Transfers**

Region	**N. Transfers**	**%**
United States	3,542	25.73
Germany	1,860	13.51
Brazil	1,237	8.99
France	877	6.37
Italy	811	5.89
UK	720	5.23
Japan	631	4.58
Canada	508	3.69
Spain	470	3.41
Others	3110	22.59
Developed	10,579	86.83
Developing	1,605	13.17

Description: This table breaks down technology transfers in Brazil between 1995 and 2015 according to the country of origin of the technology.

Table 4: **Technology and Firm Size**

Sample	**N. Firms**	**N. Workers**	**Hourly Wage**
Patent	61,363	562	58.56
Int. Technology	2,934	1569	123.92
All	5,800,587	61.85	38.75

Description: This table presents statistics of Brazilian firms according to their intellectual property in 2000. The first line contain statistics of firms with patents registered in the Brazilian patent office, the second line contain statistics of firms that received international technology transfer before 2000, and the last line contains statistics from all Brazilian firms.

Fact 2: Firms receiving technology transfers are larger than firms innovating. Table 4 shows the average number of workers and hourly wage in 2000 for firms with patents, firms with international technology, and all other firms in Brazil. Firms that have licensed technology in the past are almost three times larger and have higher hourly wage than firms with at least one patent.

Fact 3: Firms using international technology are more intensive in high-skilled workers than firms innovating. Table 4 shows the share of workers with less education than high-school, the share whose highest education is high-school, and the average years of education for firms innovating or licensing international technology. Firms innovating are more intensive in low-skill workers than firms innovating, which is surprising because innovation is a skill intensive activity and new technologies have been show to be skilled-biased.[15]

In the next section, I use exogenous variation from an innovation subsidy program to show that facts 2 and 3 can be explained by the difference in quality and bias of national and international technology.

Table 5: **Technology and Firm Skill Intensity**

Sample	**N. Firms**	**Shr. HS Drop.**	**Shr. HS Complete**	**Yrs. Educ.**
Patent	61,363	0.69	0.19	8.96
Int. Technology	2,934	0.46	0.26	10.89
All	5,800,587	0.71	0.22	9.03

Description: This table presents statistics of Brazilian firms according to their intellectual property in 2000. The first line contain statistics of firms with patent registered in the Brazilian patent office, the second line contain statistics of firms receiving international technology, and the last line statistics from all Brazilian firms.

3 Institutions: Technology Substitution Program

In 2001, the Brazilian government implemented a policy to stimulate innovation and discourage international technology transfers. The policy provided a subsidy to approved innovation projects in targeted sectors and created a 10% tax on payments for international technology transfers. The policy thus foments national technology creation and discourages international technology transfers. I call this the *Technology Substitution Program* (TSP).[16]

Time-Series Correlation with TSP. This policy not only encouraged innovation, but discouraged the transfer of technology from abroad, and in practice, it stimulated technology substitution. Figures 1a and 1b show how significant TSP is to the innovation effort. After TSP was introduced, the number of technologies transferred from outside Brazil decreased, shown in figure 1a. Simultaneously, the rate of innovation increased after introduction of the program.[17][18]

[15] Krueger (1993), Autor et al. (2003) and Akerman et al. (2015).
[16] The program was created using the name "Innovation for Competitiveness" (*Programa de Inovação para Competitividade*)
[17] In section 6.4, I show that firms have not substituted technology transfers with FDI.
[18] Figure 24 in the appendix shows an increase to the number of patents and industrial designs sent to the patent office, and the number of inventors in Brazil. Using cross-country synthetic control and differences-in-differences, Appendix A.12 shows an increase in Brazilian patents, in comparison to other countries, in response to TSP.

TSP was not motivated by sectoral trends. The goal of TSP was to increase R&D investment by private companies. As stated in the discussion leading to the program implementation (Camara dos Deputados (2000)), policymakers had two motivations for the TSP. The first was the perceived low expenditure on R&D by the country, about 0.8% of GDP. The second was the concentration of R&D in public universities.[19] Importantly for the identification, it was not created as a response to trends in labor market or as preparation for future shocks.

The tax on technology transfers wasn't created with a specific policy goal. Instead, it came from a revenue requirement from Brazilian fiscal law. The "Law of Fiscal Responsibility" requires any new expenditure to have a new revenue source arguably related to it. Given that the goal of the program was to stimulate innovation, policymakers decided to use the transfer of innovations as a source of revenue.[20]

The TSP was unexpected by the private sector. The TSP was quickly written by the federal government and approved in a regime of urgency. The main piece of legislation was released to the public and approved in 6 months, a record time for the Brazilian bureaucracy. Moreover, in the years prior to the program, the government issued a series of cuts, a reorganization of the federal budget, and tax increases. Therefore, a shift in policy wasn't expected by firms or workers.[21]

4 Empirics

I now evaluate the effect of the Brazilian technology substitution program on innovation, factor shares, and employment. The identification strategy relies on heterogeneous exposure to TSP. The program created a tax on international technology transfers and a subsidy to innovation targeted at specific sectors. The firms most exposed to the program were the ones licensing international technology when the program was introduced in sectors targeted by the subsidy. These firms had an increase in the cost of using international technology

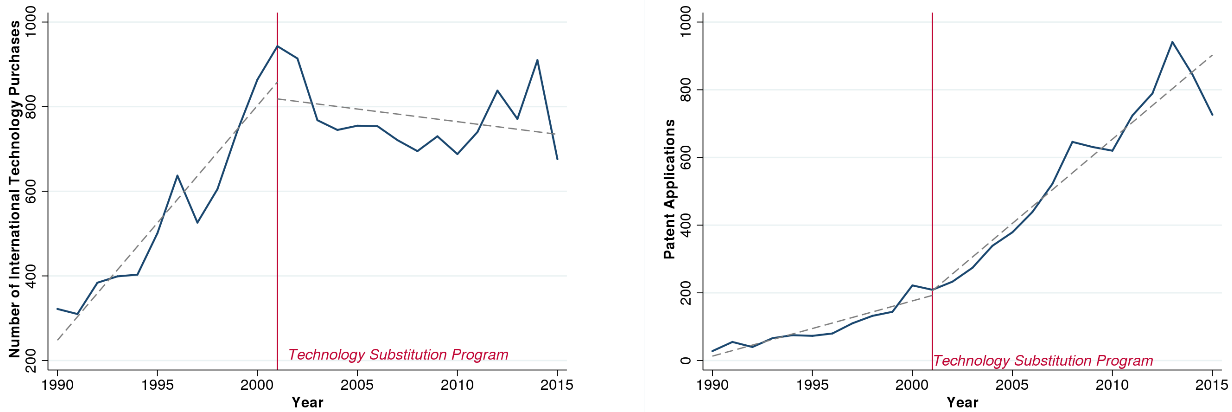
[19] The motivations and goals for this policy can be found at Camara dos Deputados (2000).

[20] For more details on the motivations behind the TSP see Camara dos Deputados (2000) and Thielmann (2014).

[21] Appendix A.13 describes other details of the program.

Figure 1: **Technology Substitution Program and Innovation**

(a) Int. Technology Transfers (b) PCT Patent Applications



Description: This figure contains time series information on the number of patent applications, and the number of technology transfers. The number of patent applications is from the OECD REGPAT, and the number of technology transfers was calculated using data extracted from the Brazilian patent office.

with a decrease in the cost to innovate. Therefore, these are the firms with more incentives to switch technology.

The identification strategy passed several validation and placebo tests. First, institutional facts guarantee that TSP was not predicted and not based on future shocks, which ensures no anticipation and exogeneity to predictable future shocks. Second, exposure to TSP does not correlate with other policy changes and aggregate shocks that occurred during the period, such as tariff changes, tax changes, federal loans, federal demand, and international prices. Third, firms did not use other methods of technology transfer, such as FDI, in response to TSP, reinforcing the idea that the program affected cross-country technology transfers. Fourth, a placebo test with fake implementation year offers no result, as expected, supporting the idea that the variation identified comes from the program introduction and not from the construction of the exposure measure. Fifth, a placebo test with firms not exposed to the program supports the idea that results are not driven by aggregate shocks that affected exposed firms.

Firms affected more by TSP increased patent applications, increased expenditure shares with low-skilled workers, and reduced overall employment. These results are robust and cannot be explained by a direct effect of tax on international transfers, changes to the type of product produced, changes to innovation quality, or adoption of robots.[22]

The increase in expenditure share and reduction in employment can be explained by firms substituting international technology for national technology. Although international technology is high TFP and high-skilled bias, national innovations are low TFP and low-skilled bias. A difference in technology TFP generates a reduction to employment when firms change technology, and an increase to expenditure share with low-skilled workers is explained by the difference in bias. The simple model in the next section formalizes this intuition and section E provides several additional evidence supporting this interpretation.

4.1 Empirical Strategy

TSP created an R&D subsidy for firms in selected sectors and a tax on international technology transfers. Firms affected more by the program were those in sectors supported by R&D subsidies that now have to pay higher taxes on technology licenses. I use variable $\textit{Exposure TSP}_{i,s(i)}$ to define these firms:

$$\textit{Exposure TSP}_i = \mathbb{I}\left\{\textit{Subsidy } s(i)\right\} \times \mathbb{I}_i\left\{\textit{Licensed Tech. Before TSP}\right\} \tag{1}$$

$s(i)$ is the sector of firm i, dummy $\mathbb{I}\left\{\textit{Subsidy } s(i)\right\}$ is one if firm i is in one of the 2-digit sectors targeted by the R&D subsidy, and $\mathbb{I}\left\{\textit{Licensed Tech. Before TSP}\right\}_i$ is a dummy that is one if a firm has ever received international technology transfer before introduction of the program, capturing reliance of the firm on international technology.[23,24]

The exposure measure in (1) is one for firms with the largest incentives to change technology. These firms experiences a decrease to the cost of innovation due to the subsidy, and an increase to the cost of using international technology due to the tax. Therefore, these firms are most likely to change technology. In the model section, I show that the choice of exposure measure is supported by the model and is informative about permanent firm

[22] Sample selection is discussed in appendix B.1. Section B.5 in the appendix shows that results are robust to sample selection and that TSP did not affect firm entry or exit, thus not biasing the estimates for survivors.

[23] As robustness, I use several other measures to capture exposure to the subsidy and international tax. For the subsidy, I construct a probability of the firm receiving a subsidy based on pre-policy characteristics and sectoral allocation of the subsidy. For tax exposure, I use dummies if the firm licensed technology 1,2,3, or 5 years before introduction of the program. These exposure measures return similar results.

[24] The targeted sectors were the ones with research related to biotechnology, aviation, health, or agriculture.

characteristics.

My main specification is:

$$y_{i,2010} - y_{i,2000} = \theta \mathit{Exposure\ TSP}_i + X_i'\beta + \epsilon_i \tag{2}$$

where $y_{i,2010}$ is an outcome of firm i in year 2010, and $y_{i,2000}$ is the same outcome in 2000. $\mathit{Exposure\ TSP}_i$ is the exposure measure defined in (1), and X_i is a set of controls.[25] Standard errors are clustered at the sector level.

The long-term difference in model (2) offers two advantages. First, it removes persistent differences between firms. By taking the differences of outcome within firm, $y_{i,s(i),2010} - y_{i,s(i),2000}$, permanent level characteristics of the firm are removed. The second is that it allows for lagged adjustment. Technology takes time to adjust; firms would need to start their invention programs, create new technologies, patent them, and implement them, and it is expected that these changes take several years.

Specification (2) identifies θ by differences-in-differences, comparing the growth rate in outcome y between firms exposed more to the program, the treatment group, and those exposed less to the program, the control group. As usual with differences-in-differences, the identifying assumption is parallel trends between control and treatment groups, i.e., were not for TSP the growth rate of y would be the same between treatment and control groups.

To test parallel trends in the pre-period and estimate the dynamic effect of the program, I use specification:

$$y_{i,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathit{Exposure\ TSP}_{i,s(i)} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{3}$$

where if there is no pre-period trend between control and treatment groups, $\theta_j = 0, \forall j < 0$. Below in the results, I show that parallel trends during the pre-period are supported for all variables I study.

[25] Controls are a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent during the past 10 years in 2000, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent..

4.2 Validation

Evidence supports the assumption of parallel trends. Program introduction was unexpected and not a response to future shocks. There is no pre-existing trend between treatment and control groups, exposure to TSP does not correlate with other programs, and exposure to TSP does not correlate with aggregate shocks to the Brazilian economy.

Antecipated Response. Discussed in Section 3, TSP was unexpected and not a response to future shocks. It was unexpected because it was created and approved urgently during a period in which the government was drastically cutting expenses. TSP was not a response to future shocks; in fact, its goal was to encourage research in some sectors, such as agriculture and aviation, to create competitive advantages. Therefore, program motivation has nothing to do with future labor market changes that affected these sectors.

Other Policies and Political Connection. If exposure measure (1) correlates with other policies implemented during the period, such as tariff or tax changes, I cannot separate the effects of TSP from those of other policies. To test if this concern is valid, I run specification (2) on a set of policy outcomes that affected firms. Table 34 in Appendix B.2 shows that control and treatment groups were exposed equally to changes to input tariffs, output tariffs, government loans, demand from the government through federal contracts, labor taxes, and overall tax payments. Table 34, column 8 shows that firms in the treatment group engaged in campaign contributions as much as the control group did, evidencing that they were equally politically connected and equally targeted by governmental benefits. Table 34 supports the idea that exposure measure (1) does not correlate with other policies implemented during the period.

Other Forms of Technology Transfers. If firms can avoid the tax on technology transfers by transferring technology through foreign direct investment, I could not identify the effect of technology substitution. I test whether firms have increased FDI in response to TSP, (Table 33). I run the baseline specification (2) on a dummy that is one if a firm is a subsidiary of a multinational firm. Table 33 shows that firms did not increase FDI in response to TSP.

Commodity Boom. Another concern is the 2000s commodity boom. Changes to international prices might have affected the treatment group more than they did the control group. In that case, I would be unable to separate the effects of TSP from that of international price changes. Table 33 shows that international price changes to products and inputs were the same for the treatment and control groups.

Placebo Tests. Exposure measure (1) uses a past firm outcome—a firm's decision to lease technology—which suggests two identification concerns; one from future shocks and another from technology leasing itself. First, a firm's decision to lease technology might be a response to a future shock. In this scenario, I would be unable to separate the effects of the shock from those of TSP.[26] A second identification problem concerns past technology leasing itself. Leasing technology in the past might affect the labor composition of a firm. I evaluate the validity of these concerns using a placebo test with a fake TSP implementation year and robustness to different timings to technology licensing. Results of these robustness tests support the idea that specification (2) is not capturing future shocks or the effect of technology leasing.[27,28]

Selection Bias. On appendix B.5, I show that TSP did not affect firm entry or exit, thus not biasing the estimates towards survivors.

[26] For example, firms might lease technology because they expect the quality of high-skilled workers to increase in the future. In this scenario, I could not discern effects from an increase to the quality of high-skilled workers and effects of TSP.

[27] Appendix B.4.1 reports results from using a fake implementation year. Results from using a different dummy for technology leasing is discussed in the robustness section.

[28] This does not mean that leasing international technology does not affect the firm. On average, firms in the treatment group signed 4 technology contracts. They thus represent experienced firms that have already adjusted labor market outcomes to the use of international technology. Any effect due to leasing is in the past and thus already captured by fixed effects. In section E.1.4, I conduct an event study on leasing of international technology, demonstrating that its effect on a firm's labor composition is quick and permanent, which supports the idea that the effect of technology leasing is absorbed by the fixed effect.

4.3 Empirical Results

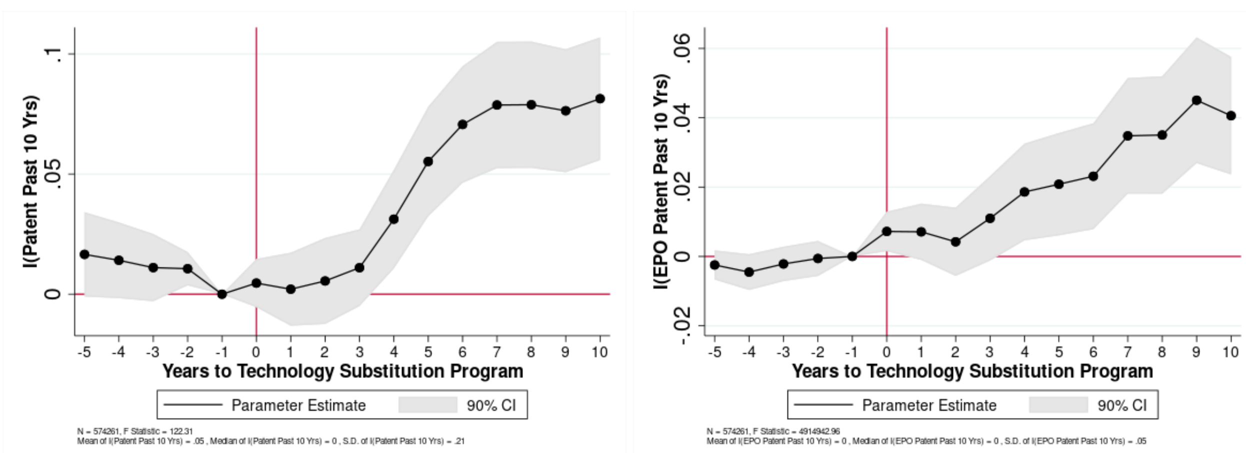
In this section, I show that as a response to TSP, firms increased patenting, increased expenditure share on low-skilled workers, and reduced total employment.

4.3.1 Effect on Innovation and Technology Adoption

Firms increased patent applications in response to TSP (Figure 2). Figure 2a shows the coefficients of regression (3) on a dummy that is one if a firm made a patent application to the patent office during the past 10 years. Figure 2b shows the coefficient of a regression on a dummy that is one if a firm submitted a patent application to the European Patent Office (EPO) under the Patent Cooperation Treaty (PCT). Since PCT patents offer worldwide protection and are more costly to acquire, they represent measures of high-quality inventions. This result suggests that firms increased both their overall number of patents and their high-quality patents.

Figure 2: **Innovation and Exposure to the TSP**

(a) I(Patent Past 10 Yrs.) (b) I(EPO Patent Past 10 Yrs.)



Description: Figure 2a contains the estimated parameter of model (3) on a dummy that is one if a firm applied for a patent in the Brazilian Patent Office during the past 10 years. Figure 2b includes a dummy that is one if a firm applied for a patent at the European Patent Office. Data are from 1995 to 2010. As controls I use a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent before TSP, and firm's employment growth between 1995 and 2000. Each control is interacted with a year-fixed effect. Standard errors are clustered at the 5-digit sector level.

Firms exposed more to TSP increased their innovation, measured as applications for patents, industrial designs, and trademarks, and were more likely to receive R&D subsidies.

Table 6 shows that firms exposed to the program increased their patenting by 4.7 p.p., in comparison to less-exposed firms, which is an economically significant impact that represents 2.5 times the average change in patenting in the economy. Table 6 also shows that exposed firms increased their likelihood of applying for patents in the European Patent Office. Column 3 shows that firms exposed to the program were also more likely to submit applications for patents or industrial designs, and, in column 4, to apply for intellectual property protection, which includes patents, trademarks, and industrial designs. The last column of table 6 shows that firms in the treatment group had a 1.7 p.p. higher probability of receiving the subsidy.[29]

Table 6: **Innovation and Exposure to the TSP**

	(1)	(2)	(3)	(4)	(5)
	$\Delta\mathbb{I}\{Patent\}$	$\Delta\mathbb{I}\{EPO\ Patent\}$	$\Delta\mathbb{I}\{Patent\ or\ Ind.\ Design\}$	$\Delta\mathbb{I}\{Any\ Intelec.\ Prop.\}$	$\Delta\mathbb{I}\{Subsidy\}$
Exposure TSP	0.0478***	0.0379***	0.0440***	0.0330*	0.0177**
	(0.0155)	(0.0111)	(0.0164)	(0.0197)	(0.00739)
N	29301	29301	29301	29301	29301
R^2	0.340	0.110	0.259	0.074	0.071
Mean Dep. Var	.019	.003	.027	.158	.006
SD Dep. Var	.252	.066	.278	.639	.076
Mean Indep. Var	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes

Description: This table reports estimated parameters of a regression of exposure to TSP on measures of changes to intellectual creation by firms. $\mathbb{I}\{Patent\}$ is a dummy that is one if a firm applied for a patent in the Brazilian Patent Office in the past 10 years, $\mathbb{I}\{EPO\ Patent\}$ is a dummy that is one if a firm applied for a patent in the European Patent Office in the past 10 years, $\mathbb{I}\{Patent\ or\ Ind.\ Design\}$ is a dummy that is one if a firm applied for a patent or industrial design in the past 10 years, $\mathbb{I}\{Any\ Intelec.\ Prop.\}$ is a dummy that is one if a firm applied for any intellectual property in the past 10 years, $\mathbb{I}\{Subsidy\}$ is a dummy that is one if a firm received subsidy in the past 10 years. The difference is taken within the firm and between 2010 and 2000. As controls, I use a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent during the past 10 years in 2000, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent.. Standard errors are clustered at the 5-digit sector level.

Firms also increased the hiring of scientists, PhDs, and patents from high-quality inventors, in response to TSP. Table 35 in the Appendix shows that in response to TSP, firms increased hiring of workers with doctorates and master's degrees, hiring of workers in scientific occupations, patents created by inventors with PhDs, and patents created by inventors with an academic background.

Firms reduced their absolute and relative use of international technology. Figure 25 in the Appendix shows that firms exposed to the program became less likely to lease technology. Table 40 in the Appendix shows that firms increased the percentage of national technology

[29] Tables 36 and 37 shows that the TSP had weaker effect on the intensive margin.

on their intangible capital, which is explained by an increase in innovation and a decrease in leasing international technology.

In conclusion, in response to the TSP firms shifted from international technology to national innovations.

4.3.2 Effect on Expenditure Shares

Firms exposed to TSP increased expenditure share with high-school dropouts and reduced expenditure share of workers with high-school completion. Firms exposed to TSP increased expenditures on high-school dropouts by 5.3 p.p., in comparison to the control group, as table 7 shows. In response to TSP, firms reduced expenditure share on workers with high-school completion and slightly increased expenditure share on workers with high-school or more education. Column 4 of table 7 reports that firms exposed to the program reduced the average years of education of its labor force by 4%.[30]

Table 7: **Expenditure Shares and Exposure to the TSP**

	(1) Δ Exp. Shr. Dropout	(2) Δ Exp. Shr. HS Complete	(3) Δ Exp. Shr. HS More	(4) Δlog(Yrs. Educ.)
Exposure TSP	0.0515***	-0.0740***	0.0209**	-0.0403***
	(0.0109)	(0.00985)	(0.00923)	(0.00856)
N	29301	29301	29301	29284
R^2	0.126	0.123	0.054	0.111
Mean Dep. Var	-.214	.171	.042	.195
SD Dep. Var	.278	.261	.16	.269
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table reports estimated parameters of a regression of exposure to TSP on measures of education at a firm. *Exp. Shr. Dropout* represents the expenditure of a firm with high-school dropouts divided by the wage bill of the firm, *Exp. Shr. HS Complete* is the expenditure of a firm with high-school complete divided by the wage bill of the firm, Δ *Exp. Shr. HS More* is the expenditure of the firm with more than high-school divided by the wage bill of the firm, and log(Yrs. Educ.) is the log of the average years of education at the firm. The difference is taken within the firm and between 2010 and 2000. As controls, I use a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent during the past 10 years in 2000, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Each control is interacted with a year-fixed effect. Standard errors are clustered at the 5-digit sector level.

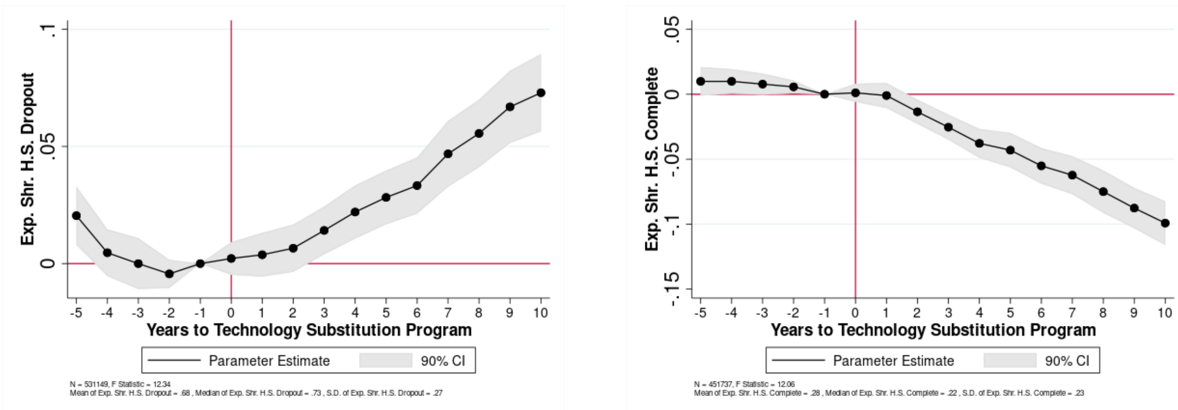
Figure 3 also shows that results are not driven by a pre-period trend. Figure 3a shows a weak, decreasing trend that reverts with the introduction of the program, and figure 3b does not show any clear trend. Section B.3.5 in the Appendix adds a linear trend as a control,

[30] Table 41 in the Appendix reproduces table 7 using factor shares, showing similar results. Table 42 shows that firms exposed to TSP reduced abstract and non-routine task content.

with results remaining the same.

Figure 3: **Expenditure Shares and Exposure to the TSP**

(a) Exp. Shr. H.S. Dropout (b) Exp. Shr. H.S. Complete



Description: Figures 3a and 3b report estimated parameters of model 3 on expenditure shares of high-school dropouts and workers with high-school completion. The difference is taken within the firm and between 2010 and 2000. As controls, I use a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent during the past 10 years in 2000, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Each control is interacted with a year-fixed effect. Standard errors are clustered at the 5-digit sector level.

In conclusion, in response to the TSP firms increased the expenditure share with low-skilled workers.

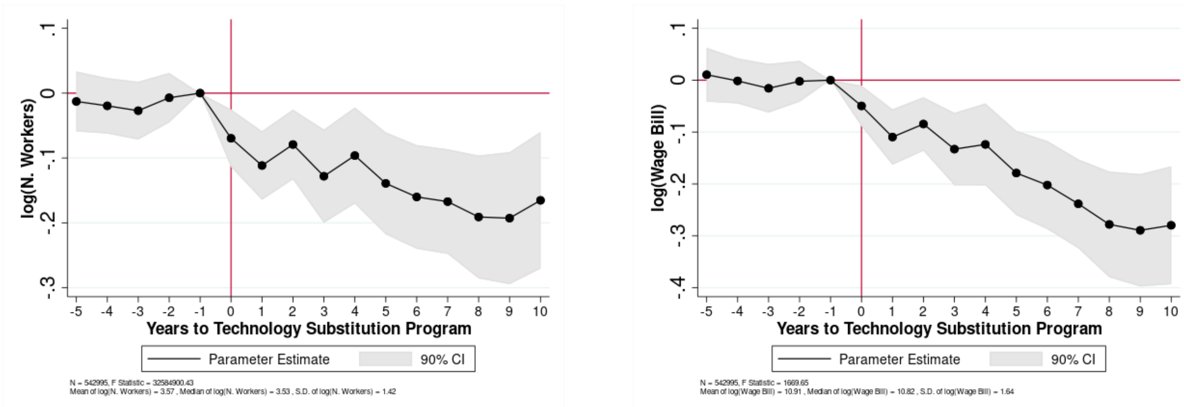
4.3.3 Effect on Firm Size

Firms reduced their employment and wage bill in response to TSP. Figure 4 shows estimated parameters of regression (3) on employment and wage bill. Figure 4 suggests that firms adjusted their sizes quickly after introduction of the program and kept their employment low after that.

Firms exposed to TSP reduced their employment by 17% during the 10 years after program introduction, according to Table 8. The effect of TSP on employment was negative across all education groups, as columns 4 through 6 show. Even high-school dropouts, who

Figure 4: **Employment and Exposure to TSP**

(a) log(N. Workers) (b) log(wage bill)



Description: Figure 4a and 4b contains the estimated parameter of model (3) on the number of workers and wage bill. As controls, I use a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent during the past 10 years in 2000, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent.. Each control is interacted with a year-fixed effect. Standard errors are clustered at the 5-digit sector level.

experienced an increase to expenditure share, had a drop in overall employment.[31,32]

Table 8: **Employment and Exposure to the TSP**

	(1)	(2)	(4)	(5)	(6)
	$\Delta log(N.Workers)$	$\Delta log(wagebill)$	$\Delta log(N.WorkersDropout)$	$\Delta log(N.WorkersHSComplete)$	$\Delta log(N.WorkersHSMore)$
Exposure TSP	-0.170***	-0.192***	-0.322***	-0.336***	-0.197***
	(0.0612)	(0.0652)	(0.0502)	(0.0587)	(0.0571)
N	29301	29301	27886	22479	14693
R^2	0.092	0.093	0.099	0.100	0.113
Mean Dep. Var	.284	.608	-.114	1.085	.66
SD Dep. Var	1.41	1.448	1.338	1.335	1.098
Mean Indep. Var	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes

Description: This table reports estimated parameters of model (2) on measures of firm size. $log(N.Workers)$ is the log of total firm employment, $log(wagebill)$ is the log of wage bill, $log(N.WorkersDropout)$ is the log of the number of high-school dropouts, $log(N.WorkersHSComplete)$ is the log of the number of high-school complete, and $log(N.WorkersHSMore)$ is the log of the number of workers with at least some college. The difference is taken within the firm and between 2010 and 2000. As controls, I use a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent during the past 10 years in 2000, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent..Standard errors are clustered at the 5-digit sector level.

Firms more exposed to TSP also decreased average wages, the probability of exporting, the probability of importing an input, and the probability of importing capital.[33] These

[31] The effect in columns 4 through 6 does not average to the total employment effect in column 1. This occurs for two reasons—selection and log-approximation. First, not all firms have workers with high-school dropouts, workers with high-school completion, or workers with more than high-school, which creates a selection problem among these variables. Second, log difference is a poor approximation of the percentage change in large numbers. Table 43 in the Appendix B.2 shows the result for a balanced sample of firms using percentage change in employment. In this case, the effect on employment is the average of the effects across education groups.

[32] Certain firms do not have workers in all educational groups. In Table 44 in the Appendix B.2, I show that results are robust when addressing the selection problem using Heckman correction.

[33] Results for wages appear in table 45 in the Appendix, and results for imports appear in table 46.

results suggest an overall negative effect on firm performance.

In conclusion, in response to the TSP firms decreased employment and wage bill.

4.4 Robustness and Alternative Specifications

In response to TSP, firms increased innovation, increased expenditure share with high-school dropouts, and decreased overall employment. This section shows that these results are robust to the addition of trends, extra controls, various exposure measures, and use of a matched differences-in-differences design. This section also discusses results from a specification allowing the effect of the tax and the subsidy to differ.

Adding Controls. Despite showing a clear trend break, figures 2a and 3a suggest a small downward trend. To ensure that results are not driven by a pre-treatment trend, figures 30 through 32 in Appendix B.3.5 reproduce the baseline regressions on innovation and expenditure share adding treatment-level linear trends. Results are robust in both sign and magnitude.

Section B.3.6 in the Appendix shows that the effects on innovation, expenditure share, and firm size are robust to adding exposure to international shocks as control.[34]

Different Exposure Measures. Results are robust to alternative measures of exposure to taxes and subsidies. In section B.3.1, I exploit heterogeneity on budget allocation of the subsidy across sectors. In Appendix B.3.2, I use as exposure to the subsidy a probability of a firm receiving the subsidy based on a full set of pre-policy characteristics. In Appendix B.3.4, I use dummies whether a firm licensed technology before 1995, 1996, 1997, 1998, or 1999 as measures of exposure. All of these specifications return the same result; as a response to TSP, firms increased innovation, increased expenditure shares of low-skilled workers, and decreased employment.

Matched Differences-in-Differences. Appendix 2.5 shows that firms in the treatment group are larger, have higher wages, and have lower expenditure shares of low-skilled workers.

[34] As a control for international shock, I use a dummy if a firm exported before TSP, a dummy if it imported any goods before TSP, and a dummy for being a subsidiary of a multinational firm.

To address this potential problem, in Appendix B.3.3 I use matched differences-in-differences, matching the treatment and control groups on the number of workers, wages, share of high-school dropouts, and state during the 5 years prior to introduction of the program. Results remain the same.

Sector Level Regression. In appendix B.5, I run the main specification using sector-level aggregates. This specification allows me to test if results are driven by survivor bias and if they are robust to changes in the composition of firms. Once again I find that the TSP led to a decrease in firm size and increase in expenditure share on low-skilled workers.

4.5 Evaluating Competing Explanations

In this section, I argue that results cannot be explained by a direct effect of taxes on technology transfers, introduction of new products by exposed firms, changes to the quality of inventions, adoption of labor-saving technologies, or changes in the means of technology transfer.

Results Cannot be Explained by the Direct Effect of the Tax. It could be the case that the tax on international technology distorted firm incentives and led them to reduce employment and the hiring of skilled workers. In Appendix B.6.1, I show that results cannot be explained by a direct effect of taxes.

To show that, I exploit differences in tax incidence and heterogeneity in tax burden across firms. First, I exploit heterogeneity in the tax incidence due to previous contractual agreements.

When signing a technology transfer agreement, firms must specify to the government the part responsible for tax payments; the technology licensor or the licensee. For 42.1% of firms in the treatment group were not required to pay the tax. Instead, the technology owner is the one legally obliged by the technology transfer contract to pay any tax incurring in the transaction. Moreover, since prices were agreed on in the contract, they could not adjust to the new tax. I show that results are robust when controlling for a dummy taking one if the firm is responsible for paying the tax on the technology transfer, this dummy controls for the direct effect of the tax on firms. Second, I exploit heterogeneity in the total tax payment required by a firm deriving from heterogeneity in technology prices. After controlling for the relative tax burden at the firm level, I obtain similar results.

Firms have not Introduced New Products. TSP might have led firms to change the type of products being produced. Firms could have begun producing low-demand products that are low-skill intensive, which would explain the results. In Appendix B.6.2, I use trademark data to show that firms did not change the type of product being produced, and thus firms changed technology but kept producing the same good.

The TSP has not Increased Innovation Quality. The program might also have led firms to produce technology of inferior quality. Such lower-quality technologies might be low-skilled biased and low efficiency, which would explain the effect on firm employment and skill bias. In Table 38 in the Appendix, I use text analysis on patent descriptions to show that the average text complexity of Brazilian patents has not changed. In Table 39, I use information from inventors' CVs to show that the average quality of the inventor was unaffected by TSP. Therefore, no evidence suggests that the quality of inventions changed.

Firms Have not Increased Adoption of Labor-Saving Machine. Another potential explanation is that firms implemented labor-saving machines as a response to TSP, which could potentially explain the decrease in firm size. In Appendix B.6.3, I show that firms reduced their import of labor-saving machines, the technology being transferred to Brazil is more similar to the textual description of robots than Brazilian patents, and that firms reduced the hiring of workers who operate robots. These results indicate that firms decreased the use of labor-saving machines.

Firms Have not Increased FDI. If firms can avoid the tax on technology transfers by transferring technology through foreign direct investment, the effects identified could capture the effect of using a new technology transfer method. I test whether firms increased FDI in response to TSP in Table 33 of in Appendix B.2. I run the baseline specification (2) on a dummy that is one if a firm a subsidiary of a multinational firm. Table 33 shows that firms did not increase FDI in response to TSP.

5 Theoretical Model

In this section, I present a model that rationalizes the empirical results. The model is then calibrated to reproduce the estimated elasticities to TSP and used to make policy-relevant counterfactuals. In the model, Brazilian firms choose between innovating or paying a fixed cost to use technology from the United States. U.S. and Brazilian innovations differ endogenously on skill bias and productivity. Brazilian innovations are more intensive in the use of low-skilled workers because there is a larger supply of low-skilled workers in Brazil than in the U.S. . Therefore, if U.S. technology offers greater productivity, a Brazilian firm switching from licensing technology from the United States to innovating increases expenditure shares on low-skilled workers and decreases total production, matching the empirical findings.

The model provides two important results— on the effect of innovation policy and on the identification of important parameters. First, innovation policy decreases aggregate production and skill premium because it leads firms in a developing country to adopt low-productivity and low-skilled biased technology. Second, the difference in bias and productivity between U.S. and Brazilian technologies can be identified with closed-form solutions from the effect of the TSP.

5.1 Environment and Equilibrium

5.1.1 Demographics

There are two countries, the United States and Brazil.[35] The model is static. Each country contains a mass one of firms and a representative consumer that owns all firms. Firms choose technology and produce the same homogeneous good using high-skilled and low-skilled labor as inputs.

[35] The countries are named merely for convenience. The idea is that one country is developed, skilled abundant, and a technology exporter while the other is underdeveloped, skilled poor, and a technology importer.

Each country is endowed with a stock of high-skilled and low-skilled workers. Let H_c be the supply of high skill workers in country c and L_c the supply of low-skill workers.

U.S. and Brazil are connected only by the trade of technology from U.S. to Brazil. Moreover, U.S. does not take into account the profit made by selling technology to Brazil, i.e., Brazil is of measure zero compared to U.S..[36]

5.1.2 U.S. Firms

Production. There is a measure one of homogeneous firms in United States. U.S. firms produce using CES production function:

$$[(Al)^\rho + (Bh)^\rho]^{\frac{\gamma}{\rho}} \tag{4}$$

where A is the productivity of low-skilled workers, l is the number of low-skilled workers in the firm, B is the productivity of high-skilled workers, and h is the number of high-skilled workers in the firm. The elasticity of substitution between l and h is $\frac{1}{1-\rho}$, with $\rho \leq 1$ and $\rho \neq 0$, and γ is the degree of decreasing returns to scale, $\gamma < 1$.

Technology Choice. Vector (A, B), which I call technology, is a choice of the firm. Firms are constrained regarding their technology choice by the technology frontier:[37]

$$\phi_{US} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}} \tag{5}$$

[36] Empirical facts support this assumption. First, Brazilian technology transfer expenditure was 0.09% of U.S. R&D investment in 2010. Second, 63% of technology transfers are between firms of the same sector and only 0.26% are being made by a firm in Research & Development, supporting the idea that technology transfers aren't made by a scientific firm specialized in creating and selling technology. Third, firms transferring technology to Brazil does not operate in developing countries or in Brazil, according to data discussed in table 16. Forth, Zuniga and Guellec (2009) shows with a survey of European and Japanese patenting companies that only 27% of companies license technology while, among the ones that do license, only 24% of technology transfers is made outside their own country. Therefore, these facts support the idea that Brazil is very small in the international technology transfer market and that firms transferring technology create technology for home operations. Finally, it is worth mentioning that this assumption has the purpose of generating heterogeneity in skill bias between Brazil and the US. Point also empirically supported in Section E.

[37] I follow Caselli and Coleman (2006), León-Ledesma and Satchi (2018), and Okoye (2016).

where ϕ_{US} is the technology level of $U.S.$ innovations, which captures how large firms are able to set A and B. $\frac{\kappa-\rho}{\kappa-\rho-\kappa\rho}$, with $\rho < \kappa \leq 1$, is the elasticity of the technology frontier, capturing how much firms can trade-off A for B.

The choice of (A, B) represents the innovation process of firms. Firms have access to several technologies according to the degree of knowledge in the country, ϕ_{US}. If the country has a large stock of knowledge and high-quality scientists, firms can choose larger values for A and B. However, at the frontier of knowledge, firms must trade-off these two efficiency factors.[38]

Firm's Problem. U.S. firms maximize profit by choosing inputs, h and l, and technology (A, B), subject to technology frontier (5):

$$\begin{aligned} V_{US} = \max_{h,l,A,B} & \left[(Al)^{\rho} + (Bh)^{\rho}\right]^{\frac{\gamma}{\rho}} - w_{H,US}h - w_{L,US}l \\ \text{s.t. } \phi_{US} = & \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}} \end{aligned} \tag{6}$$

Using first-order conditions, I find the optimal skill bias of U.S. firms, A_{US}/B_{US}, as a function of inputs and skill premium:

$$\frac{A_{US}}{B_{US}} = \left(\frac{l}{h}\right)^{\frac{\kappa-\rho}{\rho}} = \left(\frac{w_{H,US}}{w_{L,US}}\right)^{\frac{\kappa-\rho}{\rho(1-\kappa)}} \tag{7}$$

Using equation (7) and the technology frontier, we can write firm's problem after technology choice:

$$V_{US} = \max_{h,l} \phi_{US}^{\gamma} \left[l^{\kappa} + h^{\kappa}\right]^{\frac{\gamma}{\kappa}} - w_{H,US}h - w_{L,US}l \tag{8}$$

where problem (8) and (6) are equivalent. Therefore, problem (6) is equivalent to the problem of a firm that chooses inputs using a CES production function with elasticity $\frac{1}{1-\kappa}$ and TFP ϕ_{US}.

[38] Like in the real world, firms can produce the same output using various technologies. Some technologies, such as robots and computers, use highly skilled workers more efficiently, and others use low-skilled workers more efficiently. I model this choice of technology using the choice of (A, B).

5.1.3 Brazilian Firms

Brazilian firms choose between innovating or licensing technology created by a U.S. firm.[39] Firms pay a fixed cost for each technology option, pay taxes for technology transfers, and receive a subsidy for innovation.

Innovation in Brazil. If firm j innovates it pays fixed cost $\epsilon_{j,innov}$ and can choose its technology (A, B) according to the Brazilian technology frontier, given by

$$\left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}} = \phi_{BR} \tag{9}$$

where ϕ_{BR} is the technology level in Brazil.

A Brazilian firm that innovates has operating profits:

$$V_{innov,BR} = \max_{h,l,A,B} [(Al)^\rho + (Bh)^\rho]^{\frac{\gamma}{\rho}} - w_{H,BR}h - w_{L,BR}l \tag{10}$$
$$\text{s.t. } \phi_{BR} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}}$$

The problem of innovative Brazilian (10) and U.S. firms (6) differs in the price of labor and the level of the technology frontier. As I will show soon, these two differences lead Brazilian and U.S. innovators to differ on skill bias and production.

Technology Transfer. A Brazilian firm that licenses international technology must pay a fixed cost $\epsilon_{j,transf}$[40] and implements technology (A_{US}, B_{US}), created by a U.S. firm. A Brazilian firm that licenses technology has the problem:

$$V_{transf,BR} = \max_{h,l} [(A_{US}l)^\rho + (B_{US}h)^\rho]^{\frac{\gamma}{\rho}} - w_{H,BR}h - w_{L,BR}l \tag{11}$$

[39] Motivated by empirical findings discussed in section (2.5), I exclude the option of firms to trade technology among themselves and license technology from a developing country. These are small in comparison to transfers of international technology from developed countries.

[40] The fixed cost $\epsilon_{j,transf}$ captures the price and cost of implementing the technology. Since Brazil is small and does not affect prices, I assume the price of the technology is exogenous and thus model only the final cost that a firm incurs to implement U.S. technology.

Technology Choice. Considering the profit of the two technology types, Brazilian firms must choose between licensing technology or creating their own:

$$V_j = \max\left\{V_{BR,transf} - \epsilon_{j,transf} - \tau_{transf}, V_{BR,innov} - \epsilon_{j,innov} + \tau_{innov}\right\} \tag{12}$$

where $V_{BR,transf}$ is the operating profit of licensing U.S. technology, $\epsilon_{j,transf}$ is the fixed cost of licensing U.S. technology, τ_{transf} is a tax on international technology transfers,[41] $V_{BR,innov}$ is the operating profit of a firm that innovates, $\epsilon_{j,innov}$ is the fixed cost of innovating, and τ_{innov} is a subsidy for innovation.

Heterogeneity. For this toy model, firms are heterogeneous in the fixed cost required to innovate, $\epsilon_{j,innov}$, and on the fixed cost of licensing international technology, $\epsilon_{j,transf}$. The fixed cost captures the adoption cost, royalty payments, and R&D costs. It also captures other features of the real world that prevent firms from adopting better technologies, such as imperfect information or managerial practices. The joint distribution of fixed costs is $(\epsilon_{j,innov}, \epsilon_{j,transf}) \sim \Gamma$.[42]

Government in Brazil. The Brazilian government subsidizes R&D, τ_{innov}, taxes the transfer of international technology, τ_{transf}, and imposes a lump-sum tax on consumers, T.

Equilibrium. An equilibrium in this economy is given by prices, $\{w_{H,BR}, w_{L,BR}, w_{H,US}, w_{L,US}\}$, and a solution to the firms' problems such that the government's budget constraint is satisfied and the labor market in both countries clear. Section C.1 in the Appendix defines the equilibrium formally.

[41] In the data, the tax on technology transfer was not a lump sum; it was a marginal tax on the value of the technology. Since prices are exogenous and homogeneous, the marginal tax is equivalent to a lump sum. In the robustness section, I relax this assumption.

[42] I assume Γ to be a continuous and differentiable distribution, defined by R^{++}. The CDF of Γ has a positive mass in the entire domain. These assumptions guarantee a positive mass of innovators and technology lessees in any equilibrium.

5.2 Difference Between Innovators and Foreign Technology Adopters

The US, being skill-abundant, produces technology more intensive in high-skill workers than Brazilian innovators do. Consequently, technology licensees in Brazil are more skilled-intensive than Brazilian firms that innovate. If ϕ_{US}/ϕ_{BR} is high enough, licensees also have higher productivity and, as a result, are larger. Proposition 1 formalizes this intuition.

Proposition 1. *Suppose that the U.S. is skilled abundant compared to Brazil, $H_{US}/L_{US} > H_{BR}/L_{BR}$, then*

1. *Brazilian firms that license technology are more skilled intensive than Brazilian firms that innovate:*

$$\frac{h_{BR,transf}}{l_{BR,transf}} > \frac{h_{BR,innov}}{l_{BR,innov}}$$

2. *If ϕ_{US}/ϕ_{BR} is sufficiently large, Brazilian firms that license technology are larger than Brazilian firms that innovate:*

$$y_{BR,transf} > y_{BR,innov}$$

Proof. Proof available in Appendix C.2. □

Innovators use technology (A_{BR}, B_{BR}), which satisfies the Brazilian technology frontier with technology level ϕ_{BR}, and firms that import technology from the United States use technology (A_{US}, B_{US}), which satisfies the U.S. technology frontier with technology level ϕ_{US}. Due to this difference in technology frontiers across countries, depending on ϕ_{US}/ϕ_{BR}, firms that license technology in Brazil can be larger than innovators. The marginal cost of producing will depend on the skill bias and the level of the technology level of the two technologies. If $\phi_{US} = \phi_{BR}$ then Brazilian inventors will have lower marginal cost because they are using technology with optimal skill bias and thus have larger production. But, if ϕ_{US} is sufficiently larger than ϕ_{BR}, the marginal cost of firms licensing technology is lower than the marginal cost of firms innovating despite having a sub-optimal bias to Brazilian factor prices.

5.3 Effect of Innovation Policy

If ϕ_{US}/ϕ_{BR} is sufficiently large, an increase in R&D subsidies, or taxes on international technology, leads firms to switch from high-TFP and high-skilled biased U.S. technology to low-TFP and low-skilled biased Brazilian technology. Due to these changes to TFP and skill bias, production and skill premium decrease in Brazil. Proposition 2 formalizes this result.

Proposition 2. *(Effect of Innovation Subsidy on Skill Premium)*
If ϕ_{US}/ϕ_{BR} is sufficiently high, an innovation subsidy decreases production and skill premium in Brazil:

$$\frac{\partial \frac{w_{H,BR}}{w_{L,BR}}}{\partial \tau_{innov}} < 0$$
$$\frac{\partial Y_{BR}}{\partial \tau_{innov}} < 0$$

Proof. Proof available in Appendix C.3. □

6 Identification and Results

6.1 Identification

The important parameters can be identified from a change to innovation policy even in the presence of aggregate shocks and selection. First, I introduce richer heterogeneity and aggregate shocks to the model, the objective of which is to capture features that exist in the real world that create identification concerns, such as aggregate shocks and selection in technologies. Second, I introduce a policy change and identification strategy similar to the one used in the data. Third, I show that using the elasticities from the data, I can identify two of four important parameters. In the calibration section, I show that the other two parameters can be estimated outside of the model.

6.1.1 Heterogeneity and Aggregate Shocks

There are two periods, $t \in \{0, 1\}$, and firms must innovate or license technology every period.[43]

The production function in each country $c \in \{BR, US\}$ is

$$z_j \Upsilon_c^t \left[\Psi^t \alpha_j (A_j^t l)^\rho + (1-\alpha_j)(B_j^t h)^\rho\right]^{\frac{\gamma}{\rho}} \tag{13}$$

where (z_j, α_j) are firm idiosyncratic characteristics with $\alpha_j \in (0, 1)$ and $z_j \in \mathbb{R}^{++}$, Υ_c^t is a time-varying, country-specific aggregate shock, and Ψ^t is a skill biased common shock. $(z_j, \alpha_j) \sim \Gamma_{US}$ is the distribution of firm characteristics in the United States and $(z_j, \alpha_j, \epsilon_{j,innov}, \epsilon_{j,transf}) \sim \Gamma_{BR}$ is the distribution of firm characteristics in Brazil, where $\epsilon_{j,innov} = \{\epsilon^0_{j,innov}, \epsilon^1_{j,innov}\}$ and $\epsilon_{j,transf} = \{\epsilon^0_{j,transf}, \epsilon^1_{j,transf}\}$.[44]

6.1.2 Model Equivalent Technology Substitution Program

Assume the government implements fiscal policy:

$$\tau^0_{innov} = \tau^0_{transf} = T^0 = T^1 = 0; \tau^1_{j,innov} \in \{0, \tau\}; \tau \geq 0 \tag{14}$$

At time 0, there is no innovation policy, and at time 1, the government implements a subsidy financed by a tax on international technology transfers heterogeneously allocated to firms. This fiscal policy change mimics what was studied in the data.

I reproduce the same estimation procedure in the model that was implemented in the data. Define firms exposed directly to introduction of fiscal policy (14) as those that license technology during the pre-period and that were targeted by the innovation subsidy:

$$ExposedTSP = \left\{j | \tau_j \times \mathbb{I}^0_{innov} > 0\right\} \tag{15}$$

The change in skill share and labor supply of the exposed group, in comparison to the

[43] This assumption only simplifies the model and does not play a role in identification.

[44] I assume that a firm j in Brazil with idiosyncratic productivity (z_j, α_j) can only license technology from firm j in the United States with the same idiosyncratic characteristics.

non-exposed group, is:

$$\lambda_{skill} = E\left[\Delta \log\left(\frac{w^t_{L,BR} l^t_j}{w^t_{H,BR} h^t_j}\right) | j \in ExposedTSP\right] - E\left[\Delta \log\left(\frac{w^t_{L,BR} l^t_j}{w^t_{H,BR} h^t_j}\right) | j \notin ExposedTSP\right] \tag{16}$$

$$\lambda_{labor} = E\left[\Delta \log l^t_j | j \in ExposedTSP\right] - E\left[\Delta \log l^t_j | j \notin ExposedTSP\right] \tag{17}$$

λ_{skill} and λ_{labor} are the difference-in-differences estimators of the effect of TSP on exposed firms, in comparison to non-exposed firms. This is similar to the empirical strategy used in the empirical section.

6.1.3 Identification of Key Parameters

Proposition (3) shows that knowing κ and γ, I can identify, with closed form solutions and regardless of the distribution of shocks, ρ and $\frac{\phi_{BR}}{\phi_{US}}$ from the elasticities identified in the empirical section and data moments.

Proposition 3. *(Identification of Key Parameters with Selection, Aggregate Shocks and General Equilibrium)*
Suppose that the government implements policy (14) *and defines estimators as in* (16). *Assume that the production function is defined as in* (13). *Normalize* $\phi_{BR} = 1$. *Then knowing* κ *and* γ, ρ *and* ϕ_{US} *can be uniquely identified from* λ_{skill}, λ_{labor}, *the wages in the two countries, the distribution of expenditure shares, and the distribution of innovation status.*

Proof. Proof available in Appendix C.4. □

The parameters are identified because difference-in-differences estimators are informative about technology bias and TFP. If λ_{skill} is large, there must be a large difference in expenditure share between the two technologies. A large difference in expenditure shares, given the skill premium in the two countries, means that κ and ρ are far from each other. Therefore, knowing κ, I can identify ρ. If λ_{labor} is large, the two technologies must differ strongly in TFP. Therefore, knowing γ, the degree of decreasing returns to scale, I can identify the relative TFP ϕ_{US}/ϕ_{BR} using data moments.[45]

[45] Section D.2 in the appendix, shows the relationship between estimators and parameters in partial equi-

6.2 Calibration

I showed that knowing κ and γ, I can identify ρ and $\frac{\phi_{US}}{\phi_{BR}}$. In this section, I describe how the remaining parameters are identified.

According to Proposition 3, only 2 parameters can be identified. When estimating the effect of TSP using difference-in-differences, only the change to an outcome in the exposed group relative to the change in the same outcome in the non-exposed group is identified. Using this approach, I can identify the relative skill bias of the two technologies, $\frac{A_{BR}/B_{BR}}{A_{US}/B_{US}}$, and their relative TFP, $\left(\frac{\phi_{BR}}{\phi_{US}}\right)^{\gamma}$. Since the levels are taken away with the difference, the data cannot show the levels of bias or TFP of these technologies. Therefore, going from the differences to the levels is possible only after knowing two parameters.[46]

Once I calibrate κ, normalize ϕ_{BR} to one, and estimate γ, I know the change in labor demand of firms that innovate. Wages and innovation statuses are observed in the data, but the only parameters that affect the change in labor demand of Brazilian innovators are κ, ϕ_{BR}, and γ. Therefore, I know the change in labor demand in the control group and can use the estimated difference to calculate the final set of parameters.

6.2.1 Estimation of γ

The degree of decreasing returns to scale, γ, is estimated using the Levinsohn and Petrin (2003) method, with Ackerberg et al. (2015) correction. I use data on revenue and capital of firms that issued bonds or with equity traded on the stock exchange from *Economatica*. Appendix D.3 discusses these results. From the baseline estimation, $\gamma = 0.7577$, an estimate close to those from Garicano et al. (2016) (0.793), Atkeson and Kehoe (2005) (0.85), and Basu and Fernald (1997) (0.8). In Section 6.4 I show that results are robust to a wide range of estimates.

6.2.2 Calibration of κ

κ represents the elasticity of substitution between high- and low-skilled workers in the United States, according to problem (8), a parameter widely studied. Table 54, in the Appendix,

librium. Because prices are constant, these relation is cleaner.

[46] That is, after normalizing one of the technologies to 1.

shows that estimates of the elasticity of substitution in developed countries range from 0.23 to 0.56. In the main section, I use estimates from Katz and Murphy (1992) ($\kappa = 0.28$), for consistency with the development literature. In Section 6.4, I show that results are robust to several other estimates. Including the long-run elasticity of substitution estimated by Ciccone and Peri (2005).

6.2.3 Estimation of ρ

Using the calibrated value for κ, I can use the identifying equation from Proposition 3, the estimated effect of TSP on expenditure shares, wages in the two countries, the distribution of expenditure shares, and the distribution of innovation status to estimate ρ. I find that $\rho = 0.2654$.

6.2.4 Technology TFP

Using κ, γ, the estimated effect of TSP on the demand for low-skilled workers, wages in the two countries, the distribution of expenditure shares, and the distribution of innovation status, I can estimate ϕ_{US}/ϕ_{BR}. Normalizing the Brazilian TFP to 1, I find that $\phi_{US} = 1.67$, which means that U.S. technology has 67% higher TFP than Brazilian technology.

6.2.5 Other Targeted Moments

Firm heterogeneity is calibrated to reproduce the heterogeneity in the data, and factor supplies are calibrated to reproduce skill premium. I assume that all permanent idiosyncratic shocks are independent. Since there are only two technologies, only relative cost matters to the firm's technology choice, $\epsilon_{j,innov} - \epsilon_{j,transf}$. Therefore, as is common in any discrete choice model, the levels of each cost are unidentified. I assume:

$$\epsilon_{j,innov} - \epsilon_{j,transf} \sim N(\mu_\epsilon, \sigma_\epsilon)$$

where μ_ϵ, the average of relative innovation cost, is calibrated to reproduce the share of firms that license technology, and σ_ϵ is calibrated to reproduce the effect of TSP on innovation. I also assume that the distribution of idiosyncratic TFP shocks is $log(z_j) \sim N(\mu_z, \sigma_z)$, where

Table 9: **Estimated Parameters**

Parameter	Description	Target/Source	Target	Parameter	Variance
		Production function and Technology			
κ	Elasticity of substitution in US	Katz and Murphy (1992)	0.285	0.285	-
ρ	Elasticity of substitution in BR	λ_{skill}	0.012	0.265	0.0016
γ	Degree of decreasing returns	Estimation		0.757	0.0019
ϕ_{US}	Productivity of US technology	λ_{labor}	-0.192	1.668	0.2546
ϕ_{BR}	Productivity of BR technology	Normalization	1	1	-
		Technology Cost			
μ_ϵ	Mean of Innovation Cost	Shr. of Firms Licensing Tech.	0.258	0.001	3E-05
σ_ϵ	Variation of Innovation Cost	Effect of TSP on Innovation	0.035	0.001	5E-06
		Firm Heterogeneity			
μ_z	Avg. productivity shock	Normalization	0	1	-
σ_z	Variance of Firm Productivity Shock	Variance of Firm Size/Mean Firm Size	48.303	0.372	0.0043
μ_α	Avg. biased shock	Normalization	0	0	-
σ_α	Variance of Skill Bias Shock	Variance of Expenditure Share	0.052	2.992	0.143
		Factor Supply			
L_U	Supply of low-skilled workers	Initial low-skill wage	39.73	1.65E-06	4.9E-11
H_U	Supply of high-skilled workers	Initial high skill wage	123.46	2.55E-07	2.5E-12

Description: This table reports estimated parameters, calibrated values, and parameter variances. The variance was calculated using bootstrap. For the skilled wage premium in the United States, I use the average skilled wage premium of countries that sell technology to Brazil, weighted by the number of contracts.

μ_z is normalized to 0 and σ_z is calibrated to match the variance of firm size in the data. The distribution of biased shocks is $log\left(\frac{\alpha_j}{1-\alpha_j}\right) \sim N(\mu_\alpha, \sigma_\alpha)$, where μ_α is normalized to 0 and σ_α is calibrated to match the variance of firm size in the data. Finally, the supply of low- and high-skilled workers, L_{BR} and H_{BR}, are calibrated to match wages in 2000. Table 9 reports all calibrated parameters and target values.

6.3 Model Results

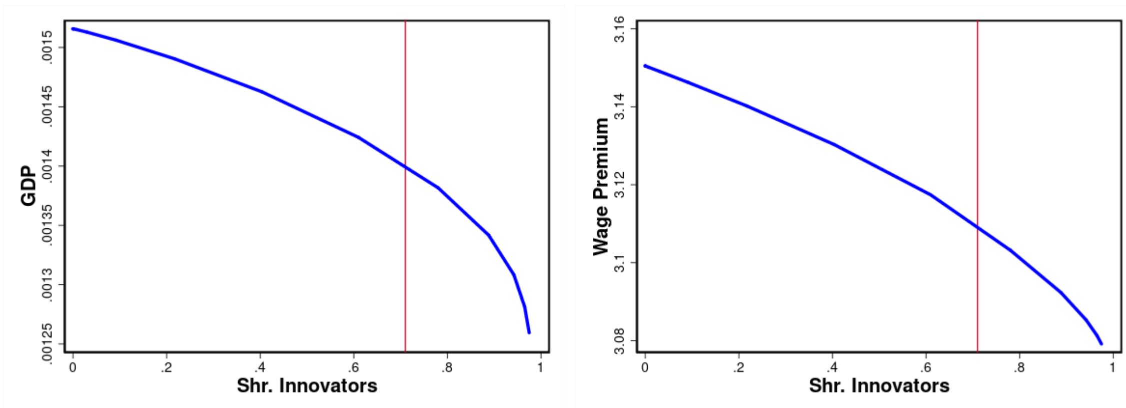
I use the model to study the aggregate effect of TSP and the effect of closing the economy to international technology transfers. The model predicts a large effect of closing the economy to international technology transfers. Moving all firms to create their own technologies would reduce production by 29% and skill premium by 1% because firms have to leave a high-TFP and high-skilled bias technology for a low-TFP and low-skilled bias one.

6.3.1 Effect of Innovation Policy

Innovation policy leads firms to switch from US technology, which is high-skill biased and high productivity, to national innovations, which are low-skill biased and low-productivity. As a consequence, it reduces skill premium and GDP. Figure 5 shows how GDP and skill premium adjust to the change in innovation rate. As expected, since TFP and skill bias reduce, there is a decrease in production and skill premium.

Figure 5: **Effect of Innovation Policy on Production and Skill Premium**

(a) GDP (b) Skill Premium



Description: This figure shows GDP and skill premium with different share of innovators in the economy. Each point in the figure is achieved by a balanced budget implementation of a subsidy for innovation and tax on international technology transfers. The red line shows the current share of innovators.

Table 10 shows how aggregate variables adjust to various innovation policies. The first line shows the aggregate effect of TSP, which led to an increase in aggregate innovation by 0.00037%, costing 0.00612% of pre-policy GDP. Columns 2 and 3 show that GDP and wage premium reduce as a result of the program.

Despite large differences between Brazilian and U.S. technology, the identified effect of TSP is small, shown in Table 10. The model is calibrated to reproduce the effect of TSP on innovation. Since the effect on innovation is small, the aggregate share of firms that switched to national innovations is also small, and thus the aggregate effect on GDP and skill premium must also be small despite large effects on the firms switching technology.

The second line of Table 10 studies the effect of increasing innovation by 1 percentage point. Such more ambitious innovation policy would require a R&D subsidy of 2% of GDP and would reduce skill premium by 0.028% and GDP by 0.2%.

The policy counterfactual offers two important findings regarding the aggregate effect of innovation and the cost of innovation policies. First, the reduction in GDP is about 10 times larger than that of the skill premium, a result driven directly by the empirical results discussed previously. The empirical section reports a large reduction in employment, suggesting a large difference in technology TFP, the change in expenditure shares is smaller,

Table 10: **Effect of Innovation Policy**

Policy	Δ Innovation	Δ GDP	Δ Skill Premium	Δw_H	Δw_L	Cost/GDP
Technology Substitution Program	0.00037%	-0.00006%	-0.00001%	-0.00006%	-0.00005%	0.00612%
1 p.p. Increase in Innovation	1.367%	-0.200%	-0.028%	-0.219%	-0.191%	2.08%
Closing the Economy to Int. Tech.	34.57%	-28.86%	-1.03%	-29.36%	-28.62%	∞

Description: This table shows the effect of various innovation programs. The first line has the effect of TSP, which gave 0.00612% of GDP as a subsidy, financed by a tax on international technology transfer. The second line implements an innovation program to increase the share of innovating firms by 1 percentage point. The last line contains the effect of forcing all firms to innovate. The first column reports the percentage change in the share of firms that innovate, the second column the percentage change in GDP, the third column the percentage change in skill wage premium, the fourth column the percentage change in skilled wage, the fifth column the percentage change in unskilled wage, and the final column the size of the R&D subsidy.

which suggests a small difference in technology bias between the two countries but a large difference in TFP. The second finding reported in counterfactual Table 10 concerns the efficacy of innovation policy. To increase innovation by 1p.p., the government must give 2% of GDP as an R&D subsidy, a result again driven by the empirical findings. On the data, the increase in innovation was small in comparison to the size of the program. Therefore, through the lens of the model, the fixed cost of innovating must represent an important factor in a firm's technology choice.

6.4 Robustness

In this section, I show that results are robust to several model assumptions.

Alternative κ. To identify ρ and ϕ_{US}, I must calibrate the elasticity of substitution in the United States, κ. In section D.5.1 in the Appendix, I show how results change with alternative κ calibrations. In the range of empirically plausible estimates, the effect of a 1 p.p. increase in innovation goes from -0.2% to -0.7%, the effect on wage premia ranges from -0.02% to -0.1%. For any of these calibrations, it is still true that the effect on skill premium is smaller than the effect on GDP.

Alternative γ. To identify ρ and ϕ_{US}, I must estimate outside of the model the degree of decreasing returns to scale, γ. In section D.5.2 in the Appendix, I use alternative estimates of this parameter and show that the model still predicts a large GDP drop in response to technology substitution and a small skill premium effect.

Alternative Innovation Definition. Patents are noisy measures of innovation and technology adoption at the firm level. It is reasonable to assume that some firms innovate without applying for a patent[47] and that some firms apply for patents without implementing a new technology.[48] I address this measurement problem, which is common in the growth literature, by introducing several new measures of innovation. In Section D.5.3 in the Appendix, I use as an innovation measure the hiring of scientists, hiring of PhDs, patents or industrial design applications, and filing applications for any intellectual property object. For small changes to innovation, results are consistent across all of these innovation measures. By increasing innovation by 1 p.p., GDP falls between 0.12% and 0.33%, and skill premium falls between 0.03% and 0.07%.

Controls and Selection. The main parameters of the model (ρ and ϕ_{US}) are identified from the effect of the TSP on expenditure share and employment (λ_{skill} and λ_{labor}, respectively). In Appendix section D.5.4, I show that results are robust to different estimates of λ_{skill} and λ_{labor}.

Alternative Distributions. In Appendix section D.5.9, I assume that the distribution of innovation cost is Gumbel or logistic, and results are again consistent with the baseline.

Elastic Labor Supply. As the skilled wage premium change, it is reasonable to assume that the labor supply adjusts to it, minimizing aggregate changes to skill wage premium and production. In Appendix D.5.5, I change the model to allow for labor supply adjustments. I found that using micro estimates of the elasticity of the labor supply, results are similar to baseline estimates.

Hiring of Scientists. Innovation itself is a skill-intensive activity. To create new technologies, firms must hire scientists and technicians. In Appendix D.5.6, I add to the model a fixed cost in terms of skilled workers and calibrate it to reproduce the expenditure share of scientists. The change in results is minimal.

[47] An example is if they do not want competitors to be aware of their technology improvement.

[48] The patent troll, discussed by Abrams et al. (2019), is a case in which firms apply for patents but do not implement a new technology.

Monopolistic Competition. In Appendix section D.5.7, I relax the assumption of decreasing returns to scale and use monopolistic competition to pin down firm's size. Appendix D.5.7 shows that results are still the same.

Exogenous Technology. The directed technological change component of the model works only to endogenize the technology of the two countries; (A_{BR}, B_{BR}) and (A_{US}, B_{US}). It is, however, possible to estimate these two parameters without making any assumptions regarding from where these technologies come. In section D.5.8 in the Appendix, I show that (A_{BR}, B_{BR}) can be identified after normalizing $A_{US} = B_{US} = 1$. I calibrate elasticity ρ using numbers from the literature and changes to factor shares of firms that innovate. For reasonable calibrations of the elasticity, the magnitude of the results are again consistent with main findings, and it is still true that the effect on production dominates the effect on skill wage premium.

Vintage Technology. A primary argument in favor of innovation policies is to allow firms to move from a vintage technology to a new, more efficient one. Since the baseline model includes only two technologies, this channel is not in the model. In Appendix section D.5.10, I add a third technology to the model—a vintage, outdated technology. Firms in Brazil must then choose among three options—license technology from the United States, innovate, or use a vintage technology. Adjusting the identification strategy to the new technology option, I show that the productivity of the vintage technology can be identified, and estimate it to be close to the productivity of Brazilian innovations. Thus, the replacement of international technology with national innovations dominates the final effect. The magnitudes of the effects of innovation policy are larger when considering the existence of vintage technology because now firms that use international technology can switch to an outdated technology instead of Brazilian innovations.

Externality of Innovation. A common argument for innovation policy is that knowledge created in a specific firm diffuses across the economy and improves the quality of the technology created by other firms. In Appendix D.5.11 I show that the exogenous variation generated by the TSP can be used to identify the magnitude of externalities in Brazilian innovations. Taking externalities into account, I find that an innovation program that increases innovation by 1 p.p. reduces output by 0.29%. Therefore, despite the positive output gain from externality, the differential in productivity between a national Brazilian technology and an international one is large enough to generate a negative effect on output.

7 Conclusion

I investigate the effect of replacing imported technology with national inventions in Brazil. I use a novel dataset on international transfers, patent applications, and employment in Brazil, with exogenous variation from a technology substitution program, to show that contrary to popular belief, innovation policies in developing countries reduce skill premium and production because they encourage substitution of international technology, which is high-productivity and high-skilled biased, with national technology, which is low-productivity and low-skilled biased. Therefore, the reliance of developing countries on imported technology increases production and inequality.

After collecting data from several administrative sources, I construct a dataset with information on innovation, technology transfers, and employment at the firm level, representing the first time such a dataset has been studied. I exploit exogenous variation from a technology substitution program in Brazil to show that replacing international technology with national technology leads firms to increase expenditure share with low-skilled workers and reduce employment.

A model of directed technological change and international technology transfers explains the empirical results. Therefore, empirical results represent the first micro-level evidence with a credible exogenous variation of cross-country differences in technology bias and productivity. Finally, I calibrate the model using the estimated elasticities, showing that technology replacement in Brazil leads to a decrease in production and skilled wage premium.

There are several possible extensions to future research following this paper. The exogenous variations from TSP can be used to estimate the externality of R&D investment, which allows for the estimation of an optimal innovation policy. Appendix section E.6, which reports results from studying the effect of minimum wage on innovation and technology licensing, shows that technology bias and technology adoption are affected by labor policy, which allows for study the long-run effect of minimum wage.

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Online Appendix to "The Labor Market Consequences of Appropriate Technology"

A Data Appendix

A.1 Regulations of Technology Transfers in Brazil

From the 60s to the early 80s, Brazil implemented a series of policies to favor the national industry: barriers to international trade, capital flows, and technology transfers. In order to regulate capital movements from and to Brazil, in 1962 the government required all intellectual property contracts to be registered and approved by the patent office.[49] The patent office's goal, at first, was to guarantee that the royalties sent abroad corresponded to a real technological transfer and that it satisfied the sectoral quotas established by the government.

The role of the patent office changed in 1971 with the introduction of a new industrial property regulation: it practically became a third party in any technology contract. The patent office was allowed to reject contracts judged unfair or against national interest, it established sectors that were not allowed to import technologies, regulated the technologies that could be contracted from overseas, seek to guarantee total control of the technology to the national producer, set limits on royalties, regulated the type of requirements the technology provider could make and increased the paper work required for approval.[50] The goal of the policymaker with these changes was to increase national production of technology and reduce the dependency on international technology.

All these restrictive measures were reversed in 1996.[51] The role of the patent office

[49] Lei nº 4.131/62.

[50] Established by the normative act number 15 of 1975 and number 32 of 1978. See Pereira et al. (2001) for more.

[51] By the law nº 9279/96

changed once again. As it was before, its only objective is to register international technology transfer and require documents guaranteeing that there were a real technology transfer, without the power to intervene or regulate these transfers.

The international technology market in Brazil was subject to more changes in the 00's. In 2001 the government created a 10% tax in any payment to technology transfers.[52] Those funds were utilized as incentive for national R&D.[53] This tax burden was temporarily alleviated in 2006 when the timing of the tax payment was relaxed.[54] This policy was reversed in 2010 with the goal of raising funds for the Olympic games.

A.2 Statistics of Technology Transfers in Brazil

In this section, I present statistics on technology transfers in Brazil. Technology contracts, provided by the patent office, include firm names but not tax identifiers, which makes it difficult to merge across administrative datasets. To find tax identifiers based on firm names, I construct a dataset with several name spellings for each firm using the Matched Employer Employee dataset RAIS and the Firm Register List, which contains names and tax identifiers for all firms that ever opened in Brazil prior to 2019. The two datasets combined provide several spellings of firm names for the same tax identifier, which allowed me to merge across datasets using exact matches and maintain a high match rate while minimizing false matches. Appendix A.3 describes the steps used to find firms' tax identifiers and the quality of the match.

Figure 6 shows the evolution of technology transfers since 1990. Panel 6a contains the total number of transfers while panel 6b contains the value of transfers as a share of GDP.[55] We can see that there was a large drop in the imports of technology when the tariff over technology purchase was introduced.

Table 11 helps us understand the purpose of the technology being implemented in each firm. According to the words describing the technology, I classify each transfer into different

[52] Law nº 10.168/00
[53] Law nº 10.332/01
[54] Decree nº 5.798 of 2006.
[55] As indicated before, the value of the contract is not observed for all transfers. To estimate the aggregate transfer value, I input the value of the technology by using observable characteristics.

Figure 6: **International Technology Purchase**

(a) **Number of Int. Technology Transfers**

(b) **Exp. with Int. Technology Transfers**

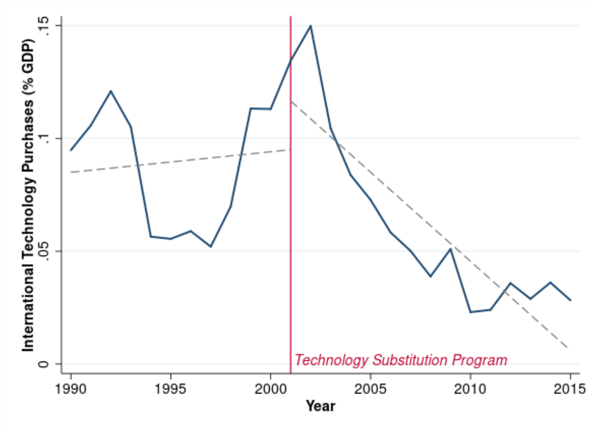


Table 11: **Content of Technology Transfers**

	N. Transfers	**%**
New Product	2,463	59.96
Tech. Service	2,226	54.19
Machine Inst.	816	19.86
Training	390	9.49
Maintenance	318	7.74
Franchise	177	4.31

Description: This table describes the content of the technology transfers. Each content is defined according to key words in the contract description. "*New Product*" is defined as containing one of the words: production, development, brand, new model or patent. "*Tech. Service*" as contracts containing: service, technical assistance, technology, knowledge, know how or consulting. Key words for "*Maintenance*" are: maintenance, replacement, reform or cleaning. "*Training*" has the key word training. "*Machine inst.*" has key words: assembly, machine, installation or construction. "*Franchise*" are transfers in which a franchise was open.

groups: introduction of a new product, technological service to increase the production line of current products, machine installation, training of employees, maintenance of equipment, and creation of a franchise. A contract can be in more than one of these classifications. Table 11 indicates that the majority of the technology being purchased by Brazilian firms is being used to create a new product or improve the production of the current production line.

Table 12 shows the number of technology transfers by sector of the buyer. The manufacturing sector is the sector responsible for much of the technology transfers.

Figure 7 helps us understand how often firms transfer technology. Figure 7a shows the

Table 12: **Sector of Technology Buyers**

Sector	N. Contacts	%
Manufacturing	8653	63.78%
Research	1138	8.39%
Electricity	783	5.77%
Transportation	755	5.56%
Retail	411	3.03%
Extractive	329	2.43%
Construction	295	2.17%
Finance	268	1.98%
Administration	193	1.42%
Information and Communication	186	1.37%
Restaurant	152	1.12%
Water and Sewage	107	0.79%
Others	102	0.75%
Agriculture	94	0.69%
Education	51	0.38%
Real State	40	0.29%
Health	6	0.04%
Public Sector	4	0.03%

distribution of the number of technology transfers by Brazilian licensees and in Figure 7b shows the distribution of number of technology transfers by licensor. It indicates that the majority of buyers and sellers engage in only one transfer.

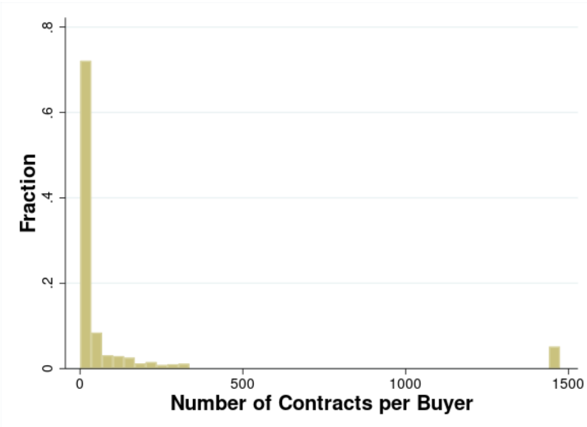
Figure 8 shows the distribution of technology price. There are a large variation in the value of technology transfer. To understand the relative importance of this investment to the firm, Figure 9a shows the technology price relative to yearly wage bill. About of 20% of technology transfers have a price larger than the yearly wage bill of the firm. Figure 9a shows that some of these transfers have a small price for the firm. This is expected given that some firms engage in technology transfers often.

Figure 9b helps us understand the overall magnitude of technology transfers at the firm level. Figure 9b displays the stock of firms investment on technology over yearly wage bill at the end of the period. More than 35% of firms, they have invested more than twice the yearly wage bill in acquiring new technologies.

Figure 10 displays the average technology transfer price by the type of the technology and its origin. Figure 10 indicates that there is not much variation of technology price by

Figure 7: **Distribution of Number of Transfers per Buyer and Seller**

(a) **Distribution of Technology Transfers per Buyer**



(b) **Distribution of Technology Transfers per Seller**

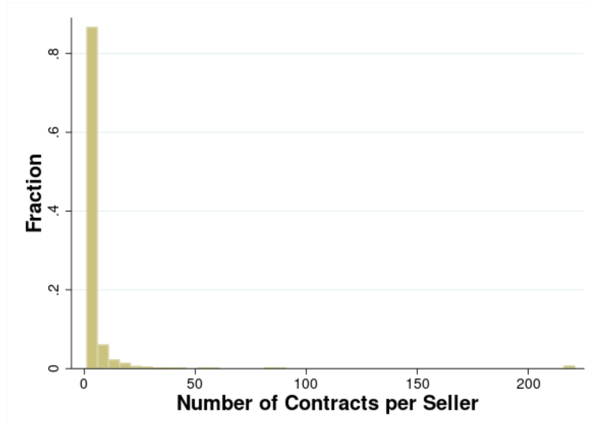


Figure 8: **Distribution of Technology Price**

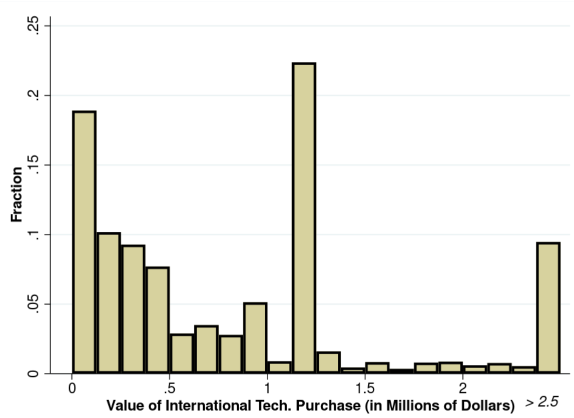
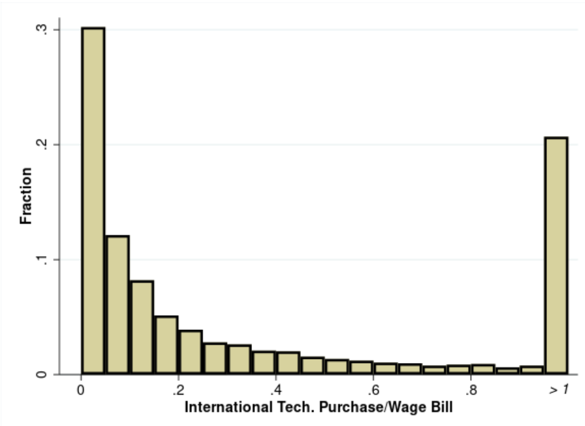
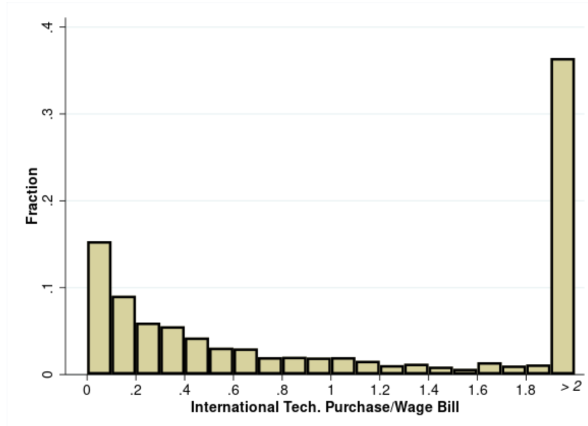


Figure 9: **Distribution of Contract Value**

(a) Distribution of Technology Transfer Price Over Yearly Wage Bill



(b) Distribution of Technology Transfer Price Over Yearly Wage Bill



type of technology nor its origin.

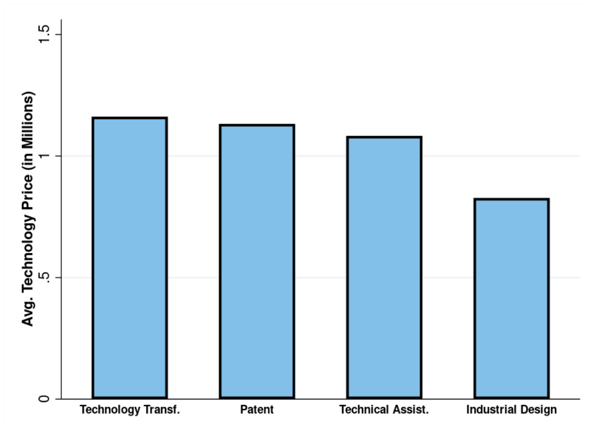
Figure 11 and Table 14 shows how national and international technology differ. Figure 11 indicates that national technology is concentrated in trademarks and the introduction of new products. Moreover, it is of higher price and less concentrated in manufacturing.

Table 15 compares firms that license international technology to firms that didn't. Table 15 shows that firms buying technology are more skilled intensive, have more establishments, have more workers, and pay a higher hourly wage.

Table 16 shows a profile of the firm licensing technology to Brazil: those are firms with several patents, engaging in few transfers and that do not operate in developing countries. This table is constructed merging by firm names with Compustat, subsidiary data from Dyreng and Lindsey (2009) and patent data from the OECD. The first panel shows the number of transfers per technology seller. The median technology seller only sold one technology to a Brazilian firm. The second panel displays the number of subsidiaries. The median technology seller has no subsidiary while 17% of technology sellers have a subsidiary in a developing country. The third panel contains the number of patents by technology seller. The median technology seller has two patents. Finally, the last panel shows that the majority of transfers are made by firms in the same sector.

Figure 10: **Avg. Tech. Price by Tech. Type and Origin**

(a) Avg. Tech. Price by Tech. Type



(b) Avg. Tech. Price by Country of Origin

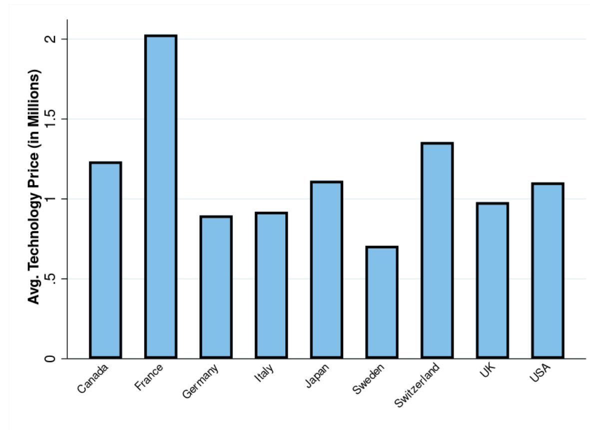
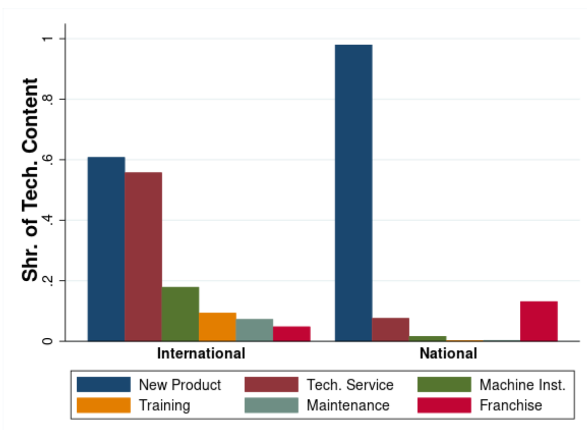


Figure 11: **Distribution of Contract Value**

(a) Technology Content by Technology Origin



(b) Technology Type by Technology Origin

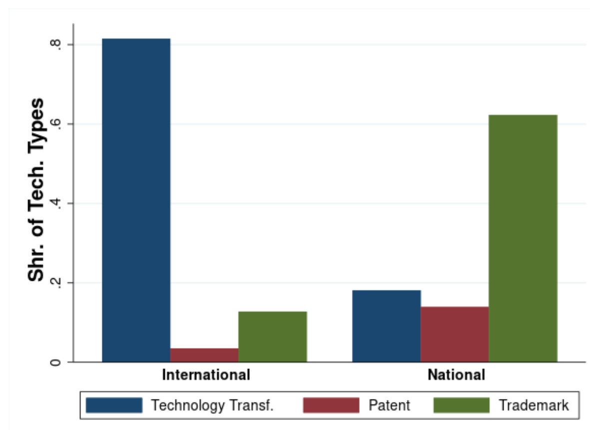


Table 13: **Technology Country of Origin**

Region	N. Transfer	Value (in millions)	% Transfer	% Value
United States	3,542	3,984	25.73	24.50
Germany	1,860	1,685	13.51	10.36
Brazil	1,237	1,171	8.99	7.20
France	877	1,646	6.37	10.13
Italy	811	1,022	5.89	6.29
UK	720	806	5.23	4.95
Japan	631	827	4.58	5.09
Canada	508	549	3.69	3.38
Spain	470	423	3.41	2.60
Others	3110	4146	22.59	25.50
Developed	10,579	14,172	86.83	87.2
Developing	1,605	1,988	13.17	12.2

Table 14: **Statistics of National and International Technology Transfers**

Variable Name	National	International	Diff.	P-Value
Observations	1237	12528	-11291	
Value	1204449	946712.1	257736.5	.002
Technology Transf.	.858	.146	.712	0
Trademark	.109	.679	-.57	0
Patent	.031	.143	-.112	0
HQ-Branch	.035	.017	.018	.002
Agriculture	.006	.012	-.006	.016
Extractive	.026	.001	.025	0
Manufacturing	.65	.412	.238	0
Electricity	.062	.009	.053	0
Water and Sewage	.007	.015	-.008	.001
Construction	.022	.013	.009	.032
Retail	.029	.04	-.011	.021
Transportation	.038	.221	-.183	0
Restaurant	.008	.036	-.028	0
Information	.013	.016	-.003	.382
Finance	.017	.04	-.023	0
Real State	.003	.004	-.001	.402
Research	.081	.096	-.015	.069
Administration	.013	.02	-.007	.049
Education	.003	.011	-.008	0
Health	0	.001	-.001	.389
Others	.006	.018	-.012	0

Description: This table presents statistics of technology transfer applications made to the Brazilian Patent Office between 1995 and 2015 according to the country of origin of the technology seller. The first panel contains information from technology contracts by type according to definition made by the Patent Office. The second panel contain information from technology seller and buyers. The line *HQ-Branch* contains the share of transfers realized between a HQ and a Branch. This statistic is identified using information from firm ownership in the National Firm Registry dataset. The last panel contain information from the value of technology transfers.

Table 15: **Labor Statistics of Firms According to Technology Purchase**

Sample	Shr. HS. Dropout	Shr. HS. Complete	Avg. Yrs. Educ.	N. Establishments	N. Workers	Hourly Wage
No Int. Tech. Bfr. 2000	0.65	0.23	9.56	13.83	256	59.69
Int. Tech. Bfr. 2000	0.46	0.26	10.89	30.95	1569	123.92

Description: This table presents labor market statistics in 2000 of firms according to their status in buying international technology. The first line contains statistics of firms that did not purchased any international technology before 2000 while the second line contains statistics of firms that purchased technology before 2000. Labor information is from RAIS.

Table 16: **Characteristics of Technology Seller**

	Mean	**Median**
Transfers		
# Transfers	3.67	1
# Transfers Compustat Match	3.44	1
# Transfers Patent Match	3.15	1
Subsidiaries		
# of Subsidiaries	1.61	0
# of Subsidiaries in Developing	0.62	0
Dummy Subsidiary in Developing	0.17	0
Dummy Subsidiary in Brazil	0.04	0
Patent		
# Patents	33.6	2
Sector		
Dummy Same Sector Transfers	63.9	1
Dummy Research & Development	0.26%	0

Description: This table presents statistics of technology sellers. The first frame contains information on the number of transfers per seller. The section "Subsidiaries" uses information from Compustat and 10K forms, collected by Dyreng and Lindsey (2009). It describes the number of subsidiaries of each technology seller matched to Compustat. The table section "Patent" contains the average and median number of patents for firms matched to the OECD Triadic patent family database. The final panel contains information on the sector of firms matched to Compustat. The line "Dummy Same Sector Transfer" contains the average and median number of transfers between firms in the same two digit NAICS sector while the last line contains a dummy if the seller of technology is in the Research & Development sector.

A.3 Finding Tax Identifiers of Technology Licensees

To match the dataset on technology transfers to information of innovation, employment, and R&D subsidy application, I have to find firms' tax identifiers. This section discusses the procedure to match firm names to tax ID numbers and shows statistics of matched and not-matched transfers.

Two datasets with firm names are used: RAIS and the firm registry database. Putting these two datasets together, I am able to recover different spellings for the same firm. RAIS contains a firm name for every year and establishment of the firm. Because the names are inputted by humans, it associates each tax identifier to different spellings of the same firm name. The firm registry database contains firm name, tax ID, sector, and location for every firm that has ever opened in Brazil before 2019. In this database, each firm has two names. One is a legal name and another the commercial name. Therefore, this two datasets provides several different spellings for the same firm name.

Each firm licensing an international technology is matched to a firm name from RAIS

Table 17: **Match Quality**

Variable	**Total**	**Matched**	**%**
N. Buyers	5,588	4,896	87.62
N. Contracts	13,765	12,132	88.14

This table presents the number of technology transfers and technology buyers that were matched to the employer-employee dataset RAIS. The column *Total* has the number of buyers and contracts extracted from the patent office. The column *Matched* has the number of buyers and contracts matched to RAIS. I limit the sample to all the contracts signed between 1995 and 2015.

and the firm registry database if the spelling is exactly the same. To increase accuracy, I also constrain on firm sector and firm state. If the firm is matched to more than one tax identifier or has no match, it is dropped. I keep only firms matched to only one tax identifier. To increase the number of matches, I also match firms relaxing the sector and state constraint but keeping only the ones with a one to one match.

Due to the use of different administrative datasets and exact match on firm names, I am able to find firm tax identifiers for 88% of firms, minimize the occurrence of false positives and do not find any selection on observables between matched and un-matched transfers.

In Table 17, I show that 87.6% of technology transfers in the sample, corresponding to 88% of firms can be matched to a tax identifier, can be matched to a tax identifier. This success rate is higher than in other papers in the literature and has the upside of reducing the false positive to the minimum due to the use of exact match instead of the standard fuzzy match. Kost et al. (2020) matches 40% of Compustat firms to trademarks using fuzzy match, Autor et al. (2016a) matches 72% of US patents to Compustat firms using an algorithm with internet searches, Kogan et al. (2017) matches 31% of granted patents on the Google Patents database to public firms in CRSP using a matching algorithm. Therefore, due to the use of RAIS and the Firm Registry Dataset, I am able to match more firms and more accurately.

Matched and not-matched transfers are similar in several observables. Figure 12 shows that matching rate is not statistically different across Brazilian states while Figure 13 shows that the match rate does not differ across time. Table 18 shows that the only difference between matched and not-matched transfers is the share of transfers of patents.

Table 18: **Statistics of Tech. Transfers Between Matched and Not Matched**

Variable	Matched to RAIS	Not-Matched to RAIS	Diff.	P-Value
Observations	12132	1633	10499	
Avg. Value	1022992	1202594	-179601.8	.014
Know-How	.776	.796	-.02	.055
Trademark	.166	.16	.006	.515
Patent	.053	.039	.014	.008

Description: This table presents statistics of technology according to the matching status of the technology buyer. The first column contain the name of the variable, the second statistic of matched contracts and the last column statistics of technology contracts with buyers not matched to RAIS.

Figure 12: **Match Rate of Technology Transfers According to State of the Buyer**

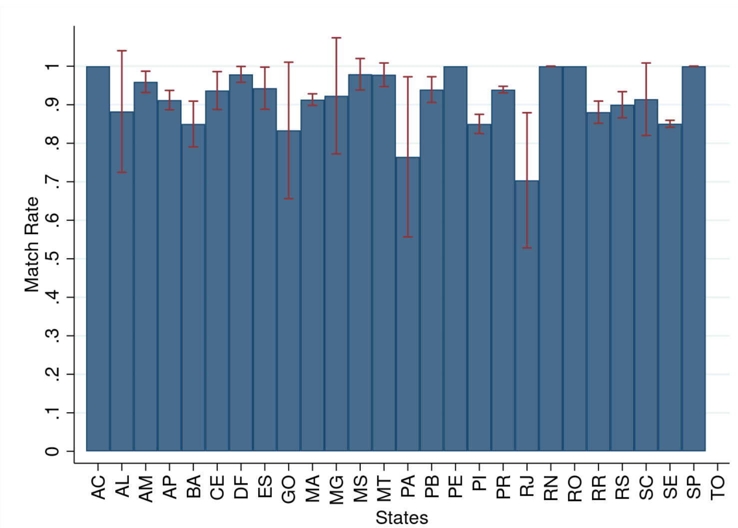


Figure 13: **Match Rate of Technology Transfers According to Year of the Transfer**

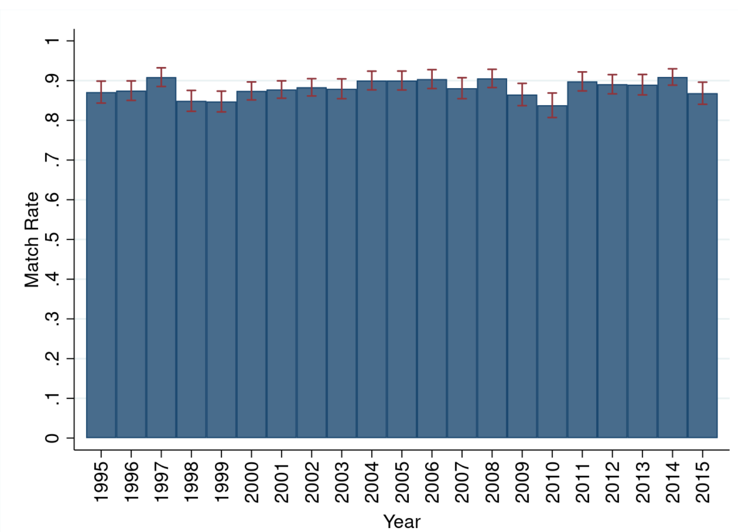


Table 19: **Statistics on Technology Transfer Inspections by Patent Office**

	Number	%	Number	%
	All		*Brazil*	
Approved	2,565	89.40	173	83.57
Extra Requirements	1,450	50.54	119	57.49
Denied	136	4.74	14	6.76

Description: This table presents statistics of technology transfer applications made to the Brazilian Patent Office between 1995 and 2015. It contains only the 2,869 (12.26%) transfers in which the enforcement outcome was observed.

A.4 Inspections of Technology Transfers

The approval of technology transfers has two evaluation phases: a formal evaluation and a technical evaluation. In the formal evaluation, technicians from the Patent Office evaluate if the firm making the technology transfer owns the right to the technology being sold. In the second evaluation step, the technical evaluation, the patent office evaluates if there is indeed a technology being transferred between firms.

The patent office might reject a contract, require changes to it or demand further documentation. For the 2,869 technology transfers where I can observe interactions with the Brazilian patent office, 70.5% had further documentation or contract changes required while 3.2% of them were denied.

A.5 Survey with Intellectual Property Lawyers

In this section, I discuss the results of the survey with intellectual property lawyers. The goal of the survey is to identify any selection on the registration of technology contracts and investigating incentives to forge technology transfers with tax deduction purposes. Intellectual property lawyers are specialized in writing and registering technology contracts. Therefore, intellectual property lawyers can inform us about the type of firms that choose not to register their contracts in the patent office and can shed light on the incentives firms face to fake technology transfers.

I contacted by email 381 law offices with specialization in intellectual property.[56] Out of the 381 contacted law offices, I received an answer from 154, a 40.4% response rate. This

[56] The contact of law offices was gathered from the web page of the Brazilian Association of Intellectual Property Agents (*Associação Brasileira dos Agentes da Propriedade Industrial*).

Table 20: **Registering Technology Transfers in the Patent Office**

Question	**Shr. Answering "Yes"**	
	International	National
Is registering tech. transfers costly relative to the contract value?	76.92	100
Can registering tech. transfers takes less than 6 months?	59.09	65.58
Can registering tech. transfers delay tech adoption?	52.75	36.27
Can registering tech. transfers be bureaucratic?	87.91	80.39
Can registering an tech. transfers require technical documents?	76.92	75.25

Table 21: **Shr. of Technology Transfers Registered in the Patent Office**

Question	Mean	Median	Mean	Median
	International		National	
Technology transfers are registered always or almost always?	0.68	1	0.12	0
Number of Contracts Registered/Number of Contracts Written	1	1.21	0.97	0.66

response rate is similar to other surveys in the development literature, such as Bloom et al. (2016), Altig et al. (2019), and Tanaka et al. (2020).

The survey was divided in 4 parts: characteristics of the respondent, national technology transfers, international technology transfers, and tax avoidance. In the first section, I ask the age, position in the company, and experience of the respondent. This section allows me to identify if the respondent is qualified to answer questions on technology transfers. In the second and third part of the survey I ask the respondent about the process of filing national and international technology transfers. In the final section, I ask the respondent about incentive firms face to fake technology transfers for tax avoidance.

Table 20 shows that the registration of technology transfers in the patent office is costly, affects the timing of the technology adoption, is bureaucratic and requires scientific documentation. The full survey is available under request.

Table 21 shows how often technology transfers are registered with the Brazilian patent office. The first line shows that respondents believe that registering international technology transfers is common while registering national technology transfers isn't. Still, the second line indicates that, for the law offices surveyed, the majority of contracts written are registered.

Table 22 shows that using fake technology transfers for a deduction in taxes isn't a common practice. In average, 13% of respondents believe that other law offices have employed this practice. Moreover, respondents believe that 15% of technology transfers ever accepted

Table 22: **Falsification of Technology Transfers for Tax Purposes**

Question	Mean	Median
Do you believe that faking technology contracts is a common practice in other law offices?	13.64	0
What is the percentage of all registered transfers that are fake?	14.56	8.5
Do you believe that the activity of the patent office deter firms from registering fake technologies?	67.42	1

could be fake while the median response is 8.5%. The last line indicates that the enforcement of the Brazilian patent office plays a role in reducing the number of falsification.

A.6 Statistics of Brazilian Patents

This section shows statistics of Brazilian patent applications.

Figure 14 shows the number of patent applications between 1990 and 2015. The figure shows a slight increase in patent applications after the introduction of the Technology Substitution Program in 2001.

Figure 14: **Patent Applications**

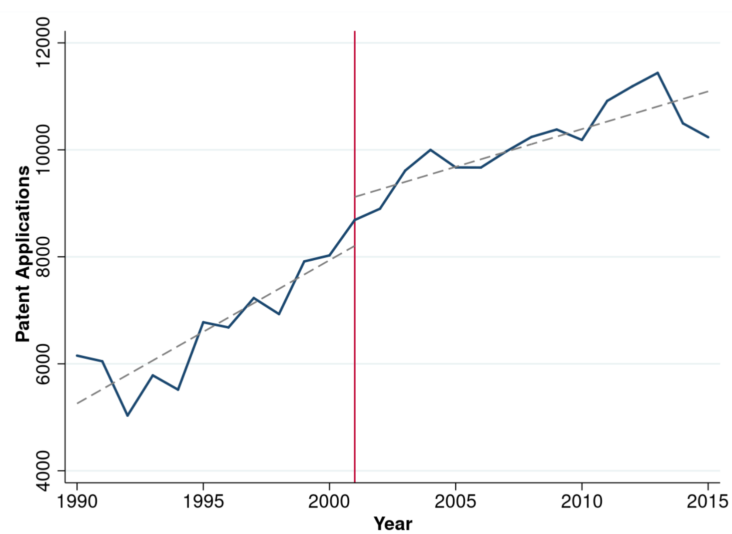


Table 23 shows the sectoral distribution of firms applying for patents in Brazil. According to Table 23, 46% of patent applications are submitted by firms in the manufacturing sector. Figure 15 shows the distribution of patent classes.

Table 23: **Sector of Patent Applications**

	Number of Patents	%
Manufacturing	6,082	46.93
Retail	2,855	22.03
Agriculture	935	7.21
Research	456	3.52
Administration	442	3.41
Construction	381	2.94
Health	358	2.76
Information and Communication	296	2.28
Others	253	1.95
Restaurant	229	1.77
Education	196	1.51
Transportation	180	1.39
Finance	72	0.56
Extractive	63	0.49
Water and Sewage	57	0.44
Electricity	54	0.42
Public Sector	41	0.32
Real State	10	0.08

This table describes the sector of the firms making patent applications. The data is from 1985 to 2019. It covers the universe of patent applications matched to the RAIS database. Firms are classified using the CNAE 1 sectoral classification.

A.7 Statistics of Brazilian Industrial Designs

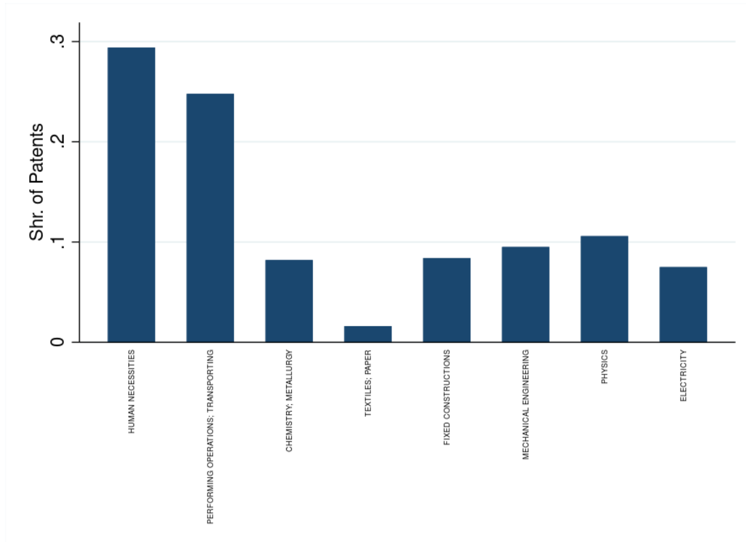
In this section, I discuss statistics of Brazilian industrial designs. Figure 16 shows an increase in the number of industrial design applications after the creation of the Technology Substitution Program in 2001. Table 24 shows the number of industrial designs according to the sector of the firm making the application. Table 24 shows that 57% of industrial designs are in the manufacturing sector. Table 25 shows the distribution of industrial design classifications according to it's two digit Locarno classification.

A.8 Statistics of Brazilian Trademarks

This section discusses statistics of trademark applications in Brazil. Figure 17 shows the number of trademark applications by year. Again, we see an step increase in the number of applications in the years after the TSP.

Trademarks can be of 6 types. They can be related to a product, a service, an advertising

Figure 15: **Patent Class Distribution**



Description: This figure shows the distribution of a 1-digit IPC patent class for patent applications between 1985 and 2019.

campaign, a set of product/services, a product certification or generic. Table 26 shows that products and service trademarks are the majority.

Table 26: **Classification of Trademark Applications**

Type	**N. of Trademarks**	**Percentage**
Product	1,004,814	54.54
Service	830,744	45.09
Advertising	3,182	0.17
Collective	1,654	0.09
Generic	1,134	0.06
Certification	953	0.05

Description: This table show statistics of trademarks submitted to the Brazilian Patent Office between 1990 and 2010. A trademark can be of 6 types. Trademarks can be associated to a product; a service; an advertising campaign; collective, i.e., when the product or service is supposed to be associated to a specific company or set of products; certification, those trademarks created to mark the conformity of a product or service with certain standards or technical specifications; or Generic, when it doesn't match any other classification.

Table 27 shows the distribution of trademarks according to it's two digit NICE classification. Table 27 shows that the majority of trademarks are related to advertising and educational services.

Figure 16: **Industrial Design Applications**

Description: This figure shows the number of industrial design applications by year.

Table 28 shows the distribution of trademarks according to the sector of the applicant. It shows that manufacturing and retail sectors are the main applicant for trademarks, as in the case for patents and industrial designs.

Table 24: **Sector of Industrial Design Applications**

Sector	**Number of I.D.**	**Percentage**
Manufacturing	3,166	57.16
Retail	1,168	21.09
Agriculture	324	5.85
Administration	152	2.74
Research	105	1.90
Health	100	1.81
Construction	89	1.61
Others	85	1.53
Restaurant	71	1.28
Transportation	61	1.10
Information and Communication	57	1.03
Education	52	0.94
Finance	47	0.85
Public Sector	18	0.32
Water and Sewage	17	0.31
Extractive	16	0.29
Electricity	7	0.13
Real State	4	0.07

Description: This table shows the number of industrial design applications between 1985 and 2010 by sector of the firm making the application. The information on sector is from RAIS.

Table 28: **Sector of Trademark Applications**

Sector	**N. Trademark**	**Percentage**
Manufacturing	5,548	54.10
Retail	1,766	17.22
Agriculture	628	6.12
Administration	338	3.30
Research	330	3.22
Information and Communication	309	3.01
Construction	268	2.61
Health	252	2.46
Others	155	1.51
Restaurant	126	1.23
Finance	115	1.12
Education	114	1.11
Transportation	105	1.02
Electricity	62	0.60
Extractive	49	0.48
Public Sector	45	0.44
Water and Sewage	37	0.36
Real State	9	0.09

Description: This table shows the number of trademark applications between 1990 and 2010 by sector of the firm making the application. The information on sector is from RAIS.

Figure 17: **Trademark Applications**

Description: This figure shows the number of trademark applications by year to the Brazilian Patent Office.

A.9 Finding Tax Identifiers for Firms with Patents

The database with patent, industrial design, and trademark applications contains only the name of the applying firm. To merge across datasets, I find tax identifiers for each applicant. The steps to link firm names to tax identifiers are described in A.3. In this section, I show that the matching of patents happened at high rates and without selection on observables. The match quality for industrial designs and trademarks are available under request.

Patent applications can be made by firms or by individual inventors, both appearing equally in the database with their names. But we only expect to find tax identifiers for patent applications made by firms. Therefore, the overall matching rate of patents is uninformative about the quality of the matching procedure. To deal with this issue, I also evaluate the matching rate among applicants with "LTDA" on it's name. "LTDA" is short for "limitada" and refers to the juridical classification of the firm. It's common for several firms to have "LTDA" at the end of it's name while it is unlikely for an Brazilian individual to be named "LTDA". Therefore, with a perfect matching procedure, we would expect to match 100% of the applicants with "LTDA" in the name.

Table 29 shows the matching rate for the whole database and for "LTDA" applicants. The matching rate for "LTDA" firms is around 87%. This success rate is higher than in other papers in the literature[57] and have the upside of reducing the false positive to the minimum due to the use of exact match instead of the standard fuzzy match.

Table 29: **Match Rate of Patent Applicants to Matched Employer-Employee Dataset**

	Total		Matched		Percentage Matched	
	All	LTDA	All	LTDA	All	LTDA
Number of Patents	173140	11796	92378	10173	0.53	0.86
Number of Inventors	101887	7491	54587	6593	0.54	0.88
Number of Firms	93599	6756	47546	5909	0.51	0.87

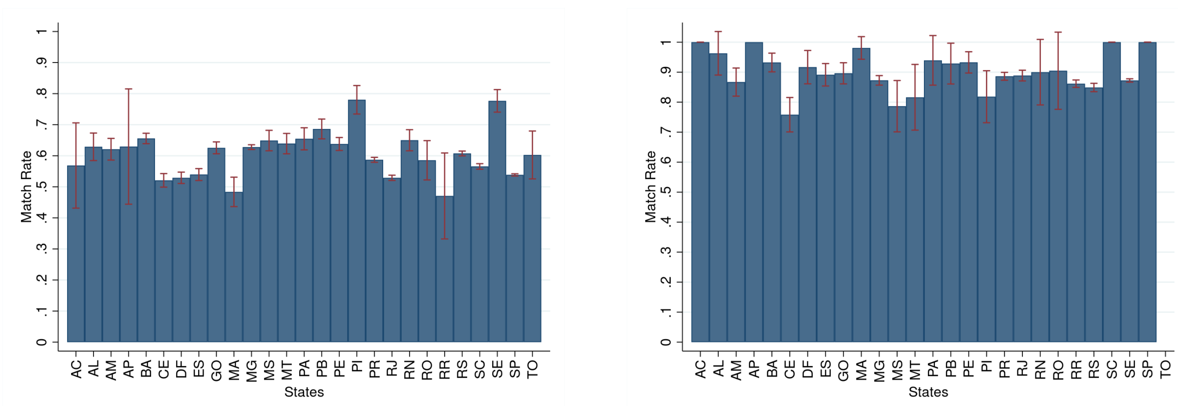
Description: This table shows the matching rate of patent applications to firms on the matched employer-employee dataset RAIS. The first line shows the matching rate by the number of patents, the second line shows the matching rate by percentage of inventors, and the final line shows the matching rate by the number of different firms. The first lines shows the number of patents, inventors, and different firms in the database. The second column shows the number of patents, inventors, and firms with "LTDA" on the name. The following two columns shows the aggregate number of matched patents, inventors, and firms. The final two columns show the matching rate for the whole dataset and for firms with "LTDA" in the name.

Figures 18 through 20 show that the matching rate is stable across regions, year, and patent class. Therefore, there is no selection on observables.

Figure 18: **Match Rate of Patent Applications According to State of the Applicant**

(a) All Patents

(b) LTDA Patents



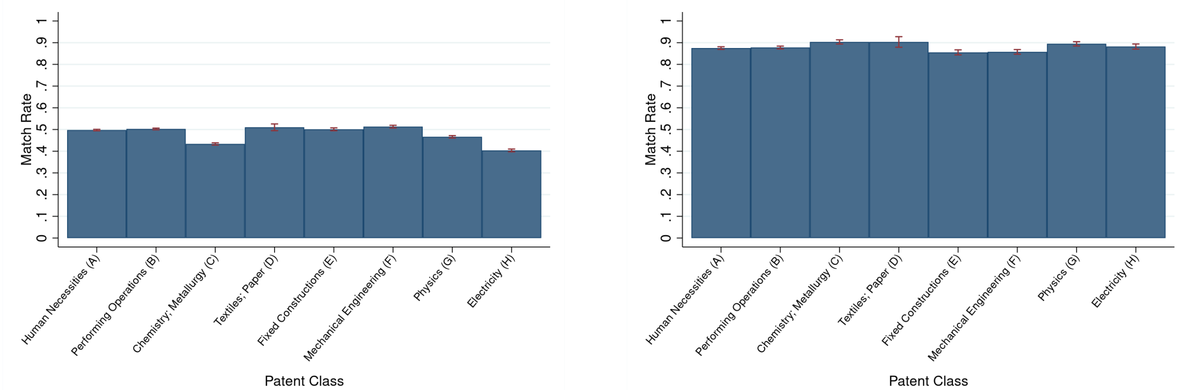
[57] Kost et al. (2020) matches 40% of Compustat firms to trademarks using fuzzy match, Autor et al. (2016a) matches 72% of US patents to Compustat firms using an algorithm with internet searches, Kogan et al. (2017) matches 31% of granted patents on the Google Patents database to public firms in CRSP using a matching algorithm. Therefore, due to the use of RAIS and the Firm Registry Dataset, I am able to match more firms and more accurately.

Figure 19: **Match Rate of Patent Applications According to Year of Application**

(a) **All Patents** (b) **LTDA Patents**

Figure 20: **Match Rate of Patent Applications According to Patent Class**

(a) **All Patents** (b) **LTDA Patents**



A.10 Statistics of R&D Subsidy

Table 30 compares labor outcomes of firms receiving the subsidy against the outcomes of firms receiving the subsidy. Table 30 shows that firms receiving the subsidy are 7 times larger, have a higher hourly wage, and more educated labor force. This is expected for two reasons. First, to begin with, firms receiving a subsidy need to have an innovation program. Second, the subsidy is awarded to firms based on the quality of their research. It's natural to expect large firms, with high wages, and an educated labor force to be more likely to engage in high-quality research and, therefore, receive the subsidy.

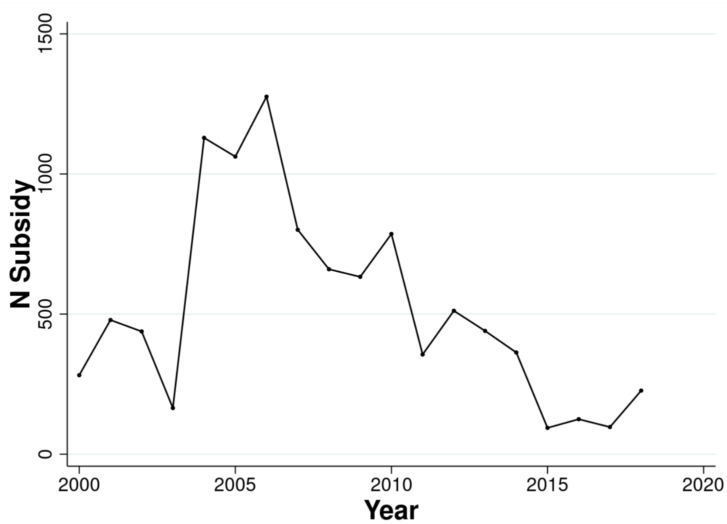
Table 30: **Statistics of Firms Receiving Subsidy in the Pre-Period**

	Hourly Wage	*Avg. Years of Education*	*Shr. of H.S. Dropout*	*Shr. H.S. Complete*	*Number of Establishments*	*N. Workers*
Not Subsidy Recipient	41.30	8.11	0.79	0.15	8.40	110.89
Subsidy Recipient	107.09	11.79	0.35	0.30	4.03	798.49

Description: This table compares statistics of the firms receiving a R&D subsidy against the firms not receiving it in 2000, before the creation of the subsidy.

Figure 21 shows the total number of subsidies provided by the FINEP between 2000 and 2019. After the creation of the TSP, the FINEP took 4 years to set up the new subsidy policy. In 2005, they started giving away the subsidies. Because they can only expend what was collected as taxes from the international technology licensing, the total number of subsidies has fallen since 2006.

Figure 21: **Number of Subsidies by Year**



Description: This figure shows the total number of subsidies given by the FINEP between 2000 and 2019. The data was provided by the FINEP.

A.11 Construction of Database with Imports of Materials and Machines

In this section, I describe the steps taken to create a database with import probabilities for each firm-product pair. Data on product-region level imports is public. But, due to financial confidentiality, data on firm imports are not available. Using an import dummy, sectoral imports, and regional imports, I create a probability for each firm of importing a specific 4 digit good.

Imports. Data on imports are collected from tariff payments at the border and made public by the Secretary of International Trade. It contains all the imports realized between 1997 and 2019 with information on year, month, 4-digits harmonized system product code, country of origin, city of the importing establishment, and value.

Sectoral Imports. Starting in 2014, the Secretary of International Trade started recording the sector of the importing firm.[58] This administrative dataset records imports by product,[59] and sector of the importing firm. This allows me to identify the sector each product is intended to be used and give us information of the firms making the imports.

Importers List. A final dataset allow us to identify the importing firm: the registry of importing firms. The Secretary of International Trade provides every year a list of all establishments that have imported any product that year. The list contains the name of the firm and its tax identifier. It does not contain any information on the product imported or its value.

Probability of Importing. Using the three datasets described, together with RAIS, we can calculate a probability of each firm to be importing a specific 4 digit product.

Using the sectoral imports, I create a cross-walk between products and sectors which informs what products each sector uses in its production process. Using the data on imports, we can create the set $\Omega_{r,s,t}$ which is the set of products imported on region r by sector s in year t.

Using RAIS to identify firms' location and sector, I can calculate the number of potential importers for each good. Let $\mathbb{N}_{r,s,t}$ be the number of firms importing at year t, city r, and sector s:

$$\mathbb{N}_{r,s,t} = \sum_j \mathbb{I}\{i \text{ imports at } t\}\,\mathbb{I}\{i \text{ is in city } r\}\,\mathbb{I}\{i \text{ is in sector } s\}$$

[58] To guarantee the anonymity of the firms involved, this dataset is not public.
[59] Products in this dataset are at the 8-digit Brazilian classification. They have the first 6 digits of the international Harmonized System plus 2 extra digits.

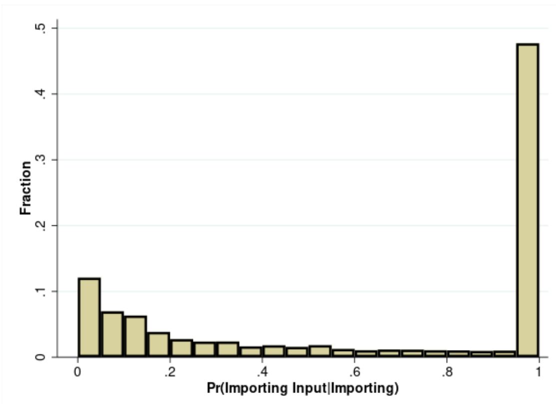
Therefore, we can calculate the probability that firm i imports product o from year t by

$$\mathbb{P}\left\{i \text{ imports product } o \text{ in year } t\right\} = \frac{\mathbb{I}\left\{o \in \Omega_{r(i),s(i),t}\right\} \mathbb{I}\left\{i \text{ imports at } t\right\}}{\mathbb{N}_{r(i),s(i),t}} \tag{18}$$

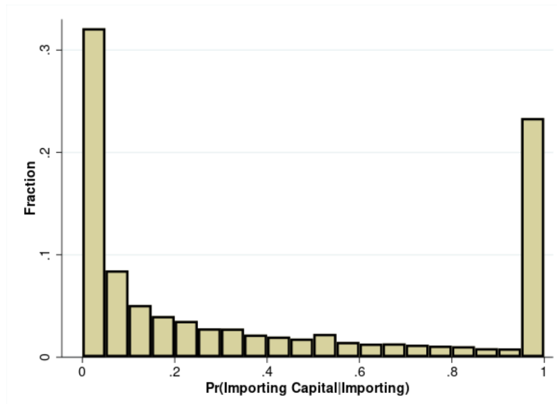
Using the same steps, I calculate the probability that a firm imports a machine, any input, or from any specific country. Figure 22 shows the distribution of importing probability for machinery and non-machinery goods.

Figure 22: **Distribution of Importing Probability Conditional on Importing**

(a) Distribution of the Probability of Importing an Input Conditional on Importing



(b) Distribution of the Probability of Importing Capital Conditional on Importing



Description: This figure shows the distribution of firm's importing a specific 4 digit product according to 18. Figure 22a shows the distribution of importing probabilities of non-machinery conditional on the firm being importing while 22b shows the distribution of importing probabilities of machinery conditional on the firm importing.

A.12 Effect of Technology Substitution Program: Cross-Country Comparison

Figure 1 shows that the technology substitution program is associated with an increase in innovation. Is this correlation driven by the technology substitution program or is it an international trend in technology creation? One could argue that a developing country, after relying on international technology for a long time, learns how to produce their own technology. In this case, the pattern observed is driven by standard development process.

In this section I use diff-in-diff to show that Brazil increased its patent production when compared to other developing countries.

The main empirical specification is given by

$$Patent_{c,t} = \sum_{j=-5}^{10} \theta_j \mathbb{I}\{t = 2001 + j, c = BR\} + \eta_c + \eta_t + \epsilon_{c,t} \tag{19}$$

where $Patent_{c,t}$ is the number of patents issued by country c in year t, $\mathbb{I}\{t = 2001+j, c = BR\}$ is a dummy taking 1 j years to the technology substitution program if country c is Brazil, η_c is a country fixed effect and η_t is a year fixed effect. The sample is limited to other Latin American countries.

The parameter of interest, θ_j, captures the difference in patent production between Brazil and the other Latin American countries j years to the technology substitution program.

Figure 23a shows the estimated parameter of model 19. It shows that the number of patents in Brazil increased by more than 500 patents compared to other Latin American countries. The period -5 is normalized to 1. We can see that prior to the program, there was a jump in the number of patents. Still, the difference between treatment and control is persistent in the following years.

Figure 23b uses synthetic control to estimate the effect of the substitution program.[60] Again, it shows that there is a large difference between the treated unit, Brazil, and the control group, an average of developing countries. The synthetic control unit is constructed by averaging a set of developing countries based on their patent emission between 1990 and 1999.[61]

A.13 Motivation for the Technology Substitution Program

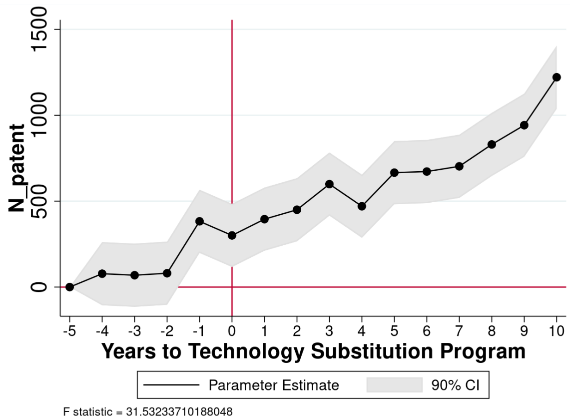
Revenue raised by the tax on technology transfers is administered by the Funding Authority for Studies and Projects (*Financiadora de Estudos e Projetos*), FINEP, and allocated to specific sectors. Innovative firms in targeted sectors can apply to FINEP to receive a subsidy for their research, with selection based on technical criteria established and judged

[60] Abadie (2020) and Abadie et al. (2010).

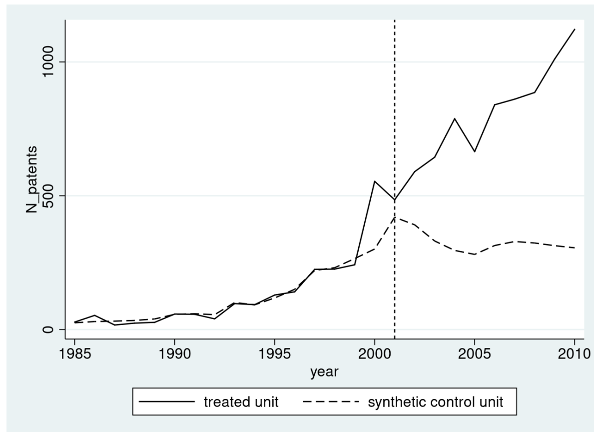
[61] The synthetic control is an average of Cuba, with .913 weight, Monaco, with .018 weight, Sweden, with 0.02 weight, Turkey, with .001 weight, British Virgin Islands, with .047 weight.

Figure 23: **Technology Substitution Program and Innovation**

(a) Number of Patents: Diff-in-Diff



(b) Number of Patents: Synthetic Control



Description: This picture presented the estimated parameters of equation 19 in panel a and the synthetic control result in panel b. In panel b, the treated unit is the total number of patents issued by Brazil and the dotted line has the average number of patents issued by Cuba, with .913 weight, Monaco, with .018 weight, Sweden, with 0.02 weight, Turkey, with .001 weight, British Virgin Islands, with .047 weight. The weights are chosen to match Brazilian patent production in the pre-period.

by a technical committee at FINEP. Revenue raised by the tax on technology transfer is transferred to 5 committees, each of which specializes in a sector and comprises scientists and policymakers who specialize in their fields. Technical committees are responsible for selecting projects that FINEP supports. An innovative firm interested in receiving support from the government must apply to FINEP with a full description of its project, the methodology to be implemented, the team involved, and a schedule. Each application is given a score according to a technical point system, and projects with the highest scores are funded. Technical decisions thus minimize political meddling during allocation of subsidies.[62]

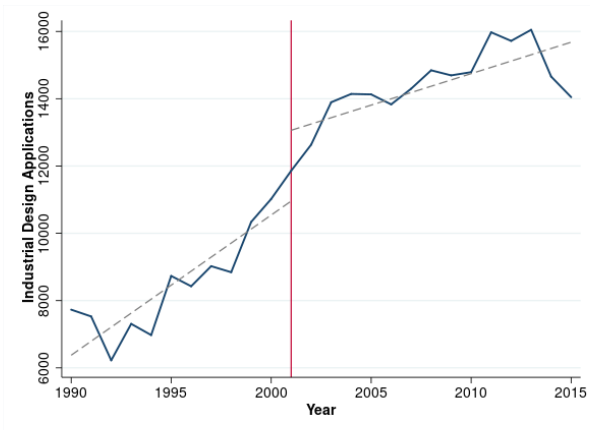
A.14 CV of Inventors

The source of the CV of inventors is the Lattes Platform. The platform was created in 1993 for R&D planning and monitoring of academic research by the Brazilian federal government. Having an updated CV hosted on the platform is required for several scientists, academics, and PhD students. Researchers in institutions that receive federal support, RAs, Master's degree holders, and PhD students who receive financial support from the federal government,

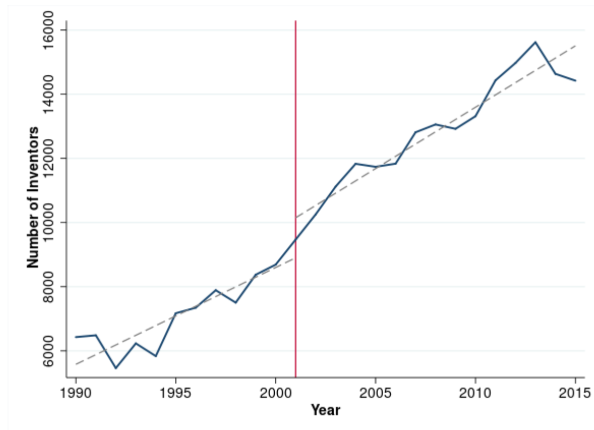
[62] For details of the selection process, see Pereira et al. (2001) and Ministério da Ciência, Tecnologia e Inovação - MCTI (2012).

Figure 24: **Technology Substitution Program and Innovation**

(a) **Patent and Industrial Design Applications to the Brazilian Patent Office**



(b) **Number of Inventors**



Description: This figure contains time series information on the number of inventors in Brazil and the number of Patents or Industrial Design applications. The number of inventors is calculated by the number of different inventors of patents or industrial designs.

and those applying for R&D subsidies, stipends, research grants, or any other government-provided research assistance, are required to maintain an updated CV on the platform. It is widely used by Brazilian scientists as their main webpage.

Table 32 reports statistics from the CVs of Brazilian inventors. Of the 102,775 inventors, 32,505 (31.6%) have a CV on the Lattes Platform. Assuming that inventors without CVs on the platform do not have PhDs, published papers, or academic positions, about 13% of inventors hold a doctorate, 26% have published an academic paper, and 17% have worked at a university.

B Empirics Appendix

B.1 Sample Selection

I drop from the analysis firms in the service and government sectors. The final sample contains firms in agriculture, livestock, mining, manufacturing, and construction sectors.

Innovation and technology transfers are activities engaged by large firms. To avoid the noise generated by small firms I consider in the analysis only firms with more than 30 workers at some point between 1995 and 2010.[63]

To ensure a balanced panel in the diff-in-diff, I keep only surviving firms between 1995 and 2010. In section B.5 I show that this selection does not cause bias because the program did not affect entry or exit.

In Appendix B.5, I relax all these sample selections studying the effect of the TSP on sectoral aggregates. I show that all results are still the same.

I also make a selection on the type of technology transfers. I only consider technology transfers the ones involving patents, industrial designs, and know-how. Therefore, I drop the ones related to trademarks. The goal is to capture changes and improvements in the production process of the firm and not the creation of a new product or ad campaign.

B.2 Additional Results and Tables

Table 33: **International Shocks and Exposure to the TSP**

	(1)	(2)	(3)
	$\Delta\mathbb{I}\{Subsidiary\}$	$\Delta log\,(Price\ Inputs)$	$\Delta log\,(Price\ Output)$
Exposure TSP	-0.000206	0.0857	0.259
	(0.000109)	(0.0441)	(0.153)
N	33648	26582	7217
R^2	0.021	0.177	0.307
Mean Dep. Var	0	.328	.63
SD Dep. Var	.013	.474	1.088
Mean Indep. Var	.089	.089	.089
SD Indep. Var	.285	.285	.285
Controls	Yes	Yes	Yes

Description: **Description**: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of ownership and international prices. The $\mathbb{I}\{Subsidiary\}$ is a dummy taking one if the firm is a subsidiary of a multinational, $log\,(Price\ Inputs)$ is the log of the average price of inputs imported by firms on each 4-digit CNAE classification, $log\,(Price\ Output)$ is the log of avergage price of products exported by firms on each 4-digit CNAE classification. As controls I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

[63] 30 workers is the bottom decile among firms applying for a patent.

Table 34: **Other Policies and Exposure to the TSP**

	(1)	(2)	(3)	(4)	(6)	(7)	(8)
	Δ Tariff Inputs	Δ Tariff Output	$\Delta\mathbb{I}\{Gov.\ Loan\}$	$\Delta\mathbb{I}\{Gov.\ Contract\}$	Δ *Labor Tax*	Δ *Tax*	$\Delta\mathbb{I}\{Campaign\ Contribution\}$
Exposure TSP	-0.0879	-1.100*	0.00217	0.00259	0.00196	-0.000645	-0.00854
	(0.0818)	(0.483)	(0.00137)	(0.00337)	(0.00216)	(0.000509)	(0.00671)
N	26582	25666	33648	33648	22466	22466	33648
R^2	0.238	0.552	0.028	0.074	0.141	0.086	0.097
Mean Dep. Var	-4.31	-1.223	.002	.024	-.015	0	.059
SD Dep. Var	1.182	5.83	.039	.154	.027	.005	.236
Mean Indep. Var	.089	.089	.089	.089	.089	.089	.089
SD Indep. Var	.285	.285	.285	.285	.285	.285	.285
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Description: **Description**: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of policy exposures. The first column has the change on tariff of inputs used by firms in the same 4-digit CNAE sector, column 2 has the change in tariffs in products produced by firms in the same 4-digit CNAE sector, the third column has a dummy if the firm took a loan from the federal bank BNDES in the past 10 years, the fourth column has a dummy if the firm signed a contract with the government in the past 10 years, column 6 has the change in average sectoral labor tax, column 7 has the change in total sectoral marginal tax, and column 8 has a dummy taking one if the firm made any campaign contribution in the past 10 years. As controls I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 35: **Patents in Past 10 Years According to Inventor Quality and Exposure to the TSP**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\mathbb{I}\{Scientist\}$	$\Delta\mathbb{I}\{PhD\ Worker\}$	$\Delta\mathbb{I}\{Patent\ PhD\ Inventor\}$	$\Delta\mathbb{I}\{Patent\ Master\ Inventor\}$	$\Delta\mathbb{I}\{Patent\ Academic\ Paper\ Inventor\}$	$\Delta\mathbb{I}\{Patent\ Professor\ Inventor\}$
Exposure TSP	0.165***	0.144***	0.0171**	0.134***	0.0152	0.0190**
	(0.0211)	(0.0200)	(0.00728)	(0.0183)	(0.00955)	(0.00768)
N	29301	29301	29301	29301	29301	29301
R^2	0.293	0.334	0.274	0.330	0.288	0.264
Mean Dep. Var	.048	.036	.002	.093	.005	.003
SD Dep. Var	.307	.324	.076	.45	.109	.082
Mean Indep. Var	.01	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on alternative measures of innovation. $\mathbb{I}\{Scientist\}$ is a dummy taking one if the firm hired in the past 10 years a scientist. I define a worker as a scientist if she has ever been hired under the two digits CBO02 classification "Researcher or Policientific Professional". Using the current CBO classification is not possible because the classification "Researcher or Policientific Professional" was added after 2003. $\mathbb{I}\{PhD\ Worker\}$ is a dummy taking one if the firm has hired a worker with a Ph.D. in the past 10 years. Again, because I only observe if a worker has a Ph.D. after 2002, I have to define a worker as having a Ph.D. if it was ever classified as having one. $\mathbb{I}\{Patent\ PhD\ Inventor\}$ is a dummy taking one if the firm issued a patent and the inventor has ever received a Ph.D. $\mathbb{I}\{Patent\ Master\ Inventor\}$ is a dummy taking one if the inventor has a master degree, $\mathbb{I}\{Patent\ Academic\ Paper\ Inventor\}$ is a dummy if the inventor was ever hired by a university, and $\mathbb{I}\{Patent\ Professor\ Inventor\}$ is a dummy taking one if the inventor was ever hired by a university. The education of the inventor is measured using the dataset constructed from academic CVs registered in the Lattes Platform. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Because I observe perfectly none of these variables over-time, which could lead to a trend due to purely selection, I control for the initial dependent variable outcome and the growth of the dependent variable between 1995 and 2000. Standard errors are clustered at the 5-digit sector level.

Table 36: **Intellectual Property in Past 10 Years and Exposure to the TSP**

	(1)	(2)	(3)	(4)
	$\Delta log(\mathbb{N}\{Patent\})$	$\Delta log(\mathbb{N}\{log(PCT\ Patent)\})$	$\Delta log(\mathbb{N}\{Patent\ or\ Ind.\ Design\})$	$\Delta log(\mathbb{N}\{Any\ Intelec.\ Prop.\})$
Exposure TSP	0.0365	0.315	-0.181	-0.147*
	(0.169)	(1.520)	(0.174)	(0.0780)
N	564	14	793	7595
R^2	0.173	0.170	0.221	0.111
Mean Dep. Var	.197	.518	.315	.256
SD Dep. Var	.983	1.124	1.159	1.099
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on intensive measures of innovation. $\mathbb{N}\{Patent\}$) is the number of patent applications to the Brazilian patent office in the past 10 years, $\mathbb{N}\{log(PCT\ Patent)\}$ is the number of PCT patent applications on the past 10 years, $\mathbb{N}\{Patent\ or\ Ind.\ Design\}$ is the total number of patent and industrial design applications, $\mathbb{N}\{Any\ Intelec.\ Prop.\}$ is the sum of all intellectual property applications in the past 10 years. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 37: **Intellectual Property in Past 10 Years and Exposure to the TSP**

	(1) $\Delta\mathbb{N}\{Patent\}$	(2) $\Delta\mathbb{N}\{PCT\ Patent\}$	(3) $\Delta\mathbb{N}\{Patent\ or\ Ind.\ Design\}$	(4) $\Delta\mathbb{N}\{Any\ Intelec.\ Prop.\}$
Exposure TSP	0.784	0.626	0.576	-0.469
	(0.537)	(0.495)	(0.718)	(2.420)
N	29301	29301	29301	29301
R^2	0.035	0.011	0.032	0.020
Mean Dep. Var	.064	.011	.169	.851
SD Dep. Var	1.657	.978	3.031	9.855
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on intensive measures of innovation. $\mathbb{N}\{Patent\}$) is the number of patent applications to the Brazilian patent office in the past 10 years, $\mathbb{N}\{log(PCT\ Patent)\}$ is the number of PCT patent applications on the past 10 years, $\mathbb{N}\{Patent\ or\ Ind.\ Design\}$ is the total number of patent and industrial design applications, $\mathbb{N}\{Any\ Intelec.\ Prop.\}$ is the sum of all intellectual property applications in the past 10 years. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 38: **Patents According to Text Complexity in Past 10 Years and Exposure to the TSP**

	(1) Δ *N. Words*	(2) Δ *N. Diff. Words*	(3) Δ *Avg. Syllables per Word*	(4) Δ *Reading Ease Index*	(5) $\Delta\mathbb{I}\{New\ Word\ in\ Patent\}$	(6) $\Delta\mathbb{I}\{First\ Word\ in\ Past\ 10\}$
Exposure TSP	30.59	15.96	0.587	0.344	0.137	0.138
	(27.32)	(13.67)	(0.492)	(4.141)	(0.0889)	(0.0941)
N	3605	3605	3605	3605	3605	3605
R^2	0.133	0.142	0.117	0.165	0.136	0.131
Mean Dep. Var	.047	-.046	.032	.91	.011	.013
SD Dep. Var	130.825	71.393	2.082	34.676	.409	.42
Mean Indep. Var	.01	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of text analysis. The first column contains the total number of words in the summary of the patent, the second the number of different words in the summary of the patent, the column 3 has the average number of syllables in per word, column 4 has the Flesch–Kincaid readability index, column 5 has a dummy taking one if the patent uses a word that was never used in a patent description before and the final column has a dummy taking one if the patent has a word first used in the past 10 years in the description of the patent. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 39: **Patents According to Inventor Quality Measures in Past 10 Years and Exposure to the TSP**

	(2) $\Delta\mathbb{E}\{PhD\ Inventor\}$	(3) $\Delta\mathbb{E}\{Master\ Inventor\}$	(5) $\Delta\mathbb{E}\{Academic\ Paper\ Inventor\}$	(7) $\Delta\mathbb{E}\{Professor\ Inventor\}$
Exposure TSP	0.00747*	0.00786	0.00864	0.00345
	(0.00427)	(0.00555)	(0.00580)	(0.00319)
N	3216	3216	3216	3216
R^2	0.170	0.115	0.142	0.131
Mean Dep. Var	.003	.005	.007	.003
SD Dep. Var	.029	.041	.05	.032
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: **Description**: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of innovation quality. $\mathbb{E}\{PhD\ Inventor\}$ is the share of patents created by inventors with a Ph.D., $\mathbb{E}\{Master\ Inventor\}$ is the share of patents created by inventors with a master or Ph.D. degree, $\mathbb{E}\{Patent\ Academic\ Paper\ Inventor\}$ is the share of patents created by an inventor that has ever published an academic paper, and $\mathbb{E}\{Professor\ Inventor\}$ is the share of patents with inventors that have ever been hired by a university. The education of the inventor is measured using the dataset constructed from academic CVs registered in the Lattes Platform. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 40: **National Technology Share and Exposure to the TSP**

	(1) $\Delta \frac{N.\ Patents}{N.\ Patents, Ind.\ Design\ or\ Int.\ Tech.}$	(2) $\Delta \frac{\$\ Patents}{\$\ Patents, Ind.\ Design\ or\ Int.\ Tech.}$	(3) $\Delta \frac{N.\ PCT\ Patent}{N.\ PCT\ Patent\ or\ Int.\ Tech.}$	(4) $\Delta \frac{\$\ EPO\ Patent}{\$\ EPO\ Patent\ or\ Int.\ Tech.}$
Exposure TSP	0.0410***	0.0396***	0.0201**	0.00134
	(0.00918)	(0.00899)	(0.00907)	(0.00411)
N	3350	3350	940	940
R^2	0.117	0.113	0.152	0.150
Mean Dep. Var	.009	.009	.013	-.006
SD Dep. Var	.097	.102	.101	.07
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of national technology share. The first column contains the share of patents on the total intellectual property of firms, the second column contains the value of patents on the total firm's intellectual stock asset, the third column contains the share of patents using only internationally registered patents. The value of patents and industrial design are calculate using the price of patents and industrial designs reassignment in the database of intellectual technology transfer. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 41: **Factor Shares and Exposure to the TSP**

	(1) $\Delta\mathbb{I}\{H.S.\ Dropout\}$	(2) $\Delta\mathbb{I}\{H.S.\ Complete\}$	(3) $\Delta\mathbb{I}\{H.S.\ More\}$	(4) Δ Shr. H.S. Dropout	(5) Δ Shr. H.S. Complete	(6) Δ Shr. H.S. More
Exposure TSP	-0.000676	-0.0558***	-0.0672***	0.0288**	-0.0598***	0.0309***
	(0.0120)	(0.0124)	(0.0124)	(0.0120)	(0.0114)	(0.00801)
N	29301	29301	29301	29301	29301	29301
R^2	0.045	0.090	0.088	0.132	0.131	0.052
Mean Dep. Var	-.028	.095	.095	-.224	.191	.033
SD Dep. Var	.232	.408	.55	.275	.261	.135
Mean Indep. Var	.01	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on the hiring of different educational groups. $\mathbb{I}\{H.S.\ Dropout\}$, $\mathbb{I}\{H.S.\ Complete\}$ and $\mathbb{I}\{H.S.\ More\}$ are dummies taking one if the firm hired at least one high school dropout, high school complete or high school or more worker, respectively. Columns 4, 5 and 6 contain the regression on the change of high school dropout, high school complete and more than high school workers. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 42: **Task Content and Exposure to TSP**

	(1) Δ *Abstract Routine*	(2) Δ *Abstract Non-Routine*	(3) Δ *Non-Routine Analytical*	(4) Δ *Number*
Exposure TSP	-0.0421**	-0.00937	-0.0373**	-0.0348*
	(0.0181)	(0.0205)	(0.0174)	(0.0178)
N	29257	29257	29257	29257
R^2	0.062	0.069	0.070	0.066
Mean Dep. Var	-.071	.004	-.013	-.019
SD Dep. Var	.476	.474	.364	.367
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table presents the coefficients of a regression of the exposure to TSP on a set of measures of task content at the firm. *Non-Routine Analytical* measures the intensity in problem solving tasks, it follows the definition of Deming (2017) using the ONET questions for "Mathematical Reasoning", "Mathematics" and "Mathematical Reasoning"; *Abstract Non-Routine* measures the intensity on creative tasks, I follow Goos et al. (2014) definitions and use ONET measures of "Originality", "Critical Thinking", "Active Learning" among others; *Abstract Routine* measures the amount of repetitive tasks that requires little physical requirement, I follow Goos et al. (2014) and use the ONET measures of "Operation Monitoring", "Operation and Control", "Quality Control Analysis" among others. *Number* measures the required facility with numbers, it follows the definition of Deming (2017) using the ONET questions for "Number Facility". To merge ONET variables to the Brazilian occupation classification, I create a crosswalk from SOC occupations to Brazilian occupation classification (CBO) using SOC-ISCO and ISCO-CBO crosswalks. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 43: **Employment Percentage Change with Balanced Sample and Exposure to the TSP**

	(1)	(2)	(3)	(4)
	$\frac{N.Workers^{2010}-N.Workers^{2000}}{N.Workers^{2000}}$	$\frac{N.HSDropout^{2010}-N.HSDropout^{2000}}{N.HSDropout^{2000}}$	$\frac{N.HSDropout^{2010}-N.HSComplete^{2000}}{N.HSComplete^{2000}}$	$\frac{N.HSMore^{2010}-N.HSMore^{2000}}{N.HSMore^{2000}}$
Exposure TSP	-0.521	0.566	-4.917*	-0.962***
	(0.430)	(0.870)	(2.854)	(0.349)
N	13058	13058	13058	13058
R^2	0.052	0.065	0.015	0.100
Mean Dep. Var	1.37	1.007	5.909	2.648
SD Dep. Var	7.472	11.368	49.071	7.67
Mean Indep. Var	.027	.027	.027	.027
SD Indep. Var	.163	.163	.163	.163
Controls	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of employment. $N.Workers^t$ is firm's total employment at year t, $N.HSDropout^t$ is the number of high-school dropouts at year t, $N.HSComplete^t$ is the number of workers with high-school complete, $N.HSMore^t$ is the number of workers with more than high-school. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level. The sample is limited to firms that have hired at least one worker of each educational group.

Table 44: **Employment and Exposure to the TSP using Heckman Selection**

	(1)	(2)	(3)
	$\Delta log(N.WorkersDropout)$	$\Delta log(N.WorkersHSComplete)$	$\Delta log(N.WorkersHSMore)$
Exposure TSP	-0.167***	-0.272***	-0.157***
	(0.0588)	(0.0648)	(0.0540)
N	26815	28848	31481
Mean Dep. Var	-.114	1.085	.66
SD Dep. Var	1.338	1.335	1.098
Mean Indep. Var	.01	.01	.01
SD Indep. Var	.101	.101	.101
Controls	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of employment correcting for selection. As instrument, for selection into hiring each educational group, I use a dummy taking one if the firm has hired any worker of that educational group in 1995. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level. The sample is limited to firms that have hired at least one worker of each educational group.

Table 45: **Wages and Exposure to the TSP**

	(1)	(2)	(3)	(4)
	$\Delta log(Avg.\ Wage)$	$\Delta log(Wage\ HS\ Dropout)$	$\Delta log(Wage\ HS\ Complete)$	$\Delta log(Wage\ HS\ More)$
Exposure TSP	-0.0225	-0.0662***	-0.0264	-0.0356*
	(0.0163)	(0.0199)	(0.0223)	(0.0205)
N	29301	27886	22479	14693
R^2	0.211	0.212	0.165	0.148
Mean Dep. Var	.324	.309	.199	.209
SD Dep. Var	.348	.331	.468	.608
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on average wage. *Wage HS Dropout* is the average wage of high school dropout workers, *Wage HS Complete* is the average wage of workers with high school complete, *Wage HS More* is the average wage of workers that have high school or more of education. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level. The sample is limited to firms that have hired at least one worker of each educational group.

Table 46: **Imports, Exports and Exposure to the TSP**

	(1)	(2)	(3)	(4)
	$\Delta\mathbb{I}\{Exporter\}$	$\Delta\mathbb{I}\{Importer\}$	$\Delta\mathbb{P}\{Prob.\ Import\ Input\}$	$\Delta\mathbb{P}\{Prob.\ Import\ Capital\}$
Exposure TSP	-0.0578**	-0.0850***	-0.0703***	-0.0582***
	(0.0235)	(0.0204)	(0.0202)	(0.0197)
N	29301	29301	29301	29301
R^2	0.046	0.060	0.057	0.056
Mean Dep. Var	.018	.029	.023	.013
SD Dep. Var	.335	.359	.277	.208
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of international trade. $\mathbb{I}\{Exporter\}$ is a dummy if the firm exported any product that year, $\mathbb{I}\{Importer\}$ is a dummy if the firm imported any product that year, $\mathbb{P}\{Prob.\ Import\ Input\}$ is the probability that the firm imported an input, $\mathbb{P}\{Prob.\ Import\ Capital\}$ is the probability that the firm imported a capital good. Goods are classified between capital and input using classification provided by the Brazilian secretary of international trade. The probability of exporting/importing is calculated intersecting exports/imports by sector and region. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 47: **Imports of Machines and Exposure to the TSP**

	(1)	(2)	(3)	(4)
	$\Delta\mathbb{P}\{Importing\ Labor\ Saving\}$	$\Delta\mathbb{P}\{Importing\ Labor\ Augmenting\}$	$\Delta\mathbb{P}\{Importing\ Machine\ Developed\}$	$\Delta\mathbb{P}\{Importing\ Machine\ Developing\}$
Exposure TSP	-0.0221**	-0.0549***	-0.0623***	0.0706***
	(0.0100)	(0.0191)	(0.0196)	(0.0142)
N	29301	29301	29301	29301
R^2	0.056	0.057	0.048	0.100
Mean Dep. Var	.003	.012	.02	.039
SD Dep. Var	.09	.198	.261	.181
Mean Indep. Var	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of international trade. $\mathbb{P}\{Importing\ Labor\ Saving\}$ is the probability that the firm is importing a labor saving machine, $\mathbb{P}\{Importing\ Labor\ Augmenting\}$ is the probability that the firm is importing a labor augmenting machine, $\mathbb{P}\{Importing\ Machine\ Developed\}$ is the probability that the firm is importing a machine from a developed country, and $\mathbb{P}\{Importing\ Machine\ Developing\}$ is the probability that the firm is importing a machine from a developing country. The probability of exporting/importing is calculated intersecting exports/imports by sector and region. Products are classified as labor saving and labor augmenting machines using text analysis as described in de Souza and Sollaci (2020). As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Table 48: **O*Net Technical Skills and Exposure to the TSP**

	(1)	(2)	(3)	(4)	(5)
	Δ *Equipment Maintenance*	Δ *Equipment Selection*	Δ *Installation*	Δ *Operation Monitoring*	Δ *Operation and Control*
Exposure TSP	-0.0216	-0.0315***	-0.0369***	-0.0146	-0.0165
	(0.0146)	(0.0117)	(0.00873)	(0.0127)	(0.0141)
N	20087	20087	20087	20087	20087
R^2	0.077	0.082	0.072	0.076	0.074
Mean Dep. Var	-.069	-.055	-.023	-.07	-.057
SD Dep. Var	.381	.304	.213	.336	.376
Mean Indep. Var	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of technical skills requirement at the firm. For each technical skill and occupation, O*Net gives a score based on the importance of that skill for that occupation. This table uses the average of each score at the firm. *Equipment Maintenance* is the O*Net skill for "performing routine maintenance on equipment and determining when and what kind of maintenance is needed", *Equipment Selection* is the O*Net skill for "Determining the kind of tools and equipment needed to do a job", *Installation* is the O*Net skill for "Installing equipment, machines, wiring, or programs to meet specifications", *Operation Monitoring* is the O*Net skill for "watching gauges, dials, or other indicators to make sure a machine is working properly", *Operation and Control* is the O*Net skill for "controlling operations of equipment or systems". As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

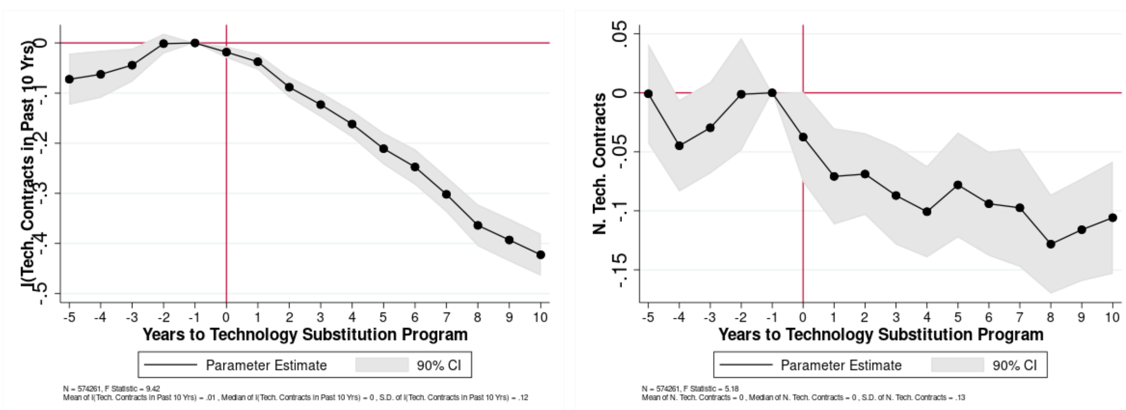
Table 49: **O*Net Technical Skills and Exposure to the TSP**

	(1) Δ *Operations Analysis*	(2) Δ *Programming*	(3) Δ *Control Analysis*	(4) Δ *Repairing*	(5) Δ *Troubleshooting*
Exposure TSP	-0.0276***	-0.0223***	-0.0248**	-0.0238*	-0.0388***
	(0.00916)	(0.00736)	(0.00961)	(0.0144)	(0.0118)
N	20087	20087	20087	20087	20087
R^2	0.089	0.070	0.082	0.078	0.074
Mean Dep. Var	-.032	-.004	-.067	-.067	-.059
SD Dep. Var	.26	.169	.267	.372	.31
Mean Indep. Var	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of technical skills requirement at the firm. For each technical skill and occupation, O*Net gives a score based on the importance of that skill for that occupation. This table uses the average of each score at the firm. *Operations Analysis* is the O*Net skill for "analyzing needs and product requirements to create a design", *Programming* is the O*Net skill for "writing computer programs for various purposes", *Control Analysis* is the O*Net skill for "conducting tests and inspections of products, services, or processes to evaluate quality or performance", *Repairing* is the O*Net skill for "repairing machines or systems using the needed tools", and *Troubleshooting* is the O*Net skill for "determining causes of operating errors and deciding what to do about it". As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Standard errors are clustered at the 5-digit sector level.

Figure 25: **International Technology Transfer and Exposure to the TSP**

(a) I(Int. Tech. Transfer Past 10 Years) (b) Number of Int. Tech. Contracts



Description: Figure 25a contains the estimated parameter of model (3) on a dummy taking one if the firm licensed international technology in the past 10 years. Figure 25b contains the number of technology contracts signed by each firm. The data is from 1995 to 2010. As controls, I use a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent. Each control is interacted with a year fixed effect. Standard errors are clustered at the 5-digit sector level.

B.3 Robustness of the Empirical Results

B.3.1 Results using Heterogeneity of Subsidy Allocation Across Targeted Sectors

The technology substitution program taxed international technology transfers and allocated the revenue of this tax as an R&D subsidy. Still, this revenue was heterogeneously allocated. Some sectors received up to 50% of it, others only 15% while some did not receive any subsidy at all. In this section, I present the results using the exposure measure taking into account the heterogeneity in revenue allocation. It's still true that firms increased innovation, increased expenditure share with low-skilled workers and decreased overall employment.

Define the exposure measure taking into account heterogeneous revenue allocation as:

$$\textit{Exposure TSP}^{hetero}_{i,s(i)} = \textit{Revenue Shr. Sector s(i)} \times \mathbb{I}_i \left\{\textit{Licensed Tech. Before TSP}\right\} \tag{20}$$

where *Revenue Shr. Sector s(i)* is the revenue share defined by law as being allocated to sector $s(i)$. As discussed before, the revenue share allocated to each sector was not based on future firm characteristics. Instead, policymakers targeted sectors of comparative advantage of the Brazilian economy. Therefore, *Revenue Shr. Sector s(i)* does not capture any sector trend.

I use the same long difference specification

$$y_{i,s(i),2010} - y_{i,s(i),2000} = \theta \textit{Exposure TSP}^{hetero}_{i,s(i)} + X'_{i,s(i)}\beta + \epsilon_{i,s(i)} \tag{21}$$

where $y_{i,s(i),2010}$ is an outcome of firm i, in sector $s(i)$ in year 2010 while $y_{i,s(i),2000}$ is the same outcome in 2000. $\textit{Exposure TSP}^{hetero}_{i,s(i)}$ is the exposure measure defined in 20. $X_{i,s(i)}$ is the same set of controls used in the main part of the paper.[64]

I test for the existence of parallel trends in the pre-period using specification

$$y_{i,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Exposure TSP}_{i,s(i)} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{22}$$

Table 50 shows that firms increased innovation, increased expenditure share with low skilled workers and decreased overall employment in response to the TSP. Table 50 shows that if 100% of TSP revenue were allocated to the sector of firm i and firm i licensed international technology before the TSP, firm i would be 17.6 p.p. more likely to apply for a patent, would increase expenditure share with high school dropouts by 5 p.p. and would

[64] Controls are a 1-digit sector-region fixed effect, employment growth between 1995 and 2000, and a dummy if the firm ever had a PCT patent.

decrease employment by 11%. Figure 26 shows that parallel trends holds in the pre-period.

Table 50: **Main Results with Heterogeneous Revenue Allocation Exposure**

	(1) $\Delta\mathbb{I}\{Patent\ Past\ 10\ Yrs\}$	(2) $\Delta\mathbb{I}\{EPO\ Patent\ Past\ 10\ Yrs\}$	(3) Δ Exp. Shr. Dropout	(4) Δ Exp. Shr. HS Complete	(5) $\Delta log(N.Workers)$	(6) $\Delta log(WageBill)$
Exposure $TSP^{hetero}_{i,s(i)}$	0.175***	0.126***	0.195***	-0.263***	-0.354*	-0.440**
	(0.0630)	(0.0419)	(0.0445)	(0.0480)	(0.213)	(0.207)
N	29301	29301	29301	29301	29301	29301
R^2	0.340	0.109	0.126	0.123	0.092	0.093
Mean Dep. Var	.019	.003	-.214	.171	.284	.608
SD Dep. Var	.252	.066	.278	.261	1.41	1.448
Mean Indep. Var	.002	.002	.002	.002	.002	.002
SD Indep. Var	.027	.027	.027	.027	.027	.027
Controls	Yes	Yes	Yes	Yes	Yes	Yes

B.3.2 Results using Probability of Receiving Subsidy

Using only sectors to predict firms' probability of receiving a subsidy has the advantage of being exogenous to firm level trends, as discussed in the institutional background of the program. Still, the fact that the subsidy is allocated based on technical criteria, such as innovation quality and qualification of the research team, ensures as well that large firms with expertise in innovation are also more likely to receive the subsidy. To exploit this variation, I construct a probability for the firm to receive the subsidy based on pre-policy characteristics and use that as exposure to the subsidy. It's still true that firms increased innovation, increased expenditure share with low skilled workers and decreased overall employment in response to the TSP.

To construct the exposure measure, first create the probability of a firm receiving the subsidy

$$\mathbb{I}_i\{Subsidy\ Between\ 2000\ and\ 2010\} = W_i'\tilde{\beta} + \epsilon_i \tag{23}$$

where $\mathbb{I}_i\{Subsidy\ Between\ 2000\ and\ 2010\}$ is a dummy taking one if firm i received an R&D subsidy between 2000 and 2010. W_i, a set of characteristics of the firm in 2000, contains firm age, log number of establishments, wage bill with scientists, dummy for state, 3 digit sector dummy, a dummy for at least one patent, a dummy for at least one international technology leasing and a dummy if the firm issued patent or leased technology. The model is estimated using logit.

Using the outcome of equation (23), I can create for each firm it's probability of receiving subsidy $\mathbb{P}_i\{Subsidy\}$ using it's pre-policy characteristics W_i. I define the exposure to the TSP using firm's subsidy probability as

$$Exposure\ TSP^{prob}_{i,s(i)} = \mathbb{P}_i\{Subsidy\} \times \mathbb{I}_i\left\{Licensed\ Tech.\ Before\ TSP\right\} \tag{24}$$

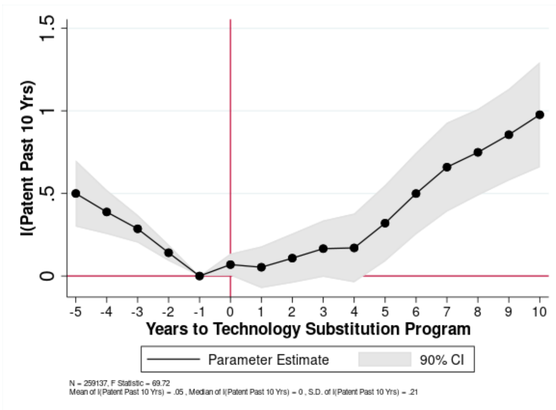
Main my specification is

$$y_{i,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times Exposure\ TSP^{prob}_{i,s(i)} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{25}$$

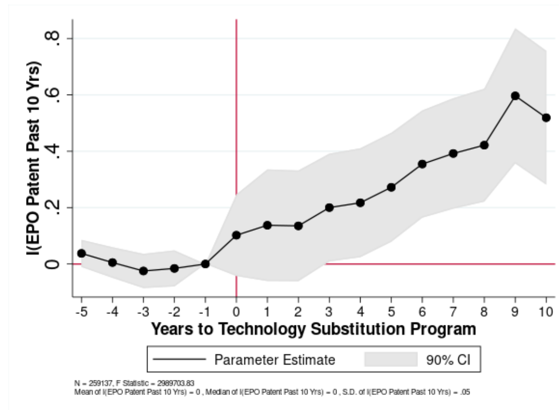
Figure 27 shows that the results are still the same. In response to the TSP, firms increased innovation, increased expenditure share with low skilled workers and decreased overall employment. Figure 27a predicts strong pre-trends because firms with patent before the subsidy are more likely to receive the subsidy.

Figure 27: **Main Results with Exposure using Probability of Receiving Subsidy**

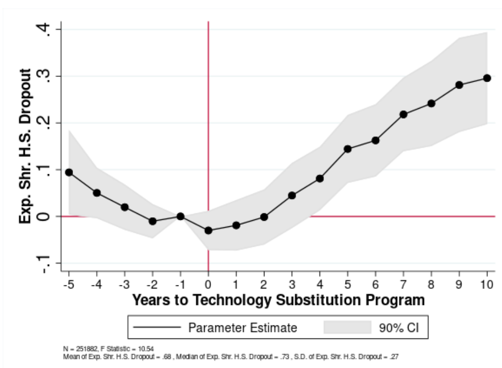
(a) I(Patent Past 10 Yrs.)



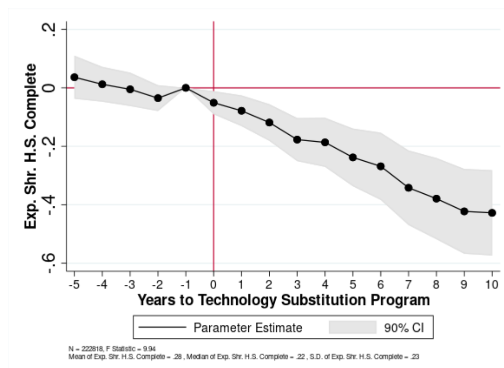
(b) I(EPO Patent Past 10 Yrs.)



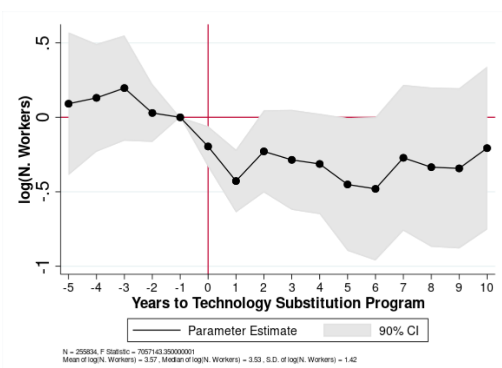
(c) Exp. Shr. H.S. Dropout



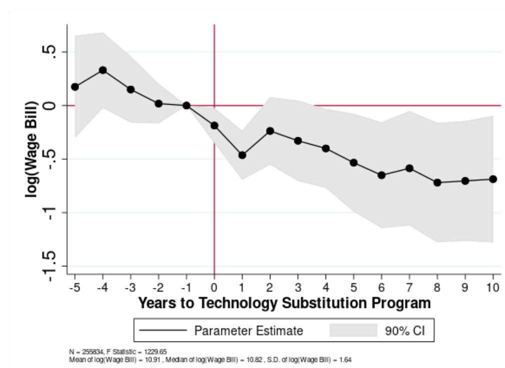
(d) Exp. Shr. H.S. Complete



(e) log(N. Workers)



(f) log(Wage Bill)



B.3.3 Results using Matched Diff-in-Diff

This section shows the results of a matched diff-in-diff. Each firm in the treatment group is matched to a similar firm in the control group and the effect of the TSP is estimated by comparing the change in outcomes between the two groups of firms. The identifying assumption is that firms are on the same trend conditional on the matched observables. The results show that firms increased innovation, increased expenditure share with low-skilled workers and decreased overall employment in response to the TSP.

First I identify a set of firms who are not in the treatment group,i.e., such that $\textit{Exposure TSP}_{i,s(i)} = 0$, but look similar in observable characteristics to the ones in the treatment group, i. e., the firms with $\textit{Exposure TSP}_{i,s(i)} = 1$. For each firm i in the treatment group I find a firm $j(i)$ in the control group with same number of workers, wage, share of high school dropout, and state in the 5 years before the introduction of the program. When multiple firms are matched, I use the one with closest propensity score.[65]

I estimate the following dynamic model:

$$y_{i,p,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Exposure TSP}_{i,s(i)} + \tag{26}$$

$$\sum_{j=-5}^{10} \mu_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathbb{I}\{\textit{Matched Pair } p\} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{27}$$

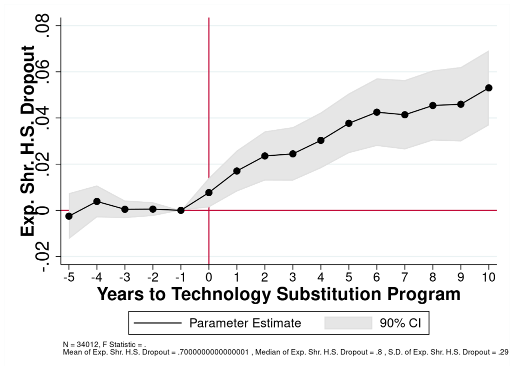
where $y_{i,p,s(i),t}$ is a labor outcome of firm i, on matched pair p, sector $s(i)$ in year t. As before, $\mathbb{I}\{j \text{ Yrs to TSP}\}$ is a dummy taking one j years to the introduction of the TSP, $\textit{Exposure TSP}_{i,s(i)}$ is a dummy if the firm is exposed to the TSP, $X_{i,s(i),t}$ is a set of controls, μ_i is a firm fixed effect and μ_t is a year fixed effect. $\mathbb{I}\{\textit{Matched Pair } p\}$ is an indicator if the firm is on the matched pair p. Each pair p contains a treated firm, with $\textit{Exposure TSP}_{i,s(i)} = 1$, and a control firm, $\textit{Exposure TSP}_{i,s(i)} = 0$. Any aggregate shock common to treatment and control groups would be captured by μ_j and not be absorbed in the effect of the TSP, θ_j.

Figure 28 displays the estimated effect of TSP using 26. The results are similar in sign and magnitude to what were identified with the main specification.

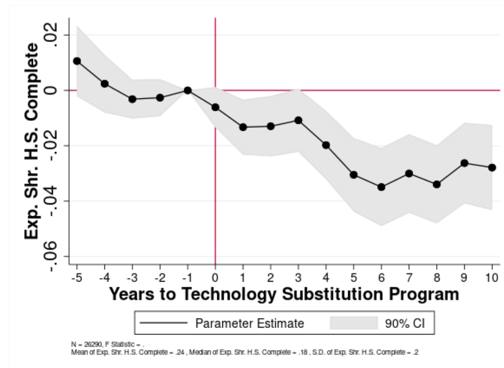
[65] For more on the matching procedure, see Iacus et al. (2012).

Figure 28: **Main Results of Matched Diff-in-Diff**

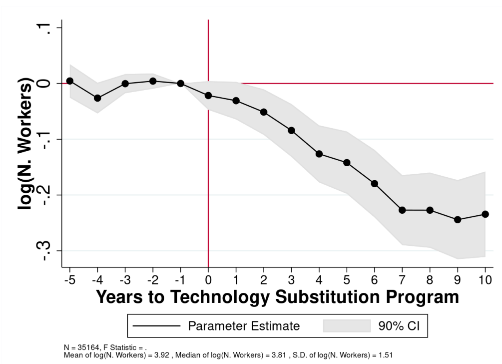
(a) Exp. Shr. H.S. Dropout



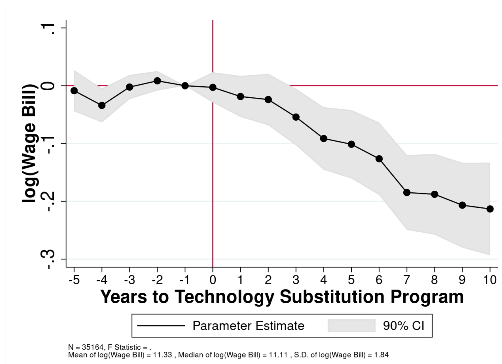
(b) Exp. Shr. H.S. Complete



(c) log(N. Workers)



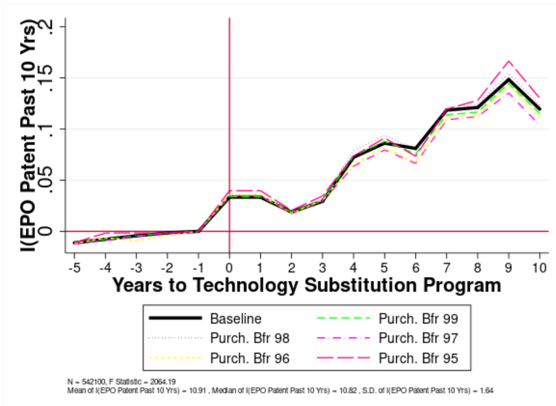
(d) log(Wage Bill)



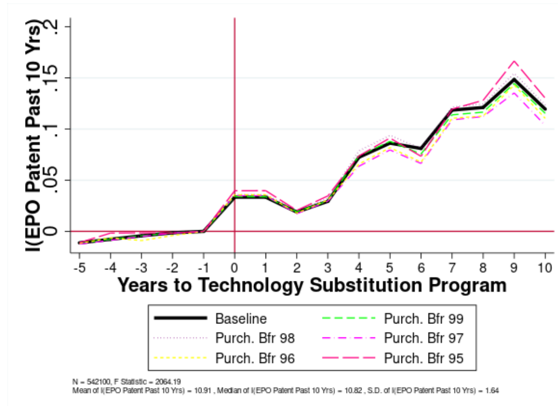
B.3.4 Results using Different Timing for Technology Transfers

Figure 29: **Main Results of Matched Diff-in-Diff**

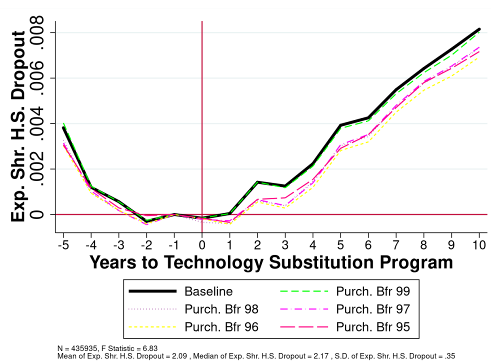
(a) I(Patent Past 10 Yrs.)



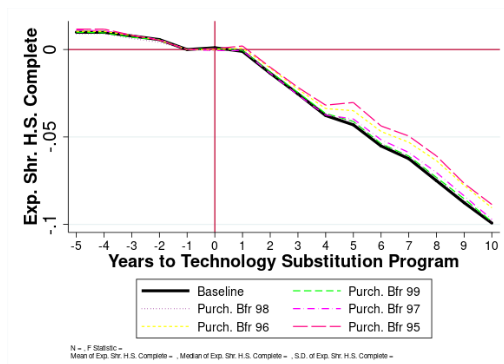
(b) I(EPO Patent Past 10 Yrs.)



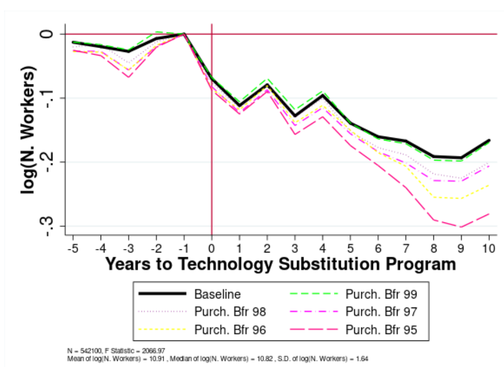
(c) Exp. Shr. H.S. Dropout



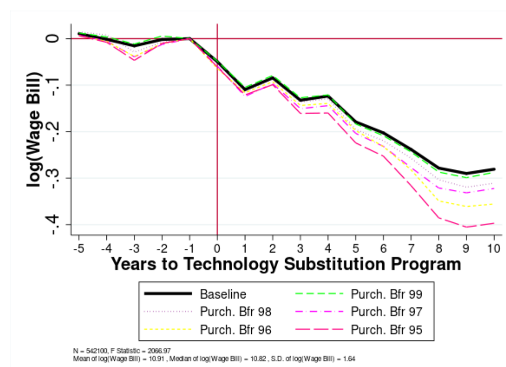
(d) Exp. Shr. H.S. Complete



(e) log(N. Workers)



(f) log(Wage Bill)



B.3.5 Results with Treatment Trends

In this section, I consider a model with a linear trend at the treatment level:

$$y_{i,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathit{Exposure\ TSP}_{i,s(i)} + X'_{i,s(i),t}\beta_t +$$
$$\alpha \times \mathit{year} \times \mathbb{I}\{j \text{ Yrs to TSP}\} + \mu_i + \mu_t + \epsilon_{i,s(i),t} \quad (28)$$

where α is the coefficient in the linear trend. Figures 30, 31 and 32 show the estimated parameters of the regression with trends on innovation, expenditure share and employment. The results are similar to the one discussed in the main part of the paper.

Figure 30: **Innovation and Exposure to the TSP with Treatment Trend**

(a) **I(Patent Past 10 Yrs.)** (b) **I(EPO Patent Past 10 Yrs.)**

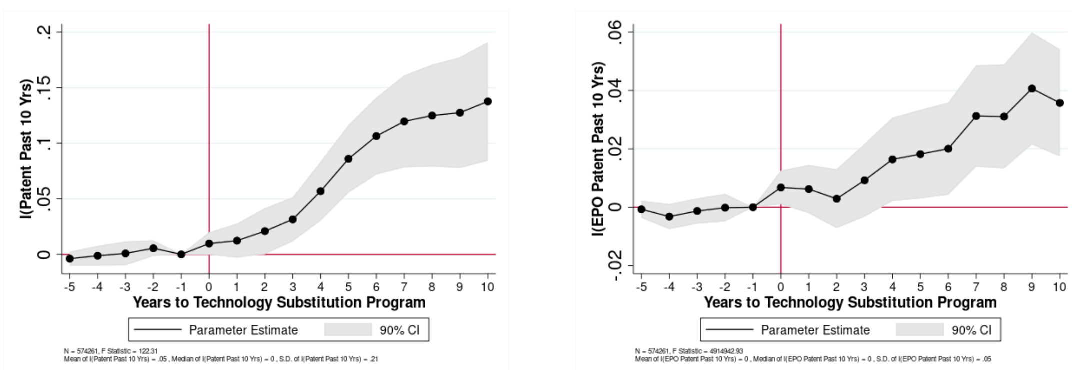


Figure 31: **Expenditure Shares and Exposure to the TSP with Treatment Trend**

(a) **Exp. Shr. H.S. Dropout** (b) **Exp. Shr. H.S. Complete**

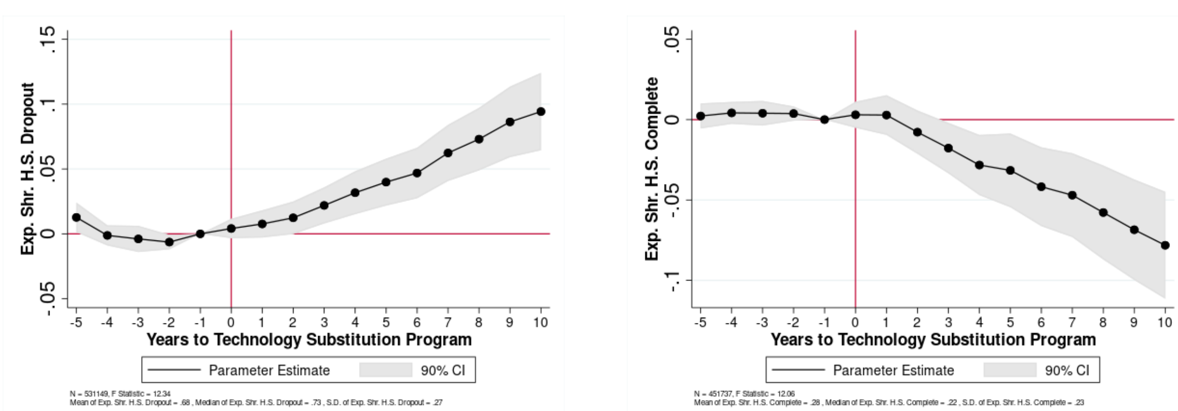
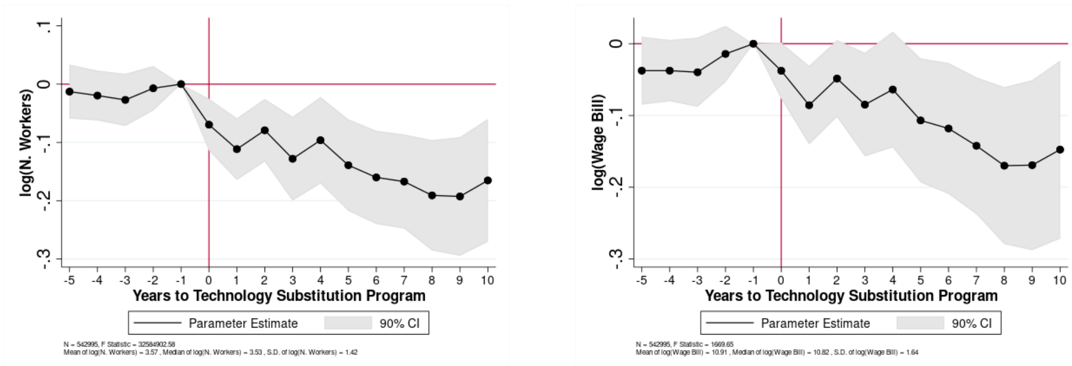


Figure 32: **Employment and Exposure to the TSP with Treatment Trend**

(a) **log(N. Workers)** (b) **log(Wage Bill)**



B.3.6 Results with Extra Controls

Table 51: **Main Results after Controlling for International Exposure**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\mathbb{I}\{Patent\ Past\ 10\ Yrs\}$	$\Delta\mathbb{I}\{EPO\ Patent\ Past\ 10\ Yrs\}$	Δ Exp. Shr. Dropout	Δ Exp. Shr. HS Complete	$\Delta log(N.Workers)$	$\Delta log(WageBill)$
Exposure TSP	0.0191	0.0338***	0.0567***	-0.0638***	-0.117*	-0.168**
	(0.0157)	(0.0115)	(0.00926)	(0.00986)	(0.0647)	(0.0677)
N	29949	29949	24794	20242	26106	26106
R^2	0.339	0.115	0.131	0.121	0.079	0.080
Mean Dep. Var	.019	.003	-.206	.157	.284	.608
SD Dep. Var	.252	.066	.248	.24	1.41	1.448
Mean Indep. Var	.01	.01	.01	.01	.01	.01
SD Indep. Var	.101	.101	.101	.101	.101	.101
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Description: This table presents the estimated parameters of a regression of the exposure to the TSP on the main outcomes. As controls, I use a 1-digit sector-region fixed effect, employment growth from 1995 to 2000, a dummy for having a patent in the past 10 years in 2000, the growth in a dummy if the firm ever had a PCT patent, a dummy if the firm is an importer in 2000, a dummy if the firm is an exporter in 2000, and a dummy if the firm is a subsidiary from a multinational in 2000. Standard errors are clustered at the 5-digit sector level.

B.4 Placebo Tests

B.4.1 Placebo Test with Fake Implementation Year

Because the exposure measure uses a past firm outcome, one might be concerned that the estimated effects could be due to some trend or predicted shock by the firm. To address this concern, this section describes the results of implementing a placebo test assuming a different implementation year for the TSP. If there is no trend-break around the fake year, we can assume that the trend break is related to 2001, the year the TSP was implemented, and not due to the special construction of the exposure measure.

Define the exposure measure with fake implementation year as

$$Exposure\ TSP^{fakeyear}_{i,s(i)} = \mathbb{I}\left\{Subsidy\ s(i)\right\} \times \mathbb{I}_i\left\{Licensed\ Tech.\ Before\ 2010\right\} \tag{29}$$

which is similar to the baseline exposure measure but assumes that the TSP was implemented in 2010.

I consider the following specification

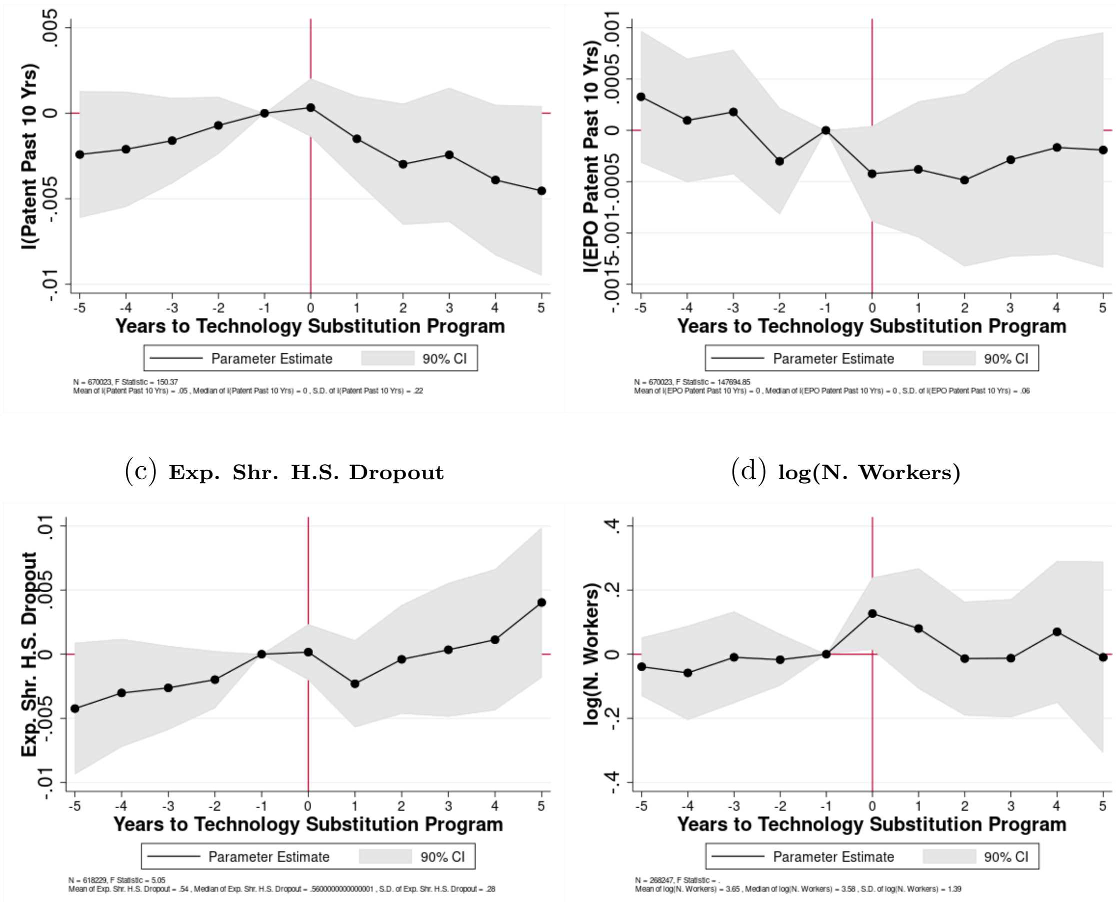
$$y_{i,s(i),t} = \sum_{j=-5}^{5} \theta_j \times \mathbb{I}\{j \text{ Yrs to 2010}\} \times \textit{Exposure TSP}^{fakeyear}_{i,s(i)} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{30}$$

where $\mathbb{I}\{j \text{ Yrs to 2010}\}$ is a set of dummies leading to the fake implementation year, $\textit{Exposure TSP}^{fakeyear}_{i,s(i)}$ is the fake exposure measure defined in (29), $X'_{i,s(i),t}$ is a set of pre-2010 controls similar to the one in the main specification, μ_i is a firm fixed effect and μ_t is a year fixed effect.

Figure 33 shows the estimated parameters of 30. As expected, there is no trend break around the fake year of introduction of the TSP.

Figure 33: **Placebo Test with Fake Implementation Year**

(a) **I(Patent Past 10 Yrs)** (b) **I(EPO Patent Past 10 Yrs)**



(c) **Exp. Shr. H.S. Dropout** (d) **log(N. Workers)**

B.5 Sector Level Regressions

In this section, I study the effect of the TSP using sectoral aggregates. Studying sectoral aggregates allows to relax the sample selection made while keeping a balanced sample. I show that the TSP had no effect on firm entry or exit, which is an important result to guarantee that the main estimates do not suffer from selection bias. I also show that the TSP affected sectoral employment and factor shares.

For each 5-digit sector classification k, define the exposure measure to the TSP as:

$$Sector\ Exposure\ TSP_k = \frac{\sum_i \mathbb{I}\left\{Subsidy\ s(i)\right\} \times \mathbb{I}\left\{Licensed\ Tech.\ Bfr\ TSP\right\}_i}{\mathbb{N}_k\left\{Firms\right\}} \tag{31}$$

where $\mathbb{I}\{Subsidy\ s(i)\}$ is a dummy taking one if firm i is in one of the two-digit sectors exposed to the subsidy and $\mathbb{N}_k\{Firms\}$ is the number of firms on sector k.

The main specification is given by

$$y_{k,2010} - y_{k,2000} = \theta Sector\ Exposure\ TSP_k + X_k'\beta + \epsilon_k \tag{32}$$

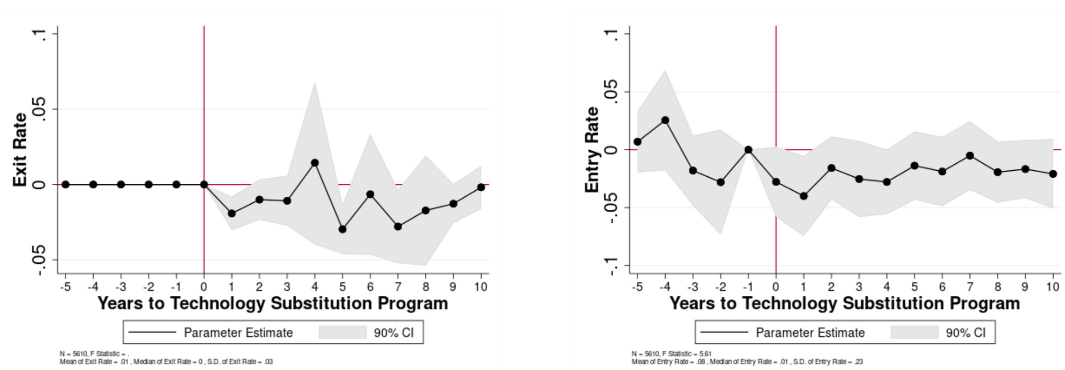
where $y_{k,2010}$ is a labor market outcome of sector k in 2010, $y_{k,2000}$ is the same outcome in 2000, $Sector\ Exposure\ TSP_k$ is the sectoral exposure measure in 31 and X_k is a set of controls.

To test for pre-period parallel trends and evaluate the dynamic effects of the program, consider the following specification:

$$y_{k,t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times Sector\ Exposure\ TSP_k + \mu_k + X_k'\beta_t + \epsilon_{k,t} \tag{33}$$

Figure 34: **Effect of TSP on Entry and Exit Rates**

(a) **Exit Rate** (b) **Entry Rate**



Description: This table displays the coefficients of specification (33) on exit rate, defined as the number of firms leaving the sector divided by the number of firms in the sector, and entry rate, defined as the number of firms entering the sector divided by the number of firms. Each regression is run at the 5-digit sectoral classification CNAE. Standard errors are clustered by sector.

Figure 34 shows no effect of the TSP in entry or exit. Table 52 shows that employment and wage bill decreased in the sectors more exposed to the TSP. Column 3 indicates that expenditure share with high school dropouts increased, like in the main results, but the effect is not-significant. Column 4 shows that the expenditure share with workers who completed high school decrease while column 5 shows that the expenditure of workers with at least some college increased.

Table 52: **Sector Labor Outcomes and Exposure to the TSP**

	(1)	(2)	(3)	(4)	(5)
	$\Delta log(N.\ Workers)$	$\Delta log(WageBill)$	Δ *Exp. Shr. H.S. Dropout*	Δ *Exp. Shr. H.S. Complete*	Δ *Exp. Shr. H.S. More*
Sector Exposure TSP	-0.523**	-0.588***	0.0688	-0.178***	0.109***
	(0.239)	(0.223)	(0.0538)	(0.0516)	(0.0336)
N	330	330	329	329	329
R^2	0.078	0.054	0.042	0.075	0.053
Mean Dep. Var	.49	.654	-.205	.161	.045
SD Dep. Var	.564	.628	.096	.089	.076
Mean Indep. Var	.047	.047	.047	.047	.047
SD Indep. Var	.117	.117	.117	.117	.117
Controls	Yes	Yes	Yes	Yes	Yes

Description: This table shows the coefficient of specification (32) on aggregate sectoral employment and aggregate sectoral wage bill. The expenditure share with high school dropouts, in column 3, is defined as the aggregate wage bill with high school dropouts divided by aggregate wage bill. In the same way, columns 4 and 5 have the expenditure share with high school complete workers and workers with at least some college. Each regression is run at the 5-digit sectoral classification CNAE1. Standard errors are clustered by sector.

B.6 Evaluating Competing Explanations

B.6.1 Effect of Tax

The tax itself could have affected firms' employment and labor force composition. Some of the firms affected by the tax could keep their technology and reduce their operation due to the heavier fiscal burden. However, using heterogeneous exposure to the tax generated by institutional features of the Brazilian tax system I show that this is not a likely explanation.

Not all the firms with technology transfer contracts were required to pay the international tax on technology transfers. Firms when signing any technology transfer contract had to indicate the part responsible for paying taxes: the licensor or the licensee. In 42.1% of the technology licensing contracts, the licensor is the taxpayer. Moreover, given that the contract price is already set, prices could not adjust right away to the higher cost. Therefore, the firms that in 2000 had a technology contract with a foreigner responsible for the tax payment were not directly exposed to the tax.[66]

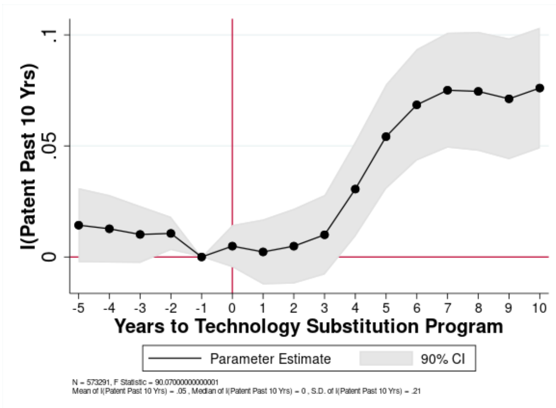
To exploit this heterogeneity in the direct effect of the tax, I run specification (3) but adding as control a dummy taking one if the firm is the taxpayer at the time of the policy introduction interacted with year. If the effects on employment and expenditure share are driven by the direct effect of the tax, we should not recover any result after controlling for the direct effect of the tax.

[66] It is still true that they would be affected by the tax when signing a new contract.

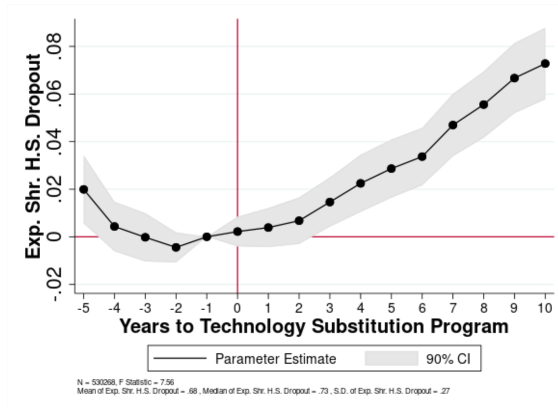
Figure 35 shows that results are the same after controlling for the direct effect of the tax.

Figure 35: **Effect of TSP after Controlling for Taxpayer Status**

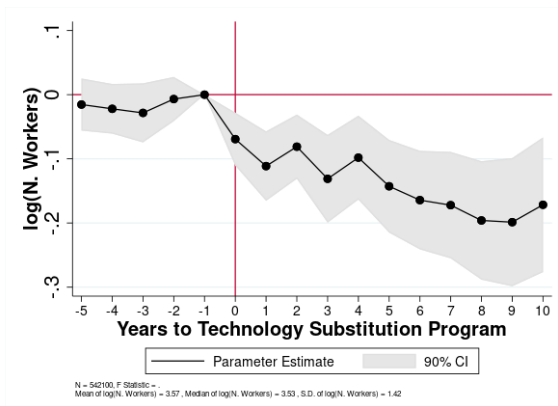
(a) **I(Patent Past 10 Yrs.)**



(b) **Exp. Shr. HS Dropout**



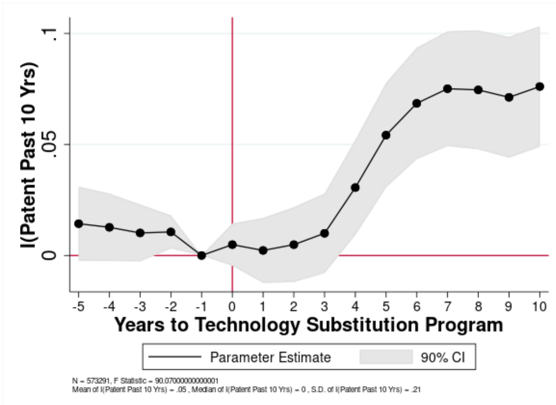
(c) **log(N. Workers)**



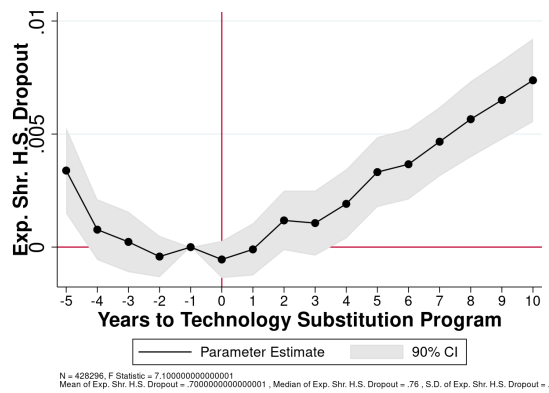
Another source of heterogeneity is on the value of technology contracts signed by the firm. We expect the effect of shifting technology to be similar between firms but the direct effect of the tax should increase with the total payment that is required from the firm. In Figure 36, I run specification 3 but adding as control the total tax burden faced by the firm relative to its wage bill in 2000 interacted with a year dummy. The results are still the same.

Figure 36: **Effect on Labor after Controlling for Tax Burden**

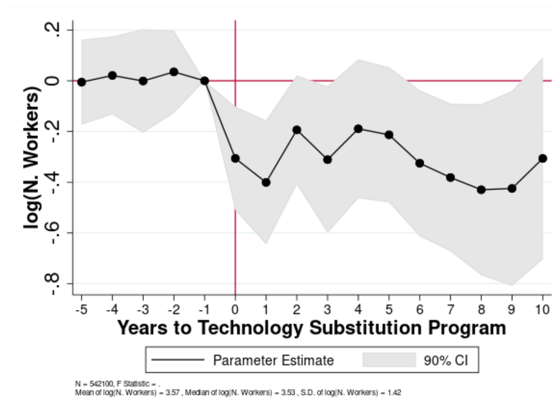
(a) **I(Patent Past 10 Yrs.)**



(b) **Exp. Shr. HS Dropout**



(c) **log(N. Workers)**



B.6.2 Introduction of New Products

Firms could be changing products in response to the TSP. It could be the case that the newly patented technologies produce products in a class that requires more low-skilled workers. Through this explanation, the difference between technologies isn't in the skill intensity but instead in the type of product being produced.

This conjecture can be tested using data on trademarks. For each trademark, I observe if the object protected is related to a product or a service, and a 4-digit classification code for the product. Using these two variables we can evaluate if the firms changed their menu of products in response to the TSP.

Table 53 demonstrates that firms did not change their menu of products in response to the TSP. Column 1 of table 53 shows the coefficient of specification (2) on a dummy taking one if the firm has a trademark on a product and zero if the firm has a trademark related to a service. If firms switched from producing products to producing services, for instance, we should observe a significant coefficient in column 1. Column 2 of table 53 runs specification (2) on a dummy taking one if the firm has a trademark in a different classification on the 10 years after the TSP than its trademarks in the 10 years prior the program. Once again we don't find a significant effect.

The results of Table 53 indicate that firms haven't changed the menu of products they produce.

Table 53: **Menu of Products and Exposure to the TSP**

	(1) $\Delta\mathbb{I}\{\textit{Product Trademark}\}$	(2) $\mathbb{I}\{\textit{Same Class Trademark}\}$
Exposure TSP	-0.0249	-0.0108
	(0.0247)	(0.0141)
N	10607	8607
R^2	0.048	0.042
Mean Dep. Var	.052	.152
SD Dep. Var	.322	.634
Mean Indep. Var	.01	.01
SD Indep. Var	.101	.101
Controls	Yes	Yes

Description: This table shows a regression of the exposure to the TSP on a set of dummies capturing changes in the products produced by the firm. The first column has results of the regression on a dummy taking one if the firm issued a trademark for a product in the past 10 years and zero if the firm issued a trademark for a service good in the past 10 years. The second column contains a dummy taking one if the firm issued a trademark in a different NICE trademark class in the 10 years after the TSP compared to the 10 years before.

B.6.3 Use of Labor Saving Machine

The drop in employment could be explained by the use of labor-saving technology (Acemoglu and Restrepo (2020), **?**, Koch et al. (2019), Bessen et al. (2019), Graetz and Michaels (2018)). It is a possibility that technology created by Brazilian firms replaces workers by machines, which explains the fall in employment. However, there is empirical evidence against this interpretation.

Firms exposed to the TSP reduced their imports of labor-saving machines and machines from developed countries, according to the Table 47. In Table 46 I show that firms exposed to the TSP are less likely to make any imports. Therefore, if firms are using labor-saving technologies, it must be through the national market which, as a developing country, is an unlikely producer of high quality labor augmenting machines.

In section E.1.1, I apply the text analysis method of Argente et al. (2017) to show that the technology being licensed to Brazil is more associated with robots than Brazilian patents, which supports the idea that firms reduced their use of labor-saving technology, not increased it.

Firms reduced the hiring of workers with technical skills to install, repair and operate machines, according to Table 48 and 49. Tables 48 and 49 use O*NET technical skills scores to show that firms reduce the hiring of workers installing, maintaining, and monitoring machines (on columns 1 to 4 of Table 48), controlling operations of equipment or systems (column 5 of Table 48), and programming (column 2 of Table 49).[67] Its unlikely that firms are installing labor saving machines but do not hire workers capable of install, repair or operate it.

C Theoretical Model Appendix

C.1 Equilibrium Definition

C.1.1 Equilibrium in the United States

Since firms are homogeneous, optimal production in U.S. firm j, $y_{j,US}$, is equal to aggregate production in U.S., Y_{US}: $y_{j,US} = y_{US} = Y_{US}$. If C_{US} is the aggregate consumption of the representative consumer, the resource constraint is:

$$C_{US} = y_{US} \tag{34}$$

Since firms are homogeneous, they have the same demand for low-skilled, l_{US}, and high-skilled workers, h_{US}. The labor market clearing condition is:

$$l_{US} = L_{US}; h_{US} = H_{US} \tag{35}$$

[67] According to the O*NET definition, it's technical skills score capture "Developed capacities used to design, set-up, operate, and correct malfunctions involving application of machines or technological systems".

Since the United States and Brazil are connected only through the trade of technology, and Brazil is of measure zero, Brazil does not affect the United States, and I thus define U.S. equilibrium separately.

Definition 1. *(Equilibrium in US)*
Equilibrium in the United States is given by a solution to firm's problem $\{l_{US}, h_{US}, A_{US}, B_{US}, y_{US}\}$, *prices* $\{w_{H,US}, w_{L,US}\}$ *and aggregate consumption* $\{C_{US}\}$ *such that*

1. *Given prices* $\{w_{H,US}, w_{L,US}\}$, $\{l_{US}, h_{US}, A_{US}, B_{US}, y_{US}\}$ *solve the firm's problem* (6)
2. *The resource constraint is satisfied:*

$$C_{US} = y_{US}$$

3. *The labor market clears:*

$$l_{US} = L_{US}; h_{US} = H_{US} \tag{36}$$

C.1.2 Equilibrium in Brazil

The government's budget constraint is given by:

$$\underbrace{\tau_{innov}\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right)}_{\text{Expenditure with Subsidy}} = \underbrace{\tau_{transf}\left(1 - \int \mathbb{I}_{j,innov} d\Gamma_j\right)}_{\text{Revenue from Transfer Tax}} + \underbrace{T}_{\text{Lump Sum Tax}} \tag{37}$$

where $\int \mathbb{I}_{j,innov} d\Gamma_j$ is the measure of firms innovating and $1 - \int \mathbb{I}_{j,innov}$ is the share of firms licensing international technology.

Let $y_{innov,BR}$ be the optimal production of a firm innovating in Brazil, $y_{transf,BR}$ be the optimal production of a firm licensing technology and C_{BR} the consumption of the representative consumer. The resource constraint is[68]

$$\underbrace{C_{BR}}_{\text{Consumption}} + \underbrace{\int_j \epsilon_{j,innov}\mathbb{I}_{j,innov}d\Gamma_j}_{\text{Cost with Innovation}} + \underbrace{\int_j \epsilon_{j,transf}(1-\mathbb{I}_{j,innov})d\Gamma_j}_{\text{Cost of Licensing Tech.}} = \tag{38}$$
$$\underbrace{y_{innov,BR}\left(\int \mathbb{I}_{j,innov}d\Gamma_j\right)}_{\text{Production of Innovating Firms}} + \underbrace{y_{transf,BR}\left(\int (1-\mathbb{I}_{j,innov})d\Gamma_j\right)}_{\text{Production of Firms Licensing Tech.}}$$

where $\int_j \epsilon_{j,innov}\mathbb{I}_{j,innov}d\Gamma_j$ is the fixed cost payed by firms innovating and $\int_j \epsilon_{j,transf}(1-\mathbb{I}_{j,transf})d\Gamma_j$ is the fixed cost payed by firms licensing technology.

The labor market clearing conditions are:

$$l_{innov,BR}\left(\int \mathbb{I}_{j,innov}d\Gamma_j\right) + l_{transf,BR}\left(\int (1-\mathbb{I}_{j,innov})d\Gamma_j\right) = L_{BR} \tag{39}$$
$$h_{innov,BR}\left(\int \mathbb{I}_{j,innov}d\Gamma_j\right) + h_{transf,BR}\left(\int (1-\mathbb{I}_{j,innov})d\Gamma_j\right) = H_{BR} \tag{40}$$

where $l_{innov,BR}$ is the low-skilled demand of firms innovating and $h_{innov,BR}$ is the high-skilled demand of firms innovating. Equivalently for $l_{transf,BR}$ and $h_{transf,BR}$.

The United States affects the Brazilian economy only through technology (A_{US}, B_{US}), so I define equilibrium in Brazil conditional on U.S. technology.

Definition C.1. (*Equilibrium in Brazil*)
Given US technology (A_{US}, B_{US}), the equilibrium in Brazil is given by a solution to the firm's problem $\{V_{BR,k}, l_{k,BR}, h_{k,BR}, y_{k,BR}\}_{k\in\{innov,transf\}}$ and $\{\mathbb{I}_{j,innov}, V_j\}_{j\in[0,1]}$, fiscal policy $\{\tau_{innov}, \tau_{transf}, T\}$, prices $\{w_{H,BR}, w_{L,BR}\}$ and aggregate consumption C_{US}, such that:

1. *Given U.S. technology (A_{US}, B_{US}), prices $\{w_{H,US}, w_{L,US}\}$ and fiscal policy $\{\tau_{innov}, \tau_{transf}, T\}$, $\{V_{innov,BR}, l_{innov,BR}, h_{innov,BR}, y_{innov,BR}\}$ solves the problem of a firm that innovates* (10)*,*
   $\{V_{transf,BR}, l_{transf,BR}, h_{transf,BR}, y_{transf,BR}\}$ solves the problem of a firm that licenses technology (11)*, and $\{\mathbb{I}_{j,innov}, V_j\}_{j\in[0,1]}$ solves the technology choice problem* (12)

2. *Fiscal policy $\{\tau_{innov}, \tau_{transf}, T\}$ satisfies the government's budget constraint* (37)*;*

[68] I assume in the main model that the fixed cost is paid in terms of the final good. In the robustness section, I assume that part of the fixed cost is hiring skilled workers.

3. Resource constraint (38) *is satisfied;*

4. The labor market clears.

C.1.3 Equilibrium

Using the definitions of equilibrium in US and in Brazil, I can define the final equilibrium in this economy.

Definition C.2. (*Equilibrium*)
The equilibrium is given by $\{V_{BR,k}, l_{k,BR}, h_{k,BR}, y_{k,BR}\}_{k\in\{innov,transf\}}$, $\{\mathbb{I}_{j,innov}, V_j\}_{j\in[0,1]}, \{\tau_{innov}, \{\tau_{transf}, T, w_{H,BR}, w_{L,BR}, C_{US}\}\}$ *and* $\{l_{US}, h_{US}, A_{US}, B_{US}, y_{US}, w_{H,US}, w_{L,US}, C_{US}\}$ *such that*

1. $\{l_{US}, h_{US}, A_{US}, B_{US}, y_{US}, w_{H,US}, w_{L,US}, C_{US}\}$ *is an equilibrium in the United States;*

2. *Given* $\{A_{US}, B_{US}\}$, $\{\{V_{BR,k}, l_{k,BR}, h_{k,BR}, y_{k,BR}\}_{k\in\{innov,transf\}}, \{\mathbb{I}_{j,innov}, V_j\}_{j\in[0,1]}, \{\tau_{innov}, \tau_{transf}, T, w_{H,BR}, w_{L,BR}, C_{US}\}\}$ *is an equilibrium in Brazil.*

C.2 Proof of Proposition 1

The factor share of firms licensing technology and of firms innovating is

$$\frac{l_{BR,transf}}{h_{BR,transf}} = \pi_{US}^{\frac{\kappa-\rho}{(1-\rho)(1-\kappa)}} \pi_{BR}^{\frac{1}{1-\rho}}$$
$$\frac{l_{BR,innov}}{h_{BR,innov}} = \pi_{BR}^{\frac{1}{1-\kappa}}$$

Therefore

$$\frac{\frac{l_{BR,transf}}{h_{BR,transf}}}{\frac{l_{BR,innov}}{h_{BR,innov}}} = \left(\frac{\pi_{US}}{\pi_{BR}}\right)^{\frac{\kappa-\rho}{(1-\rho)(1-\kappa)}}$$

Because $\kappa > \rho$, $\rho < 1$, and $\kappa < 1$, $\frac{\kappa-\rho}{(1-\rho)(1-\kappa)} > 0$. Therefore, using that $\pi_{BR} > \pi_{US}$ we have

$$\frac{\frac{l_{BR,transf}}{h_{BR,transf}}}{\frac{l_{BR,innov}}{h_{BR,innov}}} < 1$$

I now show that, for large enough ϕ_{US}, $l_{BR,transf} > l_{BR,innov}$. For simplicity, assume without loss of generality $\phi_{BR} = 1$. From the problem of firms, I can write

$$\left(\frac{l_{BR,transf}}{l_{BR,innov}}\right)^{\gamma-1} = \left(\left(\frac{1}{\phi_{US}}\right)\left(\frac{1+\pi_{US}^{\frac{\kappa}{1-\kappa}}}{1+\pi_{BR}^{\frac{\kappa}{1-\kappa}}}\right)^{\frac{\kappa-\rho}{\kappa\rho}}\right)^{\gamma}\left(\frac{1+\pi_{BR}^{\frac{\rho}{\rho-1}}\pi_{BR}^{\frac{\kappa-\rho}{(1-\rho)(1-\kappa)}}}{1+\pi_{BR}^{\frac{\rho}{\rho-1}}\pi_{US}^{\frac{\kappa-\rho}{(1-\rho)(1-\kappa)}}}\right)^{\frac{\gamma-\rho}{\rho}} \tag{41}$$

Using that $\phi_{BR} \in [\pi_{BR}^{0}, \pi_{BR}^{1}]$, 41 implies that $\lim_{\phi_{US}\to\infty} \frac{l_{BR,innov}}{l_{BR,transf}} = 0$. Therefore, if ϕ_{US} is sufficiently large, $l_{BR,transf} > l_{BR,innov}$.

Notice that if $l_{BR,transf} > l_{BR,innov}$ it must be the case that $h_{BR,transf} > h_{BR,innov}$ because $\frac{l_{BR,transf}}{h_{BR,transf}} < \frac{l_{BR,innov}}{h_{BR,innov}}$. But, if $\phi_{US} > 1$, $l_{BR,transf} > l_{BR,innov}$, and $h_{BR,transf} > h_{BR,innov}$, it must be the case that $y_{BR,transf} > y_{BR,innov}$.

C.3 Proof of Proposition 2

A small increase in the share of innovators change the relative demand for low skill workers by

$$\Delta_L = \frac{l_{BR,innov}}{H}\left(\left(1-\frac{L}{H}\frac{h_{BR,innov}}{l_{BR,innov}}\right) - \frac{h_{BR,transf}}{l_{BR,transf}}\left(1-\frac{L}{H}\frac{h_{BR,transf}}{h_{BR,transf}}\right)\right)$$

Because $\frac{h_{BR,innov}}{l_{BR,innov}} < \frac{h_{BR,transf}}{l_{BR,transf}}$ from the labor cleaning condition

$$\begin{aligned}\frac{H}{L} > \frac{h_{BR,innov}}{l_{BR,innov}} &\implies 1 > \frac{L}{H}\frac{h_{BR,innov}}{l_{BR,innov}}\\ \frac{H}{L} < \frac{h_{BR,transf}}{l_{BR,transf}} &\implies 1 < \frac{L}{H}\frac{h_{BR,transf}}{l_{BR,transf}}\end{aligned}$$

Therefore, $\Delta_L > 0$ and skill premium must go down.

C.4 Proof of Proposition 3

Define the set of firm changing technology in the treatment and control group as

$$\lambda^T_{UU} = E\left[\mathbb{I}^0_{transf}\mathbb{I}^1_{transf}|j \in ExposedTSP\right];\lambda^T_{UB} = E\left[\mathbb{I}^0_{transf}\mathbb{I}^1_{innov}|j \in ExposedTSP\right]$$
$$\lambda^C_{BB} = E\left[\mathbb{I}^0_{innov}\mathbb{I}^1_{innov}|j \notin ExposedTSP\right];\lambda^C_{BU} = E\left[\mathbb{I}^0_{innov}\mathbb{I}^1_{transf}|j \notin ExposedTSP\right]$$
$$\lambda^C_{UU} = E\left[\mathbb{I}^0_{transf}\mathbb{I}^1_{transf}|j \notin ExposedTSP\right];\lambda^C_{UB} = E\left[\mathbb{I}^0_{transf}\mathbb{I}^1_{innov}|j \notin ExposedTSP\right]$$

Define the expenditure share of firm j in time t, ES^t_j,:

$$ES^t_j = \frac{w^t_{L,BR}l^t_j}{w^t_{H,BR}h^t_j} = \begin{cases} \left(\Psi^t\right)^{\frac{\kappa}{\rho(1-\kappa)}}\left(\frac{\gamma_j}{1-\gamma_j}\right)^{\frac{\kappa}{(1-\kappa)\rho}}\left(\pi^t_B\right)^{\frac{1}{1-\kappa}} & \text{if } \mathbb{I}^1_{innov} = 1 \\ \left(\Psi^t\right)^{\frac{\kappa}{\rho(1-\kappa)}}\left(\frac{\gamma_j}{1-\gamma_j}\right)^{\frac{\kappa}{(1-\kappa)\rho}}\left(\pi^t_U\right)^{\frac{\kappa-\rho}{(1-\rho)(1-\kappa)}} & \text{if } \mathbb{I}^1_{transf} = 1 \end{cases}$$

Therefore, I can write λ_{skill} as:

$$\lambda_{skill} = \left(\lambda^T_{UU} - \lambda^C_{UU}\right)\left(\frac{\kappa-\rho}{(1-\kappa)(1-\rho)}\tilde{\pi}_U + \frac{1}{1-\rho}\tilde{\pi}_B\right) \tag{42}$$
$$+ \left(\lambda^T_{UB} - \lambda^C_{UB}\right)\left(\frac{\rho-\kappa}{(1-\rho)(1-\kappa)}\log\left(\pi^0_U\right) + \frac{1}{\rho-1}\log\left(\pi^0_B\right) + \frac{1}{1-\kappa}\log\left(\pi^1_B\right)\right) \tag{43}$$
$$- \lambda^C_{BB}\frac{1}{1-\kappa}\log\tilde{\pi}_D \tag{44}$$
$$- \lambda^C_{BU}\left(\frac{\kappa-\rho}{(1-\rho)(1-\kappa)}\log\pi^1_U + \frac{1}{1-\rho}\log\pi^1_B + \frac{1}{\kappa-1}\log\pi^0_B\right) \tag{45}$$

Therefore, I can invert 42 and write ρ as a function of κ, skill-premium, and the share of firms changing technology. Because wages and the share of firms changing technology is observable, knowing κ I can identify ρ from 42.

We can write firm skill-bias of firm j as $B^t_j/A^t_j = \theta^t_j$

$$\theta^t_j = B^t_j/A^t_j = \begin{cases} \left(1 + \left(FS^t_j\right)^{\frac{\rho-1}{\rho}}\left(\pi^t_B\right)^{-1/\rho}\pi^t_B\right)^{\frac{\kappa-\rho}{\kappa(1-\rho)}} & \text{if } \mathbb{I}^1_{innov} = 1 \\ \left(1 + \left(FS^t_j\right)^{\frac{\rho-1}{\rho}}\left(\pi^t_U\right)^{-1/\rho}\pi^t_B\right)^{\frac{\kappa-\rho}{\kappa(1-\rho)}} & \text{if } \mathbb{I}^1_{transf} = 1 \end{cases}$$

Define Λ_j^t as

$$\Lambda_j^t = \left(1 + \left(\theta_j^t\right)^{\left(\frac{\kappa\rho}{\rho-\kappa}\right)}\right)^{\frac{\rho-\kappa}{\kappa\rho}}$$

Using that $\phi_{BR} = 1$, I can write

$$\begin{aligned}\lambda_{labor} =& \frac{1}{1-\gamma} \log \phi_{US} \left(\lambda_{UB}^C - \lambda_{BU}^C - \lambda_{UB}^T\right) + \frac{\gamma}{1-\gamma} \tilde{A}_{UU} \left(\lambda_{UU}^T - \lambda_{UU}^C\right) + \frac{\gamma}{1-\gamma} \tilde{A}_{UB} \left(\lambda_{UB}^T - \lambda_{UB}^C\right) \\ & - \frac{\gamma}{1-\gamma} \lambda_{BB}^C \tilde{A}_{BB} - \frac{\gamma}{1-\gamma} \lambda_{BU}^C \tilde{A}_{BU} + \frac{\rho-\gamma}{\rho(\gamma-1)} (\lambda_{UU}^T - \lambda_{UU}^C) \tilde{ES}_{UU} + \frac{\rho-\gamma}{\rho(\gamma-1)} (\lambda_{UB}^T - \lambda_{UB}^C) \tilde{ES}_{UB} \\ & - \frac{\rho-\gamma}{\rho(\gamma-1)} \lambda_{BB}^C \tilde{ES}_{BB} - \frac{\rho-\gamma}{\rho(\gamma-1)} \lambda_{BU}^C \tilde{ES}_{BU}\end{aligned} \tag{46}$$

where

$$\tilde{A}_{UU} = E\left[\log \Lambda_j^1 - \log \Lambda_j^0 | \mathbb{I}_{innov}^0 = 1; \mathbb{I}_{innov}^0 = 0\right] \tag{47}$$

$$\tilde{ES}_{UU} = E\left[\log(1 + ES_j^1) - \log(1 + ES_j^0) | \mathbb{I}_{innov}^0 = 1; \mathbb{I}_{innov}^0 = 0\right] \tag{48}$$

Equivalently defined for $\tilde{A}_{UB}, \tilde{A}_{BU}, \tilde{A}_{BB}, \tilde{ES}_{UB}, \tilde{ES}_{BU}$, and $\tilde{A}_{BB}$. Using equation 46, ϕ_{US} can be calculated as a function of κ, ρ, the share of firms changing technology, and the average factor share at the firm.

D Identification and Results Appendix

D.1 Auxiliary Tables

Table 54: **Estimates of the Elasticity of Substitution**

Paper	**Country**	**Elasticity**	κ
Katz and Murphy (1992)	U.S.	1.4	0.29
Murphy et al. (1998)	Canada	1.4	0.26
Krusell et al. (2000)	U.S.	1.7	0.40
Card and Lemieux (2001)	U.S.	2.3	0.56
Ciccone and Peri (2005)	U.S.	1.5	0.33
Borjas (2003)	U.S.	1.3	0.23
Elsner (2013)	Europe	1.7	0.40

D.2 Identification of Key Parameters on Partial Equilibrium

Theorem D.1 shows that the estimator in empirical section 4 is informative about the bias and quality of US and Brazilian technologies. Theorem D.1 also shows that those estimators are a function of the key parameters in the model.

Theorem D.1. *(Identification of Key Parameters in Partial Equilibrium)*
Suppose that at $t = 1$ *the government implements a subsidy for innovation financed by a tax on the purchase of technology*

$$\tau^0_{innov} = \tau^0_{transf} = T^0 = T^1 = 0; \tau^1_{j,innov} \in \{0, \tau\}; \tau \geq 0 \tag{49}$$

and τ^1_{transf} *adjusts to equate governments budget constraint. Define the set of firms affected by both the tax on technology purchase and the subsidy as*

$$ExposedTSP = \left\{j | \tau_j \times \mathbb{I}^0_{innov} > 0\right\} \tag{50}$$

Define the diff-in-diff estimators with the effect of the policy on innovation, skill intensity and labor as

$$\lambda_{innov} = E\left[\Delta \mathbb{I}_{innov}^{t} | j \in ExposedTSP\right] - E\left[\Delta \mathbb{I}_{innov}^{t} | j \notin ExposedTSP\right] \tag{51}$$

$$\lambda_{skill} = E\left[\Delta \log\left(\frac{w_{L,BR}^{t} l_j^t}{w_{H,BR}^{t} h_j^t}\right) | j \in ExposedTSP\right] - E\left[\Delta \log\left(\frac{w_{L,BR}^{t} l_j^t}{w_{H,BR}^{t} h_j^t}\right) | j \notin ExposedTSP\right] \tag{52}$$

$$\lambda_{labor} = E\left[\Delta \log l_j^t | j \in ExposedTSP\right] - E\left[\Delta \log l_j^t | j \notin ExposedTSP\right] \tag{53}$$

Then, if wages are constant:

$$\lambda_{skill} = \frac{\rho}{1-\rho} \log \frac{A_{BR}/B_{BR}}{A_{US}/B_{US}} \times \lambda_{innov} = \frac{\kappa - \rho}{(1-\kappa)(1-\rho)} \log\left[\frac{w_{H,BR}^{0}/w_{L,BR}^{0}}{w_{H,US}^{0}/w_{L,US}^{0}}\right] \times \lambda_{innov}$$

$$\lambda_{labor} = f\left(\frac{\phi_{BR}}{\phi_{US}}, \gamma, \rho, \kappa, \left\{\tilde{FS}_j\right\}_j, \left\{\tilde{ES}_j\right\}_j\right) \times \lambda_{innov}$$

Where $\tilde{FS}_j$ is the log change factor share for firm j and $\tilde{ES}_j$ is the log change in expenditure share of firm j. Moreover, f is invertible in $\frac{\phi_{BR}}{\phi_{US}}$.

Theorem D.1 reproduces in the model the empirical estimates identified in the data. The policy change in (14) mimics the one observed in the data and the set 15 contains the set of firms exposed to the tax on technology transfers and the subsidy. λ_{innov} is the difference-in-difference estimator of the effect of the innovation policy change on innovation of treated firms. It compares the change in innovation on the treatment group to the change in innovation on the control group. In the same way λ_{skill} estimates the effect of the change in fiscal policy on the skill share at the firm level and λ_{labor} estimates the effect on demand for low-skilled workers.

Theorem D.1 shows that the difference-in-difference estimator is informative about cross-country technology differences. The effect of the innovation policy on expenditure shares, λ_{skill}, is a function of relative skill bias in the two countries, $\frac{A_{BR}/B_{BR}}{A_{US}/B_{US}}$. In the same way, the effect of the innovation policy on demand for low-skill workers, λ_{labor}, is a function of relative technology quality, ϕ_{BR}/ϕ_{US}.

Theorem D.1 shows that the difference-in-difference estimator can be used to identify the key parameters. The effect of innovation policy on expenditure shares is an invertible function of κ, ρ and observable data moments, such as wage premium in the two countries and the effect of the program on innovation. The effect of the innovation policy on low-skilled labor demand is a function of relative technology quality, the decreasing returns to scale, γ, the elasticity of substitution of firms buying technology ρ, the elasticity of substitution in US, κ, and data moments. Therefore, these two elasticities provide data moments that can be used to identify two model parameters.

D.3 Estimation of Returns to Scale

In this section I describe the steps to estimate the decreasing returns to scale of Brazilian firms. I use data on revenue, investment, and capital from financial reports of publicly traded firms collected by Economatica.

Using that a Cobb-Douglas production function is a first order approximation to a CES production function, I estimate the following model

$$\begin{aligned} log(Revenue) = \beta_0 + \beta_1 log(Wage\ Bill\ High\ Skill) + \beta_2 log(Wage\ Bill\ Low\ Skill) \\ + \beta_3 log(Assets) + \eta_i + \eta_t + \epsilon_{i,t} \end{aligned} \tag{54}$$

where η_i is a firm fixed effect, η_t a time fixed effect and $\beta_1+\beta_2+\beta_3$ is the degree of decreasing returns to scale. To capture the decreasing returns to scale in all factors, I also included capital on the estimation of the production function.

Table 55: **Estimates of Returns to Scale**

	(1)	(2)	(3)	(4)	(5)
	log(Revenue)	log(Revenue)	log(Revenue)	log(Revenue)	log(Revenue)
log(Wage Bill High Skill)	0.202***	0.202***	0.172***	0.184***	0.184***
	(0.0611)	(0.0611)	(0.0622)	(0.0176)	(0.0176)
log(Wage Bill Low Skill)	0.00981	0.00981	0.0168	0.0205	0.0205
	(0.0555)	(0.0555)	(0.0454)	(0.0380)	(0.0380)
log(Current Assets)	0.538***	0.538***	0.504***	0.553***	0.553***
	(0.0559)	(0.0559)	(0.102)	(0.0813)	(0.0813)
N	760	760	275	760	760
Model	OP	LP	WR	OP + ACF	LP + ACF
Return to Scale	.7496	.7496	.6932	.7577	.7577
Variance of Returns to Scale	.0037	.0037	.0106	.0019	.0019

Description: This table shows data from estimating equation (54) on data of financial reports by publicly traded Brazilian firms. As revenue I use firm's net income and assets are the current assets owned by the company. Wage bill Low Skill is the wage bill with high school dropouts while Wage Bill High Skill is the expenditure with workers with high school complete or more, this data is from RAIS. In the first column I use method of Olley and Pakes (1996), in second column method of Levinsohn and Petrin (2003), in third column I use Wooldridge (2009), in column 4 I use Olley and Pakes (1996) with Ackerberg et al. (2015) correction, and on the final column I use Olley and Pakes (1996) with Ackerberg et al. (2015) correction.

D.4 Robustness of Estimated Parameters

This section shows how the main estimated parameters, ρ and ϕ_{US}, change with the calibrated parameters κ, w_H^{US}/w_L^{US}, λ_{labor}, and λ_{skill}. ρ changes almost linearly with κ, keeping the difference in skill bias constant. But, taking κ to the upper range of its estimated value would lead to a more than twice larger value of ϕ_{US}. Changing the estimated skill-premium in the US barely affects the estimates of ρ and κ. Increasing λ_{skill} by 50% would increase ρ only marginally while ϕ_{US} moves almost one to one with λ_{labor}.

This exercises indicates that κ and λ_{labor} are two important moments affecting ϕ_{US} and ρ.

D.5 Robustness

D.5.1 Alternative κ

Figure 38 shows the effect of a 1p.p. increase in innovation on GDP and skill wage premium. Each point in the figure assumes a different κ with the whole model being estimated following the steps described in the main part of the paper.

According to Table 54, the estimates of κ are between 0.29 and 0.56. In this range, the effect of a 1p.p. increase in innovation goes from -0.2% to -0.7%. While the effect on wage premium goes from -0.02% to -0.1%. In any case, the effect on GDP is larger than the effect on skilled wage premium.

D.5.2 Alternative γ

This section shows the results under different estimates of the degree of decreasing returns to scale. Table 56 shows the results under the baseline and four other estimates. Table 56 also displays the estimated productivity of the US technology, the main parameter affected by changes in the degree of return to scale. Across the different estimates, the qualitative results are the same. I still find that the US technology is of higher productivity, an increase in innovation leads to a decrease in output, and the effect of innovation policy on skill premium is small.

Table 56: **Effect of Innovation Policy with Alternative Decreasing Returns to Scale**

	Parameters		1pp increase in innovation		Closing for Technology Transfers	
Reference	γ	ϕ_{US}	Δ GDP	Δ Skill Premium	Δ GDP	Δ Skill Premium
Baseline	0.75	1.66	-0.20%	-0.03%	-28.86%	-1.03%
Lower Bound of Estimates	0.69	1.97	-0.12%	-0.03%	-47.08%	0.08%
No Capital in Production	0.63	2.53	-0.16%	-0.04%	-59.44%	-0.19%
Basu and Fernald (1997)	0.8	1.22	-0.25%	-0.02%	-7.51%	-0.61%
Hsieh and Klenow (2009)	0.5	4.62	-0.24%	0.02%	-77.55%	-0.31%

Description: This table shows the effect of innovation policy under different degrees of decreasing returns to scale. The first line repeats the baseline estimates, the second line shows the results using the lower bound of estimates from Table 55, the third line shows the results using the estimated decreasing returns to scale when not using capital as input from Table 55, the fourth line shows the results using the decreasing returns to scale from Basu and Fernald (1997), and the last line uses the calibration of Hsieh and Klenow (2009) to the degree of decreasing returns to scale. The column γ displays the degree of decreasing returns to scale and the columns ϕ_{US} has the productivity of US technology. The other columns display the estimated effect of the Technology Substitution Program (TSP), the effect of an innovation program that increases innovation by 1p.p., and the last column contains the effect of closing the economy to international technology.

D.5.3 Alternative Innovation Definition

In this section, I show that using alternative measures of innovation delivers similar results as the baseline.

I consider four different innovation measures: 1) the application of patents or industrial designs, 2) the application of patents, industrial designs, or trademarks, 3) the hiring of a worker with a Ph.D., and 4) the hiring of an inventor.

Table 57 shows the estimated effect of the TSP in each innovation measure, the share of firms innovating according to each innovation, the estimated ϕ_{US} and estimated ρ. Table 57 shows that the share of firms innovating and the estimated productivity of US technology vary heavily according to the definition of innovation.

Table 57: **Estimated Parameters under Different Innovation Measures**

	Effect of TSP in Innovation	Shr. of Firms Innovating 10 yrs Bfr TSP	ϕ_{US}	ρ
Patent	0.035	0.742	2.538	0.265
Patent or Industrial Design	0.044	0.812	1.653	0.267
Patent or Industrial Design or Trademark	0.033	0.959	1.270	0.270
PhD Hiring	0.144	0.895	1.420	0.269
Inventor Hiring	0.165	0.871	1.446	0.269

Description: This table shows the estimated parameters using different measures of innovation. The first column has the innovation measure, the second has the share of innovating firms in the pre-period, the third column has the estimated ϕ_{US} and the last column has the estimated ρ. The first line displays the results for using patents as innovation definition, the second line defines innovation by applications for a patent or trademark, in the fourth line a firm is considered innovating if it has a patent, industrial design, or trademark, the fifth line considers a firm innovating if it hired a PhD workers, the last line considers as innovating any firm hiring a scientist according to the CBO02 classification.

Table 58 shows the effect of innovation policy on GDP and skill wage premium according to different measures of innovation. For every innovation measure, the effect of a small increase in innovation is very close to the baseline effect. Still, the last two columns of table 58 shows that the aggregate effect of closing the economy to international technology transfer will depend on the innovation measure adopted. That happens because the share of firms innovating vary with the innovation measure adopted.

Table 58: **Effect of Innovation Policy**

Innovation Measure	**Effect of 1pp Increase in Innovation**		**Effect of Closing to International Tech.**	
	GDP	*Skill Wage Premium*	*GDP*	*Skill Wage Premium*
Baseline	-0.200%	-0.028%	-28.86%	-1.03%
Patent or Industrial Design	-0.302%	-0.067%	-6.644%	-1.701%
Patent or Industrial Design or Trademark	-0.126%	-0.054%	-0.523%	-0.227%
PhD Hiring	-0.335%	-0.074%	-3.948%	-0.929%
Inventor Hiring	-0.233%	-0.063%	-3.283%	-0.940%

Description: This table shows the effect of different innovation programs under different innovation measures. The first column has the baseline effect of using patents as innovation measure, the second line defines innovation by applying for a patent or trademark, the third line a firm is considered innovating if it has a patent, industrial design or trademark, the fifth line considers a firm innovating if it hired a PhD workers, the last line considers as innovating any firm hiring a scientist according to the CBO02 classification. The second and third column displays the percent change in GDP and skill wage premium of increasing the share of innovating firms by 1 percentage point while the last column shows the effect of closing the economy to international technology transfers.

D.5.4 Controls and Selection

In this section, I use different model specifications to estimate λ_{labor} and λ_{skill}. As a consequence, the estimates of ϕ_{US}, ρ, and the effect of innovation policy differ. Table 59 shows the estimates of ϕ_{US} and ρ under different empirical model specification. Table 60 shows the effect of innovation policy on output. The main results are still true, there is large output effects with small skill-premium effect.

Table 59: **Estimated Parameters under Different Empirical Specifications**

Specification	λ_{labor}	λ_{skill}	ϕ_{US}	ρ
Baseline	-0.391	0.012	1.482	0.265
No Controls	-0.559	0.064	4.408	0.169
Control for Wage Change	-0.329	0.025	1.462	0.244
Firm Controls	-0.161	0.040	1.224	0.217
Only Continuum Firms	-0.349	0.012	1.356	0.265
Heckman Selection	-0.163	0.041	1.244	0.215

Description: This table shows the estimated ϕ_{US} and ρ under different estimates of the effect of the TSP on the log of low-skilled wage bill, λ_{labor}, and the log of the expenditure share with low-skilled workers, λ_{skill}. Each line on the table displays estimated parameters using different empirical models to estimate λ_{labor} and λ_{skill}. The first line contains the baseline estimates, the second line uses an empirical model without controls, the third line adds as controls firm-level wage change to the baseline specification, the third line adds as a control quintiles of the average wage and firm size. The fifth line uses only firms that hired high- and low-skilled workers. The final line uses the Heckman correction specification described in 44.

Table 60: **Effect of Innovation Policy under Different Empirical Specifications**

	Effect of 1pp increase in innovation		*Effect of Closing for Technology Transfers*	
Specification	*GDP*	*Skill Premium*	*GDP*	*Skill Premium*
Baseline	-0.2%	-0.028%	-28.86%	-1.03%
No Controls	-0.09%	-0.02%	-76.68%	-5.42%
Control for Wage Change	-0.37%	-0.03%	-18.60%	-1.41%
Firm Controls	-0.22%	-0.05%	-8.14%	-1.97%
Only Continuum Firms	-0.32%	-0.02%	-13.96%	-0.49%
Heckman Selection	-0.23%	-0.05%	-9.01%	-2.08%

Description: This table shows the effect of innovation policy under different calibrations. Each line shows the results using calibration with different estimated ϕ_{US} and ρ coming from different estimates of the effect of the TSP on the log of low-skilled wage bill, λ_{labor}, and the log of the expenditure share with low-skilled workers, λ_{skill}. All other parameters are calibrated following the procedure described in 6.2.

D.5.5 Elastic Labor Supply

Model In this section, I relax the assumption that labor supply is fixed. Assume that the representative consumer solves

$$\max_{H,L,C} \log\left(C - \chi_H \frac{H^{1+\upsilon}}{1+\upsilon} - \chi_L \frac{L^{1+\upsilon}}{1+\upsilon}\right) \tag{55}$$

s.t.

$$C = w_H H + w_L L + \Pi - T$$

where C is consumption, H is the supply of high skill labor, L is the supply of low skilled labor, Π is the aggregate profit and T is the lump-sum tax.

From problem (55), the supply of high and low skill workers is

$$H = \left(\frac{w_H}{\chi_H}\right)^{\frac{1}{\upsilon}}$$
$$L = \left(\frac{w_L}{\chi_L}\right)^{\frac{1}{\upsilon}}$$

Calibration and Results Following the main calibration strategy, χ_H and χ_L are estimated to reproduce the wages observed in the data and υ is calibrated following the literature.

The elasticity of the labor supply, $1/\upsilon$, is a source of debate in the literature. The micro estimates can be as low as 0.1 while the macro estimates are above 3. Table 61 shows the results under three different values of υ.

For small values of the elasticity, the estimated effect of innovation policy is close to the baseline estimates. For larger values of υ, the effect of innovation policy on production and skill wage premium approximates zero.

Table 61: **Effect of Innovation Policy**

	Effect of 1pp Increase in Innovation		*Effect of Closing to International Tech.*	
Elasticity	*GDP*	*Skill Wage Premium*	*GDP*	*Skill Wage Premium*
0.1	-0.3254%	-0.0168%	-44.7107%	-1.0580%
1	-0.0013%	-0.0014%	-0.4388%	-0.1018%
3	-0.0006%	-0.0009%	-0.1233%	-0.0097%

Description: This table shows the effect of different innovation programs under different elasticities of the labor supply.

D.5.6 Hiring of Scientists

In this section, I assume that firms have to hire high-skilled workers to innovate. Therefore, innovation policy will have two effects on skilled premium and production. One is the direct effect of replacing international technology by national innovations and the second is the effect of hiring skilled workers for innovation. This section shows that innovation policy now leads to a small change in skilled premium but a larger change in GDP.

Model. Assume that the fixed cost to innovate is given by

$$\epsilon_{j,innov} = \delta w_H + \tilde{\epsilon}_{j,innov}$$

where δ is the measure of high-skill workers hired to create a new innovation while $\tilde{\epsilon}_{j,innov}$ is a fixed cost in terms of final production.

The labor market cleaning condition is now

$$\begin{aligned} l_{innov,BR}\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right) + l_{transf,BR}\left(\int (1-\mathbb{I}_{j,innov}) d\Gamma_j\right) &= L_{BR} \\ (l_{innov,BR}+\delta)\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right) + h_{transf,BR}\left(\int (1-\mathbb{I}_{j,innov}) d\Gamma_j\right) &= H_{BR} \end{aligned}$$

Calibration and Results. δ is calibrated to reproduce the average fraction of wage bill expenditure with scientists among firms with patents, 0.14%.

Table 62 shows the results of innovation policy taking into account the demand for scientists. For a 1 p.p. increase in innovation, the effect on GDP and skill wage premium is very similar to the one identified by the baseline calibration.

Table 62: **Effect of Innovation Policy**

	GDP	*Skill Wage Premium*
1 p.p. Increase in Innovation	-0.200%	-0.022%
Closing the Economy to Int. Tech.	-29.52%	1.086%

Description: This table shows the effect of different innovation programs when taking into account the demand for scientists. The first line implements a subsidy for innovation financed by a tax on international technology transfers such that it increases innovation by 1 percentage point. The second line contains the effect of closing the economy to international technology.

D.5.7 Monopolistic Competition

In this section, I relax the assumption of homogeneous goods and assume monopolistic competition across firms. In this case, the elasticity of substitution across goods pins down firm size. I show that, using standard estimates of the elasticity of substitution across goods, the qualitative results are the same.

Assume that the utility of the representative consumer is given by

$$U = \left[\int_j y_j^\sigma dj \right]^{\frac{1}{\sigma}}$$

where y_j is consumption of product j and σ is the elasticity of substitution. The problem of firm j is

$$\begin{aligned}
&\max_{y_j, p_j, h, l, A, B} y_j p_j - w_L l - w_H h \\
&p_j = P \left(\frac{y_j}{Y} \right)^{-1/\sigma} \\
&y_j = z_j \left[\alpha_j (Al)^\rho + (1 - \alpha_j)(Bh)^\rho \right]^{1/\rho} \\
&\phi_{BR} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}} \right)^{\frac{\kappa-\rho}{\kappa\rho}}
\end{aligned}$$

where p_j is the price of product produced by firm j, P is the price index, and Y is aggregate output. The first constraint is the demand for product of firm j. The second constraint, is the production function. The last constraint is the technology frontier.

Table 63: **Effect of Innovation Policy**

Parameters		1pp increase in innovation		Closing for Technology Transfers	
σ	ϕ_{US}	Δ GDP	Δ Skill Premium	Δ GDP	Δ Skill Premium
2	5.17	-0.24%	0.03%	-79.91%	-0.29%
3	2.72	-0.15%	-0.04%	-62.38%	-0.15%
5	1.63	-0.55%	-0.01%	-23.81%	-0.95%

Description: This table shows the effect of innovation policy under different values for the elasticity of substitution. Hsieh and Klenow (2009) sets the elasticity of substitution to 3.

D.5.8 Exogenous Technology

Firms in Brazil Assume that firms in Brazil can choose between license technology from the US, (A_{US}, B_{US}), or innovate and create technology, (A_{BR}, B_{BR}). Technologies (A_{US}, B_{US}) and (A_{BR}, B_{BR}) are parameters of the model.

If the firm innovates, it solves

$$V_{innov,j} = \max_{h,l} z_j \left[\alpha_j (A_{BR} l)^\rho + (1-\alpha_j)(B_{BR} h)^\rho\right]^{\frac{\gamma}{\rho}} - w_{H,BR} h - w_{L,BR} l \tag{56}$$

While the profit of a firm licensing technology is

$$V_{transf,j} = \max_{h,l} z_j \left[\alpha_j (A_{US} l)^\rho + (1-\alpha_j)(B_{US} h)^\rho\right]^{\frac{\gamma}{\rho}} - w_{H,BR} h - w_{L,BR} l \tag{57}$$

The final technology choice of the firm is given by

$$V_j = \max \left\{V_{transf,j} - \epsilon_{j,transf} - \tau_{transf}, V_{innov,j} - \epsilon_{j,innov} + \tau_{innov}\right\} \tag{58}$$

Where the labor market cleaning condition and the government budget constraint is the same as in the baseline model.

Identification of Key Parameters As in section 6.1, I reproduce the TSP in the model and the empirical procedure of section 4. Proposition 4 shows that, knowing ρ and normalizing (A_{US}, B_{US}), I can estimate the Brazilian technology (A_{BR}, B_{BR}) if idiosyncratic shocks are persistent.

Proposition 4. *(Identification of Exogenous Technology)*
Suppose that the government implements policy 14 and define the estimators as in 16. Assume that production function is defined as in 13. Then, knowing ρ and (A_{US}, B_{US}), ρ and (A_{BR}, B_{BR}) can be uniquely identified from λ_{skill}, λ_{labor}, the wages in the two countries, the distribution of expenditure shares, and the distribution of innovation status.

Proof. Proof available in appendix D.6. □

Calibration To estimate (A_{BR}, B_{BR}), I normalize the US technology $A_{US} = B_{US} = 1$.

Table 64 shows the main results for 5 different estimations of ρ. For the first line, I use the fact that the elasticity of substitution in U.S. is still ρ and use the estimates by Murphy et al. (1998). On the second line, I use the estimate of ρ found on Table 64. For the third and fourth line, I estimate the elasticity of substitution of firms innovating. For different controls, the elasticity ranges between 0.77 and 0.9347. On the last line, I use the fact that Brazil is a developing country and use the elasticity estimated by Yu et al. (2015).

Table 64: **Estimated Brazilian Technology for Different Elasticities**

Calibration	ρ	A_{BR}	B_{BR}	A_{BR}/B_{BR}
Elasticity of Substitution In US	0.2850	0.7158	0.6655	1.0756
Baseline Estimated Elasticity	0.2655	0.7127	0.6577	1.0836
Estimation Lower Bound	0.7729	0.7430	0.7367	1.0086
Estimation Upper Bound	0.9347	0.7459	0.7443	1.0020
Chinese Elasticity	0.5200	0.7352	0.7158	1.0272

Description: This table shows the estimated Brazilian technology under different values of the elasticity ρ. On the first line, I use the elasticity of Murphy et al. (1998), on second line I estimate the model using the elasticity estimated on the main section, on the third and forth columns I use elasticity estimated from factor share changes among firms innovating, the last column uses elasticity from Yu et al. (2015).

Table 65 presents the main results. The effect on GDP and skill wage premium is larger for larger values of κ.

Table 65: **Effect of Innovation Policy**

Calibration	ρ	*GDP*	*Skill Wage Premium*
Elasticity of Substitution In US	0.2850	-0.225%	-0.023%
Baseline Estimated Elasticity	0.2655	-0.203%	-0.020%
Estimation Lower Bound	0.7729	-0.658%	-0.12%
Estimation Upper Bound	0.9347	-0.662%	-0.113%
Chinese Elasticity	0.5200	-0.601%	-0.124%

Description: This table shows the estimated Brazilian technology under different values of the elasticity ρ. On the first line, I use the elasticity of Murphy et al. (1998), on second line I estimate the model using the elasticity estimated on the main section, on the third and forth columns I use elasticity estimated from factor share changes among firms innovating, the last column uses elasticity from Yu et al. (2015).

D.5.9 Alternative Distributions

In this section, I relax the assumption that the relative cost to innovate is normally distributed.

In table 66, I assume that the relative innovation fixed cost follows either logistic or type 1 extreme value, different from the baseline assumption of normally distributed. Again, I calibrate the model to reproduce the same targets as before. Because the distribution changed, the selection into innovation will also change.

Table 66 shows that the effect of innovation policy is very similar across distributions.

Table 66: **Estimated Brazilian Technology for Different Elasticities**

	Effect of 1p.p. in Innovation		*Effect of Closing to Int. Tech.*	
Distribution	GDP	Skill Wage Premium	GDP	Skill Wage Premium
Normal	-0.20%	-0.03%	-28.86%	-1.03%
Logistic	-0.62%	-0.02%	-32.56%	-1.01%
Type 1 E.V.	-0.30%	-0.02%	-30.28%	-0.32%

Description: This table shows the effect of different innovation policies under different distributions of the relative innovation cost. The first line has the baseline estimation under the normal distribution, the second assumes the relative innovation cost is logistic distribution and the last line assumes the distribution is Type 1 extreme value.

D.5.10 Vintage Technology

Model Description Brazilian firms have access to a vintage technology $(A_{vintage}, B_{vintage})$ free of any cost. The vintage technology was created satisfying the following technology frontier:

$$\phi_{vintage} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}} \tag{59}$$

Firms in Brazil produce using production function (13). Therefore, the operating profit of producing using old technology is

$$V^t_{j,vintage,BR} = \max_{h,l} z_j \Upsilon^t_c \left[\Psi^t \alpha_j (A_{vintage} l)^\rho + (1-\alpha_j)(B^t_{vintage} h)^\rho\right]^{\frac{\gamma}{\rho}} - w^t_H h - w^t_L l$$

Technology choice of Brazilian firms is given by:

$$V_j = \max\left\{V^t_{j,BR,transf} - \epsilon^t_{j,transf} - \tau^t_{transf}, V^t_{j,BR,innov} - \epsilon^t_{j,innov} + \tau^t_{innov}, V^t_{j,vintage,BR}\right\} \quad (60)$$

Identification and Calibration With the introduction of the vintage technology, there are now an extra parameter to be identified, $\phi_{vintage}$. I show that $\phi_{vintage}$ can be identified by a triple difference approach.

As before, assume that there are two periods and production function is given by 13. Moreover, the government implements the following fiscal policy:

$$\tau^0_{innov} = \tau^0_{transf} = T^0 = T^1 = 0 \quad (61)$$

$$\tau^1_{j,innov} = \tau \mathbb{I}\left\{z_j \geq \bar{z}\right\} \quad (62)$$

where τ^1_{transf} adjusts to balance the government budget constraint.[69]

Define the set of firms licensing technology or using vintage technology that are exposed to this program as

$$ExposedUS = \left\{j | \tau_j \times \mathbb{I}^0_{US} > 0\right\}$$
$$ExposedVintage = \left\{j | \tau_j \times \mathbb{I}^0_{old} > 0\right\}$$
$$Control = \{j | j \notin ExposedUS, j \notin ExposedVintage\}$$

We can estimate the relative change in factor share and firm size in the exposed group

[69] In the data, the recipiency of the R&D subsidy is correlated with firm size, as discussed in Appendix A.10. To be able to reproduce the empirical estimates, I have to take it into account in the presence of a vintage technology. Otherwise, assuming a lump-sum R&D subsidy, the share of firms moving from vintage technology to Brazilian innovations would be larger than the predicted by the data.

by

$$\lambda_{skill}^{US} = E\left[\Delta \log\left(\frac{w_{L,BR}^{t} l_j^t}{w_{H,BR}^{t} h_j^t}\right) | j \in ExposedUS\right] - E\left[\Delta \log\left(\frac{w_{L,BR}^{t} l_j^t}{w_{H,BR}^{t} h_j^t}\right) | j \in Control\right] \tag{63}$$

$$\lambda_{labor}^{US} = E\left[\Delta \log l_j^t | j \in ExposedUS\right] - E\left[\Delta \log l_j^t | j \in Control\right] \tag{64}$$

$$\lambda_{labor}^{Vintage} = E\left[\Delta \log l_j^t | j \in ExposedUS\right] - E\left[\Delta \log l_j^t | j \in Control\right] \tag{65}$$

Proposition 5 shows that, under some identifying conditions, the ρ, ϕ_{US}, and $\phi_{vintage}$ can be identified using the effect of the innovation program on the exposed groups, data moments, and calibrated values for κ, γ and ϕ_{BR}.

Proposition 5. *(Identification of Key Parameters with Vintage Technology)*
Suppose that the government implements policy 14 and define the estimators as in 63. Assume that production function is defined as in 13. Then, knowing κ and γ, then ρ, $\frac{\phi_{US}}{\phi_{BR}}$, and $\frac{\phi_{vintage}}{\phi_{BR}}$ can be uniquely identified from λ_{labor}^{US}, $\lambda_{labor}^{vintage}$, λ_{skill}^{US}, the wages in the two countries, the distribution of expenditure shares, and the distribution of innovation status.

Proof. Proof available in Appendix D.7. □

Table 67 shows the estimated parameters. Notice that ρ and ϕ_{US} adjusted to the new identification strategy. When estimating ρ and ϕ_{US} only comparing firms licensing technology to firms innovating, the predicted difference in skill bias and productivity between US and Brazilian innovations is larger. Therefore, ρ and ϕ_{US} adjust accordingly. Moreover, $\phi_{vintage}$ is almost 1, meaning that there isn't much difference in productivity between vintage technology and Brazilian innovations.

Table 67: **Estimated Parameters of Model with Vintage Technology**

Parameter	**Description**	**Target/Source**	**Value Target**	**Parameter Value**
		Production function and Technology		
κ	Elasticity of substitution in US	Katz and Murphy (1992)	0.285	0.285
ρ	Elasticity of substitution in BR	Effect of TSP on log Factor Share	0.45	-1.304
γ	Degree of decreasing returns	Estimation		0.757
ϕ_{US}	Productivity of US technology	Effect of TSP on Demand for Low Skilled of Licensing Tech.	-1.707	2.0757
ϕ_{BR}	Productivity of BR technology	Normalization	1	1
$\phi_{vintage}$	Productivity of Vintage technology	Effect of TSP on Demand for Low Skilled of Vintage Tech.	0.0369	0.9924
		Technology Cost		
μ_ϵ	Mean of Innovation Cost	Shr. of Firms Licensing Tech. 10 yrs Bfr Program	0.012144	-6.84E-06
σ_ϵ	Variation of Innovation Cost	Effect of TSP on Innovation of Vintage	-0.434	1.25E-12
μ_{transf}	Mean of Innovation Cost	Shr. of Firms Licensing Tech. 10 yrs Bfr Program	0.0121	-4.19E-04
σ_{transf}	Variation of Innovation Cost	Effect of TSP on Innovation of Licensees	0.203	6.85E-05
$\bar{z}$	Cut-off for R&D Subsidy	Share of Firms Receiving Subsidy	0.0121	2.29
Firm Heterogeneity				
Γ_z	Dist. of Idiosyncratic Neutral Shock	Log-Normal		
μ_z	Avg. productivity shock	Normalization	0	1
σ_z	Variance of Firm Productivity Shock	Variance of Firm Size/Mean Firm Size	48.3032	0.403352367
Γ_α	Dist. of Idiosyncratic Biased Shock	Logit-Normal		
μ_α	Avg. biased shock	Normalization	0	0
σ_α	Variance of Skill Bias Shock	Variance of Expenditure Share	0.052	6.212962881
		Factor Supply		
L_U	Supply of low-skilled workers	Initial low skill wage	39.73	4.75E-006
H_U	Supply of high-skilled workers	Initial high skill wage	123.4685	5.88E-007

Description: This table shows the estimated parameters and its calibrated values. For the skilled wage premium in US, I use the average skilled wage premium of countries selling technology to Brazil weighted by the number of contracts.

Results Table 68 shows four different counterfactual innovation programs. On the first line, I reproduce the Technology Substitution Program. The second and third lines allow for the identification of the differential effect of the tax on international technology and the subsidy to innovation. The final line implements a license tax & subsidy program to increase innovation by 1 percentage point.

Table 68 shows that taking into account vintage technology dramatically increases the magnitude of the effect of innovation policy on GDP and skilled wage premium. While the baseline model predicts a decrease in 0.2% in GDP from increasing innovation by 1 p.p., Table 68 predicts a decrease in 1.6%. This happens because some of the firms licensing technology now adjust to a vintage technology. As a consequence, the drop in GDP is larger.

Lines 2 and 3 of Table 68 separate the two policy instruments implemented with the TSP; the tax on technology licensing and the subsidy to innovation. Table 68 shows that all the result of the program is coming from the tax on international technology licensing. The main reason the subsidy is ineffective is because it is targeted to large firms. Large firms, in the absence of the subsidy, would either license technology or innovate. Therefore, the subsidy cannot stimulate firms using vintage technology to adopt a Brazilian innovation.

Table 68: **Innovation Policy with Vintage Technology**

Policy Change	*Technology Transfers*	*Innovation*	*GDP*	*Wage Premium*	*Avg. Wage*	*w_H*	*w_L*
Technology Substitution Program	-15.10%	79.483%	-1.637%	-0.154%	-1.636%	-1.752%	-1.600%
TSP: Tax Only	-15.10%	79.483%	-1.637%	-0.154%	-1.636%	-1.752%	-1.600%
TSP: Subsidy Only	-0.0002%	0.001%	0.000%	0.000%	0.000%	0.000%	0.000%
1p.p. Increase in Innovation	-15.10%	79.480%	-1.636%	-0.154%	-1.636%	-1.752%	-1.600%

Description: This table shows the effect of different innovation policies in the model with vintage technology. The first line reproduces the Technology Substitution Program, the second line implements only the tax on international technology, the third line has the results of implementing only the subsidy for innovation while the final line implements a tax+subsidy program to increase innovation by 1 percentage point.

D.5.11 Externality of Innovation

Model Description Assume that the Brazilian technology frontier is given by

$$\phi_{BR}\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right)^{\beta} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}} \tag{66}$$

where $\int \mathbb{I}_{j,innov} d\Gamma_j$ is the share of firms innovating and $\beta > 0$. Constraint 66 includes a positive externality of innovation. According to constraint 66, if more firms innovate, firms can choose higher values for A and B.

To see how the externality translates into firm's productivity, it is useful to write the operating profit of a Brazilian firm that innovates:

$$V_{innov,BR} = \max_{h,l,A,B} \left[(Al)^{\rho} + (Bh)^{\rho}\right]^{\frac{\gamma}{\rho}} - w_{H,BR}h - w_{L,BR}l \tag{67}$$
$$\text{s.t. } \phi_{BR}\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right)^{\beta} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}}$$

Solving for the optimal technology choice in 67, we can re-write firm's problem as

$$V_{innov,BR} = \max_{h,l} \phi_{BR}\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right)^{\beta} \left[l^{\kappa} + h^{\kappa}\right]^{\frac{\gamma}{\kappa}} - w_{H,BR}h - w_{L,BR}l \tag{68}$$

Problem 68 shows that an increase in the share of firms innovating increases the TFP of firms innovating, which translates into higher demand for low- and high-skilled workers.

Identification and Calibration I identify externality β by comparing the employment growth between firms innovating and firms licensing technology. Assume there are two periods $t \in \{0, 1\}$ and policy 14 is implemented. Define $\lambda_{labor}^{externality}$ as the employment growth differential between firms innovating and firms licensing technology:

$$\lambda_{labor}^{externality} = E\left[\Delta \log l_j^t | \mathbb{I}_{innov}^0 = 1; \mathbb{I}_{innov}^1 = 1\right] - E\left[\Delta \log l_j^t | \mathbb{I}_{innov}^0 = 0; \mathbb{I}_{innov}^1 = 0\right] \tag{69}$$

Proposition 6 shows that ρ, ϕ_{US}, and β can be identified using the effect of the TSP, $\lambda_{labor}^{externality}$, data moments, and calibrated values for κ, γ and ϕ_{BR}.

Proposition 6. *(Identification of Key Parameters with Selection, Aggregate Shocks and General Equilibrium)*
Suppose that the government implements policy (14) *and defines estimators as in* (16) *and* (69). *Assume that the production function is defined as in* (13). *Normalize* $\phi_{BR} = 1$. *Then knowing* κ *and* γ, ρ *and* ϕ_{US} *can be uniquely identified from* λ_{skill}, λ_{labor}, $\lambda_{labor}^{externality}$, *the wages in the two countries, the distribution of expenditure shares, and the distribution of innovation status.*

Proof. Proof available in Appendix D.8. □

Results Table 69 shows that there is positive externality from Brazilian innovation. Table 70 shows that the externality is not large enough to overcome the negative effect of international technology replacement on output.

D.6 Proof of Proposition 4

Define $\theta_c = A_c/B_c$ the low skill bias and $\pi_t = \frac{w_H^t}{w_L^t}$. Expenditure share is given by

$$\frac{lw_L}{hw_H} = \left(\frac{\gamma}{1-\gamma}\right)^{\frac{1}{1-\rho}} \pi_t^{\frac{\rho}{1-\rho}} \Psi_t^{\frac{1}{1-\rho}} \theta^{\frac{\rho}{1-\rho}}$$

Let ω_{cb} be the log change in factor share of a firm with technology of country c in period

0 and technology of country b in period 1. Therefore, we can write

$$\omega_{UU} = \frac{\rho}{1-\rho} log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0}$$
$$\omega_{UB} = \frac{\rho}{1-\rho} log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} log \frac{\theta_B}{\theta_U} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0}$$
$$\omega_{BB} = \frac{\rho}{1-\rho} \log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0}$$
$$\omega_{BU} = \frac{\rho}{1-\rho} \log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} log \frac{\theta_U}{\theta_B} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0}$$

Define $\theta_c = A_c/B_c$ the low skill bias and $\pi_t = \frac{w_H^t}{w_L^t}$. Let λ_{UB}^T be the share of firms in the exposed group that licensed US technology at $t=0$ and innovated at $t=1$, λ_{BU}^C is the share of firms in the control group that switched from innovation to international technology. Therefore, we can write

$$\lambda_{skill} = \frac{\rho}{1-\rho} \left(\lambda_{UB}^T + \lambda_{BU}^C - \lambda_{UB}^C\right) log \frac{\theta_B}{\theta_U} \tag{70}$$

From equation (70), I can identify the skill bias of Brazilian technology, θ_B, using λ_{skill} and θ_U.

Following the same steps for the demand of firms for low-skilled workers, I can write

$$log \frac{A_{BR}}{A_{US}} = \frac{\lambda_{labor} - (\Lambda^T - \Lambda^C)}{\frac{\gamma}{1-\gamma} \left(\lambda_{UB}^T + \lambda_{BU}^C - \lambda_{UB}^C\right)}$$
$$\Lambda^C = \tilde{ES}_{UU}\lambda_{UU}^C + \tilde{ES}_{BB}\lambda_{BB}^C + \tilde{ES}_{UB}\lambda_{UB}^C + \tilde{ES}_{BU}\lambda_{BU}^C$$
$$\Lambda^T = \tilde{ES}_{UU}\lambda_{UU}^T + \tilde{ES}_{UB}\lambda_{UB}^C$$

where

$$\tilde{ES}_{ck} = E\left[log(1+ES_j^1)^{\frac{\gamma-\rho}{\rho}} - log(1+ES_j^0)^{\frac{\gamma-\rho}{\rho}} | t=0, \text{firm use tech } c; t=1, \text{firm use tech }, k\right]$$

D.7 Proof of Proposition 5

Define:

$$
\begin{aligned}
&\tilde{\pi}_U = \log \pi_{US}^1 - \log \pi_{US}^0 \\
&\tilde{\pi}_B = \log \pi_{BR}^1 - \log \pi_{BR}^0 \\
&\lambda_{UU}^T = E\left[\mathbb{I}_{transf}^0 \mathbb{I}_{transf}^1 | j \in ExposedUS\right]; \lambda_{UB}^T = E\left[\mathbb{I}_{transf}^0 \mathbb{I}_{innov}^1 | j \in ExposedUS\right] \\
&\lambda_{UO}^T = E\left[\mathbb{I}_{transf}^0 \mathbb{I}_{vintage}^1 | j \in ExposedUS\right]; \lambda_{BB}^C = E\left[\mathbb{I}_{innov}^0 \mathbb{I}_{innov}^1 | j \in Control\right] \\
&\lambda_{BB}^C = E\left[\mathbb{I}_{innov}^0 \mathbb{I}_{innov}^1 | j \in Control\right]; \lambda_{BU}^C = E\left[\mathbb{I}_{innov}^0 \mathbb{I}_{transf}^1 | j \in Control\right] \\
&\lambda_{UU}^C = E\left[\mathbb{I}_{transf}^0 \mathbb{I}_{transf}^1 | j \in Control\right]; \lambda_{UO}^C = E\left[\mathbb{I}_{transf}^0 \mathbb{I}_{vintage}^1 | j \in Control\right]
\end{aligned}
$$

We can write λ_{skill}^{US} as

$$
\begin{aligned}
\lambda_{skill}^{US} = &\left(\lambda_{UU}^T - \lambda_{UU}^C\right)\left(\frac{\kappa - \rho}{(1-\kappa)(1-\rho)}\tilde{\pi}_U + \frac{1}{1-\rho}\tilde{\pi}_B\right) + && (71)\\
&\left(\lambda_{UB}^T + \lambda_{UO}^T - \lambda_{UB}^C - \lambda_{UO}^C\right)\left(\frac{\rho - \kappa}{(1-\rho)(1-\kappa)}\pi_U^0 + \frac{1}{\rho - 1}\pi_B^0 + \frac{1}{1-\kappa}\pi_B^1\right) - && (72)\\
&\left(\lambda_{BB}^C + \lambda_{OO}^C\right)\frac{1}{1-\kappa}\tilde{\pi}_B - && (73)\\
&\left(\lambda_{BU}^C + \lambda_{OU}^C\right)\left(\frac{\kappa - \rho}{(1-\rho)(1-\kappa)}\pi_U^1 + \frac{1}{1-\rho}\pi_B^1 + \frac{1}{\kappa - 1}\pi_B^0\right) && (74)
\end{aligned}
$$

We can write λ_{labor}^{US} and $\lambda_{labor}^{vintage}$ as

$$
\begin{aligned}
(1-\gamma)\lambda_{labor}^{US} = &\log \phi_{vintage}\left(\lambda_{UO}^T + \lambda_{OU}^C + \lambda_{OB}^C - \lambda_{UO}^C - \lambda_{BO}^C\right) + && (75)\\
&\log \phi_{innov}\left(\lambda_{UB}^T + \lambda_{BU}^C + \lambda_{BO}^C - \lambda_{UB}^C - \lambda_{OB}^C\right) + && (76)\\
&\log \phi_{US}\left(\lambda_{UO}^C + \lambda_{UB}^C - \lambda_{OU}^C - \lambda_{BU}^C - \lambda_{UO}^T - \lambda_{UB}^T\right) + H^C - H_U^T && (77)\\
(1-\gamma)\lambda_{labor}^{vintage} = &\log \phi_{vintage}\left(\lambda_{OU}^C + \lambda_{OB}^C - \lambda_{UO}^C - \lambda_{BO}^C - \lambda_{OU}^T - \lambda_{OB}^T\right) + && (78)\\
&\log \phi_{innov}\left(\lambda_{BU}^C + \lambda_{BO}^C - \lambda_{OB}^T - \lambda_{UB}^C - \lambda_{OB}^C\right) && (79)\\
&\log \phi_{US}\left(\lambda_{UO}^C + \lambda_{UB}^C + \lambda_{OU}^T - \lambda_{OU}^C - \lambda_{BU}^C\right) + H^C - H_O^T && (80)
\end{aligned}
$$

Where H^C, H^T_O, and H^T_U are observables in the data and given by

$$
\begin{aligned}
H^C &= \sum_{k \in \{UU,UB,UO,BO,BB,OU,OO,OB\}} \lambda^C_k H^C_k \\
H^C_k &= \frac{\gamma-\rho}{\rho(\gamma-1)} E\left[log(1+ES^1_j) - log(1+ES^0_j) | k, j \in Control\right] \\
ES^t_j &= \frac{l^t_j w^t_L}{h^t_j w^t_H} \\
H^T_U &= \sum_{k \in \{UU,UB,UO\}} \lambda^T_k H^T_k \\
H^C_k &= \frac{\gamma-\rho}{\rho(\gamma-1)} E\left[log(1+ES^1_j) - log(1+ES^0_j) | k, j \in ExposedUS\right] \\
H^T_O &= \sum_{k \in \{OU,OB,OO\}} \lambda^T_k H^T_k \\
H^C_k &= \frac{\gamma-\rho}{\rho(\gamma-1)} E\left[log(1+ES^1_j) - log(1+ES^0_j) | k, j \in ExposedVintage\right]
\end{aligned}
$$

Therefore, knowing ρ and $\phi_{BR} = 1$, we have a system with three equations and three unknowns.

D.8 Proof of Proposition 6

Using the notation of 47, we can write β as

$$
\beta = \frac{(1-\gamma)\lambda^{externality}_{labor} - \gamma(\tilde{A}_{BB} - \tilde{A}_{UU}) - \frac{\gamma-\rho}{\rho}(\tilde{ES}_{BB} - \tilde{ES}_{UU})}{log\left(\Theta_1/\Theta_0\right)}
$$

where Θ_1 and Θ_0 are the share of firms innovating in period 1 and 0, respectively.

We can write λ_{labor} as

$$\begin{aligned}\lambda_{labor} =& \frac{1}{1-\gamma}\log\frac{\Theta_1^\alpha}{\phi_{US}}\left(\lambda_{UB}^T-\lambda_{UB}^C\right)-\lambda_{BB}^C\log\left(\frac{\Theta_1}{\Theta_0}\right)-\lambda_{BU}^C\alpha\log\left(\frac{\phi_{US}}{\Theta_0^\alpha}\right)\\ &+\frac{\gamma}{1-\gamma}\tilde{A}_{UU}\left(\lambda_{UU}^T-\lambda_{UU}^C\right)+\frac{\gamma}{1-\gamma}\tilde{A}_{UB}\left(\lambda_{UB}^T-\lambda_{UB}^C\right)\\ &-\frac{\gamma}{1-\gamma}\lambda_{BB}^C\tilde{A}_{BB}-\frac{\gamma}{1-\gamma}\lambda_{BU}^C\tilde{A}_{BU}+\frac{\rho-\gamma}{\rho(\gamma-1)}(\lambda_{UU}^T-\lambda_{UU}^C)\tilde{ES}_{UU}\\ &+\frac{\rho-\gamma}{\rho(\gamma-1)}(\lambda_{UB}^T-\lambda_{UB}^C)\tilde{ES}_{UB}-\frac{\rho-\gamma}{\rho(\gamma-1)}\lambda_{BB}^C\tilde{ES}_{BB}-\frac{\rho-\gamma}{\rho(\gamma-1)}\lambda_{BU}^C\tilde{ES}_{BU}\end{aligned} \tag{81}$$

Inverting 81, we can identify ϕ_{US}. ρ can be identified with expression 42.

E Additional Evidence

E.1 Summary of Additional Evidence

E.1.1 Text Analysis of National and International Technology

Using text analysis and measures of patent quality, I show that technology transferred to Brazilian firms are of better quality and more skill intensive than technology created by Brazilian firms. Moreover, countries with more skilled workers create skill intensive technology.

Table 71 shows statistics of Brazilian patents and of patents created by firms transferring technology to Brazil. To create this table, I match the name of firms selling technology to Brazil to the OECD patent database. To keep sample comparable, I only compare Brazilian patents registered in the European Patent Office.

The first panel of Table 71 shows that Brazilian patents have less citation, less inventors per patents and that Brazilian inventors are less prolific than inventors on firms transferring technology to Brazil. These facts support the conclusion that Brazilian patents are of inferior quality.

Table 71 shows in panel b that Brazilian technology is less associated to labor saving machines than international technology. To accomplish that, I create a measure of similarity to robots inspired by Argente et al. (2017). For the title of each patent I calculate the text similarity to a set of Wikipedia articles describing robots and automation.[70] Column 1 of panel b of table 71 shows the share of patents with similarity in the top decile. I also use the robot and software technology definition by Webb (2020).

Table 71: **Comparison of Brazilian Patents and Patents of Technology Seller**

	Brazilian Patents	**Tech. Seller Patents**
	Quality Measures	
Citations 3 Years After Publication	0.402	1.142
Avg. Number Inventors per Patent	2.398	4.890
Avg. Number of Patents per Inventor	3.222	8.356
	Skill Bias Measures	
Text Similarity with Robot	0.0476	0.1018
Robot (Webb (2020))	0.0003	0.0076
Software (Webb (2020))	0.0001	0.0149

Description: This table compares Brazilian patents registered in the European Patent Office and patents of firms selling technology to Brazil. It is constructed using the OECD patent database. The first panel contains different measures of patent quality. The first contains the average number of citation 3 years after the publication of the patent, the second line contains the average team size for each patent type while the third line contains the total number of patent applications per inventor. The second panel displays measures of skill bias. The first line display the share of patents with similarity to robot description in the top 10%. The measure of text similarity is calculated using Wikipedia entries describing automation and industrial robots following Argente et al. (2017). The second and third line contains the share of robots and software patents as described in Webb (2020). A patent is classified as robot if its title contain the words "robot" or "manipulat", and it does not have CPC code A61 ("medical or veterinaryscience; hygiene") or B01 ("physical or chemical processes or apparatus in general"). A patent is classified as software if it has words "software", "computer", or "program" in its title, and not "chip", "semiconductor", "bus", "circuity", or "circuitry".

E.1.2 Heterogeneous Effect of the Technology Substitution Program

According to the model of directed technological change, an increase in the supply of skilled workers in the US would decrease skill premium, increase its technology bias and increase the difference between the skill bias of the US and Brazil. Therefore, when Brazilian firms switch technology, the change in expenditure shares would be larger. The same intuition goes through in a multi-country model. Firms transferring technology from countries with a relatively large supply of skilled workers should increase their expenditure share of low skilled workers by more. In appendix E.3, I show that this is exactly the case.

E.1.3 Innovation, Capital, and Imports

There is no reason for the change in inputs composition to be limited to labor. Extending the intuition presented, we should expect firms to also reduce their use of capital, given the high interest rates in Brazil, and overall use of international inputs, given that transportation

[70] Appendix E.2 describes in detail the steps to create this measure.

cost makes national inputs less expensive. Table 46 shows that firms exposed to the TSP are less likely to become importers, to import inputs and to import capital. Table 47 shows that the drop in the import of inputs is driven by a reduction in the imports from developed countries.

E.1.4 Event-Study using International Technology

A conclusion from the model of directed technological change is that technology is biased towards abundant factors. Moreover, the bias of the technology should increase with its factor abundance. Therefore, a Brazilian firm implementing a technology from Germany, which has 29% of its population with college degree, should increase its factor share with college graduates by less than a firm implementing a technology from US, which has 44% of its population as college graduates. I test this model prediction in Appendix E.4.

In Appendix E.4, I implement an event-study strategy to study the change in labor outcomes when a firm licenses an international technology. I show that firms licensing technology from a high-skill abundant countries decrease their hiring of high school dropouts. In special, firms licensing technology from the US or other developed countries increase the share of college graduates in their labor force while the ones licensing technology from Brazil decrease it.

E.1.5 Regional Variation in Factor Supply and Technology Adoption

The model of directed technological change also has predictions for technology adoption. If the wage premium in Brazil decreases, the difference in skill bias between Brazilian technology and international technology decreases. Therefore, the factor mismatch from using international technology is smaller which increases the profit of operating with an international technology. Therefore, regions in Brazil more abundant in high-skill workers should be more likely to adopt international technology and, if they innovate, have technology high-skill biased. In Appendix E.5, I show that this model prediction is also supported by the data.

E.1.6 Minimum Wage and Technology Adoption

The model of directed technological change also has predictions for the effect of exogenous changes in skill premium, such as the ones generated by minimum wage changes. According to the model, if skill premium decreases, firms should produce technology more high-skilled biased and should be more likely to adopt international technology. I test this prediction of the model by exploiting heterogeneous exposure to exogenous variation in the minimum wage.

Between 2000 and 2010, the Brazilian nominal minimum wage increased by 237%. Inspired by Engbom and Moser (2018), Autor et al. (2016b) and Lee (1999), I construct a new firm level measure of exposure to the minimum wage. Firms that in 2000 had a larger percentage of its labor force with a wage below the 2010 minimum wage value were more affected by the minimum wage than the ones that had a lower share. Exploiting this new exposure measure I show that firms more exposed to the minimum wage were more likely to license international technology, as the model predicts.

E.2 Measure of Text Similarity to Robots

This document describes the steps taken to create similarity measures between patents and Wikipedia articles. I follow Argente et al. (2017) to develop this measure.

First, I select a set of Wikipedia articles related to robots and automation. I take the Wikipedia articles on scara, asea irb, serial manipulator, industrial robot, robot welding, robocrane, automation, cisbot, robotic arm, mobile industrial robots, robot kinematics, cartesian coordinate robot, parallel manipulator, uwa telerobot, roboturb, delta robot, schoenflies displacement, articulated robot, unimate, 5dx, and programmable universal machine for assembly.

Parsing To transform documents in vectors, we need first to determine what corresponds each element of the vector. In the baseline application, I use words and sequences of words as tokens, i.e., 1-gram and 2-gram.

Lemmatisation To avoid counting conjugations of the same word as different words, I use the WordNet lexical database (wordnet.princeton.edu), to reduce words to their root forms by removing conjugations like plural suffixes.

Selection To avoid counting frequent and uninformative words, such as "the" and "and", I drop terms that appear in more than 80% of documents.

Vectorization Following the previous steps, we can characterize each document with a vector of dummies for words it contain. Let $m \in \{1, ..., M\} = \mathcal{M}$ be the set for words in the document. Let c_{km} be a dummy variable taking 1 if document k contains word m. Therefore, document k can be represented by vector c_m with entries c_{km}.

Normalization Rare words are more important to characterize differences across documents than common words. To take that into account, we weight each word using total-frequency-inverse-document-frequency (tf-idf). Each term m of the dataset is weighted by

$$\omega_m = \log\left(\frac{K+1}{d_m+1}\right) + 1 \text{ where } d_m = \sum_k \mathbb{I}\left\{c_{km} > 0\right\}$$

After weighting, each document is weighted by word frequency vector f_k with entries

$$f_{km} = \frac{\omega_m c_{km}}{\sqrt{\sum_{m'} (\omega_m c_{km})^2}}$$

Similarity Scores Using the normalized word vector for each document, f_k, we can calculate the similarity scores. The similarity between patent j and wikipedia articles w is given by

$$s_{jw} = \sum_{m \in \mathbb{M}} f_{jm} \times f_{pm} \tag{82}$$

Final Robot Similarity For each patent, I calculate the similarity score 82 for each Wikipedia article. The final robot similarity is the max of similarity to any robot Wikipedia article:

$$\text{Robot Similarity}_k = \max_{w \text{ is a Wikipedia article}} s_{kw}$$

Then, to reduce the noise caused by outliers, I report on table 71 a dummy for similarity to robot:

$$\mathbb{I}_k\{\text{Similar to Robot}\} = \begin{cases} 1 & \text{, if Robot Similarity}_k \text{is on top decile} \\ 0 & \text{, if Robot Similarity}_k \text{is not on top decile} \end{cases}$$

E.3 Heterogeneous Effect of TSP

For each firm licensing technology before the introduction of the Technology Substitution Program, I calculate the average factor share of it's technology:

$$\text{Factor Supply Tech.}_{i,s(i),t} = \frac{\sum_{j=1}^{N(i)} \frac{H_{c(j,i)}}{L_{c(j,i)}}}{N(i)}$$

where $N(i)$ is the number of technology contracts signed by firm i before the introduction of the program, $H_{c(j,i)}$ is the number of workers with a high school diploma or more in country $c(j,i)$ which is the origin of technology j signed by firm i, $L_{c(j,i)}$ is the number of workers with less than a high school on country $c(j,i)$ which is the origin of technology j signed by firm i, $\frac{H_{c(j,i)}}{L_{c(j,i)}}$ is the factor share of technology licensed by firm i in contract j. Therefore, Factor Supply Tech.$_{i,s(i),t}$ is the average factor share of the technology licensed by firm i before the introduction of the program.[71]

[71] I choose not to use the value of the contract to weight the average because it is missing for a set of contracts. Results using predicted contract value has the same conclusions.

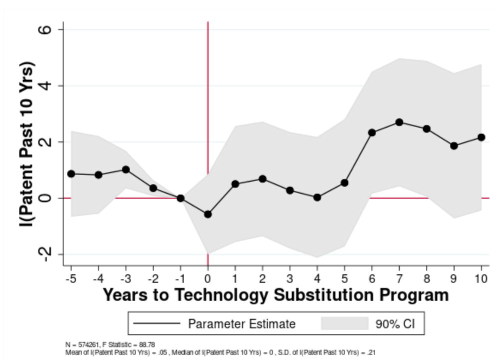
I use the following dynamic specification to test for heterogeneous effects:

$$
\begin{aligned}
y_{i,s(i),t} = & \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Exposure TSP}_{i,s(i)} + \\
& \sum_{j=-5}^{10} \kappa_j \times \text{Factor Supply Tech.}_{i,s(i),t} \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Exposure TSP}_{i,s(i)} + \\
& X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t}
\end{aligned}
\tag{83}
$$

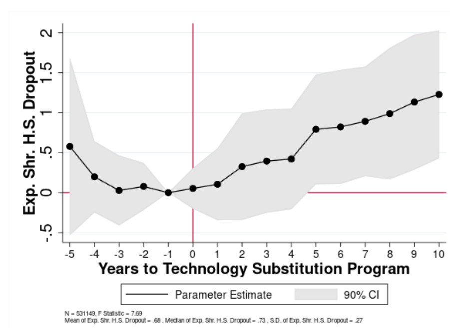
Figure 39 shows the heterogeneous effects of the TSP, measured by κ_j. As the model predicts, firms licensing technology from countries with larger supply of skilled workers increases the expenditure share of high school dropouts by more. I don't find any significant effect on innovation or employment.

Figure 39: **Employment and Exposure to the TSP with Treatment Trend**

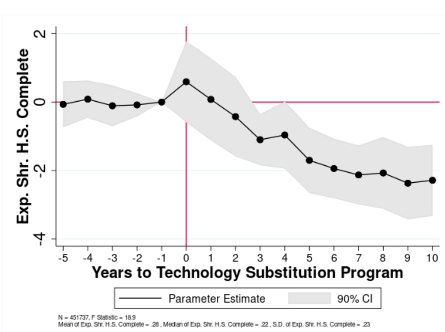
(a) **I(Patent Past 10 Yrs.)**



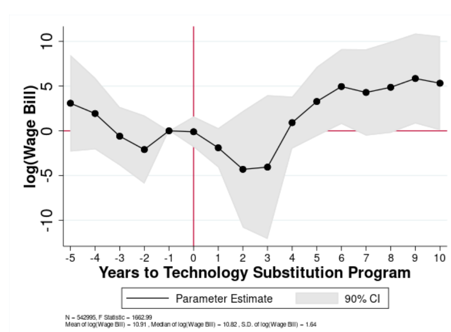
(b) **Exp. Shr. H.S. Dropout**



(c) **Exp. Shr. H.S. Complete**



(d) **log(Wage Bill)**



E.4 Diff-in-Diff with International Technology Transfers from Different Countries

In this section, I show that firms transferring technology from high-skill abundant countries increase the hiring of high-skilled workers by more than firms transferring technology from high-skill poor countries. I get to this conclusion by implementing a differences-in-differences method where the treatment group is the set of establishments implementing technology from abroad while the control group are the establishments in the same firm that haven't licensed any technology. By comparing different establishments of the same firm, I can get rid of firm level shocks and isolate the effect of technology transfers.

To get rid of firm level idiosyncratic shocks, I compare establishments within a firm. The treatment group is the set of establishments s in firm i implementing a transferred technology for the first time and the control group is the set of establishments s' in the same firm i that has not implemented any international technology in the 10 years around the technology transferred by establishment s. The assumption is then of parallel trends between establishments of the same firm.

The main specification is:

$$y_{s,i,t} = \sum_{j=-4}^{4} \theta_j \times \mathbb{I}_{s,i} \left\{ j \ \mathit{Yrs.\ to\ Tech.\ Transfer\ from\ Country}\ c(i) \right\} \times \mathit{Shr.\ Skilled\ Workers}_{c(i)} \tag{84}$$

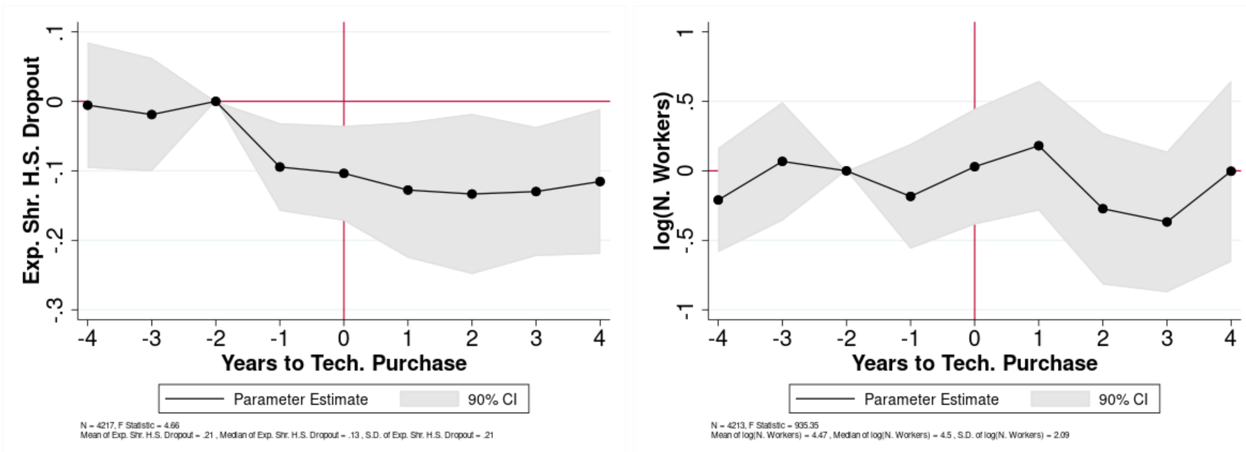
$$\sum_{j=-5}^{5} \kappa_j \times \mathbb{I}_{s,i} \left\{ j \ \mathit{Yrs.\ to\ Tech.\ Purchase\ from\ Country}\ c(i) \right\} + \mu_{i,t} + \epsilon_{i,t,c(i)} \tag{85}$$

where $y_{s,i,t}$ is a labor outcome of establishment s, of firm i, in year t. $\mathit{Shr.\ Skilled\ Workers}_{c(s,i)}$ is the share of skilled workers in the country of origin of the technology being implemented by establishment s of firm i. $\mathbb{I}_{s,i} \left\{ j \ \mathit{Yrs.\ to\ Tech.\ Transfer\ from\ Country}\ c(i) \right\}$ is a dummy that takes one j years to establishment s of firm i licensing technology from country $c(i)$. $\mu_{i,t}$ is a firm-year fixed effect capturing firm level shocks. The parameter κ_j captures the effect of licensing technology on the establishment. The parameter of interest is θ_j, captures the heterogeneous effect of receiving a technology from a skill-abundant country.

Figure 40a shows that establishments licensing technology from skill-abundant countries decrease the expenditure share of high school dropouts by more than an establishment licensing technology from a skill-poor country. I do not find any differential effect on employment.

Figure 40: **Effect of Technology Transfers from Skilled-Abundant Countries**

(a) Expenditure Shr. with H.S. Dropouts (b) log(N. Workers)



Description: This figure displays the estimated θ_j of equation (84) on expenditure shr. of high school dropouts, in Figure 40a, and on establishment employment, in Figure 40b.

E.5 Regional Variation in Factor Supply and Technology Adoption

According to the model, a large supply of high skilled workers should lead firms to adopt high-skill biased technology. In this section, I test this prediction using variation in the supply of skilled workers across Brazilian regions and show that regions with a large supply of skilled workers are more likely to license international technology and to create patents associated with robots.

The main specification is the following:

$$y_{i,r,s} = \beta HS\_shr_{r,s} + X_i'\kappa + \epsilon_{i,r,s} \tag{86}$$

where $y_{i,r,s}$ is an outcome related to technology of firm i, in region r, and sector s before 2000; and $HS\_shr_{r,s}$ is the share of workers with a high school complete or more in 2000, region r, and sector s. Controls, X_i, is a set of fixed effects for deciles of firm size and average wage. I use the outcome before 2000 to avoid capturing any variation generated by the TSP.

Table 72 shows that markets with a larger supply of skilled workers are more likely to adopt international technology. In Table 72, $\mathbb{I}\{\text{Int. Tech.}\}$ is a dummy taking one if the firm license international technology at any time before 2000, $\mathbb{I}\{\text{Patent}\}$ is a dummy if the firm applied for a patent before 2000, and $\mathbb{I}\{\text{PCT Patent}\}$ is a dummy if the firm applied for a PCT patent before 2000. Table 72 shows that firms in markets with a high supply of skilled-workers are more likely to license international technology, which is high-skill biased, than firms in markets with low supply of high-skill workers.

Table 72: **Technology Adoption and Regional Factor Share**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{I}\{\text{Int. Tech.}\} - \mathbb{I}\{\text{Patent}\}$	$\mathbb{I}\{\text{Patent}\}$	$\mathbb{I}\{\text{PCT Patent}\}$	$\mathbb{I}\{\text{Int. Tech.}\}$	$\mathbb{I}\{\text{Robot}\}$	$\mathbb{I}\{\text{Software}\}$
$HS\_shr_{r,s}$	0.0734***	0.00953	0.00811***	0.0829***	0.00599**	0.00645***
	(0.00892)	(0.00721)	(0.00198)	(0.00615)	(0.00286)	(0.00239)
N	53886	53886	53886	53886	53886	53886
R^2	0.016	0.077	0.011	0.131	0.007	0.003
Mean Dep. Var	-.034	.055	.001	.022	.003	.001
SD Dep. Var	.25	.229	.038	.146	.069	.045
Mean Indep. Var	.205	.205	.205	.205	.205	.205
SD Indep. Var	.159	.159	.159	.159	.159	.159
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Description: This table shows the estimated parameters of a regression of high skill share on technology adoption by the firm in 2000. High skill share is defined as the share of workers with high school diploma or more in RAIS for 2000. $\mathbb{I}\{\text{Int. Tech.}\}$ is a dummy taking one if the firm had purchased an international technology before 2000, $\mathbb{I}\{\text{Patent}\}$ is a dummy taking one if the firm submitted a patent for to the Brazilian patent office before 2000, $\mathbb{I}\{\text{EPO Patent}\}$ is a dummy taking one if the firm has submitted a patent to the European Patent Office before 2000. Following Webb (2020), I use text analysis and patent classes to classify a patent as robot or software. $\mathbb{I}\{\text{Robot}\}$ is a dummy if a patent is classified as related to automation and $\mathbb{I}\{\text{Software}\}$ a dummy if a patent is classified as software. As controls I use dummies for deciles of firm size and deciles of avg. wage. A patent is classified as robot if its title contain the Portuguese words for "robot" or "manipulat", and it does not have CPC code A61 ("medical or veterinaryscience; hygiene") or B01 ("physical or chemical processes or apparatus in general"). A patent is classified as software if it has Portuguese words for "software", "computer", or "program" on its title, and not "chip", "semiconductor", "bus", "circuity", or "circuitry".

Patents created in regions with a high supply of skilled workers are more skill intensive, as columns 5 and 6 of Table 72 indicates. $\mathbb{I}\{\text{Robot}\}$ is a dummy taking one if the firm issue a patent associated to robots and $\mathbb{I}\{\text{Software}\}$ is a dummy taking one if the firm issues a patent associated with software, both defined following Webb (2020). Columns 5 and 6 shows that firms in labor markets with a large supply of skilled workers are more likely to create patents associated with automation or software, which are both high-skilled biased technologies according to Webb (2020).

E.6 Minimum Wage and Technology Adoption

Using heterogenous exposure to the minimum wage, I show that an exogenous increase in skill premium lead firms to adopt high-skilled biased technologies. Between 2000 and 2010, Brazilian nominal minimum wage increased by 237%. I use as exposure measure to the minimum wage the expected cost required to adhere to it. Firms with larger minimum wage expected cost had a fall in skill wage, a relative increase in the adoption of international technology, and skilled-biased patents.

As exposure to the minimum wage, I use the percentage increase in 2000 wage bill required to satisfy the 2010 minimum wage:

$$ExpMW_i = \frac{\sum_{j=1}^{N(i)} \max\{wage_{j,i,2000}, MinimumWage_{2010}\}}{WageBill_{i,2000}} \tag{87}$$

where $wage_{j,i,2000}$ is the monthly wage of worker j in firm i, $MinimumWage_{2010}$ is the 2010 minimum wage, and $WageBill_{i,2000}$ is the wage bill of firm i. $ExpMW_i$ captures the smallest percentage increase in wage bill of firm i required by the minimum wage change.

I evaluate changes in technology adoption related to exposure to the minimum wage with:

$$y_i = \beta ExpMW_i + X_i' \kappa + \epsilon_i$$

where y_i is an outcome measuring technology adoption in firm i between 2000 and 2010, $ExpMW_i$ is the exposure to the minimum wage increase in (87), and X_i is a set of controls. As a control, I use fixed effects for region, 5-digit sector, decile of firm size, decile of average wage, decile of wage bill, dummy for applying for patent before 2000, and dummy for licensing international technology before 2000. Standard errors are clustered at the firm level.

The parameter of interest, β, is identified by comparing firms with high exposure to the minimum wage against the firms with low exposure but in same region, sector, size, wage, and technology. (87) does not capture differences in size and wages across firms because these variables are controlled for non-parametrically.

Table 73 shows that firms more exposed to the minimum wage policy had a skill premium increase and were more likely to adopt international technology. An increase in the exposure to the minimum wage by one standard deviation, leads to an increase skill premium of 121%. Firms also increased the relative probability of adopting international technology and decreased the probability of applying for patents.

Table 73: **Effect of Minimum Wage on Technology Adoption**

	(1)	(2)	(3)	(4)	(5)
	$\Delta log(\frac{\text{Hourly Wage Not HS Drop}}{\text{Hourly Wage HS Drop}})$	$\mathbb{I}\{\text{Int. Tech.}\} - \mathbb{I}\{\text{Patent}\}$	$\mathbb{I}\{\text{Int. Tech.}\}$	$\mathbb{I}\{\text{Patent}\}$	$\mathbb{I}\{\text{Scientist}\}$
$ExpMW$	-2.463*	0.670**	0.231	-0.440**	-0.0369
	(1.365)	(0.325)	(0.217)	(0.224)	(0.119)
N	8768	14616	14616	14616	14616
R^2	0.129	0.166	0.257	0.213	0.199
Mean Dep. Var	-.162	-.107	.029	.137	.056
SD Dep. Var	.391	.365	.169	.344	.229
Mean Indep. Var	.597	.995	.995	.995	.995
SD Indep. Var	.491	.071	.071	.071	.071

Description: This table presents results of an OLS regression of $ExpMW$ on the change in hourly wage premium between 2000 and 2010 at the firm, a dummy if the firm purchased an international technology between 2000 and 2010, a dummy if the firm issued a patent between 2000 and 2010, the difference between dummies for technology purchase and patent and a dummy if the firm hired a scientist between 2000 and 2010. Controls are a dummy for microregion, a dummy for a 1-digit sector classification, a dummy for deciles of firm size in 2000, a dummy for deciles of average wage, a dummy for deciles of wage bill, a dummy if the firm had a patent or technology contract before 2000. The sample is selected to firms in the manufacturing, agriculture, mining and construction sectors, that existed between 1995 and 2010, and that had more than 45 workers at some year between this period.

Table 25: **Classification of Industrial Design Applications**

Industrial Design Classification	**Number of I.D.**	**Percentage**
Articles of clothing	15,832	14.51
Furnishing	13,586	12.45
Packages	9,182	8.41
Tools and hardware	7,819	7.17
Transport	6,109	5.60
Articles of adornment	5,953	5.46
Household goods	5,550	5.09
Building units	5,351	4.90
Foodstuffs	4,742	4.35
Fluid distribution equipment	4,668	4.28
Games and toys	4,337	3.97
Machines	2,651	2.43
Clocks and watches	2,347	2.15
Lighting apparatus	2,299	2.11
Equipment for production of electricity	2,172	1.99
Telecommunication	2,133	1.95
Travel goods and personal belongings	1,966	1.80
Stationery and office equipment	1,841	1.69
Medical and laboratory equipment	1,682	1.54
Advertising equipment	1,641	1.50
Textile	1,532	1.40
Brushware	1,114	1.02
Graphic symbols and logos	920	0.84
Pharmaceutical and cosmetic products	732	0.67
Animal products	545	0.50
Photographic apparatus	518	0.47
Machines for Cooking	502	0.46
Devices and equipment against fire ha..	391	0.36
Tobacco and smokers' supplies	372	0.34
Musical instruments	275	0.25
Articles for hunting, fishing and pes..	227	0.21
Office machinery	133	0.12

Description: This table shows the number of industrial design applications between 1985 and 2010 by classification of the ID. I use the two digit Locarno classification. Industrial designs, as patents, can have more than one classification.

Table 27: **Classification of Trademark Applications**

x

Trademark Classification	**N. Trademarks**	**Percentage**
Advertising	209,186	16.81
Education	126,336	10.15
Clothing	80,863	6.50
Scientific and technological services	68,259	5.48
Scientific and audiovisual	62,072	4.99
Paper and cardboard	55,725	4.48
Pharmaceuticals	53,241	4.28
Coffee, tea, and cocoa	48,291	3.88
Cosmetics	46,701	3.75
Construction services	42,865	3.44
Insurance	42,454	3.41
Telecommunications services	32,297	2.60
Services for providing food and drink	30,654	2.46
Medical services	27,035	2.17
Transport	26,220	2.11
Meat, fish, poultry and game	25,350	2.04
Machines	20,046	1.61
Chemicals for use in industry	19,083	1.53
Raw and unprocessed agricultural prod..	17,483	1.40
Beers	17,305	1.39
Vehicles	17,097	1.37
Furniture	14,429	1.16
Alcoholic beverages	14,302	1.15
Games, toys and playthings	14,192	1.14
Materials for building and construction	13,388	1.08
Environmental control apparatus	12,828	1.03
Metal materials	12,045	0.97
Medical instruments	11,480	0.92
Leather and imitations of leather	10,527	0.85
Household or kitchen utensils	9,340	0.75
Legal services	8,824	0.71
Jewelry	8,594	0.69
Textiles	8,113	0.65
Paints	7,594	0.61
Unprocessed and semi-processed rubber	7,318	0.59
Industrial oils	6,368	0.51
Hand tools	4,016	0.32
Tobacco	3,573	0.29
Carpets, rugs, mats and matting	1,870	0.15
Yarns	1,822	0.15
Dressmakers' articles	1,804	0.14
Ropes and string	1,719	0.14
Musical instruments	1,192	0.10
Firearms	606	0.05

Description: This table shows the number of trademark applications between 1990 and 2010 submitted to the Brazilian Patent Office according to it 2 digit NICE classification.

Table 31: **Sectoral Committees and Targeted Research Areas**

Committee Name	**Revenue Shr.**	**Official Target**
Biotechnology	7.5%	Biotechnology
Aeronautical	7.5%	Aeronautical, electronic and mechanical engineering
Health	17.5%	Drugs, biotechnology and medical-hospital equipment
Agro	17.5%	Agronomy, veterinary and biotechnology
Green and Yellow	50%	General innovation and partnership between private and public

Description: This table presents the list of sectoral committees supported by the revenue from taxes on international technology transfers. The "official target" list the projects that could be supported by each committee.

Table 32: **Statistics from Inventor's CV**

Statistics	Value
Total Inventors	102,775
Inventors w/ CV	32,505
Shr. w/ PhD	0.138
Shr. w/ Paper	0.262
Shr. Academic	0.174

Description: This table shows statistics of inventors of patents or industrial designs. The first line contains the total number of inventors of patents or industrial designs. The second line contains the number of inventors with CV on the Lattes Platform. The third to fifth lines contains the share of inventors with PhD, the share with published academic papers, and the share with academic employment, assuming that the ones without CV on the Lattes Platform do not have PhD, published paper or academic employment.

Table 69: **Estimated Parameters with Externality**

	ϕ_{US}	ρ	β
Model with Externality	1.366	0.265	0.086
Baseline	1.668	0.265	0.000

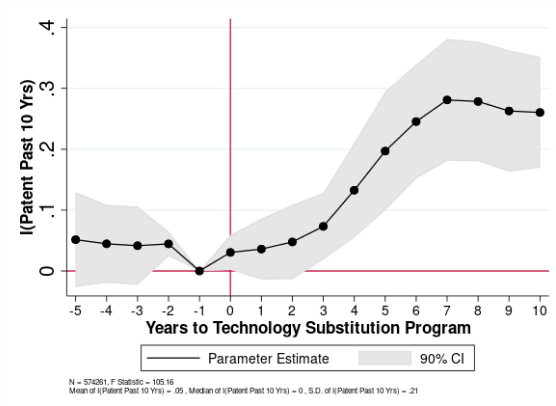
Description: This table shows the estimated parameters of the model with exterlinality. The first column contains the model version, the second column contains the estimates of the TFP of US technology,ϕ_{US}, the third column the estimates of the elasticity of substitution of the production function, ρ, and the last column the estimates of the externality, β.

Table 70: **Effect of Innovation Policy with Externality**

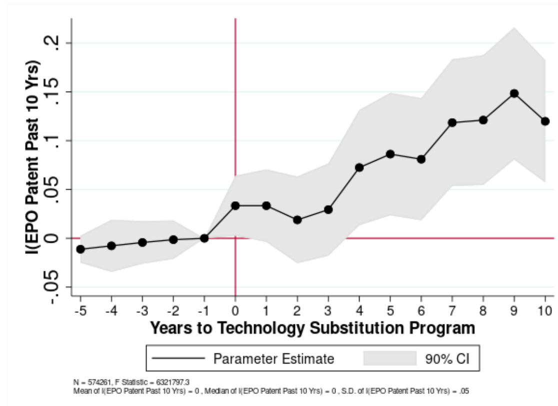
	Effect of 1 p.p. Increase in Innovation		*Effect of Closing to Int. Tech.*	
	Δ Output	**Δ Skill Premium**	**Δ Output**	**Δ Skill Premium**
Model with Externality	-0.29%	-0.02%	-10.04%	-0.74%
Baseline	-0.2%	-0.02%	-28.86%	-1.03%

Figure 26: **Main Results with Heterogeneous Revenue Allocation Exposure**

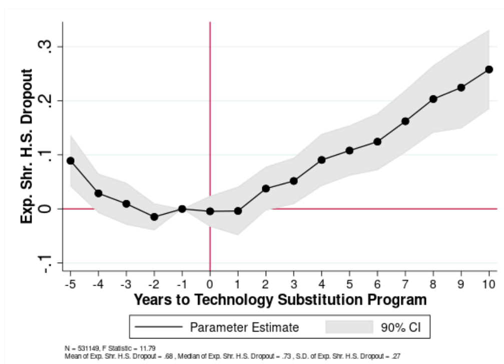
(a) I(Patent Past 10 Yrs.)



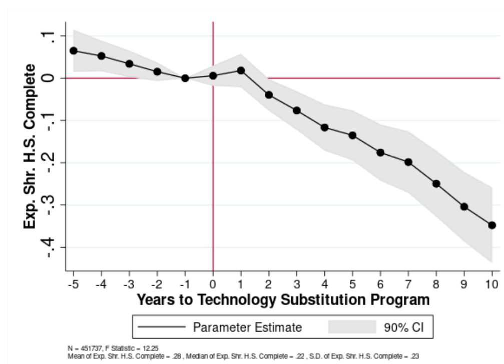
(b) I(EPO Patent Past 10 Yrs.)



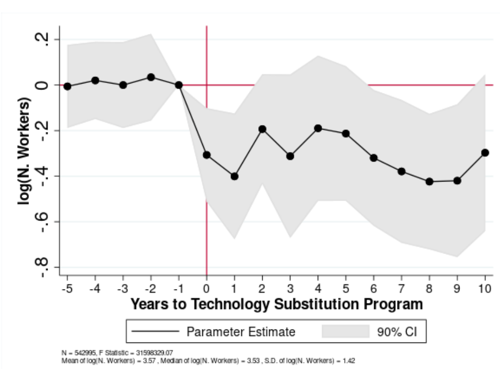
(c) **Exp. Shr. H.S. Dropout**



(d) **Exp. Shr. H.S. Complete**



(e) **log(N. Workers)**



(f) **log(Wage Bill)**

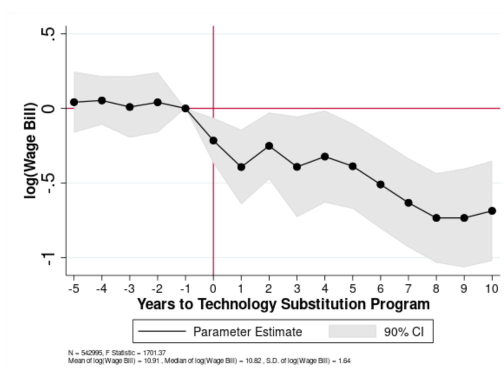
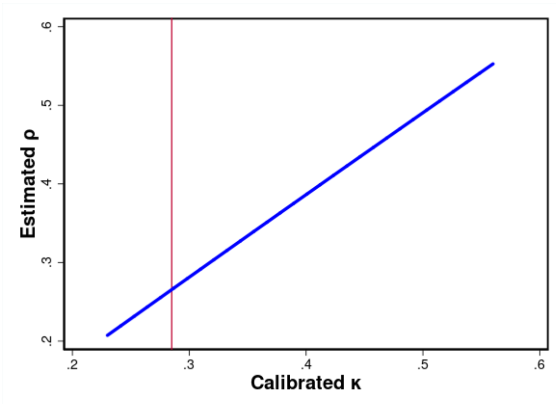
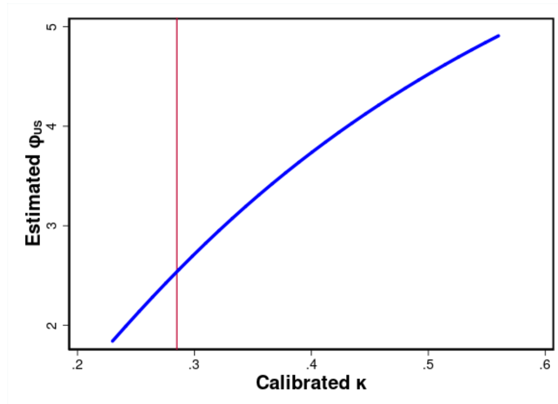


Figure 37: **Effect of a 1p.p. Increase in Innovation on Skilled Wage Premium and Parameters**

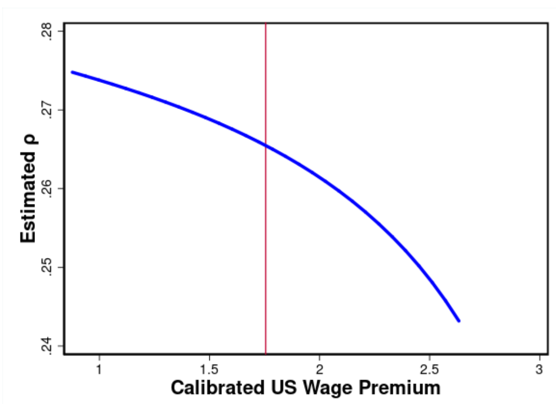
(a) Estimated ρ and calibrated κ



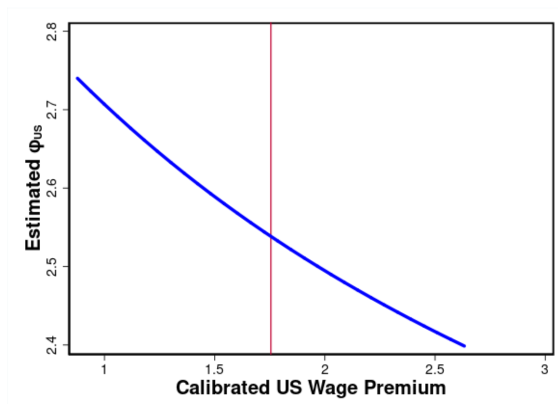
(b) Estimated ϕ_{US} and calibrated κ



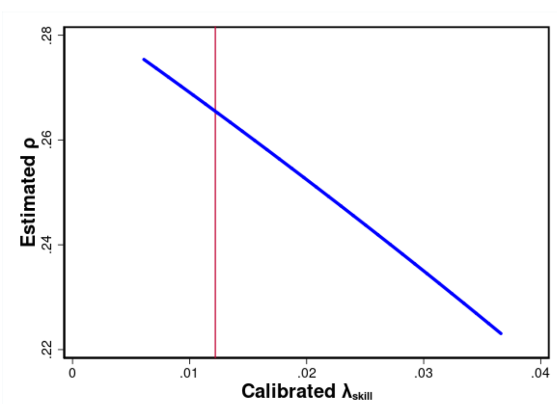
(c) Estimated ρ and calibrated w_H^{US}/w_L^{US}



(d) Estimated ϕ_{US} and calibrated w_H^{US}/w_L^{US}



(e) Estimated ρ and calibrated λ_{skill}



(f) Estimated ϕ_{US} and calibrated λ_{labor}

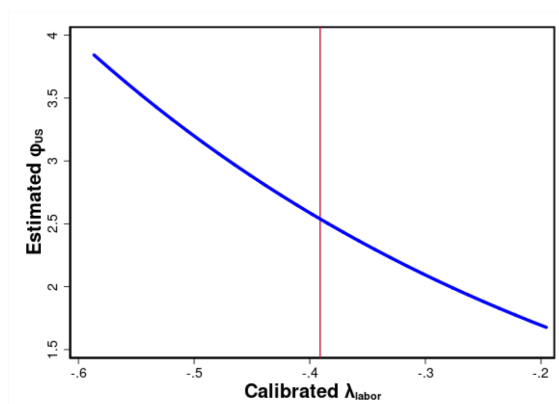


Figure 38: **Effect of a 1p.p. Increase in Innovation on GDP and Wage Premium**

(a) Elasticity of Substitution in the U.S.: κ (b) Mean of Innovation Fixed Cost: μ_ϵ