The Labor Market Consequences of Appropriate Technology

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Abstract

Developing countries rely on technology created by developed countries. In fact, only 5% of patents issued since 1990 are from developing countries. This paper shows using model and data that the dependence of developing countries on technology made by developed countries increase wage inequality in developing countries but leads to higher production. I study a Brazilian innovation program that taxed the leasing of international technology to subsidize innovation. Exploiting heterogeneous exposure, I show that the innovation program led firms to reduce technology licensing from developed countries and to increase the patenting of new technologies. These newly patented technologies are less skill-intensive and of lower productivity, leading to a decline in employment and in the share of high-skilled workers in the firm. I explain these facts with a model of directed technological change and cross-country technology transactions. Firms in a developing country can either innovate or lease technology from a developed country. These two technologies endogenously differ in productivity and skill bias due to factor supply differences in the two countries. I show that the difference in skill bias and productivity can be identified with closed-form solutions by the effect of the innovation program on the firm's expenditure share and employment. Calibrating the model to reproduce these elasticities, I find that increasing patenting by 1 p.p. decreases the skilled wage premium by 0.03% and production by 0.62%.

1 Introduction

Developing countries rely on technology imported from developed countries. Some policy makers and economists argue that this reliance on imported technology leads to lower production and higher inequality in developing countries[1] [2]. The main argument is that the technology created by developed countries is not appropriate to the supply of skills in developing countries. Guided by that, several developing countries have implemented ambitious innovation programs to induce innovation and replace imported technology.

In this paper I ask the following question: In a developing country, what is the effect of replacing imported technology with national innovations? I use a novel dataset on international transactions, patent applications, and employment for Brazil, with exogenous variation from a technology substitution program to show that, contrary to popular belief, innovation policy in developing countries reduces the skill premium and production because it induces the substitution of international technology, which is high-productivity and high-skilled biased, by national technology, which is low-productivity and low-skilled bias. Therefore, the reliance of developing countries on imported technology actually increases production and inequality.

I begin by collecting a novel dataset with information on the innovation, international technology leasing, and employment of Brazilian firms. Innovation is measured by the application of patents and industrial designs to the Brazilian Patent Office, the data is collected by web-scrapping from administrative sources for all the applications since 1985. I construct the dataset with international technology leasing by scrapping information from all the technology leasing contracts engaged by Brazilian firms since 1985[3]. Finally, employment comes from an administrative matched employer-employee dataset. This unique dataset allows me to evaluate how innovation policy affects innovation, technology leasing, expenditure shares,

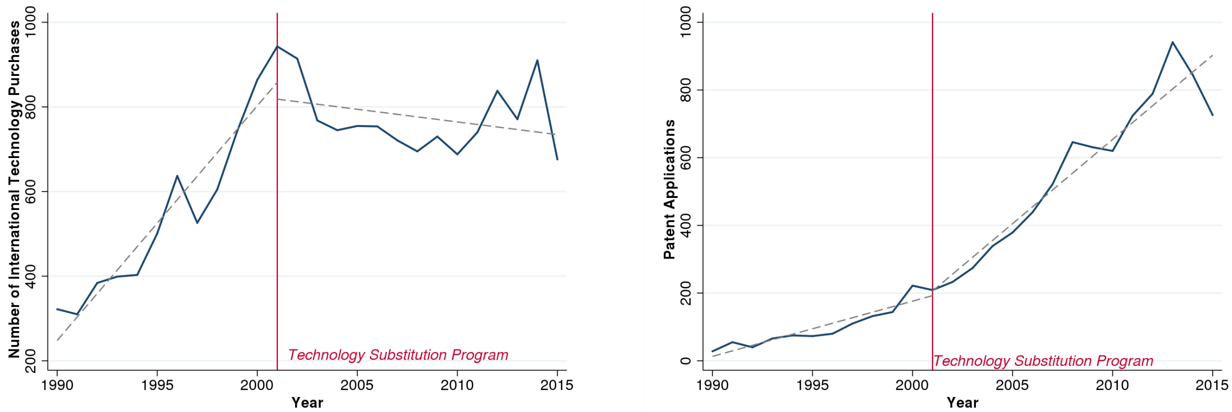
[1] Schumacher (1973), Stewart (1977), Stewart (1987), Basu and Weil (1969), Acemoglu and Zilibotti (2001), and Kaplinsky (2011) are just a few.

[2] See Ely and Bell (2009) for a discussion on innovation policy in developing countries and a discussion of appropriate technology.

[3] According to law, any international technology leasing made by a Brazilian firm has to be registered in the Patent Office for the payment flow to be approved. To complement and validate this unique dataset, I run a survey with intellectual property lawyers who have experience in writing and registering technology contracts in the patent office and conclude that the collected dataset captures real technology transfers and does not suffer from selection.

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

(a) **Int. Technology Purchase** (b) **PCT Patent Applications**



Description: This picture contains time series information on the number of international leasing contracts and patents registered under Patent Cooperation Treaty (PCT). The number of patent applications is from the OECD REGPAT. The number of technology purchases is calculated using data extracted from the Brazilian patent office.

and employment on the firm.

I also gather administrative data on R&D subsidy applications, the import of inputs, and the CV of inventors to test the implications of innovation policy on the use of other inputs and the quality of the inventions.

As an exogenous variation to technology adoption and innovation, I use the Brazilian technology substitution program. In 2001, the Brazilian government created a subsidy to R&D to targeted sectors financed by a tax on the leasing of international technology. As Figure 1 shows, after the program was created there was a slow down in international technology leasing and an increase in the number of PCT patents.[4]

My identification strategy relies on the heterogeneous exposure to the two policy instruments: the subsidy and the tax on technology leasing. Firms in sectors targeted by the subsidy and leasing international technology when the program was created were directly exposed to these two policy instruments. These more exposed firms had larger incentives to innovate; they faced a decrease in the innovation cost and an increase in the cost to use international technology. As is common with difference-in-differences, the identifying

[4] PCT patents are the patents registered under the Patent Cooperation Treaty (PCT). These are registered patents in the Brazilian Patent Office that seek international protection.

assumption is of parallel trends between the exposed and non-exposed groups. I perform a battery of placebo and exogeneity tests that, together with institutional facts, support the assumption of parallel trends.

Using heterogeneous exposure to the technology substitution program, I show that firms targeted by the program changed their technology, factor share, and total employment. I consider as exposed to the program the firms that were leasing technology before the introduction of the tax and on the sector eligible to the subsidy. In 10 years, the firms exposed to the program increased their probability of having at least one patent by 4.47 percentage points compared to the non-exposed firms, i.e., an increase of 2.5 the mean of the period. The exposed firms also increased the expenditure share with high-school dropouts by 5.3% and the average education of their labor force by 4%. The firms more exposed to the program also reduced their wage bill by 19% in the 10 years after the program.

These findings can be rationalized by a model of endogenous technology bias and international technology leasing. In the model, firms in Brazil have to choose between innovating or paying a fixed cost to lease technology from the United States. Brazilian innovating firms can choose their technology bias but are subject to operate a technology with lower productivity. Firms leasing international technology have the technology bias chosen by the foreign firm but enjoy higher productivity. Because of the factor supply difference in the two countries, U.S. inventions are high skill biased compared to Brazilian inventions.

The model predicts that innovation policy in developing countries decreases skill-premium and production. Innovation policy leads firms to switch from leasing international technology from developed countries to in-house innovations. Because these two technologies differ in productivity, firms switching technology reduce their overall production. Moreover, because these two technologies differ in skill bias, firms increase their relative demand for low-skilled workers. In equilibrium, the skill premium and aggregate production decrease.

The model delivers closed-form solutions linking the empirical estimates to the model parameters. Using the micro-elasticities, I estimate the important parameters of the model and determine how innovation affects the skill premium and production. The calibrated model predicts that increasing the share of firms with patents by 1 percentage point through an R&D subsidy decreases production by 0.62% and the wage premium by 0.03%. This result is driven by the difference in TFP across technologies, identified by the effect of the program on employment, and difference in skill bias, identified by the effect of the program on the composition of workers. The large effect on production shows that the difference in the TFP of technologies across countries is much stronger than the difference in skill bias.

One could be concerned that a simple static model with only two technologies might not capture the dynamics and complexity of technology choice. Specially, a model with only two technologies ignores the dynamic component of innovation and its replacement of old and low-TFP technology. To address this, I estimate a full dynamic model of endogenous directed technological change and technology transactions. Firms are subject to idiosyncratic TFP and skill-biased shocks. In every period, firms decide if they want to update their technology or keep their previous technology. If firms decide to update their technology, they have two options. They can innovate by themselves or lease technology from the US. Again, the model is estimated to reproduce the empirical micro-elasticicities and deliver similar quantitative results.

I show through various empirical strategies support for the conclusion of cross-country differences in technology skill bias and TFP, the driving force of my conclusion. I show backing for this claim by studying adjustments in inputs, heterogeneity in the effect of the technology substitution program, event-studies with the introduction of new technology, diff-in-diff with applications to R&D subsidy, heterogeneous exposure to minimum wage, regional differences in technology adoption, and the text analysis of patents. These numerous different approaches all provide evidence that technology bias is directed towards abundant factors and that international technology has higher productivity.

This paper has two main contributions to our understanding of directed technological change. First, I show using credible exogenous variation and micro-data that technologies created in a developing country are less intensive in high-skilled workers, which indicates that technology intensity correlates with factor shares. This is the first micro-level evidence of endogenous directed technological change. Second, this paper also quantifies the macroeconomic implications of the reliance of developing countries on technologies made by developed countries, which is important to explain cross-country income differences and design policies.

This paper is related to the literature on appropriate technology. Stewart (1977), Drandakis and Phelps (1966) and Atkinson and Stiglitz (1969) were the pioneers to discuss directed technological change, introducing the idea that technological progress is concentrated on specific technologies. For instance, a genetically modified seed would increase the production of farming activities but would have lower spillovers to manufacturing. Basu and Weil (1969) use this idea to explain why developing countries do not directly benefit from technological progress in developed countries. In their model, developing countries can still sustain large growth by merely implementing obsolete technologies from developed countries.

Acemoglu (1998), Acemoglu (2002) and Acemoglu (2003) develop a theory of endogenous directed technological change. Firms need to choose between producing machines that are complements to high-skilled or low-skilled workers. Which type of worker technology is going to complement is shaped by two effects. The first one is the price effect. If sectors intensive in high skilled workers have a higher relative price, technological progress will be directed to high-skilled workers. Because the price reflects scarcity, the price effect drives technological progress toward scarce factors. The second effect is the market size effect, where innovation targets the most abundant factor. Which effect is the dominant depends on the elasticity of substitution between the factors of production. If the factors are gross complements, i.e., their elasticity of substitution is below one, the scarcity effect dominates, and technological progress is directed to the most scarce factor.

Acemoglu and Zilibotti (2001) is the closest to this paper. Using a model of directed technological change, they showed how growth in developing countries is slowed by relying on the technology of the developed world. They found evidence for their conclusion using cross-country comparisons.

I contribute to this literature by showing through the data and model that the factor bias of a developing country's technology is different from that of a developed country's technology, which provides evidence for the claim that the technology of developed countries is inappropriate for developing countries. Still, despite having a suboptimal skill bias, I find that the technology of developed countries has overall higher TFP. Therefore, despite having sub-optimal skill bias, the technology of developed countries is still more efficient to use in developing countries than home-made inventions.

The model estimated in this paper builds on Jones (2005), Caselli and Coleman (2006), and León-Ledesma and Satchi (2018). In this branch of the endogenous directed technological change literature, firms select not only input quantities but also technology. Firms need to trade off factor efficiency in the production function according to a technology frontier. They show that firms use the most expensive production factors more efficiently. Caselli and Coleman (2006) use this result to explain cross-country differences in the efficiency of high- and low-skilled workers implied by a growth accounting method.

I contribute to this literature by showing the implications of directed technological change to innovation policy in developing countries and estimating the key parameters of the model using microdata and a credible exogenous variation. In this paper, I extend the model presented in the studies of Caselli and Coleman (2006) and León-Ledesma and Satchi (2018) to quantify the macroeconomic implications of innovation. I expand the model proposed by Acemoglu and Zilibotti (2001) by allowing the developing country to create their own technology. I show that these simple model extensions have important predictions for innovation policy, production, and skill premium with uncertain aggregate effects. Up to this point, the literature on endogenous directed technological change has relied on cross-country comparisons to find evidence for their theoretical claims. As is widely known, these methodologies are subject to omitted variable bias and reverse causality concerns. This paper presents the first effort to overcome these difficulties. Using microdata, I identify the key parameters of the model and confirm its predictions for the effect of innovation policy.

This paper also contributes to the literature that studies the effect of technological progress on the labor market.

Krueger (1993) shows that the introduction of computers increased wages and the skill premium, while Autor et al. (2003) show that computerization leads to a change in the type of tasks performed by workers. Akerman et al. (2015) show that the adoption of broadband internet is a skill-biased technological progress. Meanwhile, Acemoglu and Restrepo (2020), de Souza and Sollaci (2020), Koch et al. (2019), Bessen et al. (2019) and Graetz and Michaels (2018) has show that robots replace workers and decrease wages.

I contribute to this literature by showing that technological progress is not necessarily skill biased and driven by automation. Using a model and data, I show that innovation in developing countries is low skill biased. Moreover, I show that an innovation subsidy lead

Brazilian firms to reduce the imports of labor saving machines, and the hiring of workers that install, operate or make maintenance of robots. Therefore, Brazilian technological progress is not skill biased or driven by automation.

2 Data

I collect from various administrative sources firm level data on employment, imports, and applications for R&D subsidy. I extract from the Brazilian Patent Office web-page data on patents, industrial designs, trademarks, and technology leasing. To validate the dataset on technology leasing, I run a survey with intellectual property lawyers. From the webpage of the Ministry of Science I extract data from the CV of inventors.

Technology Lease Brazilian firms leasing or reassigning intellectual property from any firm in the world must register their contracts on the Brazilian patent office. This paper uses data extracted from all the technology leasing contracts registered in the Brazilian patent office to understand how innovation and international technology leasing affects the macroeconomy.

Firms are either required or have incentives to register their technology contract on the patent office. This feature guarantees a representative sample of all technology transactions can be collected. If the contract is signed with a firm outside Brazil, firms must register the contract in the patent office for the international transfer of payments to be allowed by the Central Bank[5]. If the contract is signed between two Brazilian firms, the lessee is eligible to tax benefits if the contract is registered in the patent office.[6]. Therefore, all international technology transactions and a sample of national technology transactions are registered in the Brazilian Patent Office.

[5]The requirement to register technology transactions in the Patent Office was created by law nº4.131 in 1962, during the period of capital controls in Brazil. The goal of the requirement was to limit the payment of royalties and make it harder for firms to break the capital control regulation. After the capital control was lifted, the government still maintained this requirement. Section A.1 discuss all the regulations on technology transactions in Brazil.

[6]The corporate tax break on royalty payment was created in 1958 by law number 3.470. The decree number 3000 of 1999 create conditions to this deduction. According to this decree, to have tax deduction the firm must register its transaction in the patent office and the technology transfer cannot be signed between headquarters and subsidiary.

The patent office does not have a simple passive role: based on the description of the contract, it can either accept, reject or demand changes to it. This feature ensures that each transaction is indeed capturing real technology transfer between firms. A contract is rejected if a board of technicians concludes that there is no significant transfer of technology or know-how in the transaction. More information is required when the documentation provided is not informative about the ownership of the technology or it does not prove the transfer of know-how or intellectual property. About 70.5% of the contracts had extra information being required while 3.2% of them were denied. On appendix A.5 I discuss in detail the process of registration and inspections of technology contracts.

By scrapping information from the patent office webpage, I construct a dataset with information on all technology transactions registered in the Brazilian Patent Office. For transparency, the patent office allows the public to consult their contract database. By scrapping information from technology transaction contracts, I construct a dataset with the name of the firms involved, a description of the contract or service offered, value, sector of the buyer, country of origin and the type of the contract[7]. Moreover, I also observe the interaction of the firm registering the contract with the patent office. A full set of statistics on technology transactions is provided in appendix A.3. Moreover, appendix A.2 describes in detail the steps taken to create this unique dataset.

The technology contracts, as provided by the patent office, have firm names but not tax identifiers. To identify 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 has ever opened in Brazil before 2019. These two datasets together provide several spellings of firm name for the same tax identifier which allows to merge across dataset using exact match and keep a high match rate while minimizing the occurrence of false matches. On appendix A.4 I describe in detail all the steps to find firms' tax identifiers and the quality of the match.

This is the first time a dataset registering technology origin at the firm level has being used. To evaluate its extension and ability to measure real technology transfers across firms,

[7]The description of the technology transferred and the value of the contract is not observed for all contracts.

I run a survey with intellectual property lawyers, which are specialized in writing and registering technology transfers. The survey indicates that registering technology transactions is costly, bureaucratic and requires technical documentation. Moreover, the universe of international technology transfers are registered in the Brazilian patent office and firms are unlike to fake technology transactions for tax purposes. Details on the survey and further statistics are provided on appendix A.6.

Table 1 shows basic statistics of technology transactions in Brazil. It indicates that technology transactions are over know-how, i.e., knowledge not protected by property rights, and represents a large investment for the firm. The first panel of table 1 breaks down the number of technology contracts according to its type. Know-How Transfer are contracts in which the buyer acquire a technology from the seller that is not protected by property rights[8]. This contract type represents about 79% of all transactions. The panel two indicates that there are 5,484 unique buyers. Appendix A.3 shows that the median firm engage in one transaction but a small set of very large firms routinely are lessee of technology. Panel 2 also indicates that only 3% of contracts are signed between branches of the same firm. The final panel shows that the average technology price is above one million dollars. Appendix A.3 describes in detail statistics of technology transaction in Brazil.

Patent, Trademark and Industrial Design Applications To measure firm's innovation efforts, I collect a dataset with information on patents, trademarks and industrial design applications submitted to the Brazilian Patent Office. Using this large set of intellectual property objects I can construct different measures of innovation at the firm.[9]

The dataset with information on patents, trademarks and industrial designs is constructed by scrapping information from the Brazilian patent office. It contains the universe of patents, trademarks and industrial designs submitted to the Brazilian patent office between 1995 and 2015.

[8]For instance, patent, trademarks and industrial design do not fell in this class.

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

Table 1: **Statistics on Technology Transaction Inspections by Patent Office**

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

Description: This table presents statistics of technology transaction applications made to the Brazilian Patent Office between 1995 and 2015. 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 transactions 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 transactions.

For each patent I observe the date of submission, the name of the company who owns the patent, the name of the inventors, the CPC and IPC classes, if the patent was accepted by the patent office, a dummy if the patent owner seeks international protection, the title of the patent, and a description of the patent. For each industrial design application I observe the date of submission, the name of the company who owns the industrial design, the name of the inventors, the class, if the industrial design was accepted by the patent office, and the title. For each trademark I observe the the date of submission, the type of the trademark, the class of the trademark, if the trademark was accepted, and the owner of the trademark.

To match across datasets I find firm tax identifiers using exact match on firm names in RAIS and the Firm Registry database, the same approach implemented for technology transactions. Appendix A.10 shows that there is no statistical difference between matched and not matched patents and I am able to match 86% of patents owned by firms.

Table 2 show a set of baseline statistics of patents, trademarks and industrial designs in Brazil. Appendix A.7, A.8 and A.9 gives a full set of statistics on this database.

Table 2: **Statistics on Technology Transaction Inspections by Patent Office**

	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 of patents, trademarks and industrial design applications submitted by Brazilian firms and inventors to the Brazilian Patent Office. The first line shows the number of different patents, trademarks and industrial designs. The second line contains the number of unique applicants submitting applications of 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. On the trademark database there is no author identifier.

R&D Subsidy Applications and Recipiency I use an administrative dataset on applications for federal R&D subsidies to identify exposure to R&D subsidy programs.

The R&D subsidy applications data is from the Funding Authority for Studies and Projects (*Financiadora de Estudos e Projetos*), FINEP. FINEP is the federal agency responsible to assign R&D subsidies and tax breaks to firms. FINEP is divided in 16 technical committees. Each committee is responsible to select innovation projects on their field according to a pre-determined technical criteria. FINEP can provide a cash transfer, subsidize credit or tax break for the selected firms.

I observe information on all subsidies for R&D given by FINEP since 2000. I observe the name of the firm, tax identifier, value of the subsidy, description of the project, sector of the project and type of subsidy. Moreover, for a subset of subsidies, those granted through public calls, I observe not only the firms receiving the subsidy but the ones applying for it. Appendix A.11 describes in detail the application and selection process of firms for federal subsidy. It also shows detailed statistics on R&D subsidy in Brazil.

Table 3 shows that a small set of firms applied and received R&D subsidy. But, for the ones that received subsidy, it was a large support corresponding to more than 3 times the yearly wage bill in average. The appendix A.11 shows that firms receiving R&D are larger, more intensive in skilled workers and concentrated in manufacturing.

CV of Inventors To measure the quality of inventions, I create a dataset with information extracted from the CV of inventors of patents and industrial designs. The CVs are gathered from the Lattes Platform, a administrative database of academic CVs.

The Lattes Platform was created in 1993 for R&D planning and monitoring of academic research by the Brazilian federal government. Having an updated CV hosted in the Lattes

Table 3: **Statistics on Technology Transaction Inspections by Patent Office**

Statistic	**Value**
Number of Firms	2,437
Number of Subsidies	9,925
Avg. Subsidy (in thousands of dollar)	2,140
Median Subsidy (in thousands of dollar)	386
Avg. Subsidy/Yr. Wage Bill	3.22

Description: This table shows statistics of R&D subsidy applications in Brazil. The data is from the Funding Authority for Studies and Projects and contain statistics on all subsidies granted from 2000 to 2018.

Table 4: **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.

Platform is required for several scientists, academics, and PhD students. Researchers on institutions receiving federal support; RAs, masters, and PhD students receiving financial support from the federal government, and those applying for R&D subsidy, stipend, research grants, and any other government provided research assistance are required to have an updated CV uploaded in the Lattes Platform. It's widely used by Brazilian scientists as their main webpage.

Table 4 shows statistics of Brazilian inventors. From the total of 102,775 inventors of patents or industrial designs, 32,505 (31,6%) have a CV uploaded to the Platform Lattes. Assuming that inventors without CV in the platform Lattes does not have PhD, published papers or academic positions, about 13% of inventors have a doctorate degree, 26% has ever published an academic paper while 17% has ever being hired by an university.

Imports of Materials and Machines To identify how innovation and technology adoption affects the use of inputs other than labor, I construct a dataset containing 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 this dataset is described in de Souza and Sollaci (2020).

Matched Employer-Employee Data The main source of labor force information is the administrative dataset RAIS - *Relação Anual de Informações Sociais.* It is collected by the Brazilian Ministry of Labor and covers the universe of formal firms. Its use has been widespread in different areas of economics in recent years[10]. In RAIS, each observation contains yearly information on a worker where firm's and worker's tax ids are observable. With this information, I can link workers and firms over time within RAIS and across databases. It also contains, since 2002, the name of the company. Which is useful to match across datasets even when the other dataset does not contain a tax identifier.

RAIS contains data on employment, worker demographics and firm characteristics. I observe wages, hours of work, date of hiring/firing, the establishment of work and occupation. I also observe workers' demographic characteristics: age, gender, education, and race. Firms' sector and establishment locations are also observed.

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.

Facts on Innovation and Technology Transactions On section A.13 in the appendix, I show three new facts on innovation and technology transactions in Brazil. First, Brazilian firms lease technology from developed countries. About 87% of technology leasing contracts are between a Brazilian firm and a firm in a developed country. Second, Firms leasing technology are larger than firms innovating. Third, firms innovating are more intensive in high school dropouts than firms innovating.

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

3 Institutions: Technology Substitution Program

In 2000 the Brazilian government implemented a policy to stimulate innovation and discourage international technology purchase. The policy provided subsidies, credit and tax break to approved innovation projects. These expenses are financed by a 10% tax on payments of international technology. As a consequence, this policy foments national technology creation and discourages international technology leasing. Therefore, I call it the *Technology Substitution Program*[11].[12]

The revenue raised by the tax on technology leasing is administered by the Funding Authority for Studies and Projects (*Financiadora de Estudos e Projetos*), FINEP, and allocated to specific sectors. Innovative firms on the targeted sectors can apply to the FINEP to receive a subsidy for their research. The selection of subsidize projects is based on a technical criteria established and judged by a technical committee in the FINEP. The revenue raised by the tax on technology leasing is transferred to 5 committees. Each committee is specialized in a sector and composed of scientists and policymakers specialized in that field. The technical committees are responsible to select the projects supported by the FINEP. An innovative firm interested in receiving support from the government must apply to the 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 pre-determined technical point system. The projects with the highest score are funded. Therefore, the technical decision making minimizes the political meddling in the allocation of subsidies.[13]

This set of policies did not only encouraged innovation, it also discouraged leasing of technology from abroad. Therefore, in practice, it stimulated technology substitution. Figures A.12 to 2d indicate how significant the TSP is to the Brazilian innovation efforts. After the TSP was introduced, the number of technology purchased from outside of Brazil decreased,

[11] The program was originally created under the name "Innovation for Competitiveness" (*Programa de Inovação para Competitividade*)

[12] Firms leasing technology from abroad have to justify the international movement of capital to the Central Bank. In case they were paying royalties for the transference of know-how, patents, industrial design or other industrial intellectual property rights, they were required to pay 10% of the transferred value as taxes. Intellectual property transactions between national firms are also subject to the tax.

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

as shown in figure A.12. At the same time the rate of innovation increased with the introduction of the program. There was an increase in the number of PCT patents, number of patents and industrial designs sent to the Brazilian patent office and the number of inventors in Brazil.

In appendix A.12 I show using cross-country synthetic control and diff-in-diff that there was an increase in Brazilian patenting compared to other countries as response to the TSP. This results reinforces the idea that the TSP led firms to innovate and reduce technology purchase.

In appendix A.14 I show that the program wasn't predicted, it wasn't created as response to trends in the labor market, that the subsidized sectors were selected based on past outcomes, and that the tax on technology transactions wasn't created with a specific policy goal. These features will be important for the identification strategy I use.

4 Empirics

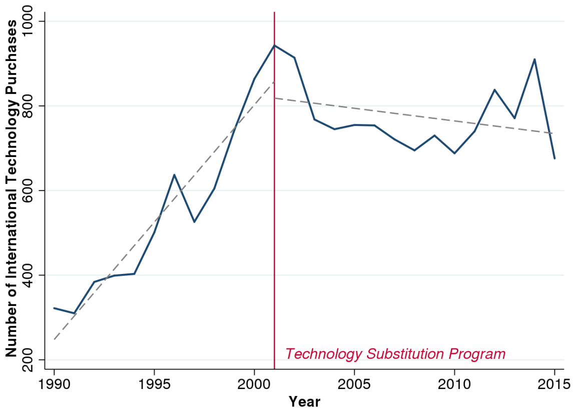
In this section, I evaluate the effect of the Brazilian technology substitution program on innovation, factor shares, and employment.

My main identification strategy relies on heterogeneous exposure to the Technology Substitution Program (TSP). The program created an innovation subsidy target at specific sectors financed by a tax on the international leasing of technology. The firms most exposed to the program were the ones in the sectors targeted by the subsidy who relied on international technology when the program was introduced.

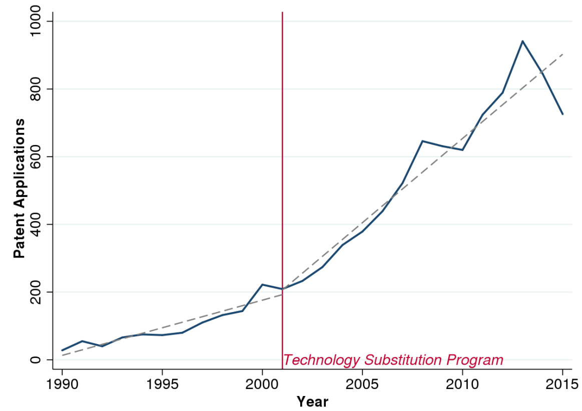
The diff-in-diff with heterogeneous exposure passes important validation and placebo tests. First, institutional facts guarantee that the TSP was unpredicted and not based on future shocks, which ensures no anticipation and exogeneity to predictable future shocks. Second, exposure to the TSP is not correlated with other policy changes and aggregate shocks happening in the period, such as tariff change, tax change, federal loan, federal demand, and international prices. Third, firms did not use other methods of technology transfer such as FDI in response to the TSP, reinforcing the idea that the program affected cross-country technology transfers. Fourth, a placebo test with fake implementation year

Figure 2: **Technology Substitution Program and Innovation**

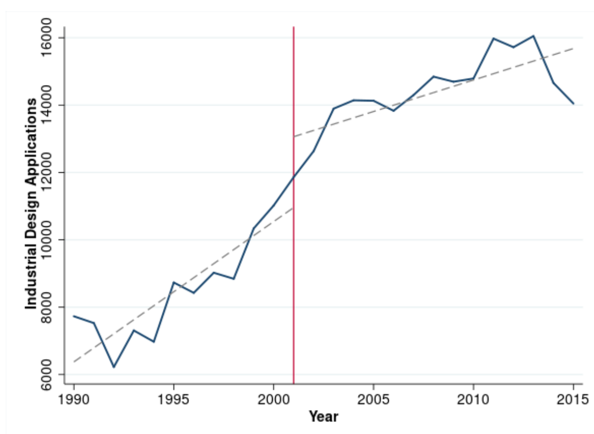
(a) **Int. Technology Purchase**



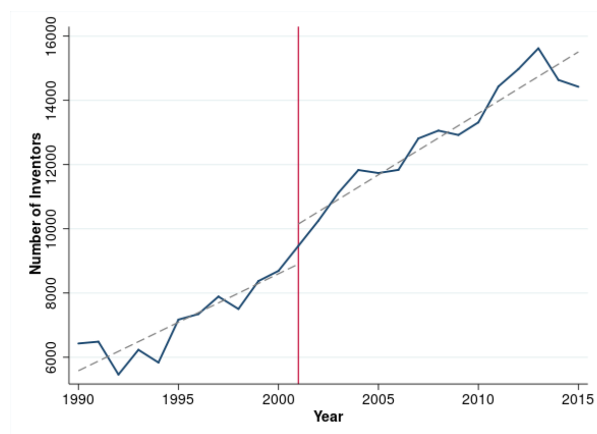
(b) **PCT Patent Applications**



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



(d) **Number of Inventors**



Description: This picture contains time series information on the number of scientists in the Brazilian private sector (excluding universities), the number of patent applications, the number of contracts signed and the share of firms using Brazilian technology. The number of scientists is calculated using RAIS. A scientist is defined as workers classified in occupation 20 of the CBO02: researchers and science professionals. A cross-walk to CBO94 is constructed to extend this class to years where the CBO02 is not available. The number of patent applications is from the OECD REGPAT. The number of technology purchases is calculated using data extracted from the Brazilian patent office.

deliveries no result, as expected, supporting the idea that the variation identified comes from the program introduction. And fifth, a placebo test with firms not exposed to the program supports the idea that results are not driven by aggregate shocks affecting the exposed firms.

Firms more affected by the TSP increased their patent applications, increased the expenditure share with low skill workers, and reduced overall employment. These results are robust and cannot be explained by the direct effect of the tax on international leasing, changes in the type of product produced, changes in the quality of innovation, or the adoption of robots.

The increase in expenditure share and reduction in employment can be explained by firms substituting international technology for national technology. While international technology is high TFP and high-skilled bias, national innovations are low TFP and low-skilled bias. The difference in technology TFP generates a drop in employment when firms change technology while the increase in expenditure share with low-skilled workers is explained by the difference in bias. The simple model in the next section will formalize the intuition.

4.1 Sample Selection

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

Innovation and technology leasing is an activity mostly 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[14].

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 transaction. I only consider technology transactions the ones involving patents, industrial designs, and know-how. Therefore, I drop

[14] 30 workers is the bottom decile among firms applying for a patent.

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.

4.2 Empirical Strategy

The Technology Substitution Program created a R&D subsidy for firms in selected sectors and a tax on the leasing of international technology. The firms more affected by this program were the ones on sectors supported by R&D subsidy that now have to pay higher taxes on their technology lease. I use the variable $\textit{Exposure TSP}_{i,s(i)}$ to define these firms:

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

The dummy $\mathbb{I}\left\{\textit{Subsidy } s(i)\right\}$ takes one if the firm is in one of the 2 digit sectors targeted by the R&D subsidy while $\mathbb{I}\left\{\textit{Leased Tech. Before TSP}\right\}_i$ is a dummy taking one if the firm has ever leased international technology before the introduction of the program, this dummy captures the reliance of the firm on international technology[15].

The exposure measure in 1 takes one for the firms with largest incentives to change technology. These firms had in one hand a decrease in the cost of innovation, due to the subsidy, and in the other an increase in the cost of using international technology, due to the tax. Therefore, these firms should be the ones most likely to change technology. In the model section I show that the choice of this exposure measure is supported by the model and is informative about permanent characteristics of the firm.

My main specification is given by

$$y_{i,s(i),2010} - y_{i,s(i),2000} = \theta \textit{Exposure TSP}_{i,s(i)} + X'_{i,s(i)}\beta + \epsilon_{i,s(i)} \tag{2}$$

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. $\textit{Exposure TSP}_{i,s(i)}$ is the exposure measure defined in 1. $X_{i,s(i)}$ is a set of

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

controls[16]. Standard errors are clustered at the sector level.

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

Specification 2 identifies θ by differences-in-differences. It compares the growth rate in outcome y between the firms more exposed to the program, the treatment group, and the ones less exposed to the program, the control group. As usual in differences-in-differences, the identifying assumption is parallel trends between control and treatment groups. Also due to the use of differences-in-differences, we cannot say anything about aggregate effects. In special, 2 is uninformative about the effect of the policy on wages and production.

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

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

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

4.3 Validation

There are several supporting evidence for the assumption of parallel trends. The program introduction was unexpected and not a response to future shocks, the government targeted sectors based on pre-period characteristics, there is no pre-existing trend between treatment and control groups, the exposure to the TSP does not correlate with other programs and the exposure to the TSP does not correlate with aggregate shocks hitting the Brazilian economy.

[16] Controls are 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, and the growth in a dummy if the firm ever had a PCT patent.

As discussed in section 3, the TSP was unexpected and not a response to future shocks. The TSP was unexpected because it was created and approved in a regiment of urgency in a period the government was coming from tax cuts. The TSP was not a response to future shocks, in fact, its goal was to induce research in sectors of Brazilian comparative advantage, such as agriculture and aviation. Therefore, the program motivation has nothing to do with future labor market changes affecting these sectors.

If the exposure measure 1 correlates with other policies implemented in the period, such as tariff or tax changes, we won't be able to tease apart the effect of TSP from the effect of other policies. To test if this concern is valid, I run specification 2 on a set of policy outcomes affecting firms. Table 37 on appendix B.1 shows that control and treatment groups are equally exposed to changes in input tariffs, output tariffs, government loans, demand from the government through federal contracts, labor taxes, and overall tax payment. Table 37 also shows in column 8 that firms on the treatment group engaged in campaign contributions as much as the control group, evidence that they are equally politically connected and equally targeted by governmental benefits. Table 37 supports the idea that the exposure measure 1 does not correlates with other policies implemented in the period.

If firms can get around the tax on technology leasing by transferring technology through foreign direct investment we would not be able to identify the effect of technology substitution. I test if firms have increased FDI as response to the TSP in table 36. I run the baseline specification 2 on a dummy taking one if the firm is owned by an international headquarter. Table 36 shows that firms did not increased FDI as response to the TSP.

Another concern comes from the 2000's commodity boom. It could be the case that changes in international prices affected more the treatment group than the control group. In this case, I would not be able to tease apart the effect of the TSP from the effect of international price changes. Table 36 shows that the international price change for products and inputs is the same for the treatment and control group.

Another concern left to be tested is if the exposure measure 1 correlates with other shocks affecting the economy. For instance, it could be the case that an aggregate shock affected large firms more than smaller ones[17], this shock would then affect more the treatment group

[17]Such as the exposure to trade competition from China, or a shock to the terms of trade.

than the control group because size correlates with international technology leasing. To test for the potential existence of these shocks, in appendix B.4.1 I perform a placebo test where I match each firm on the treatment group to a firm in the control group based on the number of workers, average wage, the share of high school dropouts and location in the pre-period following Iacus et al. (2012). In appendix B.4.1, I show that assuming these firms to be the treated group while dropping the real treated firms does not lead to the same effects as in the main results. This proves that there is no shock correlated with observable matched characteristics affecting firms.

The exposure measure 1 uses a past firm outcome: the firm's decision to lease technology. This fact brings two identification concerns. First, the firm's decision to lease technology could be a response to a future shock. In this scenario, we would not be able to tease apart the effect of the shock from the effect of the TSP[18]. A second identification concern comes from the effect of the past technology leasing itself. It could be the case that leasing a technology in the past itself affects the labor composition of the firm. I evaluate the validity of these concerns with a placebo test using a fake TSP implementation year, robustness with different timings to the technology leasing, and add controls to capture the effect of technology leasing. The results of these robustness exercises support the idea that specification 1 is not capturing future shocks nor the effect of technology leasing.[19][20]

4.4 Empirical Results

In this section, I show that as a response to the Technology Substitution Program firms increased their patenting, increase their expenditure share with low-skilled workers, and

[18]For instance, it could be the case that firms lease technology because they expect the quality of high skill workers to increase in the future. In this scenario, we won't be able to tell apart the effect of an increase in the quality of high skilled workers to the effect of the TSP.

[19]Appendix B.4.2 describes in detail the result with fake implementation year, B.3.4 adds controls that capture the effect of technology leasing in the past while the results with a different dummy for technology leasing is discussed in the robustness section.

[20]This does not mean that the leasing of international technology does not affect the firm. On average, the firms in the treatment group have signed 4 technology contracts. Therefore, those are experienced firms that have already adjusted their labor market outcomes to the use of international technology. Therefore, any effect due to the leasing of international technology is in the past and already captured by the fixed effects. On section F I implement an event-study on the leasing of international technology and show that it's effect on the labor composition of the firm is quick and permanent, which supports the idea that the effect of technology leasing is absorbed by the fixed effect.

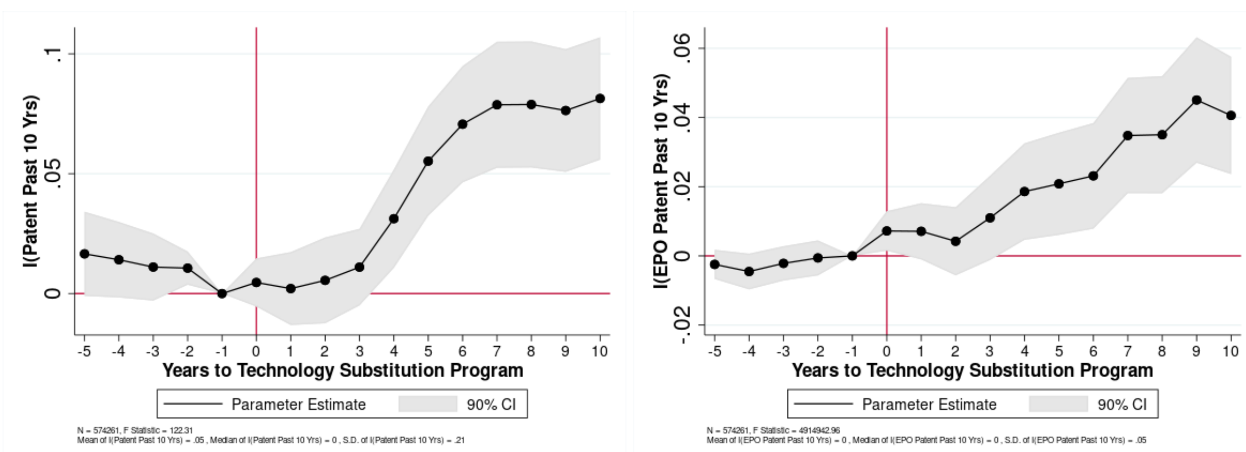
reduced total employment.

4.4.1 Effect on Innovation and Technology Adoption

Firms increased their patent applications in response to the technology substitution program, according to figure 3. Figure 3a displays the coefficients of regression 71 on a dummy taking one if the firm made a patent application to the Brazilian patent office in the past 10 years while figure 3b displays the coefficient of a regression on a dummy taking one if the firm submitted a patent application to the European Patent Office (EPO) under the Patent Cooperation Treaty (PCT). Because PCT patents have worldwide protection and are more costly to get, those are a measure of high-quality inventions. This result indicates that firms increased both its overall number of patents and its high quality patents.

Figure 3: **Innovation and Exposure to the TSP**

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



Description: Figure 3a contains the estimated parameter of model 71 on a dummy taking one if the firm applied for a patent in the Brazilian Patent Office in the past 10 years. Figure 3b contains a dummy taking one if the firm applied for a patent in the European Patent Office. The data is 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 in the past 10 years in 2000, and the growth in 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.

Firms more exposed to the TSP increased their innovation effort as measured by the application for patents, industrial designs, trademarks, and were more likely to receive R&D subsidy. Table 5 shows that firms exposed to the program increased their patenting by 4.7 p.p. compared to the less exposed firms, which is an economically significant impact: it represents 2.5 times the average change in patenting in the economy. Table 5 also shows that the 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 design and, in column 4, to apply for any intellectual property protection, which includes patents, trademarks, or industrial designs. The last column of table 5 shows that firms in the treatment group had a 1.7 p.p. higher probability of receiving the subsidy.

Table 5: **Innovation in Past 10 Years and Exposure to the TSP**

	(1) $\Delta\mathbb{I}\{Patent\}$	(2) $\Delta\mathbb{I}\{EPO\ Patent\}$	(3) $\Delta\mathbb{I}\{Patent\ or\ Ind.\ Design\}$	(4) $\Delta\mathbb{I}\{Any\ Intelec.\ Prop.\}$	(5) $\Delta\mathbb{I}\{Subsidy\}$
Exposure TSP	0.0478***	0.0379***	0.0440***	0.0330*	0.0177**
	(0.0155)	(0.0111)	(0.0164)	(0.0197)	(0.00739)
N	33692	33692	33692	33692	33692
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 presents the estimated parameters of a regression of the exposure to the TSP on measures of changes in intellectual creation by the firm. $\mathbb{I}\{Int.\ Patent\}$ is a dummy taking one if the firm has ever applied for an international patent, $\mathbb{I}\{Scientist\}$ is a dummy taking one if the firm has ever hired a scientist, $\mathbb{I}\{Patent\}$ is a dummy taking one if the firm has ever applied for a patent, $\mathbb{I}\{Trademark\}$ is a dummy taking one if the firm has ever applied for a trademark and $\mathbb{I}\{Industrial\ Design\}$ is a dummy taking one if the firm has ever applied for an industrial design. 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, and the growth in 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 os scientists, Ph.D. workers, and patents by high-quality inventors in response to the TSP. Table 38 in the appendix shows that in response to the TSP firms increased the hiring of workers with doctors or master degrees, the hiring of workers in scientific occupations, the patents created by inventors with a Ph.D. degree, and the patents create by inventors with an academic background. These results support the idea of an overall increase in innovation at the treated firms compared to the control group.

Firms reduced their absolute and relative use of international technology. Figure 32 on appendix F shows that firms exposed to the program became less likely to lease technology and signed fewer technology contracts. Table 43 in the appendix shows that firms increased the share of national technology on their relative intangible capital, which is explained by an increase in innovation and a decrease in the leasing of international technology.

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

4.4.2 Effect on Expenditure Shares

Firms exposed to the TSP increased their expenditure share with high school dropouts and reduced the expenditure share of workers with high school completion. Firms exposed to the TSP increased their expenditure share with high school dropouts by 5.3 p.p. compared to the control group, as table 6 shows. In response to the TSP, firms reduced their expenditure share of workers with high school completion and slightly increased the expenditure share of workers with high school or more. Column 4 in table 6 indicates that firms exposed to the program reduced the average years of education of its labor force by 4%. Table 44 in the appendix reproduces table 6 using factor shares and show that the results are similar. Table 45 shows that firms exposed to the TSP reduced abstract and non-routine task content.

Table 6: **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

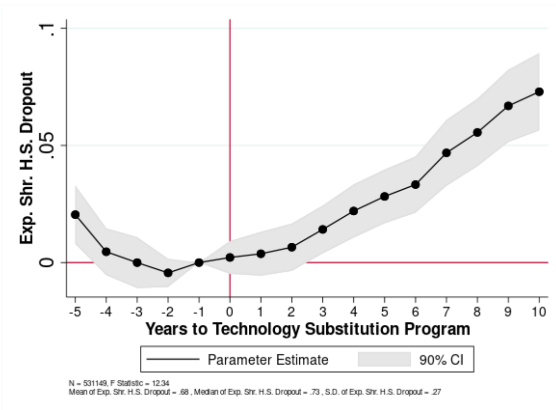
Description: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of education at the firm. *Exp. Shr. Dropout* is the expenditure of the firm with H.S. Dropouts divided by the Wage Bill of the firm, *Exp. Shr. HS Complete* is the expenditure of the firm with H.S. Complete divided by the Wage Bill of the firm, Δ *Exp. Shr. HS More* is the expenditure of the firm with H.S. More divided by the Wage Bill of the firm and log(Yrs. Educ.) is the log of the average years of education on the firm. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period. Standard errors are clustered at the 5 digit sector classification.

Figure 4 also shows that the results are not driven by a pre-period trend. Figure 4a appears to show a weak decreasing trend which reverts with the introduction of the program while figure 4b does not shows any clear trend. In section B.3.3 in the appendix, adds as control a linear trend and shows that the results are still the same.

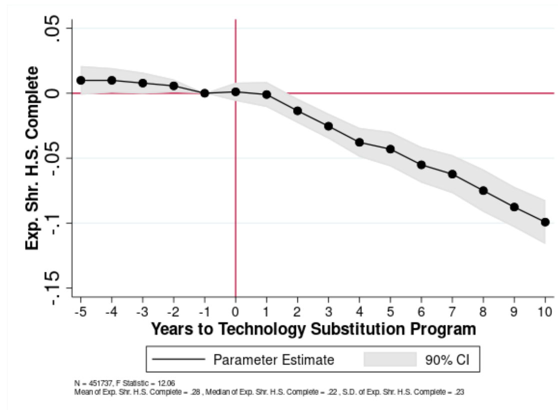
In conclusion, in response to the TSP firms increased the expenditure share with low-skilled workers.

Figure 4: **Expenditure Shares and Exposure to the TSP**

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



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



Description: Figure 3a and 3b contains the estimated parameter of model 71 on the expenditure share with high school dropouts and workers with high school completion. 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, and the growth in 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.

4.4.3 Effect on Firm Size

Firms reduced their employment and wage bill in response to the TSP. Figure 5 shows the estimated parameters of regression 71 on employment and wage bill. Figure 5 indicates that firms adjusted their size quickly after the introduction of the program and kept their employment low after that.

The firms exposed to the TSP reduced their employment by 17% in the 10 years after the program introduction, according to 7. The effect of the TSP on employment was negative on all educational groups, as columns 4 to 6 shows. Even high school dropouts, which had an increase in expenditure share, had a drop in overall employment[21][22].

The firms more exposed to the TSP also decreased average wage, probability of exporting, probability of importing an input and the probability of importing capital[23]. These results

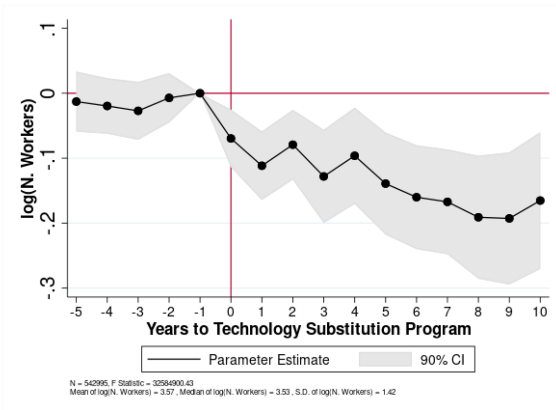
[21] A careful reader might be concerned that the effect on columns 4 to 6 does not average to the total employment effect in column 1. This happens for two reasons: selection and log-approximation. First, not all firms have high school dropouts, workers with high school completion, or workers with high school more, which creates a selection problem on these variables. Second, log difference is a bad approximation to percentage change for large numbers. Table 46 in the appendix show 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 on different educational groups.

[22] On table 47 in the appendix I show that the results are robust when addressing the selection problem with a Heckman correction.

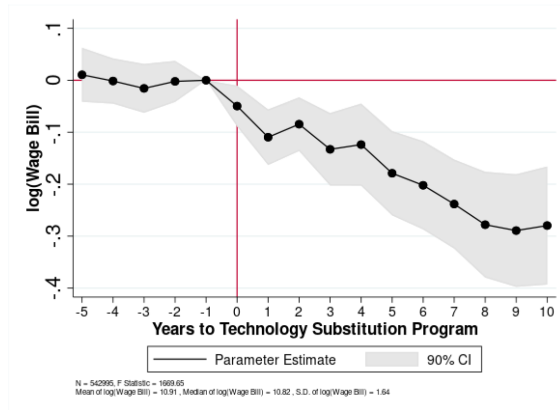
[23] The result on wages is presented on table 48 in the appendix and the result on imports on table 49

Figure 5: **Employment and Exposure to the TSP**

(a) log(N. Workers)



(b) log(Wage Bill)



Description: Figure 3a and 3b contains the estimated parameter of model 71 on the expenditure share with high school dropouts and workers with high school completion. 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, and the growth in 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.

Table 7: **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 presents the 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 in the number of high school dropouts, $log(N.WorkersHSComplete)$ is the log in the number of high-school complete, and $log(N.WorkersHSMore)$ is the log in 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 dummy for microregion interacted with a 1 digit sector dummy, firm's employment growth in the pre-period and number of international patents in the pre-period. Standard errors are clustered at the 5 digit sector classification.

suggest a overall negative effect on firm's performance.

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

4.5 Robustness and Alternative Specifications

In response to the 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, different exposure measures, and the use of a matched differences-in-differences design. This section also discusses the results of a triple differences approach.

Treatment Linear Trends Despite showing a clear trend break, figures 3a and 4a show a possible small downward trend. To ensure results are not driven by a pre-treatment trend, figures 40 to 42 on appendix reproduce the effect on innovation and expenditure share adding treatment level linear trends. The results are robust in sign and magnitude.

Adding Controls Section B.3.4 in the appendix shows that the effects on innovation, expenditure share and firm size are robust to controls of pre-policy firm size and exposure to international shocks[24].

Different Exposure Measures Results are robust to alternative measures of exposure to the tax and the subsidy. On section B.2.1, I exploit heterogeneity on budget allocation of the subsidy across sectors. In appendix B.2.2, I use as subsidy exposure a probability of the firm receiving the subsidy based on a full set of pre-policy characteristics. In appendix B.3.1, I use as exposure dummies if the firm leased technology before 1995, 1996, 1997, 1998 or 1999. All these different specifications deliver the same result: as a response to the TSP, firms increased innovation, increased expenditure share with low-skilled workers, and decreased employment.

Matched Diff-in-Diff Appendix A.13 shows that the firms in the treatment group are larger, have higher wages, and lower expenditure share with low skilled workers. To attack this potential problem, in appendix B.3 I implement a matched diff-in-diff, matching treatment and control on the number of workers, wage, share of high school dropouts, and state in the 5 years before the introduction of the program. The results are still the same.

Triple Difference In appendix B.3.2 I run a specification allowing the exposure to the subsidy and the exposure to the tax to have different coefficients. This specification is informative about the source of variation driving the main results. It indicates that the results are mainly driven by the firms exposed to the tax, but not necessarily driven by

[24] As a control for international shock I use a dummy if the firm exported before the TSP, a dummy imported any good before the TSP, and a dummy for being internationally owned pre-policy

the tax itself. Firms receiving the tax were also more likely to receive the subsidy than an average firm in the targeted sectors.[25]

4.6 Evaluating Competing Explanations

In this section, I argue that the results cannot be explained by the direct effect of the technology leasing tax on firms, the introduction of new products by the exposed firms, the change in the quality of the inventions, or the adoption of labor-saving technologies.

Effect of Tax It could be the case that the tax on international technology distorted firm incentives and let them to reduce employment and hiring of skilled workers. In appendix B.6.1, I show that the results cannot be explained by the direct effect of the tax. First, I exploit heterogeneity in the tax requirement due to previous contractual agreement. 42.1% of firms in the treatment group were not required to pay the tax. Instead, the technology owner is the one making the payments out of pocket. Moreover, given that prices were agreed in the contract, they could not adjust to the new tax. I show that results are robust when controlling for a tax requirement dummy. Second, I exploit heterogeneity on the total tax payment required by the firm coming from heterogeneity in technology price. After controlling for the relative tax burden at the firm level, I obtain similar results.

Introduction of New Products It could be the case that the TSP led firms to change the type of product 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 produce. Therefore, firms changed technology but kept producing the same good.

Effect of Innovation Quality The program could have led firms to produce technology of inferior quality. These lower quality technologies could be low skilled bias and low efficiency, which would explain the effect on firm employment and skill bias. In table 41 in the

[25] On section F I isolate the effect of the subsidy. I use a difference in differences approach comparing the firms applying for the subsidy that received it to the ones that applied but had the subsidy denied. I found an increase in the expenditure share with low-skilled workers for the firms leasing international technology before the subsidy.

appendix I use text analysis on patent descriptions to show that the average text complexity of Brazilian patents hasn't changed. In table 42 I use information from the CV of inventors to show that the average quality of inventor wasn't affected by the TSP. Therefore, there is no evidence that the quality of inventions have changed.

Use of Labor-Saving Machine Another possible explanation is that firms adopted labor-saving machines as a response to the TSP. In appendix B.6.3 I show that firms reduced their imports of labor-saving machines, that the technology being leased to Brazil is more associated with robots than Brazilian patents, that firms reduced the hiring of workers operating robots, and that wages of all educational groups fall.

5 Theoretical Model

In this section, I present a model that rationalizes the empirical results[26]. The model is then calibrated to reproduce the micro-elasticities and is used to make policy-relevant counterfactuals. In the model, firms in Brazil choose between innovating or paying a fixed cost to lease technology from the US. US and Brazilian innovations differ endogenously on skill-bias and productivity. Brazilian innovations are more intensive in the use of low skilled workers compared to US innovations because there is a larger supply of skilled workers in Brazil. Therefore, if US technology is of higher productivity, a firm switching from leasing technology from the US to innovating will increase its expenditure share with low skilled workers and decrease its total production, matching the empirical findings.

The model teaches two important lessons: one on the effect of innovation policy and one on the identification of important parameters. Innovation policy decreases aggregate production and skilled wage premium because it leads firms in a developing country to adopt low productivity and low-skilled biased technology. We also learn from the model that the important unknown parameters governing the aggregate effects can be identified from the micro-data using closed-form solutions.

[26]The model expands on Caselli and Coleman (2006) and León-Ledesma and Satchi (2018) by adding multiple countries, technology transactions, and firm heterogeneity

5.1 Environment and Equilibrium

5.1.1 Demographics

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

The vector (A, B), which I call technology, is a choice of the firm. Firms are constrained in their technology choice by the technology frontier[27]:

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

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

The choice of (A, B) is the innovation process of firms. Firms have access to a menu of different 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. But, at the frontier of knowledge, firms need to trade-off these two efficiency factors.[28]

Technology (A, B) has two important features: a skill bias and a TFP. The skill-bias of a technology is given by the ratio of efficiency of the two factors of production, B/A. The skill bias dictates how much more efficient high skill workers are relative to low skill workers.

[27] I follow Caselli and Coleman (2006) and León-Ledesma and Satchi (2018).

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

While technology TFP is given by ϕ_{US} in constraint 5. Higher ϕ_{US} allows the firm to choose higher values for A and B.

Firms in US maximize profit choosing inputs, h and l, and technology, (A, B), subject to the technology frontier 5:

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

From the first order conditions, we can find the optimal skill-bias of the US firms (A_{US}/B_{US}) as a function of inputs and wage-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 the 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 choosing inputs with a CES production function with elasticity $\frac{1}{1-\kappa}$.

5.1.2 Equilibrium in U.S.

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

$$C_{US} = y_{US} \tag{9}$$

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

$$l_{US} = L_{US}; h_{US} = H_{US} \tag{10}$$

Given that the US and Brazil are connected only through the trade of technology and Brazil is of measure zero, Brazil does not affect the US and we can define US equilibrium separately.

Definition 1. *(Equilibrium in US)*
The equilibrium in US 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 firm's problem 6

2. The resource constraint is satisfied:

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

3. The labor market clears:

$$l_{US} = L_{US}; h_{US} = H_{US} \tag{11}$$

5.1.3 Brazilian Firms

Firms in Brazil choose between innovating or leasing the technology created by a US-based firm.[29] Firms pay a fixed cost for each technology option, pay tax for technology lease, and receive a subsidy for innovation.

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

$$\left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}} = \phi_{BR} \tag{12}$$

[29] Inspired by the empirical facts on A.13, I exclude the options of firms to trade technology among themselves and to lease technology from a developing country. As discussed in the empirical facts section, those are small compared to the lease of international technology from developed countries.

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

A Brazilian firm innovating has operation profits given by

$$V_{innov,BR} = \max_{h,l,A,B} \left[(Al)^{\rho} + (Bh)^{\rho}\right]^{\frac{\gamma}{\rho}} - w_{H,BR}h - w_{L,BR}l \qquad (13)$$
$$\text{s.t. } \phi_{BR} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}}$$

The problem of an innovative Brazilian firm 13 and a US-based firm 6 differ in the price of labor and on the level of the technology frontier. These two differences lead Brazilian innovators and US innovators to differ in skill bias and production.

A Brazilian firm leasing technology has to pay fixed cost $\epsilon_{j,lease}$[30] and implements technology (A_{US}, B_{US}), created by a US based firm. A Brazilian firm leasing technology has problem given by

$$V_{lease,BR} = \max_{h,l} \left[(A_{US}l)^{\rho} + (B_{US}h)^{\rho}\right]^{\frac{\gamma}{\rho}} - w_{H,BR}h - w_{L,BR}l \qquad (14)$$

Considering the profit of the two technology types, Brazilian firms have to choose between leasing technology or creating their own:

$$V_j = \max\left\{V_{BR,lease} - \epsilon_{j,lease} - \tau_{lease}, V_{BR,innov} - \epsilon_{j,innov} + \tau_{innov}\right\} \qquad (15)$$

where $V_{BR,lease}$ is the operating profit of leasing US technology, $\epsilon_{j,lease}$ is the fixed cost of leasing US technology, τ_{lease} is a tax on the leasing of international technology[31], $V_{BR,innov}$ is the operating profit of a firm innovating, $\epsilon_{j,innov}$ is the fixed cost of innovating, and τ_{innov} is a subsidy for innovation.

Firms are heterogeneous on the fixed cost required to innovate, $\epsilon_{j,innov}$, and on the fixed cost of leasing international technology, $\epsilon_{j,lease}$. Let the joint distribution of fixed costs be

[30] The fixed cost $\epsilon_{j,lease}$ captures the price and the cost of implementing the technology. Since Brazil is small and do not affect prices, I assume the price of the technology is exogenous and only model the final cost the firm faces to implement US technology. In the dynamic model, technology prices are endogenous and decided by bargaining.

[31] In the data, the tax on technology lease wasn't a lump-sum. In fact, 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.

given by $(\epsilon_{j,innov}, \epsilon_{j,lease}) \sim \Gamma$[32].

Let $\mathbb{I}_{j,innov}$ be a dummy taking one if firm j innovates:

$$\mathbb{I}_{j,innov} = \begin{cases} 0 & \text{if } V_{BR,lease} - \epsilon_{j,lease} - \tau_{lease} \geq V_{BR,innov} - \epsilon_{j,innov} + \tau_{innov} \\ 1 & \text{if } V_{BR,lease} - \epsilon_{j,lease} - \tau_{lease} < V_{BR,innov} - \epsilon_{j,innov} + \tau_{innov} \end{cases}$$

5.1.4 Government in Brazil

The government in Brazil subsidize R&D, τ_{innov}, tax the lease of international technology, τ_{lease}, and impose a lump-sum tax on consumers, T. Its budget constraint is given by

$$\underbrace{\tau_{innov}\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right)}_{\text{Expenditure with Subsidy}} = \underbrace{\tau_{lease}\left(1 - \int \mathbb{I}_{j,innov} d\Gamma_j\right)}_{\text{Revenue from Lease Tax}} + \underbrace{T}_{\text{Lump Sum Tax}} \tag{16}$$

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 leasing international technology.

5.1.5 Equilibrium in Brazil

Let $y_{innov,BR}$ be the optimal production of a firm innovating in Brazil, $y_{lease,BR}$ be the optimal production of a firm leasing technology and C_{BR} the consumption of the representative consumer. The resource constraint is given by[33]

$$\underbrace{C_{BR}}_{\text{Consumption}} + \underbrace{\int_j \epsilon_{j,innov} \mathbb{I}_{j,innov} d\Gamma_j}_{\text{Cost with Innovation}} + \underbrace{\int_j \epsilon_{j,lease}(1 - \mathbb{I}_{j,innov}) d\Gamma_j}_{\text{Cost of Leasing Tech.}} = \tag{17}$$

$$\underbrace{y_{innov,BR}\left(\int \mathbb{I}_{j,innov} d\Gamma_j\right)}_{\text{Production of Innovating Firms}} + \underbrace{y_{lease,BR}\left(\int (1 - \mathbb{I}_{j,innov}) d\Gamma_j\right)}_{\text{Production of Firms Leasing Tech.}}$$

[32] I assume Γ to be a continuous and differentiable distribution defined on R^{++}. Moreover, de CDF of Γ has a positive mass in the whole domain. These assumptions guarantee that there will be a positive mass of innovators and technology lessee in any equilibrium.

[33] 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 paid with hiring of skilled workers.

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

The labor market clearing conditions are given by

$$l_{innov,BR}\left(\int \mathbb{I}_{j,innov}d\Gamma_j\right) + l_{lease,BR}\left(\int (1-\mathbb{I}_{j,innov})d\Gamma_j\right) = L_{BR} \tag{18}$$

$$h_{innov,BR}\left(\int \mathbb{I}_{j,innov}d\Gamma_j\right) + h_{lease,BR}\left(\int (1-\mathbb{I}_{j,innov})d\Gamma_j\right) = H_{BR} \tag{19}$$

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 $l_{lease,BR}$ and $h_{lease,BR}$.

Notice that the US affects the Brazilian economy only through the technology (A_{US}, B_{US}). So we can define the equilibrium in Brazil conditional on the US technology.

Definition 5.1. (*Equilibrium in Brazil*)
Given US technology (A_{US}, B_{US}), the equilibrium in Brazil is given by a solution to firm's problem $\{V_{BR,k}, l_{k,BR}, h_{k,BR}, y_{k,BR}\}_{k\in\{innov,lease\}}$ and $\{\mathbb{I}_{j,innov}, V_j\}_{j\in[0,1]}$, fiscal policy $\{\tau_{innov}, \tau_{lease}, T\}_{t\in\{0,1\}}$, prices $\{w_{H,BR}, w_{L,BR}\}$ and aggregate consumption C_{US} such that

1. *Given US technology (A_{US}, B_{US}), prices $\{w_{H,US}, w_{L,US}\}$ and fiscal policy $\{\tau_{innov}, \tau_{lease}, T\}$, $\{V_{innov,BR}, l_{innov,BR}, h_{innov,BR}, y_{innov,BR}\}$ solves the problem of a firm innovating 13, $\{V_{lease,BR}, l_{lease,BR}, h_{lease,BR}, y_{lease,BR}\}$ solves the problem of a firm leasing technology 14 and $\{\mathbb{I}_{j,innov}, V_j\}_{j\in[0,1]}$ solves the technology choice problem 15 for every $t \in \{0,1\}$*
2. *Fiscal policy $\{\tau_{innov}, \tau_{lease}, T\}$ satisfy government's budget constraint* 16*;*
3. *The resource constraint 17 is satisfied;*
4. *The labor market clears.*

5.1.6 Equilibrium

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

Definition 5.2. (*Equilibrium*)
The equilibrium is given by $\{V_{BR,k}, l_{k,BR}, h_{k,BR}, y_{k,BR}\}_{k\in\{innov,lease\}}$,

$\{\mathbb{I}_{j,innov}, V_j\}_{j\in[0,1]}, \{\tau_{innov}, \{\tau_{lease}, T, w_{H,BR}, w_{L,BR}, C_{US}\}\}$ *and* $\{l_{US}, h_{US}, A_{US}, B_{US}, y_{US}, w_{H,US}, w_{L,US}, C_{US}\}$ *such that*

1. $\{l_{US}, h_{US}, A_{US}, B_{US}, y_{US}, w_{H,US}, w_{L,US}, C_{US}\}_{t\in\{0,1\}}$ *is an equilibrium in US;*

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

5.2 Cross-Country Difference in Technology Skill-Bias

Differences in factor supply across countries create differences in technology skill bias. This statement is formalized by theorem 1.

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

1. skill premium is higher in Brazil

2. US's and Brazil's inventors adopt technology of different bias: $\frac{A_{US}}{B_{US}} \neq \frac{A_{BR}}{B_{BR}}$

Proof. Proof on appendix C.1. □

Figure 6a illustrates the problem of an innovating firm. It shows the isoquant faced by the firm before and after the technology choice. Conditional on using technology (A', B'), the firm faces isoquant I' with elasticity $\frac{1}{1-\rho}$. But, each firm innovating has access to a set of (A, B), not only a point. Therefore, firms are choosing between isoquant I', I'', I''', or any other that satisfies the technology frontier. The lower envelope of all the isoquants that satisfy the technology frontier gives the isoquant after technology choice I. As problem 8 suggests, the isoquant after the technology choice has elasticity $\frac{1}{1-\kappa}$[34].

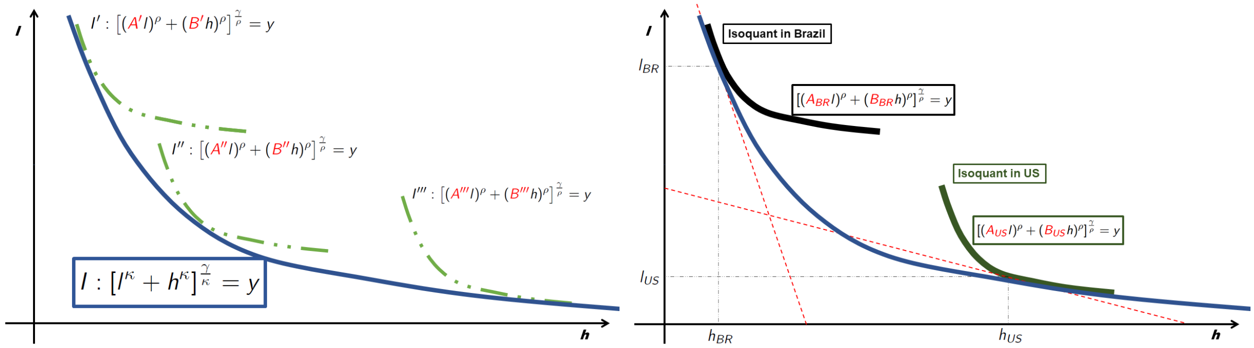
Figure 6b illustrates the difference in technology choice between Brazilian inventors and US inventors with the simplifying assumption that $\phi_{US} = \phi_{BR}$. Because these two countries differ in factor share, Brazil and US firms face different skill premium. The US has a lower skilled premium than Brazil because it is abundant in high skilled workers. This compels US

[34] The previously stated assumption that $\kappa > \rho$ guarantees that we are in an interior solution.

firms to create technology more intensive in the use of skilled workers than the technology created by Brazilian firms.[35].

Figure 6: **Innovation, Skill-Bias and Wage Premium**

(a) Isoquant Before and After Innovation (b) Cross-Country Difference in Skill-Bias



Description: Figure6a shows the isoquant for technologies (A', B'), (A'', B''), and (A''', B'''). The isoquant I is the isoquant face by the firm after choosing the optimal technology, as in problem 8. The figure 6b contains the isoquant of Brazilian invetors and US's inventors.

Therefore, US and Brazilian inventors create technology of different biases. But that is not the only difference in technology across countries. Because the technology frontier differs on the level, i.e., $\phi_{BR} \neq \phi_{US}$, the technologies of the two countries also differ TFP.

5.3 Within Country Difference in Skill Intensity and Size

The fact that the US and Brazil create technologies of different TFP and bias implies that firms in Brazil differ on size and skill intensity. Proposition 2 formalizes this intuition.

Proposition 2. Suppose that US is skilled abundant compared to Brazil, $H_{US}/L_{US} > H_{BR}/L_{BR}$, then

1. Brazilian firms leasing technology are more skilled intensive than Brazilian firms innovating:

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

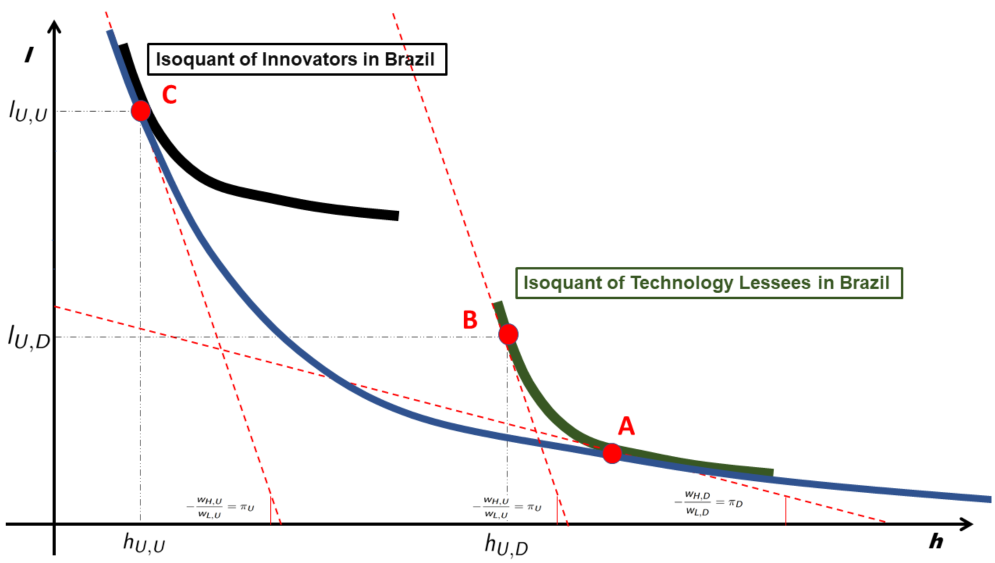
[35]The bias of the technology will depend on parameters. If high skill and low skilled workers are substitutes, $\rho > 0$, then US technology is skilled bias compared to the Brazilian technology: $A_{US}/B_{US} < A_{BR}/B_{BR}$. While if $\rho < 1$ the opposite happens and the US technology is low skilled biased compared to the Brazilian technology: $A_{US}/B_{US} > A_{BR}/B_{BR}$.

2. If ϕ_{US}/ϕ_{BR} is sufficiently large, Brazilian firms leasing technology are larger than Brazilian firms innovating:

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

Innovators use technology (A_{BR}, B_{BR}), which is a function of Brazilian skilled premium, while firms leasing technology from US use technology (A_{US}, B_{US}), which is a function of US skilled premium. Because of this difference, innovators in Brazil are always less skilled intensive than Brazilian firms that lease technology. Figure 7 illustrates this result. US firms face skilled-premium $\frac{w_{H,US}}{w_{L,US}}$ so they decide produce at point A in the figure and choose technology (A_{US}, B_{US}). The firms leasing technology must stick to the same isoquant of US innovators but facing Brazilian prices, so the firms leasing technology choose to produce at point B in the figure. Brazilian innovators, on the other hand, face skilled-premium $\frac{w_{H,BR}}{w_{L,BR}}$ and choose to produce at point B in figure 7. Brazilian firms leasing technology also use technology (A_{US}, B_{US}) but face prices $\frac{w_{H,US}}{w_{L,US}}$ so their optimal choice of factors is on point C in the figure, implying that firms leasing technology are more intensive in skilled workers.

Figure 7: **Within Country Difference in Skill Intensity**



Description: Figure6a shows the isoquant for technologies (A', B'), (A'', B''), and (A''', B'''). The isoquant I is the isoquant face by the firm after choosing the optimal technology, as in problem 8. The figure 6b contains the isoquant of Brazilian invetors and US's inventors.

Innovators use technology (A_{BR}, B_{BR}), which satisfy Brazilian technology frontier with technology level ϕ_{BR}, while firms importing technology from the US use technology (A_{US}, B_{US}), which satisfy US technology frontier with technology level ϕ_{US}. Because of this difference in technology frontier across countries, firms leasing technology in Brazil can be larger than innovators. Notice that because Brazilian technology is created taking into account Brazilian wage premium, it has the optimal skill bias $\frac{A_{BR}}{B_{BR}}$ to be operated in Brazil. Therefore, because of this bias gain, firms leasing technology are larger only if the efficiency of US technology is sufficiently larger.

5.4 Effect of Innovation Policy

An increase in R&D subsidy (or tax in international technology) leads firms to switch from high-TFP and high-skill biased US technology to low-TFP and low-skill biased Brazilian technology. Because of the change in TFP and skill-bias, production and skill-premium go down in Brazil.

As shown by theorem 2, innovating firms are more intensive in the use of low skill workers. Therefore, when there is an increase in the share of innovative firms, there is a relative increase in the demand for low skill workers. For the labor market to clear, it must be the case that wage premium does down. Proposition 3 formalizes this result.

Proposition 3. (Effect of Innovation Subsidy on Skill Premium)
An increase in the innovation subsidy τ_{innov} decreases wage-premium in Brazil:

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

Proof. Proof available on appendix C.3. □

Proposition 4 shows that innovation policy decreases consumption and GDP if the US technology is of sufficient high TFP. Firms need to trade-off marginal cost and fixed cost when choosing a technology. Firms switch to innovation when there is an artificial reduction in the fixed cost of innovating due to an increase in innovation subsidy. When firms make this change, as proposition 2 indicates, firms take a technology with higher marginal cost but lower fixed cost. As a consequence of this technology choice, production decreases. Moreover, consumption goes down due to the reduced production and the increased expenditure with technologies fixed cost.

Proposition 4. (Effect of Innovation Subsidy on Production)
An innovation subsidy in Brazil decreases consumption:

$$\frac{\partial C_{BR}}{\partial \tau_{innov}} < 0$$

If ϕ_{US}/ϕ_{BR} is sufficiently high, an innovation subsidy in Brazil decreases production:

$$\frac{\partial Y_{BR}}{\partial \tau_{innov}} < 0$$

6 Identification and Results

6.1 Identification

The model predicts innovation policy in Brazil to reduce skilled wage premium and production. The magnitude of these effects depends on four parameters: ρ, κ, γ, and ϕ_{BR}/ϕ_{US}[36].

The elasticity of substitutions, ρ and κ, determine the expenditure shares of innovators and of firms leasing technology. Therefore, the aggregate effect of innovation policy on skill premium is crucially affected by ρ and κ.

Because ϕ_{BR}, ϕ_{US} and γ directly affect production, the aggregate effect of innovation policy on production is a function of the TFP of the two technologies.

In this subsection, I show that the important parameters can be identified from a change in innovation policy even in the presence of aggregate shocks and selection. This section proceeds as follows. First, I introduce to the model richer heterogeneity and aggregate shocks. The objective is to capture features existing in the real world that bring identification concerns. Second, I introduce in the model policy change and identification strategy similar to the one used in the data. Third, I show that using the elasticities from the model we can

[36] Without loss of generality, we can normalize one of the technology frontiers to one.

identify two out of four key parameters. In the calibration section, I show that the other two parameters can be calibrated from data or from the literature.

6.1.1 Heterogeneity and Aggregate Shocks

There are two periods $t \in \{0, 1\}$. Firms need to innovate or to lease technology every period[37].

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

$$z_j^t \Upsilon_c^t \left[\Psi^t \alpha_j^t (A_j^t l)^\rho + (1 - \alpha_j^t)(B_j^t h)^\rho\right]^{\frac{\gamma}{\rho}} \tag{20}$$

where (z_j^t, α_j^t) are firm idiosyncratic characteristics, Υ_c^t is a time-varying country-specific aggregate shock, and Ψ^t is a skill biased common shock. $\alpha_j^t \in (0, 1)$ and $z_j \in \mathbb{R}^{++}$.

Define $z_j = \{z_j^0, z_j^1\}$ and $\alpha_j = \{\alpha_j^0, \alpha_j^1\}$. Then, $(z_j, \alpha_j) \sim \Gamma_{US}$ be the distribution of firm characteristics in US and $(z_j, \alpha_j, \epsilon_{j,innov}, \epsilon_{j,lease}) \sim \Gamma_{BR}$ be the distribution of firm characteristics in Brazil, where $\epsilon_{j,innov} = \{\epsilon_{j,innov}^0, \epsilon_{j,innov}^1\}$ and $\epsilon_{j,lease} = \{\epsilon_{j,lease}^0, \epsilon_{j,lease}^1\}$.

Notice that, because firms differ in TFP and biased productivity, there will be selection on technology types. If ϕ_{US}/ϕ_{BR} is large enough, high z_j^t firms will select in international technology because firm TFP and technology TFP are complements.[38]

Heterogeneity in firm's skill bias productivity also generates heterogeneity in technology. To see that its useful to derive the optimal skill bias of a firm innovating:

$$\frac{A_{j,c}^t}{B_{j,c}^t} = \left(\Psi^t \frac{\alpha_j^t}{1 - \alpha_j^t}\right)^{\frac{\rho-\kappa}{\rho(\kappa-1)}} \left(\frac{w_{H,c}^t}{w_{L,c}^t}\right)^{\frac{\rho-\kappa}{(\kappa-1)\rho}}$$

Therefore, heterogeneity in firms' idiosyncratic biased productivity generates heterogeneity in firms' technology skill bias.

I assume that a firm j in Brazil with idiosyncratic productivity shocks (z_j^t, α_j^t) can only lease technology from firm j in the US with the same idiosyncratic shocks.[39]

[37] This assumption only simplifies the model and doesn't play an important role in identification. In the robustness section I introduce dynamics and show that results are still similar.

[38] The selection pattern with respect to the skill biased shock is non-monotonic.

[39] In practical terms, one can think j as capturing products. As I show below, this is a crucial assumption for getting closed-form solutions. Still, I relax this assumption in the dynamic model.

6.1.2 Model Equivalent Technology Substitution Program

Assume the government implements the following fiscal policy:

$$\tau^0_{innov} = \tau^0_{lease} = T^0 = T^1 = 0; \tau^1_{j,innov} \in \{0, \tau\}; \tau \geq 0 \tag{21}$$

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

I reproduce in the model the same estimation procedure implemented in the data.

Define the firms directly exposed to the introduction of the R&D program as the ones leasing technology in the pre-period that were targeted by the innovation subsidy:

$$ExposedTSP = \left\{ j | \tau_j \times \mathbb{I}^0_{innov} > 0 \right\} \tag{22}$$

The change in skill share and labor supply of the exposed group compared to the non-exposed group is given by:

$$\lambda_{skill} = E\left[\Delta \log \left(\frac{w^t_{L,BR} l^t_j}{w^t_{H,BR} h^t_j} \right) | j \in ExposedTSP \right] - E\left[\Delta \log \left(\frac{w^t_{L,BR} l^t_j}{w^t_{H,BR} h^t_j} \right) | j \notin ExposedTSP \right] \tag{23}$$

$$\lambda_{labor} = E\left[\Delta \log l^t_j | j \in ExposedTSP\right] - E\left[\Delta \log l^t_j | j \notin ExposedTSP\right] \tag{24}$$

λ_{skill} and λ_{labor} are the diff-in-diff estimator of the effect of the TSP on the exposed firms compared to the others. Its similar to empirical strategy used on the main empirical section.

6.1.3 Identification of Key Parameters with Firm Heterogeneity and General Equilibrium

Proposition 5 shows that knowing κ and γ, we can identify with closed form solutions ρ and $\frac{\phi_{BR}}{\phi_{US}}$ from the elasticities identified on the empirical section and data moments.

Proposition 5. (Identification of Key Parameters with Selection, Aggregate Shocks and General Equilibrium)

Suppose that the government implements policy 53 and define the estimators as in 55. Assume that production function is defined as in 20. Then, if

1. Firm idiosyncratic characteristics are permanent:

$$z_j^0 = z_j^1; \alpha_j^0 = \alpha_j^1; \epsilon_{j,innov}^0 = \epsilon_{j,innov}^1; \epsilon_{j,lease}^0 = \epsilon_{j,lease}^1$$

2. Firm j in Brazil can only lease technology from firm j in US.

Then, knowing κ and γ, ρ and $\frac{\phi_{BR}}{\phi_{US}}$ 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.

Theorem 5 shows that the two key parameters can be identified using the variation created by the introduction of policy 53 even in the presence of selection, aggregate shocks, and general equilibrium adjustments. More importantly, the distribution of shocks or aggregate shocks does not matter for the estimation of these parameters. The firm idiosyncratic characteristic, (z_j, α_j), is removed by comparing the same firm across time while aggregate shocks, Υ_c^t and Ψ^t, are removed by taking the difference between treatment and control group.

The diff-in-diff estimators are both informative about the difference in bias and TFP of the two technologies. If λ_{skill} is large, it must be the case that there is a large difference in expenditure share between the two technologies. A large difference in expenditure shares, given wage 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, it must be the case that the two technologies strongly differ 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.

There are three important assumptions underlying the identification result in proposition 5: persistence of shocks and segmentation of technology markets by j.[40]

Firms are assumed to have a permanent idiosyncratic shock. This allows me to get rid

[40] These two assumptions are relaxed in the dynamic model. Imposing more structure in the model, the key parameters can still be identified by SMM.

of the firm idiosyncratic difference when taking the difference within the same firm across time.

The final identifying assumption is that firm j in Brazil can only lease technology from firm j in the US. This assumption allows the idiosyncratic component of technology to be teased out since it is common in both national and international technology. A way to interpret this assumption empirically is that firms cannot change products as a response to the innovation program. Otherwise, I would not be able to tell apart the employment changes due to technology from the ones due to product changes. In the data, firms did not change products as was discussed in the empirical section.

6.2 Calibration

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

According to theorem 5, 2 parameters can be identified. Why? Because the data informs only about the difference. When estimating the effect of the TSP using diff-in-diff, we learn about the change in an outcome in the exposed group relative to the change in the same outcome in the non-exposed group. With this approach, we learn about the relative skill bias of the two technologies, $\frac{A_{BR}/B_{BR}}{A_{US}/B_{US}}$, and their relative TFP, $\left(\frac{\phi_{BR}}{\phi_{US}}\right)^{\gamma}$. Because the levels are taken away with the difference, the data is silent about the level bias and level TFP of these technologies. Therefore, going from the differences to the levels is possible only after knowing two parameters[41].

Once I calibrate κ, normalize ϕ_{BR} to one and estimate γ, I know the change in labor demand of firms innovating in Brazil. Notice that prices and innovation status are observed in the data while the only parameters affecting 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.

[41] After normalizing one of the technologies to 1.

Table 8: **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

6.2.1 Estimation of γ

The degree of decreasing returns to scale, γ, is estimated using 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. Appendix D.2 discuss the results. On the baseline estimation $\gamma = 0.7577$. This estimate is closed to the estimates of Garicano et al. (2016), 0.793, Atkeson and Kehoe (2005), 0.85, and Basu and Fernald (1997), 0.8.

6.2.2 Calibration of κ

κ is the elasticity of substitution in the US, according to problem 8. This parameter has been widely studied. Table 8 shows that the estimates of the elasticity of substitution in developed countries goes from 0.23 to 0.56. In the main section of the paper I use the estimates of Katz and Murphy (1992), $\kappa = 0.28$.

6.2.3 Estimation of ρ

Using the calibrated value for κ, I can use the identifying equation from theorem 5, the estimated effect of the 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 $\rho = 0.2654$. Because $\rho > 0$, low-skill and high-skill workers are complements. Implying that technology of developed countries is high-skill biased while technology from developing countries are low-skill biased.

6.2.4 Technology TFP

Using κ, γ, the estimated effect of the TSP on 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 $\phi_{US} = 1.67$.

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.

First, I assume that all the permanent idiosyncratic shocks are independent.

Because there are only two technologies, only the relative cost matters for the firm's technology choice, $\epsilon_{j,innov} - \epsilon_{j,lease}$. Therefore, as is common in any discrete choice model, the levels of each cost are not identified. I assume that:

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

Where μ_ϵ, the average of relative innovation cost, is calibrated to reproduce the share of firms leasing technology while σ_ϵ is calibrated to reproduce the effect of the TSP on innovation.

I assume that the distribution of idiosyncratic TFP shocks is $log(z_j) \sim N(\mu_z, \sigma_z)$. Where 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 normalize to 0 and σ_α is calibrated to match the variance of firm size in the data.

Finally, the supply of low skill and high skill workers, L_{BR} and H_{BR}, are calibrated to match wages in 2000.

Table 9 shows all the calibrated parameters and target values.

6.3 Model Results

I use the model to study the selection of firms into technology types, the aggregate effect of the TSP, and the effect of closing the economy to international technology transfers.

The model shows that high idiosyncratic TFP firms select into international technology

Table 9: **Estimated Parameters**

Parameter	Description	Target/Source	Value Target	Parameter Value	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	Effect of TSP on log Factor Share	0.0122	0.2654	0.00167
γ	Degree of decreasing returns	Estimation		0.757	0.00194
ϕ_{US}	Productivity of US technology	Effect of TSP on Demand for Low Skilled Workers	-0.192	1.6685	0.25465
ϕ_{BR}	Productivity of BR technology	Normalization	1	1	-
		Technology Cost			
μ_ϵ	Mean of Innovation Cost	Shr. of Firms Leasing Tech. 10 yrs Bfr Program	0.258	0.0008	0.00003
σ_ϵ	Variation of Innovation Cost	Effect of TSP on Innovation	0.0352	0.0011	0.000005
		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	0.3725	0.0043
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	2.9918	0.1437
		Factor Supply			
L_U	Supply of low-skilled workers	Initial low skill wage	39.73	1.65E-06	4.95E-11
H_U	Supply of high-skilled workers	Initial high skill wage	123.46	2.55E-07	

Description: This table shows the estimated parameters, it's calibrated values and the variance of the parameter. The variance is calculated by bootstrap. As skilled wage premium in US I use the average skilled wage premium of countries selling technology to Brazil weighted by the number of contracts.

while the selection pattern on the skill-biased shock is U-shaped. This explains the empirical findings in A.13.

The model predicts that the TSP increased aggregate innovation by 0.037%%, reduced skilled-premium by 0.1%%, and reduced production by 0.6%%. The effect on skill-premium and production is due to the difference in technology TFP and skill-bias. Firms switching from international technology to national technology are moving from a high-TFP and high-skilled biased technology to a low-TFP and low-skilled biased technology. Still, these effects are small in aggregate. This happens because, as a response to the TSP, only a small share of firms switched from international technology to national technology.

The model predicts a large effect of closing the economy to international technology transfers. As large firms are forced to move from international technology to innovation, the drop in production increases because these firms represent a larger percentage of aggregate production. Moving all firms to create their own technologies would reduce production by 57% and skill-wage premium by 0.13%.

6.3.1 Selection on Technology Types

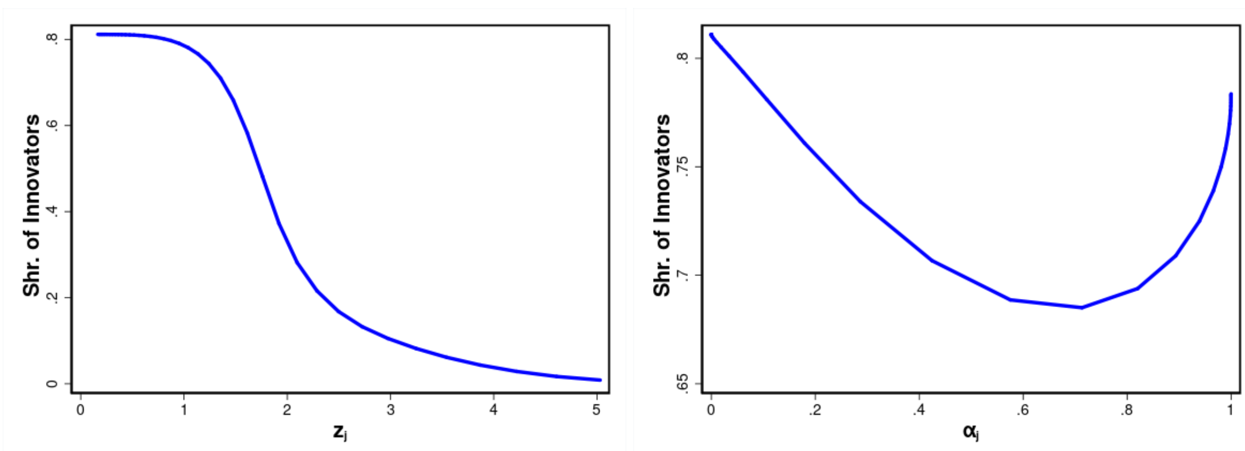
Figure 8 shows that heterogeneity in the idiosyncratic TFP z_j and in the skill-biased productivity α_j leads to selection into innovation. Each figure displays the share of firms innovating against the idiosyncratic TFP, z_j, and against the skill bias idiosyncratic productivity.

High z_j firms select into international technology, according to figure 8a. Because firm productivity and technology productivity are a complements, high idiosyncratic TFP firms have more to gain from producing using a high TFP technology. Therefore, high skill neutral productivity firms are less likely to innovate and more likely to lease international technology.

The skill bias productivity shock α_j will affect firms' profit and lead to selection. Firms with intermediary but above mean α_j have higher profits, as figure 9 indicates, because they have the optimal skill intensity to exploit Brazilian factor supply. Therefore, these firms with middle-high skill-biased productivity have more to lose from using a low-TFP technology and they choose to lease international technology, as figure 8b shows. Still, in terms of magnitude, the selection on skill bias is much weaker.

Figure 8: **Selection on Technology Types**

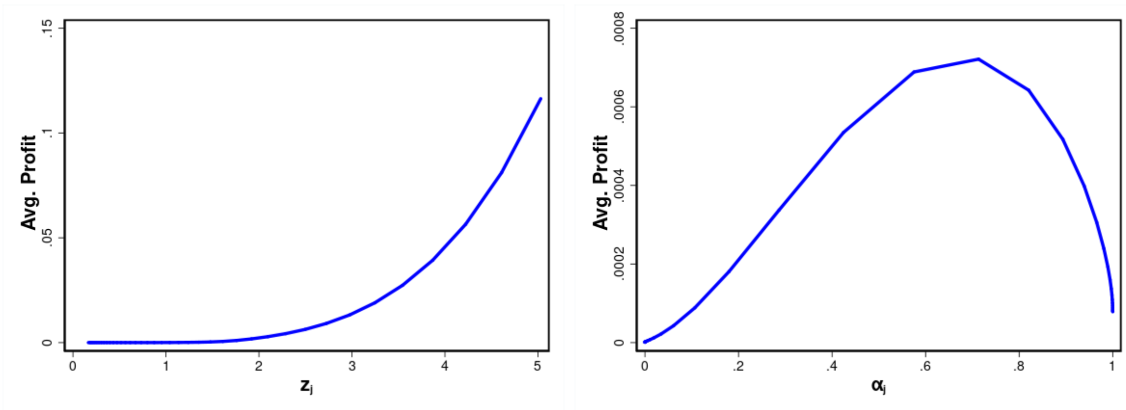
(a) Skill Neutral Idiosyncratic Productivity (b) Skill Bias Idiosyncratic Productivity



Description: This figure shows the share of firms innovating according to it's TFP idiosyncratic productivity z_j and to it's skill biased productivity, γ_j.

Figure 9: **Average Profit According to Productivity**

(a) Skill Neutral Idiosyncratic Productivity (b) Skill Bias Idiosyncratic Productivity



Description: This figure shows the average profit according to firm's TFP idiosyncratic productivity z_j and to it's skill biased productivity, γ_j.

6.3.2 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 consequence, it reduces wage premium and GDP.

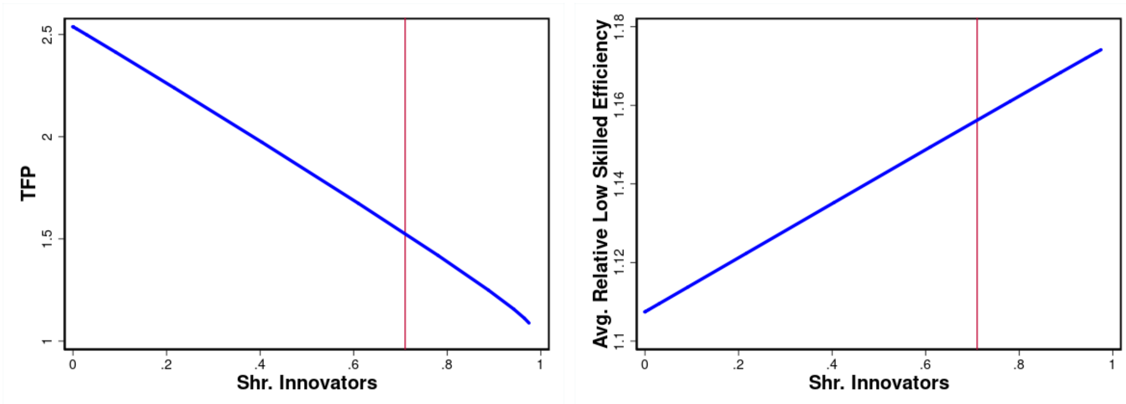
Figure 10 shows what happens to average TFP and average relative low skilled productivity as the government increases the share of innovating firms through an innovation subsidy (or technology tax). Because Brazilian innovations are of lower productivity, there is a decrease in average TFP in the economy. Moreover, because Brazilian technology is low-skilled biased there is an increase in overall skill bias in the economy. Therefore, technological progress in developing countries is low-skilled biased.

Figure 11 shows how GDP and skill premium adjust to the change in innovation policy. As expected, because TFP and skill bias goes down, there is a decrease in production and skill premium.

Table 10 shows how aggregate variables adjust to different innovation policies. The first line shows the aggregate effect of the TSP. The program led to an increase in aggregate innovation by 0.00037% costing 0.00612% of pre-policy GDP. As consequence of the program, columns 2 and 3 shows that GDP and wage premium goes down.

Figure 10: **Effect of Innovation Policy on TFP and Skill-Bias**

(a) $E\left[z_j\phi_j\right]$ (b) $E\left[\alpha_j \frac{A_j}{B_j}\right]$



Description: This figure shows the average TFP and skill bias in the economy. The average TFP is calculated using the firm idiosyncratic TFP and the technology TFP: $E\left[z_j\phi_j\right]$. Where z_j is firm TFP and ϕ_j is the technology TFP used by firm j. The skill bias is calculated also using firm and technology skill bias: $E\left[\alpha_j \frac{A_j}{B_j}\right]$. Where α_j is the skill bias productivity of firm j and $\frac{A_j}{B_j}$ is the technology bias of firm j.

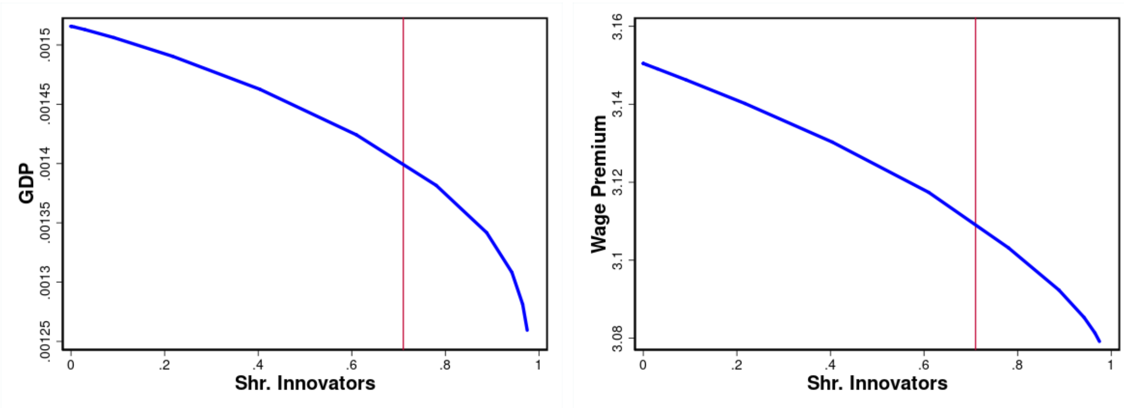
Despite the large difference between Brazilian and US technology, the identified effect of the TSP is small according to table 10. The model is calibrated to reproduce the effect of the TSP on innovation. Given that the effect is small, the aggregate share of firms switching to national innovations is also small. Therefore, the aggregate effect on GDP and skill premium must be small as well.

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 has two important lessons: on the aggregate effect of innovation and on the cost of innovation policies. First, the drop in GDP is about 10 times larger than the drop in the skill premium. This quantitative result is directly driven by the empirical results discussed before. While the empirical section finds a large drop in employment, implying a large difference in technology skill bias, the change in expenditure shares is smaller, which implies a small difference in technology bias between the two countries. The second lesson from the counterfactual table 10 is about the efficacy of innovation policy. Just to increase innovation by 1p.p., the government has to give 2% of GDP as R&D subsidy. This result is again driven by the empirical results. The increase in innovation was relatively small

Figure 11: **Effect of Innovation Policy on Production and Wage-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 leasing.

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 different innovation programs. The first line has the effect of the TSP, which gave 0.00612% of GDP as subsidy financed by a tax on international technology leasing. The second line implements a innovation program to increase the share of innovating firms by 1 percentage point while the last line has the effect of forcing all firms to innovate. The first column has the percentage change in the share of firms innovating, the second column has the percentage change in GDP, the third column has the percentage change in skill wage premium, the fourth column has the percentage change in skilled wage, the fifth column has the percentage change in unskilled wage, the final column contains the size of the R&D subsidy implemented.

compared to the size of the program. Therefore, the cost of innovating must an important factor in firms technology choice.

6.4 Robustness

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

Alternative κ To identify ρ and ϕ_{US}, I have to calibrate the elasticity of substitution in the US, κ. On section D.4.1 in the appendix, I show how the results change with alternative κ calibrations. In the range of empirically plausible estimates, 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 in skilled wage premium.

Alternative Innovation Definition Patents are noisy measure of innovation and technology adoption at the firm. It's reasonable to think that some firms innovate without issuing a patent[42] and that some firms apply for patent without implementing a new technology[43]. I attack this measurement problem, common on the growth literature, introducing several new measures of innovation. On section D.4.2, I use as innovation measure hiring of scientist, hiring of a PhD worker, patents or industrial design applications and the application for any intellectual property object. For small changes in innovation, the results are very consistent across all these innovation measures. By increasing innovation by 1pp, GDP would fell between 0.12% and 0.33%, while skilled wage premium would fell between 0.03% and 0.07%.

Elastic Labor Supply As skilled wage premium changes, it's reasonable to think that labor supply would adjust to it, minimizing the aggregate change on skill wage premium and production. In appendix D.4.3, I change the model to allow for labor supply adjustments. I found that, using micro estimates of the elasticity of labor supply, the results are very similar to the baseline estimates.

Hiring of Scientists Innovation itself is a skill intensive activity. To create new technologies, firms have to hire scientists and technicians. In appendix D.4.4, I add to the model a fixed cost in term of skilled workers and calibrate it to reproduce the expenditure share with scientists. The change in results is minimal.

Exogenous Technology The directed technological change component of the model only works to endogenize the technology of the two countries; (A_{BR}, B_{BR}) and (A_{US}, B_{US}). Still, it's possible to estimate these two parameters without making any assumption on where these technologies are coming from. On section D.4.5 in the appendix, I show that (A_{BR}, B_{BR}) can be identified after normalizing $A_{US} = B_{US} = 1$. I estimate the elasticity ρ using numbers from the literature and change in factor share of firms innovating. For reasonable calibrations of the elasticity, the magnitude of the results are again consistent with the main findings.

[42] If, for instance, they don't want their competitor to be aware of their technology improvement.

[43] The patent troll, as discussed by Abrams et al. (2019) , is a case of firms applying for patents but not implement a new technology.

In any case, it is still true that the effect on production dominates the effect on skill wage premium.

Alternative Distributions On section D.4.6, I assume that the distribution of innovation cost is Gumbel or logistic. The results are again consistent with the baseline.

Vintage Technology One of the main arguments in favor of innovation policies is to allow firms to move from an vintage technology to a new and more efficient technology. Because the baseline model has only two technologies, this channel is not on the model. On section D.4.7 I add to the model a third technology: a vintage and outdated technology. Firms then have to choose between three options: lease technology from the US, innovate or use a vintage technology. Using triple differences, I show that the productivity of the vintage technology can be identified and estimate it to be very close to the productivity of Brazilian innovations. Because of that, the replacement of international technology by national innovations dominate the final effect. Still, the magnitudes of the effects of innovation policy is larger when taking into account the existence of vintage technology because now firms using international technology can also switch to an outdated technology instead of Brazilian innovations.

7 Conclusion

In this paper, I investigate the effect of replacing imported technology by national inventions in Brazil. I use a novel dataset on international transactions, patent applications, and employment for Brazil, with exogenous variation from a technology substitution program to show that, contrary to popular belief, innovation policy in developing countries reduces the skill premium and production because it induces the substitution of international technology, which is high-productivity and high-skilled biased, by national technology, which is low-productivity and low-skilled bias. Therefore, the reliance of developing countries on imported technology actually increases production and inequality.

Collecting data from several administrative sources, I construct a dataset with information on innovation, technology transactions, and employment at the firm. As far as I am aware, this is 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 by national technology led firms to increase expenditure share with low-skilled workers and reduce employment.

A model of directed technological change and international technology transactions can explain the empirical results. Therefore, the empirical results are 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 micro-elasticities and show that technology replacement in Brazil would lead to a decrease in production and skilled wage premium.

There are several extensions for future research. The exogenous variation from the Technology Substitution Program can be used to estimate the externality of R&D investment, which allows to estimate an optimal R&D subsidy. Moreover, section F.15, studying the effect of minimum wage on innovation and technology leasing, shows that technology bias and adoption is affected by labor policy. While an extension of F.11 can be used to understand how R&D subsidies affect the career of scientists. Section 49 also indicates that directed technological change has implications for international policy. Therefore, there is a long venue of research to be explored studying the data collected, the TSP, and the model of directed technological change.

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A Data Appendix

A.1 Regulations of Technology Transactions in Brazil

From the 60s to early 80s, Brazil implemented a series of policies to favor the national industry: barriers to international trade, capital flows and technology transfer. 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[44]. The patent office's goal, at first, was to guarantee that the royalties send abroad corresponded to a real technological transfer and that it satisfy the sectoral quotas established by the government.

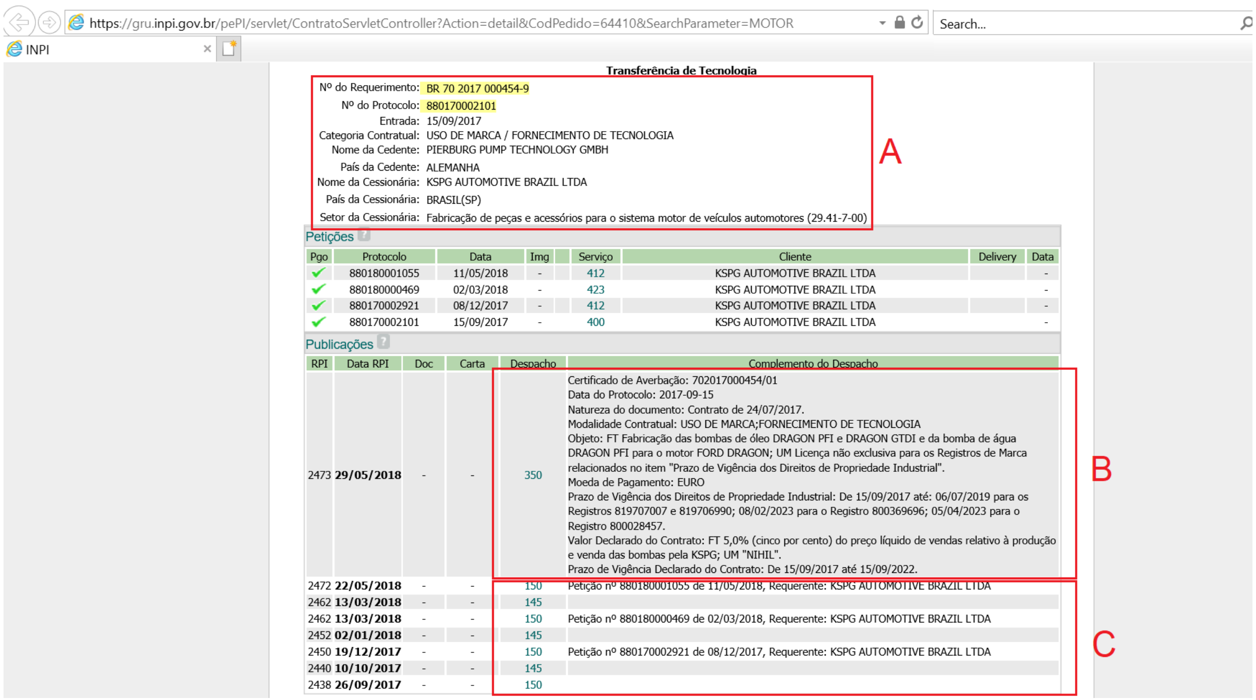
The role of the patent office changed in 1971 with the introduction of a new industrial property regulation: it practically become a third party in any technology contract. It was allowed to reject contracts judged unfair or against national interest, established sectors that were not allowed to import 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.[45] The goal of the policy maker in with these changes was to increase national production of technology and reduce the dependency of international technology.

All these restrictive measures were reversed in 1996[46]. The role of the patent office changed once again. As 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 transactions.

The international technology market in Brazil were subject to more changes in the 00's. In 2001 the government create a 10% tax in any payment to abroad due to technology transactions[47]. Those funds were utilized to as incentive to national R&D [48]. This tax burden

[44] Lei nº 4.131/62.
[45] Established by the normative act number 15 of 1975 and number 32 of 1978. See **?** for more.
[46] By the law nº 9279/96
[47] Law nº 10.168/00
[48] Law nº 10.332/01

Figure 12: **Patent Office Web Page with Information on Technology Transaction**



Description:

was temporarily alleviated in 2006 when the timing of the tax payment was relaxed[49]. This policy was reversed in 2010 with the goal of raising funds to the Olympic games.

A.2 Scrapping Patent Office Web Page

In this subsection I explain how the patent office web page was scrapped to construct the dataset with information on technology transactions.

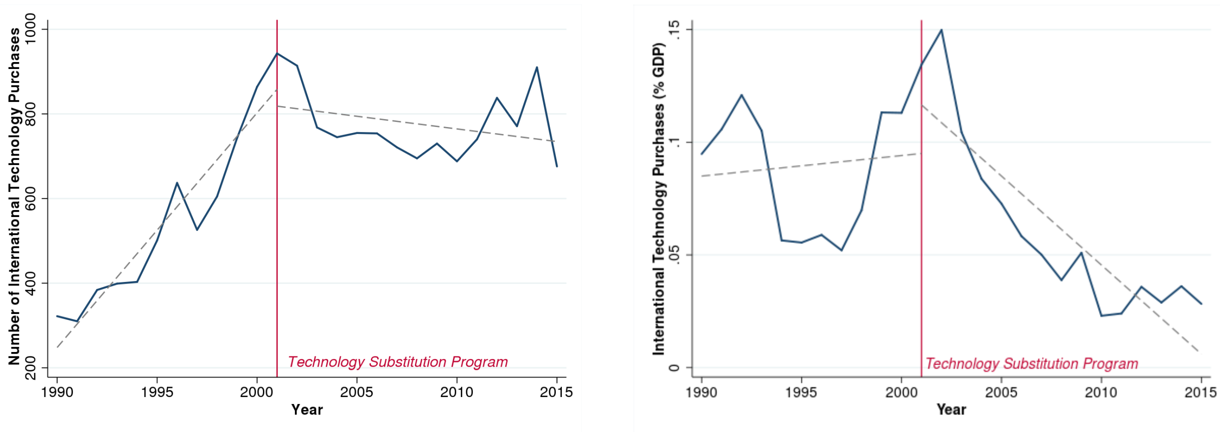
For each technology transaction submitted to the patent office, a page similar to figure 12 can be found. On panel A, it records the identifying code of the transaction, the date of filling, the type of transaction[50], name of buyer and seller, country of seller, state of Brazilian buyer and sector of buyer. Panel B contains a detailed information on the technology being

[49]Decree nº 5.798 of 2006.

[50]The patent office has the following technology transaction types: license for trademark use, brand assignment, patent exploration license, patent assignment, compulsory patent license, industrial design exploration license, industrial design assignment, integrated circuit topography license, assignment of integrated circuit topography, compulsory integrated circuit topography license, franchise, technology provision, and Technical and Scientific Assistance Services

Figure 13: **International Technology Purchase**

(a) **Number of Int. Technology Purchase** (b) **Exp. with Int. Technology Purchase**



transferred. It contains the date of approval of the technology transaction, the type of technology being transferred, a short description of the technology, the currency of payment, the duration of the contract, the value of the contract and the duration of the contract. Panel C contains information on the interaction between the firm registering the transaction and the patent office. From panel C we can infer if the patent office required changes in the contract, required further documentation or the contract were not approved.

A.3 Statistics of Technology Transactions in Brazil

In this section I present statistics of technology transactions in Brazil.

Figure 13 shows the evolution of technology transactions since 1990. Panel (a) contains the total number of transactions while panel (b) contains the value of transactions as a share of GDP[51]. 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 what is the purpose of the technology being implemented in each firm. According to the words describing the technology, I classify each transaction in different groups: introduction of a new product, technological service to increase 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.

[51]As indicated before, the value of the contract is not observed for all transactions. To estimate the aggregate transaction value I input the value of the technology by using observable characteristics.

Table 11: **Content of Technology Transactions**

	N. Transactions	**%**
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 transactions. Each content is define 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 key word training. "*Machine inst.*" has key words: assembly, machine, installation or construction. "*Franchise*" are transactions in which a franchise were open.

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 transaction per sector of the buyer. The manufacturing sector is the sector responsible for much of the technology transfers.

Figure 14 helps us understand how often firms buy and sell technology. It shows in panel in figure 14a the distribution of number of technology purchase by Brazilian buyers and in figure 14b the distribution of number of technology transaction per sellers. It indicates that the majority of buyers and sellers engage in only one transaction. Still, the figure shows that some few firms sell technology and buy technology very often.

Figure 15 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 16a shows the technology price relative to yearly wage bill. About of 20% of technology transactions have price larger than the yearly wage bill of the firm. Figure 16a shows that some of these transactions have small price for the firm. This is expected given that some firms engage in technology transactions often.

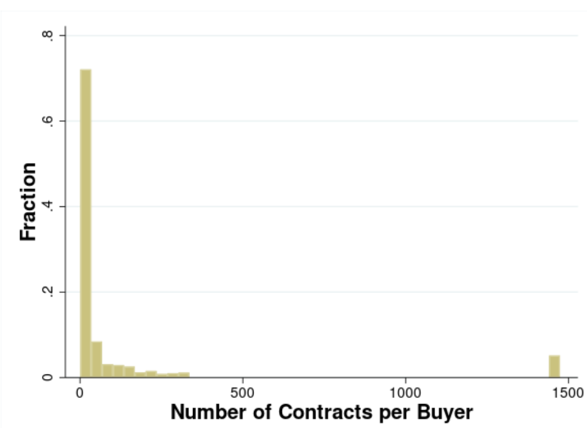
Figure 16b helps us understand the overall magnitude of technology transactions at the firm level. Figure 16b displays the stock of firms investment on technology over yearly wage bill at the end of the period. For more than 35% of firms, they have invested more than twice the yearly wage bill in acquiring new technologies.

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%

Figure 14: **Distribution of Number of Transactions per Buyer and Seller**

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



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

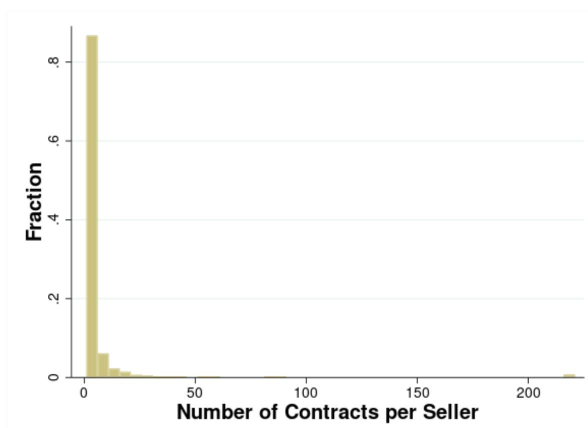


Figure 15: **Distribution of Technology Price**

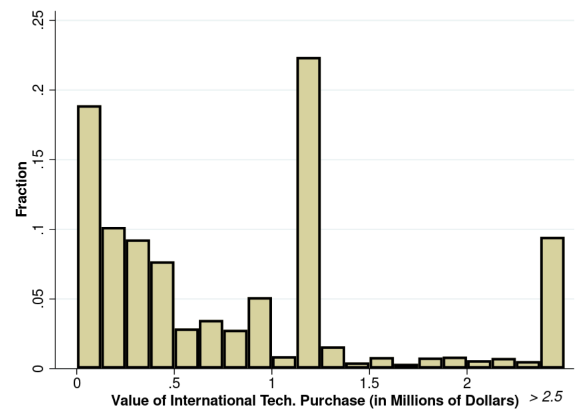
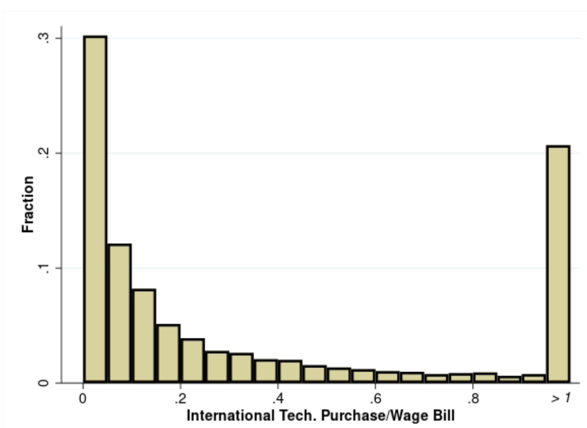


Figure 16: **Distribution of Contract Value**

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



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

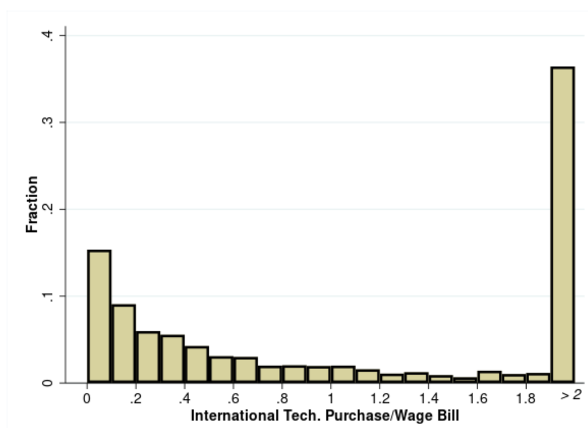
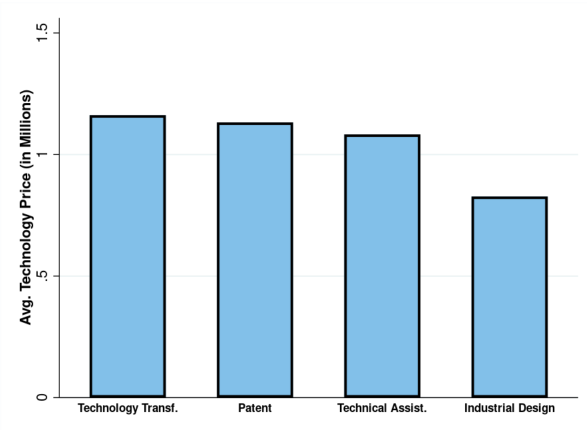


Figure 17: **Avg. Tech. Price by Tech. Type and Origin**

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



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

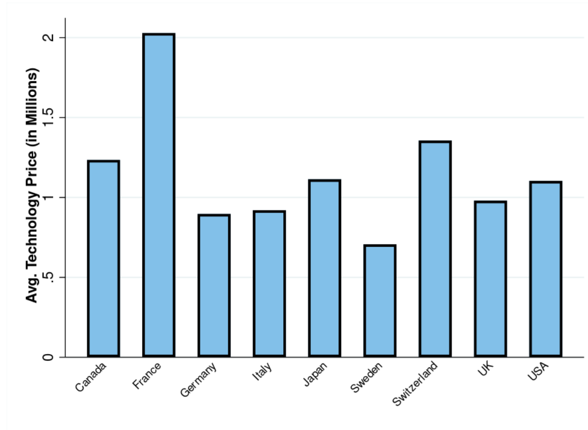


Figure 17 displays the average technology transaction price by the type of the technology and its origin. I break technology transactions in 4 types. The ones where a know-how not protected is transferred, this is the technology transfer type, the one where the property right of a patent is transferred or leased, the ones where the property right of a industrial design is transferred or leased, and technical assistance, when a firms provides technical service. Figure 17 indicates that there is not much variation of technology price by type of technology nor its origin.

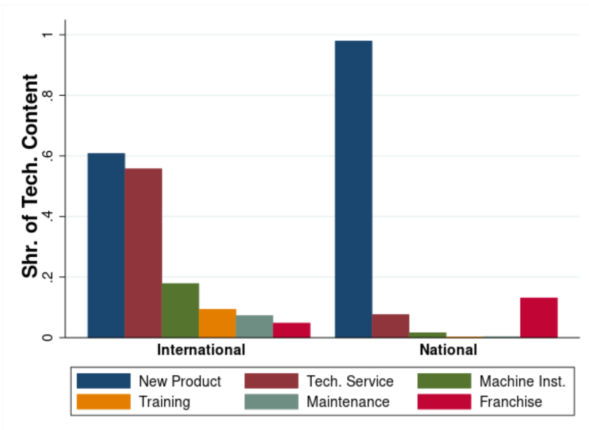
Figure 18 and table 14 shows how national and international technology differ. Figure 18 indicates that national technology is concentrated in trademarks and the introduction of new products. Moreover, it is of higher price and less concentrated in manufacturing.

Table 15 compares firms that purchase 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 higher hourly wage.

Table 16 shows a profile of the firm selling technology to Brazil: those are firms with several patents, engaging in few transactions 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 transactions per technology seller. The median technology seller only sold one technology to a Brazilian firm. The second panel displays the number of subsidiaries. The

Figure 18: **Distribution of Contract Value**

(a) Technology Content by Technology Origin



(b) Technology Type by Technology Origin

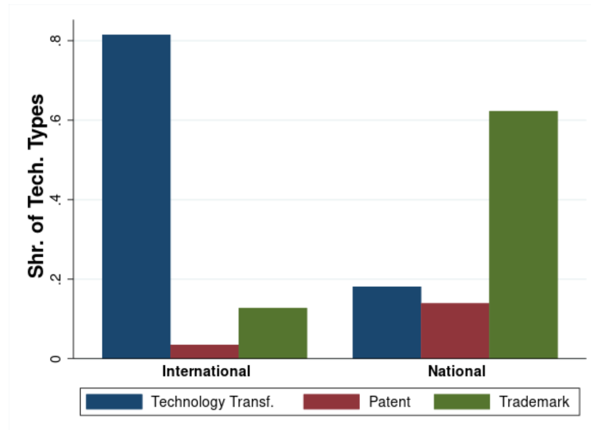


Table 13: **Technology Country of Origin**

Region	N. Transactions	Value (in millions)	% Transactions	% 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 Transactions**

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 transaction 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 transactions 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 transactions.

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**
Transactions		
# Transactions	3.67	1
# Transactions Compustat Match	3.44	1
# Transactions 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 Transaction	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 transactions 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 Transaction" contains the average and median number of transactions between firms in the same two digit NAICS sector while the last line contains a dummy if the seller of technology is on Research & Development sector.

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 transactions are made by firms in the same sector.

A.4 Finding Tax Identifiers of Technology Lessee

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

Two dataset with firm names are used: RAIS and the firm registry database. Putting this two datasets together I am able to recover different spellings for the same firm. RAIS contains firm name for every year and establishment of the firm. Therefore, one tax identifier will have multiple spellings for the same firm name. The firm registry database contains firm

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 transactions 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.

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 buying an international technology is matched to a firm name from RAIS and the firm registry database if the spelling is exactly the same. To increase accuracy, I also constraint 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 watched 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 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 transactions. From table 17, we have that 87.6% of the technology transactions in the sample, corresponding to 88% of firms, can be matched to a tax identifier. This success rate is higher than in other papers in the literature[52] 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.

This matching procedure yields a matching rate of 88%. Moreover, matched and not-matched transactions are similar in several observables. Figure 19 shows that matching rate is not statistically different across Brazilian states while figure 20 shows that the match rate

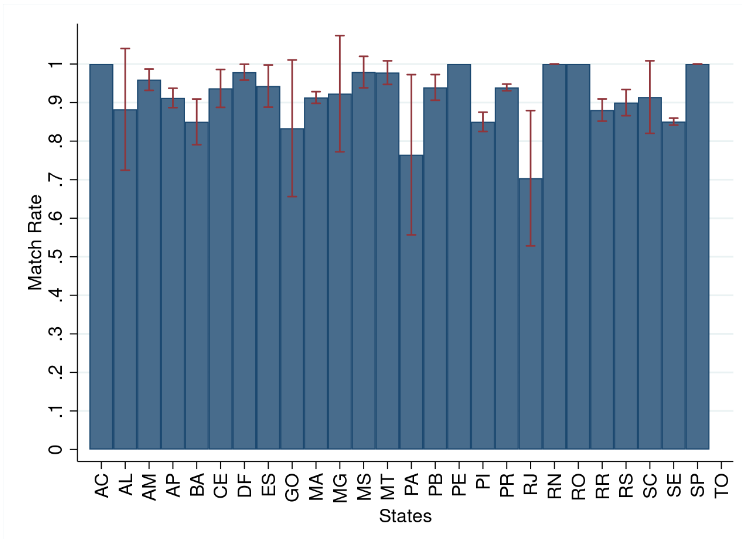
[52] Kost et al. (2020) matches 40% of Compustat firms to trademarks using fuzzy match, Autor et al. (2016a) matches 72% of US patents to Compustat firms using an algorithm with internet searches, Kogan and Stoffman (2017) matches 31% of granted patents on the Google Patents database to public firms 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.

Table 18: **Statistics of Tech. Transactions 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
Tech. Transf.	.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 19: **Match Rate of Technology Transaction According to State of the Buyer**



does not differ across time. Table 18 shows that the only difference between matched and not-matched transaction is on the share of transfers of patents.

A.5 Inspections of Technology Transactions

The approval of technology transactions 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 of 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 in it or demand further docu-

Figure 20: **Match Rate of Technology Transaction According to Year of the Transaction**

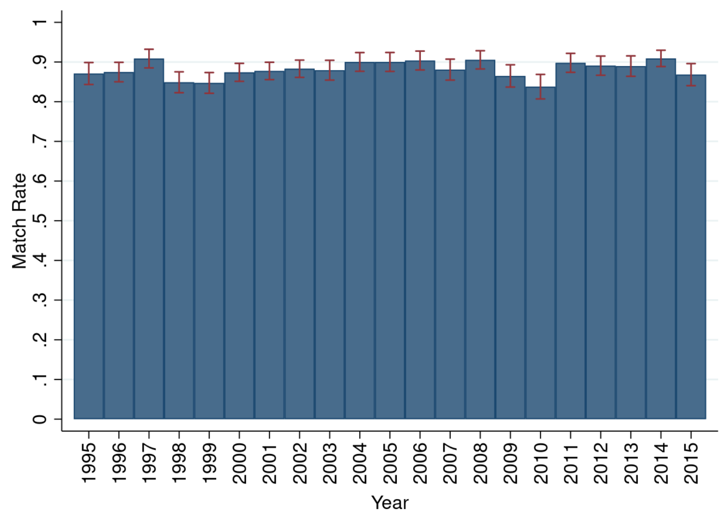


Table 19: **Statistics on Technology Transaction Inspections by Patent Office**

	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 transaction applications made to the Brazilian Patent Office between 1995 and 2015. It contains only the 2,869 (12.26%) transactions in which the enforcement outcome was observed.

mentation. For the 2,869 technology transactions 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.6 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 transactions with tax deduction purposes. Intellectual property lawyers are specialized in writing and registering technology contracts. Therefore, intellectual property lawyers can inform us of the type of firm choosing not to register their contracts in the patent office and can shed light on the incentives firms face to

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

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

fake technology transfers.

I contacted by email 381 law offices with specialization on intellectual property[53]. Out of the 381 contacted law offices, I received an answer from 154, a 40.4% response rate. This 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 transactions. In the second and third part of the survey I ask the respondent about the process of filling national and international technology transactions. In the final section I ask the respondent about incentive firms face to fake technology transactions for tax avoidance.

Table 20 shows that the registration of technology transactions in the patent office is costly, affects the timing of the technology adoption, is bureaucratic and requires scientific documentation.

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

Table 22 shows that using fake technology transactions for a deduction in taxes isn't a common practice. In average, 13% of respondents believe that other law offices have

[53]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 21: **Shr. of Technology Transaction Registered in the Patent Office**

Question	Mean	Median	Mean	Median
	International		National	
Technology transactions 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

Table 22: **Falsification of Technology Transactions 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 transactions 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

employed this practice. Moreover, respondents believe that 15% of technology transactions ever accepted 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.7 Statistics of Brazilian Patents

XX [PATENT CLASS DISTRIBUTION]

A.8 Statistics of Brazilian Industrial Designs

A.9 Statistics of Brazilian Trademarks

A.10 Finding Tax Identifiers for Firms with Patents

A.11 Statistics of R&D Subsidy

[DESCRIPTION OF THE SELECTION PROCESS]

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

Figures to show that the technology substitution program is associated with an increase in national technology share. Is this correlation driven by the technology substitution program

Figure 21: **Patent Applications**

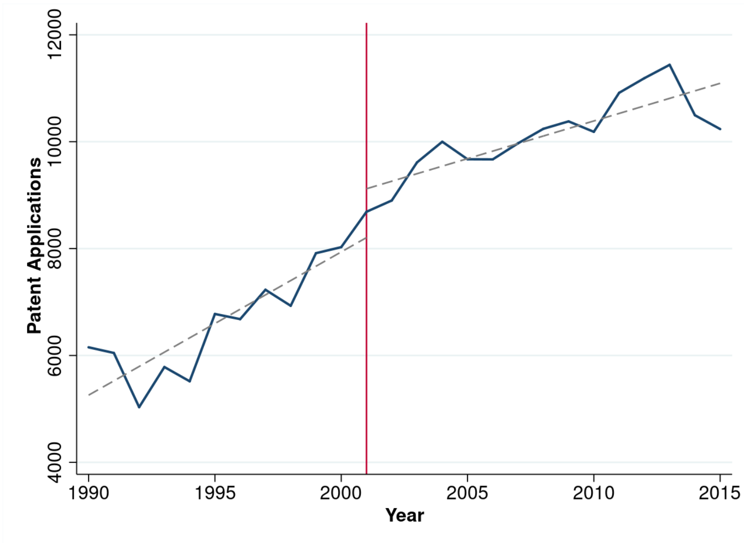


Table 23: **Sector of Patent Applications**

	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 firm making the patent application. 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.

Figure 22: **Industrial Design Applications**

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

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

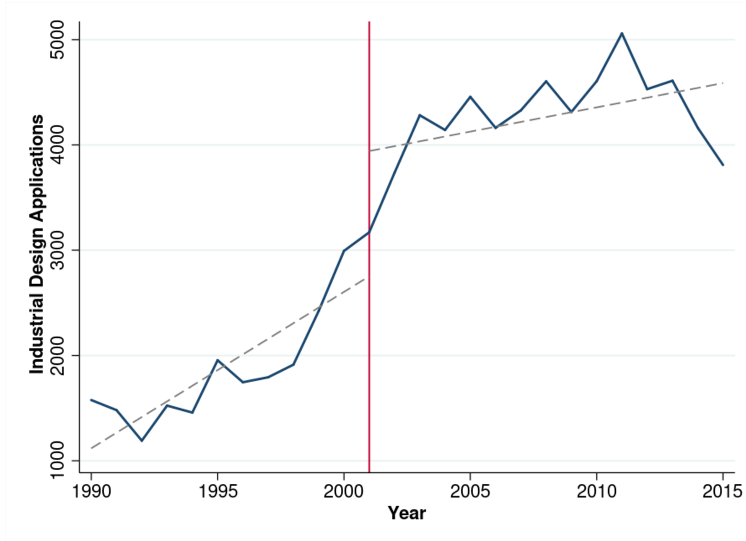
Description: This table shows the number of industrial design applications between 1985 and 2010 by sector of the firm making the application. The information on sector is from RAIS.

Table 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 digits Locarno classification. Industrial designs, as patents, can have more than one classification.

Figure 23: **Trademark Applications**



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

Table 26: **Classification of Industrial Design 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: **Classification of Industrial Design Applications**

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 28: **Classification of Industrial Design 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.

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

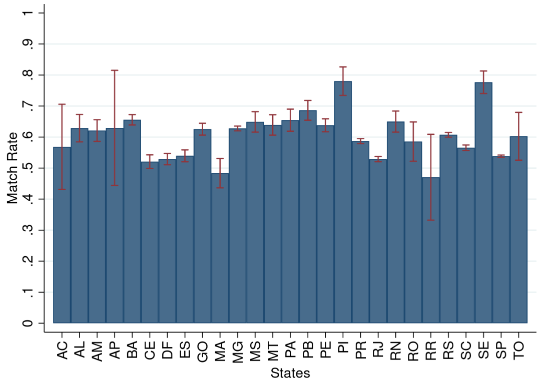
	Total		**Matched**		**Percentage Matched**	
	All	LTDA	All	LTDA	All	LTDA
Number of Patents	173140	11796	92378	10173	0.53	0.86
Number of Inventors	101887	7491	54587	6593	0.54	0.88
Number of Firms	93599	6756	47546	5909	0.51	0.87

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

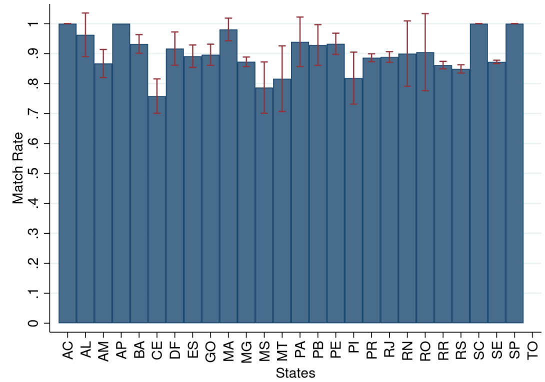
	hour_wage	avg_yrs_educ	shr_hdropout	shr_hcomplete	shr_hmore	n_stablis
Not Subsidy Recipient	41.30	8.11	0.79	0.15	0.06	8.4
Subsidy Recipient	107.09	11.79	0.35	0.30	0.35	4.0

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.

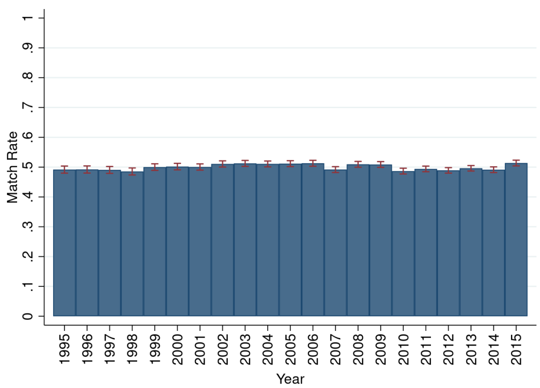
(a) **All Patents**



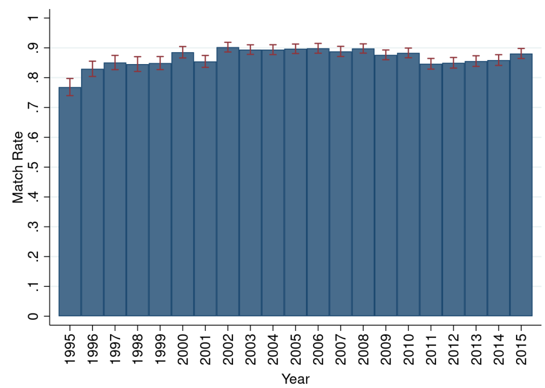
(b) **LTDA Patents**



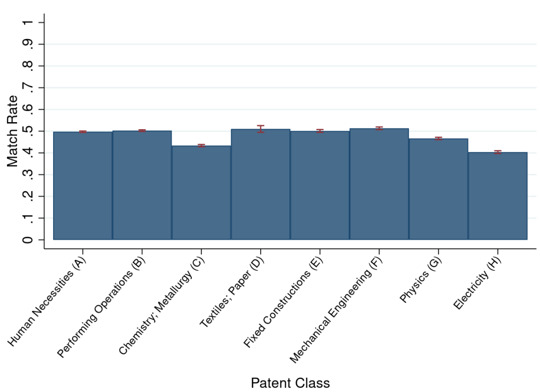
(a) **All Patents**



(b) **LTDA Patents**



(a) **All Patents**



(b) **LTDA Patents**

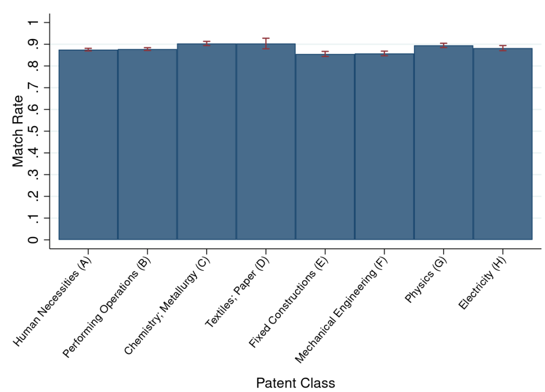


Figure 27: **Average Subsidy by Sector**

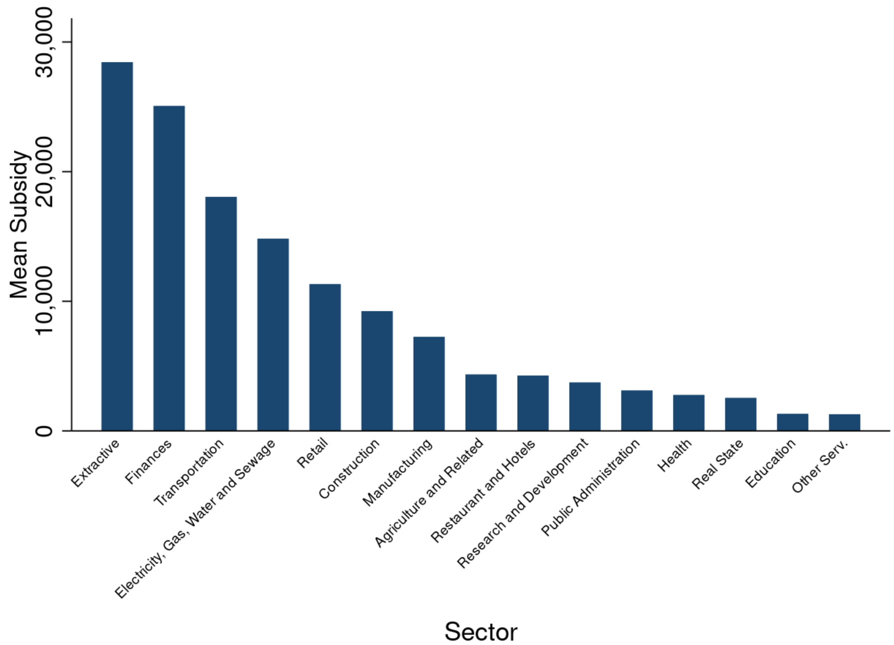


Figure 28: **Number of Subsidies by Year**

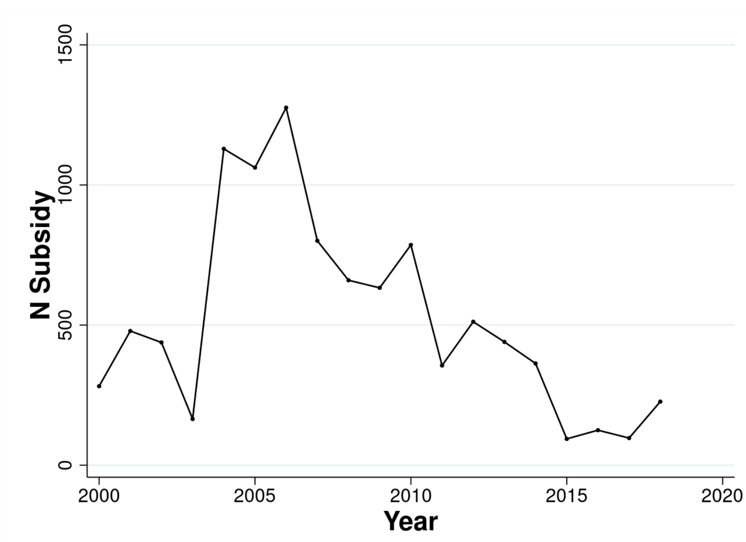


Figure 29: **Value of Subsidies by Year**

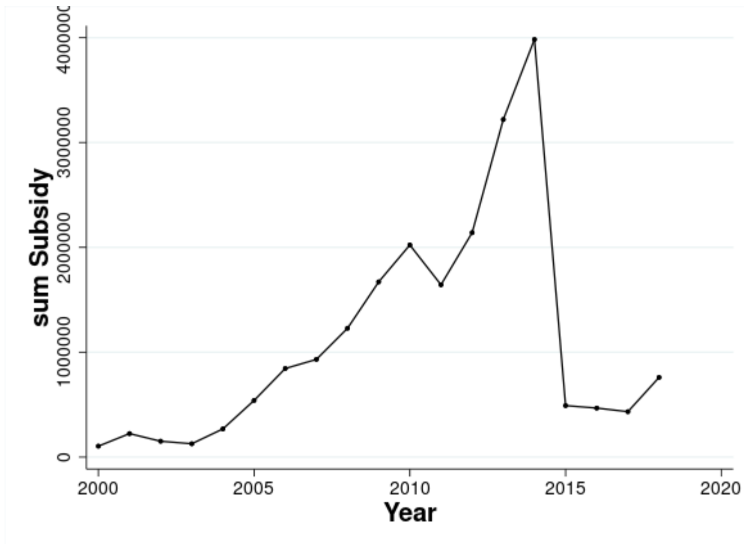
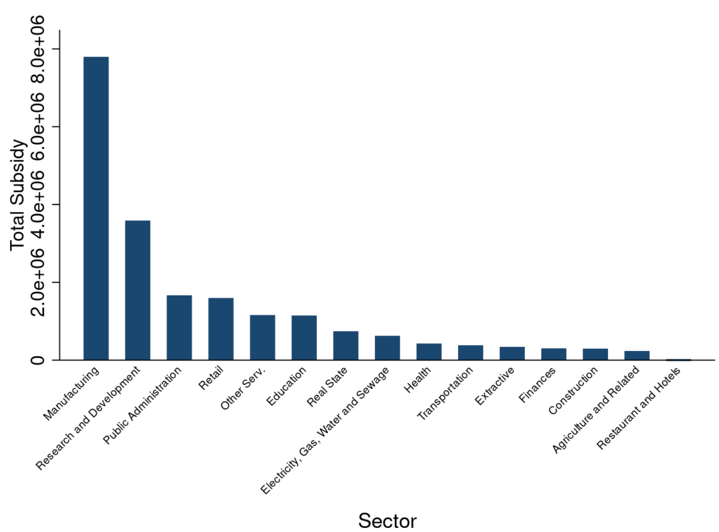


Figure 30: **Subsidies by Sector**



or is it an international trend in technology creation? One could argue that a developing country, after relying in international technology for long, learn 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 and reduced its imports of technology when compared to other developing countries. In top of that, sectors with more exposure to the technology substitution program, as measured by the stock of patents before 1995, increased its patent production by more than sectors with lower exposure.

The main empirical specification is given by

$$Patent_{c,t} = \sum_{j=-5}^{10} \theta_j \mathbb{I}\{t = 2001 + j, c = BR\} + \eta_c + \eta_t + \epsilon_{c,t} \tag{25}$$

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 31a shows the estimated parameter of model 31. 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.

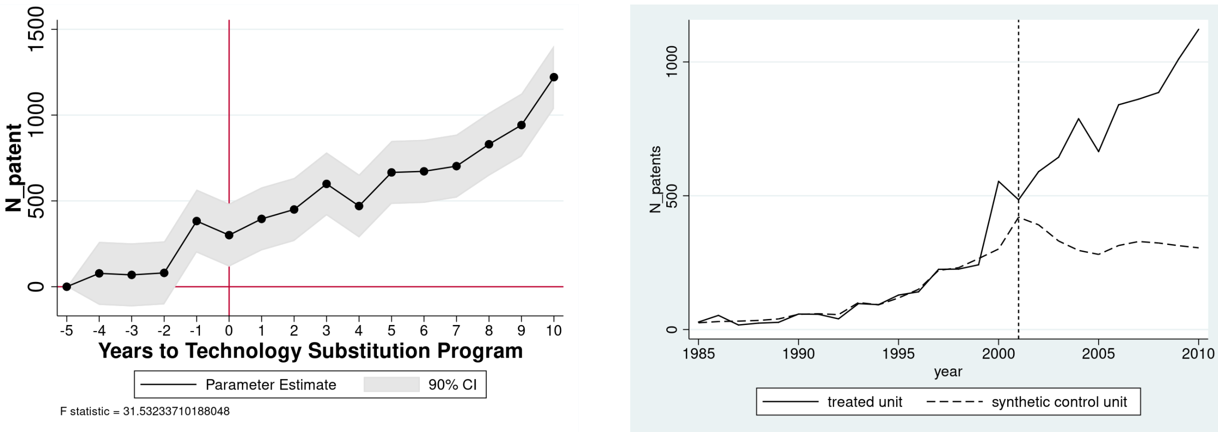
Figure 31 use synthetic control to estimate the effect of the substitution program[54]. Again, it shows that there is a large difference between the treated unit, Brazil, and the control group, an average of developing countries. The synthetic control unit is constructed by averaging a set of developing countries based on their patent emission between 1990 and 1999[55].

[54]XX references for synthetic control.

[55]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 31: **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 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.

Are the sectors more exposed to the technology substitution program the ones that increased their patent production by more relatively to other developing countries? To answer this question we use the following system of equations:

$$Patent_{s,c,t} = \theta_s \mathbb{I}\{t \geq 2001, c = BR\} + \eta_s + \eta_c + \eta_t + \epsilon_{s,c,t}$$
$$\theta_s = \beta Patent_{s,t \leq 1995} + \epsilon_s$$

The first equation estimates the effect of the technology substitution program at the sector level. θ_s tells the difference in patent production in sector s after the technology substitution program. The control group is the patent production by sector s in other Latin American Countries. The second equation estimates how the effect of the program correlates with the stock of patents before 1995, our main instrument.

Table 31 shows that Brazilian sectors where the number of patents increased by more, compared to the same sector in other countries, had larger patent production prior to 1995.

The results in this section give us the idea that a Brazilian specific shock is increasing its number of patent produced and that this increased is driven by sectors with large patent production before 1995. Given that the only technology program in this period was

Table 31: **Technology Substitution Program and Instrument**

	(1)
	θ_s
$Patent_{s,t\leq 1995}$	1.034***
	(0.380)
N	100
R^2	0.070
F	7.391

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010

the technology substitution program, it is unlikely to believe that the driver force of these correlations is some other policy or shock.

A.13 Facts on Innovation and Technology Transactions in Brazil

In this section I show three new facts on innovation and technology leasing in Brazil. First, Brazilian firms mainly lease technology from developed countries. Second, firms buying leasing technology are larger than firms innovating. Third, firms leasing technology are more intensive in high skill workers than firms innovating.

Inspired by these three new facts, I show using exogenous variation from an innovation policy that differences in technology productivity and bias can explain why firms with international technology are larger and skilled intensive. This conclusion is crucial to understand how innovation affects wage skill premium and production in a developing country. Guided by these results, on section XX I show that a model explaining these three new facts predicts innovation policy to reduce production and wage premium by leading firms to switch to low TFP and low-skilled biased technology.

Fact 1: Brazilian firms leasing technology from developed countries Table 32 displays the number of technology transactions by country of origin of the technology[56]. The first panel shows that United States, Germany and Brazil are the three main countries of origin of the technology. The bottom panel of table 32 breaks down the technology according

[56]I do not observe technology leasing valua by all the transactions, for that reason I use the number of transactions instead. Table 13 on appendix uses extrapolation on technology licensing price to replicate this table.

Table 32: **Technology Country of Origin**

Region	**N. Transactions**	**%**
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

Table 33: **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. The first line contain statistics of firms with patent registered in the Brazilian patent office, the second line contain statistics of firms buying international technology without and the last line information from all Brazilian firms.

to the development status of the country using definition provided by the World Bank. The bottom panel of table 32 shows that the majority of technology licensed by Brazilian firms is from developed countries. Table 13 on appendix shows that this is true even when using predicted technology licensing value.

Fact 2: Firms leasing technology are larger than firms innovating Table 33 shows the average firm size and hourly wage in 2000 for firms with patent, firms with international technology and all other firms in Brazil. Firms with international technology are almost three times larger and have higher hourly wage than firms with patents, i.e., using national technology.

Fact 3: Firms buying technology are more intensive in high skilled workers Table 33 shows the average share of high-school dropouts, high school complete and average years

Table 34: **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

of education at the firm. Firms innovating have more high school dropouts and lower average years of education.

This is a surprising finding. Innovation is a skill intensive activity and new technologies have been show to be skilled bias[57]. Therefore, its natural to expect innovative firms to be the most intensive in skilled workers.

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. In the model section I show that fact 1 can explain this difference in technology bias.

A.14 Motivation for the Technology Substitution Program

The goal of the technology substitution program was to increase R&D investment by private companies. It was not created as response to trends in labor market or as preparation for future shocks. Policy makers 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 on public universities[58].

The tax on technology transactions wasn't created with a specific policy goal. Instead, it was created due to legal requirements of the Brazilian fiscal law. The Brazilian fiscal law establishes that any new expenditure needs to have a new revenue source. Moreover, the revenue source must be related to the new expenditure. Given that the goal of the program was to stimulate innovation, policy makers decided to use transaction of innovations as source of revenue.[59]

[57]Krueger (1993), Autor et al. (2003) and Akerman et al. (2015).

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

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

Table 35: **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 36: **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: This table shows the parameter of a regression of *Exposure TSP* on the change of a dummy taking one if the firm is an international subsidiary.

The TSP was quickly written by the federal government and approved in regime of urgency. In addition, in 2001 the government come from a period of cuts in the federal budget. These two facts support the idea that firms could not adjust their innovation efforts or labor to the news of the policy. The main piece of legislation of the program was approved in 6 months, a record time for the Brazilian bureaucracy. Moreover, in the years prior to the subsidies for innovation, the government issued a series of cuts, a re-organization of the federal budget and tax increases. Therefore, a shift in policy wasn't expected by firms or workers.

Table 37: **Other Policies and Exposure to the TSP**

	(1) Δ Tariff Inputs	(2) Δ Tariff Output	(3) $\Delta\mathbb{I}\{Gov.\ Loan\}$	(4) $\Delta\mathbb{I}\{Gov.\ Contract\}$	(6) Δ *Labor Tax*	(7) Δ *Tax*	(8) $\Delta\mathbb{I}\{Campaign\ Contribution\}$
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: This table shows the parameter of a regression of *Exposure TSP* on a set of policy variables. Column 1 contains the average tariif on inputs of firm i while column 2 contains the average tariff on outputs of firm i. Column 3 contains a dummy taking one if the firm received a subsidize loan from the federal bank BNDES, column 4 contains a dummy taking one if the firm signed a contract selling products to the federal government, column 6 has a average sectoral labor tax while column 7 has the overall sectoral tax burden. Column 8 contains a dummy if the firm made a political campaign contribution in the past 10 years.

B Empirics Appendix

B.1 Additional Results and Tables

Table 38: **Patents in Past 10 Years According to Inventor Quality and Exposure to the TSP**

	(1) $\Delta\mathbb{I}\{Scientist\}$	(2) $\Delta\mathbb{I}\{PhD\ Worker\}$	(3) $\Delta\mathbb{I}\{Patent\ PhD\ Inventor\}$	(4) $\Delta\mathbb{I}\{Patent\ Master\ Inventor\}$	(5) $\Delta\mathbb{I}\{Patent\ Academic\ Paper\ Inventor\}$	(6) $\Delta\mathbb{I}\{Patent\ Professor\ Inventor\}$
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	33692	33692	33692	33692	33692	33692
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 measures of changes in intellectual creation by the firm.

Table 39: **Intellectual Property in Past 10 Years and Exposure to the TSP**

	(1) $\Delta log(\mathbb{N}\{Patent\})$	(2) $\Delta log(\mathbb{N}\{log(PCT\ Patent)\})$	(3) $\Delta log(\mathbb{N}\{Patent\ or\ Ind.\ Design\})$	(4) $\Delta log(\mathbb{N}\{Any\ Intelec.\ Prop.\})$
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 measures of changes in intellectual creation by the firm. $\mathbb{I}\{Int.\ Patent\}$ is a dummy taking one if the firm has ever applied for an international patent, $\mathbb{I}\{Scientist\}$ is a dummy taking one if the firm has ever hired a scientist, $\mathbb{I}\{Patent\}$ is a dummy taking one if the firm has ever applied for a patent, $\mathbb{I}\{Trademark\}$ is a dummy taking one if the firm has ever applied for a trademark and $\mathbb{I}\{Industrial\ Design\}$ is a dummy taking one if the firm has ever applied for an industrial design. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period.

Table 40: **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	33692	33692	33692	33692
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 measures of changes in intellectual creation by the firm. $\mathbb{I}\{Int.\ Patent\}$ is a dummy taking one if the firm has ever applied for an international patent, $\mathbb{I}\{Scientist\}$ is a dummy taking one if the firm has ever hired a scientist, $\mathbb{I}\{Patent\}$ is a dummy taking one if the firm has ever applied for a patent, $\mathbb{I}\{Trademark\}$ is a dummy taking one if the firm has ever applied for a trademark and $\mathbb{I}\{Industrial\ Design\}$ is a dummy taking one if the firm has ever applied for an industrial design. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period.

Table 41: **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.

Table 42: **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: This table presents the estimated parameters of a regression of the exposure to the TSP on measures of changes in intellectual creation by the firm. $\mathbb{I}\{Int.\ Patent\}$ is a dummy taking one if the firm has ever applied for an international patent, $\mathbb{I}\{Scientist\}$ is a dummy taking one if the firm has ever hired a scientist, $\mathbb{I}\{Patent\}$ is a dummy taking one if the firm has ever applied for a patent, $\mathbb{I}\{Trademark\}$ is a dummy taking one if the firm has ever applied for a trademark and $\mathbb{I}\{Industrial\ Design\}$ is a dummy taking one if the firm has ever applied for an industrial design. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period.

Table 43: **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) $\Delta\frac{N.\ Int.\ Tech.}{N.\ EPO\ Patent\ or\ Int.\ Tech.}$	(4) $\Delta\frac{\$\ Int.\ Tech.}{\$\ EPO\ Patent\ or\ Int.\ Tech.}$
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 changes in intellectual creation by the firm. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period.

Table 45: **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. Appendix **??** describes how these measures were constructed. *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 **?** 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 **?** and use the ONET measures of "Operation Monitoring", "Operation and Control", "Quality Control Analysis" among others. *Number* measures the use of numbers, it follows the definition of Deming (2017) using the ONET questions for "Number Facility".

Table 44: **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	33692	33692	33692	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.

Table 48: **Wages and Exposure to the TSP**

	(1) $\Delta log(Avg.\ Wage)$	(2) $\Delta log(Wage\ HS\ Dropout)$	(3) $\Delta log(Wage\ HS\ Complete)$	(4) $\Delta log(Wage\ HS\ More)$
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 measures of changes in intellectual creation by the firm. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period.

Table 46: **Employment Percentage Change with Balanced Sample and Exposure to the TSP**

	(1) $\frac{N.Workers^{2010}-N.Workers^{2000}}{N.Workers^{2000}}$	(2) $\frac{N.HSDropout^{2010}-N.HSDropout^{2000}}{N.HSDropout^{2000}}$	(3) $\frac{N.HSDropout^{2010}-N.HSComplete^{2000}}{N.HSComplete^{2000}}$	(4) $\frac{N.HSMore^{2010}-N.HSMore^{2000}}{N.HSMore^{2000}}$
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 regression 2 on employment change at the firm. The sample is selected to firms that hired high school dropouts workers, high school complete workers and workers with more than high school.

Table 47: **Employment and Exposure to the TSP using Heckman Selection**

	(1) $\Delta log(N.WorkersDropout)$	(2) $\Delta log(N.WorkersHSComplete)$	(3) $\Delta log(N.WorkersHSMore)$
Exposure TSP	-0.167***	-0.272***	-0.157***
	(0.0588)	(0.0648)	(0.0540)
N	26815	28848	31481
R^2			
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 regression 2 on employment change at the firm correcting for selection in the hiring of each educational group. Column one shows the effect of TSP on log change of H.S. dropouts using as exogenous shifter to selection into hiring H.S. dropouts a dummy taking one if the firm hired H.S. dropouts in 1995. The same method is implemented in column 2 and 3 for workers with H.S. complete and H.S. more.

Table 49: **Imports, Exports and Exposure to the TSP**

	(1) $\Delta\mathbb{I}\{Exporter\}$	(2) $\Delta\mathbb{I}\{Importer\}$	(3) $\Delta\mathbb{P}\{Prob.\ Import\ Input\}$	(4) $\Delta\mathbb{P}\{Prob.\ Import\ Capital\}$
Exposure TSP	-0.0578**	-0.0850***	-0.0703***	-0.0582***
	(0.0235)	(0.0204)	(0.0202)	(0.0197)
N	33692	33692	33692	33692
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 changes in intellectual creation by the firm. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period.

Table 50: **Imports of Machines and Exposure to the TSP**

	(1) $\Delta\mathbb{P}\{Importing\ Labor\ Saving\}$	(2) $\Delta\mathbb{P}\{Importing\ Labor\ Augmenting\}$	(3) $\Delta\mathbb{P}\{Importing\ Machine\ Developed\}$	(4) $\Delta\mathbb{P}\{Importing\ Machine\ Developing\}$
Exposure TSP	-0.0221**	-0.0549***	-0.0623***	0.0706***
	(0.0100)	(0.0191)	(0.0196)	(0.0142)
N	33692	33692	33692	33692
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 changes in intellectual creation by the firm. As controls I use a dummy for microregion interacted with a 1 digit sectoral dummy, firm's employment growth in the pre-period and number of international patents in the pre-period.

Table 51: **O*Net Technical Skills and Exposure to the TSP**

	(1) Δ *Equipment Maintenance*	(2) Δ *Equipment Selection*	(3) Δ *Installation*	(4) Δ *Operation Monitoring*	(5) 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:

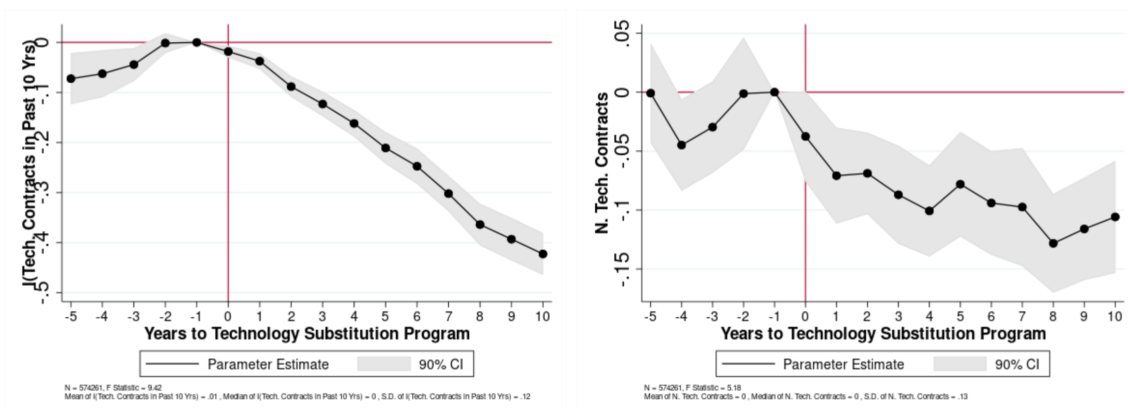
Table 52: **O*Net Technical Skills and Exposure to the TSP**

	(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:

Figure 32: **International Technology Leasing and Exposure to the TSP**

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



B.2 Robustness of the Empirical Results

B.2.1 Results using Heterogeneity of Subsidy Allocation Across Targeted Sectors

The technology substitution program taxed international technology leasing and allocated the revenue of this tax as 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 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:

$$\textit{Exposure TSP}_{i,s(i)}^{hetero} = \textit{Revenue Shr. Sector s(i)} \times \mathbb{I}_i \{\textit{Leased Tech. Before TSP}\} \tag{26}$$

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 in future firm characteristics. Instead, policy makers 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 different specification

$$y_{i,s(i),2010} - y_{i,s(i),2000} = \theta \textit{Exposure TSP}_{i,s(i)}^{hetero} + X'_{i,s(i)}\beta + \epsilon_{i,s(i)} \tag{27}$$

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. $\textit{Exposure TSP}_{i,s(i)}^{hetero}$ is the exposure measure defined in 26. $X_{i,s(i)}$ is the same set of controls used in the main part of the paper[60].

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

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

Table 53 shows that firms increased innovation, increased expenditure share with low skilled workers and decreased overall employment in response to the TSP. Table 53 shows that if 100% of TSP revenue were allocated to the sector of firm i and firm i leased 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 decrease employment by 11%. Figure 33 shows that parallel trends holds in the pre-period.

[60]Controls are 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, and the growth in a dummy if the firm ever had a PCT patent.

Table 53: **Main Results with Heterogeneous Revenue Allocation 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 $TSP^{hetero}_{i,s(i)}$	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	33692	33692	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

Description:

B.2.2 Results using Probability of Receiving Subsidy

Using only sectors to predict firm's probability of receiving subsidy has the advantage of being exogenous to firm level trend, 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, insures 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

$$\mathbb{I}_i\{Subsidy\ Between\ 2000\ and\ 2010\} = W_i'\tilde{\beta} + \epsilon_i \tag{29}$$

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 29, 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

$$Exposure\ TSP^{prob}_{i,s(i)} = \mathbb{P}_i\{Subsidy\} \times \mathbb{I}_i\left\{Leased\ Tech.\ Before\ TSP\right\} \tag{30}$$

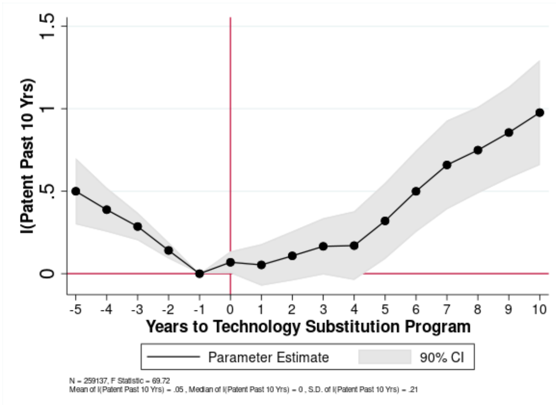
Main my specification is

$$y_{i,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times Exposure\ TSP^{prob}_{i,s(i)} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{31}$$

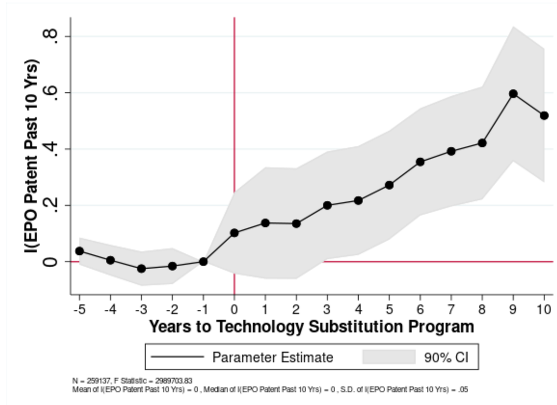
Figure 34 shows that the results are still the same. In response to the TSP, firms increased innovation, increased expenditure share with low skilled workers and decreased overall employment.

Figure 34: **Main Results with Exposure using Probability of Receiving Subsidy**

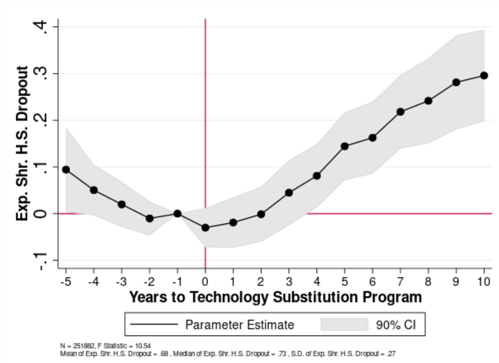
(a) I(Patent Past 10 Yrs.)



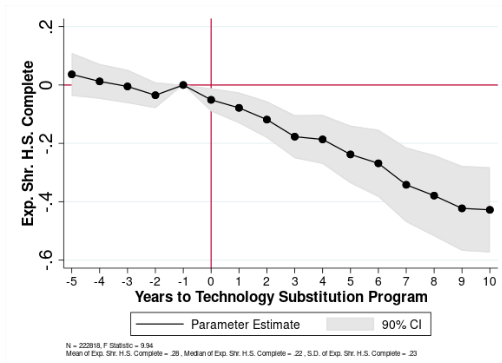
(b) I(EPO Patent Past 10 Yrs.)



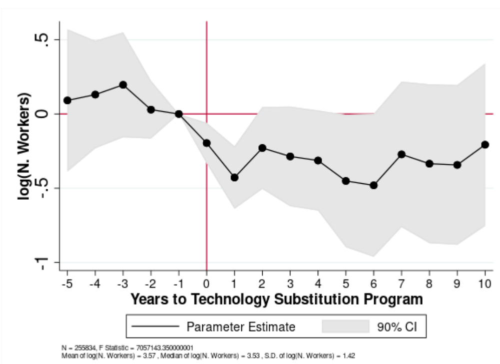
(c) Exp. Shr. H.S. Dropout



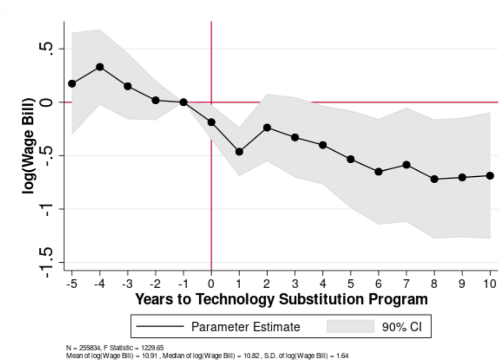
(d) Exp. Shr. H.S. Complete



(e) log(N. Workers)



(f) log(Wage Bill)



B.3 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 change in outcomes between the two group 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.[61]

I estimate the following dynamic model:

$$y_{i,p,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Exposure TSP}_{i,s(i)} + \tag{32}$$

$$\sum_{j=-5}^{10} \mu_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathbb{I}\{\textit{Matched Pair } p\} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{33}$$

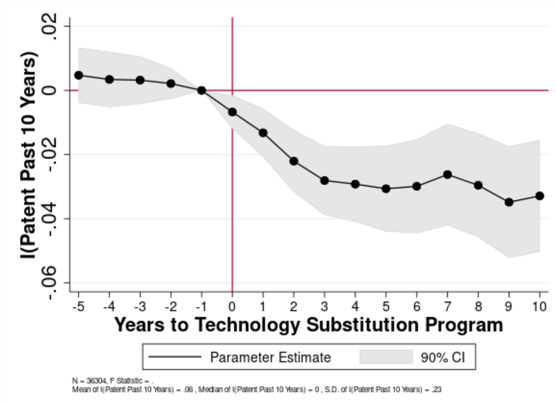
where $y_{i,p,s(i),t}$ is a labor outcome of firm i, on matched pair p, sector $s(i)$ in year t. As before, $\mathbb{I}\{j \text{ Yrs to TSP}\}$ is a dummy taking one j years to the introduction of the TSP, $\textit{Exposure TSP}_{i,s(i)}$ is a dummy if the firm is exposed to the TSP, $X_{i,s(i),t}$ 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 35 display the estimated effect of TSP using 32. The results are similar in sign and magnitude to what were identified with the main specification.

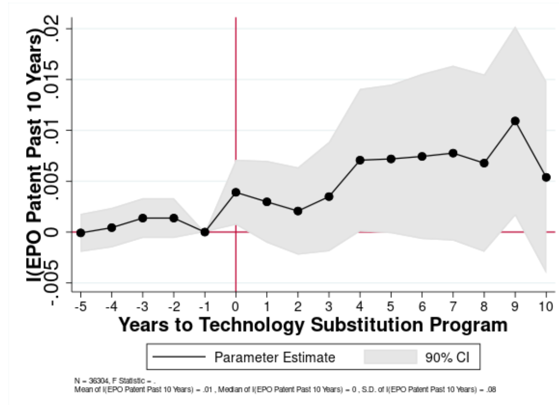
[61] For more on the matching procedure, see **??**.

Figure 35: **Main Results of Matched Diff-in-Diff**

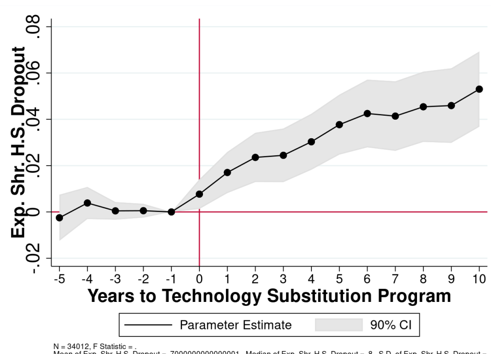
(a) I(Patent Past 10 Yrs.)



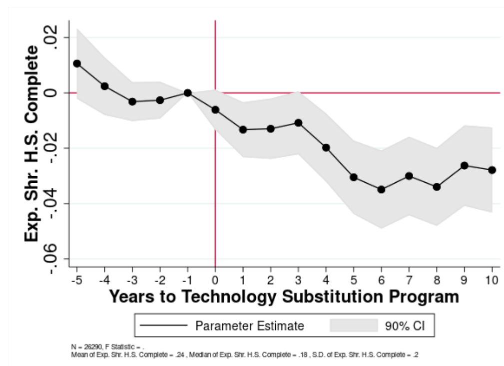
(b) I(EPO Patent Past 10 Yrs.)



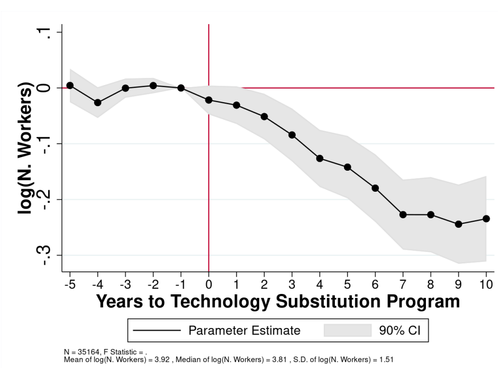
(c) Exp. Shr. H.S. Dropout



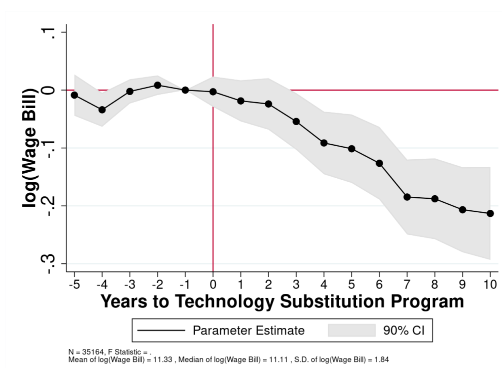
(d) Exp. Shr. H.S. Complete



(e) log(N. Workers)



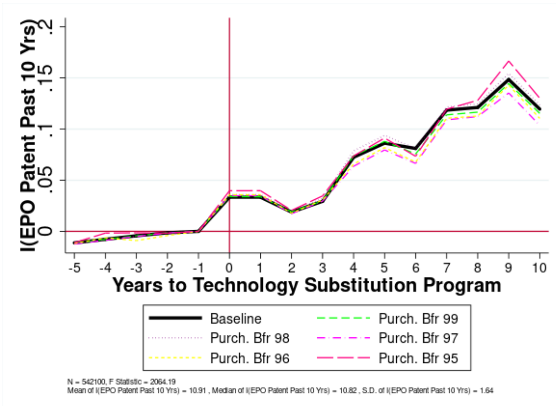
(f) log(Wage Bill)



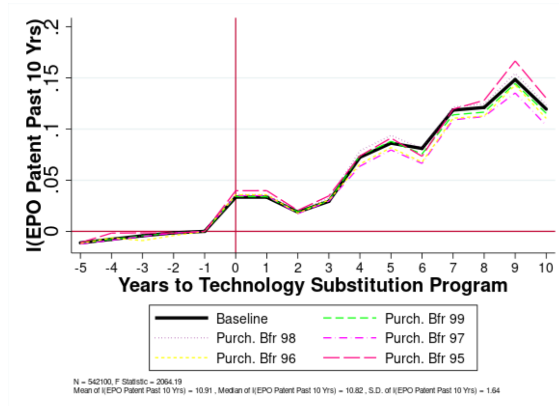
B.3.1 Results using Different Timing for Technology Leasing

Figure 36: **Main Results of Matched Diff-in-Diff**

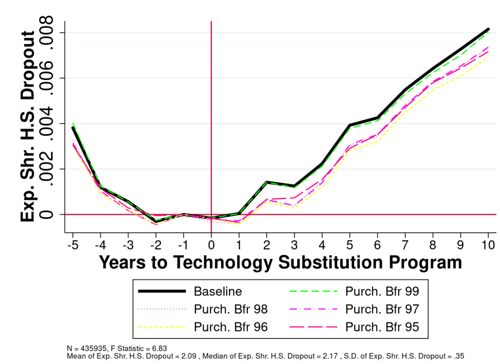
(a) I(Patent Past 10 Yrs.)



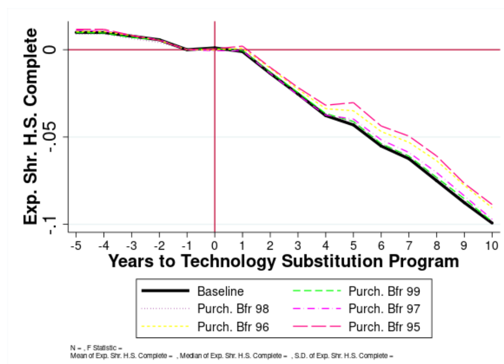
(b) I(EPO Patent Past 10 Yrs.)



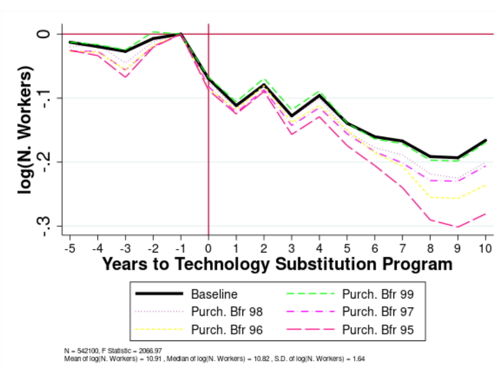
(c) Exp. Shr. H.S. Dropout



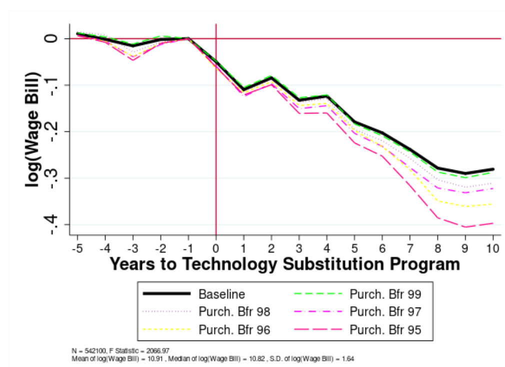
(d) Exp. Shr. H.S. Complete



(e) log(N. Workers)



(f) log(Wage Bill)



B.3.2 Results using Triple Difference

Which variation drives the results: the sectoral exposure to the R&D subsidy or the dummy for past technology leasing? To answer this question I use a triple difference model allowing the exposure to the subsidy and the exposure to the tax to have different coefficients. Employing triple difference I show in this section that firms leasing international technology in the pre-period increased patenting, decrease the leasing of international technology, increased expenditure share with high school dropouts and decreased employment. The firms exposed to the subsidy weakly increased patent applications and employment but, in magnitude, both effects are weaker than the effect suffered by the firms exposed to the tax. Still, this result does not let us conclude that the effect identified is from the tax in technology leasing: firms leasing international technology in the pre-period were also more likely to receive the subsidy.

The dynamic triple difference model is given by

$$\begin{aligned} y_{i,s(i),t} = &\sum_{j=-5}^{10} \theta_j^{subsidy} \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathbb{I}\left\{Subsidy\ s(i)\right\} + \\ &\sum_{j=-5}^{10} \theta_j^{tax} \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathbb{I}_i \left\{Leased\ Tech.\ Before\ TSP\right\} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \end{aligned} \tag{34}$$

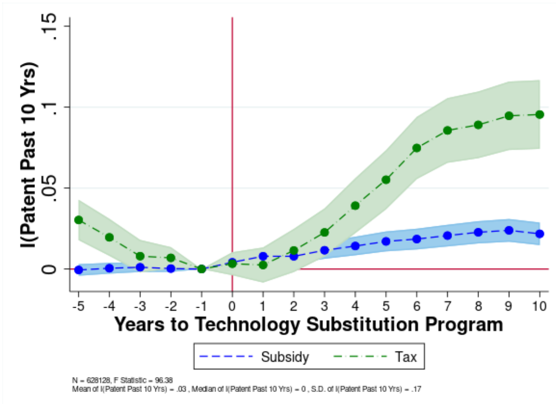
where $\theta_j^{subsidy}$ captures the effect of being more exposed to the subsidy while θ_j^{tax} captures the effect of being more exposed to the tax.

Figures 37, 38 and 39 shows the coefficients of the triple difference specification on the main variables.

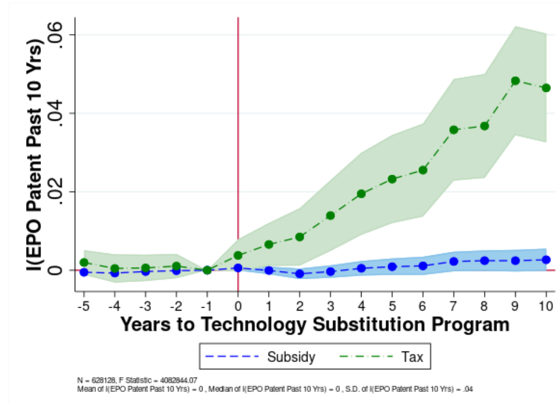
XX - put more detail and discussion in here

Figure 37: **Effect of Exposure to Tax and Subsidy on Innovation and Subsidy Recipiency**

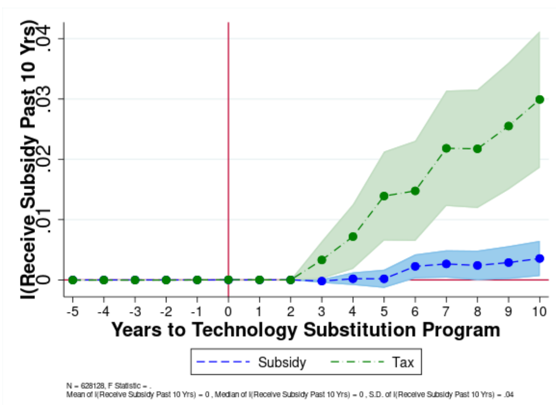
(a) **I(Patent Past 10 Yrs.)**



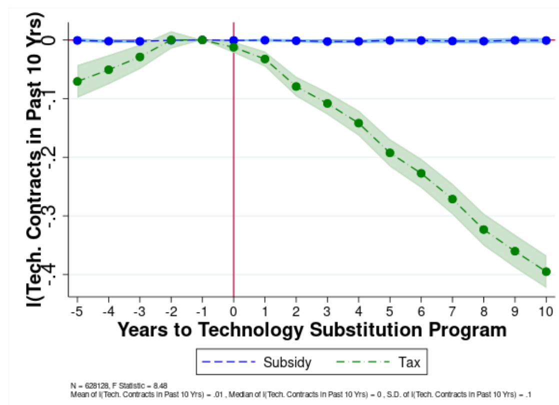
(b) **I(EPO Patent Past 10 Yrs.)**



(c) **I(Subsidy Past 10 Yrs.)**



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



(e) **I(EPO Patent Past 10 Yrs.)**

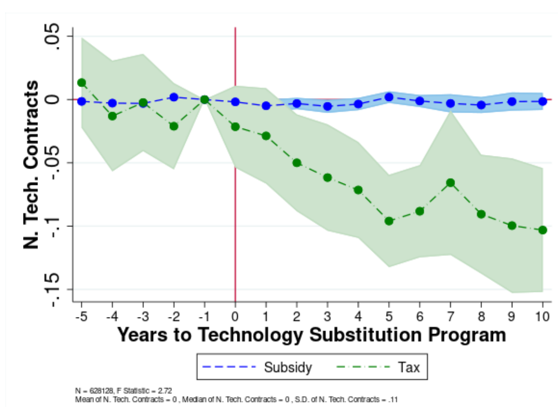
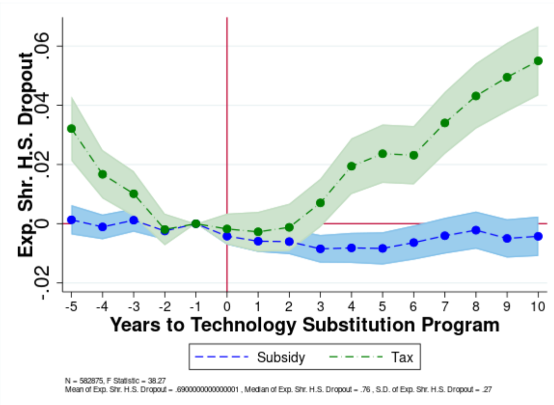


Figure 38: **Effect of Exposure to Tax and Subsidy on Expenditure Shares**

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



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

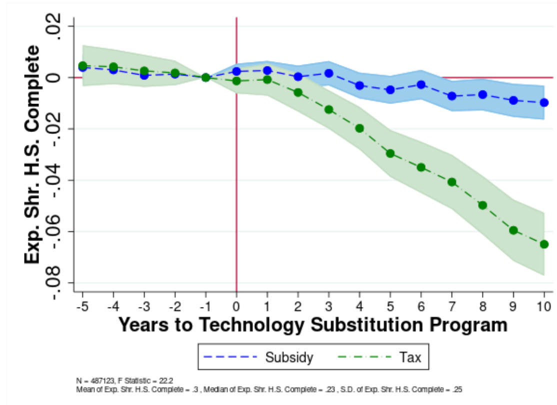
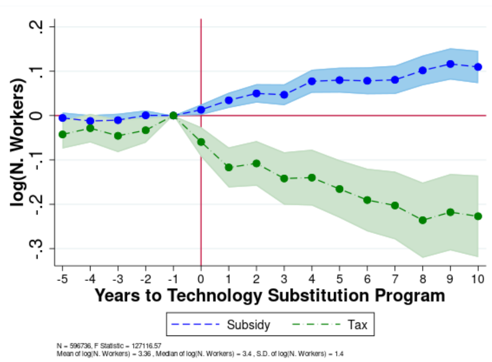
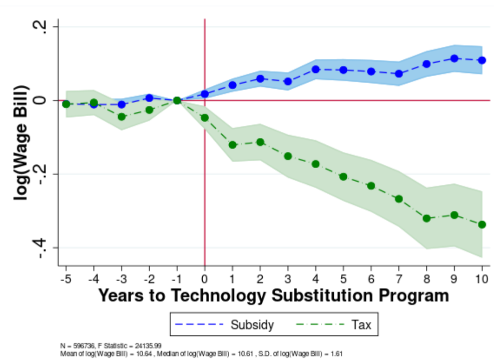


Figure 39: **Effect of Exposure to Tax and Subsidy on Employment**

(a) **log(N. Workers)**



(b) **log(Wage Bill)**



B.3.3 Results with Treatment Trends

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

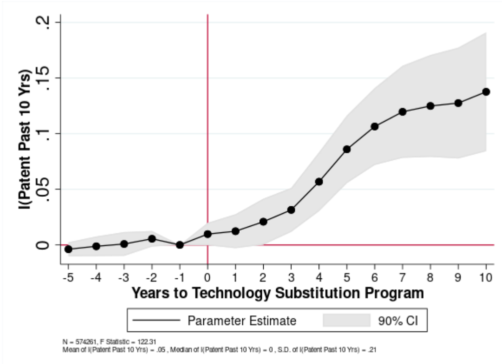
$$y_{i,s(i),t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathit{Exposure\ TSP}_{i,s(i)} + X'_{i,s(i),t}\beta_t +$$

$$\alpha \times \mathit{year} \times \mathbb{I}\{j \text{ Yrs to TSP}\} + \mu_i + \mu_t + \epsilon_{i,s(i),t} \quad (35)$$

where α is the coefficient in the linear trend. Figures 40, 41 and 42 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 40: **Innovation and Exposure to the TSP with Treatment Trend**

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



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

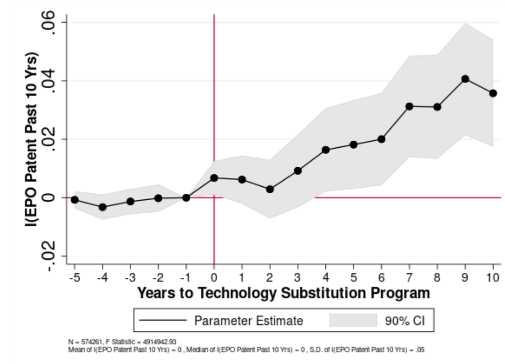
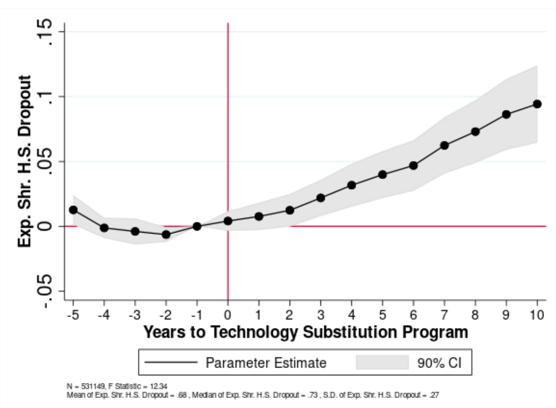


Figure 41: **Expenditure Shares and Exposure to the TSP with Treatment Trend**

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



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

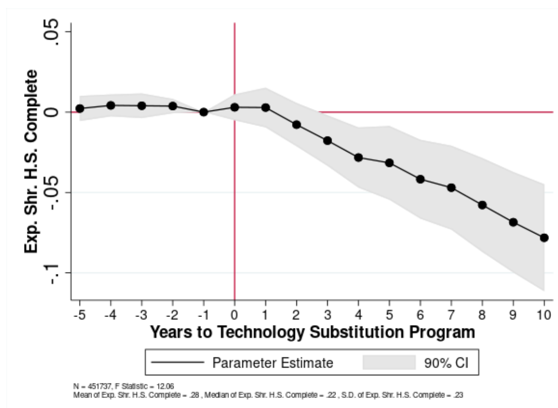
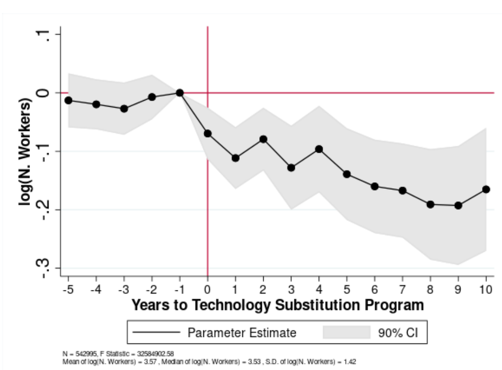
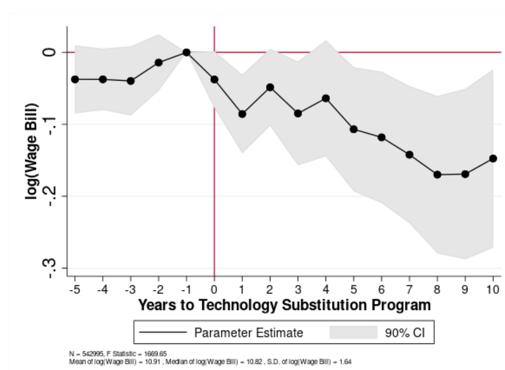


Figure 42: **Employment and Exposure to the TSP with Treatment Trend**

(a) **log(N. Workers)**



(b) **log(Wage Bill)**



B.3.4 Results with Extra Controls

Table 54: **Main Results after Controlling for Pre-Period Firm Size and Wage**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\mathbb{I}\{\textit{Patent Past 10 Yrs}\}$	$\Delta\mathbb{I}\{\textit{EPO Patent Past 10 Yrs}\}$	Δ Exp. Shr. Dropout	Δ Exp. Shr. HS Complete	$\Delta log(N.Workers)$	$\Delta log(WageBill)$
Exposure TSP	0.0302*	0.0348***	0.0404***	-0.0599***	-0.00326	0.0116
	(0.0155)	(0.0111)	(0.0114)	(0.0104)	(0.0642)	(0.0675)
N	33692	33692	29301	29301	29301	29301
R^2	0.346	0.112	0.131	0.129	0.224	0.219
Mean Dep. Var	.019	.003	-.214	.171	.284	.608
SD Dep. Var	.252	.066	.278	.261	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 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 issue a trademark for a product in the past 10 years and zero if the firm issue a trademark for a service good in the past 10 years. The second column contains a dummy taking one if the firm issue a trademark in a different NICE trademark class in the 10 years after the TSP compared to the 10 years before.

Table 55: **Main Results after Controlling for International Exposure**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\mathbb{I}\{\textit{Patent Past 10 Yrs}\}$	$\Delta\mathbb{I}\{\textit{EPO Patent Past 10 Yrs}\}$	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 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 issue a trademark for a product in the past 10 years and zero if the firm issue a trademark for a service good in the past 10 years. The second column contains a dummy taking one if the firm issue a trademark in a different NICE trademark class in the 10 years after the TSP compared to the 10 years before.

B.4 Placebo Tests

B.4.1 Placebo Test with Fake Treatment Group

In this section I describe the placebo test with fake treatment group. This test allows to tell if the results being attributed to the TSP are common to firms similar to the ones in the treatment group.

The first step to implement the placebo test is to create a set of firms who are not in the treatment group but look similar in observable characteristics to the ones in the treatment group. So, 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. When multiple firms are matched, I use the one with closest propensity score.

Using the results from the matching procedure, I consider the following specification without having the treated firms

$$y_{i,t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \mathbb{I}\{\textit{Matched to a Treated Firm}_{i,s(i)}\} + \mu_i + X'_{i,s(i),t}\beta_t + \epsilon_{i,s(i),t} \tag{36}$$

where $\mathbb{I}\{\textit{Matched to a Treated Firm}_{i,s(i)}\}$ is a dummy taking one if firm i is matched to a firm in the treatment group.

Figure 43 presents the coefficients of regression 36. It shows no significant result on patenting and a convoluted movement in factor shares. But, figure 43 also show a significant increase in employment after the TSP among the fake treatment, which goes on the opposite direction to what happened to the true treated firms.

None of the effects identified on the fake treatment are similar in sign, magnitude or pattern to the ones identified in the main results, which alleviates the concern that the main results are driven by aggregate shocks. But the presence of movement in some of these variables, such as employment and factor share, could indicate that the results from the empirical section are downward biased. To alleviate these concerns, I also use a matched diff-in-diff strategy taking as control groups the firms matched to the treated ones.

B.4.2 Placebo Test with Fake Implementation Year

This section describes the results of implementing a placebo test assuming a different implementation year for the program. 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 the special construction of the exposure measure.

Define the exposure measure with fake implementation year as

$$\textit{Exposure TSP}^{fakeyear}_{i,s(i)} = \mathbb{I}\left\{\textit{Subsidy } s(i)\right\} \times \mathbb{I}_i\left\{\textit{Leased Tech. Before 2010}\right\} \tag{37}$$

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

I consider the following specification

$$y_{i,s(i),t} = \sum_{j=-5}^{5} \theta_j \times \mathbb{I}\{j \text{ Yrs to 2010}\} \times \mathit{Exposure\ TSP}^{fakeyear}_{i,s(i)} + X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \tag{38}$$

where $\mathbb{I}\{j \text{ Yrs to 2010}\}$ is a set of dummies leading to the fake implementation year, $\mathit{Exposure\ TSP}^{fakeyear}_{i,s(i)}$ is the fake exposure measure defined in 37, $X'_{i,s(i),t}$ 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 44 shows the estimated parameters of 38. XX

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 and 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:

$$\mathit{Sector\ Exposure\ TSP}_k = \frac{\sum_i \mathbb{I}\{\mathit{Subsidy}\ s(i)\} \times \mathbb{I}\{\mathit{Leased\ Tech.\ Bfr\ TSP}\}_i}{\mathbb{N}_k\{\mathit{Firms}\}} \tag{39}$$

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

The main specification is given by

$$y_{k,2010} - y_{k,2000} = \theta \mathit{Sector\ Exposure\ TSP}_k + X'_k\beta + \epsilon_k \tag{40}$$

where $y_{k,2010}$ is a labor market outcome of sector k in 2010, $y_{k,2000}$ is the same outcome in 2000, $\mathit{Sector\ Exposure\ TSP}_k$ is the sectoral exposure measure in 39 and X_k is a set of controls.

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

Table 56: **Sector Labor Outcomes and Exposure to the TSP**

	(1) $\Delta log(N.\ Workers)$	(2) $\Delta log(WageBill)$	(3) Δ *Exp. Shr. H.S. Dropout*	(4) Δ *Exp. Shr. H.S. Complete*	(5) 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 40 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.

consider the following specification:

$$y_{k,t} = \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Sector Exposure TSP}_k + \mu_k + X_k' \beta_t + \epsilon_{k,t} \tag{41}$$

Figure 45 shows no effect of the TSP in entry or exit. Table 56 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 high school complete workers decrease while column 5 shows that the expenditure of workers with at least some college increased.

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.

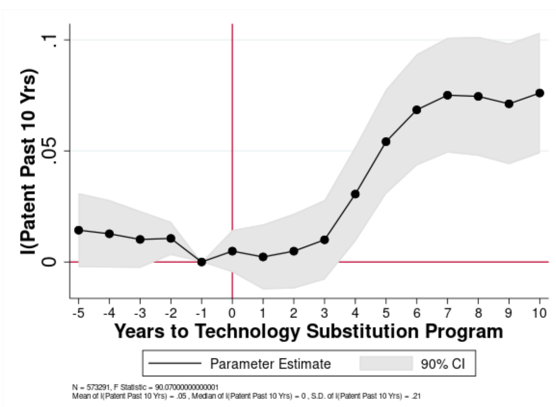
Not all the firms with technology leasing contracts were required to pay the international tax on technology leasing. Firms when signing any technology leasing contract had to indicate the part responsible for paying taxes: the leaser or the lessee. In 42.1% of the technology leasing contracts, the leaser 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[62].

To exploit this heterogeneity in the direct effect of the tax, I run specification 71 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.

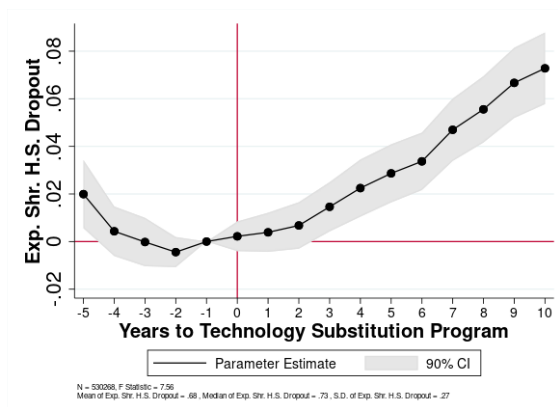
Figure 46 shows that results are the same after controlling for the direct effect of the tax.

Figure 46: **Effect of TSP after Controlling for Taxpayer Status**

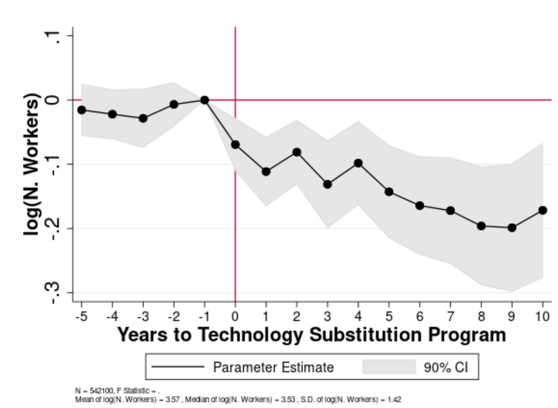
(a) **I(Patent Past 10 Yrs.)**



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



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



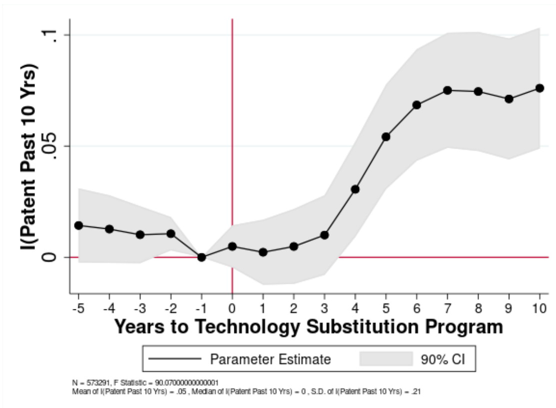
Another source of heterogeneity is on the value of technology contracts signed by the firm. We expect the effect of shifting technology to be similar between firms but the direct

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

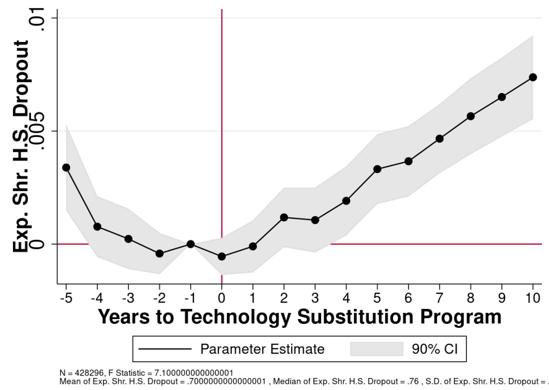
effect of the tax should increase with the total payment it is required from the firm. On figure 47 I run specification 71 but adding as control the total tax burden faced by the firm relative to its wage bill in 2000 interacted with a year dummy. The results are still the same.

Figure 47: **Effect on Labor after Controlling for Tax Burden**

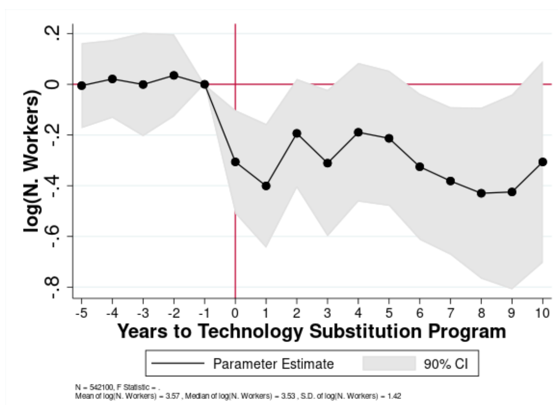
(a) **I(Patent Past 10 Yrs.)**



(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

Table 57: **Patents According to Inventor Quality in Past 10 Years and Exposure to the TSP**

	(1)	(2)
	$\Delta\mathbb{I}\{Product\ Trademark\}$	$\mathbb{I}\{Same\ Class\ Trademark\}$
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 issue a trademark for a product in the past 10 years and zero if the firm issue a trademark for a service good in the past 10 years. The second column contains a dummy taking one if the firm issue a trademark in a different NICE trademark class in the 10 years after the TSP compared to the 10 years before.

of products in response to the TSP.

Table 57 demonstrates that firms did not change their menu of products in response to the TSP. Column 1 of table 57 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 57 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 57 indicate that firms haven't changed the menu of products their produce.

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), de Souza and Sollaci (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 50 in the appendix. On table 49 I show that firms exposed to the TSP are less likely to make any import. 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 F.1 I apply the text analysis method of Argente et al. (2017) to show that the technology being leased 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 58 and 52 in the appendix. Tables 58 and 52 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 58), controlling operations of equipment or systems (column 5 of table 58), and programming (column 2 of table 52).[63] Its unlikely that firms are installing labor saving machines but do not hire workers capable of install, repair or operate it.

The effect on wages is not compatible with the introduction of labor saving machines. Table 48 shows that average wages of all educational groups go down in response to the TSP. If firms were installing high productivity machines, we would expect the opposite sign.

C Theoretical Model Appendix

C.1 Proof of proposition 1

Assuming that $\rho < \kappa$, $\rho \neq 0$, and $\kappa \neq 0$, innovator's problem has an interior solution. In that case, from the first order condition, the optimal technology skill bias in technology c is

$$\frac{A_c}{B_c} = \left(\frac{w_{H,c}}{w_{L,c}}\right)^{\frac{\kappa-\rho}{\kappa\rho}}$$

[63]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".

Therefore, as long as skill wage premium differ across countries, technology bias will differ across countries.

From the labor market cleaning condition in the US and the first order condition of firms, we can write skilled wage premium as

$$\frac{L_{US}}{H_{US}} = \left(\frac{w_{H,US}}{w_{L,US}}\right)^{\frac{\kappa-\rho}{\rho(1-\kappa)}} \implies \frac{w_{H,US}}{w_{L,US}} = \left(\frac{L_{US}}{H_{US}}\right)^{1-\kappa}$$

Denote ω as the share of innovators in Brazil and $\pi_c = \frac{w_{H,c}}{w_{L,c}}$. In that case, using that $\frac{L_{BR}}{H_{BR}} > \frac{L_{US}}{H_{US}}$ and $\kappa > \rho$:

$$\lambda = 0 \implies \pi_{BR}^{\lambda=0} = \left(\frac{L_{BR}}{H_{BR}}\right)^{1-\kappa} > \left(\frac{L_{US}}{H_{US}}\right)^{1-\kappa} = \pi_{US}$$
$$\lambda = 1 \implies \pi_{BR}^{\lambda=1} = \left(\frac{L_{BR}}{H_{BR}}\right)^{1-\rho} > \pi_{BR}^{\lambda=0} > \pi_{US}$$

Now I show that the skilled wage premium is decreasing in the share of innovating firms. From labor market cleaning condition:

$$\frac{L}{H} = \frac{\lambda l_{BR,innov} + (1-\lambda) l_{BR,lease}}{\lambda h_{BR,innov} + (1-\lambda) h_{BR,lease}}$$

For a small change in λ, the relative labor demand for low skilled workers change by

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

Using results of proposition **??** and the market cleaning condition, it must be the case that $\frac{H}{L} > \frac{h_{BR,innov}}{l_{BR,innov}}$ and $\frac{H}{L} < \frac{h_{BR,lease}}{l_{BR,lease}}$. Therefore, the relative demand for low-skilled workers decrease and skilled wage premium must go down. Therefore, $\pi_{BR} \in (\pi_{BR}^0, \pi_{BR}^1)$.

C.2 Proof of proposition ??

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

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

Therefore

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

Because $\kappa > \rho$, $\rho < 1$, and $\kappa < 1$, $\frac{\kappa-\rho}{(1-\rho)(1-\kappa)} > 0$. Therefore

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

[XX CONTINUE PROOF HERE]

C.3 Proof of proposition ??

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

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

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

$$\frac{H}{L} > \frac{h_{BR,innov}}{l_{BR,innov}} \implies 1 > \frac{L}{H}\frac{h_{BR,innov}}{l_{BR,innov}}$$
$$\frac{H}{L} < \frac{h_{BR,lease}}{l_{BR,lease}} \implies 1 < \frac{L}{H}\frac{h_{BR,lease}}{l_{BR,lease}}$$

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

C.4 Proof of proposition ??

Aggregate production is given by

$$Y = \lambda y_{BR,innov} + (1-\lambda) y_{BR,lease}$$

If $y_{BR,lease} > y_{BR,innov}$, Y increases for a small change in λ.

Aggregate expenditure with innovations and leasing technology is

$$\begin{aligned} E_{innov} &= \int_{\underline{\epsilon}_{lease}}^{\infty} \int_{\underline{\epsilon}_{innov}}^{V_{BR,innov} - V_{BR,lease} + (\tau_{innov} - \tau_{lease})} \epsilon_{j,innov} d\Gamma_j \\ E_{lease} &= \int_{\underline{\epsilon}_{lease}}^{\infty} \int_{V_{BR,innov} - V_{BR,lease} + (\tau_{innov} - \tau_{lease})}^{\infty} \epsilon_{j,lease} d\Gamma_j \end{aligned}$$

C.5 Proof of Proposition 6

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

$$\begin{aligned} \omega_{UU} &= \frac{\rho}{1-\rho} log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0} \\ \omega_{UB} &= \frac{\rho}{1-\rho} log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} log \frac{\theta_B}{\theta_U} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0} \\ \omega_{BB} &= \frac{\rho}{1-\rho} \log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0} \\ \omega_{BU} &= \frac{\rho}{1-\rho} \log \frac{\pi_1}{\pi_0} + \frac{1}{1-\rho} log \frac{\theta_U}{\theta_B} + \frac{1}{1-\rho} \log \frac{\Psi_1}{\Psi_0} \end{aligned}$$

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 leased 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

$$\lambda_{skill} = \frac{\rho}{1-\rho}\left(\lambda^T_{UB} + \lambda^C_{BU} - \lambda^C_{UB}\right) log\frac{\theta_B}{\theta_U} \tag{42}$$

From equation 42, 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

$$\begin{aligned}
&log\frac{A_{BR}}{A_{US}} = \frac{\lambda_{labor} - (\Lambda^T - \Lambda^C)}{\frac{\gamma}{1-\gamma}\left(\lambda^T_{UB} + \lambda^C_{BU} - \lambda^C_{UB}\right)} \\
&\Lambda^C = \tilde{ES}_{UU}\lambda^C_{UU} + \tilde{ES}_{BB}\lambda^C_{BB} + \tilde{ES}_{UB}\lambda^C_{UB} + \tilde{ES}_{BU}\lambda^C_{BU} \\
&\Lambda^T = \tilde{ES}_{UU}\lambda^T_{UU} + \tilde{ES}_{UB}\lambda^C_{UB}
\end{aligned}$$

where

$$\tilde{ES}_{ck} = E\left[log(1+ES^1_j)^{\frac{\gamma-\rho}{\rho}} - log(1+ES^0_j)^{\frac{\gamma-\rho}{\rho}} | t=0, \text{firm use tech } c; t=1, \text{firm use tech } , k\right]$$

C.6 Proof of Proposition 7

Define:

$$\begin{aligned}
&\tilde{\pi}_U = \log\pi^1_{US} - \log\pi^0_{US} \\
&\tilde{\pi}_B = \log\pi^1_{BR} - \log\pi^0_{BR} \\
&\lambda^T_{UU} = E\left[\mathbb{I}^0_{lease}\mathbb{I}^1_{lease}|j \in ExposedUS\right]; \lambda^T_{UB} = E\left[\mathbb{I}^0_{lease}\mathbb{I}^1_{innov}|j \in ExposedUS\right] \\
&\lambda^T_{UO} = E\left[\mathbb{I}^0_{lease}\mathbb{I}^1_{vintage}|j \in ExposedUS\right]; \lambda^C_{BB} = E\left[\mathbb{I}^0_{innov}\mathbb{I}^1_{innov}|j \in Control\right] \\
&\lambda^C_{BB} = E\left[\mathbb{I}^0_{innov}\mathbb{I}^1_{innov}|j \in Control\right]; \lambda^C_{BU} = E\left[\mathbb{I}^0_{innov}\mathbb{I}^1_{lease}|j \in Control\right] \\
&\lambda^C_{UU} = E\left[\mathbb{I}^0_{lease}\mathbb{I}^1_{lease}|j \in Control\right]; \lambda^C_{UO} = E\left[\mathbb{I}^0_{lease}\mathbb{I}^1_{vintage}|j \in Control\right]
\end{aligned}$$

We can write λ^{US}_{skill} as

$$\lambda^{US}_{skill} = \left(\lambda^T_{UU} - \lambda^C_{UU}\right)\left(\frac{\kappa-\rho}{(1-\kappa)(1-\rho)}\tilde{\pi}_U + \frac{1}{1-\rho}\tilde{\pi}_B\right) + \tag{43}$$

$$\left(\lambda^T_{UB} + \lambda^T_{UO} - \lambda^C_{UB} - \lambda^C_{UO}\right)\left(\frac{\rho-\kappa}{(1-\rho)(1-\kappa)}\pi^0_U + \frac{1}{\rho-1}\pi^0_B + \frac{1}{1-\kappa}\pi^1_B\right) - \tag{44}$$

$$\left(\lambda^C_{BB} + \lambda^C_{OO}\right)\frac{1}{1-\kappa}\tilde{\pi}_B - \tag{45}$$

$$\left(\lambda^C_{BU} + \lambda^C_{OU}\right)\left(\frac{\kappa-\rho}{(1-\rho)(1-\kappa)}\pi^1_U + \frac{1}{1-\rho}\pi^1_B + \frac{1}{\kappa-1}\pi^0_B\right) \tag{46}$$

We can write λ^{US}_{labor} and $\lambda^{vintage}_{labor}$ as

$$(1-\gamma)\lambda^{US}_{labor} = \log\phi_{vintage}\left(\lambda^T_{UO} + \lambda^C_{OU} + \lambda^C_{OB} - \lambda^C_{UO} - \lambda^C_{BO}\right) + \tag{47}$$

$$\log\phi_{innov}\left(\lambda^T_{UB} + \lambda^C_{BU} + \lambda^C_{BO} - \lambda^C_{UB} - \lambda^C_{OB}\right) + \tag{48}$$

$$\log\phi_{US}\left(\lambda^C_{UO} + \lambda^C_{UB} - \lambda^C_{OU} - \lambda^C_{BU} - \lambda^T_{UO} - \lambda^T_{UB}\right) + H^C - H^T_U \tag{49}$$

$$(1-\gamma)\lambda^{vintage}_{labor} = \log\phi_{vintage}\left(\lambda^C_{OU} + \lambda^C_{OB} - \lambda^C_{UO} - \lambda^C_{BO} - \lambda^T_{OU} - \lambda^T_{OB}\right) + \tag{50}$$

$$\log\phi_{innov}\left(\lambda^C_{BU} + \lambda^C_{BO} - \lambda^T_{OB} - \lambda^C_{UB} - \lambda^C_{OB}\right) \tag{51}$$

$$\log\phi_{US}\left(\lambda^C_{UO} + \lambda^C_{UB} + \lambda^T_{OU} - \lambda^C_{OU} - \lambda^C_{BU}\right) + H^C - H^T_O \tag{52}$$

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 Identification and Results Appendix

D.1 Identification of Key Parameters on Partial Equilibrium

Theorem D.1 shows that the estimator on empirical section XX 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 on Partial Equilibrium)*
Suppose that at $t = 1$ *the government implements a subsidy for innovation financed by a tax on the purchase of technology*

$$\tau^0_{innov} = \tau^0_{lease} = T^0 = T^1 = 0; \tau^1_{j,innov} \in \{0, \tau\}; \tau \geq 0 \tag{53}$$

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

$$ExposedTSP = \left\{j|\tau_j \times \mathbb{I}^0_{innov} > 0\right\} \tag{54}$$

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

$$\lambda_{innov} = E\left[\Delta\mathbb{I}^t_{innov}|j \in ExposedTSP\right] - E\left[\Delta\mathbb{I}^t_{innov}|j \notin ExposedTSP\right] \tag{55}$$

$$\lambda_{skill} = E\left[\Delta\log\left(\frac{w^t_{L,BR}l^t_j}{w^t_{H,BR}h^t_j}\right)|j \in ExposedTSP\right] - E\left[\Delta\log\left(\frac{w^t_{L,BR}l^t_j}{w^t_{H,BR}h^t_j}\right)|j \notin ExposedTSP\right] \tag{56}$$

$$\lambda_{labor} = E\left[\Delta\log l^t_j|j \in ExposedTSP\right] - E\left[\Delta\log l^t_j|j \notin ExposedTSP\right] \tag{57}$$

Then, if wages are constant:

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

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

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 on the model the empirical estimates identified on the data. The policy change on 53 mimics the one observed in the data and the set 54 contains the set of firms exposed to the tax on technology lease 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.2 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

$$log(Revenue) = \beta_0 + \beta_1 log(Wage\ Bill\ High\ Skill) + \beta_2 log(Wage\ Bill\ Low\ Skill) + \beta_3 log(Assets) + \eta_i + \eta_t + \tag{58}$$

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 production function.

D.3 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

Table 58: **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 58 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), on second column method of Levinsohn and Petrin (2003), on third column I use Wooldridge (2009), on 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.

the difference in skill bias constant. But, taking κ to the upper range of it's 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.4 Robustness

D.4.1 Alternative κ

Figure 49 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 8, 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 in skilled wage premium.

D.4.2 Alternative Innovation Definition

In this section, I show that using alternative measures of innovation delivers similar results to 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 Ph.D., and 4) the hiring of an inventor.

Table 59 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 59 shows that the share of firms innovating and the estimated productivity of US technology vary heavily according to the definition of innovation.

Table 59: **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, 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 she hired a PhD workers, the last line considers as innovating any firm hiring a scientist according to the CBO02 classification.

Table 60 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 60 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.

D.4.3 Elastic Labor Supply

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

Table 60: **Effect of Innovation Policies**

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 she has a patent, industrial design or trademark, the fifth line considers a firm innovating if it hired a PhD workers, the last line consider 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.

$$\max_{H,L,C} \log\left(C - \chi_H \frac{H^{1+\upsilon}}{1+\upsilon} - \chi_L \frac{L^{1+\upsilon}}{1+\upsilon}\right) \tag{59}$$

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 59, 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 is 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 Policies**

	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.4.4 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 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

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

Calibration and Results δ is calibrated to reproduce the average 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 Policies**

	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 leasing such that it increases innovation by 1 percentage point. The second line contains the effect of closing the economy to international technology.

D.4.5 Exogenous Technology

Firms in Brazil Assume that firms in Brazil can choose between leasing technology from 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

$$V_{innov,j} = \max_{h,l} z_j \left[\alpha_j (A_{BR} l)^\rho + (1-\alpha_j)(B_{BR} h)^\rho\right]^{\frac{\gamma}{\rho}} - w_{H,BR} h - w_{L,BR} l \tag{60}$$

While the profit of a firm leasing technology is

$$V_{lease,j} = \max_{h,l} z_j \left[\alpha_j (A_{US} l)^\rho + (1-\alpha_j)(B_{US} h)^\rho\right]^{\frac{\gamma}{\rho}} - w_{H,BR} h - w_{L,BR} l \tag{61}$$

The final technology choice of the firm is given by

$$V_j = \max\left\{V_{lease,j} - \epsilon_{j,lease} - \tau_{lease}, V_{innov,j} - \epsilon_{j,innov} + \tau_{innov}\right\} \tag{62}$$

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 6 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 6. (Identification of Exogenous Technology)
Suppose that the government implements policy 53 and define the estimators as in 55. Assume that production function is defined as in 20. Then, if

1. Firm idiosyncratic characteristics are permanent:

$$z_j^0 = z_j^1; \alpha_j^0 = \alpha_j^1; \epsilon_{j,innov}^0 = \epsilon_{j,innov}^1; \epsilon_{j,lease}^0 = \epsilon_{j,lease}^1$$

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 on appendix C.5. □

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

Table 63 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 9. For third and fourth line I estimate the elasticity of substitution on firms innovating. For different controls, the elasticity goes 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 63: **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 64 presents the main results. The effect on GDP and skill wage premium is larger for larger values of κ.

Table 64: **Effect of Innovation Policies**

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.4.6 Alternative Distributions

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

On table 65 I assume that the relative innovation fixed cost is either logistic or type 1 extreme value, other than 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 65 shows that the effect of innovation policy is very similar across distributions.

Table 65: **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.4.7 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:

$$\phi_{vintage} = \left(A^{\frac{\kappa\rho}{\kappa-\rho}} + B^{\frac{\kappa\rho}{\kappa-\rho}}\right)^{\frac{\kappa-\rho}{\kappa\rho}} \tag{63}$$

Firms in Brazil produce using production function 20. Therefore, the operating profit of producing using old technology is

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

Technology choice of Brazilian firms is given by:

$$V_j = \max\left\{V^t_{j,BR,lease} - \epsilon^t_{j,lease} - \tau^t_{lease}, V^t_{j,BR,innov} - \epsilon^t_{j,innov} + \tau^t_{innov}, V^t_{j,vintage,BR}\right\} \tag{64}$$

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 20. Moreover, the government implements the following fiscal policy:

$$\tau^0_{innov} = \tau^0_{lease} = T^0 = T^1 = 0 \tag{65}$$

$$\tau^1_{j,innov} = \tau \mathbb{I}\left\{z_j \geq \bar{z}\right\} \tag{66}$$

where τ^1_{lease} adjust to balance government budget constraint[64].

Define the set of firms leasing technology or using vintage technology that are exposed

[64] On the data, the recipiency of the R&D subsidy is correlated with firm size, as discussed in appendix A.11. 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.

to this program as

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

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

$$\lambda^{US}_{skill} = E\left[\Delta \log\left(\frac{w^t_{L,BR} l^t_j}{w^t_{H,BR} h^t_j}\right)|j \in ExposedUS\right] - E\left[\Delta \log\left(\frac{w^t_{L,BR} l^t_j}{w^t_{H,BR} h^t_j}\right)|j \in Control\right] \tag{67}$$

$$\lambda^{US}_{labor} = E\left[\Delta \log l^t_j | j \in ExposedUS\right] - E\left[\Delta \log l^t_j | j \in Control\right] \tag{68}$$

$$\lambda^{Vintage}_{labor} = E\left[\Delta \log l^t_j | j \in ExposedUS\right] - E\left[\Delta \log l^t_j | j \in Control\right] \tag{69}$$

Proposition 7 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 7. (Identification of Key Parameters with Vintage Technology)
Suppose that the government implements policy 53 and define the estimators as in 67. Assume that production function is defined as in 20. Then, if

1. Firm idiosyncratic characteristics are permanent:

$$z^0_j = z^1_j; \alpha^0_j = \alpha^1_j; \epsilon^0_{j,innov} = \epsilon^1_{j,innov}; \epsilon^0_{j,lease} = \epsilon^1_{j,lease}$$

2. Firm j in Brazil can only lease technology from firm j in US.

Knowing κ and γ, then ρ, $\frac{\phi_{US}}{\phi_{BR}}$, and $\frac{\phi_{vintage}}{\phi_{BR}}$ can be uniquely identified from λ^{US}_{labor}, $\lambda^{vintage}_{labor}$, λ^{US}_{skill}, the wages in the two countries, the distribution of expenditure shares, and the distribution of innovation status.

Proof. Proof available on appendix C.6. □

Table 66 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 leasing 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 different in productivity between vintage technology and Brazilian innovations.

Table 66: **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 Leasing 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 Leasing 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_{lease}	Mean of Innovation Cost	Shr. of Firms Leasing Tech. 10 yrs Bfr Program	0.0121	-4.19E-04
σ_{lease}	Variation of Innovation Cost	Effect of TSP on Innovation of Lease	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 it's calibrated values. As skilled wage premium in US I use the average skilled wage premium of countries selling technology to Brazil weighted by the number of contracts.

Table 67 shows four different counterfactual innovation programs. On the first line, I reproduce the Technology Substitution Program. The second and third lines allows to identify the differential effect of the tax on international technology and the subsidy to innovation. The final line implements a leasing tax&subsidy program to increase innovation by 1 percentage point.

Table 67 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 67 predicts a decrease in 1.6%. This happens because part of the firms leasing technology now adjust to a vintage technology. As consequence, the drop in GDP is larger.

Lines 2 and 3 of table 67 separate the two policy instruments implemented with the TSP; the tax on technology leasing and the subsidy to innovation. Table 67 shows that all the result of the program is coming from the tax on international technology leasing. The main reason the subsidy is ineffective is because it is targeted to large firms. Large, in the absence of the subsidy, would either lease technology or innovate. Therefore, the subsidy cannot stimulate firms using vintage technology to adopt a Brazilian innovation.

Table 67: **Innovation Policy with Vintage Technology**

Policy Change	*Leasing*	*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.

E Additional Evidence

F Additional Evidence

The main claim of this paper is that cross-country differences in technology quality and skill bias generate a negative effect of innovation policy on production and skill-premium in the special context of a developing country. In this section I show additional support for this result using text analysis of Brazilian and international patents, exogenous variation on wage premium coming from heterogeneous exposure to minimum wage, the effect of the TSP on imports, the heterogeneous effect of the TSP, event-study comparing firms leasing technology, event-study comparing firms leasing technology against firms issuing a patent, diff-in-diff with applicants for R&D subsidy and regional variation on factor supply and technology adoption.

Table 68: **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 measure 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 display 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).

F.1 Text Analysis of National and International Technology

Using text analysis and measures of patent quality, I show that technology leased by 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 68 shows statistics of Brazilian patents and of patents created by firms leasing 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 68 shows that Brazilian patents have less citation, less inventors per patents and that Brazilian inventors are less prolific than inventors on firms leasing technology to Brazil. These facts support the conclusion that Brazilian patents are of inferior quality.

Table 68 shows on 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[65]. Column 1 of panel b of table 68 shows the share of patents with similarity in the top decile. I also use the robot and software technology definition by Webb (2020).

[65] Appendix F.9 describes in detail the steps to create this measure.

F.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 US would decrease skill premium, increase it's technology bias and increase the difference between skill bias of 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 leasing technology from countries with relatively large supply of skilled workers should increase its expenditure share with low skilled workers by more. On appendix F.10 I show that this is exactly the case.

F.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 high interest rates in Brazil, and overall use of international inputs, given that transportation cost makes national inputs less expensive. Table 49 shows that firms exposed to the TSP are less likely to become importers, to import inputs and to import capital. Table 50 shows that the drop in the import of inputs is driven by a reduction in the imports from developed countries.

F.4 Diff-in-Diff with Applications for R&D Subsidy

The main empirical specification does tease apart the effect of the tax from the effect of the subsidy. As consequence, we cannot empirically tell if the subsidy or the tax on technology lease are responsible for the main empirical findings.

In appendix F.11 I isolate the effect of the subsidy. I use diff-in-diff comparing firms that successfully applied to the subsidy against firms that applied to the subsidy but did not received it. Because the subsidy is allocated based on technical criterias, I expect the fixed effect to remove any endogeneity related to the subsidy recipiency.

Appendix F.11 shows that, in average, the subsidy led to an increase in patenting and no change in the educational composition of firms. Due to existing pre-trends, I cannot say anything about the effect of the subsidy on firm size.

But, appendix F.11 also shows that the subsidy had heterogeneous effect on education. Firms leasing international technology before the introduction of the program increased their hiring of high school dropouts and decreased the average education of its labor force.

F.5 Event-Study using Brazilian Patents and International Technology

Another strategy to identify the differences between Brazilian technology and international technology is to study the change in firm outcomes when the two technologies are implemented. On appendix F.12 I implement an event study comparing a firm that issued a patent to a firm leasing international technology. This strategy allows me to identify changes in labor outcomes of innovators relative to firms leasing international technology. Once again I find that firms issuing a patent increase the expenditure share with high school dropouts relative to firms leasing international technology. I also find a relative decrease in average years of education but no effect on employment.

F.6 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 it's factor abundance. Therefore, a Brazilian firm implementing a technology from Germany, which has 29% of 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 population as college graduates. I test this model prediction on appendix F.13.

On appendix F.13 I implement an event-study strategy to study the change on labor outcomes when the firm lease an international technology. I show that firms leasing technology from college graduate abundant countries increase their hiring of college graduate workers. In special, firms leasing technology from US or other developed countries increase the share of college graduates in their labor force while the ones leasing technology from Brazil decrease it.

To make a causal argument about the difference in effect of technologies from different countries I use exogenous variation coming from rejected leasing contracts. As discussed before, a leasing contract can be rejected by the Brazilian patent office which stops the transaction given that payments are not allowed to flow outside of Brazil by the Brazilian Central Bank. Using the rejected contracts as control for the approved contracts, I show that firms leasing technology from countries abundant in college graduates increase their hiring of college graduates.

F.7 Regional Variation in Factor Supply and Technology Adoption

The model of directed technological change also has predictions to the technology adoption. If 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 F.14 I show that this model prediction is also supported by the data.

F.8 Minimum Wage and Technology Adoption

The model of directed technological change also has predictions to 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 bias and should be more likely to adopt international technology. I test this prediction of the model by exploiting heterogeneous exposure to exogenous variation in minimum wage.

Between 2000 and 2010, 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 forced with wage bellow the 2010 minimum wage value were more affected by the minimum wage than the ones which had a lower share. Exploiting this new exposure measure I show on appendix F.15 that firms more exposed to the minimum wage were more likely to lease international technology, as the model predicts.

F.9 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 correspond each element of the vector. In mine 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

$$s_{jw} = \sum_{m \in \mathbb{M}} f_{jm} \times f_{pm} \tag{70}$$

Final Robot Similarity For each patent, I calculate the similarity score 70 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 68 a dummy for similarity to robot:

$$\mathbb{I}_k\{\text{Similar to Robot}\} = \begin{cases} 1 & \text{, if Robot Similarity}_k \text{is on top decile} \\ 0 & \text{, if Robot Similarity}_k \text{is not on top decile} \end{cases}$$

F.10 Heterogeneous Effect of TSP

For each firm leasing 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 high school or more on 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 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 leased by firm i in contract j. Therefore, Factor Supply Tech.$_{i,s(i),t}$ is the average factor share of the technology leased by firm i before the introduction of the program.[66]

I use the following dynamic specification to test for heterogeneous effect:

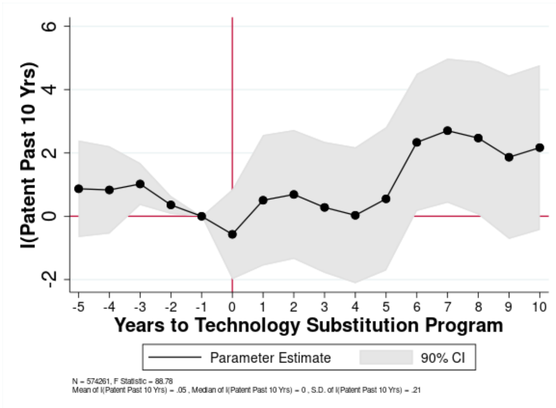
$$\begin{aligned} y_{i,s(i),t} = & \sum_{j=-5}^{10} \theta_j \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Exposure TSP}_{i,s(i)} + \\ & \sum_{j=-5}^{10} \kappa_j \times \text{Factor Supply Tech.}_{i,s(i),t} \times \mathbb{I}\{j \text{ Yrs to TSP}\} \times \textit{Exposure TSP}_{i,s(i)} + \\ & X'_{i,s(i),t}\beta_t + \mu_i + \mu_t + \epsilon_{i,s(i),t} \end{aligned} \tag{71}$$

Figure 50 shows the heterogeneous effects of the TSP, measured by κ_j. As the model predicts, firms with leasing technology from countries with larger supply of skilled workers increase the expenditure share with high school dropouts by more. I don't find any significant effect on innovation or employment.

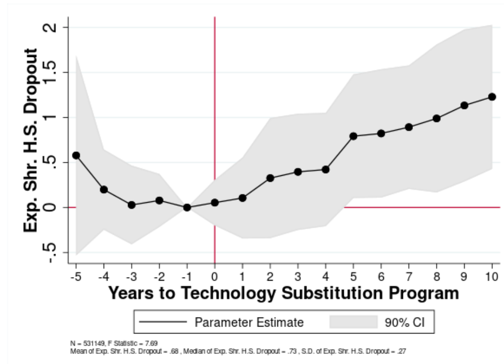
[66] I choose not to use the value of the contract to weight the average because it is missing to a set of contracts. Results using predicted contract value has the same conclusions.

Figure 50: **Employment and Exposure to the TSP with Treatment Trend**

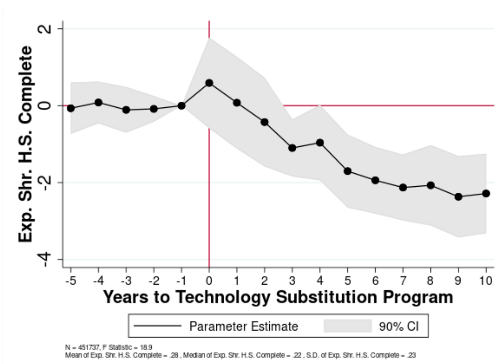
(a) **I(Patent Past 10 Yrs.)**



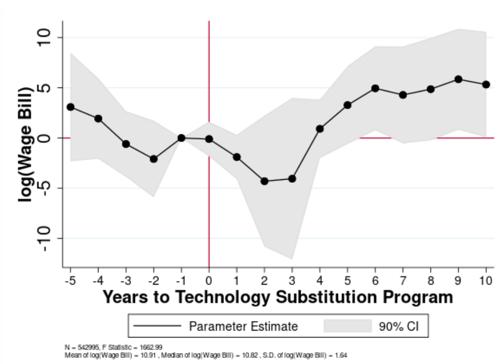
(b) **Exp. Shr. H.S. Dropout**



(c) **Exp. Shr. H.S. Complete**



(d) **log(Wage Bill)**



F.11 Diff-in-Diff with Applications for R&D Subsidy

What effect the subsidy alone had on innovation, expenditure share and employment? In this section I implement a difference-in-difference strategy with firms applying for R&D subsidy that isolates the effect of the subsidy. I find that, in average, the subsidy had a small effects on innovation and no significant effect on employment. However, these non-significant average effects hide a large degree of heterogeneity. I find that the subsidy decreased expenditure share with low skilled workers on firms previously leasing international technology.

The *Funding Authority for Studies and Projects* subsidize innovation project of firms. Firms with an innovation project can apply for different subsidy types: tax rebate, cash grants or subsidized lending. Applications are program (topic) specific and there are 88 programs.

Each application is technically evaluated and receive a score. The final score is a weighted average of scores on 1) coherence and clarity of the goals and methodology, 2) scientific relevance, 3) qualification of the research team, 3) proximity to the supported topic and 4) viability, i.e., the likelyhood that the research will be concluded.

Firms are ranked according to their score and the budget is allocating according to firm's score. Therefore, firms with larger score receive the subsidy[67].

Given that to receive the subsidy a firm needs to find a research idea, hire a team of scientists and write a project, we cannot simply compare firms that receive the subsidy against the ones that don't. Because these firms are so fundamentally different, they could be in different trends.

To identify the causal effect of the subsidy I compare the successful applications to the subsidy against the rejected applications. The assumption is that there is parallel trends between the treatment and control groups and that any level difference can be taken away by the fixed effects.

I implement the following dynamic model:

$$
\begin{aligned}
y_{i,r(i),t} = & \sum_{j=-5}^{5} \beta_j \times \mathbb{I}\{\text{Treatment}\} \times \mathbb{I}\{j \text{ Yrs to Subsidy Application}\} + \\
& \sum_{j=-5}^{5} \theta_j \times \mathbb{I}\{j \text{ Yrs to Subsidy Application}\} + \mu_{t,r(i)} + \mu_i + \epsilon_{i,t,r(i)}
\end{aligned}
$$

where $y_{i,r(i),t}$ is outcome of firm i, at year t applying to program $r(i)$, $\mathbb{I}\{\text{Treatment}\}$ is a dummy if application is accepted, $\mathbb{I}\{j \text{ Yrs to Subsidy Application}\}$ is a dummy taking one j years to subsidy application, $\mu_{t,r(i)}$ is a year-program fixed effect, μ_i is a firm fixed effect. Standard errors are clustered at firm level.

Figure 51 shows that the subsidy increased the probability of firms applying for PCT patents, i.e., patents with international protection, while decreased the probability of firms to apply for patents at the Brazilian patent office. This could signal that the subsidy lead to an increase in the quality of patents being created.

Figure 52 shows the estimates of the dynamic effect on firm's employment. There is a

[67] The score each firm receives is not observed

clear trend in the period that gets reversed. But in general it's not clear that there is any effect on employment or wages coming from the subsidy.

Figure 53 shows the effect of the subsidy on the educational composition at the firms. The subsidy had no effect on the educational composition of firms.

These results indicate that the subsidy had no significant effect on firm's labor composition and employment while affecting its patenting. I show now that this average result hides heterogeneous effect according to firm's technology.

To show the effect of the subsidy on firms leasing international technology, I use the following specification

$$\begin{aligned} y_{i,r(i),t} = &\sum_{j=-5}^{5} \kappa_j \times \mathbb{I}\{\text{Tech. Lease Bfr.}\} \times \mathbb{I}\{\text{Treatment}\} \times \mathbb{I}\{j \text{ Yrs to Subsidy Application}\} \\ &\sum_{j=-5}^{5} \beta_j \times \mathbb{I}\{\text{Treatment}\} \times \mathbb{I}\{j \text{ Yrs to Subsidy Application}\}+ \\ &\sum_{j=-5}^{5} \theta_j \times \mathbb{I}\{j \text{ Yrs to Subsidy Application}\} + \mu_{t,r(i)} + \mu_i + \epsilon_{i,t,r(i)} \end{aligned}$$

where $\mathbb{I}\{\text{Tech. Lease Bfr.}\}$ is a dummy taking one if the firm leased international technology while κ captures the relative effect of the innovation subsidy on firms leasing international technology.

Figure 54 shows the relative effect of the subsidy on innovation at firms leasing international technology. The figure show no significant effect. This result indicates that firms with international technology are as likely as firms without international technology to lease a patent.

Figure 55 shows the effect of the subsidy on the composition of workers on firms leasing international technology. Firms leasing international technology that received the subsidy increased their share of high school dropouts and decreased the average years of education of its labor force.

Figure 56 shows the effect of the subsidy on the employment of firms leasing international technology. As before, there is a pre-trend before firms received the subsidy, making any conclusion questionable.

F.12 Event-Study Comparing the International Technology Lease and Innovation

$$y_{i,t} = \sum_{j=-5}^{5} \theta_j \times \mathbb{I}\{j \;\; Yrs. \;\; to \;\; Patent \;\; Application\}$$
$$\sum_{j=-5}^{5} \kappa_j \times \mathbb{I}\{j \;\; Yrs. \;\; to \;\; Tech. \;\; Purchase \;\; or \;\; Patent \;\; Application \;\}+\mu_i+\mu_t+\epsilon_{i,t,c(i)}$$

F.13 Event-Study Comparing International Technology Lease from Different Countries

$$y_{i,t} = \sum_{j=-5}^{5} \theta_j \times \mathbb{I}\{j \;\; Yrs. \;\; to \;\; Tech. \;\; Purchase \;\; from \;\; Country \;\; c(i)\} \times Shr. \;\; College_{c(i)}$$
$$\sum_{j=-5}^{5} \kappa_j \times \mathbb{I}\{j \;\; Yrs. \;\; to \;\; Tech. \;\; Purchase \;\; from \;\; Country \;\; c(i)\}+\mu_i+\mu_t+\epsilon_{i,t,c(i)}$$

$$y_{i,t} = \sum_{j=-5}^{5} \theta_j \times \mathbb{I}\{j \;\; Yrs. \;\; to \;\; Tech. \;\; Purchase \;\; from \;\; Country \;\; c(i)\} \times Shr. \;\; College_{c(i)}$$
$$\sum_{j=-5}^{5} \kappa_j \times \mathbb{I}\{j \;\; Yrs. \;\; to \;\; Tech. \;\; Purchase \;\; from \;\; Country \;\; c(i)\}+\mu_i+\mu_t+\epsilon_{i,t,c(i)}$$

XX - add here rejected contracts

F.14 Regional Variation in Factor Supply and Technology Adoption

$$\mathbb{I}_{i,r,s}\{Int. \;\; Tech.\} = \beta HS\_shr_{r,s} + X_i'\kappa + \epsilon_{i,r,s}$$

⋆ $\mathbb{I}_{i,r,s}\{Int.\ Tech.\}$: a dummy if firm i, in region r and sector s purchased technology before 2000

Table 69: **Technology Adoption and Regional Factor Share**

	(1)	(2)	(3)	(4)
	$\mathbb{I}\{\text{Int. Tech.}\} - \mathbb{I}\{\text{Patent}\}$	$\mathbb{I}\{\text{Patent}\}$	$\mathbb{I}\{\text{EPO Patent}\}$	$\mathbb{I}\{\text{Int. Tech.}\}$
$HS\_shr_{r,s}$	0.0734***	0.00953	0.00811***	0.0829***
	(0.00892)	(0.00721)	(0.00198)	(0.00615)
N	53886	53886	53886	53886
R^2	0.016	0.077	0.011	0.131
Mean Dep. Var	-.034	.055	.001	.022
SD Dep. Var	.25	.229	.038	.146
Mean Indep. Var	.205	.205	.205	.205
SD Indep. Var	.159	.159	.159	.159
Controls	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. As controls I use dummies for deciles of firm size and deciles of avg. wage.

- ⋆ $HS\_shr_{r,s}$: is the share of workers with high school complete or more in 2000 in region r sector s
- ⋆ X_i: FE for deciles of firm size and avg. wage

F.15 Minimum Wage and Technology Adoption

$$ExpMW_i = \frac{\sum_{j=1}^{N(i)} \max\{wage_{j,2000}, MinimumWage_{2010}\}}{WageBill_{i,2000}}$$

$$\mathbb{I}_i\{\textit{Int. Tech. btw 2000 and 2010}\} - \mathbb{I}_i\{\textit{Patent btw 2000 and 2010}\} = \beta ExpMW_i + X_i'\kappa + \epsilon_i$$

- ⋆ $\mathbb{I}_i\{\textit{Int. Tech. btw 2000 and 2010}\}$: purchased international tech. between 2000 and 2010
- ⋆ $\mathbb{I}_i\{\textit{Patent. btw 2000 and 2010}\}$: issued a patent between 2000 and 2010
- ⋆ X_i: fixed effects for pre-period values of region, sector, size decile, avg. wage decile, wage bill decile, patent, international technology purchase or intellectual property

Table 70: **Technology Adoption and Regional Factor Share**

	(1) $\mathbb{I}$\{Skill Intensive Class\}	(2) $\mathbb{I}$\{Automation\}	(3) $\mathbb{I}$\{Software\}
$HS\_shr_{r,s}$	0.0649***	0.00599**	0.00645***
	(0.0123)	(0.00286)	(0.00239)
N	53886	53886	53886
R^2	0.031	0.007	0.003
Mean Dep. Var	.023	.003	.001
SD Dep. Var	.266	.069	.045
Mean Indep. Var	.205	.205	.205
SD Indep. Var	.159	.159	.159
Controls	Yes	Yes	Yes

Description: This table shows the estimated parameters of a regression of high skill share on different measures of technology skill intensity. High skill share is defined as the share of workers with high school diploma or more in RAIS for 2000. To calculate the skill intensity of each patent I first calculate the average share of college graduates per patent class at the year the patent is issued, excluding the firm issuing the patent. The dummy $\mathbb{I}$\{Skill Intensive Class\} takes one if the firm issued a patent in the past in a class with high skill intensity larger than the median. Following Webb (2020), I use text analysis to classify patent's skill intensity. As controls I use dummies for deciles of firm size and deciles of avg. wage.

Table 71: **Effect of Minimum Wage on Technology Adoption**

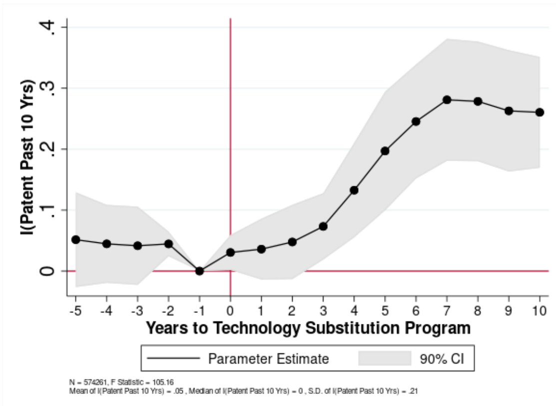
	(1) $\Delta log(\frac{\text{Hourly Wage HS Drop}}{\text{Hourly Wage Not HS Drop}})$	(2) $\mathbb{I}\{\text{Int. Tech.}\} - \mathbb{I}\{\text{Patent}\}$	(3) $\mathbb{I}$\{Int. Tech.\}	(4) $\mathbb{I}$\{Patent\}	(5) $\mathbb{I}$\{Scientist\}
$ExpMW$	-2.463*	0.670**	0.231	-0.440**	-0.0369
	(1.365)	(0.325)	(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.

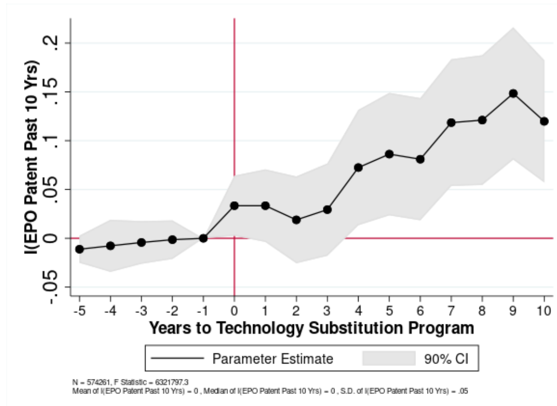
β identified comparing similar firms but that differ on a specific measure of wage distribution

Figure 33: **Main Results with Heterogeneous Revenue Allocation Exposure**

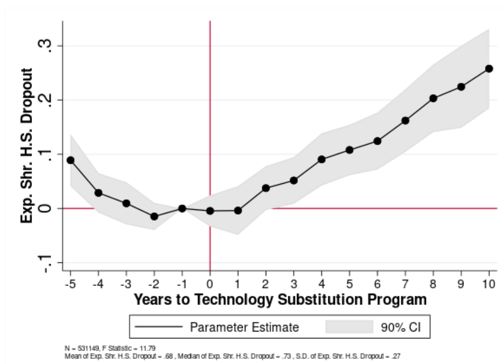
(a) I(Patent Past 10 Yrs.)



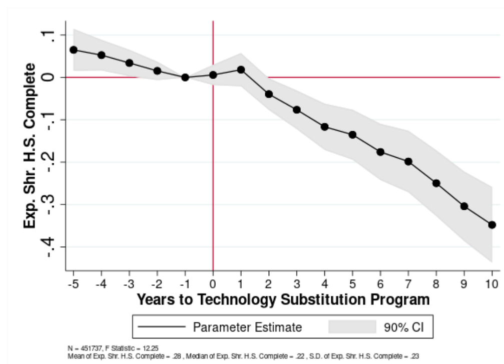
(b) I(EPO Patent Past 10 Yrs.)



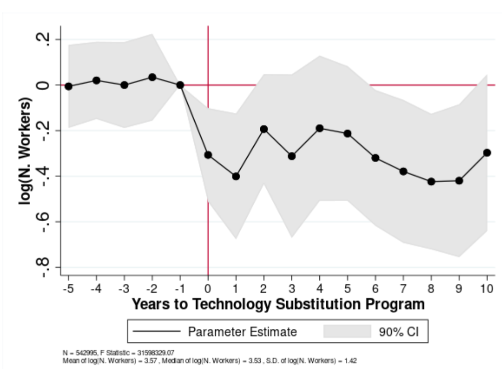
(c) **Exp. Shr. H.S. Dropout**



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



(e) **log(N. Workers)**



(f) **log(Wage Bill)**

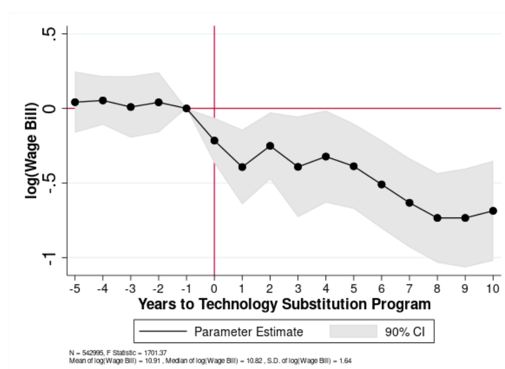
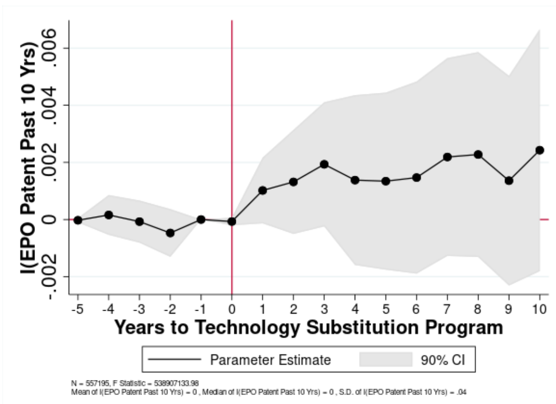
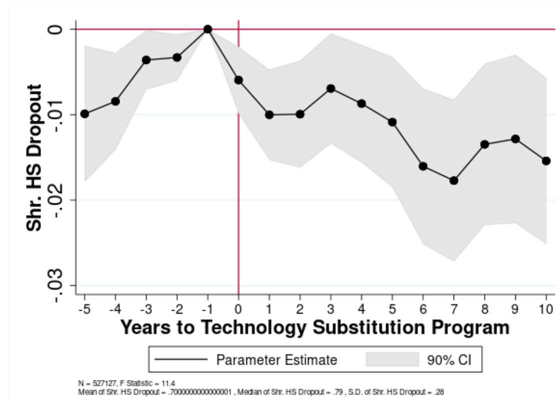


Figure 43: **Results of Placebo Test with Fake Treatment Group**

(a) **I(Patent Last 10 Yrs)**



(b) **Shr. H.S. Dropout**



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

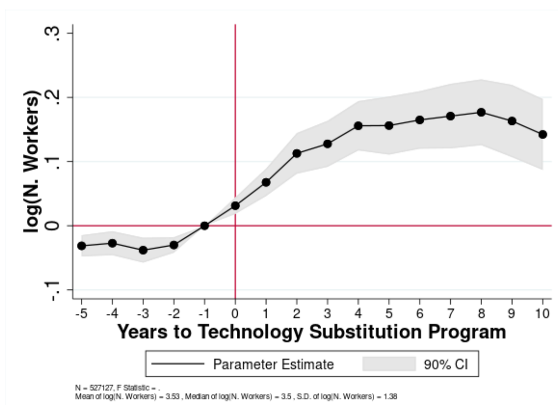
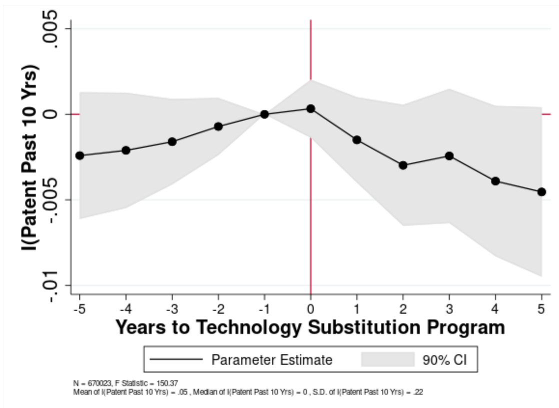
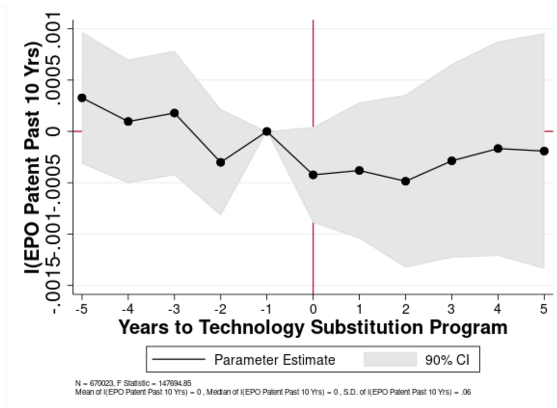


Figure 44: **Placebo Test with Fake Implementation Year**

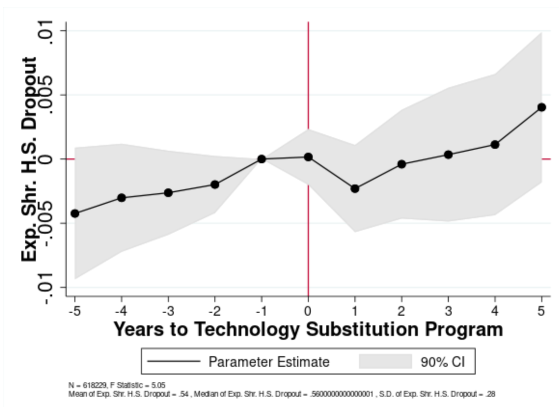
(a) **I(Patent Past 10 Yrs)**



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



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



(d) **log(N. Workers)**

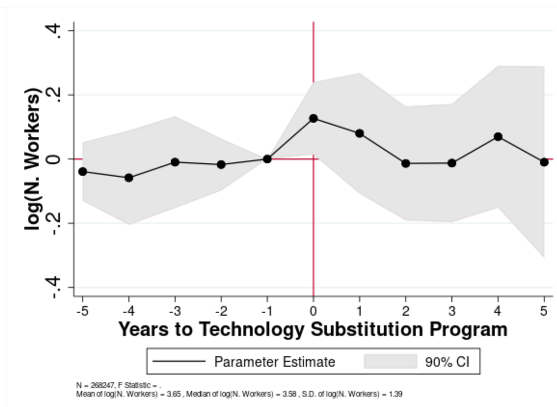
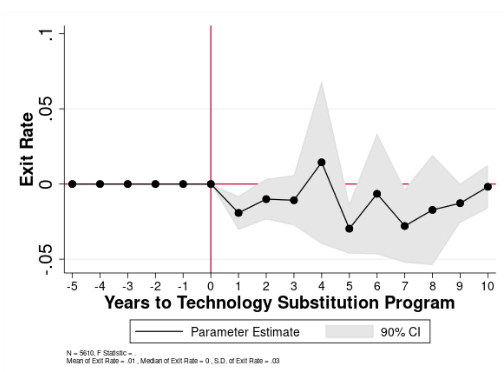
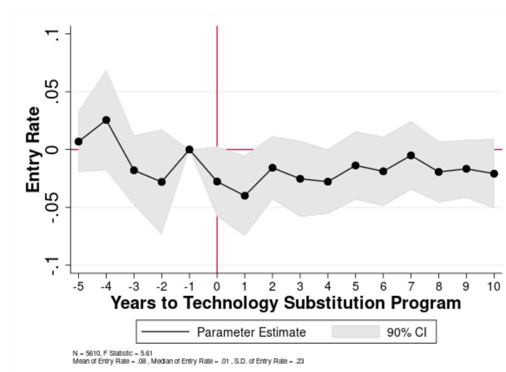


Figure 45: **Effect of TSP on Entry and Exit Rates**

(a) **Exit Rate**



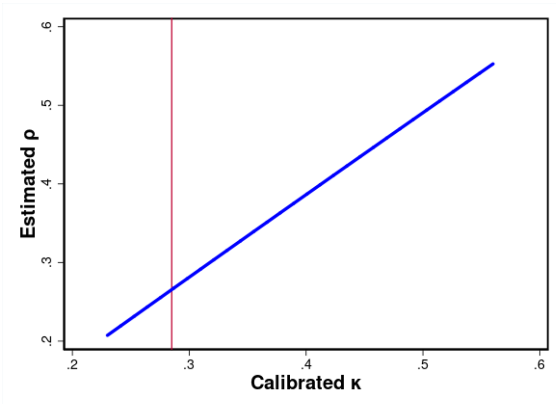
(b) **Entry Rate**



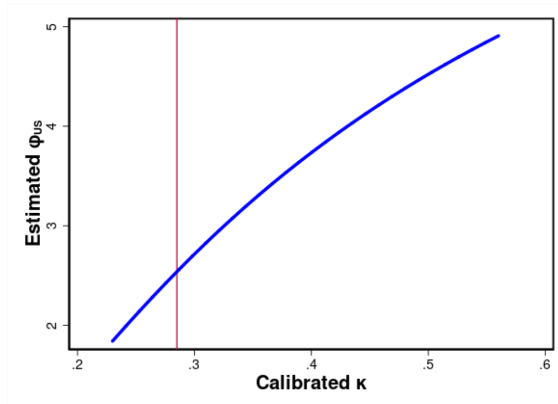
Description: This table displays the coefficients of specification 41 on exit rate, defined as the number of firms leaving the sector divided by the number of firms in the sector, and entry rate, defined as the number of firms entering the sector divided by the number of firms. Each regression is run at the 5 digit sectoral classification CNAE1. Standard errors are clustered by sector.

Figure 48: **Effect of a 1p.p. Increase in Innovation on Skilled Wage Premium and Parameters**

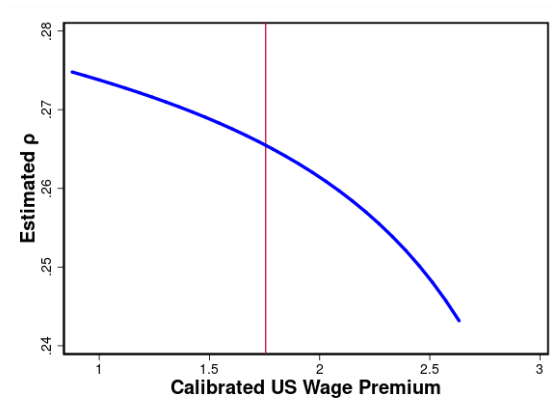
(a) Estimated ρ and calibrated κ



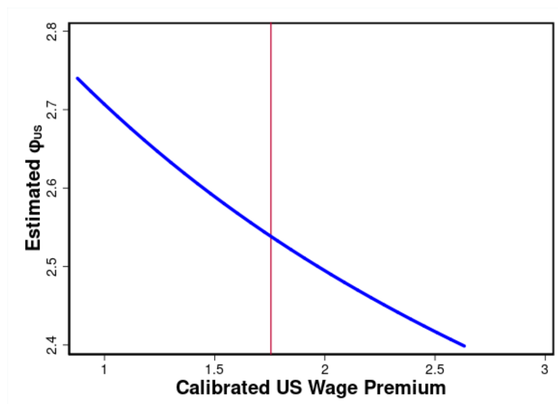
(b) Estimated ϕ_{US} and calibrated κ



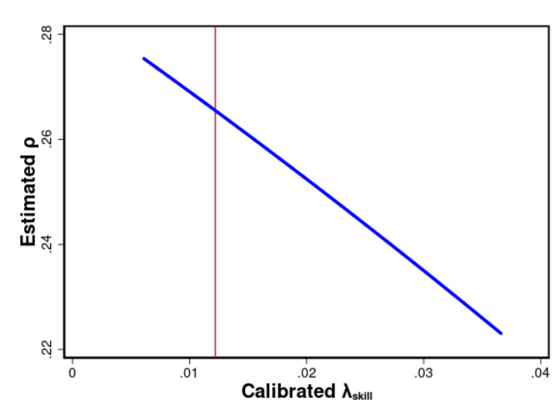
(c) Estimated ρ and calibrated w_H^{US}/w_L^{US}



(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}

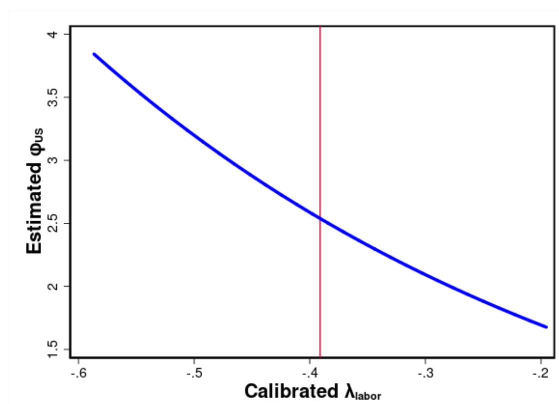


Figure 49: **Effect of a 1p.p. Increase in Innovation on GDP and Wage Premium**

(a) Elasticity of Substitution in the U.S.: κ (b) Mean of Innovation Fixed Cost: μ_ϵ

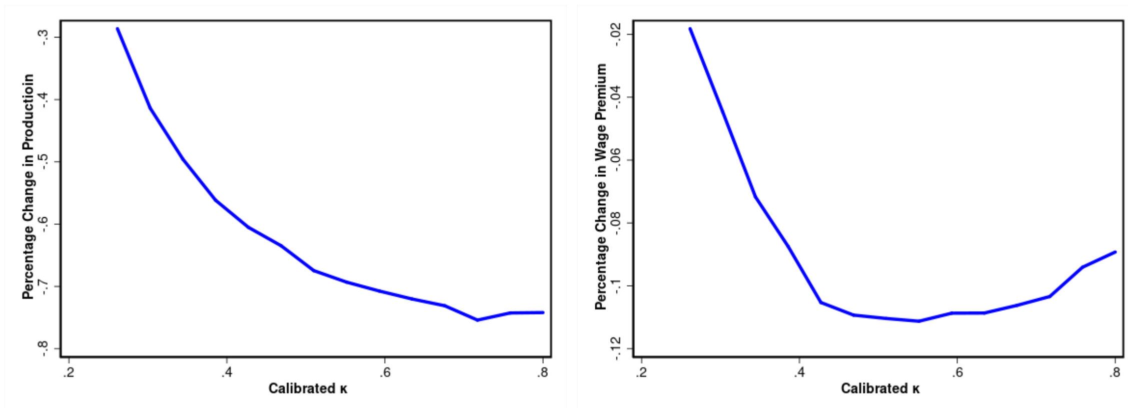


Figure 51: **R&D Subsidy and Innovation**

(a) **I(PCT Patent)** (b) **I(Patent)**

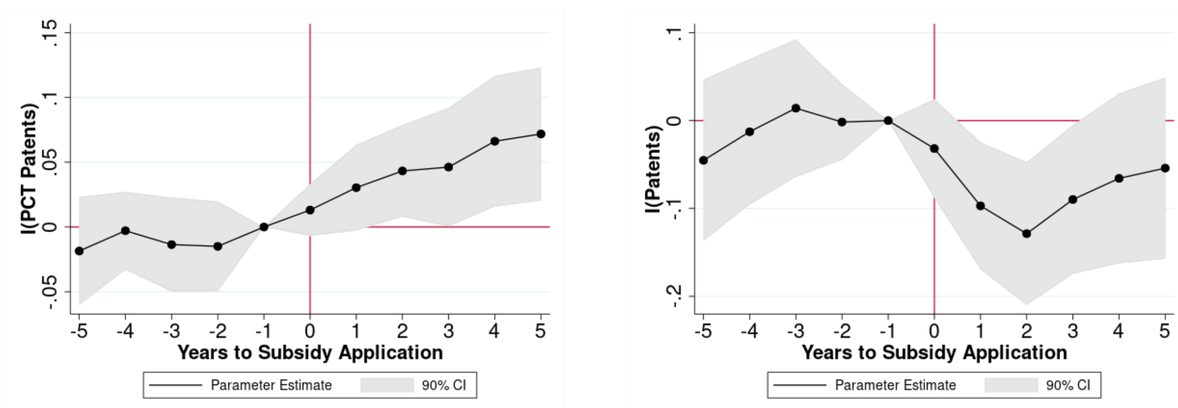


Figure 52: **R&D Subsidy and Employment**

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

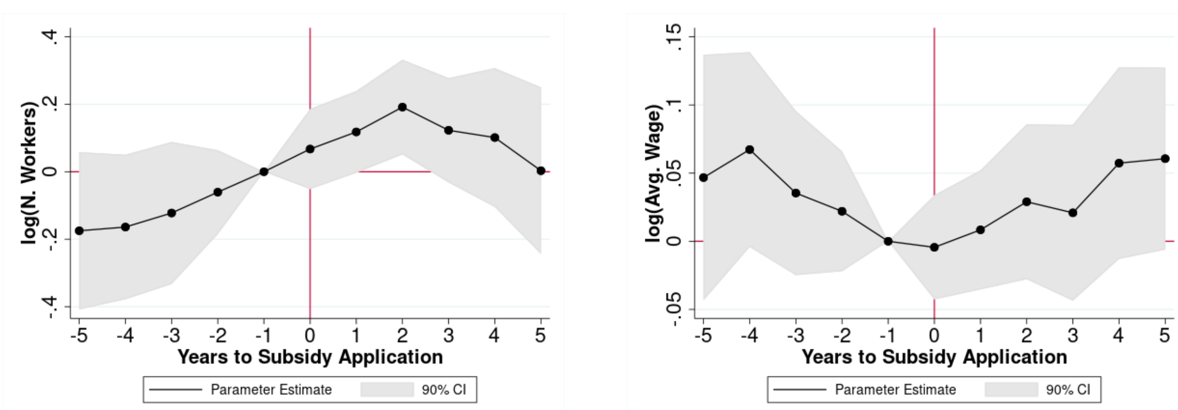
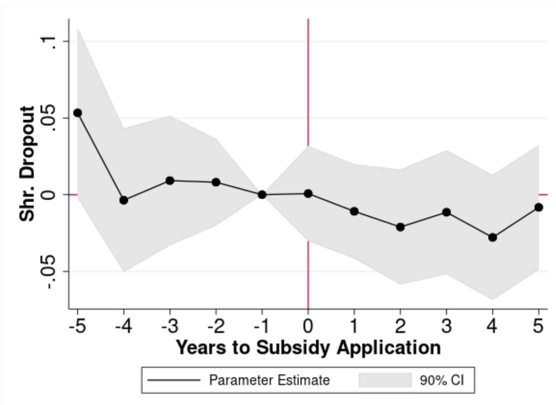


Figure 53: **R&D Subsidy and Education**

(a) **Shr. HS. Dropout**



(b) **log(Avg. Yrs. Educ.)**

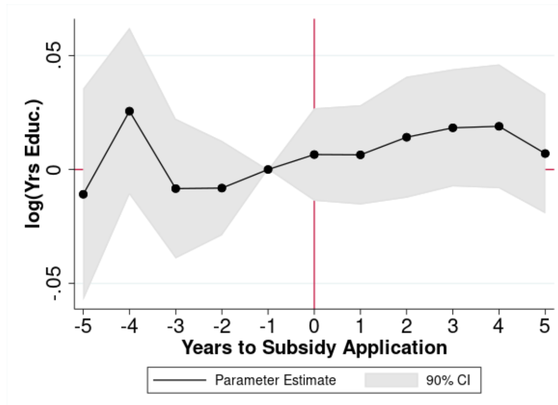
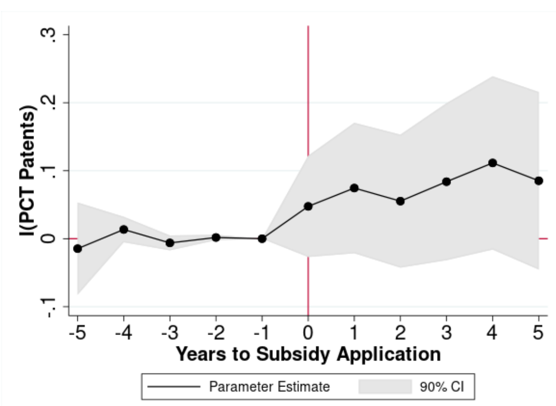


Figure 54: **Effect of R&D Subsidy on Innovation of Firms Leasing Tech.**

(a) **I(PCT Patent)**



(b) **I(Patent)**

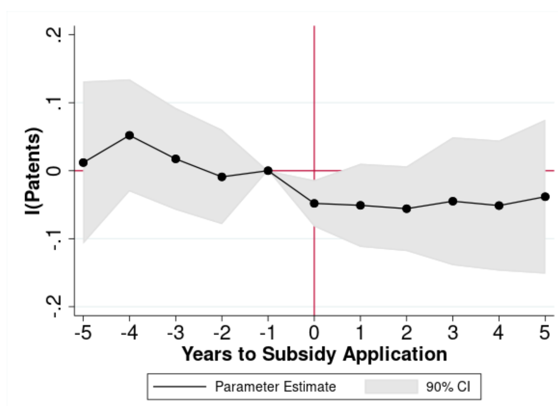
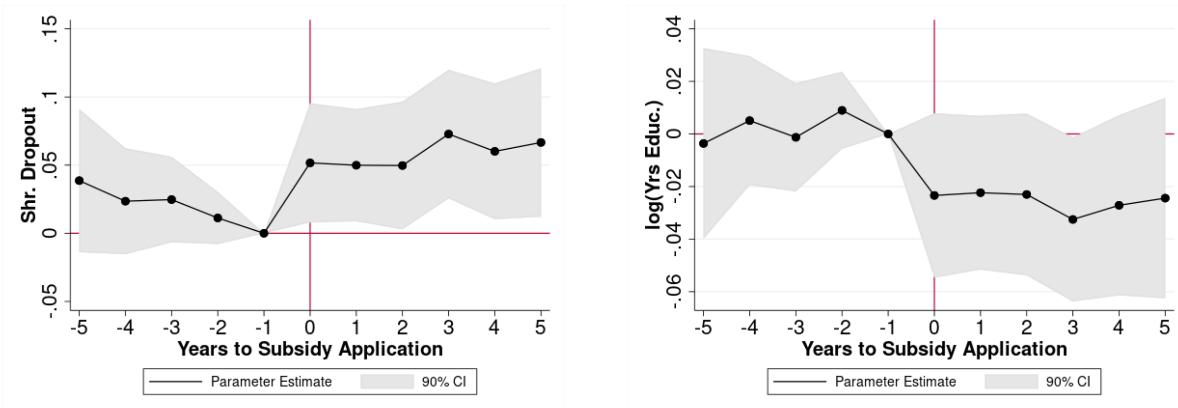


Figure 55: **Effect of R&D Subsidy on Education of Firms Leasing Tech.**

(a) **Shr. HS. Dropout** (b) **log(Avg. Yrs. Educ.)**



Event

Figure 56: **Effect of R&D Subsidy on Employment of Firms Leasing Tech.**

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

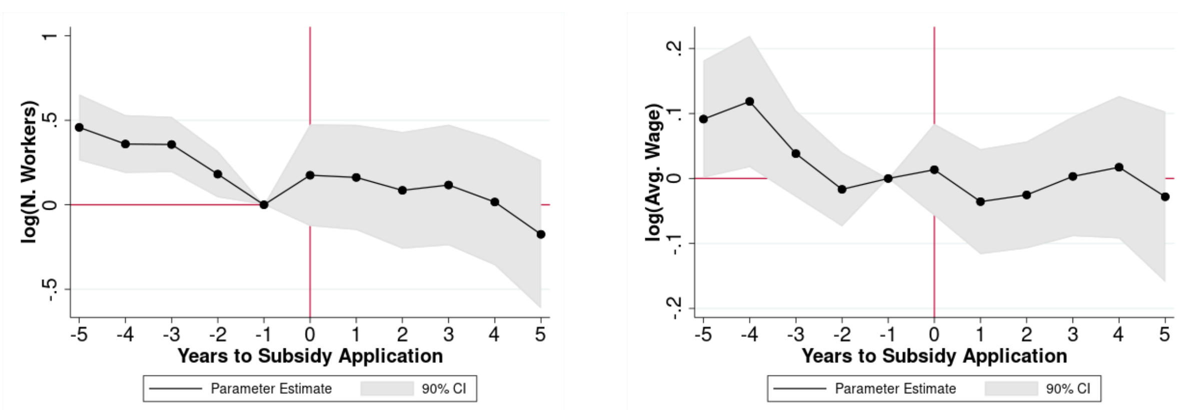


Figure 57: **Patent Application and Shr. College Graduates**

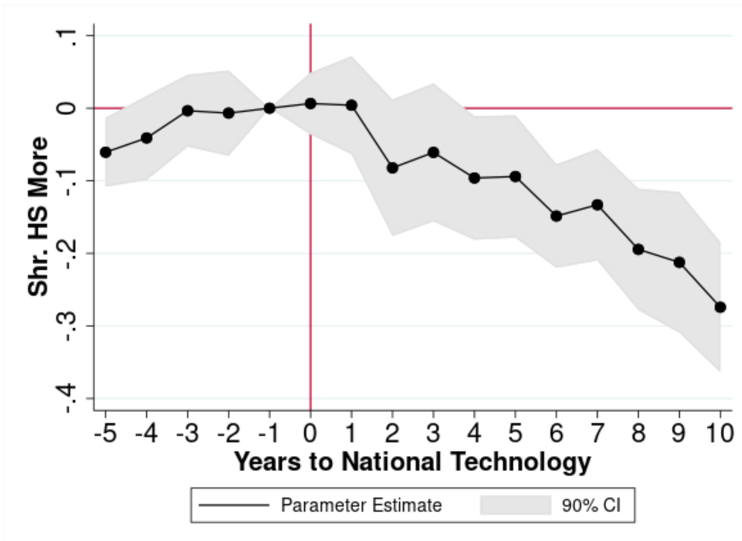


Figure 58: **Patent Application and Shr. HS Dropout**

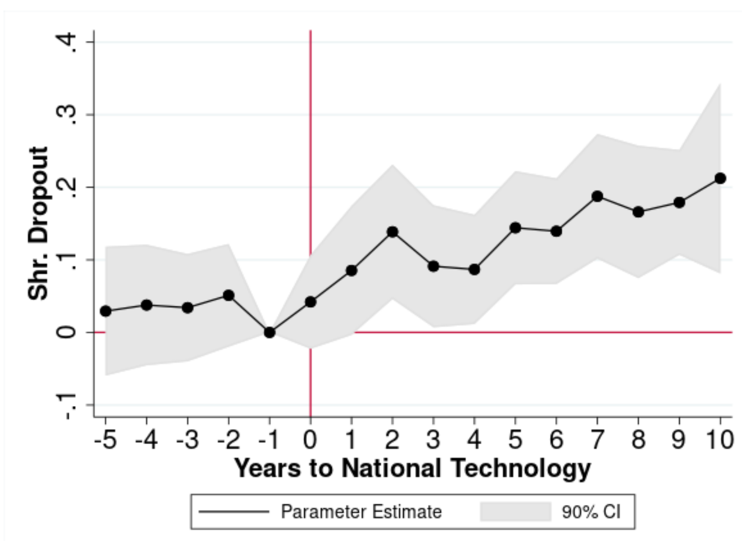


Figure 59: **Patent Application and Yrs. of Education**

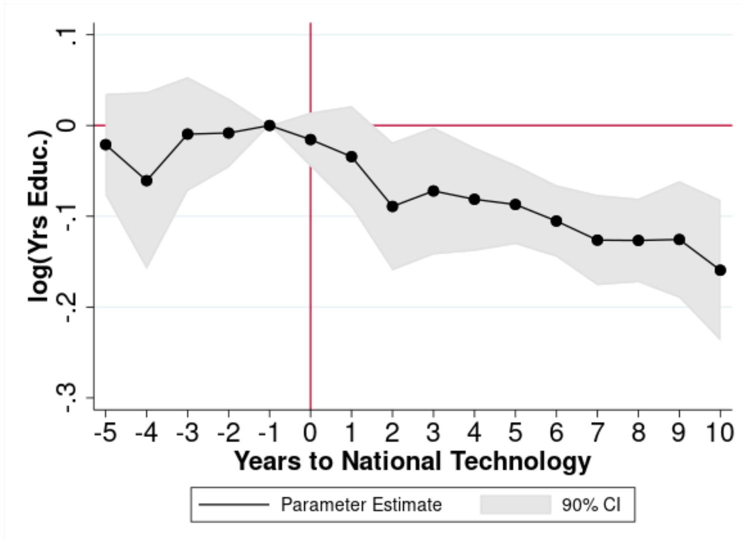
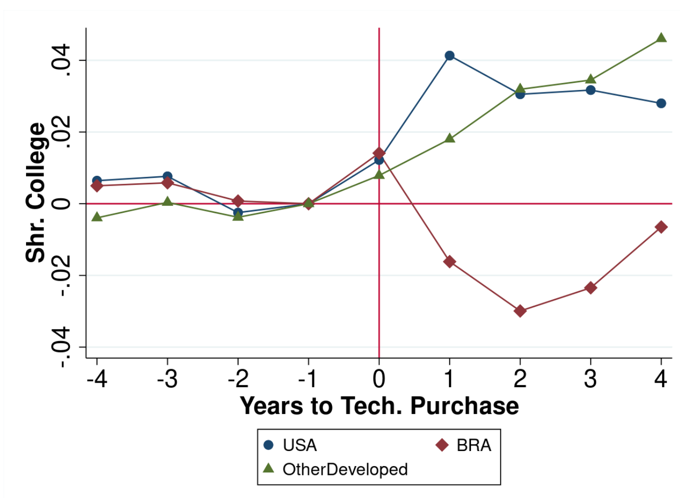
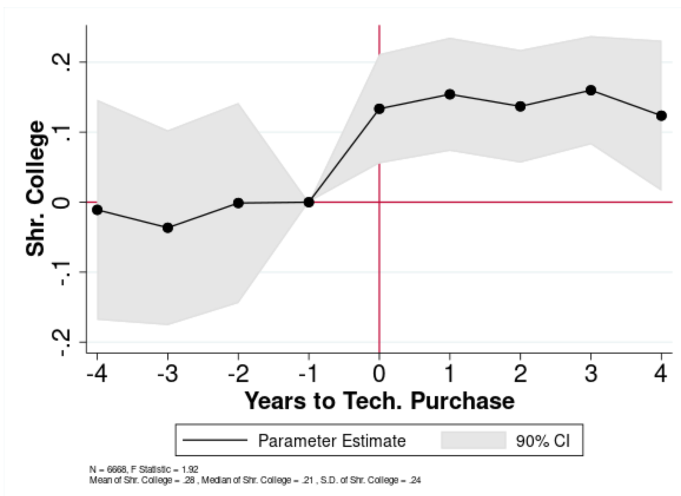


Figure 60: **College Graduate Hiring and Technology of Different Countries**



Description: Standard errors are clustered at the firm level. Observations are weighted by the number of workers in the year before the technology purchase.

Figure 61: **College Graduate Hiring and Factor Share of the Technology Supplier**



Description: Standard errors are clustered at the firm level. Observations are weighted by the number of workers in the year before the technology purchase.