R&D Subsidy and Import Substitution: Growing in the Shadow of Protection*

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Abstract

We study the effect of an innovation subsidy on the long-run growth of firms in a developing country. Using administrative microdata for Brazil and difference-in-differences, we find that R&D subsidies led to long-run firm growth despite predominantly generating low-impact innovations. Firms grew by expanding their product lines towards products with high import tariffs producing local versions of foreign goods. Heterogeneity by firm characteristics is consistent with the subsidy alleviating financial constraints. Our results challenge the traditional view that direct innovation subsidies foster high-quality innovation, suggesting instead that, in developing countries, they facilitate entry into protected markets.

JEL Codes: O3, O14, O25

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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 (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). We are 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 1454 firms with over 10 billion US 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, we 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. These effects are stronger for financially constrained firms. Overall, these findings suggest that R&D subsidies promote firm growth and import substitution in developing countries despite not pushing forward the frontier of knowledge.

[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.

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 the consistency of the proposal and the quality of the research 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 are on average 9.9 times the yearly wage bill of firms and firms have two years to conclude the project.

We collected a new firm-level administrative dataset that contains information on innovation, R&D subsidy applications, exports, imports, employment, and credit 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. We also use data from the Brazilian credit registry, a confidential loan-level dataset covering all credit operations in Brazil.

To identify the causal impact of R&D subsidies, we 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, we 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, we exactly match treatment and control firms using the government's technical criteria for subsidy allocation. We allow several unmatched years to test the assumption of parallel trends between control and treatment firms. We 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. We also show that firms are similar on a wide range of unmatched variables, including measures of the quality of their research proposal.

We break down the results into 6 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

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

innovations. Firms increased the hiring of scientists by 36% and patenting by 10%. They also hired more 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. Most of the scientists hired due to the subsidy have little experience in R&D. 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, and exports. 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. Next, we investigate how firms manage to grow despite not creating impactful innovations.

Third, firms diversified their product lines rather than enhancing existing ones. We 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, we link patents to product level tariffs. We 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 in Brazil.

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. Even more than 10 years after the subsidy, firms cannot break into the market of developed countries.

Finally, heterogeneity by firm characteristics is consistent with the subsidy alleviating financial constraints. The effect of the subsidy on firm size and on the hiring of scientists is larger for smaller firms facing higher spreads on their credit.

Putting all the pieces together, these results suggest that the R&D subsidy program in Brazil drove firm growth by facilitating the entry of financially constrained firms into high-tariff markets with domestically produced versions of foreign goods. Despite that, the R&D subsidy program had large returns. For every $1 of innovation subsidy, the government collected $2.2 in present payroll taxes.

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. We 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 we 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

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

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

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

2 Institutions

In this section, we discuss the design of innovation subsidies in Brazil. As it is relevant for the identification strategy, we argue that the subsidy is assigned according to pre-determined technical criteria in narrowly defined call for projects.

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

[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).

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

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 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.

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

Table 1: Mean Weight in Different Criteria

Criteria	Avg. Weight
Feasibility	0.38
Capacity	0.23
Inventiveness	0.18
Profitability	0.01
Others	0.20
Observations	359

Description: This table describes the average weight in different technical criteria for a sample of call for projects. The sample is composed of call for projects available on online archives of the Funding Authority. For each criterion in the original call for project, we classify them into a criterion related to feasibility, to firm capacity, to the inventiveness of the project, or to the profitability of the project. We call a criteria related to feasibility if it evaluates the clarity and coherence of the project, clarity and coherence of the methodology, the feasibility of the chronogram, and the adherence of the project to the topic of the call for project. We call a criterion related to the firm capacity if it evaluates past firm innovation, the quality of the research team, and/or the available R&D infrastructure at the firm. We call a criteria related to inventiveness if it evaluates the degree of innovativeness or potential spillovers of the research project. We call a criteria related to profitability if it relates to the potential market success of the project. We call a criteria other if it doesn't fit any of the descriptions. Those include, for instance, if the project uses sustainable energy, if the firm is composed of national owners, if the project received investment from the private sector, or others.

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, as shown in Table 1. First is the feasibility of the project and adherence to the theme. Projects with a sound methodology and reasonable execution time are more likely to receive a subsidy. Moreover, projects on topics closely related to the theme of the call for projects receive a higher score. 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 degree of inventiveness of the project. Firms proposing groundbreaking innovations get higher scores than those proposing to recreate innovations that already exist. Table 1 describes the weights in the three most common criteria for a sample of call for projects available online.

Subsidy Coverage. The subsidy is either a grant or subsidized lending. Grants are 40.33% of our sample, offering direct funding without repayment, while subsidized loans account for 59.67%, featuring favorable repayment terms. Firms have two years to complete their projects upon signing the contract. The Funding Authority covers between 80% and 90% of eligible project expenses, requiring firms to finance the remaining 10% to 20% through external sources or their own funds. Subsidies are specifically allocated to cover the fixed costs associated with new ideas, including all R&D expenses and capital investments necessary to introduce a new product or process. The subsidy does not cover variable costs such as materials or operation workers.

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

In this section, we describe how we compiled a new firm-level administrative dataset containing information on innovation, R&D subsidy applications, exports, imports, employment, and credit for all firms in Brazil. We leverage this dataset to examine how the subsidy impacted firm innovation and growth. We use credit data to study if the effect of the subsidy is larger for financially constrained firms.

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. From 2003 onward, RAIS also reports the hiring of PhD workers and scientists, which allows us to use it to measure innovation effort. According to Goolsbee (1998), expenditure on scientists constitutes most of the R&D spending. To construct a consistent measure of R&D workers, we call scientist any worker that has ever being employed in a R&D occupation or that has a PhD.

R&D Subsidy Applications and Recipiency. We 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 16 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.

SCR Credit Registry. Credit data comes from SCR (*Sistema de Informações de Crédito*), a system that contains information received by the Brazilian Central Bank (BCB) on each credit contract. Data includes credit category, source of funding, contracted value, current balance, interest rates, and delinquency. Using the classification provided by the SCR, we classify loans into investments, such as the purchase of a machine, new plant, or R&D expenditures, or working capital. Systematically consistent data is available since 2004. [9] [10]

Patent and Trademark. To measure innovation, we 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, we 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. We 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)). The data is available from 1995 to 2007.

In addition to using it to understand penetration in international markets, we 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.

[9] The dataset contains all loans by financial institutions to a firm with more than US$ 1,732 in loans. Given the size of the firms in our sample, this is not a binding threshold.

[10] All confidential information from SCR was handled exclusively by BCB staff.

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
E [Investment Loans/Yr. Wage Bill]	0.15

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.

3.2 Facts of R&D Subsidy in Brazil

In this section, we show four relevant facts about R&D subsidy. First, the subsidy is large, representing 10 times the yearly wage bill of firms. Second, the projects financed by the R&D subsidy are 66 times larger than the projects financed via the banking system, already suggesting that firms might be facing borrowing constraints. Third, the subsidy targets the manufacturing sector. Within manufacturing, there is a wide scope of firms being subsidized. In special, there is no correlation between import tariffs and the subsidy.

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 10 times the yearly wage bill 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.

R&D Subsidies are 66 Times Larger than Private Sector Loans. Figure 1 and Table 2 put the R&D subsidy in comparison to financing provided by the private sector.

Table 2 shows in the last line the average bank loans for investments relative to firm's yearly wage bill the year prior the first subsidy application.[11] On average, firms receiving R&D subsidy received bank loans that are only 15% of their yearly wage bill. This result indicates that the projects covered by the subsidy are significantly larger than what the banking sector in Brazil usually finances.

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 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 2 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, as shown in Figure 7 in the Appendix. The subsidy covers such a wide range of manufacturing sectors that there is no correlation between the subsidy and import tariffs, as shown in Figure 12 in the appendix.

4 Empirics

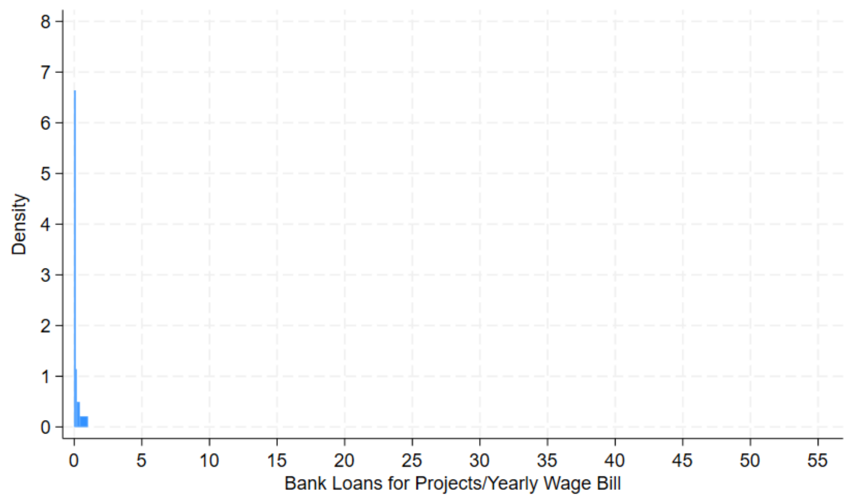
The main identification strategy is a matched difference-in-differences design that compares close winners and close losers of the subsidy application, similarly to Hirvonen et al. (2022) and Choi and Levchenko (2021). We match firms based on the variables used by the Funding Authority to award grants,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

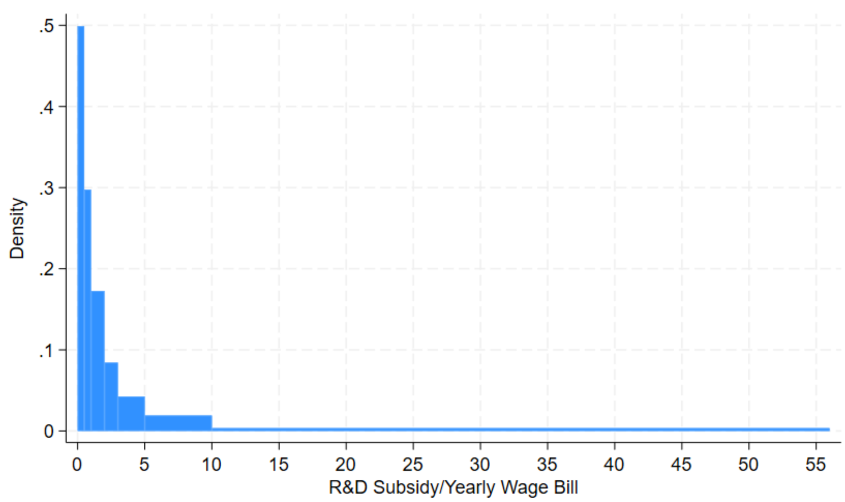
[11] Bank loans are classified either as working capital or investment by the Brazilian Central Bank.

Figure 1: Distribution of R&D Subsidy and Bank Loans

(a) Distribution of Investment Bank Loans

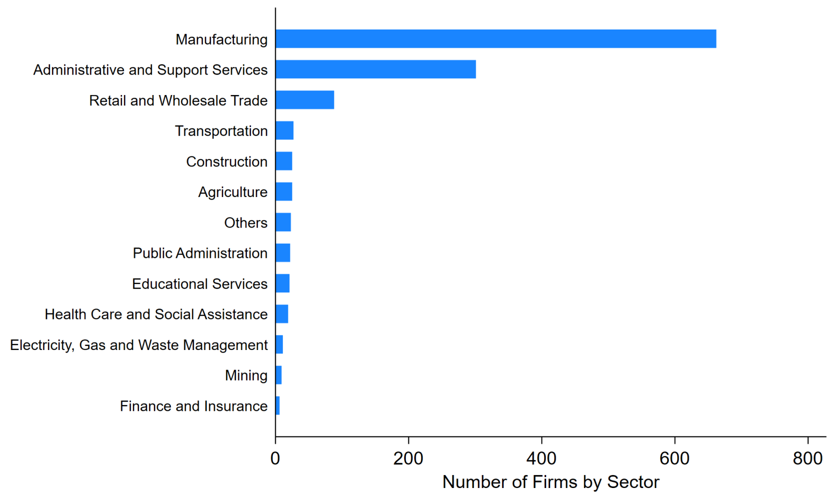


(b) Distribution of R&D Subsidy



Description: This figure shows the distribution of investment related bank loans and R&D subsidies relative to wage bill winsorized at 95%. The sample is composed of firms applying for R&D subsidy. The statistics are calculated the year prior to the first R&D subsidy application.

Figure 2: Subsidy by Sector



Description: This figure contains the number of subsidies according to the sector of the firm awarded the subsidy.

Matching. To identify the causal effect of innovation subsidies, we match treatment to control firms at their first subsidy application following Iacus et al. (2012). 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 projects but did not receive the innovation subsidy.

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, we 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 we 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, we 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.[12]

[12]Figure 9 in the Appendix shows that these variables can predict 70% of the variation in subsidy recipiency.

In the baseline specification, we do not match within sectors because most project calls are sector-specific.

In the robustness section, we increase the number of variables and the span of the matching. Instead of matching only in the year prior to submitting an application, we match withing up to 2 years before subsidy application. We 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.

Balance Test. Treatment and control firms are similar in employment outcomes, quality of the research team, quality of the research project, sector, and geographical location. Table 4 shows the differences between control and treatment groups on a set of untargeted moments.[13] The first panel shows that their workforces have the same average wage and education, providing indirect evidence that firms have similar levels of technological development. The second panel demonstrates that the research teams in both treatment and control firms have similar average wages and education levels, suggesting that firms have comparable capacities for developing and implementing new ideas.

The third panel indicates that firms are also similar in the quality of their projects. The first row presents the Flesh-Kincaid readability index of the project title, which measures text complexity. In patents, this index has been shown to correlate with citations. The second and third columns show that firms' proposals have the same scientific and market value. The implied scientific value of a project is the expected number of citations a patent with that title would receive. Similarly, the implied market value of the project is the expected stock market variation a patent with the same title would generate. Appendix A.1 describes how we use text analysis to estimate the scientific and market value of the R&D subsidy proposals using data from Kogan et al. (2017). Firms are also equally likely to propose projects similar to their past patents. Furthermore, Figure 8 in the Appendix shows that treatment and control groups are equally distributed across sectors and regions.

[13]Table 17 in the Appendix shows that firms are comparable on targeted variables.

Table 4: Balance Test on Untargetted Variables

	(1) Treatment	(2) Control	(3) (2) - (1)
	Employment Outcomes		
Avg. Wage	2392.74	2367.45	-25.29
	(1548.96)	(2147.76)	(0.88)
Avg. Yrs. of Education	11.52	11.50	-0.01
	(1.85)	(2.03)	(0.94)
	Quality of Research Team		
Avg. Wage of Researchers	7863.94	7430.36	-433.58
	(4941.63)	(5150.53)	(0.43)
Avg. Yrs. of Educ. of Researchers	14.77	15.07	0.29
	(1.68)	(1.67)	(0.10)
	Quality of Project		
Flesh-Kincaid Index	-1.07	-0.91	0.17
	(47.44)	(52.27)	(0.97)
Implied Project Market Value	1.12	1.13	0.00
	(0.47)	(0.45)	(0.94)
Implied Project Scientific Value	0.58	0.59	0.01
	(0.22)	(0.25)	(0.70)
Similarity with Past Patents	0.05	0.04	-0.00
	(0.09)	(0.09)	(0.77)
Observations	208	324	532

Description: This table shows statistics of matched treatment and control firms. Column 1 has the average for different variables for the treatment group and column 2 for the control. The standard deviation are in parenthesis. The last column shows the difference between treatment and control. The last column shows * if the p-value is below 0.10, ** if the p-value is below 0.05, and *** if the p-value is below 0.01. Appendix A.1 describes how the project market and scientific value are calculated. "Similarity with Past Patents" is the cosine text similarity between the project and the firm's previous patents.

Empirical Model. The main empirical model is given by

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

where $y_{i,t}$ is an outcome of firm i in year t, $\mathbb{I}_{i,t} \{Innovation\ Subsidy\}$ 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 $y_{i,t}$.

We are also interested in the effect of the innovation subsidy on the long-run. We extend the main empirical model to allow the effect of the subsidy to differ on the short, middle, and long-run:

$$y_{i,t} = \theta_{short}\mathbb{I}_{i,t}\left\{\textit{Subs. 0-2 Yrs}\right\} + \theta_{mid}\mathbb{I}_{i,t}\left\{\textit{Subs. 3-5 Yrs}\right\} + \theta_{long}\mathbb{I}_{i,t}\left\{\textit{Subs. 6+ Yrs}\right\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t} \tag{2}$$

where θ_{short} captures the effect of the subsidy up to two years after the first application, i.e., while the firm is still receiving grants from the government. θ_{mid} and θ_{long} capture the effect of the subsidy in the mid- and long-run.

The identifying assumption is of parallel trends – i.e., if it was not for the innovation subsidy, treatment and control firms would experience similar rates of growth in the outcome variable $y_{i,t}$. To test for this assumption, we also estimate the following dynamic model:

$$\begin{aligned} y_{i,t} = &\sum_j \theta_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} \times \mathbb{I}_i\left\{\text{Treatment}\right\} + \\ &\sum_j \alpha_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

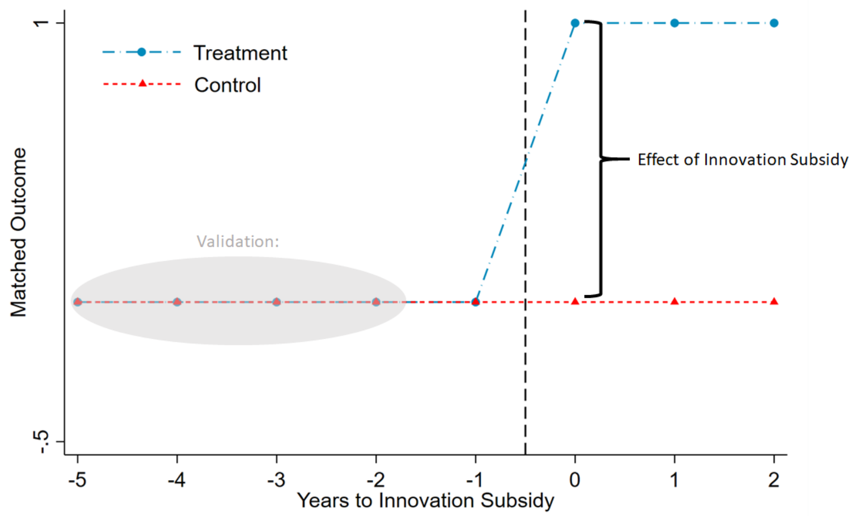
where $\mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\}$ is a dummy that takes one j years to a subsidy application. If parallel trends in the pre-period are valid, $\theta_j \approx 0, \forall j < 0$.

Identifying Variation. 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

In this section, we describe two validation exercises. First, we implement a placebo test showing that results cannot be explained by unobservable shocks that happen to correlate with subsidy application. Second, the assignment of R&D subsidies does not correlate with campaign contribution or other industrial policies.

Figure 3: Identifying Variation



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, we implemented two placebo tests. First, we excluded all treated firms and randomly assigned a placebo treatment to firms whose projects were rejected. After that, we followed the previously described matching strategy but used the placebo treatment instead. In the second placebo approach, instead of random assignment, we 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 19 and 20 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 21 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

Our main result is that the R&D subsidy program in Brazil drove firm growth by facilitating the entry of financially constrained firms into high-tariff markets with domestically produced versions of foreign goods. We build this conclusion in several steps. First, we show that an innovation subsidy increases the innovation effort by firms without increasing the quality of their innovations. 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 Mercosur countries. Fifth, the subsidy had a larger impact on small and financially constrained firms.

After understanding the inner workings of the innovation subsidy, we computed its impact on other firms and the return on investment. For every dollar of innovation subsidy, the government collects $2.2 in payroll taxes, without significant spillover or market-rivalry effects in other firms.

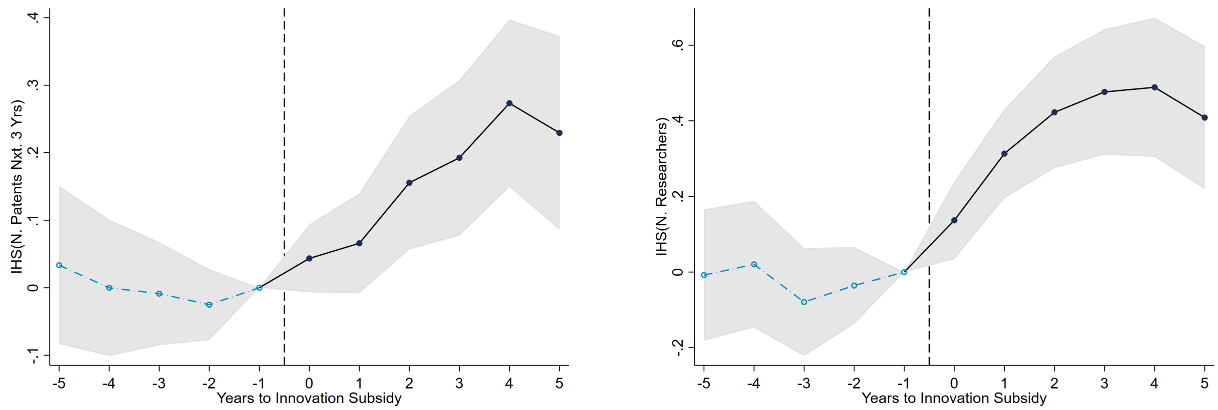
Effect on Innovation: Increase in Low-Quality Innovation. The R&D subsidy increased innovation efforts but only led to low-citation patents. Figure 4 shows the effect of the innovation subsidy on patent applications. Prior to the subsidy, treatment and control groups maintained similar trends, confirming the identifying assumption. After firms received the subsidy, they grew in patent applications and scientists' employment.[14]

Judging from Table 5, 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 26 in the appendix, firms recruited scientists in the hard science and applied fields, such as engineering and automation sciences. The effect of the R&D subsidy

[14] Patent applications are not an everyday occurrence for firms in Brazil. As investment, it is lumpy, which increases standard errors. To deal with that, we aggregate patent applications in a 3-year window. We chose the 3-year window because it is the shortest window within which de Souza (2022) found an effect on patent applications. In Table 25 we show in the robustness section that a 5-year window delivers the same results.

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.

on the number of scientists is persistent over the long-run, although less precisely estimated.

According to Table 6, which displays the effect on various quality-weighted innovation 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.[15] 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.

Table 7 provides 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 7 shows that firms did not increase the wages or education of their R&D team or general work-force.

As further evidence that the subsidy isn't leading to high-quality innovations, Table 24 in the Appendix shows that firms are employing former high-skill technicians in their R&D teams instead of experienced scientists. Table 24 shows how innovation subsidies

[15] In Table 25, patents are weighted by the number of citations that they received up to 5 years after the publication. The conclusions are still the same.

Table 5: Innovation Subsidy and Innovation Effort

	(1) $\mathbb{IHS}\,(N.\ Patent)$	(2) $\mathbb{I}\,(Patent)$	(3) $\mathbb{IHS}\,(N.\ Scientists)$	(4) $\mathbb{I}\,(N.\ Scientists)$	(5) $\mathbb{IHS}\,(N.\ Trademarks)$
Panel A. Simple DD					
$\mathbb{I}\{Subsidy\}$	0.112**	0.0736***	0.189**	0.0574*	0.162*
	(0.0536)	(0.0285)	(0.0831)	(0.0313)	(0.0898)
Panel B. Extended DD					
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.0968*	0.0598*	0.126*	0.0412	0.211**
	(0.0571)	(0.0322)	(0.0750)	(0.0310)	(0.0903)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.177***	0.112***	0.187*	0.0639*	0.190*
	(0.0638)	(0.0343)	(0.0959)	(0.0377)	(0.104)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.0734	0.0576	0.296**	0.0827*	0.0862
	(0.0758)	(0.0427)	(0.122)	(0.0435)	(0.132)
N	9358	9358	9358	9358	9358

Description: This table shows the effect of the innovation subsidy on firm innovation measures. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. 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; and in column 5 it is the inverse hyperbolic sine of the number of trademarks. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

affect hiring scientists from different occupations. Columns 3 to 5 show that the subsidy did not increase the employment of individuals who were previously scientists, engineers, or health professionals. Instead, scientists employed by the innovation subsidy had backgrounds as technicians, such as mechatronics, chemical, and laboratory technicians, or operational workers.

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 even in the long-run. Figure 5 displays the innovation subsidy's impact on the wage bill. Before the subsidy, treatment 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 after the subsidy, treatment firms increased their wage bill by 40%.

Table 8 confirms that the innovation subsidy led to a substantial expansion of firms, even

Table 6: Effect of Innovation Subsidy on Quality Weighted Patents

	(1) $\mathbb{IHS}$ (*Citations*)	(2) $\mathbb{IHS}$(*Citation Weighted Patents*)	(3) $\mathbb{IHS}$(*Inventor Wage Weighted Patents*)	(4) $\mathbb{IHS}$(*Inventor Educ. Weighted Patents*)
Panel A. Simple DD				
$\mathbb{I}\{Subsidy\}$	0.0135	0.00177	0.135	0.0820
	(0.0273)	(0.00174)	(0.163)	(0.0929)
Panel B. Extended DD				
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	-0.00380	0.00578	0.115	0.0657
	(0.0246)	(0.00640)	(0.194)	(0.106)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.0524	0.00277	0.236	0.136
	(0.0531)	(0.00395)	(0.228)	(0.130)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	-0.0118	-0.00492	0.0607	0.0507
	(0.0366)	(0.00332)	(0.241)	(0.139)
N	9358	9358	9358	9358

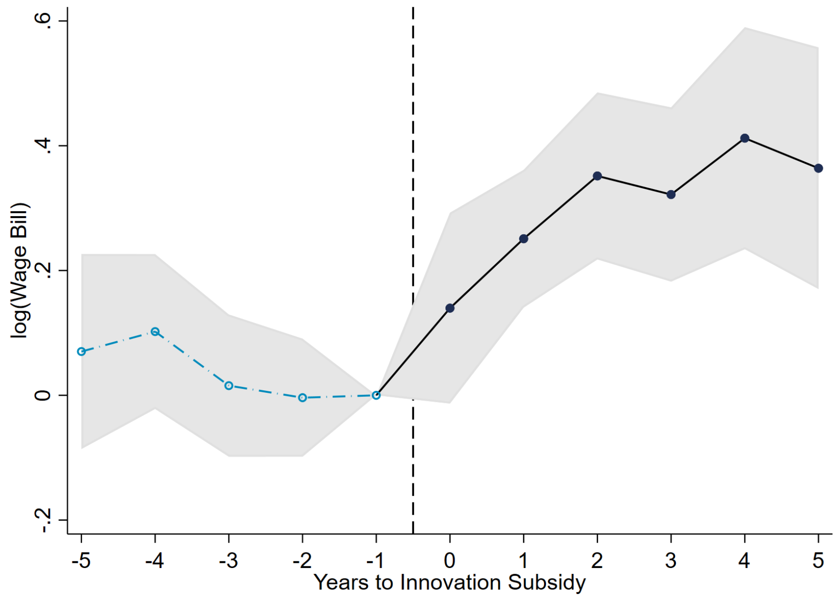
Description: This table shows the effect of the innovation subsidy on measures of quality-weighted innovation. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The left-hand side in column 1 is the inverse hyperbolic sine of the number of citations received 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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 7: Effect of Innovation Subsidy on Quality of Workers

	(1) *log(Avg. Wage of Scientists)*	(2) *log(Yrs. Educ. of Scientists)*	(3) *log(Avg. Wage)*	(4) *log(Yrs. Educ.)*
Panel A. Simple DD				
$\mathbb{I}\{Subsidy\}$	0.0535	0.00149	-0.00485	0.00622
	(0.0445)	(0.0120)	(0.0549)	(0.0102)
Panel B. Extended DD				
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.00325	0.00239	-0.0266	0.00594
	(0.0468)	(0.0125)	(0.0273)	(0.0103)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.0476	-0.00101	-0.0108	0.00578
	(0.0559)	(0.0144)	(0.0324)	(0.0116)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.149**	0.00501	0.0394	0.00655
	(0.0638)	(0.0170)	(0.0358)	(0.0133)
N	5949	5942	9358	9352

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 in the first panel and model 2 in the second panel. 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.Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

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



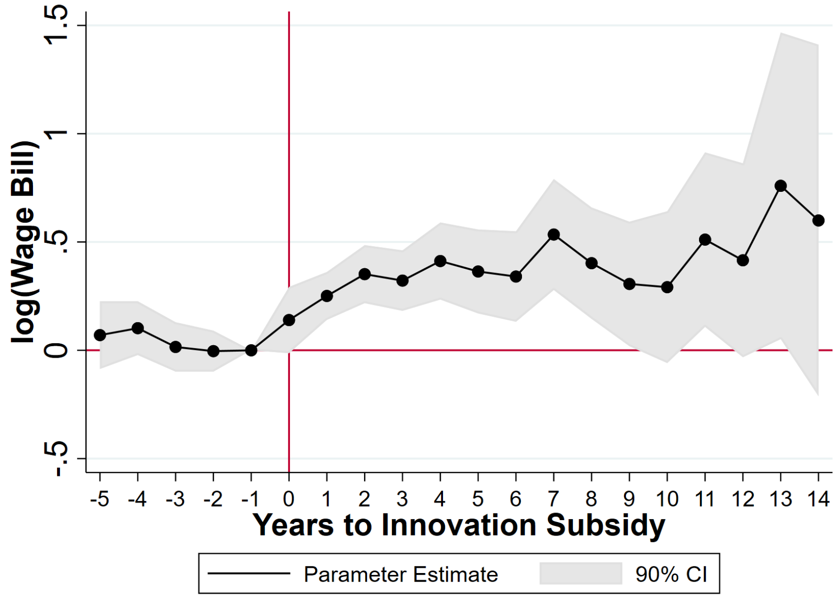
Description: This figure shows the dynamic effect of the innovation subsidy on firms' wage bill. Each dot is the estimated coefficient, while the gray area is the 10% confidence interval. The x-axis measures the distance to the subsidy application and the y-axis the estimated effect of the innovation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

Table 8: Effect of the Innovation Subsidy on Firm Size

	(1) log (*Workers*)	(2) log (*Wage Bill*)	(3) log (*Establishments*)	(4) log (*N. Municipalities*)	(5) $\mathbb{IHS}$ (*Exports*)
*P*anel A. Simple DD					
$\mathbb{I}\{Subsidy\}$	0.264***	0.259***	0.115**	0.0596**	1.379***
	(0.0922)	(0.0954)	(0.0549)	(0.0281)	(0.457)
*P*anel B. Extended DD					
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.236***	0.210**	0.112**	0.0376	1.222**
	(0.0847)	(0.0868)	(0.0483)	(0.0254)	(0.479)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.287***	0.277***	0.119**	0.0875***	1.797***
	(0.102)	(0.104)	(0.0603)	(0.0311)	(0.690)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.317**	0.356**	0.115	0.0633	1.701*
	(0.149)	(0.146)	(0.0845)	(0.0443)	(0.958)
N	9358	9358	9358	9358	5600

Description: This table shows the effect of the innovation subsidy on firm size. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. 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, and column 5 the inverse hyperbolic sine of exports. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Figure 6: Effect of Innovation Subsidy on Wage Bill on the Long Run



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.

though they created low-quality patents. The R&D subsidy increased firm's employment, wage bill, the number of establishments, the number of establishments in different cities, and export.[16]

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 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, we 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. We make this

[16]Table 23 in the Appendix shows that workers are equally coming from outside of the labor-force, from other competitors in the same sector, and from firms in different sectors.

Table 9: Effect of Innovation Subsidy on Product Variety

	(1) $\mathbb{IHS}\{$*Product Patents*$\}$	(2) $\mathbb{IHS}\{$*Process Patents*$\}$	(3) $\mathbb{IHS}\{$*# Patent Classes*$\}$	(4) $\mathbb{IHS}\{$*# Trademark Classes*$\}$	(5) $\mathbb{IHS}\{$*# Export Products*$\}$	(6) $\mathbb{IHS}\{$*# Import Inputs*$\}$
Panel A. Simple DD						
$\mathbb{I}\{$*Subsidy*$\}$	0.0893*	0.00953	0.159**	0.0971**	0.443***	0.365***
	(0.0508)	(0.0168)	(0.0806)	(0.0419)	(0.101)	(0.119)
Panel B. Extended DD						
$\mathbb{I}\{$*Subsidy 0-2 Years*$\}$	0.0716	0.0123	0.0611	0.0799**	0.406***	0.401***
	(0.0535)	(0.0209)	(0.0610)	(0.0375)	(0.104)	(0.115)
$\mathbb{I}\{$*Subsidy 3-5 Years*$\}$	0.145**	0.0242	0.141*	0.0979**	0.550***	0.276
	(0.0593)	(0.0207)	(0.0849)	(0.0458)	(0.155)	(0.181)
$\mathbb{I}\{$*Subsidy 6+ Years*$\}$	0.0643	-0.00796	0.284**	0.118**	0.574**	-0.0152
	(0.0721)	(0.0258)	(0.120)	(0.0552)	(0.252)	(0.326)
N	9358	9358	9358	9358	5600	5600

Description: This table shows the effect of the innovation subsidy on product variety. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. 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, we 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, we 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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

point in two steps: first, we show that firms introduced new products; then we show that these products are in high-tariff markets.

Table 9 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.[17] 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.[18]

Firms enter high import tariff markets in Brazil, shielding them from international competition. In Table 10, columns 1 and 2 show the innovation subsidy's impact on patents in high and low import tariff markets. To calculate this, we linked patents to products using patent classes, defining high-tariff patents as those in the top quartile of average tariffs and

[17] To classify patents as product or process, we 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, we classify patents as process if, on average, USPTO patents in the same set of patent classes are more likely to be process than product. Because not all combinations of patent classes have enough observations, some observations are missed, increasing the standard error.

[18] 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 27 shows that these results still hold using log and variation from firms that already had patents, trademarks, exports, and imports.

Table 10: 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) $\mathbb{IHS}\{$*Citations to High Tariff Pat.*$\}$	(4) $\mathbb{IHS}\{$*Citations to Low Tariff Pat.*$\}$	(5) $\mathbb{IHS}\{$*Exp. High Tariff Prod.*$\}$	(6) $\mathbb{IHS}\{$*Exp. Low Tariff Prod.*$\}$
Panel A. Simple DD						
$\mathbb{I}\{$*Subsidy*$\}$	0.0718***	0.00229	0.0822***	0.0214	1.183**	0.200
	(0.0276)	(0.0250)	(0.0296)	(0.0314)	(0.458)	(0.123)
Panel B. Extended DD						
$\mathbb{I}\{$*Subsidy 0-2 Years*$\}$	0.0668**	0.00166	0.0647**	-0.00586	1.048**	0.193
	(0.0302)	(0.0283)	(0.0326)	(0.0392)	(0.463)	(0.140)
$\mathbb{I}\{$*Subsidy 3-5 Years*$\}$	0.0844**	0.0209	0.115***	0.0503	1.613**	0.195
	(0.0350)	(0.0328)	(0.0394)	(0.0362)	(0.740)	(0.160)
$\mathbb{I}\{$*Subsidy 6+ Years*$\}$	0.0670	-0.00840	0.0597	0.0182	1.309	0.379
	(0.0410)	(0.0398)	(0.0435)	(0.0392)	(0.903)	(0.445)
N	9358	9358	9358	9358	5600	5600

Description: This table shows the effect of the innovation subsidy on product variety. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. 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, we use the crosswalk by Lybbert and Zolas (2014) and calculate the HS product codes associated with each patent. Then, we 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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

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.

Rather than moving sectors, firms are moving towards high import tariff products within their sectors. Table 28 in the appendix shows the effect of the innovation subsidy on the number of patents associated with high or low import tariff products within 1-, 2-, or 3-digit sectors. The innovation subsidy only increased patenting of patents associated to products on the top quartile of import tariff within each sector. These results show that there are synergies between innovation subsidies and import tariffs, two of the most common types of industrial policy (Juhász et al. (2022)).

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 11 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 12. The table shows firms increased ex-

Table 11: Effect of Innovation Subsidy on Origin of Input Imports and Citation

	(1) $\mathbb{I}\{Imp.\ Mercosur\}$	(2) $\mathbb{I}\{Imp.\ S.\ America\}$	(3) $\mathbb{I}\{Imp.\ Europe\}$	(4) $\mathbb{I}\{Imp.\ N.\ America\}$	(5) $\mathbb{IHS}\{Citation\ to\ BR\}$	(6) $\mathbb{IHS}\{Citation\ to\ Foreign\}$
Panel A. Simple DD						
$\mathbb{I}\{Subsidy\}$	0.0271	0.0331	0.0983***	0.0687*	0.0480*	0.126**
	(0.0276)	(0.0377)	(0.0351)	(0.0365)	(0.0245)	(0.0535)
Panel B. Extended DD						
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.0391	0.0383	0.0975***	0.0814**	0.0302	0.108
	(0.0397)	(0.0394)	(0.0377)	(0.0381)	(0.0281)	(0.0753)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.0127	0.0459	0.1000**	0.0443	0.0689**	0.195***
	(0.0530)	(0.0571)	(0.0461)	(0.0554)	(0.0346)	(0.0616)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	-0.146	-0.154	0.0500	-0.0708	0.0413	0.0631
	(0.134)	(0.140)	(0.0966)	(0.100)	(0.0357)	(0.0637)
N	5600	5600	5600	5600	9358	9358

Description: This table shows the effect of the innovation subsidy on import and citation. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. 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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 12: Effect of Innovation Subsidy on Exports

	(1) $\mathbb{I}\{Exp.\ Mercosur\}$	(2) $\mathbb{I}\{Exp.\ South\ America\}$	(3) $\mathbb{I}\{Exp.\ Europe\}$	(4) $\mathbb{I}\{Exp.\ North\ America\}$
Panel A. Simple DD				
$\mathbb{I}\{Subsidy\}$	0.106***	0.0820**	0.0149	0.0173
	(0.0344)	(0.0338)	(0.0381)	(0.0386)
Panel B. Extended DD				
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.0784**	0.0591	0.0801**	0.0522
	(0.0372)	(0.0374)	(0.0360)	(0.0391)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.190***	0.151***	-0.188***	-0.0711
	(0.0463)	(0.0443)	(0.0696)	(0.0574)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.143*	0.128	-0.184**	-0.162
	(0.0869)	(0.0859)	(0.0908)	(0.137)
N	5600	5600	5600	5600

Description: This table shows the effect of the innovation subsidy on imports and citations. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. 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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

ports 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.[19]

The Subsidy Alleviated Financial Constraints. The heterogeneity of the effect across firm characteristics is consistent with the subsidy alleviating financial constraints. Smaller firms facing higher interest rates grew and innovated the most from R&D subsidies.

We estimate heterogeneity on the effect of the innovation subsidy using causal forest (Wager and Athey (2018)). Causal forest estimates a non-linear relationship between the

[19] Tables 29 and 30 in the appendix reproduces these table using inverse hyperbolic sine.

treatment effect and a set of firm characteristics, allowing for the estimation of a distribution of treatment effects. We allow the effect of the innovation subsidy to vary according to the subsidy value, interest rate spreads on bank loans, employment, and firm age. For a detailed discussion of the implementation, see Appendix B.1.

Table 13 shows the distribution of the treatment effect of the innovation subsidy on the number of workers, number of scientists, and number of patents. All firms substantially increased their employment and innovation in response to the subsidy. In a 5-year window, the firm that grew the least did so by 25%.

Table 13: Distribution of the Effect of the Innovation Subsidy

	$\theta^{log(N.\ Workers)}$	$\theta^{\mathbb{IHS}(N.\ Researchers)}$	$\theta^{\mathbb{IHS}(N.\ Pat.\ Nxt.\ 3)}$
Mean	0.397	0.382	0.116
Standard Deviation	0.076	0.144	0.068
10th Percentile	0.297	0.176	0.031
25th Percentile	0.337	0.263	0.065
Median (50th Percentile)	0.401	0.392	0.115
75th Percentile	0.449	0.480	0.162
90th Percentile	0.494	0.576	0.220
N	355	355	355

Description: This tables describes the distribution of treatment effects. The treatment effect is calculated using a long difference and causal forest (Wager and Athey (2018)). Appendix B.1 describes in detail the implementation of the causal forest. Column 1 summarizes distribution of the treatment effect of the innovation subsidy on the number of workers, column 2 on the inverse hyperbolic sine on the number of researcher and column 3 on the number of patents.

Table 14 shows that financial constraints is an important determinant of the effect of the innovation subsidy. Table 14 shows the correlation between the subsidy treatment effect and firm characteristics. The effect of the subsidy is larger for small firms facing large credit spreads. Astonishingly, column 1 of table 14 shows that a 1% increase in the subsidy value has an equal effect as a 1% increase in the credit spread!

Table 14: Correlation Between Treatment Effect and Firm Characteristics

	(1) $\theta^{log(N.\ Workers)}$	(2) $\theta^{\mathbb{IHS}(N.\ Researchers)}$	(3) $\theta^{\mathbb{IHS}(N.\ Pat.\ Nxt.\ 3)}$
$log\,(Subsidy\ Value)$	0.0271***	0.0740***	0.0111***
	(0.00317)	(0.00511)	(0.00292)
$log\,(Credit\ Spread_{t=-1})$	0.0237***	0.0374***	-0.00553**
	(0.00263)	(0.00430)	(0.00246)
$log\,(N.\ Workers_{t=-1})$	-0.00962***	-0.0122***	-0.0173***
	(0.00287)	(0.00466)	(0.00266)
$log\,(Age_{t=-1})$	0.00416	-0.0228**	-0.00679
	(0.00576)	(0.00909)	(0.00519)
N	323	352	352
R^2	0.314	0.447	0.192

Description: This table shows the correlation between treatment effects and characteristics of the firms. On the first column the left-hand side is the effect of the innovation subsidy on employment, on column 2 the effect on the number of scientists, and on column 3 the effect on patents. *Subsidy Value* is the total subsidy that the firm received on its first application. $Credit\ Spread_{t=-1}$ is the average spread on bank loans before applying for the innovation subsidy. $Age_{t=-1}$ is firm's age. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

The Subsidy didn't Spillover to other Firms or Displaced Competitors. One of the main arguments in favor of innovation subsidies is spillovers. One of the argument against it is that it negatively affects competitors. In this section, we estimate the spillover and market rivalry effects of the innovation subsidy following Bloom et al. (2013) and Jaffe (1986). We show that the innovation subsidy did not spillover to other firms or had a negative impact on competitors. This result is consistent with the idea that firms are creating low-quality versions of foreign products. Because these innovations don't have a significant scientific contribution, they do not spillover to other firms. Because they are introducing new products in the local market, firms are only taking market share of foreigners.

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

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

We 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:

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

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

To identify the effect of spillover and product market rivalry, consider the following model:[20]

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

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

[20]One might be tempted to look at regional effects to identify spillovers. The problem of that strategy is that a firm located in the same region of a subsidy recipient is exposed not only to more knowledge but also to higher input demand, higher wages, lower prices of the subsidized good, among others. Therefore, regional effects are not informative about knowledge spillovers.

Table 15: Spillover and Market Rivalry of Innovation Subsidy

	(1)	(2)	(3)	(4)	(5)
	$log(Workers)$	$log(Establishments)$	$log(Wage\ Bill)$	$\mathbb{IHS}(Wage\ Bill\ Scientists)$	$\mathbb{IHS}(Patents)$
$\log(Spilltech_{i,t}+1)$	-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.

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 15, the subsidy did not generate a spillover or market rivalry effect, which is consistent with the mechanics of the innovation subsidy discussed before. Table 15 shows the effect of spillover and market rivalry in a set of firm characteristics. Despite the 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.

The Subsidy Paid for Itself. Due to the large and persistent effect of the subsidy on wage bill, the government collected enough in payroll taxes to pay for it. Equation 5 calculates the return in payroll taxes for every dollar of the innovation subsidy:

$$return = \tau \frac{\sum_t \beta^t (e^{\theta_t^{log(Wage\ Bill)}} - 1)\overline{Wage\ Bill}}{\overline{Subsidy}} \tag{5}$$

where τ is the payroll tax rate, β is the time discounting, $\theta_t^{log(Wage\ Bill)}$ is the effect of the innovation subsidy t years later, $\overline{Wage\ Bill}$ is the average wage bill of recipients, and $\overline{Subsidy}$ is the average subsidy. The numerator in 5 is the total payroll revenue generated by the average R&D subsidy. Therefore, 5 is the return in payroll revenue for every dollar of innovation subsidy.

Table 16 shows that ever dollar of innovation subsidies generated 2.2 dollars in tax revenue. Therefore, the subsidy paid for itself.[21]

Table 16: Tax Return of the Innovation Subsidy

Parameter	Source	Value
τ	Tax Revenue/GDP	0.3
β	Inverse of Federal Funds Rate	0.88
$\theta_t^{log(Wage\ Bill)}$	For $t \leq 14$, Figure 6. $\theta_t^{log(Wage\ Bill)} = 0.59, \forall t > 14$	
$\overline{Wage\ Bill}$	Avg. wage bill of matched firms	R$ 18.8
$\overline{Subsidy}$	Avg. subsidy of matched firms	R$7.7
return		2.2

Description: This table shows statistics to calculate expression 5.

5.2 Alternative Explanations

In this section, we discuss other forces that could drive the main result but we didn't find them to be relevant. In special, we argue that subsidy recurrence does not drive its long-run effect, that there is no private sector crowd in, that the Funding Authority is not targeting high-tariff projects, and that the results are not valid only to marginal subsidy winners.

Subsidy Recurrence Does Not Drive the Long-Run Effects. It could be the case that the persistent effect of the innovation subsidy is due to recurrence. Backing this idea, Figure 10 in the appendix shows that firms receiving subsidies today are slightly more likely to receive subsidies in the future. To understand if recurrence drives the long-run effect of the subsidy, in Appendix C.1, we use an instrumental variable approach to isolate the effect of the first subsidy from the effect of subsequent subsidies. We rewrite specification 1 using

[21] There are several caveats to this back of envelope calculation. We are not taking into account the general equilibrium effect of the innovation subsidy, its effect on import tariff revenue, nor the fiscal cost of raising funds.

the sum of all subsidies received by the firm in the past rather than a dummy indicating if the firm received its first subsidy application. This approach controls for increases in the stock of subsidies received by the firm. We instrument the sum of subsidies with a dummy if the first subsidy application was successful, as used in the baseline specification. The instrumental variable approach shows that the subsidy had a persistent effect on firm growth even for firms whose R&D subsidy did not increase over time.

Private Sector Crowd In. Table 31 shows that there is no evidence for crowd in. Specifically, firms increased their bank loans (column 1) due to an increase in working capital loans (column 4) and not due to investment loans (column 3). Firms did not increase their access to credit relative to their size (column 2), nor did they use the assets purchased with the subsidy to obtain further credit (column 5), or gain access to better, cheaper credit (column 7). Taken together, these results from Table 31 suggest that firms gained access to credit because they are larger, not because the subsidy led to increased access to credit.

Subsidy Does Not Target High-tariff Projects. It could be the case that, instead of firms directing their innovations to high-tariff markets, the Funding Authority itself targets high tariff products. To evaluate if that is the case, we link each call for projects to a list of Harmonized System codes that are covered by that call for projects. Figure 12 shows that there is no correlation between call for projects and subsidies.

Marginal Subsidy Recipients. The identification strategy compares marginal subsidy winners to marginal losers. It could be the case that marginal winners have ideas of lower quality compared to average subsidy winners, which could explain the lack of effects on innovation quality. Table 32 tests this hypothesis by allowing the effect of the subsidy to vary according to the number of firms granted subsidies in the call for projects. The rationale is that the quality of the marginal idea should be even more inferior in calls where the Funding Authority awarded subsidies to several firms due to a large budget. However, Table 32 does not find evidence that projects awarded subsidies in calls with a large number of recipients differ from those in other calls.

Subsidy Does Not Change the Direction of Firm's Innovation. It could be the case that the subsidy itself leads firms to change the direction of their innovation. For instance, firms could propose projects in high tariff markets because those are easier to justify as having high profitability. If this is true, the subsidy should affect the share of patents in different patent classes, leading firms to move towards high tariff classes. However, Figure 13 in the Appendix shows no evidence that firms are changing the composition of their patents.

6 Robustness

In this section, we 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 33 to 35, we estimate the effect of the innovation subsidy using a set of controls instead of matching on pre-determined characteristics. Using controls, we 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 36 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 we identify could be attributed to differences in the managerial capacities of firms. To deal with that, we also match firms on the wage of their CEOs, which should capture the ability of the managerial team.[22] Table 37 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 38 in the appendix, we also match on the main sector of the firm. Notice that the 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 39 we also match firms on the number of PhD workers and the average wage of PhD workers. Table 39 shows the main takeaway is still true.

Matching on Project Quality. Another looming concern is that part of the effects we identify comes from differences in the quality of the research proposal. To deal with this possibility, we 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 40 shows that the main take away remains the same and that precision even increases.

Matching on Two Years Before the Innovation Subsidy. Table 41 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 41 results are still the same despite the lower number of observations.

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

Informality. Some fear that everything in developing countries is driven by informality. As discussed in Section 3.2, firms applying for innovation subsidy are larger than the average firm in Brazil, which are usually subject to strict labor market inspections. Still, some could fear that the effects identified are not valid because firms are hiding their true size by hiring informal workers. If that is true, firms should receive fines for hiring informal workers when inspected. Table 42 shows that the innovation subsidy does not affect the probability of a firm being fined for hiring informal workers despite the large increase in the number of labor inspections that they received.

Dealing with Zeros. We use the inverse hyperbolic sine transformation to handle variables that can take zero values, such as the number of patents or exports. We conduct a series of robustness tests to demonstrate that our results are robust to alternative transformations. Following the suggestion by Chen and Roth (2023), Table 43 utilizes the percentile of the left-hand side variable, which is well-defined at zero and imposes curvature on abnormally high values. Table 44 employs the log transformation plus one, and Table 45 explores the extensive margin.

All these transformations support the same interpretation: the innovation subsidy led to an increase in innovation and firm growth without affecting the quality of patents. Additionally, they indicate that firms introduced new products in high tariff markets.

7 Conclusion

In this paper, we use a matched difference-in-differences approach to understand the effect of an innovation subsidy on firm growth. We find that the innovation subsidy increases firm growth by inducing entry of borrowing constrained firms into high-tariff markets with local versions of foreign products. Despite the lack of novelty in their innovation, the subsidy paid for itself because awardees are persistently larger.

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, we 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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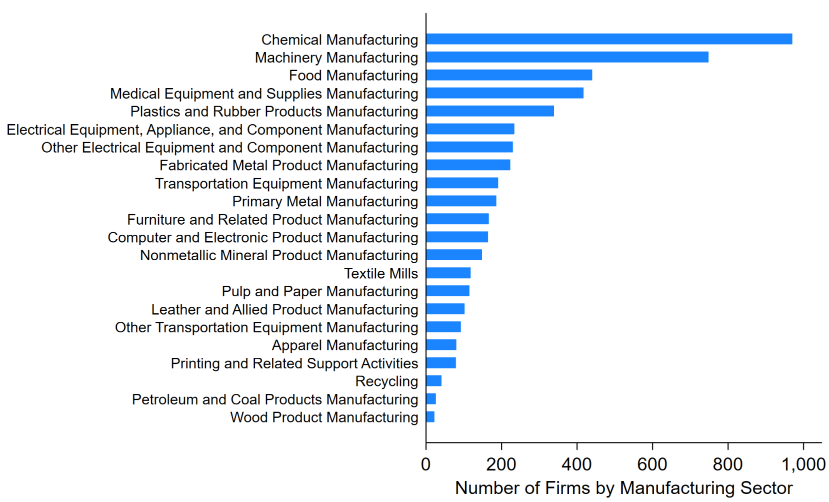
Figure 7: Subsidy by Manufacturing Sector



Description: This figure contains the number of subsidies according to the sector of the firm awarded the subsidy.

A Validation Appendix

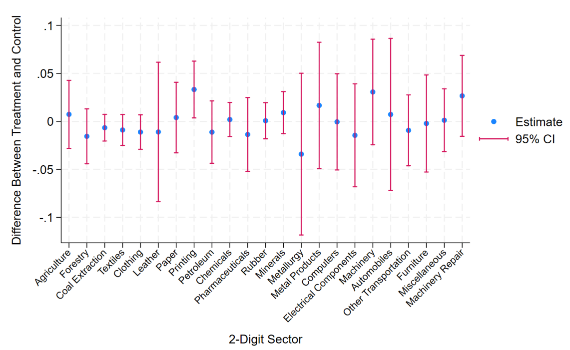
Table 17: Balance Test on Matched Variables

	(1) Treatment	(2) Control	(3) (2) - (1)
N. Workers	663.42	767.35	103.93
	(1020.24)	(4448.32)	(0.74)
N. Patents	0.01	0.01	-0.01
	(0.15)	(0.09)	(0.59)
Citations	0.07	0.13	0.07
	(0.97)	(1.68)	(0.60)
Value Requested	9.00	7.00	-1673474.50
	(14.00)	(11.00)	(0.15)
Observations	208	324	532

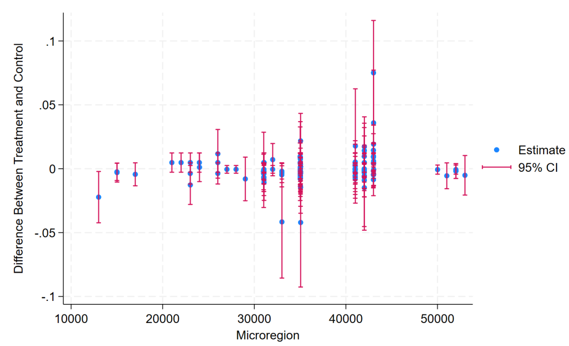
Description: This table shows statistics of matched treatment and control firms. Column 1 has the average for different variables for the treatment group and column 2 for the control. The standard deviation are in parenthesis. The last column shows the difference between treatment and control. The last column shows * if the p-value is below 0.10, ** if the p-value is below 0.05, and *** if the p-value is below 0.01.

Figure 8: Difference Between Matched Treatment and Control in Sectoral and Regional Composition

(a) Difference in Sectoral Composition Between Treatment and Control



(b) Difference in Regional Composition Between Treatment and Control



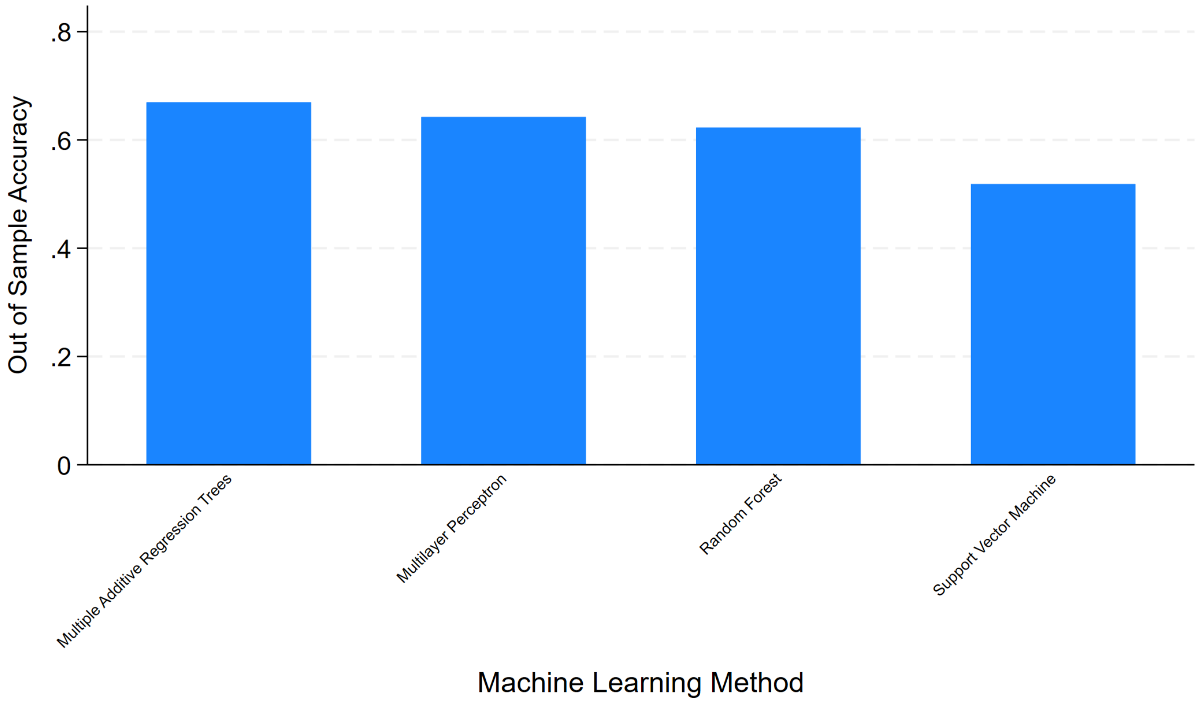
Description: This figure plots the difference between matched treatment and control in the share of firms in different sectors and microregions in Brazil. In Figure 8a the x-axis are different sectors and the y-axis is the difference between matched treatment and control firms in the share of firms in each sector. In Figure 8b the x-axis are different microregion codes and the y-axis is the difference between matched treatment and control firms in each microregion. Although it looks like that some of these dots overlap, that is not the case.

Table 18: Comparison Between Matched and Unmatched Firms

	(1) Matched	(2) Unmatched	(3) (2) - (1)
N. Firms on Call for Projects	82.94	62.36	-20.58***
	(18.94)	(30.96)	(0.00)
N. Workers	632.22	516.59	-115.63
	(3244.05)	(2035.75)	(0.44)
N. Patents	0.01	0.01	0.01
	(0.11)	(0.15)	(0.45)
Citations	0.07	0.43	0.36*
	(1.09)	(4.98)	(0.10)
Value Requested	7314560.50	7195543.50	-119016.86
	(12633071.00)	(19732724.00)	(0.90)
Avg. Wage	2291.72	2283.35	-8.37
	(2056.77)	(1993.58)	(0.94)
Avg. Yrs. of Education	11.61	12.34	0.73***
	(2.01)	(2.11)	(0.00)
Avg. Wage of Researchers	7528.64	8496.86	968.22**
	(5161.48)	(6261.14)	(0.02)
Avg. Yrs. of Educ. of Researchers	14.88	15.52	0.64***
	(1.70)	(1.71)	(0.00)
Flesh-Kincaid Index	-0.81	-0.36	0.44
	(50.89)	(51.64)	(0.87)
Implied Project Market Value	1.12	1.11	-0.01
	(0.45)	(0.52)	(0.78)
Implied Project Scientific Value	0.59	0.59	0.01
	(0.24)	(0.25)	(0.56)
Similarity with Past Patents	0.05	0.06	0.01
	(0.09)	(0.13)	(0.25)
Observations	532	1,067	1,599

Description: This table shows statistics of matched and unmatched firms. Unmatched firms are the ones that are dropped from the analysis because no comparison group was found. Column 1 has the average for different variables for the matched group and column 2 for the unmatched group. The standard deviation are in parenthesis. The last column shows the difference between treatment and control. The last column shows * if the p-value is below 0.10, ** if the p-value is below 0.05, and *** if the p-value is below 0.01. Appendix A.1 describes how the project market and scientific value are calculated. "Similarity with Past Patents" is the cosine text similarity between the project and the firm's previous patents.

Figure 9: Predicting Subsidy using Different Machine Learning Methods



Description: This figure plots the out of sample accuracy of different models. The sample is randomly divided in a training and a testing set. Each model is predicts subsidy recipiency using number of workers, number of patents, total number of citations, and value requested. The figure plots the accuracy of each model on the testing sample.

Table 19: Random Placebo Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}\,(N.\ Patent)$	$\mathbb{IHS}\,(Citations)$	$\log\,(Wage\ Bill)$	$\mathbb{IHS}\,(Exports)$	$\mathbb{IHS}\,\{Product\ Patent\}$	$\mathbb{IHS}\,\{Process\ Patent\}$	$\mathbb{IHS}\,\{\#\ Export\ Products\}$	$\mathbb{IHS}\,\{N.\ Patent\ High\ Tariff\ Prod.\}$	$\mathbb{IHS}\,\{N.\ Patent\ Low\ Tariff\ Prod.\}$
$\mathbb{I}\,\{\text{Subsidy}\}$	0.0181	-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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 20: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 21: 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*)
$\mathbb{I}$ {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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

A.1 Using Text Analysis to Infer the Scientific and Economic Value of Innovation Projects

In this section, we describe how to use text analysis to infer the scientific and market value of the innovation projects submitted to the Granting Authority. These projections are successful in predicting the recipiency of the innovation subsidy and the quality of future innovation.

Inference of scientific value of project. For each project submitted to the Granting Authority, we construct a projection of the number of citations a patent with the same name to that project would have received. Using data from Patstat, we calculate for each word that has ever appeared in a patent the average number of citations received by patents containing that word:[23]

$$citation_j = \frac{average\ number\ of\ citations\ on\ patents\ containing\ word\ j}{average\ number\ of\ words\ on\ the\ title\ of\ patents\ containing\ wordj} \tag{6}$$

$citation_j$ is the average number of citations that patents with the word j have received. As Kelly et al. (2021) has shown, breakthrough technologies are associated with the introduction of new words that become commonly used after their first introduction. Words such as micro-RNA, multi-transactional, and electronic-monetary are associated with a high number of citations.

For each title of an R&D project, we calculate the average number of citations that project would have received if it was a patent:

[23] To avoid having the results driven by the subsidy, we use only US patents before 2000. The sample is the same used by Kogan et al. (2017).

$$Scientific\ Value_p = \sum_j \frac{\mathbb{I}\{Project\ p\ has\ word\ j\} \times citation_j}{Number\ of\ Words\ on\ the\ Project\ Title} \tag{7}$$

Inference of market value of project. To infer the market value of a project, we use data from Kogan et al. (2017). For each patent accepted by the USPTO, Kogan et al. (2017) estimates its market value using stock market variation around the time that the patent was approved. Re-writing equations 6 and 7 using the patent value, we can infer the value of a patent using

$$value_j = \frac{average\ market\ value\ of\ patents\ containing\ word\ j}{average\ number\ of\ words\ on\ the\ title\ of\ patents\ containing\ wordj} \tag{8}$$

$$Economic\ Value_p = \sum_j \frac{\mathbb{I}\{Project\ p\ has\ word\ j\} \times value_j}{Number\ of\ Words\ on\ the\ Project\ Title} \tag{9}$$

Inferred scientific value predict R&D subsidy recipiency. Table 22 shows the correlation between receiving the subsidy and the scientific and economic value of projects. Table 22 finds that projects with larger scientific value are more likely to receive the subsidy but there is a weak negative correlation with the economic value of the project.

According to the discussion on 2, the scientific potential of a project is one of the main criteria for assigning the subsidy. Supporting that, Table 22 finds that projects with larger scientific value are more likely to receive the subsidy. Moreover, there subsidy recipiency has a weak negative correlation with the economic value of the project, which is expected given that the economic potential of a project is not heavily rewarded by the Funding Authority.

Table 22: Correlation Between Scientific and Economic Value with Subsidy Recipiency

	(1) $\mathbb{I}\{Subsidy\}$	(2) $\mathbb{I}\{Subsidy\}$	(3) $\mathbb{I}\{Subsidy\}$
$log\left(Scientific\ Value_p\right)$	0.0552**	0.0552**	0.248***
	(0.0238)	(0.0236)	(0.0931)
$log\left(Economic\ Value_p\right)$	-0.0344	-0.0344	-0.137*
	(0.0218)	(0.0216)	(0.0832)
Method	OLS	Probit	Tobit
N	4388	4388	4388
R^2	0.316	0.2639	0.2650

Description: This table shows the correlation between the inferred scientific and economic value of projects with a dummy if the firm received the subsidy. The controls are a fixed effect for call for projects, log of the number of workers at the firm on the year before the application, the total number of patent applications that the firm has ever made, and the total number of citations received by the firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

B Results Appendix

Table 23: Effect of Innovation Subsidy on the Origin of Workers

	(1) $log\left(N.\ Workers\ f/\ Out\ Labor\ Force\right)$	(2) $log\left(N.\ Workers\ f/\ Same\ Sector\right)$	(3) $log\left(N.\ Workers\ f/\ Diff\ Sector\right)$
Panel A. Simple DD			
$\mathbb{I}\{Subsidy\}$	0.300***	0.396***	0.263***
	(0.0827)	(0.120)	(0.0849)
Panel B. Extended DD			
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.266***	0.401***	0.237***
	(0.0756)	(0.110)	(0.0759)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.357***	0.396***	0.288***
	(0.0978)	(0.133)	(0.0992)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.311**	0.388**	0.302**
	(0.129)	(0.182)	(0.131)
N	9065	5164	8980

Description: This table shows the effect of the innovation subsidy on the hiring of workers from different sectors. We classify each worker according to the position they held before the year before joining a firm in the sample. Column 1 contains the number of workers who were not employed before joining the firm. Column 2 contains the number of workers who came from the same 2-digit sector and column 3 contains the number of workers coming from a different 2-digit sector. Standard errors are clustered at the firm level. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 24: Effect of Innovation Subsidy on the Origin of Scientists

	(1) $\mathbb{IHS}$ (*Scient. Same Sec.*)	(2) $\mathbb{IHS}$ (*Scient. Diff Sec.*)	(3) $\mathbb{IHS}$ (*Scient. Bfr.*)	(4) $\mathbb{IHS}$ (*Engineer Bfr.*)	(5) $\mathbb{IHS}$ (*Health Bfr.*)	(6) $\mathbb{IHS}$ (*Technician Bfr.*)	(7) $\mathbb{IHS}$ (*Operation Bfr.*)
*P*anel A. Simple DD							
$\mathbb{I}\{Subsidy\}$	0.0370	0.116***	-0.00168	0.00797	0.0280*	0.0755***	0.0491***
	(0.0296)	(0.0407)	(0.00926)	(0.0240)	(0.0158)	(0.0281)	(0.0141)
*P*anel B. Extended DD							
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.0253	0.0910**	-0.00726	-0.00799	0.0213*	0.0579**	0.0346**
	(0.0251)	(0.0362)	(0.00603)	(0.0213)	(0.0119)	(0.0255)	(0.0135)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.0392	0.141***	-0.00345	0.0172	0.0286	0.0781**	0.0496***
	(0.0354)	(0.0461)	(0.0109)	(0.0277)	(0.0181)	(0.0336)	(0.0159)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.0556	0.123**	0.0117	0.0227	0.0396	0.104***	0.0758***
	(0.0448)	(0.0571)	(0.0181)	(0.0361)	(0.0244)	(0.0391)	(0.0196)
N	7059	7059	7059	7059	7059	7059	7059

Description: This table shows the effect of the innovation subsidy on the hiring of scientists from different sectors and occupations. Workers are identified as scientists if they have CBO 2002 occupation number 20. Because this occupational code is available only after 2003, these regressions use only data after 2003. We classify each worker hired as scientist according to the position they held before joining a firm in the sample. Column 1 contains the number of scientists that before joining the firm were in a firm in the same 2-digit CNAE1 sector. Column 2 contains the number of scientists that before joining the firm were in a firm in a different 2-digit CNAE1 sector. Column 3 contains the number of scientists that before joining the firm were employed as scientist as well. Column 4 contains the number of scientists that before joining the firm were employed as an engineer. Column 5 contains the number of scientists that before joining the firm were employed as a health professional such as biologist or medical doctor. Column 6 contains the number of scientists that before joining the firm were employed as a health professional such as biologist or medical doctor. Column 7 contains the number of scientists that before joining the firm were employed as technicians, code 3 of the CBO 2002 classification, such as mechatronics, chemical, and laboratory technicians. Column 8 contains the number of scientists that before joining the firm were employed as operation workers, code 7 of the CBO 2002 classification, such as plant operation supervisors and machinery operators. Standard errors are clustered at the firm level. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 25: Innovation Subsidy and Innovation Effort

	(1) $\mathbb{IHS}$ (*N. Patents Nxt. 5*)	(2) $\mathbb{I}$ (*Patents Nxt. 5*)	(3) $\mathbb{IHS}$ (*N. Trademarks Nxt. 5*)
$\mathbb{I}$ {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. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 26: Innovation Subsidy and Scientists Field

	(1) IHS (*Engineering*)	(2) IHS (*Biology*)	(3) IHS (*Meteorology*)	(4) IHS (*Automation*)	(5) IHS (*Health*)	(6) IHS (*Agronomy*)	(7) IHS (*Humanities*)	(8) IHS (*Hard Sciences*)	(9) 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. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 27: Effect of Innovation Subsidy on Log Product Variety

	(1) $log\{\#\ Pat.\ Class\}$	(2) $log\{\#\ Trademark\ Class\}$	(3) $log\{\#\ Export\ Products\}$	(4) $log\{\#\ Import\ Products\}$
$\mathbb{I}\{Subsidy\}$	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. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 28: 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) $\mathbb{IHS}\{N.\ Patent$ $High\ Tariff\ Prod.\}$	(4) $\mathbb{IHS}\{N.\ Patent$ $Low\ Tariff\ Prod.\}$	(5) $\mathbb{IHS}\{N.\ Patent$ $High\ Tariff\ Prod.\}$	(6) $\mathbb{IHS}\{N.\ Patent$ $Low\ Tariff\ Prod.\}$
$\mathbb{I}\{Subsidy\}$	0.0590**	0.0229	0.0513**	0.0183	0.0673**	0.0166
	(0.0284)	(0.0265)	(0.0241)	(0.0305)	(0.0263)	(0.0324)
Quartile at	1-digit sector	1-digit sector	2-digit sector	2-digit sector	3-digit sector	3-digit sector
N	9358	9358	9358	9358	9358	9358
R^2	0.608	0.704	0.521	0.676	0.603	0.650

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, 3, and 5 is the number of patent applications in the next three years in high import tariff patent classes. To estimate the tariff of each patent, we use the crosswalk by Lybbert and Zolas (2014) and calculate the HS product codes associated with each patent. Then, we average the import tariff for each patent and count as high tariff the ones in the top quartile of each sector. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 29: Effect of Innovation Subsidy on Imports

	(10) $\mathbb{IHS}\{Imp.\ Mercosur\}$	(11) $\mathbb{IHS}\{Imp.\ South\ America\}$	(12) $\mathbb{IHS}\{Imp.\ Europe\}$	(13) $\mathbb{IHS}\{Imp.\ North\ America\}$
$\mathbb{I}\{Subsidy\}$	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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 30: Effect of Innovation Subsidy on Exports

	(1) $\mathbb{IHS}\{Exp.\ Mercosur\}$	(2) $\mathbb{IHS}\{Exp.\ South\ America\}$	(3) $\mathbb{IHS}\{Exp.\ Europe\}$	(4) $\mathbb{IHS}\{Exp.\ North\ America\}$
$\mathbb{I}\{Subsidy\}$	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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

B.1 The Causal Forest Approach for Heterogeneous Treatment Effects

We 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, we 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.

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

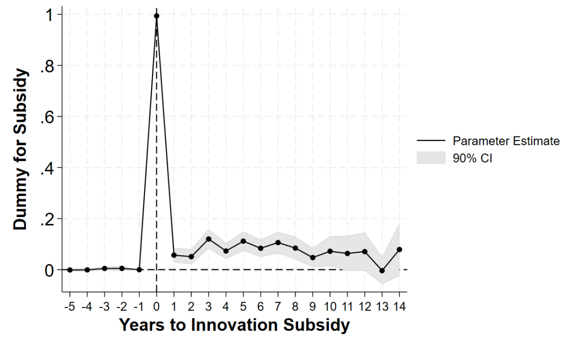
$$\Delta y_i = \theta \mathbb{I}_i \left\{ Innovation\ Subsidy \right\} + \mu_{g(i)} + \epsilon_i$$

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.

Figure 10: Effect of Innovation Subsidy on the Likelihood of Receiving other R&D Subsidies



Description: This figure shows the dynamic effect of the innovation subsidy on the likelihood of receiving a R&D subsidy. 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 a dummy taking one if the firm received an innovation subsidy that year. Standard errors are clustered at the firm level.

C Alternative Explanations Appendix

C.1 Multiple R&D Subsidies

In this section, we use an instrumental variables approach to isolate the effect of the first R&D subsidy from subsequent R&D subsidies received by the firm. Figure 10 shows the effect of the R&D subsidy on the likelihood of a firm receiving an R&D subsidy. By design, the R&D subsidy is zero prior to treatment and increases to one at zero. However, after receiving the first subsidy, there remains a likelihood of around 7% that the firm will receive another R&D subsidy. Therefore, it is reasonable to be concerned that the long-run effects discussed in 5.1 are driven by subsequent subsidies. In this section, we demonstrate that the subsidy has a persistent effect on firm size even when accounting for additional R&D subsidies.

Re-write specification 1 to account for the fact that the subsidy that the firm is receiving is increasing over time:

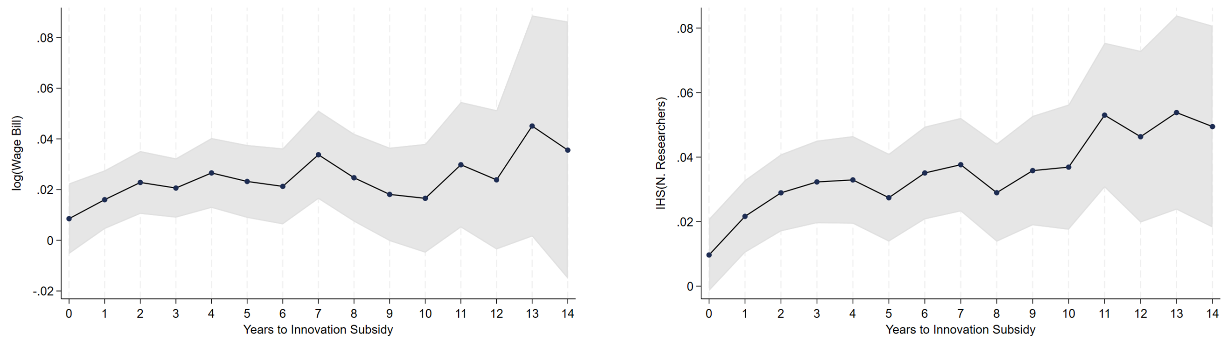
$$\begin{aligned} y_{i,t} = &\sum_j \theta_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} \times log\left(Subsidy\ Value_{i,t}\right) + \\ &\sum_j \alpha_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t} \end{aligned} \tag{10}$$

where $Subsidy\ Value_{i,t}$ is the sum in Brazilian reais of all R&D subsidy received by firm i up

Figure 11: Effect of Innovation Subsidy on the Long-Run

(a) Wage Bill

(b) Number of Scientists



Description: This figure shows the dynamic effect of the innovation subsidy on firms' wage bill and number of researchers according to model 10. 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, in Figure 11a, or on the number of researchers, in Figure 11b. The first stage is given by 11. Standard errors are clustered at the firm level.

to year t. If the firm did not receive any innovation subsidy, we set $Subsidy\ Value_{i,t}$ to one.

Parameters θ_j captures the effect of an one time increase in the innovation subsidy.. If the effect of the innovation subsidy on the long-run comes only from further subsidies, it should be the case that θ_j should decrease over time.

After the first subsidy application, increases in innovation subsidy are endogenous. To deal with that, we instrument the subsidy with a dummy if the firm was successful on its first application, as in the baseline model:

$$log\left(Subsidy\ Value_{i,t}\right) = \sum_j \theta_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} \times \mathbb{I}_i\left\{\text{Treatment}\right\} + \sum_j \alpha_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t} \tag{11}$$

Results. Figures 11a and 11b show the effect of the innovation subsidy on the wage bill and on the number of researchers in the long-run. The figures show that the marginal effect of one dollar of R&D subsidy is stable over time. Therefore, the firm growth in the long-run doesn't come from further R&D subsidies.

C.2 Private Sector Crowd-in

Table 31: Effect of Innovation Subsidy on Bank Loans

	(1) $\mathbb{IHS}\,(Loans)$	(2) $\frac{Loans}{Wage\ Bill}$	(3) $\mathbb{IHS}\,(Invest.\ Loans)$	(4) $\mathbb{IHS}\,(Working\ Cap.\ Loans)$	(5) $\mathbb{IHS}\,(Collateralized\ Loans)$	(6) $\mathbb{IHS}\,(Uncollateralized\ Loans)$	(7) *Avg. Interest Rate*
Panel A. Simple DD							
$\mathbb{I}\{Subsidy\}$	0.887*	-19.23	-0.158	0.908*	0.244	0.963*	-0.373
	(0.493)	(14.54)	(0.603)	(0.518)	(0.579)	(0.503)	(11.58)
Panel B. Extended DD							
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.439	-0.671	-0.344	0.407	0.0420	0.437	1.865
	(0.488)	(27.09)	(0.600)	(0.511)	(0.572)	(0.491)	(10.76)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	1.262**	-9.513	-0.0194	1.328**	0.586	1.362**	1.280
	(0.539)	(21.27)	(0.678)	(0.568)	(0.646)	(0.556)	(12.31)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	1.166*	-83.96	-0.00775	1.219*	0.0345	1.368**	-8.649
	(0.621)	(68.46)	(0.785)	(0.640)	(0.759)	(0.630)	(14.58)
N	6516	5678	6516	6516	6516	6516	5626

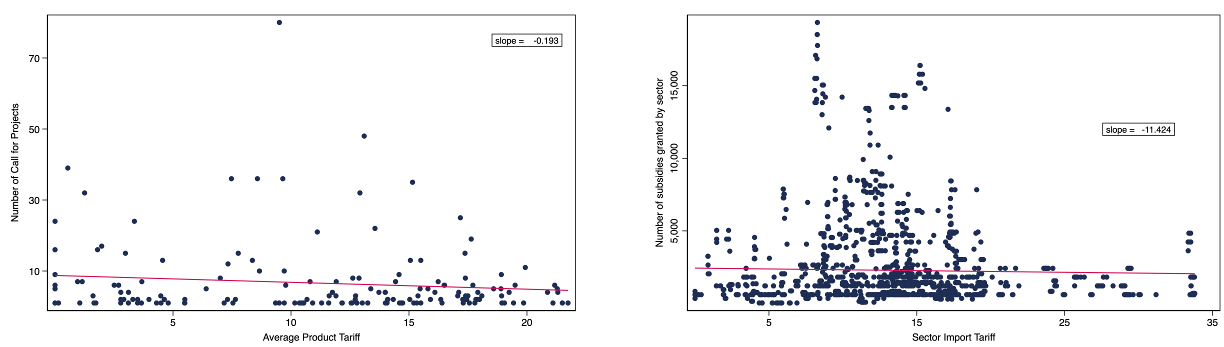
Description: This table shows the effect of the innovation subsidy on access to credit. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The left-hand side in column 1 is the inverse hyperbolic sine of firm's outstanding bank credit in Brazilian reais; in column 2 is the fraction of bank credit to wage bill; in column 3 is firm's outstanding investment related bank credit; in column 4 is firm's outstanding credit for working capital; in column 5 credit with a collateral; in column 6 is the credit without collateral; and in column 6 is the average interest rate on outstanding loans. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

C.3 Subsidy and High-Tariff Projects

Figure 12: Correlation Between Tariffs and Subsidies

(a) Correlation Between Call for Projects and Tariffs

(b) Correlation Between Sector of the Subsidized Firm and Tariffs



Description: These figures show the correlation between innovation subsidy and tariffs. Figure 12a plots the correlation between the Harmonized System codes covered by different call for projects and their import tariff in 2000. This figure is limited to the set of call for projects with description available online. Figure 12b plots the correlation between the number of subsidy recipients in each sector and the average sectoral import tariff.

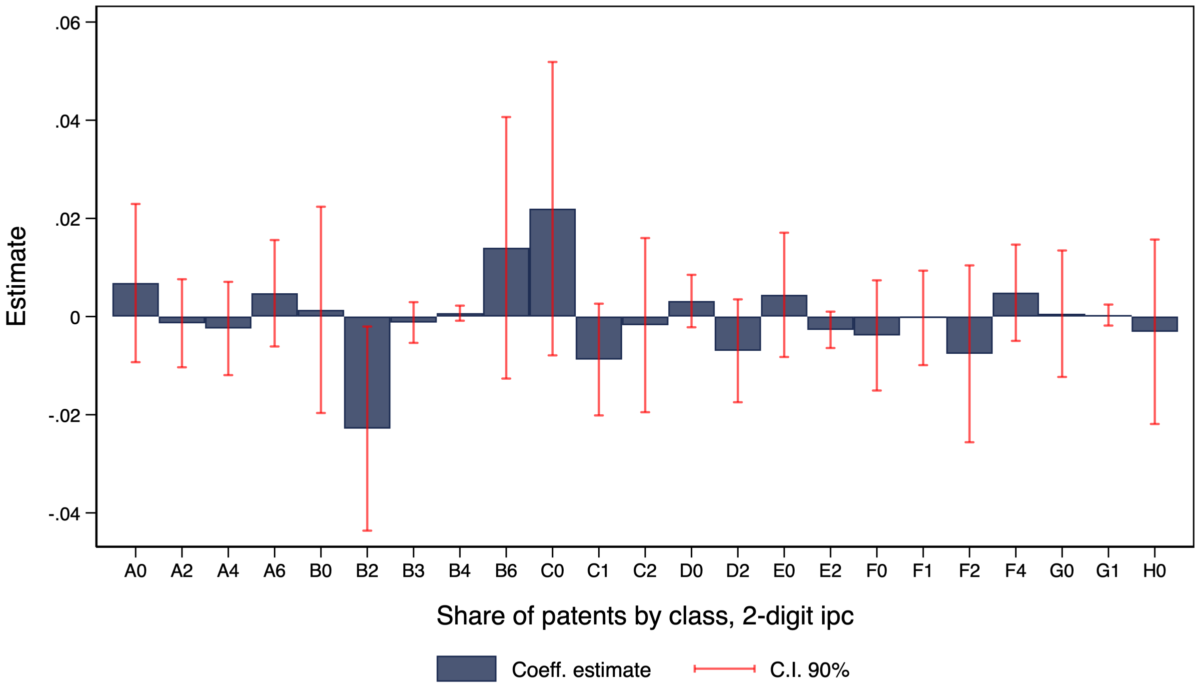
C.4 Marginal Subsidy Recipients

Table 32: Main Results Interacting for Dummy for High Budget Call

	(1) $\mathbb{I}\,(N.\ Patent\ Nxt.\ 3)$	(2) $\mathbb{IHS}\,(Citations)$	(3) $\log\,(Wage\ Bill)$	(4) $\mathbb{IHS}\,(Exports)$	(5) $\mathbb{IHS}\,\{Prod\ Pat\}$	(6) $\mathbb{IHS}\,\{Proc\ Pat\}$	(7) $\mathbb{IHS}\,\{\#\ Export\ Products\}$	(8) $\mathbb{IHS}\,\{N.\ Pat\ High\ Tar\ Prod.\}$	(9) $\mathbb{IHS}\,\{N.\ Pat\ Low\ Tar\ Prod.\}$
$\mathbb{I}\{Subsidy\}$	0.0709**	0.00648	0.239**	1.352***	0.0984	0.0214	0.447***	0.0654**	0.0141
	(0.0325)	(0.0147)	(0.108)	(0.465)	(0.0600)	(0.0193)	(0.103)	(0.0324)	(0.0300)
$\mathbb{I}\{Subsidy\ in\ High\ Budget\ Call\}$	0.00775	0.0200	0.0586	1.073	-0.0259	-0.0337	-0.164	0.0183	-0.0336
	(0.0522)	(0.0441)	(0.158)	(1.894)	(0.0904)	(0.0294)	(0.330)	(0.0484)	(0.0464)
N	9358	9358	9358	5600	9358	9358	5600	9358	9358
R^2	0.532	0.158	0.865	0.834	0.638	0.399	0.864	0.582	0.718

Description:

Figure 13: Effect on Share of Patents in Different Patent Classes



Description:

C.5 Marginal Subsidy Recipients

C.6 Robustness Appendix

Table 33: Main Results using Control Function

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}(N.\ Patent\ Nxt.\ 3)$	$\mathbb{IHS}(Citations)$	$\log(Wage\ Bill)$	$\mathbb{IHS}(Exports)$	$\mathbb{IHS}\{Product\ Patent\}$	$\mathbb{IHS}\{Process\ Patent\}$	$\mathbb{IHS}\{\#\ Export\ Products\}$	$\mathbb{IHS}\{N.\ Patent\ High\ Tariff\ Prod.\}$	$\mathbb{IHS}\{N.\ Patent\ Low\ Tariff\ Prod.\}$
					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 34: Main Results using Control Function with Project Call FE

	(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				
$\mathbb{I}\,\{\textit{Subsidy}\}$	0.0348*	-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				
$\mathbb{I}\,\{\textit{Subsidy}\}$	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				
$\mathbb{I}\,\{\textit{Subsidy}\}$	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 35: 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 36: Main Results using Variation from Subsidy Value

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}\,(\textit{N. Patent Nxt. 3})$	$\mathbb{IHS}\,(\textit{Citations})$	$\log\,(\textit{Wage Bill})$	$\mathbb{IHS}\,(\textit{Exports})$	$\mathbb{IHS}\,\{\textit{Product Patent}\}$	$\mathbb{IHS}\,\{\textit{Process Patent}\}$	$\mathbb{IHS}\,\{\#\ \textit{Export Products}\}$	$\mathbb{IHS}\,\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\,\{\textit{N. Patent Low Tariff Prod.}\}$
Panel A. Simple DD									
$\log\,\{\textit{Vl Subsidy}\}$	0.00452**	0.000956	0.0163**	0.0964***	0.00570*	0.000725	0.0309***	0.00430**	0.000415
	(0.00190)	(0.00190)	(0.00644)	(0.0311)	(0.00341)	(0.00115)	(0.00691)	(0.00183)	(0.00173)
Panel B. Extended DD									
$\log\,\{\textit{Vl Subsidy 0-2 Years}\}$	0.00357*	-0.000231	0.0123**	0.0873***	0.00483	0.000992	0.0287***	0.00412**	0.000663
	(0.00215)	(0.00172)	(0.00589)	(0.0324)	(0.00358)	(0.00144)	(0.00709)	(0.00202)	(0.00195)
$\log\,\{\textit{Vl Subsidy 3-5 Years}\}$	0.00720***	0.00382	0.0185***	0.120**	0.00949**	0.00168	0.0376***	0.00481**	0.00171
	(0.00228)	(0.00375)	(0.00699)	(0.0465)	(0.00404)	(0.00140)	(0.0106)	(0.00232)	(0.00228)
$\log\,\{\textit{Vl Subsidy 6+ Years}\}$	0.00321	-0.00101	0.0223**	0.112*	0.00333	-0.000550	0.0386**	0.00412	-0.000784
	(0.00291)	(0.00265)	(0.00989)	(0.0651)	(0.00496)	(0.00180)	(0.0174)	(0.00276)	(0.00288)
N	9197	9197	9197	5510	9197	9197	5510	9197	9197

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 37: Main Results Matching on CEO Wage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{I}\,(\textit{N. Patent Nxt. 3})$	$\mathbb{IHS}\,(\textit{Citations})$	$\log\,(\textit{Wage Bill})$	$\mathbb{IHS}\,(\textit{Exports})$	$\mathbb{IHS}\,\{\textit{Product Patent}\}$	$\mathbb{IHS}\,\{\textit{Process Patent}\}$	$\mathbb{IHS}\,\{\#\ \textit{Export Products}\}$	$\mathbb{IHS}\,\{\textit{N. Patent High Tariff Prod.}\}$	$\mathbb{IHS}\,\{\textit{N. Patent Low Tariff Prod.}\}$
Panel A. Simple DD									
$\mathbb{I}\{\textit{Subsidy}\}$	0.0665**	0.00733	0.267**	1.163**	0.0977	0.0123	0.413***	0.0734*	0.0189
	(0.0333)	(0.0126)	(0.105)	(0.451)	(0.0701)	(0.0212)	(0.109)	(0.0432)	(0.0323)
Panel B. Extended DD									
$\mathbb{I}\{\textit{Subsidy 0-2 Years}\}$	0.0542	-0.00736	0.193**	0.950**	0.0524	0.00930	0.366***	0.0534	-0.000794
	(0.0369)	(0.0242)	(0.0907)	(0.454)	(0.0642)	(0.0202)	(0.110)	(0.0409)	(0.0306)
$\mathbb{I}\{\textit{Subsidy 3-5 Years}\}$	0.0960**	0.0253	0.289***	1.824**	0.143*	0.0268	0.573***	0.0793	0.0310
	(0.0410)	(0.0357)	(0.109)	(0.714)	(0.0796)	(0.0216)	(0.171)	(0.0501)	(0.0374)
$\mathbb{I}\{\textit{Subsidy 6+ Years}\}$	0.0511	0.00142	0.353**	1.328	0.107	0.000659	0.419	0.0930	0.0310
	(0.0507)	(0.0388)	(0.168)	(1.134)	(0.103)	(0.0481)	(0.279)	(0.0595)	(0.0601)
N	7772	7772	7772	4633	7772	7772	4633	7772	7772

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 38: Main Results Matching on Sector

	(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.*}
Panel A. Simple DD									
$\mathbb{I}$\{*Subsidy*\}	0.0756*	0.0169	0.326**	1.236**	0.0695	0.00260	0.495***	0.0770*	-0.00170
	(0.0401)	(0.0255)	(0.127)	(0.537)	(0.0723)	(0.0267)	(0.122)	(0.0400)	(0.0323)
Panel B. Extended DD									
$\mathbb{I}$\{*Subsidy 0-2 Years*\}	0.0592	0.0350	0.327***	1.277**	0.0585	-0.00515	0.484***	0.0735*	-0.00992
	(0.0449)	(0.0245)	(0.112)	(0.594)	(0.0768)	(0.0321)	(0.126)	(0.0427)	(0.0342)
$\mathbb{I}$\{*Subsidy 3-5 Years*\}	0.117**	0.0522	0.312**	0.834	0.124	0.0168	0.533***	0.0935*	0.0153
	(0.0500)	(0.0493)	(0.143)	(0.791)	(0.0877)	(0.0322)	(0.192)	(0.0530)	(0.0449)
$\mathbb{I}$\{*Subsidy 6+ Years*\}	0.0539	-0.0516	0.360*	1.088	0.0286	-0.00201	0.296	0.0636	-0.00570
	(0.0578)	(0.0482)	(0.200)	(1.189)	(0.0940)	(0.0261)	(0.316)	(0.0538)	(0.0472)
N	6151	6151	6151	3657	6151	6151	3657	6151	6151

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 39: Main Results Matching on Quality of Research Team

	(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.*}
Panel A. Simple DD									
$\mathbb{I}$\{*Subsidy*\}	0.0835***	0.00435	0.324***	1.170**	0.0962*	0.00356	0.442***	0.0585*	0.00219
	(0.0307)	(0.00689)	(0.109)	(0.489)	(0.0541)	(0.0133)	(0.113)	(0.0342)	(0.0274)
Panel B. Extended DD									
$\mathbb{I}$\{*Subsidy 0-2 Years*\}	0.0537	-0.0140	0.277***	0.974*	0.0492	-0.00294	0.394***	0.0290	-0.0112
	(0.0335)	(0.0229)	(0.0927)	(0.498)	(0.0579)	(0.0160)	(0.111)	(0.0378)	(0.0273)
$\mathbb{I}$\{*Subsidy 3-5 Years*\}	0.126***	0.0340	0.384***	1.851**	0.138*	0.0225	0.616***	0.0695	0.0132
	(0.0402)	(0.0248)	(0.123)	(0.783)	(0.0703)	(0.0176)	(0.191)	(0.0465)	(0.0371)
$\mathbb{I}$\{*Subsidy 6+ Years*\}	0.0828*	-0.0133	0.394**	1.399	0.124*	-0.00909	0.375	0.0865**	0.0164
	(0.0429)	(0.0386)	(0.166)	(1.119)	(0.0721)	(0.0266)	(0.310)	(0.0425)	(0.0448)
N	8036	8036	8036	4805	8036	8036	4805	8036	8036

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 40: Main Results Matching on Project Quality

	(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.*}
Panel A. Simple DD									
$\mathbb{I}$\{*Subsidy*\}	0.106***	0.0138	0.285***	1.436***	0.130**	0.00436	0.492***	0.0735**	0.0262
	(0.0313)	(0.0304)	(0.107)	(0.469)	(0.0607)	(0.0158)	(0.110)	(0.0360)	(0.0293)
Panel B. Extended DD									
$\mathbb{I}$\{*Subsidy 0-2 Years*\}	0.0835**	-0.0163	0.232**	1.320***	0.102*	-0.000849	0.463***	0.0718**	0.00334
	(0.0343)	(0.0313)	(0.0908)	(0.493)	(0.0608)	(0.0207)	(0.111)	(0.0363)	(0.0296)
$\mathbb{I}$\{*Subsidy 3-5 Years*\}	0.142***	0.0414	0.309***	1.712**	0.153**	0.0197	0.602***	0.0690	0.0327
	(0.0402)	(0.0567)	(0.113)	(0.703)	(0.0735)	(0.0195)	(0.188)	(0.0455)	(0.0364)
$\mathbb{I}$\{*Subsidy 6+ Years*\}	0.0984**	0.0204	0.349*	1.594	0.144*	-0.00461	0.461	0.0821*	0.0520
	(0.0420)	(0.0413)	(0.181)	(1.108)	(0.0805)	(0.0262)	(0.304)	(0.0495)	(0.0419)
N	7432	7432	7432	4428	7432	7432	4428	7432	7432

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

	(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.*}
Panel A. Simple DD									
$\mathbb{I}$\{*Subsidy*\}	0.0678**	0.00343	0.270**	1.522***	0.0453	-0.00883	0.401***	0.0669**	-0.0153
	(0.0336)	(0.00849)	(0.107)	(0.505)	(0.0599)	(0.0267)	(0.105)	(0.0331)	(0.0310)
Panel B. Extended DD									
$\mathbb{I}$\{*Subsidy 0-2 Years*\}	0.0605	0.00734	0.169*	1.427***	0.0325	0.0164	0.391***	0.0598*	0.00159
	(0.0373)	(0.0226)	(0.0960)	(0.508)	(0.0620)	(0.0250)	(0.110)	(0.0349)	(0.0301)
$\mathbb{I}$\{*Subsidy 3-5 Years*\}	0.0933**	0.0541**	0.265**	1.721**	0.0658	-0.00156	0.430***	0.0534	-0.00319
	(0.0402)	(0.0248)	(0.111)	(0.797)	(0.0698)	(0.0279)	(0.164)	(0.0410)	(0.0379)
$\mathbb{I}$\{*Subsidy 6+ Years*\}	0.0532	-0.0578*	0.422**	2.128*	0.0454	-0.0481	0.482*	0.0920*	-0.0472
	(0.0476)	(0.0345)	(0.183)	(1.192)	(0.0825)	(0.0475)	(0.278)	(0.0504)	(0.0567)
N	6669	6669	6669	4066	6669	6669	4066	6669	6669

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.

Table 42: Effect of Innovation Subsidy on Labor Market Inspections

	(1) $\mathbb{IHS}$ {*N. Inspection*}	(2) $\mathbb{IHS}$ {*N. Informal Infraction*}	(3) $\mathbb{IHS}$ {*N. Inspection without Infraction*}	(4) $\mathbb{IHS}$ {*N. Inspection without Infraction*}
$\mathbb{I}$ \{*Subsidy*\}	0.134**	0.00682	0.150***	0.0512
	(0.0664)	(0.00711)	(0.0509)	(0.0569)
N	11403	11403	11403	11403
R^2	0.561	0.250	0.556	0.405

Description: This table shows the effect of the innovation subsidy on labor market inspections and infractions. Each column displays the coefficient of Model 1. The left-hand side in column 1 is inverse hyperbolic sine of the number of labor inspections that the firm received in a year, in column 2 is the inverse hyperbolic sine of the number of infractions for hiring informal workers, in column 3 the number of inspections that did not find any infraction, and in column 4 the number of inspections that found any labor market infraction. Standard errors are clustered at the firm level.

Table 43: Main Results using Percentile Transformation

	(1) *Per(N. Patent Nxt. 3)*	(3) *Per(Citations)*	(2) *Per(Citation Weighted Patents)*	(3) *Per(Exports)*	(4) *Per{Product Patent}*	(5) *Per{Process Patent}*	(6) *Per{# Export Products}*	7 *Per{N. Patent High Tariff Prod.}*	8 *Per{N. Patent Low Tariff Prod.}*
*P*anel A. Simple DD									
$\mathbb{I}\{Subsidy\}$	6.799**	0.937	0.228	7.312**	5.529**	0.960	7.484***	5.559***	-0.432
	(2.670)	(0.979)	(0.217)	(2.902)	(2.624)	(1.378)	(2.877)	(1.959)	(1.743)
*P*anel B. Extended DD									
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	5.523*	0.270	0.387	6.202**	4.140	0.610	6.199**	5.079**	-0.990
	(3.004)	(1.446)	(0.455)	(3.054)	(2.795)	(1.857)	(3.030)	(2.148)	(2.042)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	10.43***	1.245	0.361	9.954**	8.985***	2.423	10.58**	6.502***	0.477
	(3.205)	(1.455)	(0.450)	(4.404)	(3.134)	(1.826)	(4.330)	(2.404)	(2.271)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	5.240	1.165	-0.158	10.78*	4.204	0.0458	12.24**	5.310*	-0.136
	(3.979)	(0.996)	(0.132)	(5.661)	(3.961)	(1.901)	(5.819)	(3.058)	(2.633)
N	9358	9358	9358	5600	9358	9358	5600	9358	9358

Description: This table shows the effect of the innovation subsidy on the main variables of interest using their percentile on the distribution. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The left-hand side in column 1 is the percentile of the number of patent applications that will be made by the firm during the next three years; in column 2 it is the percentile of citations that will be received by the firm during the next 3 years; in column 3 it is the percentile of citation weighted patents; in column 4 it is the percentile of exports; in column 5 it is the percentile of product patents; in column 6 it is the percentile of process patents; in column 7 it is the percentile of 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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 44: Main Results using Log + 1

	(1) *log(N. Patent Nxt. 3)*	(3) *log(Citations)*	(2) *log(Citation Weighted Patents)*	(3) *log(Exports)*	(4) *log{Product Patent}*	(5) *log{Process Patent}*	(6) *log{# Export Products}*	7 *log{N. Patent High Tariff Prod.}*	8 *log{N. Patent Low Tariff Prod.}*
*P*anel A. Simple DD									
$\mathbb{I}\{Subsidy\}$	0.0883**	0.0124	0.00248	1.329***	0.0706*	0.00751	0.389***	0.0549**	0.00310
	(0.0421)	(0.0149)	(0.00228)	(0.435)	(0.0399)	(0.0130)	(0.0853)	(0.0215)	(0.0196)
*P*anel B. Extended DD									
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.0768*	0.000497	0.00457	1.182***	0.0568	0.00948	0.358***	0.0511**	0.00157
	(0.0447)	(0.0148)	(0.00504)	(0.456)	(0.0419)	(0.0162)	(0.0874)	(0.0234)	(0.0221)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.139***	0.00857	0.00254	1.722***	0.113**	0.0190	0.482***	0.0644**	0.0175
	(0.0502)	(0.0169)	(0.00320)	(0.658)	(0.0466)	(0.0160)	(0.131)	(0.0272)	(0.0256)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.0589	0.0303	-0.000538	1.611*	0.0523	-0.00593	0.501**	0.0513	-0.00345
	(0.0594)	(0.0222)	(0.00109)	(0.922)	(0.0566)	(0.0198)	(0.214)	(0.0318)	(0.0314)
N	9358	9270	9355	5600	9358	9358	5600	9358	9358

Description: This table shows the effect of the innovation subsidy on the main variables of interest using log + 1. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The left-hand side in column 1 is the log plus one of the number of patent applications that will be made by the firm during the next three years; in column 2 it is the log plus one of citations that will be received by the firm during the next 3 years; in column 3 it is the log plus one of citation weighted patents; in column 4 it is the log plus one of exports; in column 5 it is the log plus one of product patents; in column 6 it is the log plus one of process patents; in column 7 it is the log plus one of 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. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 45: Main Results using a Dummy

	(1) $\mathbb{I}(N.\ Patent\ Nxt.\ 3)$	(2) $\mathbb{I}(Citation)$	(3) $\mathbb{I}(Exports)$	(4) $\mathbb{I}\{Product\ Patent\}$	(5) $\mathbb{I}\{Process\ Patent\}$	(6) $\mathbb{I}\{N.\ Patent\ High\ Tariff\ Prod.\}$	(7) $\mathbb{I}\{N.\ Patent\ Low\ Tariff\ Prod.\}$
*P*anel A. Simple DD							
$\mathbb{I}\{Subsidy\}$	0.0736***	0.00946	0.0722**	0.0601**	0.00980	0.0574***	-0.00438
	(0.0285)	(0.00989)	(0.0332)	(0.0282)	(0.0140)	(0.0203)	(0.0180)
*P*anel B. Extended DD							
$\mathbb{I}\{Subsidy\ 0\text{-}2\ Years\}$	0.0598*	0.00273	0.0571	0.0449	0.00615	0.0524**	-0.0104
	(0.0322)	(0.0146)	(0.0351)	(0.0301)	(0.0189)	(0.0222)	(0.0211)
$\mathbb{I}\{Subsidy\ 3\text{-}5\ Years\}$	0.112***	0.0126	0.107**	0.0974***	0.0247	0.0671***	0.00489
	(0.0343)	(0.0147)	(0.0498)	(0.0339)	(0.0186)	(0.0249)	(0.0234)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.0576	0.0118	0.130**	0.0463	0.000553	0.0549*	-0.000849
	(0.0427)	(0.0101)	(0.0641)	(0.0429)	(0.0193)	(0.0318)	(0.0270)
N	9358	9358	5600	9358	9358	9358	9358

Description: This table shows the effect of the innovation subsidy on the main variables of interest. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The left-hand side in column 1 is a dummy if the firm makes a patent application in the next three years; in column 2 it is a dummy if the firm received one citation in the next 3 years; in column 3 it is a dummy if the firm exports; in column 4 it is a dummy if the firm apply for a product patents; in column 5 it is a dummy if the firm apply for a process patents; in column 6 it is a dummy if the firm applies for a patent associated with products whose tariff is in the top quartile; and in column 7 it is a dummy if the firm applies for a patent associated with products whose tariff is in the bottom quartile. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.