R&D Subsidy and Import Substitution:

Growing in the Shadow of Protection

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Abstract

I study the effect of an innovation subsidy on the growth of firms in a developing country. Using administrative microdata for Brazil and difference-in-differences, I find that innovation subsidies drive firm growth by facilitating firm entry into high-tariff markets with domestically produced versions of foreign goods. After receiving an innovation subsidy, firms issue more patents, expand their workforce, and diversify their product line. However, these patents receive minimal citations, while also heavily citing foreign patents. Firms increase imports of foreign inputs and expand their product line towards products with high import tariff. Despite that, in the most conservative estimate, every $1 of innovation subsidy generated $10 in present value wages.

JEL Codes: O3, O14, O25

Key Words: R&D subsidy, industrial policy, industrial development

1 Introduction

Several developing countries invest in ambitious R&D programs. While these programs have been extensively studied in developed countries, little is known about how they affect innovation and firm growth in developing countries. Some theorize that R&D subsidies can promote greater firm growth in such economies due to their tight borrowing constraints (Hall

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(2002),Restuccia (2004),Buera et al. (2011),Cavalcanti et al. (2021), among many others). However, critics contend that developing countries often generate low-quality innovations, and firms may grow by adopting technologies from developed countries instead of creating their own (Caselli and Coleman (2001),Comin and Hobijn (2010),de Souza (2022), among others). I am the first to evaluate a large innovation subsidy program in a developing country, its effect on long-run firm growth, and its particular interaction with other industrial policies.

In the past 20 years, Brazil implemented a large-scale R&D subsidy program, subsidizing 2299 firms with over 72 billion dollars. One example of these firms is Eurofarma, a pharmaceutical company that used the subsidy to launch a biotechnology lab. Instead of venturing into uncharted waters, Eurofarma created a biosimilar version of filgrastim, a widely studied compound previously imported from the US and Europe. Although it did not develop a new treatment or breakthrough product, Eurofarma grew significantly in the following years, dominating the Brazilian and South American markets due to its competitive edge: a 14% import tariff on filgrastim.[1,2]

This paper shows that the case of Eurofarma is not isolated. Using microdata and frontier causal-inference methods, I show that an R&D subsidy in Brazil led firms to create a local version of foreign products. Despite that, firms significantly increased their workforce and production because high tariffs protected them from competition against foreign producers. Overall, these findings suggest that R&D subsidies efficiently promote firm growth and import substitution in developing countries despite not pushing forward the frontier of knowledge.

In Brazil, firms with research projects can submit applications for R&D subsidy in thematic calls for projects. The subsidy is assigned according to a set of technical criteria, including the quality of the research team, the contribution of the project, and the quality of the management team. To reduce political influence, the project is evaluated by an anonymous board of specialists. The subsidy is closely monitored by the government through live bank audits, personalized cost-tracking software, and a team of auditors. The subsidies on

[1]Filgrastim is a biological product that has to be refrigerated, making its long distance transportation more costly.

[2]According to public sources, Eurofarma grew 23% in 2022 and expanded its biological line to other countries in South America.

average are 322% of the yearly wage bill of firms.

I collected a new firm-level administrative dataset that contains information on innovation, R&D subsidy applications, exports, imports, and employment of the universe of firms in Brazil. Innovation data is collected from the Brazilian patent office, including patent and trademark applications.[3] R&D subsidy application data, covering all applications since 2000, come from the Financier of Studies and Projects. International trade data is from customs records and employment from the matched employer-employee dataset RAIS.

To identify the causal impact of R&D subsidies, I employ a matched difference-in-differences approach that compares close winners and close losers of R&D subsidy applications, inspired by Hirvonen et al. (2022) and Choi and Levchenko (2021). For every firm receiving the subsidy, I select a control firm that applied to the same project call, with an equal chance of receiving the subsidy but that ultimately was not successful. Exploiting the richness of the data, I exactly match treatment and control firms using the government's technical criteria for subsidy allocation. I allow several unmatched years to test the assumption of parallel trends between control and treatment firms. I validated the identification strategy showing pre-period parallel trends for all variables of interest, showing that subsidy recipiency doesn't correlate with political connection or other policies, and with several placebo tests.

I break down the results into 5 main takeaways that shed light on the R&D subsidy mechanisms. The first takeaway is that the R&D subsidy led firms to create low-impact innovations. Firms increased the hiring of scientists by 36% and patenting by 10%. They also hired more PhD workers and scientists in the engineering fields. But the citations received by the firms or quality-weighted patent applications were not affected by the subsidy. Firms also did not increase the average quality of their workforce or scientists. These results suggest that firms are creating more innovations but these are low-impact.

The second takeaway is that, despite creating low-quality innovations, the R&D subsidy led to a large expansion of firms. Firms that received the R&D subsidy, compared to the control group, increased their employment and wage bill by 27% and 26%, respectively. They also increased their number of establishments, their geographical spread, exports, and

[3] The data was also used by de Souza (2022)

imports. Moreover, the effect on firm growth is persistent: 14 years after the subsidy, the treatment firms were 40% larger than the control firms. This result is surprising because patent citation and market potential are correlated (Kogan et al. (2017)). Therefore, patents rarely cited should not lead to a large and persistent increase in firm size, as is the case here.

Third, firms diversified their product lines rather than enhancing existing ones. I show that the R&D subsidy drove the creation of product patents, instead of process patents. Moreover, firms expanded the number of different inputs they import and products they export. They were also more inclined to develop patents and trademarks in new classes. All these results align with the notion of firms broadening their product lines.

Fourth, firms managed to expand despite the low-quality of their innovations because they introduced new products to markets with high import tariffs, allowing them to grow in the shadow of protection. By using a crosswalk between patent classes and product codes, I link patents to product level tariffs. I show that firms are more likely to create patents and trademarks on classes with high import tariffs. Moreover, firms are more likely to export products that face high import tariffs.

The fifth main takeaway is that to produce these goods, firms import inputs and ideas from developed countries and export their output to other Mercorsur countries, which have zero tariffs against Brazil and similarly high-tariffs against developed countries. The subsidy increased input imports and citations to Europe and North America but not to other developing countries. On the other hand, the subsidy led to an increase in exports to other countries in Mercosur but not to Europe or North America.

Putting all the pieces together, these results suggest that the R&D subsidy program in Brazil drove firm growth by facilitating their entry into high-tariff markets with domestically produced versions of foreign goods. Despite that, the R&D subsidy program had large returns. In the most conservative estimate, every $1 of innovation subsidy generated $10 in present value wages.

This paper relates to the literature studying the effect of R&D subsidies. Mostly studying OECD countries, this literature has found R&D subsidies targeting small firms to increase citation weighted innovation and to spillover to other firms (Howell (2017), Bronzini and

Iachini (2014)).[4] The effect of R&D subsidies on large firms is varied, with most studies finding null effects. Chen and Gupta (2017) is one of the few papers to study an R&D tax credit in a developing country. They suggest that it increased R&D investment by the private sector and spilled over to other firms.

This paper contributes to this literature by uncovering a new channel through which innovation subsidies affect firms in developing countries. I show that, despite leading to low-quality innovations with no identifiable externality, the R&D subsidies in Brazil led to large and persistent firm growth by allowing them to enter new local and foreign markets. The effects that I identify are large even on large and old firms, showing the relevance of borrowing constraints in developing countries.

This paper also contributes to the literature on industrial policy, which has studied the effect of subsidies, place based policy, import tariffs and other active government interventions.[5] One of the common arguments for industrial policy is the infant industry argument: at early stages of development, an industry needs protection against foreign competitors until its able to catch up to them (Lane (2020)). Related to that, Juhász (2018), using variation from the Napoleonic Blockades, found long-run gains from trade protection. Moreover, Irwin (2000) argues that tariffs in tinplate in the US led to its early development. de Souza and Li (2022), on the other hand, show that import tariffs lead to large losses at downstream firms. Studying place based policies, Schweiger et al. (2022), Alder et al. (2016), and Hanlon (2019) find evidence for agglomeration and spillover effects. Fan and Zou (2021) found that a place based policy only reallocated industrialization across China instead of increasing it. Studying South Korea's industrial policies, Lee (1996) found productivity growth not to correlate with subsidies or import tariffs while Lane (2021) and Choi and Levchenko (2021) found large effects of subsidized credit on long-run firm growth. Studying an innovation subsidy policy in India, Rotemberg (2019) found a subsidy to negatively affect non-recipients if the product is not internationally traded. Criscuolo et al. (2019), studying the UK, show that investment subsidies increase manufacturing investment among small firms but not large ones.[6] I con-

[4] For a literature review, see Hall (2019), Hall and Van Reenen (2000).

[5] For a survey of the literature, see Lane (2020).

[6] Other papers studying industrial policy are Aghion et al. (2015), Manelici and Pantea (2021), and Giorcelli (2019). For a survey of the literature, see Lane (2020).

tribute to this literature by studying the effect of R&D subsidies, one of the most discussed type of industrial policy, in a developing country and show that R&D subsidies can interact with other types of industrial policies.

2 Institutions

The Funding Authority for Studies and Projects. The Funding Authority for Studies and Projects grants funds or provides subsidized credit to support the development of products, services, or processes. It comprises 16 sectoral committees, each responsible for overseeing project calls within their respective sectors.[7] As per legal requirements, each committee's budget is calculated based on various tax revenues; therefore it is not subject to political discretion.[8] These sectoral committees can issue project calls on specific topics within their sector, following recommendations from a board of specialists. Additionally, the Funding Authority maintains an ongoing open call for projects, welcoming applications from any sector.

The Application Process. To qualify for a subsidy, firms must apply to the Funding Authority, which selects projects based on technical criteria. Applicants submit a package of documents, including a technical proposal, a business plan, a history of balance sheets, and compliance certifications.

The technical proposal, which is standardized by the Funding Authority, contains the heart of the methodological and scientific contribution of the project. Divided into sections that describe in detail the project, its market, the methodology, the research team, the timeline, and the use of funds, the proposal identifies the project's innovative contribution and how it will affect the Brazilian market. Also documented are all the scientists on the project, their CVs, a timeline of each step of the project, the associated costs of these steps, and major expenditure items.

The second important document in the application is the business plan, which describes

[7]For instance, the committee on Energy usually releases a broad call for project in all energy related areas.

[8]For instance, the petroleum committee is financed with a tax on petroleum royalties.

the implementation of the project and its financial viability. The firm details its previous experience with R&D, its experience in the market for the new product, and the project's degree of innovation compared to solutions already existing in the market. The firm also describes the market that the project will get into, including potential clients, suppliers, competitors, and risks. Finally, the firm describes the project's financial viability, the total investment, and the expected cash flow for the next 5 years.

The Selection Criteria. Each application is evaluated by a board of technicians on the basis of pre-determined technical criteria in a single blinded process. In each call for projects, an anonymous board of technicians is appointed by the sectoral committee overseeing it. The board consists of specialists from the Funding Authority, the Patent Office, the government, and academia.

Each technician scores the applications using a set of pre-determined criteria. A firm's final score is the weighted average of all criteria. While the specific criteria and weights vary from call to call, there are three common and important criteria. First is the degree of inventiveness of the project. Firms proposing groundbreaking innovations get higher scores than those proposing to recreate innovations that already exist. The second most common criteria is the quality of the research team and the firm's innovation experience. Firms with more qualified scientists and a history of successful innovations are more likely to receive the subsidy. Finally, the third most important criteria is the technical and financial viability of the project. The Funding Authority is more likely to fund projects that have a greater financial viability.

Enforcement and Expenditure Control. Selected firms receive the subsidy in multiple installments, closely monitored by the Funding Authority. All project funds are placed in a shared account between the firm and the Funding Authority. Transferring these funds to another account or using them for expenses not related to the project is strictly prohibited. As a result, the Funding Authority maintains real-time, direct oversight of the use of funds. Subsidy installments align with the firm's proposed timeline. Changes to the timeline must be evaluated and approved by the Funding Authority, an onerous process that further delays the distribution of funds.

To ensure transparency, firms must report their expenditures from the joint bank account every six months and prior to each installment. The Funding Authority provides its own expense tracking software to facilitate these reports.

Severe consequences await firms and managers that misuse or misreport funds. In such instances, firms must repay all grants received from the Funding Authority and face a 10% fine on the total subsidy amount. Furthermore, the firm is barred from future applications to calls for projects, and managers may be held civilly and criminally liable.

3 Data and Summary Statistics

3.1 Data

Matched Employer-Employee Labor data comes from the matched employer-employee dataset RAIS (*Relação Anual de Informações Sociais*), an administrative dataset collected by the Brazilian Ministry of Labor. RAIS follows the universe of formal firms and workers over time, starting in 1985, linking them to their tax identifiers. RAIS contains information on wages, occupation, education, sector, location, and other demographic information. RAIS also reports the hiring of PhD workers and scientists, which allows me to use it to measure innovation effort. According to Goolsbee (1998), expenditure on scientists constitutes most of the R&D spending.

R&D Subsidy Applications and Recipiency I use administrative data on all R&D subsidy applications managed by Funding Authority for Studies and Projects since 2000. This dataset contains information that identifies the firm, the call for projects, the value requested, the date of the subsidy, a description of the project, the type of subsidy, and whether the firm was awarded the subsidy. This dataset provides a unique opportunity to study the innovation policy of a developing country. It is a large innovation program, granting more than 72 billion dollars to 2,299 competing firms. It covers a 20-year window (2000 to 2020), and with a large variation in the subsidies granted.

Table 1: 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 a CV on the Lattes Platform. The third to fifth line record 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.

Patent and Trademark To measure innovation, I use a dataset with information on patent and trademark applications submitted to the Brazilian Patent Office (de Souza (2022)). The dataset was constructed by scraping information from the Patent Office, covering all applications submitted between 1995 and 2015.

Patent applications, the standard measure of innovation effort at the firm level, have been used in other papers that have studied innovation subsidy (Howell (2017), Bronzini and Iachini (2014)). Departing from them, I also study how innovation subsidy affects product creation and diversification at the firm by measuring it with trademarks. Each trademark is associated with a product or publicity campaign. As firms create new products, they also create new trademarks to protect them.

Export and Import I use administrative data with the universe of firm-level export and import, collected from custom records by SECEX. It contains information on export and import of products at the 8 digit NCM code, firm id, country of origin/destination, value, and weight. The data has been used by others to understand firm exporting decision (Helpman et al. (2016)).

In addition to using it to understand penetration in international markets, I use it to measure the span of products produced by firms and to identify the markets that firms have entered. Flach and Irlacher (2018) used this data for a similar purpose.

Table 2: Statistics on R&D Subsidy

Statistic	Value
Number of Uniq. Firms	1,454
Number of Subsidies	2,299
Avg. Subsidy (in thousands of dollar)	7,309
Median Subsidy (in thousands of dollar)	1,559
E [Subsidy/Yr. Wage Bill]	9.96

Description: This table reports statistics on R&D subsidy applications in Brazil. Data are from the Funding Authority for Studies and Projects, which contains statistics on all subsidies granted from 2000 to 2020.

CV of Inventors To measure invention quality, I create a dataset using information extracted from the CVs of inventors of patents and industrial designs. The CVs were gathered from the Lattes Platform, an administrative database of academic CVs in Brazil. The platform was created in 1993 by the Brazilian federal government for R&D planning and monitoring of academic research. Most scientists, academics, and PhD students are required to post an updated CV in the platform. Researchers in institutions that receive federal support, RAs, those with Master's degree, and PhD students who receive financial support from the federal government as well as those who apply for R&D subsidies, stipends, research grants, or any other government-provided research assistance, are required to maintain an updated CV on the platform. Many Brazilian scientists use it as their main webpage.

Table 1 reports statistics from the CVs of Brazilian inventors. Of 102,775 inventors, 32,505 (31,6%) have a CV on the Lattes Platform. Assuming that inventors without CVs on the platform do not have PhDs, published papers, or academic positions, about 13% of inventors hold a doctorate, 26% have published an academic paper, and 17% have worked at a university.

3.2 Facts of R&D Subsidy in Brazil

R&D Subsidy is 10 Times Yearly Wage Bill. Table 2 show statistics of the innovation subsidy. On average, each innovation subsidy is 7 million dollars – an amount that, on average, represents 9 times the yearly wage bill of firms

Applicants are Large but have Little History of Innovation. Table 3 compares statistics of firms applying for an innovation subsidy against the overall distribution of firms

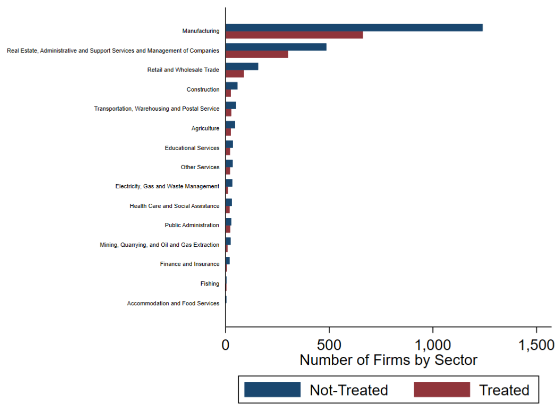
Table 3: Statistics on R&D Subsidy

	(1) Subsidy Applicants			(2) All Brazilian Firms		
	Mean	Median	SD	Mean	Median	SD
Workers	536.74	70.5	1970.10	15.78	3	136.34
Avg. Wage	2076.85	1593.71	1675.24	712.33	579.7	617.71
Avg. Yrs. Educ.	10.51	10.41	2.36	9.03	9	2.76
N. Establishment	4.04	1	16.94	1.29	1	4.73
Stock N. Patents	.197	0	1.36	.001	0	.069
At Least One Patent	.072	0	.25	.0003	0	.019

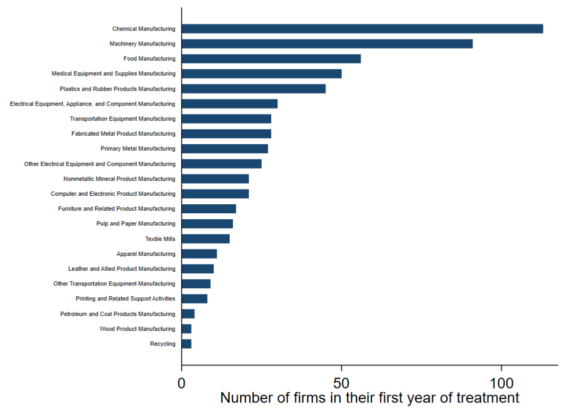
Description: This table reports statistics on R&D applicants in 1999, the year before the first subsidy application in the sample.

Figure 1: Subsidy by Sector

(a) Subsidy Application by Sector



(b) Subsidy Application in Manufacturing



Description: These figures show the number of subsidy applications by sector. In Figure 1a, blue identifies the total number of subsidy applicants by sector whose requests were reject. Red identifies the applicants that received the subsidy. Figure 1b contains all subsidy applicants within manufacturing.

in Brazil. Firms that apply for a subsidy are larger, pay higher wages, have more establishments, and have more patents. Yet their experience innovating is small. Only 7% of the firms that apply for a subsidy have a patent.

R&D Subsidy Targets Manufacturing Sector. Figure 1 shows the distribution of subsidy applicants by sector. Most subsidies are allocated to the manufacturing sector. Within manufacturing, chemicals and machinery receive most of the subsidy.

4 Empirics

The main identification strategy is a matched difference-in-differences design that compares close winners and close losers of the subsidy application, similarly to Hirvonen et al. (2022) and Choi and Levchenko (2021). I match firms based on the variables used by the Funding Authority to award grants, using only data from the year prior to the grant application. This leaves several years and variables unmatched, which I later used for validation.

The identification strategy is validated by a battery of tests. To begin with, matched firms resemble one another in terms of several unmatched characteristics. Subsequently, the strategy passes different placebo tests. Moreover, treatment and control are equally likely to have government connections, reducing the concern about political interference.

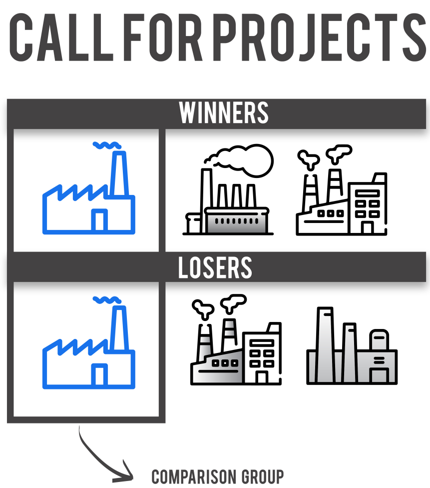
Matching To identify the causal effect of innovation subsidies, I match treatment to control firms. Each treatment firm j that receives an innovation subsidy in year t is matched to a set of similar firms, $g(j)$, that applied for the same call for papers but did not receive the innovation subsidy.

Figure 2 illustrates the matching strategy. Although winners and losers are different in most calls for projects, in some cases, some firms won or lost subsidies by a narrow margin. These marginal winners share many features with marginal losers. By comparing the change in trajectory between the two firms, I can identify the effect of the innovation subsidy. This identification assumes that the only difference in growth rate between marginal winners and losers comes from the subsidy, which I access by checking pre-period trends, differences in unmatched variables, and by performing placebo tests for unobserved shocks.

Using information from the year prior to the subsidy application, I match firms using four key variables correlated with features evaluated by the Funding Authority: the number of employees, the number of patents, the number of citations received, and the subsidy grant requested. The number of employees and the value requested measure a project's technical and financial development, while the number of patents and number of citations received measure the quality of the research and the degree of inventiveness of the firm. In the baseline specification, I do not match within sectors because most project calls are sector-specific.

In the robustness section, I increase the number of variables and the span of the matching.

Figure 2: Matching



Instead of matching only in the year prior to submitting an application, I match withing up to 2 years before subsidy application. I also include among the matching variables the research team's wages and education (which reflect the innovation team's quality), the CEO's wage (which reflects the executing team's quality), project quality measures, and project text similarity. For additional information, see section 6.

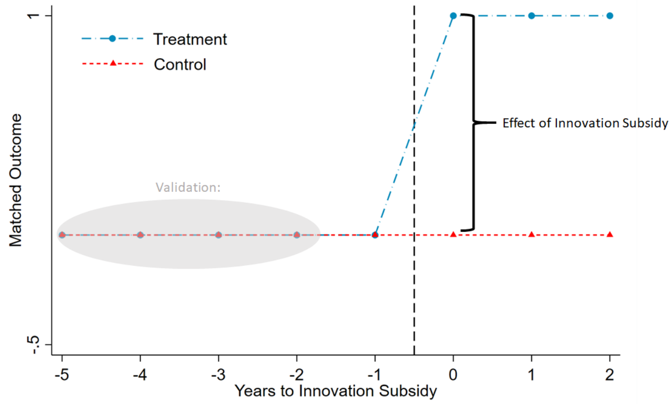
Main Empirical Model The main empirical model is given by

$$y_{i,t} = \theta \mathbb{I}_{i,t} \{ \textit{Innovation Subsidy} \} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is an outcome of firm i in year t, $\mathbb{I}_{i,t} \{ \textit{Innovation Subsidy} \}$ is a dummy that takes one if the firm received the innovation subsidy after its first application, μ_i is a firm fixed effect, and $\mu_{g(i),t}$ is a time-fixed effect common for all firms to matched-group $g(i)$. θ, the parameter of interest, captures the effect of the innovation subsidy on variable $y_{i,t}$.

The identifying assumption is of parallel trends – i.e., if it was not for the innovation

Figure 3: Identifying Variation



subsidy, treatment and control firms would experience similar rates of growth in the outcome variable $y_{i,t}$. To test for this assumption, I also estimate the following dynamic model

$$y_{i,t} = \sum_j \theta_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} \times \mathbb{I}_i \{\text{Treatment}\} + \sum_j \alpha_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t} \quad (2)$$

where $\mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\}$ is a dummy that takes one j years to a subsidy application. If parallel trends in the pre-period are valid, $\theta_j \approx 0, \forall j < 0$.

Figure 3 illustrates the identifying variation. It comes from comparing the growth rate of variable $y_{i,t}$ in a firm that successfully applied for an innovation subsidy and another firm that is similar in several observable characteristics but did not receive the innovation subsidy. If the assumption of parallel trends is true, these two firms should be similar in the years leading up to the innovation subsidy application.

4.1 Validation

Comparison Between Treatment and Control. Table 15 in the appendix, which catalogues the difference between control and treatment in relevant variables, reveals that they are statistically the same in almost all variables. In the results section, I show that firms have similar trends in all variables of interest.

Placebo Test with Fake Treatment Group. Are the results driven by unobservable shocks? It could be the case, for instance, that firms receiving grants also apply for other government programs, which biases the estimates. To test this, I implemented two placebo tests. First, I excluded all treated firms and randomly assigned a placebo treatment to firms whose projects were rejected. After that, I followed the previously described matching strategy but used the placebo treatment instead. In the second placebo approach, instead of random assignment, I distributed the placebo treatment to firms with similar numbers of employees, numbers of patents, numbers of citations received, and subsidy grant requested to the treatment group. Tables 16 and 17 in the appendix demonstrate that neither of these specifications predict a correlation between placebo treatment and firm growth rates.

Political Connections. A looming concern in developing countries is always the possibility of political interference and corruption. To get this (partially) out of our minds, Table 18 in the appendix shows that treatment and control firms are equally likely to make campaign contributions and to receive subsidized loans from other sources.

5 Results

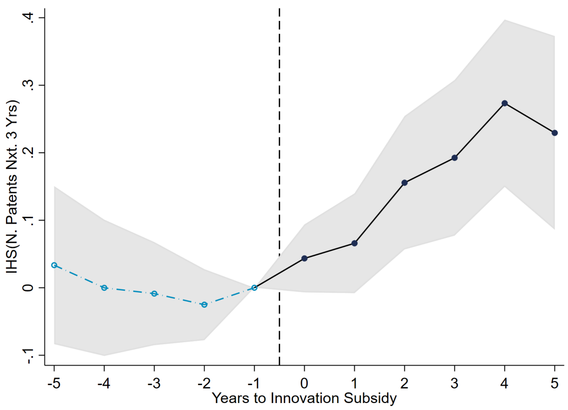
5.1 Main Results

I divide the main results into four points. First, I show that an innovation subsidy increases the innovation effort by firms without increasing the quality of their innovation. Second, despite creating low-quality products, firms expand significantly and enter new markets. Third, innovation is directed at new products in high-tariff markets, providing firms with a competitive edge over foreign competitors. Fourth, firms increase input imports from developed countries and final product exports to other Mercorsur countries. In summary, the innovation subsidy encouraged firms to expand production in high-import tariff markets by creating local varieties of international products using inputs and ideas from developed countries, which are then exported to other developing nations.

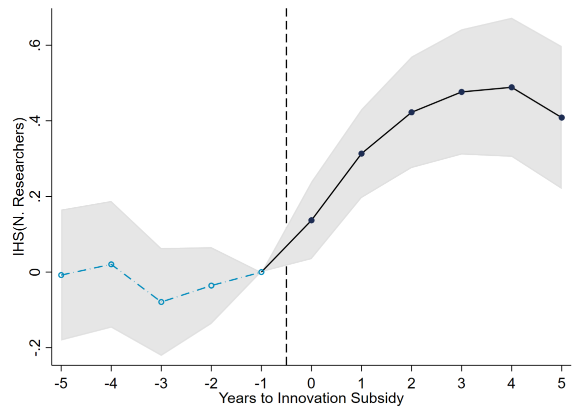
After understanding the inner workings of the innovation subsidy, I computed its impact on other firms and the return on investment. For every dollar of innovation subsidy, the

Figure 4: Effect of Innovation Subsidy on Innovation

(a) Number of Patents in the Next Three Years



(b) Number of Scientists



Description: These figures show the dynamic effects of innovation subsidies on patent applications and the hiring of researchers. The x-axis measures the distance to the subsidy application and the y-axis the estimated effect of the innovation subsidy. Each dot is the estimated coefficient; the gray area is the 10% confidence interval. Figure 4a shows the effect of the subsidy on the inverse hyperbolic sine of the number of patents during the next 3 years. Figure 4b shows the effect on the number of scientists. Standard errors are clustered at the firm level.

government generates \$10 in discounted present value wages, without significant spillover or market-rivalry effects in other firms.

Effect on Innovation: Increase in Low-Quality Innovation. The R&D subsidy increased innovation efforts but only led to low-citation patents. Figure 4 shows the effect of the innovation subsidy on patent applications. Prior to the subsidy, treatment and control groups maintained similar trends, confirming the identifying assumption. After firms received the subsidy, they grew in patent applications and scientists' employment.[9]

Judging from Table 4, the innovation subsidy significantly boosted firms' innovation efforts. Firms increased patent applications by 10% and the likelihood of filing at least one patent by 6%. Columns 3 to 5 also indicate a substantial expansion in scientist hiring. According to Table 20 in the appendix, firms recruited scientists in the hard science and applied fields, such as engineering and automation sciences.

According to Table 5, which displays the effect on various quality-weighted innovation

[9]Patent applications are not an everyday occurrence for firms in Brazil. As investment, it is lumpy, which increases standard errors. To deal with that, I aggregate patent applications in a 3-year window. I chose the 3-year window because it is the shortest window within which de Souza (2022) found an effect on patent applications. In Table 19 I show in the robustness section that a 5-year window delivers the same results.

Table 4: Innovation Subsidy and Innovation Effort

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{IHS}\,(N.\ Patent)$	$\mathbb{I}\,(Patent)$	$\mathbb{IHS}\,(N.\ Scientists)$	$\mathbb{I}\,(N.\ Scientists)$	$\mathbb{IHS}\,(N.\ Ph.D.)$	$\mathbb{IHS}\,(N.\ Trademarks)$
$\mathbb{I}\,\{Subsidy\}$	0.105**	0.0659**	0.364***	0.115***	0.109**	0.169*
	(0.0477)	(0.0256)	(0.0929)	(0.0357)	(0.0539)	(0.0877)
N	11403	11403	11403	11403	11403	11403
R^2	0.624	0.526	0.811	0.551	0.859	0.670

Description: This table shows the effect of the innovation subsidy on firm innovation measures. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications made by the firm during the next three years. In column 2 it is a dummy if the firm makes at least one patent application during the next three years; in column 3 it is the inverse hyperbolic sine of the number of scientists; in column 4 it is a dummy if the firm has at least one R&D worker; in column 5 it is the inverse hyperbolic sine of the number of workers with PhDs; and in column 6 it is the inverse hyperbolic sine of the number of trademarks. Standard errors are clustered at the firm level.

measures, although patent applications increased, the innovation subsidy did not boost the number of impactful innovations. Columns 1 and 2 show that the citations received by the firm and the patents weighted by their citations were not affected. Columns 3 and 4, which use the average wage and years of education of inventors to infer the quality of patents, support the same conclusion.

Tables 6 and 21 provide further evidence that firms did not increase the quality of their products. According to Verhoogen (2008) and Kugler and Verhoogen (2012), product quality and wages are associated: higher quality products require higher quality inputs, including higher quality workers, which, in turn, require higher wages. Table 6 shows that firms did not increase the wages or education of their R&D team or general work-force. Moreover, if these firms were producing high-impact ideas, their scientists would have increased academic engagement. Table 21 in the appendix shows that inventors associated with such firms did not publish more papers, participate in academic seminars, or receive prizes.

These results contrast with findings from developed countries. Bronzini and Iachini (2014) found that an innovation subsidy for large firms crowds out private R&D investment and does not increase overall R&D expenditure. Criscuolo et al. (2019) also found that an investment subsidy to large firms does not boost investment because these firms manipulate the system. Furthermore, when R&D subsidies do increase innovation, as in Howell (2017), what increases are high-quality patents.

Effect on Firm Dynamics: Large and Persistent Increases in Growth. Although subsidized firms created low-quality innovations, they substantially expanded their activity. Figure 2 displays the innovation subsidy's impact on the wage bill. Before the subsidy, treat-

Table 5: Effect of Innovation Subsidy on Quality Weighted Patents

	(1)	(2)	(3)	(4)
	$\mathbb{IHS}$ (*Citations*)	$\mathbb{IHS}$ (*Citation Weighted Patents*)	$\mathbb{IHS}$ (*Inventor Wage Weighted Patents*)	$\mathbb{IHS}$ (*Inventor Educ. Weighted Patents*)
$\mathbb{I}\{Subsidy\}$	0.000374	0.00161	0.148	0.0895
	(0.0258)	(0.00158)	(0.149)	(0.0844)
N	11403	11403	11403	11403
R^2	0.131	0.120	0.449	0.459

Description: This table shows the effect of the innovation subsidy on measures of quality-weighted innovation. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of the number of citations received by the firm during the next three years. In column 2 it is the inverse hyperbolic sine of the number of patent applications awarded during the next three years weighted by the citations that these patents received three years after their publication. In column 3 it is the number of patent applications during the next three years weighted by the monthly wage of the inventors in the patent, while in column 4 it is the number of patent applications during the next three years weighted by the years of education of the inventors. Standard errors are clustered at the firm level.

Table 6: Effect of Innovation Subsidy on Quality of Workers

	(1)	(2)	(3)	(4)
	log(Avg. Wage Scientists)	*log(Yrs. Educ. Scientists)*	*log(Avg. Wage)*	*log(Avg. Yrs. Educ.)*
$\mathbb{I}\{Subsidy\}$	0.0505	0.000436	-0.00529	0.00581
	(0.0450)	(0.0121)	(0.0281)	(0.0102)
N	5954	5947	9358	9352
R^2	0.709	0.524	0.841	0.812

Description: This table shows the effect of the innovation subsidy on measures of quality of the workforce. Each column displays the coefficient of model 1. The left-hand side in column 1 is the log average monthly wage of the research team; in column 2 it is the log years of education of scientists; in column 3 it is the average wage of the whole workforce; and in column 4 it is the average years of education. Standard errors are clustered at the firm level.

ment and control firms maintained the same trend, once again validating the identification assumption. After the subsidy, treatment firms notably increased their wage bill: five years later, treatment firms increased their wage bill by 40%.

Table 7 confirms that the innovation subsidy led to a substantial expansion of firms, even though they created low-quality patents. It also shows that the R&D subsidy increased firm's employment, wage bill, the number of establishments, the number of establishments in different cities, exports, and imports.

The effect of the subsidy on firm size is long-lasting: 14 years after the subsidy, the treatment firms are still 50% larger than the control firms. Figure 6 plots all the estimates that can be identified of the effect of the innovation subsidy on the wage bill.

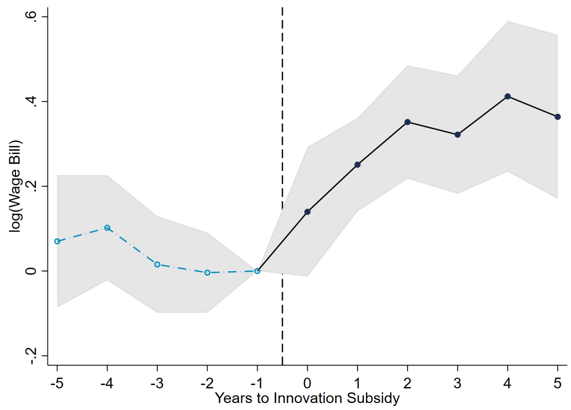
This result is counterintuitive. From previous work, we expected citations to measure

Table 7: Effect of the Innovation Subsidy on Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)
	log (*Workers*)	log (*Wage Bill*)	log (*Establishments*)	log (*N. Municipalities*)	$\mathbb{IHS}$ (*Exports*)	$\mathbb{IHS}$ (*Imports*)
$\mathbb{I}\{Subsidy\}$	0.274***	0.269***	0.119**	0.0602**	1.437***	1.141**
	(0.0924)	(0.0960)	(0.0557)	(0.0281)	(0.514)	(0.528)
N	9358	9358	9353	9358	7059	7059
R^2	0.837	0.861	0.834	0.832	0.814	0.740

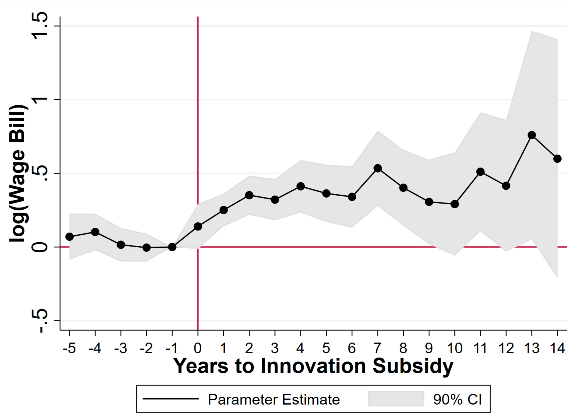
Description: This table shows the effect of the innovation subsidy on firm size. Each column displays the coefficient of model 1. The left-hand side in column 1 is the log number of workers at the firm, in column 2 the wage bill, in column 3 the number of establishments, in column 4 the number of different municipalities with at least one establishment, column 5 the inverse hyperbolic sine of exports, and column 6 the inverse hyperbolic sine of imports. Standard errors are clustered at the firm level.

Figure 5: **Effect of Innovation Subsidy on Wage Bill**



Description: This figure shows the dynamic effect of the innovation subsidy on firms' wage bill. Each dot is the estimated coefficient, while the gray area is the 10% confidence interval. The x-axis measures the distance to the subsidy application and the y-axis the estimated effect of the innovation subsidy on the wage bill. Standard errors are clustered at the firm level.

Figure 6: **Effect of Innovation Subsidy on Wage Bill**



Description: This figure shows the dynamic effect of the innovation subsidy on firms' wage bill. Each dot is the estimated coefficient and the gray area is the 10% confidence interval. The x-axis measures the distance to the subsidy application and the y-axis the estimated effect of the innovation subsidy on the wage bill. Standard errors are clustered at the firm level.

Table 8: Effect of Innovation Subsidy on Product Variety

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{IHS}\{Product\ Patent\}$	$\mathbb{IHS}\{Process\ Patent\}$	$\mathbb{IHS}\{\#\ Pat.\ Class\}$	$\mathbb{IHS}\{\#\ Trademark\ Class\}$	$\mathbb{IHS}\{\#\ Export\ Products\}$	$\mathbb{IHS}\{\#\ Import\ Products\}$
$\mathbb{I}\{Subsidy\}$	0.0852*	0.00826	0.148**	0.0737*	0.451***	0.470***
	(0.0453)	(0.0146)	(0.0742)	(0.0428)	(0.111)	(0.137)
N	11403	11403	11403	11403	7059	7059
R^2	0.636	0.383	0.846	0.839	0.853	0.766

Description: This table shows the effect of the innovation subsidy on product variety. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of the number of product patent application in the next three years. To classify patents as product or process, I extrapolate the data constructed by Bena and Simintzi (2022), who classify patents as product or process using USPTO data on patent claims. Because claims are not available for patents in Brazil, I classify patents as process if, on average, USPTO patents with same patent class are more likely to be process than product. The left-hand side in column 2 is the inverse hyperbolic sine of the number of process patent applications in the next three years; in column 3 it is the inverse hyperbolic sine of the number of different 3-digit IPC patent classes for which the firm has ever made patent applications; in column 4 it is the number of different trademark classes; in column 5 it is the current number of different products exported; and in column 6 it is the number of different imported products. Standard errors are clustered at the firm level. Standard errors are clustered at the firm level.

the market potential of an idea. Therefore, patents rarely cited should not lead to a large and persistent increase in firm size, as is the case here. To solve this puzzle, I evaluate next the direction of this innovation.

Effect on Product Lines: Expansion Towards High-Import Tariff Markets. Firms expanded despite the low quality of their innovation by introducing new products to high import tariff markets, allowing them to grow in the shadow of protection. I make this point in two steps: first, I show that firms introduced new products; then I show that these products are in high-tariff markets.

Table 8 shows that the innovation subsidy prompted firms to introduce new products. Columns 1 and 2 reveal that the subsidy increased product innovations, not process innovations.[10] Columns 3 and 4 indicate firms expanded the number of patent and trademark classes in their portfolio, which suggests that they are broadening their product lines. Column 5 shows an increase in exported product variety, and column 6 an expansion in input variety. Thus, the subsidy empowered firms to enter new markets.[11]

Firms enter high import tariff markets in Brazil, shielding them from international competition. In Table 9, columns 1 and 2 show the innovation subsidy's impact on patents in high and low import tariff markets. To calculate this, I linked patents to products using patent classes, defining high-tariff patents as those in the top quartile of average tariffs and

[10]To classify patents as product or process, I extrapolate the data constructed by Bena and Simintzi (2022), who classify patents as product or process using USPTO data on patent claims. Because claims are not available for patents in Brazil, I classify patents as process if, on average, USPTO patents in the same patent class are more likely to be process than product.

[11]One could suspect that these results are mechanically driven by the inverse hyperbolic sine. If firms are issuing more patents for the first time, mechanically the number of different patent classes will increase. Table 22 shows that these results still hold using log and variation from firms that already had patents, trademarks, exports, and imports.

Table 9: Effect of Innovation Subsidy on the Direction of Innovation

	(1) $\mathbb{IHS}\{N.\ Patent\ High\ Tariff\ Prod.\}$	(2) $\mathbb{IHS}\{N.\ Patent\ Low\ Tariff\ Prod.\}$	(3) $\mathbb{IHS}\{Citation\ to\ High\ Tariff\ Pat.\}$	(4) $\mathbb{IHS}\{Citation\ to\ Low\ Tariff\ Pat.\}$	(5) $\mathbb{IHS}\{Exp.\ High\ Tariff\ Prod.\}$	(6) $\mathbb{IHS}\{Exp.\ Low\ Tariff\ Prod.\}$
$\mathbb{I}\{Subsidy\}$	0.0635***	0.00284	0.0736***	0.0212	1.232**	0.335*
	(0.0239)	(0.0229)	(0.0271)	(0.0300)	(0.493)	(0.201)
N	11403	11403	11403	11403	7059	7059
R^2	0.574	0.711	0.430	0.487	0.822	0.745

Description: This table shows the effect of the innovation subsidy on product variety. Each column displays the coefficient of model 1. The left-hand side in column 1 is the number of patent applications in the next three years in high import tariff patent classes. To estimate the tariff of each patent, I use the crosswalk by Lybbert and Zolas (2014) and calculate the HS product codes associated with each patent. Then, I average the import tariff for each patent and count as high tariff the ones in the top quartile. The left-hand side in column 2 is the number of patent applications during the next three years in the bottom quartile of import tariffs; in column 3 it is the number of citations made to patents in the top quartile of import tariff; in column 4 it is the number of citations made to patents in the bottom quartile; in column 5 it is the inverse hyperbolic sine of exports on high import tariff products; and in column 6 it is exports of products in the bottom quartile of import tariffs. Standard errors are clustered at the firm level.

Table 10: Effect of Innovation Subsidy on Origin of Input Imports and Citation

	(1) $\mathbb{I}\{Imp.\ Mercosur\}$	(2) $\mathbb{I}\{Imp.\ South\ America\}$	(3) $\mathbb{I}\{Imp.\ Europe\}$	(4) $\mathbb{I}\{Imp.\ North\ America\}$	(5) $\mathbb{IHS}\{Citation\ to\ BR\}$	(6) $\mathbb{IHS}\{Citation\ to\ Foreign\}$
$\mathbb{I}\{Subsidy\}$	0.0435	0.0541	0.120***	0.0931**	0.0433*	0.118**
	(0.0366)	(0.0369)	(0.0374)	(0.0403)	(0.0233)	(0.0495)
N	7059	7059	7059	7059	11403	11403
R^2	0.586	0.597	0.670	0.633	0.372	0.440

Description: This table shows the effect of the innovation subsidy on import and citation. Each column displays the coefficient of Model 1. The left-hand side in column 1 is a dummy if the firm imports inputs from the Mercorsur, composed of Argentina, Paraguay, Venezuela, and Uruguay. The left-hand side in column 2 is a dummy if the firm imports inputs from other South American countries; in column 3 it is a dummy if the firm imports from Europe; in column 4 it is a dummy if the firm imports from North America; in column 5 it is a dummy the inverse hyperbolic sine of citation to Brazilian firms; and in column 6 it is a dummy the inverse hyperbolic sine of citations to foreign firms. Standard errors are clustered at the firm level.

low-tariff patents in the low quartile of average tariffs. Columns 3 and 4 show that these patents build on others in high-tariff markets. Finally, columns 5 and 6 reveal that firms export products with high import tariffs in response to the innovation subsidy.

Effect on International Trade: Selling to Developing Countries Ideas from Developed Countries. To create new products, firms build on ideas and inputs from developed countries. Table 10 shows the subsidy increased citation and input imports from Europe and North America, but not from developing countries. These results are consistent with Brazilian firms creating local versions of foreign goods. To develop these innovations, Brazilian firms cite foreign firms. To produce these goods, Brazilian firms import their inputs.

These products created with ideas and inputs from developed countries are then shipped to other developing countries, according to Table 11. The table shows firms increased exports to Mercosur and South American countries but not to developed countries. Mercosur countries have zero import tariffs against Brazil and similar import tariffs on other nations, which guarantees that Brazilian exports are protected against international competition.[12]

Return of Innovation Subsidy: \$1 Generates \$10 in Wages. How much economic activity does every dollar of subsidy generate? Unfortunately, without data on revenue I cannot answer this question. What I can do is address an equally relevant question: How

[12] Table 24 in the appendix reproduces the table using inverse hyperbolic sine.

Table 11: Effect of Innovation Subsidy on Exports

	(1)	(2)	(3)	(4)
	$\mathbb{I}\{Exp.\ Mercosur\}$	$\mathbb{I}\{Exp.\ South\ America\}$	$\mathbb{I}\{Exp.\ Europe\}$	$\mathbb{I}\{Exp.\ North\ America\}$
$\mathbb{I}\{Subsidy\}$	0.101***	0.0825**	0.0224	0.0271
	(0.0362)	(0.0365)	(0.0388)	(0.0378)
N	7059	7059	7059	7059
R^2	0.763	0.759	0.685	0.673

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of Model 1. The left-hand side in column 1 is a dummy if the firm exports to the Mercorsur, which consists of Argentina, Paraguay, Venezuela, and Uruguay. The left-hand side in column 2 is a dummy if the firm exports to other South American countries; in column 3 it is a dummy if the firm exports to Europe; and in column 4 it is a dummy if the firm exports to North America. Standard errors are clustered at the firm level.

much labor income does every dollar of subsidy generates? To calculate the return on a dollar of subsidy, I use the following equation:

$$return = \frac{\sum_{t=0}^{14} \beta^t \theta_t \overline{Wage\ Bill}}{\overline{Subsidy}} \tag{3}$$

where β is the time discount, θ_t is the effect of the innovation subsidy on the wage bill as plotted in 6, $\overline{Wage\ Bill}$ is the average wage bill, and $\overline{Subsidy}$ is the average innovation subsidy.

The equation in 3 calculates how much \$1 of innovation subsidy generates in wages, which is a lower bound on the overall benefit of the subsidy. It does not capture the effect of innovation subsidy on profits or capital nor the effect it has on other firms through spillover or cheaper inputs. It also does not capture the costs of collecting revenue through distortive taxes, so it captures only the benefits of the subsidy.

Table 12 shows wage returns at different time discount rates. At a reasonable rate of 0.98, the innovation subsidy matches the wage bill in the first 15 years and yields 12.5 times its value in the long term. At an unreasonably low rate of 0.96, the subsidy generates \$10.6 for every \$1.

5.2 Other Results

Heterogeneity of Treatment Effects. Are the effects of the innovation subsidy constrained to small firms, as Bronzini and Iachini (2014) have found for developed countries? To answer this question, I estimate the heterogeneous treatment effect of the innovation

Table 12: Return in Wage-Bill from One Dollar Invested in Innovation Subsidy

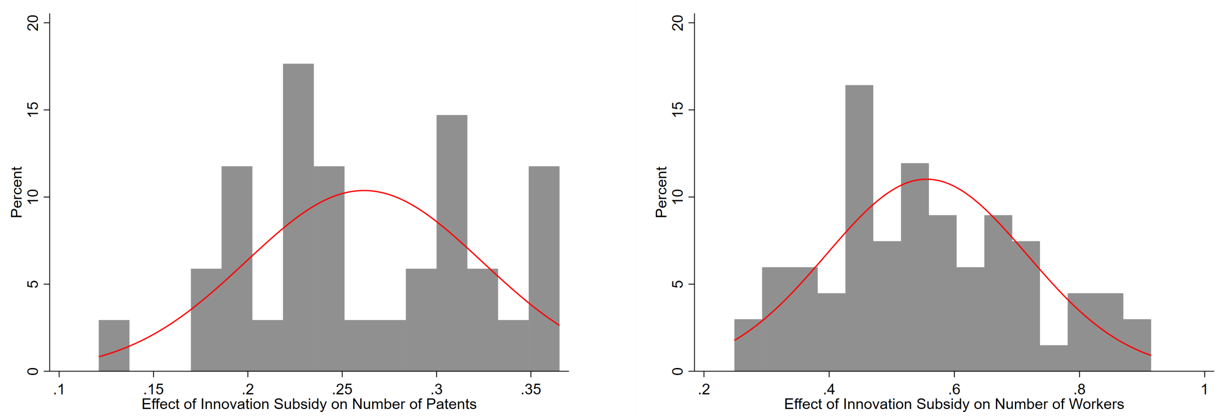
Time Discounting (β)	Return
0.99	13.53
0.98	12.49
0.97	11.54
0.96	10.68

Description: This table displays the wage bill generated by one dollar of innovation subsidy. It reports the estimate of equation 3 under different time discounting.

Figure 7: Distribution of Treatment Effects

(a) Number of Patents

(b) Number of Workers



Description: This figure shows the distribution of treatment effects. The treatment effect is calculated using a long difference and the causal forest (Wager and Athey (2018)). Appendix 7.3 describes in detail the implementation of the causal forest. Figure 7a plots the distribution of the treatment effect of the innovation subsidy on the inverse hyperbolic sine of the number of patents during the next three years. Figure 7b shows the distribution of the treatment effect of the innovation subsidy on log employment.

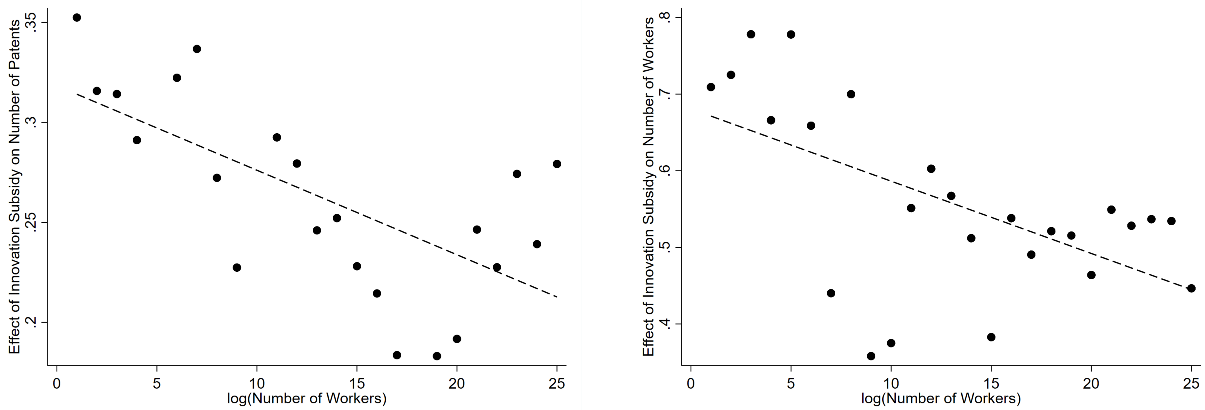
subsidy using a causal forest (Wager and Athey (2018)). For a detailed discussion of the implementation, see Appendix 7.3. I find that even firms with more than 20 thousand workers undergo a large increase in innovation and employment after they receive a R&D subsidy.

Figure 7 shows the distribution of the treatment effect of the innovation subsidy on the inverse hyperbolic sine of the number of patents and the log number of workers. The most important take-away of this figure is that all firms substantially increased their patenting and employment in response to the innovation subsidy. In a 5-year window, the firm that increased the least did so by 25%.

Figure 8 shows the correlation between the treatment effect and the number of employees one year prior to applying for the subsidy. Larger firms increase their size and patenting

Figure 8: Correlation of Treatment Effect and Initial Employment

(a) Effect on Number of Patents (b) Effect on Number of Workers



Description: This figure shows the correlation of the treatment effect with log employment. The x-axis has the log of total employment one year before the subsidy application; the y-axis has the treatment effect. The treatment effect is calculated using a long difference and causal forest (Wager and Athey (2018)). Appendix 7.3 describes in detail the implementation of the causal forest.

by less than smaller firms. Nonetheless, large firms do respond to innovation subsidies. These results indicate that in developing countries even large firms face significant credit constraints.

Spillover and Product Market Rivalry. In this section, I study how other firms are affected by the innovation subsidy. I estimate the spillover and market rivalry effects of the innovation subsidy following Bloom et al. (2013) and Jaffe (1986). Let $T_i = (T_{i,1}, ..., T_{i,132})$ be the share of patents in each patent 3-digit IPC class by firm i before 2000, the year of the sample's first innovation subsidy. Define the technological proximity between firms i and j as

$$tech_{i,j} = \frac{\left(T_i T_j'\right)}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}}$$

The exposure of firm i to firms that received the innovation subsidy is:

$$Spilltech_{i,t} = \sum_j spilltech_{i,j} \mathbb{I}_{j,t} \left\{ Treatment\ Applied\ to\ Subsidy \right\}$$

Similarly, I can define the exposure of firm i to firms that applied to the innovation subsidy but did not received it as

$$SpilltechControl_{i,t} = \sum_j spilltech_{i,j} \mathbb{I}_{j,t} \{Control\ Applied\ to\ Subsidy\}$$

I calculate the market rivalry effect using sectors. Let $S_i = (S_{i,1}, ..., S_{i,527})$ be the share of employment of firm i in different CNAE sectors. The product market rivalry between products of firm i and firm j is:

$$SIC_{ij} = \frac{\left(S_i S_j'\right)}{\left(S_i S_i'\right)^{1/2} \left(S_j S_j'\right)^{1/2}}$$

Exposure to innovation subsidy thorough market rivalry can be calculated as:

$$SpillSIC_{i,t} = \sum_j SIC_{i,j} \mathbb{I}_{j,t} \{Treatment\ Applied\ to\ Subsidy\}$$
$$SpillSICControl_{i,t} = \sum_j SIC_{i,j} \mathbb{I}_{j,t} \{Control\ Applied\ to\ Subsidy\}$$

To identify the effect of spillover and product market rivalry, consider the following model:

$$y_{i,t} = \lambda^{spill} \log(Spilltech_{i,t} + 1) + \lambda^{SIC} \log(SpillSIC_{ij} + 1) + X_{i,t}'\Lambda + \mu_i + \mu_t + \epsilon_{i,t} \quad (4)$$

where $y_{i,t}$ is an outcome of firm i at time t, λ^{spill} captures the spillover effect of being technologically close to firms that receive the innovation subsidy, and λ^{SIC} captures the product market rivalry of being close to those firms. X_i has a set of fixed effects containing a region-time fixed effect, $SpilltechControl_{i,t}$ and $SpillSICControl_{i,t}$. The region-time fixed effect removes any local demand effect generated by the subsidy. $SpilltechControl_{i,t}$ and $SpillSICControl_{i,t}$ capture any trends that lead firms to apply for the innovation subsidy or the government to target particular sectors.

According to Table 13, the subsidy did not generate a spillover or market rivalry effect, which is consistent with the mechanics of the innovation subsidy discussed before. Table 13 shows the effect of spillover and market rivalry in a set of firm characteristics. Despite the

Table 13: **Spillover and Market Rivalry of Innovation Subsidy**

	(1) $log(Workers)$	(2) $log(Establishments)$	(3) $log(Wage\ Bill)$	(4) $\mathbb{IHS}(Wage\ Bill\ Scientists)$	(5) $\mathbb{IHS}(Patents)$
$\log(Spilltech_{i,t}+1)$	-0.0157	-0.00485	-0.0149	-0.0408	-0.00389
	(0.0268)	(0.0134)	(0.0284)	(0.0674)	(0.0147)
$\log(SpillSIC_{ij}+1)$	-0.0407	-0.00105	-0.0687	-0.0501	-0.0468*
	(0.0451)	(0.0190)	(0.0482)	(0.120)	(0.0252)
N	85748	85745	85748	85748	85748
R^2	0.916	0.960	0.934	0.800	0.662

Description: This table shows the effect of the innovation subsidy on other firms through spillover or product market rivalry. Each column displays the coefficients of model 4. The sample is limited to firms that have not applied to an innovation subsidy and that had at least one patent in 1999, one year prior to the sample's first subsidy application. The left-hand side in column 1 is the log number of workers at the firm; in column 2 it is the number of establishments; in column 3 it is the number of wage bills; in column 4 it is the inverse hyperbolic sine of the number of scientists; and in column 5 it is the inverse hyperbolic sine of the number of patent applications during the next 3 years. Standard errors are clustered at the firm level.

Table 14: **Effect of Innovation Subsidy on Workers**

	(1) $log\,(Avg.\ Wage)$	(2) $log\,(Avg.\ Yrs.\ Educ.)$	(3) $log\,(N.\ H.S.\ Dropout)$	(4) $log\,(N.\ H.S.\ Complete)$	(5) $log\,(N.\ More\ than\ H.S.)$	(6) $Shr.\ H.S.\ Dropout$	(7) $Shr.\ H.S.\ Complete$	(8) $Shr.\ More\ than\ H.S.$
$\mathbb{I}\{Subsidy\}$	-0.00529	0.00581	0.257***	0.292***	0.227***	-0.00710	0.0166	-0.00934
	(0.0281)	(0.0102)	(0.0992)	(0.0962)	(0.0864)	(0.0139)	(0.0137)	(0.0112)
N	9358	9352	8597	8817	8697	9358	9358	9358
R^2	0.948	0.812	0.851	0.836	0.872	0.821	0.675	0.817

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of model 1. The left-hand side in column 1 is the log of monthly earnings. In column 2 it is the log of average years of education; in column 3 it is the number of workers whose education is less than high school; in column 4 it is the log of the number of workers with high school education; in column 5 it is the log of the number of workers with more than high-school education; in column 6 it is the share of workers with less than high school education; in column 7 it is the share of workers with high school education; and in column 8 it is the share of workers with more than high school education. Standard errors are clustered at the firm level.

large number of observations, none of the coefficients is statistically significant.

If firms are creating local versions of foreign goods, there shouldn't be any spillover or market rivalry effects. Because firms are creating technologies inside the frontier of knowledge, other firms don't learn anything new from them. Because firms are introducing new products to the Brazilian markets, market rivalry affects the foreign firms but not local Brazilian firms. Therefore, these results are consistent with the main mechanics of the innovation subsidy in Brazil.

Effect on Workers. The innovation subsidy did not affect wages or the composition of workers. Table 14 shows the effect of the innovation subsidy on wages, education and the composition of workers by education group. Table 25 in the appendix shows the effect of the innovation subsidy on different task content measures. These results indicate that the innovation subsidy increased employment among all educational groups but did not change the composition of workers. Table 25 in the appendix shows that the task composition of firms also did not change. According to Hirvonen et al. (2022), who found similar result in a study of capital subsidy, this is evidence that firms, rather than making improvements in their current products, expanded their product lines.

6 Robustness

In this section, I show that the main results are robust to using a control function approach, exploiting variation from the subsidy value, or by changing the matching procedure to include the wage of the CEO, sector, different variables measuring the quality of the research team, the quality of the research project, or further lagged outcomes of the firms.

Controls. In Tables 26 to 28, I estimate the effect of the innovation subsidy using a set of controls instead of matching on pre-determined characteristics. Using controls, I can use the whole sample of subsidy applicants, without having to cut the sample to make the matching. But, the identifying assumption is that, conditional on the controls, the assignment of the subsidy is random. Overall, the main results remain the same.

Subsidy Value. The specification in 1 does not exploit variation in the value of the subsidy. Table 29 in the appendix shows the main regressions but exploiting variation in the size of the subsidy. The main message is still the same: firms increase innovation, expand employment and exports, and introduce new products in high-tariff markets.

Matching on CEO Wage. A factor that affects the selection of firms is the quality of the management team. A good manager should be able to write a compelling proposal and contribute to the financial viability of the project. One could reasonably be concerned that some of the effects I identify could be attributed to differences in the managerial capacities of firms. To deal with that, I also match firms on the wage of their CEOs, which should capture the ability of the managerial team.[13] Table 30 confirms that the main takeaway is still the same.

Matching on Sector. The main matching strategy does not control for sectoral differences between firms because most calls for projects are sector-specific. Nonetheless, one could worry that sectoral shocks are driving part of the results. To deal with this possibility, in Table 31 in the appendix, I also match on the main sector of the firm. Notice that the

[13]The CEO is defined as the individual with highest wage with a managerial occupation.

number of observations decreases significantly because there are fewer matches than before. As consequence, standard errors increase and significance decrease. But guided by the point estimates, it looks still true that firms are patenting more but without being cited, they expand employment, create more product patents than process patents, expand the number of exported goods, and create patents on high tariff classes. Some of these results are not statistically different from zero.

Matching on Further Variables of the Quality of the Research Team. Given that the quality of the research team is one of the most important considerations when granting the subsidy, in Table 32 I also match firms on the number of PhD workers, the average wage of PhD workers, the score of the quality of the education of inventors, the number of academic papers inventors have written, and the number of prizes they have received.[14]. Table 32 shows the main takeaway is still true.

Matching on Project Quality. Another looming concern is that part of the effects I identify comes from differences in the quality of the research proposal. To deal with this possibility, I also match firms on the Flesch-Kincaid readability index of their proposal abstract, which has been shown to correlate with citations on patents (Ashtor (2022)). Table 33 shows that the main take away remains the same and that precision even increases.

Matching on Two Years Before the Innovation Subsidy. Table 34 shows the main results matching control and treatment on their outcome 2 years before the innovation subsidy application. This specification allows me to remove any particular trend that has not been controlled for. The table 34 results are still the same despite the lower number of observations.

7 Conclusion

In this paper, I use a matched difference-in-differences approach to understand the effect of an innovation subsidy on firm growth. I find that the innovation subsidy increases firm

[14] Data on inventor's characteristics comes from Lattes and was collected by de Souza (2022)

growth by inducing firm entry into high-tariff markets with local versions of foreign products. Despite the lack of novelty in their innovation, the subsidy generated large returns for the government: in the worst case scenario, every \$1 generated \$10 in wage bills.

These discoveries have three important implications. First, in developing countries, financial frictions are an important source of low investment in R&D . If large firms could finance their innovations using the private banking system, I would not have found large effects of the innovation subsidy on these firms. Second, there is an interaction between industrial policies. Because firms are introducing new products in high import tariff markets, import tariffs play a role in increasing the returns of innovation subsidy. Finally, the nature of innovation in developing countries resemble imitation.

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7.1 Validation Appendix

Table 15: Comparison Between Matched Treatment and Control

Variable	Control	Treated	Difference	P value
Number of Patents	1.76	1.94	-.18	.84
Numer of Employees	609	649.2	-40.19	.88
Value Requested	6055553	9754767	-3699214	.001
Number of Citations	.06	.06	-.000099	.999
Number of Scientists	24.74	9.86	14.88	.168
Avg. Wage	2230.39	2381.51	-151.12	.397
Number of Establishments	2.76	4.56	-1.79	.052
Wage Bill	1386259	1492023	-105763.5	.856
Avg. Yrs. of Education	11.67	11.54	.127	.466
Shr. H.S. Dropout	.35	.36	-.006	.78
Shr. H.S. Complete	.34	.36	-.01	.351
Shr. More High School	.29	.27	.024	.296

Table 16: Random Placebo Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}\,(\textit{N. Patent})$	$\mathbb{IHS}\,(\textit{Citations})$	$\log\,(\textit{Wage Bill})$	$\mathbb{IHS}\,(\textit{Exports})$	$\mathbb{IHS}\,\{\textit{Product Patent}\}$	$\mathbb{IHS}\,\{\textit{Process Patent}\}$	$\mathbb{IHS}\,\{\textit{\# Export Products}\}$	$\mathbb{IHS}\,\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\,\{\textit{N. Patent Low Tariff Prod.}\}$
$\mathbb{I}\,\{\text{Subsidy}\}$	0.0181	-0.00156	-0.0445	-0.334	-0.00784	0.0122	-0.000539	-0.00893	0.00543
	(0.0164)	(0.0188)	(0.0484)	(0.365)	(0.0289)	(0.00894)	(0.0767)	(0.0186)	(0.0139)
N	17115	17115	6483	10595	17115	17115	10595	17115	17115
R^2	0.528	0.248	0.728	0.819	0.634	0.398	0.856	0.550	0.597

Description: This table shows the effect of the placebo innovation subsidy on main firm outcomes. Each column displays the coefficient of model 1 but uses the placebo subsidy instead of the real one. Firms that received the subsidy are dropped and the subsidy dummy is randomly assigned to firms that have applied for but have not received the subsidy. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be made by the firm during the next three years. In column 2 the left-hand side is the inverse hyperbolic sine of citations that will be received by the firm during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents during the next three years associated with products that have a tariff on the top quartile; and in column 9 it is the number of patents that during the next three years will be associated with products a that have tariff in the bottom quartile. Standard errors are clustered at the firm level.

Table 17: Matched Placebo Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}\,(N.\ Patent)$	$\mathbb{IHS}\,(Citations)$	$\log\,(Wage\ Bill)$	$\mathbb{IHS}\,(Exports)$	$\mathbb{IHS}\,\{Product\ Patent\}$	$\mathbb{IHS}\,\{Process\ Patent\}$	$\mathbb{IHS}\,\{\#\ Export\ Products\}$	$\mathbb{IHS}\,\{N.\ Patent\ High\ Tariff\ Prod.\}$	$\mathbb{IHS}\,\{N.\ Patent\ Low\ Tariff\ Prod.\}$
$\mathbb{I}\,\{\text{Subsidy}\}$	0.00664	-0.0295	0.115	0.0796	0.0000289	0.00111	-0.000734	-0.0134	-0.00793
	(0.0274)	(0.0278)	(0.0834)	(0.585)	(0.0421)	(0.0157)	(0.104)	(0.0231)	(0.0213)
N	6468	6468	2714	4004	6468	6468	4004	6468	6468
R^2	0.503	0.137	0.716	0.818	0.609	0.347	0.865	0.550	0.721

Description: This table shows the effect of the placebo innovation subsidy on the main firm outcomes. Each column displays the coefficient of model 1 but uses the placebo subsidy instead of the real one. Firms that received the subsidy are dropped and the subsidy dummy is randomly assigned to firms that have applied for but have not received the subsidy. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be made by the firm during the next three years. In column 2 the left-hand side is the inverse hyperbolic sine of citations that will be received by the firm during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents during the next three years that will be associated with products that have a tariff in the top quartile; and in column 9 it is the number of patents during the next three years that will be associated with products that have a tariff in the bottom quartile. Standard errors are clustered at the firm level.

Table 18: Innovation Subsidy and Political Connections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\mathbb{I}\,(Subsidize\ Loan)$	$\mathbb{I}\,(Campaign\ Contribution)$	$\mathbb{I}\,(Subsidize\ Loan\ Nxt.\ 3)$	$\mathbb{I}\,(Campaign\ Contribution\ Nxt.\ 3)$	$\mathbb{IHS}\,(Subsidize\ Loan)$	$\mathbb{IHS}\,(Campaign\ Contribution)$	$\mathbb{IHS}\,(Subsidize\ Loan\ Nxt.\ 3)$	$\mathbb{IHS}\,(Campaign\ Contribution\ Nxt.\ 3)$
$\mathbb{I}\,\{\text{Subsidy}\}$	0.000216	0.00130	-0.00960	-0.0196	0.0144	-0.0226	-0.114	-0.285
	(0.00843)	(0.00982)	(0.0251)	(0.0323)	(0.150)	(0.103)	(0.441)	(0.341)
N	7602	7602	7059	7059	7602	7602	7059	7059
R^2	0.250	0.288	0.504	0.507	0.262	0.281	0.528	0.511

Description: This table shows the effect of the innovation subsidy on firm innovation measures at each firm. Each column displays the coefficient of model 1. The left-hand side in column 1 is a dummy if a firm received a subsidy from BNDES; in column 21 is a dummy if the firm made a campaign contribution in the last election; in column 3 1 is a dummy if the firm will receive a subsidized loan during the next 3 years; and in column 4 1 is a dummy if the firm will make a campaign contribution during the next 3 years. Standard errors are clustered at the firm level.

7.2 Results Appendix

Table 19: Innovation Subsidy and Innovation Effort

	(1)	(2)	(3)
	$\mathbb{IHS}\,(N.\ Patents\ Nxt.\ 5)$	$\mathbb{I}\,(Patents\ Nxt.\ 5)$	$\mathbb{IHS}\,(N.\ Trademarks\ Nxt.\ 5)$
$\mathbb{I}\,\{\text{Subsidy}\}$	0.144**	0.0784***	0.175*
	(0.0560)	(0.0263)	(0.103)
N	10860	11403	10860
R^2	0.696	0.589	0.726

Description: This table shows the effect of the innovation subsidy on measures of innovation at the firm. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications made by the firm on the next five years, in column 2 the left hand side is a dummy if the firm makes at least one patent application in the next five years, and column 3 it is the inverse hyperbolic sine of the number of trademarks in the next 5 years. Standard errors are clustered at the firm level.

Table 20: Innovation Subsidy and Scientists Field

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$IHS\,(Engineering)$	$IHS\,(Biology)$	$IHS\,(Meteorology)$	$IHS\,(Automation)$	$IHS\,(Health)$	$IHS\,(Agronomy)$	$IHS\,(Humanities)$	$IHS\,(Hard\ Sciences)$	$IHS\,(Electromechanics)$
$\mathbb{I}\,\{Subsidy\}$	0.186***	0.0146	0.0286	0.0384	0.00721	-0.00352	0.0112	0.0380	0.0384
	(0.0503)	(0.0261)	(0.0231)	(0.0250)	(0.0186)	(0.00948)	(0.0108)	(0.0271)	(0.0250)
N	11403	11403	11403	11403	11403	11403	11403	11403	11403
R^2	0.709	0.754	0.704	0.550	0.805	0.801	0.781	0.693	0.550

Description: This table shows the estimates of model 1 on the number of scientists in different fields. The first column shows the effect on the hiring of civil, electrical, electronic, mechanical, metallurgical, chemical, and other types of engineers. The second column shows the effect on the hiring of researchers who specialize in environmental, animal, microorganism, or parasite biology; it includes geneticists and bioengineers. The third column denotes the hiring of scientists in meteorology and related fields. The fourth line refers to research by mechatronic, control, and automation engineers as well as specialists in industrial automation. The fifth column contains the hiring of medical and veterinary researchers. The sixth column has the number of scientists who specialize in agronomy, agriculture, fishing, animal science, and related fields. The seventh column has the number of scientists hired in the social sciences, including economics, history, and related fields. The eighth column contains the hiring of physicists, mathematicians, chemists, and specialists in related fields. Standard errors are clustered at the firm level.

Table 21: Innovation Subsidy and Academic Outcomes

	(1)	(2)	(3)	(4)
	$\mathbb{I}\,(Papers\ Nxt.\ 3)$	$\mathbb{I}\,(Academic\ Prizes)$	$\mathbb{I}\,(Academic\ Seminars)$	$\mathbb{I}\,(Books)$
$\mathbb{I}\,\{Subsidy\}$	0.0253	-0.00309	0.0205	-0.00317
	(0.0156)	(0.0134)	(0.0143)	(0.00848)
N	11403	11403	11403	11403
R^2	0.681	0.647	0.651	0.595

Description: This table shows the effect of the innovation subsidy on measures of academic activity of patent or industrial design inventors at the firm. Each column displays the coefficient of model 1. The left-hand side in column 1 is a dummy if an inventor publish an academic paper in the next three years. In column 2 the left-hand side is a dummy if an inventor receives an academic prize in the next three years; in column 3 it is a dummy if the inventor participates in an academic seminar in the next 3 years; and in column 4 it is a dummy if he publishes a book in the next three years. Standard errors are clustered at the firm level.

Table 22: Effect of Innovation Subsidy on Log Product Variety

	(1)	(2)	(3)	(4)
	$log\,\{\#\ Pat.\ Class\}$	$log\,\{\#\ Trademark\ Class\}$	$log\,\{\#\ Export\ Products\}$	$log\,\{\#\ Import\ Products\}$
$\mathbb{I}\,\{Subsidy\}$	0.256**	0.0491	0.225*	0.397***
	(0.107)	(0.0558)	(0.117)	(0.115)
N	2902	5202	2572	2913
R^2	0.912	0.852	0.846	0.829

Description: This table shows the effect of the innovation subsidy on product variety. Each column displays the coefficient of model 1. The left-hand side in column 1 is the log of the number of different 3-digit IPC patent classes for which the firm has ever submitted patent applications. In column 2 the left-hand side is the log number of different trademark classes; in column 3 it is the log number of different products exported; and in column 4 it is the log number of different imported products. Standard errors are clustered at the firm level.

Table 23: Effect of Innovation Subsidy on Imports

	(10)	(11)	(12)	(13)
	$\mathbb{IHS}\,\{Imp.\ Mercosur\}$	$\mathbb{IHS}\,\{Imp.\ South\ America\}$	$\mathbb{IHS}\,\{Imp.\ Europe\}$	$\mathbb{IHS}\,\{Imp.\ North\ America\}$
$\mathbb{I}\,\{Subsidy\}$	0.528	0.721	1.766***	1.378***
	(0.458)	(0.467)	(0.489)	(0.507)
N	7059	7059	7059	7059
R^2	0.629	0.642	0.707	0.667

Description: This table shows the effect of the innovation subsidy on imports. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of inputs imported from the Mercorsur, which is composed of Argentina, Paraguay, Venezuela, and Uruguay. The left-hand side in column 2 is the inverse hyperbolic sine of inputs imported from South America; in column 3 it is the inverse hyperbolic sine of imports from Europe; and in column 4 it is the inverse hyperbolic sine of imports from North America. Standard errors are clustered at the firm level.

Table 24: Effect of Innovation Subsidy on Exports

\textbf{}	(1)	(2)	(3)	(4)
	$\mathbb{IHS}\,\{Exp.\ Mercosur\}$	$\mathbb{IHS}\,\{Exp.\ South\ America\}$	$\mathbb{IHS}\,\{Exp.\ Europe\}$	$\mathbb{IHS}\,\{Exp.\ North\ America\}$
$\mathbb{I}\,\{Subsidy\}$	1.620***	1.592***	0.541	0.543
	(0.465)	(0.480)	(0.509)	(0.499)
N	7059	7059	7059	7059
R^2	0.805	0.809	0.749	0.734

Description: This table shows the effect of the innovation subsidy on imports. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of inputs exported to the Mercorsur, which is composed of Argentina, Paraguay, Venezuela, and Uruguay. The left-hand side in column 2 is the inverse hyperbolic sine of exports to South America; in column 3 it is the inverse hyperbolic sine of exports to Europe; and in column 4 it is the inverse hyperbolic sine of exports to North America. Standard errors are clustered at the firm level.

Table 25: Effect of Innovation Subsidy on Task Content

	(1) *Abstract Routine*	(2) *Abstract Non-Routine*	(3) *Routine Manual*	(4) *Routine*	(5) *Coordination*
$\mathbb{I}\{Subsidy\}$	0.00244	0.00227	-0.00109	0.0318	0.0139
	(0.0239)	(0.0272)	(0.0233)	(0.0233)	(0.0259)
N	9357	9357	9357	9357	9357
R^2	0.813	0.740	0.809	0.696	0.601

Description:

7.3 The Causal Forest Approach for Heterogeneous Treatment Effects

I use causal forest to identify the heterogeneity in treatment effects. The goal is estimate the effect of the subsidy conditional on a set of characteristics of the firms. In technical terms, I estimate the Conditional Average Treatment Effect (CATE): $E\left[Y_{1,i} - Y_{0,i} | X_i = x\right]$, where $Y_{1,i}$ and $Y_{0,i}$ denote the potential outcome of firm i with and without the subsidy, while X is a set of observable characteristics. Causal forest, as proposed by Wager and Athey (2018) and Athey et al. (2019), allows for a fully non-parametric relationship between the treatment effect and the set of controls X.

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

$$\Delta y_i = \theta \mathbb{I}_i \left\{Innovation\ Subsidy\right\} + \mu_{g(i)} + \epsilon_i$$

where Δy_i is the difference in outcome y_i one year before and 5 years after the innovation subsidy, $\mathbb{I}_i \left\{Innovation\ Subsidy\right\}$ is a dummy if the firm was successful in the first subsidy application, and $\mu_{g(i)}$ is the group fixed effect. This equation can be re-written as

$$\Delta y_i - E\left[\Delta y_i | g(i)\right] = \theta(X_i) \left(\mathbb{I}_i \left\{Innovation\ Subsidy\right\} - E\left[\mathbb{I}_i \left\{Innovation\ Subsidy\right\} | g(i)\right]\right) + \epsilon_i$$

where $\theta(X_i)$ is the conditional average treatment effect of the innovation subsidy on a firm with covariates X_i. X_i contains the value requested for the grant, the number of employees one year before the grant application, 1-digit sector, the state, the number of patents,the number of scientists, and the total citations received by the firm. As the name suggests, in a causal forest approach, $\theta(X_i)$ is calculated as the average of several causal trees. Each causal tree is calculated as follows. First, the sample is randomly divided into two groups: one is used to estimate the sample splits (leafs); the other, used for estimation of the CATE, which is called "honest approach". Second, a random set of the covariates X_i is selected. Third, the algorithm searches for a split of the sample to maximize the difference in treatment effects in each of the sub-groups, ensuing that in each leaf there are treatments and controls. Forth, the process continues until the leaf or the heterogeneity in treatment effects between leafs is too small. This process is repeated 10,000 times and averaged out on the estimation sample.

7.4 Robustness Appendix

Table 26: Main Results using Control Function

	(1) $\mathbb{I}$ (*N. Patent Nxt. 3*)	(2) $\mathbb{IHS}$ (*Citations*)	(3) log (*Wage Bill*)	(4) $\mathbb{IHS}$ (*Exports*)	(5) $\mathbb{IHS}$ {*Product Patent*}	(6) $\mathbb{IHS}$ {*Process Patent*}	(7) $\mathbb{IHS}$ {*# Export Products*}	(8) $\mathbb{IHS}$ {*N. Patent High Tariff Prod.*}	(9) $\mathbb{IHS}$ {*N. Patent Low Tariff Prod.*}
					No Controls				
$\mathbb{I}\{Subsidy\}$	0.0565***	-0.0247	0.313***	1.264***	0.0809***	0.0248***	0.388***	0.0426***	0.0385***
	(0.0124)	(0.0156)	(0.0671)	(0.302)	(0.0214)	(0.00755)	(0.0689)	(0.0126)	(0.0127)
N	33978	33978	21572	21034	33978	33978	21034	33978	33978
R^2	0.493	0.143	0.877	0.816	0.620	0.482	0.843	0.572	0.579
					Baseline				
$\mathbb{I}\{Subsidy\}$	0.0590***	-0.00170	0.309***	0.931***	0.0871***	0.0125	0.306***	0.0502***	0.0243*
	(0.0142)	(0.00681)	(0.0679)	(0.338)	(0.0243)	(0.00806)	(0.0748)	(0.0149)	(0.0145)
N	26082	26082	19901	16146	26082	26082	16146	26082	26082
R^2	0.509	0.737	0.878	0.815	0.642	0.483	0.849	0.579	0.604
					Baseline + Scientists' Wage				
$\mathbb{I}\{Subsidy\}$	0.0769***	-0.00522	0.246***	1.417***	0.132***	0.0171	0.402***	0.0856***	0.0377
	(0.0209)	(0.0117)	(0.0889)	(0.459)	(0.0387)	(0.0129)	(0.0994)	(0.0237)	(0.0235)
N	14679	14679	12397	9087	14679	14679	9087	14679	14679
R^2	0.529	0.750	0.851	0.821	0.661	0.506	0.853	0.596	0.628

Description: This table shows the effect of the innovation subsidy on the main firm outcomes. Each column displays the coefficient of model 1. The left hand side in column 1 is the inverse hyperbolic sine of the number of patent applications made by the firm on the next three years, in column 2 is the inverse hyperbolic sine of citations received by the firm in the next 3 years, in column 3 the log of wage bill, in column 4 the inverse hyperbolic sine of exports, in column 5 the inverse hyperbolic sine of product patents, in column 6 the inverse hyperbolic sine of process patents, in column 7 the number of different export products, in column 8 the number of patents in the next three years associated to products with tariff on the top quartile, and in column 9 the number of patents in the next three years associated with products with tariffs in the bottom quartile. The baseline panel adds as controls the number of employees the year before the subsidy application, the inverse hyperbolic sine of the number of patents, the inverse byperbolic sine of the total number of citations received, and the log of the subsidy grant requested. The "Baseline + Scientists' Wage" adds as control the inverse hyperbolic sine of the wage of the scientists. Standard errors are clustered at the firm level.

Table 27: Main Results using Control Function with Project Call FE

	(1) $\mathbb{I}$ (*N. Patent Nxt. 3*)	(2) $\mathbb{IHS}$ (*Citations*)	(3) log (*Wage Bill*)	(4) $\mathbb{IHS}$ (*Exports*)	(5) $\mathbb{IHS}$ {*Product Patent*}	(6) $\mathbb{IHS}$ {*Process Patent*}	(7) $\mathbb{IHS}$ {*# Export Products*}	(8) $\mathbb{IHS}$ {*N. Patent High Tariff Prod.*}	(9) $\mathbb{IHS}$ {*N. Patent Low Tariff Prod.*}
					No Controls				
$\mathbb{I}\{Subsidy\}$	0.0348*	-0.0781**	0.112	1.545***	0.0574	0.0236**	0.514***	0.0441*	0.0137
	(0.0205)	(0.0314)	(0.0833)	(0.405)	(0.0396)	(0.0117)	(0.0968)	(0.0234)	(0.0211)
N	33810	33810	21327	20930	33810	33810	20930	33810	33810
R^2	0.510	0.159	0.890	0.823	0.633	0.498	0.849	0.584	0.595
					Baseline				
$\mathbb{I}\{Subsidy\}$	0.0523**	-0.00248	0.220***	0.810*	0.0714*	0.00479	0.323***	0.0602**	-0.0117
	(0.0218)	(0.0126)	(0.0834)	(0.441)	(0.0413)	(0.0131)	(0.102)	(0.0260)	(0.0223)
N	25977	25977	19779	16081	25977	25977	16081	25977	25977
R^2	0.524	0.749	0.890	0.823	0.653	0.498	0.855	0.592	0.617
					Baseline + Scientists' Wage				
$\mathbb{I}\{Subsidy\}$	0.0820***	-0.00196	0.177*	1.049*	0.139***	0.00336	0.344***	0.0978***	0.00903
	(0.0274)	(0.0158)	(0.0966)	(0.553)	(0.0530)	(0.0170)	(0.121)	(0.0337)	(0.0292)
N	14574	14574	12295	9022	14574	14574	9022	14574	14574
R^2	0.555	0.770	0.871	0.831	0.676	0.530	0.861	0.614	0.647

Description: This table shows the effect of the innovation subsidy on main firm outcomes. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications the firm will make during the next three years; in column 2 it is the inverse hyperbolic sine of citations the firm will receive during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents that during the next three years will be associated with products whose tariff is in the top quartile; and in column 9 it is the number of patents that during the next three years will be associated with products whose tariffs are in the bottom quartile. The baseline panel adds as controls the number of employees the year before the subsidy application, the inverse hyperbolic sine of the number of patents, the inverse byperbolic sine of the total number of citations received, and the log of the subsidy grant requested. The "Baseline + Scientists' Wage" adds as control the inverse hyperbolic sine of the wage of the scientists. Standard errors are clustered at the firm level.

Table 28: Main Results using Control Function with Project Call and Sector FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}(\textit{N. Patent Nxt. 3})$	$\mathbb{IHS}(\textit{Citations})$	$\log(\textit{Wage Bill})$	$\mathbb{IHS}(\textit{Exports})$	$\mathbb{IHS}\{\textit{Product Patent}\}$	$\mathbb{IHS}\{\textit{Process Patent}\}$	$\mathbb{IHS}\{\#\ \textit{Export Products}\}$	$\mathbb{IHS}\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\{\textit{N. Patent Low Tariff Prod.}\}$
					No Controls				
$\mathbb{I}\{\textit{Subsidy}\}$	0.0546*	-0.0687	0.0792	0.816*	0.0783	0.0383**	0.367***	0.0559	0.00282
	(0.0288)	(0.0429)	(0.0907)	(0.447)	(0.0576)	(0.0170)	(0.105)	(0.0349)	(0.0278)
N	18068	18068	18068	9526	18068	18068	9526	18068	18068
R^2	0.597	0.265	0.914	0.869	0.691	0.583	0.881	0.660	0.673
					Baseline				
$\mathbb{I}\{\textit{Subsidy}\}$	0.0596**	-0.00655	0.149	0.850*	0.0934*	0.0209	0.319***	0.0704**	-0.00608
	(0.0284)	(0.0178)	(0.0957)	(0.460)	(0.0550)	(0.0168)	(0.108)	(0.0356)	(0.0284)
N	16787	16787	16787	9200	16787	16787	9200	16787	16787
R^2	0.614	0.788	0.913	0.870	0.712	0.579	0.884	0.671	0.679
					Baseline + Scientists' Wage				
$\mathbb{I}\{\textit{Subsidy}\}$	0.0460	-0.00844	0.141	0.830	0.119	0.0122	0.305**	0.107**	-0.0142
	(0.0397)	(0.0246)	(0.127)	(0.610)	(0.0804)	(0.0228)	(0.140)	(0.0504)	(0.0404)
N	9807	9807	9807	5644	9807	9807	5644	9807	9807
R^2	0.642	0.815	0.904	0.878	0.737	0.602	0.892	0.707	0.703

Description: This table shows the effect of the innovation subsidy on the main firm outcomes. Each column displays the coefficient of model 1. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that the firm will make during the next three years; in column 2 it is the inverse hyperbolic sine of citations that the firm will receive during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents that during the next three years will be associated with products whose tariffs are in the top quartile; and in column 9 it is the number of patents that during the next three years will be associated with products whose tariffs are in the bottom quartile. The baseline panel adds as controls the number of employees the year before the subsidy application, the inverse hyperbolic sine of the number of patents, the inverse byperbolic sine of the total number of citations received, and the log of the subsidy grant requested. The "Baseline + Scientists' Wage" adds as control the inverse hyperbolic sine of the wage of the scientists. Standard errors are clustered at the firm level.

Table 29: Main Results using Variation from Subsidy Value

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}(\textit{N. Patent Nxt. 3})$	$\mathbb{IHS}(\textit{Citations})$	$\log(\textit{Wage Bill})$	$\mathbb{IHS}(\textit{Exports})$	$\mathbb{IHS}\{\textit{Product Patent}\}$	$\mathbb{IHS}\{\textit{Process Patent}\}$	$\mathbb{IHS}\{\#\ \textit{Export Products}\}$	$\mathbb{IHS}\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\{\textit{N. Patent Low Tariff Prod.}\}$
log(Subsidy Vl.)	0.00396**	-0.00000548	0.0169***	0.101***	0.00538*	0.000611	0.0316***	0.00376**	0.000424
	(0.00169)	(0.00184)	(0.00648)	(0.0352)	(0.00302)	(0.000996)	(0.00773)	(0.00157)	(0.00157)
N	11214	11214	9197	6942	11214	11214	6942	11214	11214
R^2	0.531	0.132	0.861	0.814	0.639	0.383	0.855	0.577	0.712

Description: This table shows the effect of the innovation subsidy on the main firm outcomes. Each column displays the coefficient of model $y_{i,t} = \theta \log(\textit{Vl Subsidy}) \mathbb{I}_{i,t}\{\textit{Innovation Subsidy}\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t}$, where *Vl Subsidy* is the value requested for the grant. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be made by the firm during the next three years; in column 2 it is the inverse hyperbolic sine of citations that will be received by the firm during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents during the next three years that will be associated with products whose tariff is in the top quartile; and in column 9 it is the number of patents during the next three years that will be associated with products whose tariffs is in the bottom quartile. Standard errors are clustered at the firm level.

Table 30: Main Results Matching on CEO Wage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}(\textit{N. Patent Nxt. 3})$	$\mathbb{IHS}(\textit{Citations})$	$\log(\textit{Wage Bill})$	$\mathbb{IHS}(\textit{Exports})$	$\mathbb{IHS}\{\textit{Product Patent}\}$	$\mathbb{IHS}\{\textit{Process Patent}\}$	$\mathbb{IHS}\{\#\ \textit{Export Products}\}$	$\mathbb{IHS}\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\{\textit{N. Patent Low Tariff Prod.}\}$
$\mathbb{I}\{\textit{Subsidy}\}$	0.094***	0.001	0.269**	1.647***	0.121**	0.0003	0.544***	0.064**	0.026
	(0.029)	(0.029)	(0.106)	(0.557)	(0.053)	(0.014)	(0.123)	(0.030)	(0.026)
N	9072	9072	7459	5616	9072	9072	5616	9072	9072
R^2	0.541	0.176	0.876	0.836	0.679	0.353	0.867	0.614	0.759

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of model 1 but adds the wage of the CEO to the matching procedure. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be made by the firm during the next three years; in column 2 it is the inverse hyperbolic sine of citations that will be received by the firm during the next 3 years; in column 3 it is the log of wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents that during the next three years will be associated with products whose tariff is in the top quartile; and in column 9 it is the number of patents in the next three years that will be associated with products whose tariffs are in the bottom quartile. Standard errors are clustered at the firm level.

Table 31: Main Results Matching on Sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}(\textit{N. Patent Nxt. 3})$	$\mathbb{IHS}(\textit{Citations})$	$\log(\textit{Wage Bill})$	$\mathbb{IHS}(\textit{Exports})$	$\mathbb{IHS}\{\textit{Product Patent}\}$	$\mathbb{IHS}\{\textit{Process Patent}\}$	$\mathbb{IHS}\{\#\ \textit{Export Products}\}$	$\mathbb{IHS}\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\{\textit{N. Patent Low Tariff Prod.}\}$
$\mathbb{I}\{\textit{Subsidy}\}$	0.081**	0.046	0.467***	0.502	0.085	0.022	0.301*	0.041	0.026
	(0.040)	(0.058)	(0.139)	(0.759)	(0.067)	(0.019)	(0.168)	(0.042)	(0.033)
N	5607	5607	4628	3471	5607	5607	3471	5607	5607
R^2	0.595	0.437	0.866	0.846	0.770	0.450	0.879	0.705	0.854

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of model 1 but adds the 2-digit CNAE sector of the firm to the matching procedure. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be made by the firm during the next three years; in column 2 it is the inverse hyperbolic sine of citations that the firm will receive during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents that during the next three years will be associated with products whose tariff is in the top quartile; and in column 9 it is the number of patents that during the next the next three years will be associated with products whose tariffs are in the bottom quartile. Standard errors are clustered at the firm level.

Table 32: Main Results Matching on Quality of Research Team

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}(\textit{N. Patent Nxt. 3})$	$\mathbb{IHS}(\textit{Citations})$	$\log(\textit{Wage Bill})$	$\mathbb{IHS}(\textit{Exports})$	$\mathbb{IHS}\{\textit{Product Patent}\}$	$\mathbb{IHS}\{\textit{Process Patent}\}$	$\mathbb{IHS}\{\#\ \textit{Export Products}\}$	$\mathbb{IHS}\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\{\textit{N. Patent Low Tariff Prod.}\}$
$\mathbb{I}\{\textit{Subsidy}\}$	0.093***	0.001	0.300***	1.280**	0.097**	0.013	0.461***	0.047*	-0.002
	(0.028)	(0.002)	(0.103)	(0.580)	(0.047)	(0.009)	(0.126)	(0.027)	(0.019)
N	9408	9408	7583	5824	9408	9408	5824	9408	9408
R^2	0.560	0.309	0.875	0.821	0.698	0.383	0.854	0.627	0.787

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of model 1 but adds the number of PhD workers, the average wage of PhD workers, the score on the quality of the education of inventors, the number of academic papers inventors have written, and the number of prizes they have received to the matching strategy. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be made by the firm during the next three years; in column 2 it is the inverse hyperbolic sine of citations that will be received by the firm during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents that during the next three years will be associated with products whose tariff is in the top quartile; and in column 9 it is the number of patents that during the next three years will be associated with products whose tariffs are the bottom quartile. Standard errors are clustered at the firm level.

Table 33: Main Results Matching on Project Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}\,(N.\ Patent\ Nxt.\ 3)$	$\mathbb{IHS}\,(Citations)$	$\log\,(Wage\ Bill)$	$\mathbb{IHS}\,(Exports)$	$\mathbb{IHS}\,\{Product\ Patent\}$	$\mathbb{IHS}\,\{Process\ Patent\}$	$\mathbb{IHS}\,\{\#\ Export\ Products\}$	$\mathbb{IHS}\,\{N.\ Patent\ High\ Tariff\ Prod.\}$	$\mathbb{IHS}\,\{N.\ Patent\ Low\ Tariff\ Prod.\}$
$\mathbb{I}\,\{Subsidy\}$	0.099***	0.002	0.278**	1.684***	0.127**	0.003	0.556***	0.068**	0.028
	(0.028)	(0.029)	(0.108)	(0.557)	(0.054)	(0.014)	(0.123)	(0.031)	(0.026)
N	9030	9030	7432	5590	9030	9030	5590	9030	9030
R^2	0.540	0.176	0.875	0.837	0.676	0.344	0.868	0.610	0.760

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of model 1 but adds to the matching strategy the Flesch-Kincaid readability index of their proposal's abstract. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be submitted by the firm during the next three years; in column 2 it is the inverse hyperbolic sine of citations that will be received by the firm during the next 3 years; in column 3 it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents that during the next three years will be associated with products whose tariff is in the top quartile; and in column 9 it is the number of patents that during the next three years will be associated with products whose tariffs is in the bottom quartile. Standard errors are clustered at the firm level.

Table 34: Main Results Matching on 2 Years Leading to the Subsidy Application

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}\,(N.\ Patent\ Nxt.\ 3)$	$\mathbb{IHS}\,(Citations)$	$\log\,(Wage\ Bill)$	$\mathbb{IHS}\,(Exports)$	$\mathbb{IHS}\,\{Product\ Patent\}$	$\mathbb{IHS}\,\{Process\ Patent\}$	$\mathbb{IHS}\,\{\#\ Export\ Products\}$	$\mathbb{IHS}\,\{N.\ Patent\ High\ Tariff\ Prod.\}$	$\mathbb{IHS}\,\{N.\ Patent\ Low\ Tariff\ Prod.\}$
$\mathbb{I}\,\{Subsidy\}$	0.0586*	0.000390	0.264**	1.579***	0.0370	-0.00506	0.416***	0.0555*	-0.0155
	(0.0312)	(0.00704)	(0.107)	(0.589)	(0.0550)	(0.0236)	(0.122)	(0.0302)	(0.0272)
N	7812	7812	6669	4836	7812	7812	4836	7812	7812
R^2	0.563	0.232	0.866	0.827	0.713	0.408	0.859	0.638	0.812

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of model 1 but matches outcomes one year before and 2 years before the subsidy application. The left-hand side in column 1 is the inverse hyperbolic sine of the number of patent applications that will be made by the firm during the next three years; in column 2 it is the inverse hyperbolic sine of citations that will be received by the firm during the next 3 years; in column 3it is the log of the wage bill; in column 4 it is the inverse hyperbolic sine of exports; in column 5 it is the inverse hyperbolic sine of product patents; in column 6 it is the inverse hyperbolic sine of process patents; in column 7 it is the number of different export products; in column 8 it is the number of patents that during the next three years will be associated with products whose tariffs are in the top quartile; and in column 9 it is the number of patents that during the next three years will be associated with products whose tariffs are in the bottom quartile. Standard errors are clustered at the firm level.