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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 from Brazil and a quasi-experimental design that compares near-winners to near-losers of R&D subsidy applications, we find that the program had a persistent effect on firm size: fourteen years after receiving the subsidy, subsidized firms were 59% larger. The effect is strongest among small and young firms facing high borrowing costs, which is consistent with the subsidy alleviating financial constraints. This growth, however, did not come from firms developing frontier innovations. Instead, firms used the subsidy to expand their product lines into high-tariff markets, producing local versions of foreign goods.

JEL Codes: O3, O14, O25

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

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1 Introduction

R&D subsidies are a central instrument of industrial policy (Hall and Van Reenen 2000). While these programs have been extensively studied in developed countries (Bronzini and Iachini 2014, Andrieu and Morrow 2024, Hirvonen et al. 2022), little is known about how they affect innovation and firm growth in developing countries. R&D subsidies could induce breakthrough innovations, ease financial constraints, and promote long-run growth (Fieldhouse and Mertens 2023, Choi and Levchenko 2021, Shin 2018), especially in countries with underdeveloped financial systems like Brazil (Cavalcanti et al. 2021). This paper provides the first empirical evidence on the long-run effects of a large innovation subsidy program in a developing country, showing that it led to a persistent expansion in firm size, not through high-impact innovations, but by facilitating entry into markets protected from foreign competition.

In the past 20 years, Brazil has operated a large-scale R&D subsidy program, providing over 10 billion US dollars to 1,454 firms. One of these firms is Eurofarma, a pharmaceutical company that used the subsidy to launch a biotechnology lab (Finep 2015). Rather than develop a novel drug, Eurofarma used the subsidy to create its own version of filgrastim, a widely studied compound previously imported from the US and Europe¹. Although the drug was already known, it was the first time that a company in Latin America replicated its production process (Gabi 2016). Despite not being a breakthrough innovation, the product allowed Eurofarma to grow rapidly, capturing the Brazilian and South American markets from foreign competitors in part due to Eurofarma’s competitive edge: as a domestic producer, Eurofarma did not face the 14% import tariff that applied to its foreign competitors.^{2,3}

This paper shows that the case of Eurofarma reflects a broader pattern. Using a matched difference-in-differences design comparing near-winners with near-losers within the same

¹Filgrastim was first patented in 1991 by the US company Amgen. The patent expired in 2013. According to Caruso (2016), Eurofarma’s filgrastim is similar to the original drug in terms of identity, structure, purity, stability, and bioactivity.

²Filgrastim is a biological product that has to be refrigerated, making its long distance transportation more costly.

³According to Panorama Farmacêutico (2023), Eurofarma grew 13% in 2022 and expanded its biological line to other countries in South America.

grant competition, we find that an R&D subsidy has produced a persistent expansion in firm size: fourteen years after receiving the subsidy, recipient firms maintained wage bills and exports more than 59% higher than comparable non-recipients. The effects were most pronounced among small and young firms facing high interest rates, but they had no impact on quality-weighted innovation. Tracing the mechanism, we find that firms used the subsidy to import advanced machinery, introduce new products in high-tariff markets, and file patents that disproportionately cite inventions from advanced economies. These products were then exported to developing countries that imposed high import tariffs against developed countries but low or zero tariffs against Brazil, while never penetrating the markets of developed countries. Overall, the evidence suggests that the program relaxed financial constraints and enabled the adoption of foreign technologies in high-tariff product lines, promoting firm growth through import substitution rather than through frontier innovation. These findings highlight the significance of financial constraints, the complementarities between industrial policy tools, and the importance of foreign technology adoption for firm growth in developing countries.

The R&D subsidy in Brazil is administered by the Funding Authority for Studies and Projects, a public agency that allocates subsidies through thematic calls for projects, each focused on narrowly defined products or technologies. The topic of each call is selected by a sector-specific technical committee, which is advised by external consultants and academic researchers, targeting emerging technologies in each sector. Proposals are evaluated by panels of anonymous academic experts using predetermined scoring criteria, ensuring selection based solely on technical merit. After receiving subsidies, firms have two years to complete their projects under close government oversight, including live bank audits, expense reports, customized cost-tracking software, and dedicated audit teams. This institutional framework limits political discretion and enforces the execution of funded projects.⁴

To identify the long-run effects of the innovation subsidy, we first assemble a comprehensive firm-level panel that tracks every Brazilian company across innovation, trade, employment, credit, and subsidy application. We link five administrative sources: (i) all R&D

⁴The Funding Authority is designed to be institutionally insulated from political influence: its budget is fixed as a share of federal tax revenue; it is audited by four independent agencies; and it is governed by a board drawn largely from academia.

subsidy applications since 2000 from the Funding Authority; (ii) patent and trademark filings from the Brazilian Patent Office; (iii) customs records on exports and imports; (iv) worker-level data from the matched employer–employee RAIS dataset (*Relação Anual de Informações Sociais*); and (v) the Brazilian credit registry, a confidential loan-level database covering all credit operations. We also identify patent inventors in RAIS, allowing us to obtain information on their wages, education, and experience, which we use to infer the quality of their patent. This dataset allows us to measure how the subsidy affected international trade, employment, and credit up to fourteen years after firms received it.

The data reveal that subsidized projects are far larger than what firms typically finance through bank credit or internal resources. First, the subsidy is sixty-six times greater than the investment loans these firms obtain from banks, showing that the subsidy is much larger than a typical project funded by the banking sector. Second, on average, the award is ten times the annual payroll of recipients, making the projects large relative to internal cash flows. Third, firms face spreads of 24% per year, which is common in the Brazilian banking system, where the average spread is 45% (Cavalcanti et al. 2021). Taken together, these facts suggest that recipients would have difficulties financing the subsidized project through internal liquidity or conventional bank credit.

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 variables that correlate with the government’s technical criteria for subsidy allocation. We allow several unmatched years and covariates to test the assumption of parallel trends between control and treatment firms.

We validate the identification strategy through four exercises. First, we show that treatment and control firms are similar on a wide range of unmatched characteristics, including workforce composition, research team quality, project quality, sectoral distribution, and areas of specialization. Second, we find no correlation between subsidy receipt and measures

of political connection, suggesting that allocation was not influenced by political factors. Third, a battery of placebo tests confirms that the results are unlikely to be driven by spurious correlations. Fourth, we show that pre-period parallel trends hold for the main variables of interest. Together, these checks support the view that differences in growth after the subsidy are likely driven by the program itself rather than confounding trends.

Our first finding is that the R&D subsidy triggered a large and persistent expansion in firm size. On average, recipient firms increased employment by 27% and the wage bill by 26%, while also expanding their number of establishments, geographic coverage, and exports. These effects persisted over time: fourteen years after receiving the subsidy, treated firms were 59% larger than control firms. This effect was strongest among small and young firms facing higher interest rates and generated no crowd-out of private credit, suggesting that the subsidy promoted growth by easing financial constraints.

Our second finding reveals that, despite firm expansion, the subsidy led to only modest innovation gains. Firms increased scientist hiring by 36% and patenting by 10%. However, the subsidy had no effect on patent citations, citation-weighted patents, workforce skills, research team quality, or patenting by highly paid or highly educated inventors. Most new research hires came from technician or operational roles with little prior innovation experience. These results suggest that, unlike in developed countries, the R&D subsidy is not driving growth through frontier innovations.

A potential explanation for this disconnect between firm growth and innovation quality is that firms expanded by introducing new products into markets protected by high import tariffs, allowing them to grow in the shadow of protection. Consistent with this product-line expansion, we find that the subsidy led to more product rather than process patents, broadened the range of inputs imported and goods exported, and increased patenting and trademarking in new classes. This expansion was concentrated in high-tariff markets. Using a concordance between patent classes and product codes, we find that firms were more likely to patent and export products only in the top quartile of import tariffs in Brazil, with no effect on low-tariff goods. As in the Eurofarma case, these patterns offer a plausible explanation for how firms grew despite producing low-quality innovations: high import tariffs protected them from competition with firms at the frontier of knowledge.

Our fourth finding is that firms used the subsidy to adopt foreign technologies and expand into protected export markets. The subsidy increased imports of high-tech machinery from Europe and North America and raised patent citations to those regions, indicating the adoption of technologies from developed countries. On the export side, the subsidy increased sales to countries with high tariffs against Europe or North America, but not to these countries directly. More than a decade later, firms have not penetrated developed-country markets, suggesting that their incremental innovations cannot compete with frontier technologies. Overall, the evidence suggests that the subsidy allowed financially constrained firms to adopt foreign technologies and expand into protected, high-tariff markets.

We conclude by translating the estimated employment effects into a metric of the tax return of the subsidy. Using the identified effect of the subsidy on wage bills, we calculate the tax return as the present value of payroll taxes generated by the subsidy divided by the value of the subsidy itself.⁵ Because the subsidy generated a large and persistent increase in firm size, the estimated return ranges from \$1.01 to \$5.50 per dollar across all alternative calibrations. Therefore, counting only payroll tax revenues, the results indicate that the subsidy likely paid for itself.

These conclusions are consistent across several robustness checks. First, a control-function approach that includes all applicants, not just marginal winners and losers, delivers similar results, indicating that the effects are not constrained to firms at the cutoff. Second, adding measures of managerial skill, research team strength, and project quality to the matching strategy gives the same conclusion, suggesting that the results are not driven by differences in project quality. Third, matching on sectors or longer horizons does not change the conclusions, indicating that they are not driven by sector-specific shocks or trends. Fourth, using labor inspections and fines to infer informal hiring shows that informality does not account for the results. Finally, the conclusions are the same under alternative treatments of zeros (Chen and Roth 2023). Across all these exercises, we conclude that the subsidy led firms to expand not through breakthrough innovations but by introducing new products in

⁵This metric assumes that other firms are not affected by the subsidy and that it generates no general equilibrium effects. Those are strong assumptions that are unlikely to hold. Still, this is a useful exercise for comparing the gains of the program to its size. Extending the method of Bloom et al. (2013), we find no evidence that the subsidy generates knowledge spillovers or market-rivalry effects on other Brazilian firms, which supports the idea that the subsidy has only weak effects on other firms.

high-tariff markets.

This paper contributes to the literature on industrial policy by documenting the long-run effects of an R&D subsidy and tracing the mechanisms behind these effects. In developed economies, R&D subsidies have been shown to increase innovation, accelerate technology adoption, and create spillovers to neighboring firms (Hirvonen et al. 2022, Fieldhouse and Mertens 2023, Andrieu and Morrow 2024). These benefits are typically concentrated among smaller, financially constrained firms (Bronzini and Iachini 2014). Similarly, subsidy programs have been found to generate firm growth, though often at the cost of increased misallocation (Choi and Levchenko 2021, Kim et al. 2021, Lee and Shin 2023, Manelici and Pantea 2021). Garin and Rothbaum (2024) and Choi and Levchenko (2021) find positive effects of industrial policies in the long-run. In developing countries, policies that promote the adoption of foreign technologies have generated lasting gains in productivity and firm performance (Juhász 2018, Giorcelli 2019, de Souza et al. 2024).

We make two contributions to the literature on industrial policy. First, using firm-level microdata from multiple sources and a quasi-experimental design, we provide new evidence that a large-scale innovation subsidy in a developing country can lead to long-run firm growth. Second, we move beyond average effects to trace the mechanisms behind this growth, showing that the subsidy worked in combination with trade protection and alleviated financial frictions. This interaction between industrial policies has not, to our knowledge, been documented before.

This paper is also related to the literature on the role of financial constraints in development. Mostly based on quantitative models, this literature argues that financial constraints are a major barrier to growth in developing countries (Shin 2018, Buera et al. 2020, 2011, 2014, Kaboski and Townsend 2011). Beyond limiting productivity through selection into entrepreneurship, financial constraints also lead to lower accumulation of high-productivity machinery (Caunedo and Keller 2021). Using the same bank loan dataset that we use, Cavalcanti et al. (2021) finds that Brazilian firms face an average loan spread of 45% and that removing frictions in the banking sector would increase GDP by 39%. We contribute to this literature by studying an intervention that alleviated financial constraints, enabling firms to make substantial investments in capital and R&D to adopt foreign technologies. Our results

provide empirical causal evidence for the importance of financial constraints in development.

This paper is organized as follows. Section 2 outlines the design of the innovation subsidy program in Brazil, which allocates funding through multiple calls for projects, each governed by a set of technical criteria. Section 3 describes our data sources. In Section 4, we present the identification strategy, which is a matched difference-in-differences approach comparing near-winners to near-losers within the same call. Section 5 presents the main finding: the R&D subsidy program in Brazil drove firm growth by facilitating the entry of financially constrained firms into high-tariff markets with technologies adopted from developed countries. Section 6 examines alternative mechanisms, such as knowledge spillovers, but finds them largely irrelevant to the main result. Section 7 demonstrates that our findings are robust across a wide range of matching and identification strategies. Section 8 concludes.

2 Institutions

In this section, we describe how the Brazilian innovation subsidy program is designed to safeguard technical decision-making and ensure accountability. There are four relevant features. First, political discretion is limited: the Funding Authority’s budget is a fixed share of federal tax revenue, its leaders come mainly from academia, and four independent bodies audit its actions. Second, topic selection is narrow and technical: sixteen sectoral committees, advised by consultants and researchers, define project calls targeting specific products or technologies. Third, allocation is merit-based and insulated from influence: firms submit detailed proposals that are scored by a panel of anonymous experts using preannounced criteria, and awards go to the highest-ranked projects. Fourth, use of funds is tightly controlled: projects must be completed within two years; disbursements flow through a jointly controlled account; expenditures are tracked in real time with standardized software; and firms file semiannual reports under threat of penalties for misuse. Together, these safeguards limit political interference, base decision-making on technical merit, and enforce strict spending controls. In the empirical section, we exploit this institutional setting to identify the causal effect of the subsidy.

The Funding Authority for Studies and Projects runs the R&D subsidy program.

It supports innovation by offering grants and subsidized credit for the development of new products, services, and processes. The Funding Authority is divided into 16 sectoral technical committees, each responsible for evaluating and managing projects in their field. Both the Authority’s budget and the budgets of its committees are set as fixed proportions of federal revenue. This legal structure protects the program’s funding from political discretion and interference from other areas of the government.

Technical leadership and expert committees. Since its creation, the Funding Authority and its technical committees have been led by technical experts (Carlotto and de Toledo 2024, Dias and Serafim 2011). All the presidents from 2000 to 2015, the period of analysis, held doctoral degrees and were hired directly from academic positions.⁶ The Authority’s sixteen technical committees follow the same principle, drawing members from universities, government agencies, and research institutes.⁷

Institutional autonomy with strict oversight. The sixteen sectoral technical committees have the autonomy to define which topics within their sectors receive R&D subsidies, but this autonomy is contained within a framework of strict oversight to ensure technical decision-making. The Funding Authority has to justify its actions to four separate regulatory agencies. As a public enterprise, it must publish annual financial statements along with a detailed list of funded projects and the criteria used for selection.⁸ Oversight is reinforced by the National Fund for Scientific and Technological Development, a separate agency that monitors all subsidies granted by the Funding Authority. Each year, the Authority must submit technical justifications for each call for proposals, detail how funds were allocated, and report on the progress of subsidized projects. As part of the Ministry of Science, the Funding Authority submits yearly reports to the Ministry. Finally, because it administers subsidized credit, it must comply with Central Bank regulations on credit risk and submit

⁶See Table A1, in the Appendix, for a list of the presidents of the Funding Authority and a description of their qualifications.

⁷Each committee member serves a fixed two-year term to ensure broad representation from the scientific community.

⁸It is also subject to the random audits studied by Avis et al. (2018).

annual risk assessments for all subsidized loans. Together, these layers of oversight ensure that decision-making remains transparent and guided by technical merit.

Selection of calls for projects based on input from external consultants. Each year, the sixteen sectoral committees commission independent studies to identify emerging technologies and strategic priorities within their domains.⁹ Based on these studies, each committee publishes a public report outlining its recommended priority areas and providing a technical justification for each area.¹⁰ Using these reports, the committees submit to the Funding Authority a proposed list of calls for projects, along with suggested selection criteria. Over the following year, the Funding Authority opens these calls for projects if enough funds are available.¹¹

The application process includes a technical proposal and a business plan. Once a call for projects is open, firms can apply to the Funding Authority, which evaluates submissions based on technical merit. Applicants submit a package of documents, including a technical proposal, a business plan, balance sheet history, and compliance certifications.¹²

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

⁹These studies are often conducted by the Center for Strategic Studies, a federal research agency (Centro de Gestão e Estudos Estratégicos (CGEE) 2010).

¹⁰For example, in 2002, the Energy Committee prioritized renewable energy and energy efficiency in its proposed calls (de Macedo, Isaias Carvalho 2002).

¹¹According to Dias and Serafim (2011), the academic community in general is the main determinant of the agenda of technology policy in Brazil, including the Funding Authority.

¹²According to Cirani et al. (2016), who interviewed managers at firms that received the subsidy, the application package includes detailed technical and personnel information.

degree of innovation compared to solutions already 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 five years.

Applications are evaluated by a board of anonymous experts. Each application is evaluated by a board of technical experts through a single-blind process, mimicking the peer-review system used in academic publishing. For each call, the overseeing sectoral committee appoints an anonymous evaluation board composed of specialists from the Funding Authority, the Patent Office, government agencies, and academia. All members sign confidentiality agreements, and their identities remain undisclosed, even after the evaluation process concludes.¹³

Applications are ranked according to a set of technical criteria. Each proposal is reviewed by all evaluators, who assign scores based on a set of predefined technical criteria. To support their evaluations, reviewers also write a report explaining the reasoning behind each score. The final score is the weighted average across all criteria and evaluators.

Although the specific criteria and their weights vary by call, three criteria are more common, according to Table 1: feasibility, team quality, and inventiveness.¹⁴ The first is project feasibility. Proposals with a clear methodology and realistic timeline are more likely to be approved. The objective is to discard projects that are unlikely to be completed. The second is the quality of the research team and the firm’s prior innovation experience: firms with highly qualified scientists and a proven track record tend to score higher. The third is inventiveness. Projects that propose novel, original solutions get a better score than those that replicate existing technologies. Table 1 describes the weights in the three most common criteria for a sample of calls for projects available online. It is important to highlight that no calls give additional weight to proposals targeting high-tariff markets.

¹³Finep (2025) is the only documented instance in which the Funding Authority disclosed the number of evaluators involved. In that case, eighteen technical specialists assessed twenty-one project proposals.

¹⁴In some calls for projects, the selection process has two stages. The first is eliminatory, where proposals deemed unfeasible are excluded. The second is classificatory, where each remaining project receives a score based on technical criteria. To ensure comparability across all calls, Table 1 assigns equal weight to the feasibility component, even when it appears as part of the eliminatory stage.

Table 1: **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 calls for projects. The sample is composed of calls 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. In some calls for projects, the selection process has two stages. The first is eliminatory, where proposals deemed unfeasible are excluded. The second is classificatory, where each remaining project receives a score based on technical criteria. To ensure comparability across all calls, we assigns equal weight to the feasibility component, even when it appears as part of the eliminatory stage. 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.

Subsidy covers fixed costs and firms have two years to finish their projects. 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%. The repayment plan of these loans usually includes negative real interest rates, and firms only start paying them back after the project is running. 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 operational workers.

Strict enforcement and oversight of subsidy use. Firms receiving the subsidy are subject to close scrutiny by the Funding Authority throughout the project. Funds are disbursed in multiple installments and held in a joint bank account shared by 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. This structure gives the Funding Authority direct, real-time oversight and control over all financial transactions. Misuse of these funds can be quickly addressed by blocking this joint account.

Subsidy installments are released in accordance with the project’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 (Cirani et al. 2016).

To ensure transparency, firms must submit detailed financial reports every six months and before each new installment. These reports must justify every transaction in the joint account, linking each expense to the original project and including corresponding receipts. To support this process, the Funding Authority provides its own expense-tracking software. Each technical sectoral committee oversees the project implementation and reports to the agencies overseeing the Funding Authority the progress in each project (MCTI 2024).

Fines and charges for misuse of the subsidy. Firms found misusing or misreporting funds must repay all grants received from the Funding Authority and face a 10% fine on the total subsidy amount. The firm is also barred from future applications to calls for projects, and managers are held 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. We leverage this dataset to examine how the subsidy impacts firm innovation and growth. We use credit data to study whether the effect of the subsidy is larger for financially constrained firms.

Matched Employer-Employee. Labor data come 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, 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 efforts. According to Goolsbee (1998), expenditures on scientists constitutes most of the R&D spending. To construct a consistent measure of R&D workers, we call a scientist any worker who has ever been employed in an R&D occupation or who holds a PhD. We use data ranging from 1995 to 2015.

R&D subsidy applications and reciprocity. We use administrative data on all R&D subsidy applications managed by the Funding Authority for Studies and Projects from 2000 onward. This dataset contains information identifying 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.

SCR Credit Registry. Credit data come from SCR (*Sistema de Informações de Crédito*), a system that contains information received by the Brazilian Central Bank (BCB) on each credit contract. We observe 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, a new plant, or R&D expenditures, or working capital. Systematically consistent data are available since 2004.¹⁵

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 subsidies (Howell 2017, Bronzini and Iachini 2014). Departing from them, we also study how innovation subsidies affect product

¹⁵Between 2004 and 2012, the dataset contains all loans by financial institutions to clients with more than US\$ 1,732 in in total loans. The reporting threshold, set in local currency, has fallen over time, reaching currently less than US\$40. Given the size of the firms in our sample, none of these thresholds are binding. All confidential information from SCR was handled exclusively by BCB staff.

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.

Exports and imports. We use administrative data from SECEX (*Secretaria de Comércio Exterior*) covering the universe of firm-level exports and imports recorded in customs data. The dataset reports, for each transaction, the firm identifier, product at the 8-digit Harmonized System (HS) level, country of origin or destination, value, and weight. The data have been used by others to understand firms’ exporting decisions (Helpman et al. 2016). The data are available from 1995 to 2007. We use this data to understand penetration in international markets, measure the span of products produced by firms, and to identify the markets that firms have entered.

3.2 Facts of R&D Subsidy in Brazil

This section presents four key facts about the R&D subsidy. First, the subsidy is large: on average, it is ten times a firm’s annual wage bill, meaning a single grant can fund projects that require heavy capital and R&D investments. Second, the projects supported by the subsidy are 66 times larger than those financed through banks, suggesting that the banking system usually does not support projects of comparable scale. Third, the firms applying for these subsidies face high borrowing costs, with a credit-weighted spread of 24%. These conditions are not specific to the firms applying for the subsidy, they reflect the nationwide borrowing frictions documented by Cavalcanti et al. (2021). Fourth, while most grants go to manufacturing, they span a broad range of products and show no correlation with import tariffs, suggesting the Funding Authority does not target high-tariff products. Together, these facts suggest that the R&D subsidy is a major cash infusion for firms operating under tight credit constraints that otherwise struggle to fund innovation.

R&D subsidy is 10 times the yearly wage bill. Table 2 shows statistics on the innovation subsidy. The median innovation subsidy is worth 1 million dollars, with an average of \$5.7 million dollars. Relative to firm size, the average ratio of the subsidy amount to the

annual wage bill is 10. Therefore, compared to firm size, the subsidy provides a relatively large capital injection to firms.

Table 2: **Statistics of R&D Subsidy and Credit Access**

Statistic	Value
<i>Subsidy</i>	
Number of Subsidies Awarded	2,299
Median Subsidy Amount (thousand USD)	1,193
Median Annual Wage Bill (thousand USD)	2,340
E [Subsidy/Yr. Wage Bill]	10.18
<i>Credit Access</i>	
E [Investment Loans/Yr. Wage Bill]	0.15
Average Interest Rate on Bank Loans	33.15%
Average Interest Rate Spread on Bank Loans	24.23%

Description: This table reports summary statistics of R&D subsidies in Brazil. It shows the number of subsidies granted, the average subsidy amount, the average yearly wage bill of recipient firms, and the ratio of subsidies and investment loans to yearly wage bills. Data come from the Funding Authority for Studies and Projects and cover all subsidies granted between 2000 and 2020. Subsidy and wage bill amounts are expressed in 2010 U.S. dollars. Investment loans are measured as the total debt in investment bank loans in the year prior to the subsidy application, while the wage bill refers to the firm's total payroll in that same year. All firm statistics are calculate the year prior receiving their first subsidy.

R&D subsidies are 66 times larger than bank loans. Figure 1 and Table 2 compare R&D subsidies to investment loans from banks. As shown in the second panel of Table 2, firms that later received a subsidy had, on average, investment loans amounting to just 15% of their annual wage bill in the year prior to their first application.¹⁶ Figure 1 illustrates the distribution of investment loans and R&D subsidies relative to firm's wage bills. Bank loans rarely exceed a firm's annual wage bill, whereas most R&D subsidies are substantially larger. This difference indicates that the projects supported by the R&D subsidy are far larger than those that the Brazilian banking sector typically finances among this set of firms.

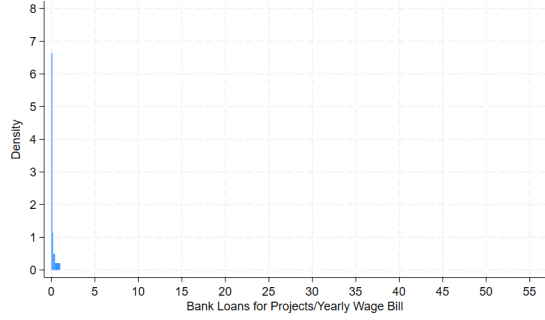
Applicants are financially constrained. The last two rows of Table 2 show the borrowing costs of subsidy applicants at baseline. Their credit-weighted spread is 24% per year, below Brazil's average of 45% reported by Cavalcanti et al. (2021) but far above levels abroad, such as 3% in the U.S. and 7.5% in Argentina.¹⁷ These high borrowing costs point

¹⁶We classify bank loans as working capital or investment using a detailed credit category classification from the credit registry.

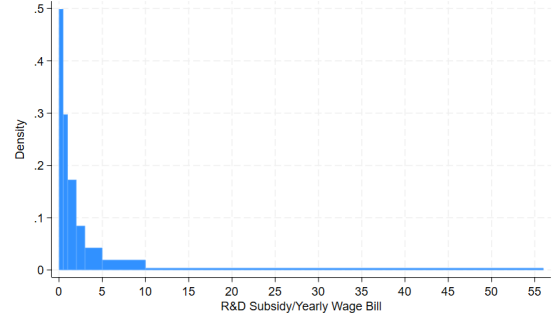
¹⁷According to data from the International Financial Statistics database for 2024.

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 presents the distribution of investment bank loans and R&D subsidies relative to firms' wage bills, winsorized at the 95th percentile. Panel (a) shows the distribution of investment-related bank loans, while panel (b) shows the distribution of R&D subsidies. The sample consists of firms applying for R&D subsidies, with statistics computed in the year prior to their first subsidy application. Investment loans are defined as the total debt in investment bank loans in the year before the first subsidy application, while the wage bill refers to the firm's total payroll in that same year..

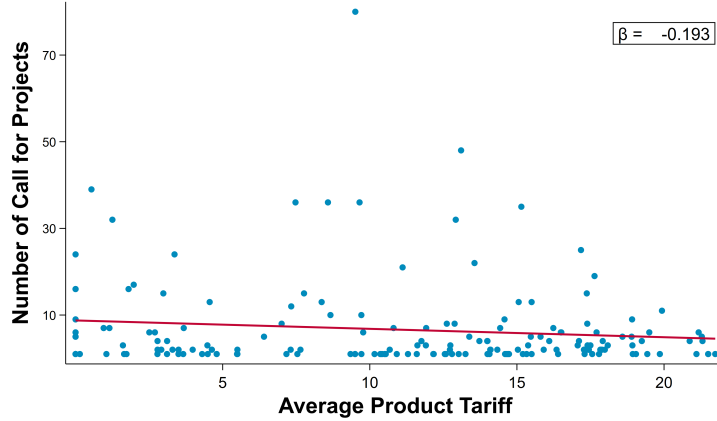
to binding credit frictions that could make large R&D investments prohibitively expensive.

R&D subsidy targets manufacturing and does not correlate with tariffs. Figure B1 in the Appendix shows that most R&D subsidies go to firms in the manufacturing sector. Within manufacturing, chemicals and machinery account for the largest shares (Figure B2).

Since the subsidy spans such a broad range of manufacturing sub-sectors, there's no meaningful correlation between it and import tariffs, as shown in Figure 2. To build this figure, we linked calls for projects to the Harmonized System (HS) product codes they could support, then compared the number of calls per product to Brazilian import tariffs in 2000. The data show no clear relationship between tariffs and the products targeted by the Funding Authority.¹⁸ Therefore, the increase in innovation directed to high-tariff markets that we observe in the results section cannot be explained by the Funding Authority targeting those sectors.

¹⁸Figure B3 uses all calls for projects and the sector of the subsidized firm to infer product coverage. It also finds no correlation between subsidies and the Funding Authority's project selection.

Figure 2: No Correlation Between Tariffs and Call for Projects



Description: This figure 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 B3 uses all call for project extracting tariff from the sector of the firm receiving the subsidy.

4 Empirical Strategy

The main identification strategy is a matched difference-in-differences design. It compares firms that narrowly won a subsidy with those that narrowly lost. Each “winner” (treatment) is matched to a “loser” (control) who applied to the same narrowly defined call for projects and was ranked similarly on the main variables used by the Funding Authority. Because these firms were nearly identical on observable characteristics, the subsidy allocation was almost a coin toss. The effect of the subsidy is identified from the differential growth between treatment and matched control after the subsidy grant.

To validate the identification strategy, we conduct several exercises. First, we demonstrate throughout the analysis that pre-period parallel trends hold for all key outcomes, satisfying the usual difference-in-differences test. Second, we show these matched firms are also comparable across numerous unmatched characteristics, including the quality of their workforce, their research team, their project, sectoral distribution, and areas of specialization. Third, placebo tests assigning “fake” subsidies at alternative times or to other firms produce null results, indicating that the results are unlikely to be driven by confounding from sector-specific or time-specific shocks. Taken together, these checks reinforce confidence that any post-subsidy divergence between treatment and control reflects the causal impact of the subsidy.

We also test whether political connections influenced the allocation of subsidies. First, we show that the variables used in the matching procedure predict subsidy receipt with approximately 70% accuracy, and that adding indicators of political connection does not improve this predictive power, indicating that political ties do not help firms receive a subsidy. Second, we show that subsidized firms are not more likely to make campaign contributions or receive other benefits from the government. Third, using data on the employment trajectories of the Funding Authority staff, we find no evidence of “revolving door” political capture, i.e., no systematic pattern of firms hiring former agency employees. Together, these tests suggest that the allocation of subsidies was mostly driven by the observable project criteria already controlled for and not by political connections, which is consistent with the lengthy discussion in the institutional settings section.

4.1 Matching on Subsidy Allocation Criteria

Although winners and losers of a call for projects are different in most cases, there are cases in which some firms won or lost a subsidy by a narrow margin. In these cases, marginal winners are similar in many dimensions to marginal losers. We identify the effect of the innovation subsidy by comparing the change in outcomes between narrow winners and narrow losers in the set of calls for projects that were narrowly decided. This identification strategy assumes that the only systematic difference in growth rates between marginal winners and losers after the application is the subsidy itself. We validate this assumption by checking pre-treatment trends, comparing unmatched variables, and conducting placebo tests for unobserved shocks.

We match treatment to control firms at their first subsidy application using coarsened exact matching following Iacus et al. (2012). Each treatment firm j that receives an innovation subsidy in year t is matched to a set of firms, $g(j)$, that applied for the same call for projects but did not receive the innovation subsidy and were similar on a set of matching variables.¹⁹

¹⁹In practice, this is how we implement the matching, which follows Iacus et al. (2012) closely and is the standard in the literature (Furman et al. 2021, Cabel 2020, Gumpert et al. 2023). We begin by identifying all firms applying to a given call for projects in the year t that are making their first subsidy application. For these firms, we discretize the matching variables using data from year $t - 1$. Firms are then grouped based on their exact position in the discretized grid for each variable—meaning that all firms within a group share the same values across all discretized dimensions, although there are small differences in the continuous variables matched. We retain only the groups that include at least one treated and one control firm. Following Iacus et al. (2012), we also recover the weights used for each matched group. These weights guarantee that groups

The group $g(j)$, therefore, contains a set of approximately similar firms that applied for the same call for projects in year t , with only one of them receiving the innovation subsidy.²⁰

Using data from the year prior to the subsidy application, we match firms on 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 value of the subsidy grant requested. The number of employees and the value of the subsidy grant requested measure a project’s technical and financial development, while the number of patents and number of citations received measure the quality of the research and the degree of inventiveness of the firm. In the baseline specification, we do not match within sectors because most project calls are sector-specific.

Figure C5 shows that different machine learning models using only the four matching variables can explain up to 70% of the variation in subsidy allocation.²¹ Adding indicators of political connectedness or other firm characteristics does not improve predictive accuracy and, in some cases, reduces it due to overfitting. This suggests that the parsimonious set of matching variables strongly correlates with the criteria used by the Funding Authority in allocating subsidies. Furthermore, as discussed in the previous section, it strengthens the idea that there is little political interference in the allocation of subsidies, which we test further in Section 4.4.

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 in the two years before the 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 executive team’s quality), the project quality measures, and the sector. For additional information, see Section 7.

$g(j)$ with multiple controls do not have more weight in estimation.

²⁰We limit the sample to firms that are making their first subsidy application in t . This is a common assumption in this setting because future subsidy applications might be affected by the first subsidy grant. Therefore, we are identifying the effect of the first subsidy grant. We isolate the effect of subsequent grants in the robustness section and Appendix E.2.

²¹The matching variables aim to capture the feasibility, capacity, and inventiveness of firms’ projects, which are the top three most important criteria. However, as Table 1 shows, these criteria account for only 79% of the total score of the firm. Therefore, it is unlikely that these variables alone could perfectly predict subsidy grant.

4.2 Balance Test

In this subsection, we show that treatment and control firms are similar in the composition of their workforce, firm characteristics, quality of the research team, quality of the research project, area of specialization, sector, and geographical distribution, which strengthens the identification strategy for two reasons. First, firms' similarity in the quality of their workforce, research team, and project makes it unlikely that differences in growth after the subsidy are driven by differences in innovation quality. Second, because firms are also similar on a wide range of other characteristics, it is more credible that the subsidy itself, not pre-existing differences, explains any divergence in outcomes after the subsidy.²²

Table 3 shows the differences between control and treatment groups in a reduced set of untargeted moments.²³ We leave to Tables C3 to C6 in the Appendix a balance test on a larger set of variables. We discuss these tables in detail below.

Treatment and control have workers of the same quality. The first panel of Table 3 shows that workers in treatment and control firms have similar wages and education levels on average, suggesting they employ workforces of comparable quality. Table C3, in the Appendix, reinforces this conclusion: the two groups also match on hourly wages, gender ratios, task composition, and the number of workers across different educational backgrounds.

Treatment and control have researchers of the same quality. The second panel of Table 3 shows that research teams in treatment and control firms have similar average wages and education levels, indicating that both groups have comparable capacity to develop and implement new ideas. Table C4 reinforces this conclusion: the two groups also match in the demographic composition of scientists, team size, total wage bill for scientists, and areas of specialization.

²²In Table C7, in the Appendix, we show that matched and unmatched firms are similar in number of employees, number of patents, subsidy value requested, workforce composition, and project quality metrics. However, they differ in the characteristics of their research team. To address concerns about external validity, in Section E.5.1 we apply a control function approach that uses the full sample of applicants.

²³Table C2 in the Appendix shows that firms are comparable on the targeted variables.

Table 3: Treatment and Control are Similar on Several Untargetted Moments

	(1) <i>Treatment</i>	(2) <i>Control</i>	(3) <i>(2) - (1)</i>
Worker Composition			
Avg. Wage	2,392.74 (1,548.96)	2,367.45 (2,147.76)	-25.29 (0.88)
Avg. Yrs. of Education	11.52 (1.85)	11.50 (2.03)	-0.02 (0.94)
Quality of Research Team			
Avg. Wage of Researchers	7,863.94 (4,941.63)	7,430.36 (5,150.53)	-433.58 (0.43)
Avg. Yrs. of Educ. of Researchers	14.77 (1.68)	15.07 (1.67)	0.30 (0.10)
Quality of Project			
Flesh-Kincaid Index	-1.07 (47.44)	-0.91 (52.27)	0.16 (0.97)
Implied Project Market Value	1.12 (0.47)	1.13 (0.45)	0.01 (0.94)
Implied Project Scientific Value	0.58 (0.22)	0.59 (0.25)	0.01 (0.70)
Score by AI Expert Evaluator	2.42 (1.01)	2.30 (1.05)	-0.12 (0.18)
Similarity with Past Patents	0.05 (0.09)	0.04 (0.09)	-0.01 (0.77)
Observations	208	324	532

Description: This table compares matched treatment and control firms on a reduced set of untargeted characteristics. Column 1 shows means for the treatment group, column 2 for the control group, and column 3 reports the difference. Standard deviations are shown in parentheses for columns 1 and 2, and p-values for the difference are reported in column 3. Asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Project market and scientific values are estimated following description in Appendix C.2. Appendix C.3 describes how the AI expert score is calculated. The variable *Avg. Wage* refers to the average monthly wage of all workers at the firm in 2010 Reais, while *Avg. Yrs. of Education* captures the average years of schooling of the workforce. The measure *Avg. Wage of Researchers* corresponds to the average monthly wage of employees in occupations related to R&D in 2010 Reais, and *Avg. Yrs. of Educ. of Researchers* reflects the average educational attainment among employees in occupations related to R&D. The *Flesh–Kincaid Index* is a readability score of the project’s title, where lower values indicate more technical language. The *Implied Project Market Value* represents the predicted stock market reaction to a hypothetical patent with the project’s title, whereas the *Implied Project Scientific Value* represents the predicted number of citations of such a patent. The *Score by AI Expert Evaluator* is an inventiveness score, ranging from 1 to 5, assigned by a large-language-model trained to mimic expert reviewers. Finally, *Similarity with Past Patents* measures the cosine text similarity between the project proposal and the firm’s prior patents.

Treatment and control have projects of the same quality. The third panel of Table 3 compares the quality of the projects proposed by treatment and control firms. As a first proxy, we use the Flesch–Kincaid readability score of each project’s title. In patent data, lower scores are associated with more technically sophisticated inventions and higher citation counts (Ante 2022, Kong et al. 2023). Treatment and control proposals have statistically similar scores, suggesting comparable levels of technical sophistication.

The third panel of Table 3 also estimates the scientific and market value of proposed projects using text analysis. Scientific value is defined as the expected number of citations a patent with that title would receive; market value is defined as the expected stock market response to such a patent. Appendix C.2 details the method used to generate these estimates, using data from Kogan et al. (2017), and shows that projects with higher scientific value are more likely to receive the subsidy. In both cases, treatment and control firms show no statistically significant differences, suggesting their projects were equally promising, both in research impact and commercial potential.

We complement these metrics with a score by a large language model (LLM) prompted to act as an expert evaluator. Using role prompting, we instruct the model to adopt the perspective of a specialist on the evaluation board. We provide it with the firm’s name, project description, all matching variables, the average wage and years of education of scientists, and the name and wage of the CEO.²⁴ We ask the model to evaluate each project on a scale from 1 to 5 based on its inventiveness. The model draws not only from the supplied information but also from prior knowledge it associates with the company, its scientists, and the CEO. In Section C.3, we detail the procedure and show that, in the full sample, the model’s scores predict which projects receive subsidies—suggesting it captures meaningful aspects of project quality. As Table 3 shows, treatment and control firms receive statistically similar scores from the AI evaluator.

The final line of Table 3 reports the text similarity between each firm’s project proposal and its prior patents. This measure captures how closely their projects build on past work. Treatment and control firms have the same score, indicating that both groups show similar continuity in their research agendas.

Treatment and control are of the same size. Table C5, in the Appendix, compares treatment and control firms on several measures of firm size. The two groups are similar in the number of establishments, total wage bill, exports and imports.²⁵

²⁴Role prompting is a technique in which the LLM is asked to adopt a specific role. Zhang and Soh (2023) shows that this improves performance of LLMs. We also use n-shot prompting suggested by Zhang and Soh (2023).

²⁵Table C5 reports a weakly significant difference in firm age at the 10 percent level. Given the number of balance checks performed, some spurious differences are expected to happen by chance. The observed

Treatment and control are distributed equally across regions, sectors, and fields of specialization. Figure C4, in the Appendix, compares the distribution of regions, sectors, and patent technical classes between treatment and control. It finds no meaningful differences across any of these dimensions, indicating that the groups are similarly distributed in geographic, sectoral, and technological terms. Table C6, in the Appendix, also shows that treatment and control are equally likely to have patents in high- or low-import-tariff classes.

4.3 Empirical Model

Main Empirical Model. The main empirical model is given by

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

where $y_{i,t}$ is an outcome of firm i , such as the log wage bill or number of citations, in year t , belonging to the match group $g(i)$. The term $\mathbb{I}_{i,t} \{Innovation\ Subsidy\}$ is a treatment dummy that switches on after the first subsidy application for treated firms, i.e., those that received the subsidy in year t ; for control firms, it remains zero throughout.^{26,27}

As discussed in Section 4.1, in the matched sample each firm i is assigned to a group $g(i)$ consisting of comparable firms that applied to the same call for projects. Therefore, $\mu_{g(i),t}$ is a group-year fixed effect that captures shocks common to all firms in matched group $g(i)$, such as general equilibrium forces, sectoral shocks, or the act of developing a research idea itself.²⁸ Intuitively, the $\mu_{g(i),t}$ fixed effect guarantees that each treated firm is compared

age gap is only two years, making it unlikely to drive any meaningful result. In the robustness section, alternative matching strategies eliminate this difference while preserving the main findings.

²⁶This specification does not exploit variation in the size of the innovation subsidy across treated firms. Instead, it estimates the effect of receiving the average subsidy. We favor this approach because it relies on a clean comparison between matched treatment and control firms that applied for similar subsidy amounts. In Section E.5.2, we show that results remain consistent when explicitly incorporating variation in subsidy size.

²⁷Some outcome variables, such as the number of citations or patent applications, can take a value of zero. Following standard practice in the innovation literature, we add one before taking the logarithm, so the estimated effect reflects the percentage change in one plus the outcome. All results are robust to alternative transformations, including the inverse hyperbolic sine—which approximates the logarithm while preserving zeros (Bellemare and Wichman 2020)—and a binary indicator for positive values.

²⁸As shown in Section 4.2, treatment and control are similar in a wide range of variables. Any shock to these variables should be captured by the $\mu_{g(i),t}$ fixed effect. Moreover, because they are equally distributed across sectors and regions, the fixed effect also captures general equilibrium effects.

only to its matched control firms, so identification comes from deviations within these tightly defined groups. Finally, the firm fixed effect μ_i absorbs all time-invariant differences between firms.

The sample is constrained to the matched treatment and control firms. Under the standard parallel-trends assumption, θ identifies the causal effect of the innovation subsidy on the outcome $y_{i,t}$. Standard errors are clustered at the firm level.

Extended Empirical Model. We extend the main empirical model to allow the effect of the subsidy to differ in the short, middle, and long-run:

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

where θ_{short} captures the effect of the subsidy during the first two years after the application, while the firm is still receiving the government support. By year three, most projects are complete and the funding has ended. As a result, θ_{mid} measures the medium-run impact, from one to three years after the subsidy ends. θ_{long} captures the long-run effect, defined as six or more years after the grant. Given the span of the data, θ_{long} is identified using variation extending up to 14 years post subsidy.

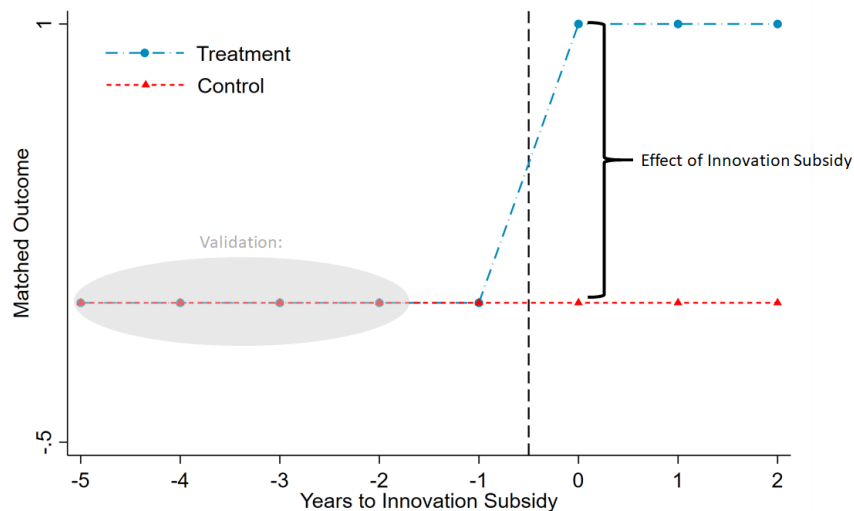
Dynamic Model. In difference-in-differences, the identifying assumption is parallel trends, i.e., if it were not for the innovation subsidy, $y_{i,t}$ would grow at the same rate across firms. To validate this assumption, we also estimate the following dynamic model:

$$y_{i,t} = \sum_j \theta_j \times \mathbb{I}_{i,t} \{j \ Yrs \ to \ Subsidy \ Application\} \times \mathbb{I}_i \{Treatment\} + \sum_j \alpha_j \times \mathbb{I}_{i,t} \{j \ Yrs \ to \ Subsidy \ Application\} + \mu_{g(i),t} + \mu_i + \epsilon_{i,t} \quad (3)$$

where $\mathbb{I}_{i,t} \{j \ Yrs \ to \ Subsidy \ Application\}$ is a dummy that takes one j years relative 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 for the parameter of interest, θ . The subsidy effect is identified by comparing the growth rate of the outcome variable $y_{i,t}$ between subsidized firms and observationally similar firms that applied to the same call for projects but were not selected. Because of the matching procedure and extensive balance checks, the two groups of firms are similar in the year before the subsidy. However, we deliberately leave several pre-treatment years unmatched, allowing us to test the assumption of parallel trends: if it holds, both firms should grow at similar rates in the years leading up to the subsidy application. The subsidy's effect is then identified from post-subsidy divergence: the change in the growth rate of $y_{i,t}$ for the funded firm relative to its matched, observationally similar, unfunded counterpart.

Figure 3: **Identifying Variation**



4.4 Validation

In this section, we describe three validation exercises. First, we implement a placebo test showing that results are unlikely to be explained by unobservable shocks that happen to correlate with a subsidy application. Second, the assignment of R&D subsidies does not correlate with campaign contributions or other industrial policies. Third, hiring former employees of the Funding Authority does not increase the probability of receiving the subsidy.

Placebo Test with Fake Treatment Group. To test whether results could be driven by shocks correlated with the subsidy grant, we implement two placebo tests. First, we exclude all treated firms and randomly assign a placebo treatment to firms whose projects were rejected. After that, we follow the previously described matching strategy but use the placebo treatment instead. In the second placebo approach, instead of random assignment, we distribute the placebo treatment to firms with similar numbers of employees, numbers of patents, numbers of citations received, and subsidy grant requested to those of the treatment group but whose projects were rejected. Tables C10 and C11 in the Appendix demonstrate that neither of these specifications predicts a correlation between placebo treatment and firm growth rates.

Political Connections. Table C12 provides two complementary checks against the possibility that our results are driven by political favoritism. First, the subsidy has no effect on campaign contributions, indicating that recipients are not paying politicians back for the subsidy. Second, subsidy receipt is uncorrelated with borrowing from BNDES, a state development bank that provides subsidized loans, has a strong connection to the ruling party, and has been the source of many corruption cases in the past (Sadami et al. 2024, Carvalho 2014). Taken together, the absence of both post-award contributions and BNDES borrowing suggests that the allocation of innovation subsidies is not embedded in a broader network of political exchanges.

Regulatory Capture. Another concern is regulatory capture. It’s possible that the Funding Authority may issue project calls targeting specific products to benefit a small set of firms. Research by Dal Bó (2006), Lucca et al. (2014), and Tabakovic and Wollmann (2018) highlights revolving-door employment—where industry insiders move between the agency and private firms—as a primary risk factor for regulatory capture. To test for revolving-door institutional capture, we identify firms with revolving-door connections to the Funding Authority, which we define as firms that have hired former Funding Authority employees or that have had workers who are now employed at the Funding Authority. Only 3.2% of firms have had such connections. Table C13 in the Appendix shows that these connections do not

correlate with success in subsidy applications.

5 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 technologies adopted from developed countries. We arrive at this conclusion with four results. First, we show that the subsidy led to a long-lasting increase in firm size that persisted for at least 14 years. This growth was most pronounced among firms with high credit spreads, suggesting that the policy alleviated binding financial constraints that had previously prevented investment.

Second, although the subsidy increased innovation efforts, it did not improve the quality of innovation: total citations received, citation-weighted patents, and inventor quality were not affected. This result is also confirmed by the characteristics of the scientists hired. Most were inexperienced, often with backgrounds as technicians or operational workers. This result suggests that firm growth was driven by incremental innovations rather than breakthroughs at the technological frontier.

Third, firms used the subsidy to expand their product lines into high-tariff markets, where tariff protection gave them a cost advantage over foreign competitors. The key evidence is that the subsidy increased patenting and exports only for products associated with high import tariffs in Brazil. Therefore, one interpretation of these results is that firms managed to grow, despite creating only incremental innovations, because of tariff protection.

Fourth, firms developed new products by drawing on ideas and inputs from developed countries, as shown by increased citations to foreign patents and imports of intermediate and machines inputs. Yet their exports were directed primarily to developing countries where the tariff structure shielded them from competition with advanced economies. Taken together, these patterns suggest that the R&D subsidy promoted growth not by fostering cutting-edge innovation, but by import substitution in protected markets, a result that contrasts with the findings for developed countries (Fieldhouse and Mertens 2023, Howell 2017).

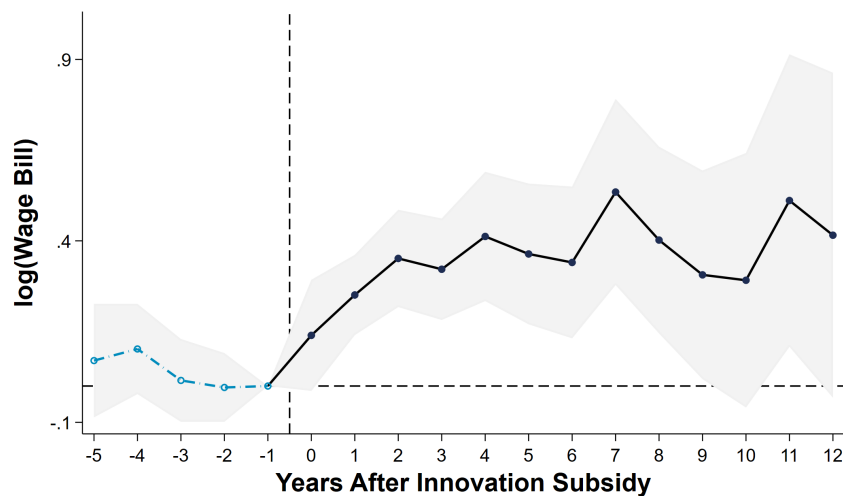
After understanding the subsidy’s mechanism, we estimate its return on investment. In our main calibration, for every dollar spent, the government collects \$2.20 in payroll taxes.

This high fiscal return comes from the large and persistent effect of the subsidy on the wage bill. We find no evidence of meaningful knowledge spillovers or displacement effects on other domestic firms, which is consistent with the idea that the subsidy replaced only foreign firms.

5.1 Persistent Firm Expansion by Relaxing Credit Constraints

Large and persistent increase in firm size. Figure 4 shows the effect of the subsidy on wage bills over time. We extend the estimates up to twelve years after the subsidy to understand its long-run effects. Naturally, estimates for later years are identified from firms treated early in the sample, reducing the effective number of observations and increasing standard errors. However, even with this loss of precision, the point estimates are remarkably stable in the long run.

Figure 4: **Innovation Subsidy led to Persistent Increase in Wage Bill**



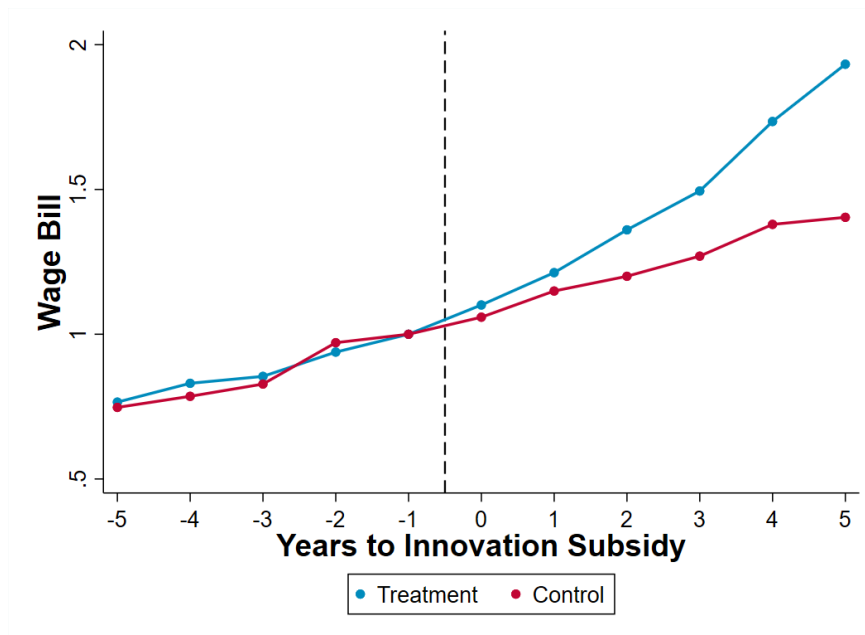
Description: This figure shows the dynamic effect of the innovation subsidy on firms' wage bill. Each dot is the estimated coefficient and the gray area is the 10% confidence interval. The x-axis measures the distance to the subsidy application and the y-axis the estimated effect of the innovation subsidy on the wage bill. Standard errors are clustered at the firm level, and the sample of firms is balanced between -5 and 5 years around the subsidy application.

Before the subsidy, treatment and control firms followed parallel trends, supporting the identifying assumption. In year 0, treated firms began receiving funds. During the following two-year implementation period, their wage bills grew faster than those of matched control firms. By year 3, the gap stabilized, with treated firms about 40% larger. Crucially, the gap persisted well beyond the end of public funding: a full twelve years after the initial

grant, treated firms still maintained a wage bill roughly 40% higher than that of otherwise similar applicants who did not receive the subsidy. Figure D6 in the Appendix extends these dynamic estimates to all coefficients that we can identify. The effect of the subsidy on firm size persists up to 14-years after the grant and increases over time to 59%.

Figure 5 illustrates the identifying variation by plotting the average wage bill of treatment and control firms, normalized to 1 in the year before the subsidy. Treated firms experience faster growth following the subsidy, while control firms continue along their pre-subsidy trajectory. This divergence shows that the estimated effect is driven by growth among recipients, not by a slowdown in control firms. The lack of any shift in the control group suggests there were only small general equilibrium effects. A likely explanation is that, since the identifying variation comes from a single firm receiving the subsidy, the shock is too small to generate equilibrium responses across the broader economy.²⁹

Figure 5: **Growth Identified from an Increase in Treatment Firms**



Description: This figure illustrates the identifying variation by comparing the evolution of average wage bills between treatment and control firms. Both series are normalized to 1 in the year before the subsidy application. The x-axis measures years relative to the subsidy application, while the y-axis shows the normalized wage bill. We include all innovation subsidies after 2003.

²⁹In Section E.1, we estimate the knowledge spillovers and market-rivalry effects of the innovation subsidy. We find no evidence of either effect, consistent with our main conclusion that the subsidy led firms to innovate inside the existing technological frontier and to expand into markets previously dominated by foreign competitors.

Table 4 corroborates the visual evidence by quantifying the subsidy’s impact on different metrics of firm size. Panel A reports average treatment effects: the R&D subsidy increased employment and the wage bill by 26% (Columns 1–2); the number of establishments by 11% (Column 3); the number of establishments in different cities by 6% (Column 4); and exports by more than 100% (Column 5). Taken together, these estimates show that the program generated a substantial and wide-ranging expansion in firm scale.

Panel B of Table 4 decomposes the average effect into three post-treatment horizons: short (0–2 years), medium (3–5 years), and long (6 years or more). The subsidy increased employment, wage bill, and exports even more than six years later, when the firm wasn’t receiving funds from the government. While the effect on the number of establishments remains economically meaningful, it is no longer statistically significant, likely due to increased variance from smaller long-run samples. These results reinforce the conclusion that the subsidy generated a large and persistent increase in firm size.

Table 4: **Subsidy Caused Wide and Sustained Firm Expansion**

	(1) <i>log(Workers)</i>	(2) <i>log(Payroll)</i>	(3) <i>log(Branches)</i>	(4) <i>log(Locations)</i>	(5) <i>log(Exports)</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	0.264*** (0.0922)	0.259*** (0.0954)	0.115** (0.0549)	0.0596** (0.0281)	1.329*** (0.435)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.236*** (0.0847)	0.210** (0.0868)	0.112** (0.0483)	0.0376 (0.0254)	1.182*** (0.456)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.287*** (0.102)	0.277*** (0.104)	0.119** (0.0603)	0.0875*** (0.0311)	1.722*** (0.658)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.317** (0.149)	0.356** (0.146)	0.115 (0.0845)	0.0633 (0.0443)	1.611* (0.922)
<i>N</i>	9,358	9,358	9,358	9,358	5,600

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 log of exports plus one. Because export values can be zero for many firms, we add one before taking the logarithm. Table E37 confirms the robustness of the results by using two alternative approaches to handle zeros: the inverse hyperbolic sine of exports, which approximates the log while preserving the zeros (Bellemare and Wichman 2020), and a dummy for whether the firm exports at all. All results point to similar conclusions. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Stronger effect among credit-constrained firms. According to Cavalcanti et al. (2021), there is a large variance in interest rates across firms due to frictions in the Brazilian banking sector, leading to some firms being able to access cheaper credit than others. Exploiting

this, we show in Table 5 how the subsidy’s effect varies with credit access. To measure credit access, we calculate each firm’s average credit-weighted interest rate on bank loans in the years leading up to the subsidy. We classify firms in the top tercile of this distribution as “credit constrained” and allow the effect of the subsidy to differ for them relative to other firms.³⁰ To address the fact that financially constrained firms applied for larger subsidies, we augment our baseline model in Panel B by interacting the subsidy indicator with the log of the subsidy amount requested. This metric captures the effect of the subsidy per log-dollar amount.

Table 5: **Effect of Subsidy is Larger in More Credit Constraints Firms**

	(1) <i>log(Workers)</i>	(2) <i>log(Payroll)</i>	(3) <i>log(Branches)</i>
<i>Panel A: Heterogeneous Effects by Credit Constrain</i>			
<i>Less Constr.</i> $\times \mathbb{I}\{\text{Subsidy}\}$	0.204* (0.109)	0.169 (0.112)	0.0980 (0.0825)
<i>Constr.</i> $\times \mathbb{I}\{\text{Subsidy}\}$	0.278** (0.110)	0.300** (0.117)	0.123 (0.0767)
<i>Panel B: Heterogeneous Effects of Subsidy Value by Credit Constrain</i>			
<i>Less Constr.</i> $\times \mathbb{I}\{\text{Subsidy}\} \times \log(\text{Subs. Val.})$	0.0134* (0.00708)	0.0121* (0.00721)	0.00644 (0.00537)
<i>Constr.</i> $\times \mathbb{I}\{\text{Subsidy}\} \times \log(\text{Subs. Val.})$	0.0206** (0.00825)	0.0228*** (0.00869)	0.0101* (0.00554)
<i>N</i>	4,219	4,219	4,215

Description: This table shows how the effect of the innovation subsidy varies according to firms’ access to credit. Firms are classified as “credit constrained” if they fall in the top tercile of the distribution of average loan spreads prior to subsidy application, and “less constrained” otherwise. Panel A estimates heterogeneous treatment effects by interacting the subsidy indicator with indicators for constrained and less constrained firms: $y_{i,t} = \theta_1 \mathbb{I}_i\{\text{Constr.}\} \times \mathbb{I}_t\{\text{Subs}\} + \theta_2 \mathbb{I}_i\{\text{Less Constr.}\} \times \mathbb{I}_t\{\text{Subs}\} + \mu_{g(i),t} + \mu_i + \varepsilon_{i,t}$. Panel B interacts these indicators with the log of the subsidy amount requested to estimate the effect of each additional log-dollar of subsidy across credit access groups: $y_{i,t} = \theta_3 \mathbb{I}_i\{\text{Constr.}\} \times \mathbb{I}_t\{\text{Subs}\} \times \log(\text{Subs. Value}_i) + \theta_4 \mathbb{I}_i\{\text{Less Constr.}\} \times \mathbb{I}_t\{\text{Subs}\} \times \log(\text{Subs. Value}_i) + \mu_{g(i),t} + \mu_i + \varepsilon_{i,t}$. The outcome variables in columns 1 to 3 are, respectively, the log number of workers, log of payroll, and log number of establishments. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 5 shows that firms facing higher interest rates, i.e., those more financially constrained, grew more than did firms with easier access to credit. Panel B of Table 5, which estimates the effect of the subsidy per log dollar, reinforces this result: credit-constrained firms increased employment, the wage bill, and the number of establishments at nearly twice the rate of firms with cheaper access to credit.

In Appendix D.2, we show that the subsidy has a stronger effect on smaller and younger firms facing higher interest rates, consistent with the subsidy easing financial constraints.

³⁰Due to data confidentiality restrictions, we cannot disaggregate the sample further.

We reach this conclusion by estimating heterogeneous treatment effects with random causal forest (Athey et al. 2019), which accounts for heterogeneity in a broad set of firm characteristics and controls for differences in subsidy size. Among all features, interest rates are the main source of heterogeneity: firms with higher borrowing costs expand more. Size and age also matter, with small and young firms seeing the largest gains.

No private sector crowd-out. If markets are efficient, the subsidy should crowd out private-sector borrowing. Table 6 shows no evidence of crowd-out: firms increased their bank loans (column 1), driven by short-term working-capital loans, which include credit cards, (column 4) rather than by investment loans (column 3). Firms did not increase their access to credit relative to their size (column 2), nor did they gain access to better, cheaper credit (column 5).³¹ These results are consistent with credit rationing: before and after the subsidy, firms still struggle to access long-term credit.

Table 6: **Subsidy Did Not Crowd Out Bank Loans**

	(1) <i>log(Loans)</i>	(2) <i>Loans/Payroll</i>	(3) <i>log(Invest. Loans)</i>	(4) <i>log(Working Cap. Loans)</i>	(5) <i>Avg. Interest Rate</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	0.857* (0.475)	-19.23 (14.54)	-0.157 (0.574)	0.878* (0.499)	-0.373 (11.58)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.422 (0.470)	-0.671 (27.09)	-0.334 (0.571)	0.390 (0.493)	1.865 (10.76)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	1.219** (0.519)	-9.513 (21.27)	-0.0265 (0.646)	1.287** (0.547)	1.280 (12.31)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	1.129* (0.598)	-83.96 (68.46)	-0.0106 (0.748)	1.181* (0.617)	-8.649 (14.58)
<i>N</i>	6,516	5,678	6,516	6,516	5,626
<i>R</i> ²	0.666	0.117	0.594	0.669	0.802

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 dependent variable in column 1 is the log of the firm's outstanding bank loans in Brazilian reais plus one; in column 2 the ratio of bank loans to payroll; in column 3 the log of outstanding investment-related loans plus one; in column 4 the log of outstanding working-capital loans plus one; and in column 5 the average interest rate on outstanding loans. Because some firms may have no loans in a given category, we add one before taking logarithms to preserve zero values. Tables E38 and E39 confirm the robustness of these results by, respectively, using the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and a dummy equal to one if the firm has any loans in each category. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

³¹Table D14 shows that firms did not use the capital investment enabled by the subsidy to get access to collateralized loans. They only increased uncollateralized loans, which include short-term loans like working-capital loans.

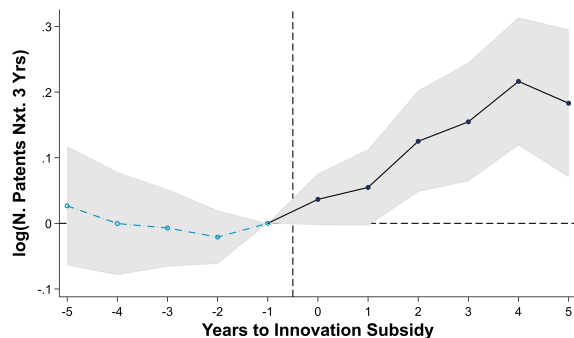
Takeaway: Persistent firm expansion by relaxing credit constraints. These results show that the innovation subsidy led to a persistent increase in firm size, likely because it relaxed firms' credit constraints. The following sections examine the types of innovations that drove this growth.

5.2 More R&D Effort but Not Better Innovations

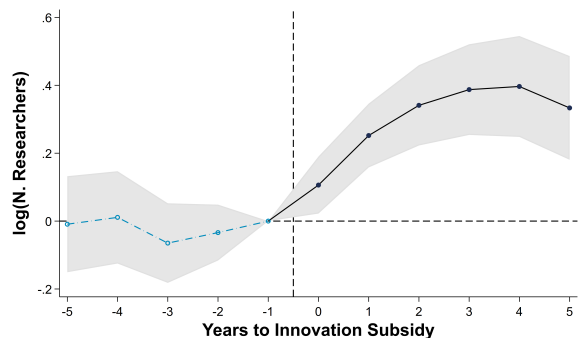
Increase in innovation effort. Figure 8 plots the effect of the innovation subsidy on two measures of innovation effort: patent applications and the number of scientists. In the years before the subsidy, treatment and control firms followed nearly identical trends, reinforcing the credibility of our identification strategy. After receiving the subsidy, firms expanded both their patenting activity and their scientific workforce. Five years later, they had increased patent applications by 20% and the employment of scientists by 40%.³²

Figure 6: **Innovation Subsidy Increased Patenting and Hiring of Scientists**

(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 6a shows the effect of the subsidy on the number of patents during the next 3 years plus one. Figure 6b shows the effect on the number of scientists plus one. Standard errors are clustered at the firm level, and the sample of firms is balanced between -5 and 5 years around the subsidy application.

Table 7 reports the effects of the innovation subsidy on several measures of innovation effort. Column 1 shows an increase in patent applications, and Column 2 shows a 6% increase

³²Patent applications are not an everyday occurrence for firms in Brazil. As investment, it is lumpy, sporadic, and takes time to respond. To deal with that, we aggregate patent applications in a three-year forward window. We chose the three-year window because it is the shortest window within which de Souza (2022) found an effect on patent applications. In Table D15 we show in the robustness section that a five-year window delivers the same results.

in the likelihood of filing at least one patent. Beyond patenting, Column 3 shows a weak increase in trademark registrations, suggesting that the rise in innovation was also linked to the introduction of new products. Taken together, these results confirm that the subsidy stimulated additional R&D investments.

Columns 4 and 5 of Table 7 show that the subsidy expanded firms' R&D teams, with effects that persisted and grew over time. Specifically, the number of scientists increased by 15%, and the likelihood that a firm employed at least one scientist rose by 5%. In the long run, these effects increased to 23% and 8%, respectively. Appendix Table D16 shows that new R&D hires are allocated to engineering research.

Table 7: **Subsidy Increased Innovation Effort**

	(1) <i>log(N. Patents)</i>	(2) <i>ℙ(Patent)</i>	(3) <i>log(N. Trademarks)</i>	(4) <i>log(N. Scientists)</i>	(5) <i>ℙ(Scientist)</i>
<i>Panel A: Simple DD</i>					
<i>ℙ{Subsidy}</i>	0.0883** (0.0421)	0.0736*** (0.0285)	0.139* (0.0739)	0.154** (0.0684)	0.0574* (0.0313)
<i>Panel B: Extended DD</i>					
<i>ℙ{Subsidy 0–2 Yrs}</i>	0.0768* (0.0447)	0.0598* (0.0322)	0.181** (0.0741)	0.102* (0.0613)	0.0412 (0.0310)
<i>ℙ{Subsidy 3–5 Yrs}</i>	0.139*** (0.0502)	0.112*** (0.0343)	0.160* (0.0857)	0.155** (0.0788)	0.0639* (0.0377)
<i>ℙ{Subsidy 6+ Yrs}</i>	0.0589 (0.0594)	0.0576 (0.0427)	0.0773 (0.108)	0.239** (0.101)	0.0827* (0.0435)
<i>N</i>	9,358	9,358	9,358	9,358	9,358

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 log of the number of patent applications made by the firm during the next three years plus one; 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 log of the number of trademarks in the next three years plus one; in column 4 it is a dummy if the firm has at least one R&D worker; and in column 5 it is the log of the number of scientists plus one. Because these variables can be zero for many firms, we add one before taking the logarithm, following many others in the innovation literature (Bloom et al. 2019, 2016, Abrams et al. 2013, Krieger et al. 2022). Table E40 confirms the robustness of the results by using two alternative approaches to handle zeros: the inverse hyperbolic sine transformation, which approximates the log while preserving the zeros (Bellemare and Wichman 2020), and a dummy for whether the firm has at least one patent, scientist, or trademark. All results point to similar conclusions. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

No effect on quality-weighted innovation. Table 8 shows that the increase in R&D effort did not translate into more impactful inventions. Column 1 indicates that the subsidy had no effect on the total number of citations received by the firm. Column 2 reports similarly null results for citation-weighted patents, a standard measure of innovation quality in studies of growth (Hall et al. 2005, Trajtenberg 1990, Akcigit et al. 2016) and of R&D policies (Howell 2017, Dechezleprêtre et al. 2023). Extending the time horizon does not change the picture:

long-run estimates remain statistically insignificant and are, if anything, slightly negative, suggesting that the control firms eventually receive marginally more citations.

Columns 3 and 4 of Table 8 reinforce the conclusion that the subsidy did not lead to high-quality innovations, using inventor characteristics as proxies for patent quality. Column 3 shows no effect on the number of patents weighted by inventor wages, and Column 4 similarly reports null results when weighted by inventors' years of education. These alternative measures confirm that, despite increased innovation activity, the subsidy didn't generate high-quality inventions.

Table 8: **Subsidy Did Not Increase Quality-Weighted Innovation**

	(1) <i>log(Citations)</i>	(2) <i>log(Citation Weighted Patents)</i>	(3) <i>log(Inventor Wage Weighted Patents)</i>	(4) <i>log(Inventor Educ. Weighted Patents)</i>
<i>Panel A: Simple DD</i>				
$\mathbb{I}\{Subsidy\}$	0.0155 (0.0147)	0.00229 (0.00212)	0.224 (0.166)	0.123 (0.0874)
<i>Panel B: Extended DD</i>				
$\mathbb{I}\{Subsidy\ 0-2\ Years\}$	0.00219 (0.0149)	0.00454 (0.00501)	0.112 (0.178)	0.0601 (0.0910)
$\mathbb{I}\{Subsidy\ 3-5\ Years\}$	0.0232 (0.0210)	0.00248 (0.00318)	0.287 (0.208)	0.155 (0.109)
$\mathbb{I}\{Subsidy\ 6+\ Years\}$	0.0198 (0.0202)	-0.00108 (0.000933)	0.310 (0.233)	0.176 (0.124)
<i>N</i>	9,358	9,358	9,358	9,358

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 dependent variable in column 1 is the log of the number of citations received by the firm plus one; in column 2, the log of citation-weighted patent counts plus one; in column 3, the log of patents weighted by the wages of inventors plus one; and in column 4, the log of patents weighted by the years of education of inventors plus one. Because citation and weighted patent counts can be zero for many firms, we add one before taking the logarithm, following many others in the innovation literature (Bloom et al. 2019, 2016, Abrams et al. 2013, Krieger et al. 2022). Table E41 confirms the robustness of the results by using two alternative approaches to handle zeros: the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and a dummy for whether the firm receives any citations at all. All results point to similar conclusions. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

The scientists hired are inexperienced: they have technical or operational backgrounds. Table 9 shows the effect of the subsidy on the origin of the research team. To calculate that, we use the panel dimension of the data to identify the prior occupations of every scientist in the sample. Columns 1 and 2 show that the subsidy did not increase the

hiring of individuals previously employed as scientists or engineers, while Column 3 finds only a modest effect on former health professionals, such as biologists or biochemists. In contrast, Columns 4 and 5 reveal that firms expanded their R&D teams primarily by hiring individuals with backgrounds as technicians or operational workers, such as mechatronics, chemical, and laboratory technicians. These patterns persist in the long run, even after public funding has ended. This hiring pattern reinforces earlier evidence that the subsidy did not generate high-quality innovation: if firms were advancing the technological frontier, we would expect them to have hired experienced inventors or highly trained scientists; however, they did not.

Table 9: R&D Hires Don't Have Experience in Research

	(1) <i>log(Scient. Bfr.)</i>	(2) <i>log(Engineer Bfr.)</i>	(3) <i>log(Health Bfr.)</i>	(4) <i>log(Technician Bfr.)</i>	(5) <i>log(Operation Bfr.)</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	-0.00102 (0.00714)	0.00701 (0.0190)	0.0218* (0.0123)	0.0585*** (0.0218)	0.0382*** (0.0109)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Years}\}$	-0.00529 (0.00424)	-0.00254 (0.0155)	0.0154 (0.00957)	0.0448** (0.0194)	0.0278*** (0.0107)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Years}\}$	-0.00186 (0.00855)	0.0104 (0.0236)	0.0255* (0.0142)	0.0599** (0.0267)	0.0368*** (0.0123)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	0.00764 (0.0137)	0.0180 (0.0287)	0.0248 (0.0183)	0.0829*** (0.0307)	0.0613*** (0.0151)
<i>N</i>	7,059	7,059	7,059	7,059	7,059

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. Column 1 contains the log of the number of scientists that, before joining the firm, were employed as scientists plus one. Column 2 contains the log of the number of scientists that, before joining the firm, were employed as engineers plus one. Column 3 contains the log of the number of scientists that, before joining the firm, were employed as health professionals, such as biologists or medical doctors, plus one. Column 4 contains the log of the number of scientists that, before joining the firm, were employed as technicians (CBO 2002 code 3), such as mechatronics, chemical, and laboratory technicians, plus one. Column 5 contains the log of the number of scientists that, before joining the firm, were employed as operation workers (CBO 2002 code 7), such as plant operation supervisors and machinery operators, plus one. Because the number of hires in each occupation can be zero, we add one before taking the logarithm, following many others in the innovation literature (Bloom et al. 2019, 2016, Abrams et al. 2013, Krieger et al. 2022). Table E42 and E43 confirms the robustness of the results by using two alternative approaches to handle zeros: the inverse hyperbolic sine of the variables, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and a dummy for whether the firm hired at least one scientist from that occupation. Standard errors are clustered at the firm level. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Takeaway: Growth without breakthrough innovation. Our findings so far show that firms grow persistently larger without producing impactful innovations. How, then, can they dominate markets for over a decade with inventions that are rarely cited and developed by former operational workers? In the next section, we show that firms use the subsidy to expand into high-tariff markets, where they can grow in the shadow of import tariff protection.

5.3 Growth Through Import Substitution

Firms expanded – despite the low quality of their innovations – by introducing new products into high import tariff markets, allowing them to grow in the shadow of protection. We make this point in two steps: first, we show that firms introduced new products; then we show that these products are in high-tariff markets.

The subsidy led firms to introduce new products. Table 10 shows that firms used the subsidy to expand product variety, rather than to improve production processes. Columns 1 and 2 present the effect of the subsidy on the number of product and process patents.³³ The subsidy led to an increase in product patents (albeit less significantly due to missing data in the classification of patents), while its effect on process patents was zero.

Columns 3 and 4 of Table 10 show that the subsidy increased the number of distinct patent and trademark classes. Because each class corresponds to a different technological field or product category, this expansion signals greater product variety. Columns 5 and 6 provide further evidence that firms are introducing new products: they expanded the number of different products they export and the variety of inputs they import. Together, the results in Table 10 suggest that the subsidy led firms to expand the number of different products that they produce.

Innovation is directed toward high-tariff markets, protecting local firms from international competition. Building on the previous finding that firms are introducing new products, Table 11 examines which markets these innovations target. Columns 1 and 2 show the effect of the subsidy on patenting activity directed toward high- and low-tariff markets. To construct these measures, we map each patent’s IPC class to a Harmonized System (HS) product code using the concordance from Lybbert and Zolas (2014), merge in Brazil’s pre-treatment import tariffs at the HS level, and compute a patent-specific average tariff. We then rank all Brazilian patents by their tariff levels, calling the top quartile “high-

³³To 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 a patent as a process patent 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 dropped, increasing the standard error.

tariff” (column 1) and the bottom quartile “low-tariff” (column 2). Column 1 of Table 11 shows that the innovation subsidy increased the number of patents in high-tariff markets, without any effect on patents targeting low-tariff markets.

Table 10: **Subsidy Increased Product Variety**

	(1) <i>log(Product Patents)</i>	(2) <i>log(Process Patents)</i>	(3) <i>log(# Patent Classes)</i>	(4) <i>log(# Trademark Classes)</i>	(5) <i>log(# Export Products)</i>	(6) <i>log(# Import Inputs)</i>
<i>Panel A: Simple DD</i>						
$\mathbb{I}\{\text{Subsidy}\}$	0.0706* (0.0399)	0.00751 (0.0130)	0.137** (0.0656)	0.0781** (0.0325)	0.389*** (0.0853)	0.321*** (0.102)
<i>Panel B: Extended DD</i>						
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Years}\}$	0.0568 (0.0419)	0.00948 (0.0162)	0.0550 (0.0490)	0.0644** (0.0290)	0.358*** (0.0874)	0.353*** (0.0977)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Years}\}$	0.113** (0.0466)	0.0190 (0.0160)	0.122* (0.0687)	0.0791** (0.0356)	0.482*** (0.131)	0.244 (0.155)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	0.0523 (0.0566)	-0.00593 (0.0198)	0.241** (0.0988)	0.0945** (0.0429)	0.501** (0.214)	-0.000166 (0.275)
<i>N</i>	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 log of the number of product patent applications in the next three years plus one. 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 the same patent class are more likely to be process than product. The left-hand side in column 2 is the log of the number of process patent applications in the next three years plus one; in column 3 it is the log of the number of different 3-digit IPC patent classes for which the firm has ever made patent applications plus one; in column 4 it is the log of the number of different trademark classes plus one; in column 5 it is the log of the current number of different products exported plus one; and in column 6 it is the log of the number of different imported products plus one. Because these measures can be zero, we add one before taking the logarithm, following the tradition in the innovation literature (Bloom et al. 2019, 2016, Abrams et al. 2013, Krieger et al. 2022). Table E44 confirms the robustness of the results by using the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and Table E45 by using a dummy for whether the firm introduced at least one product, process, trademark class, export product, or import input. All results point to similar conclusions. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Columns 3 and 4 of Table 11 reinforce the import-substitution interpretation by examining whose ideas subsidized firms build upon. These columns show the effect of the innovation subsidy on citations by Brazilian firms to patents linked to products facing high or low import tariffs. Because citations reflect the technologies that firms draw on, an increase in citations to high-tariff patents suggests they are deliberately building upon technologies relevant to tariff-protected product lines. That is precisely what we observe: the subsidy increases citations to high-tariff patents (Column 3) but has no effect on citations to low-tariff patents (Column 4).

Columns 5 and 6 of Table 11 show the effect of the subsidy on exports, providing a direct measure of the products that firms bring to market. The results show a substantial increase

in exports of products protected by high import tariffs in Brazil, but no significant effect on exports of low-tariff products. Taken together, these findings suggest that firms are using the subsidy to launch new products in markets where higher tariffs protect them from foreign competition.

Table 11: **Innovation and Export are Concentrated in High-Tariff Products**

	(1) <i>log(Patent High Tariff Prod.)</i>	(2) <i>log(Patent Low Tariff Prod.)</i>	(3) <i>log(Citations High Tariff Pat.)</i>	(4) <i>log(Citations Low Tariff Pat.)</i>	(5) <i>log(Exports High Tariff Prod.)</i>	(6) <i>log(Exports Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>						
$\mathbb{I}\{\text{Subsidy}\}$	0.0549** (0.0215)	0.00310 (0.0196)	0.0657*** (0.0244)	0.0170 (0.0265)	1.143** (0.436)	0.185 (0.115)
<i>Panel B: Extended DD</i>						
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.0511** (0.0234)	0.00157 (0.0221)	0.0518* (0.0264)	-0.00605 (0.0323)	1.018** (0.441)	0.177 (0.130)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.0644** (0.0272)	0.0175 (0.0256)	0.0930*** (0.0327)	0.0426 (0.0311)	1.546** (0.704)	0.189 (0.153)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0513 (0.0318)	-0.00345 (0.0314)	0.0460 (0.0361)	0.0130 (0.0328)	1.245 (0.864)	0.358 (0.411)
<i>N</i>	9,358	9,358	9,358	9,358	5,600	5,600

Description: This table shows the effect of the innovation subsidy on the direction of innovation and exports. 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 of the number of patent applications in the next three years in high-tariff patent classes plus one. To estimate the tariff of each patent, we use the concordance by Lybbert and Zolas (2014) to map IPC classes to HS product codes, compute a patent-specific average tariff, and classify patents in the top quartile as high tariff. Column 2 is the log of the number of patent applications in the next three years in the bottom quartile of import tariffs plus one. Column 3 is the log of the number of citations made to patents in the top quartile of import tariffs plus one, and column 4 is the log of the number of citations made to patents in the bottom quartile plus one. Column 5 is the log of exports of products in the top quartile of import tariffs plus one, and column 6 is the log of exports of products in the bottom quartile of import tariffs plus one. Because these measures can be zero, we add one before taking the logarithm, following the tradition in the innovation literature (Bloom et al. 2019, 2016, Abrams et al. 2013, Krieger et al. 2022). Tables E46 and E47 confirm the robustness of the results by, respectively, using the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and a dummy for whether the firm has any patents, citations, or exports in the high- or low-tariff categories. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Not sector switching but within-sector product expansion. Rather than switching sectors, firms are moving towards high import tariff products within their sectors. Table D17 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 associated with products in the top quartile of import tariff within each sector. Therefore, firms are moving towards the set of products with the highest import tariff within their sector and not moving sectors entirely.

Direction is not led by calls for 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 this, we link each call for projects to a list of Harmonized System codes that are covered by that call. Figure 2 shows that there is no correlation between call for projects and tariffs. What is happening here is that, within the set of products covered by a call for projects, firms are targeting those with the highest import tariff.

Takeaway: Growth through import substitution. These results show that firms grow by introducing new products into markets protected by high import tariffs. This conclusion is important for two reasons. First, it reconciles earlier findings: firms are becoming persistently larger despite producing low-impact innovations with inexperienced scientists, because they are entering markets with limited foreign competition, where even marginal innovations can succeed under the cost advantage provided by tariffs. Second, it highlights the complementarity between innovation subsidies and import tariffs, two of the most widely used industrial policy tools (Juhász et al. 2022). In the next subsection, we show that firms are primarily exporting to markets with high import tariffs against developed countries, which further supports this interpretation.

5.4 Adopting Foreign Technology for Domestic Import Substitution

Adoption of foreign high-tech machinery. Table 12 reports the effects of the innovation subsidy on imports of capital goods, intermediate goods, and machinery. Columns 1 and 2 show that the subsidy increased imports of capital and intermediate goods, with a stronger effect on capital goods. Column 3 reveals that, within capital goods, the largest gains come from machinery. Columns 4 and 5, using the U.S. Census “advanced technology products” (ATP) list, show that firms expanded their imports of advanced-technology machinery. These results show that firms are adopting high-tech machinery and highlight the importance of financial constraints: to enter the high-tariff markets described in Section 5.3, firms needed to increase investments in imported high-tech machines.

Table 12: Subsidy Increased Imports of Machines

	(1) <i>log(Imp. Capital Goods)</i>	(2) <i>log(Imp. Intermediate Goods)</i>	(3) <i>log(Imports of Machines)</i>	(4) <i>log(Imports of Adv. Tech.)</i>	(5) <i>log(Imp. of Adv. Tech. Machines)</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	1.125** (0.475)	0.752* (0.420)	1.542*** (0.433)	1.141** (0.454)	1.332*** (0.421)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Years}\}$	1.252** (0.500)	0.819** (0.406)	1.517*** (0.438)	0.886* (0.465)	1.177*** (0.427)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Years}\}$	0.550 (0.761)	0.549 (0.633)	1.665** (0.704)	1.637** (0.688)	1.566** (0.653)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	1.508 (1.404)	-0.127 (1.288)	0.834 (1.380)	3.866*** (1.306)	3.603*** (1.345)
<i>N</i>	5,600	5,600	5,600	5,600	5,600

Description: This table shows the effect of the innovation subsidy on imports of capital and intermediate goods. Each column reports the coefficient of model 1 in Panel A and model 2 in Panel B. The dependent variable in column 1 is the log of imports of capital goods plus one, in column 2 the log of imports of intermediate goods plus one, in column 3 the log of imports of machinery within capital goods plus one, in column 4 the log of imports of advanced technology products plus one, and in column 5 the log of imports of advanced technology machinery plus one, according to the U.S. Census ATP list. The classification of goods comes from SECDEX, and machines are defined as HS codes 8401-9209. Because these measures can be zero, we add one before taking the logarithm. Tables E49 and E48 confirm the robustness of the results by, respectively, using the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and a dummy for whether the firm has any imports in each category. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Firms import ideas and inputs from developed countries. Table 13 shows the effect of the subsidy on the origin of imports and citations to understand whose ideas and technologies firms are adopting. Columns 1 and 2 show no effect on imports from Mercosur or South America, while Columns 3 and 4 show an increase in imports from Europe and North America. A similar pattern appears in citations: firms increased citations to foreign companies (Column 6) more than to local Brazilian firms (Column 5).

Consistent with the idea of import substitution, Figure 7 shows that firms are adopting ideas and inputs from the same high-income countries. The figure plots the effect of the innovation subsidy on machine imports on the y-axis, and its effect on citations on the x-axis. There is a strong positive correlation between the two effects: firms adopt ideas from the same countries from which they import machines. Taken together, these results suggest that firms are using the subsidy to locally produce ideas from developed countries using machinery imported from those same countries.³⁴

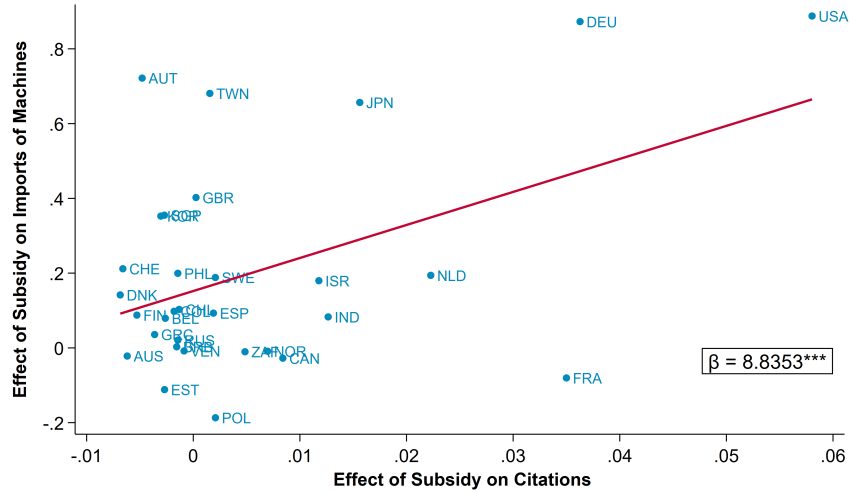
³⁴Table D18, in the Appendix, shows that these are still true even when adding controls.

Table 13: Subsidy Increased Imports and Citations from Europe and N. America

	(1) <i>log(Imp. Mercosur)</i>	(2) <i>log(Imp. S. America)</i>	(3) <i>log(Imp. Europe)</i>	(4) <i>log(Imp. N. America)</i>	(5) <i>log(Citation to BR)</i>	(6) <i>log(Citation to foreign)</i>
<i>Panel A: Simple DD</i>						
$\mathbb{I}\{\text{Subsidy}\}$	0.310 (0.444)	0.451 (0.453)	1.348*** (0.421)	0.928*** (0.435)	0.0384* (0.0203)	0.106** (0.0464)
<i>Panel B: Extended DD</i>						
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Years}\}$	0.382 (0.461)	0.449 (0.470)	1.351*** (0.441)	1.123** (0.436)	0.0250 (0.0234)	0.0909 (0.0652)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Years}\}$	0.318 (0.651)	0.727 (0.671)	1.367** (0.574)	0.566 (0.677)	0.0563** (0.0286)	0.164*** (0.0534)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	−1.213 (1.607)	−1.119 (1.601)	0.524 (1.227)	−1.259 (1.294)	0.0306 (0.0296)	0.0522 (0.0554)
<i>N</i>	5,600	5,600	5,600	5,600	9,358	9,358

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 dependent variable in column 1 is the log of imports from Mercosur countries (Argentina, Paraguay, Venezuela, and Uruguay) plus one; column 2 is the log of imports from other South American countries plus one; column 3 is the log of imports from Europe plus one; and column 4 is the log of imports from North America plus one. Column 5 is the log of citations to Brazilian patents plus one, and column 6 is the log of citations to foreign patents plus one. Because these measures can be zero, we add one before taking the logarithm. Tables E51 and E50 confirm the robustness of the results by, respectively, using the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and a dummy for whether the firm has any imports or citations in each category. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Figure 7: Firms Adopt Machines and Ideas from the Same Countries



Description: This figure shows the correlation between the effect of the innovation subsidy on imports of machines and its effect on patent citations for different countries. The y-axis reports the estimated effect on imports of machines and the x-axis reports the estimated effect on citations. Each point corresponds to a country.

Exports are directed to markets with favorable import tariffs. These products, created with ideas and machines from developed countries, are then shipped to other developing countries, as shown in Table 14, which reports the effect of the innovation subsidy on exports to different destinations. The subsidy increased exports to Mercosur and other South American countries, but not to developed countries. Mercosur countries have a common external tariff and zero tariff against each other, which guarantees that Brazilian exports are protected against international competition even in these countries.

Figure 8 makes this argument concrete by showing that the subsidy's effect on exports is stronger in countries with higher tariffs on imports from North America and Europe. On the x-axis, the figure shows each destination's average tariff in 2000; on the y-axis, it plots the effect of the subsidy on exports. Firms export more to markets where high tariffs protect them from direct competition with the same developed countries they're sourcing machines and ideas from. This pattern reinforces our conclusion that firms can expand exports without breakthrough innovations because foreign tariffs shield them from direct competition with the very ideas they are imitating.³⁵

Takeaway: Foreign technology adoption for import substitution. This section shows that firms are using the innovation subsidy to adopt foreign ideas and capital to enter high-tariff markets. They export these products to other developing countries, where tariffs shield them from competition with goods from advanced economies. Prior to the subsidy, firms had not entered these markets because doing so required substantial investment in imported capital and R&D, costs that financially constrained firms likely could not afford.

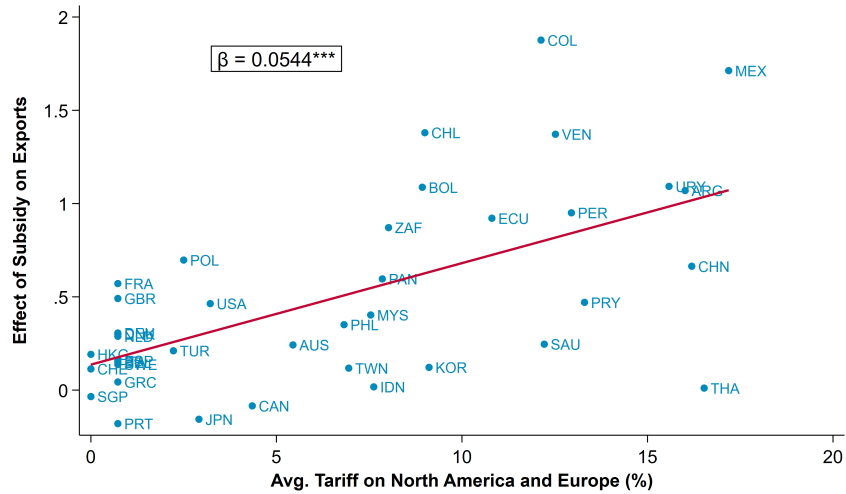
³⁵Table D19 in the Appendix shows that these are still true even when adding controls.

Table 14: Firms Export to South America but not to Developed Countries

	(1) <i>log(Exp. Mercosur)</i>	(2) <i>log(Exp. S. America)</i>	(3) <i>log(Exp. Europe)</i>	(4) <i>log(Exp. N. America)</i>
<i>Panel A: Simple DD</i>				
$\mathbb{I}(\text{Subsidy})$	1.598*** (0.416)	1.526*** (0.420)	0.389 (0.465)	0.339 (0.472)
<i>Panel B: Extended DD</i>				
$\mathbb{I}(\text{Subsidy } 0\text{--}2 \text{ Years})$	1.331*** (0.445)	1.253*** (0.458)	1.122*** (0.434)	0.721 (0.484)
$\mathbb{I}(\text{Subsidy } 3\text{--}5 \text{ Years})$	2.454*** (0.586)	2.363*** (0.566)	-1.806** (0.838)	-0.524 (0.707)
$\mathbb{I}(\text{Subsidy } 6+ \text{ Years})$	1.900* (1.141)	2.070* (1.120)	-2.287* (1.293)	-2.323 (1.606)
<i>N</i>	5,600	5,600	5,600	5,600

Description: This table shows the effect of the innovation subsidy on exports by destination. Each column reports the coefficient of model 1 in Panel A and model 2 in Panel B. The dependent variable in column 1 is the log of exports to Mercosur countries (Argentina, Paraguay, Venezuela, and Uruguay) plus one; in column 2 it is the log of exports to other South American countries plus one; in column 3 it is the log of exports to Europe plus one; and in column 4 it is the log of exports to North America plus one. Because these measures can be zero, we add one before taking the logarithm. Tables E53 and E52 confirm the robustness of these results by, respectively, using the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020), and dummy for whether the firm exports to each destination. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Figure 8: Firms Export to Countries with High Tariffs Against North America and Europe



Description: This figure shows the relationship between the effect of the innovation subsidy on exports and the average tariffs imposed by destination countries against North America and Europe. The x-axis measures the average tariff in 2000 for each export destination, while the y-axis reports the estimated effect of the subsidy on exports. Each point represents a destination country.

5.5 The subsidy paid for itself

Despite leading to the development of low-impact innovations targeted at tariff-protected markets, the subsidy generated significant and persistent growth. As a way to understand the efficacy of the program, this section calculates its return on investment: for every dollar spent on the innovation subsidy, how much the government recovers in payroll tax revenue.

Back-of-the-envelope return on the subsidy. We calculate the government’s return on investment using the following formula:

$$return = \tau \frac{\sum_t \beta^t (e^{\theta_t} - 1) \overline{Wage\ Bill}}{\overline{Subsidy}} \quad (4)$$

where τ is the payroll tax rate, β is the discount factor, θ_t is the effect of the innovation subsidy on the log wage bill t years after treatment, $\overline{Wage\ Bill}$ is the average wage bill among subsidy recipients, and $\overline{Subsidy}$ is the average subsidy amount. The numerator in equation 4 captures the total payroll tax revenue generated by the average subsidy, making 4 the estimated fiscal return in payroll tax revenue for every dollar spent on the innovation subsidy. Because the government taxes multiple variables affected by the subsidy, we view (4) as a conservative approximation.

Calibration. We calibrate τ in Equation 4 to 30%, reflecting the average tax revenue as a share of GDP in Brazil. The discount factor β is set to 0.88 to approximate the inverse of the average federal funds rate during this period. We calibrate θ_t , the effect of the innovation subsidy on the wage bill, using the dynamic estimates in D6. To be conservative, we set $\theta_t = 0, \forall t > 14$. We calibrate the average wage bill and average subsidy to their values in the matched sample.

Every \$1 of subsidy collects \$2.2 in payroll taxes. Table 15 shows the estimated return. For every \$1 of R&D subsidy, the government recovers \$2.2 in payroll tax revenue. Meaning, therefore, that the subsidy paid for itself. In appendix D.4, we show several robustness to this calibration. We find returns ranging from \$1.01 to \$5.50.

The return on the subsidy is consistently large for three reasons. First, it produces a substantial and lasting increase in firm size, which leads to sustained growth in government revenues. Second, recipient firms were already large before receiving support, so a 35% long-run increase in their wage bill translates into a significant rise in payroll tax collections. Third, although the subsidy is sizable relative to bank loans, it amounts to just 40.1% of the average wage bill in the matched sample. Taken together, these factors imply a high fiscal return: large and persistent revenue gains compared with a relatively modest cost.

Table 15: **Tax Return of the Innovation Subsidy**

Parameter	Source	Value
τ	Tax Revenue/GDP	0.3
β	Inverse of Federal Funds Rate	0.88
θ_t	For $t \leq 14$, Figure D6. $\theta_t = 0, \forall t > 14$	
return		2.2

Description: This table reports the calibrated inputs used to compute the fiscal return in Equation (4) and the resulting value of the expression. The parameter τ denotes the payroll tax rate calibrated to the ratio of tax revenue to GDP. The discount factor β is set to match the inverse of the average federal funds rate over the sample period. The sequence θ_t corresponds to the estimated dynamic effects of the innovation subsidy on the log wage bill at horizon t , taken from Figure D6. The reported return is identified according to Equation (4) using the average wage bill and subsidy on the matched sample.

Caveats. An important caveat to this back-of-the-envelope calculation is that it does not account for effects on other firms. Although Section E.1 finds no evidence of knowledge spillovers or market rivalry among non-recipient firms, the subsidy could still affect the broader economy through general equilibrium effects. In particular, factoring in the impact on firms upstream and downstream of recipients would likely increase the estimated return because they were affected through higher demand and lower input costs. We view this exercise as suggestive evidence of the program’s success. We leave a more rigorous model-based evaluation to future research.

6 Ruling Out Alternative Mechanisms

In this section, we rule out three alternative mechanisms that could explain our main result. First, we find no evidence that the subsidy affected other firms through knowledge spillovers or increased competition. This is consistent with treated firms introducing incremental

adaptations of foreign technologies rather than frontier breakthroughs, leaving little new knowledge to diffuse and no increase in competition among domestic firms. Second, the subsidy did not change the direction of innovation. Therefore, firms entered high-tariff markets not because they were required to, but because the subsidy made such entry possible. Third, the results are not driven by the matching procedure focused on near-losers; our findings hold beyond marginal recipients.

No knowledge spillover or market rivalry effect. In Section E.1 of the Appendix, we test whether firms that did not receive the subsidy were indirectly affected through knowledge spillovers or product market rivalry. To do so, we extend the strategy proposed by Bloom et al. (2013) and Jaffe (1986) in two steps. First, we calculate how close each non-applicant firm is to applicant firms in two dimensions: technological proximity, based on patent portfolios, and market proximity, based on sectoral employment shares. These proximity measures identify firms most likely to benefit from knowledge spillovers or face more competitive pressure. In the second step, we implement a regression comparing post-subsidy growth between firms more exposed to treated firms and those more exposed to control firms. This method employs the same source of identifying variation used throughout the paper but compares firms based on their proximity to treated versus control firms.

We find that the innovation subsidy neither spilled over to other firms nor harmed domestic competitors, consistent with our main results. Firms that were technologically close to recipients grew at the same rate as those close to control firms, and firms operating in similar markets showed no difference in post-subsidy performance. These patterns support the interpretation that treated firms introduced marginal adaptations of foreign technologies. Because these innovations offered little scientific novelty, they generated no knowledge spillovers. And because the products targeted markets previously served by imports, firms gained market share by displacing foreign—not domestic—competitors.

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 E11 in the Appendix shows no evidence that firms are changing the composition of their patents.

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 E24 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, which is exogenous to the distribution of ideas because the budget of the Funding Authority is a fixed percentage of government’s tax revenue. However, Table E24 does not find evidence that projects awarded subsidies in calls with a large number of recipients differ from those in other calls.³⁶

7 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. We also show that results are not driven by informality and are robust to different methods to deal with zeros.

Control-Function with all subsidy applicants. In the main part of the paper, we limit the analysis to the matched firms. This method limits the sample size but guarantees that treatment and control firms are comparable. In Section E.5.1 of the Appendix, we re-estimate

³⁶To further validate our findings, Section E.5.1 of the Appendix re-estimates the main regressions using a control-function approach that includes all subsidy applicants.

the main regressions using a control-function approach that includes all subsidy applicants. In this specification, we explicitly control for the firm characteristics used by the Funding Authority in awarding the subsidy. The identifying assumption is that these variables fully account for differences between treated and untreated firms—a stronger assumption than in the matched sample design. In exchange, the analysis broadens the sample, allowing us to estimate the subsidy’s effects on firms beyond the original matched framework. The results remain consistent: the subsidy led to firm growth by facilitating entry in high tariff markets.

Subsidy value. The main specification does not exploit variation in subsidy size. To address this limitation, Table E27 in the Appendix re-estimates the main regressions explicitly using the actual subsidy amounts received by each firm. The results remain consistent: firms receiving subsidies show greater increases in innovation, employment, and exports, and are more likely to introduce new products into high-tariff markets.

Matching on CEO wage to account for management quality. 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.³⁷ Table E28 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. Figure C4a, supporting that, shows that the sectoral distribution is the same between treatment and control firms. To further corroborate that results are not driven by sectoral composition, in Table E29 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 remains true that firms are patenting more but without being cited, they expand employment,

³⁷The CEO is defined as the individual with highest wage with a managerial occupation.

create more product patents than process patents, expand the number of exported goods, and create patents on high tariff classes.

Matching on additional indicators of research-team quality. Given that the quality of the research team is one of the most important considerations when granting the subsidy, Table E30 also matches firms on the number of PhD workers and the average wage of PhD workers, confirming that the main takeaway still holds.

Matching on project quality. In Section 4.2, we showed that treatment and control groups are similar across several non-matched variables, including the quality of their research ideas. To guarantee further that results do not come from differences in the quality of the research proposal, we also match firms on the Flesch-Kincaid readability index of their proposal titles, which has been shown, in the context of patents, to correlate with citations (Ashtor 2022). Table E31 shows that the main takeaway remains the same and that precision even improves.

Matching on the two years preceding the innovation subsidy. Table E32 shows the main results when matching control and treatment firms on subsidy value, employment, number of patents, and citations in the year of the subsidy application and the preceding year. This specification removes any residual trends not otherwise controlled for. The results in Table E32 remain unchanged despite the smaller number of observations.

Results are not driven by changes in informality. As discussed in Section 3.2, firms applying for the innovation subsidy are larger than the average firm in Brazil, which is usually subject to strict labor market inspections. Still, one might worry that the effects identified are not valid because firms could be concealing their true size by hiring informal workers. If that were the case, firms would be more likely to receive fines for hiring informal workers when inspected. Table E33 reports the effect of the subsidy on the probability of being fined for labor market infractions in general or specifically for hiring informal workers. Table E33 shows that the subsidy increased the number of labor market inspections that the firm received but that it has not led to more infractions for hiring informal workers.

Dealing with zeros. We use the log plus one transformation to handle variables that can take zero values, such as the number of patents or exports, which is common in the literature studying innovation (Bloom et al. 2019, 2016, Abrams et al. 2013, Krieger et al. 2022). 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 E34 utilizes the percentile of the left-hand side variable, which is well-defined at zero and imposes curvature on abnormally high values. Table E35 employs the inverse hyperbolic sine transformation plus one, and Table E36 explores the extensive margin. Section E.5.5 shows all the results using the dummies and the inverse hyperbolic sine. None of these transformations changes any of our conclusions.

8 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 could be 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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A Institutions

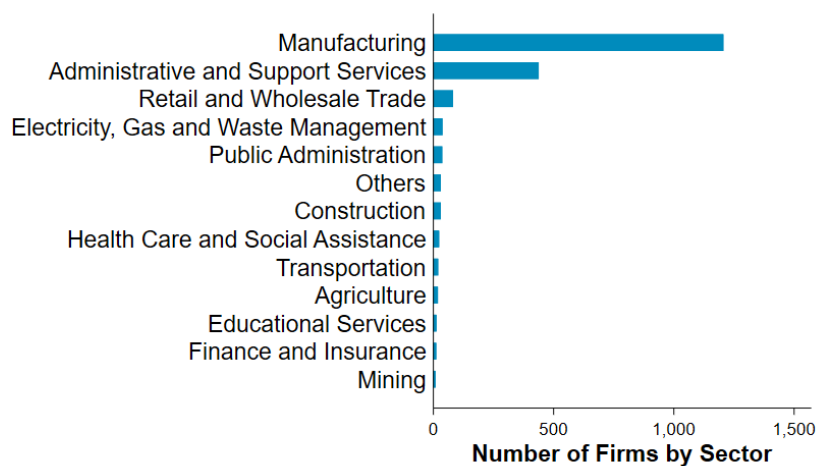
Table A1: List of Presidents of the Funding Authority 2003–2018

<i>President Name</i>	<i>Period</i>	<i>Previous Occupation</i>	<i>Previous Institution</i>	<i>PhD University</i>	<i>Education / Career Path</i>
Marcos Cintra	2016–2018	Professor	FGV-RJ	Harvard	PhD in Economics from Harvard; academic and research career
Wanderley de Souza	2015	Professor	UFRJ	UFRJ	Physician, scientist; member of the Brazilian Academy of Sciences and National Academy of Science
Glauco Arbix	2011–2015	Professor	USP	USP	Sociologist; specialist in innovation policy; academic career and management in science, technology & innovation
Luís Fernandes	2007–2011 and 2015	Professor and Secretary of Ministry of Science	PUC-RJ, UFRJ	IUPERJ	PhD in Political Science; specialist in science & technology policy
Odilon Marcuzo do Canto	2005–2006	Professor	UFSM	University of California – Berkeley	PhD in Nuclear Engineering
Sérgio Machado Rezende	2003–2005	Professor and City Secretary of Science	UFPE and Olinda	MIT	Physicist; member of the Brazilian Academy of Sciences

Description: This table shows the origin of presidents of the Funding Authority for Studies and Projects.

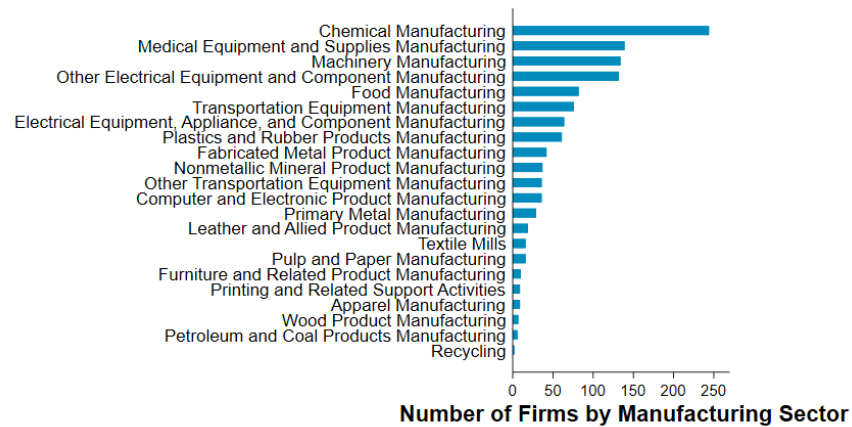
B Facts of R&D Subsidy in Brazil

Figure B1: Subsidy Targets Manufacturing Sector



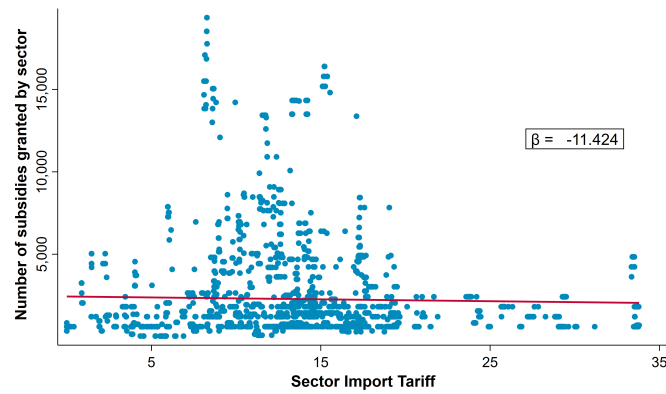
Description: This figure reports the distribution of subsidies across sectors.

Figure B2: Subsidy within Manufacturing Sector



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

Figure B3: Correlation Between Sector of the Subsidized Firm and Tariffs



Description: This Figure plots the correlation between the number of subsidy recipients in each sector and the average sectoral import tariff.

C Empirical Strategy

C.1 Balance Test

Table C2: Balance Test on Matched Variables

	(1) <i>Treatment</i>	(2) <i>Control</i>	(3) <i>(2) - (1)</i>
	Matched Variables		
N. Workers	663.42 (1,020.24)	767.35 (4,448.32)	103.93 (0.74)
N. Patents	0.01 (0.15)	0.01 (0.09)	0.00 (0.59)
Citations	0.07 (0.97)	0.13 (1.68)	0.06 (0.60)
Value Requested	9.47 (14.00)	7.80 (11.00)	-1.67 (0.15)
Observations	208	324	532

Notes: This table shows statistics of matched treatment and control firms for the variables used in the matching procedure. Column 1 has the average for different variables for the treatment group and column 2 for the control. Columns 1 and 2 have the standard deviation in parentheses, and column 3 has the p-value of the difference. 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.

Table C3: Balance Test on Additional Variables of Worker Characteristics

	(1) <i>Treatment</i>	(2) <i>Control</i>	(3) <i>(2) - (1)</i>
Wages			
Hourly Wage	56.02 (38.79)	60.27 (62.65)	4.25 (0.38)
Avg. Wage	2,392.74 (1,548.96)	2,367.45 (2,147.76)	-25.29 (0.88)
Workforce Composition			
Share Male	0.74 (0.19)	0.71 (0.21)	-0.03 (0.22)
Avg. Yrs. of Education	11.52 (1.85)	11.50 (2.03)	-0.02 (0.94)
Share High School Dropout	0.37 (0.26)	0.37 (0.27)	0.00 (0.78)
Share High School Complete	0.36 (0.19)	0.35 (0.21)	-0.01 (0.55)
Share More than High School	0.27 (0.24)	0.28 (0.26)	0.01 (0.86)
Number High School Dropout	280.00 (575.47)	287.01 (1,576.93)	7.01 (0.95)
Number High School Complete	246.36 (402.07)	252.13 (1,277.42)	5.77 (0.95)
Number More than High School	137.06 (275.29)	228.20 (1,668.90)	91.14 (0.44)
Wage by Education Level			
Wage High School Dropout	1,530.02 (817.64)	1,569.11 (1,213.62)	39.09 (0.70)
Wage High School Complete	1,906.49 (1,053.23)	1,837.66 (1,195.03)	-68.83 (0.51)
Wage More than High School	3,986.45 (1,915.74)	3,765.06 (2,417.06)	-221.39 (0.27)
Task Content			
Routine Task Content	0.24 (0.30)	0.21 (0.35)	-0.03 (0.33)
Observations	208	324	532

Notes: 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. Columns 1 and 2 have the standard deviation in parentheses, and column 3 has the p-value of the difference. The last column shows the difference between treatment and control. Wages are in 2010 R\$. 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.

Table C4: Balance Test on Additional Characteristics of R&D Scientists

	(1) <i>Treatment</i>	(2) <i>Control</i>	(3) <i>(2) - (1)</i>
Demographics and Education			
Share Male (R&D)	0.77 (0.34)	0.78 (0.37)	0.01 (0.81)
Avg. Wage (R&D)	7,544.61 (7,687.20)	6,642.03 (4,245.93)	-902.58 (0.29)
Avg. Yrs. of Education (R&D)	14.42 (1.84)	14.60 (2.06)	0.18 (0.54)
Share High School Dropout (R&D)	0.08 (0.24)	0.09 (0.24)	0.01 (0.80)
Share High School Complete (R&D)	0.22 (0.32)	0.19 (0.35)	-0.03 (0.66)
Share More than High School (R&D)	0.70 (0.37)	0.72 (0.40)	0.02 (0.82)
Field of R&D Scientists			
Number in Biology	0.12 (0.69)	0.48 (6.23)	0.36 (0.39)
Number in Meteorology	0.32 (2.65)	0.10 (0.61)	-0.22 (0.15)
Number in Automation	0.15 (0.52)	0.10 (0.48)	-0.05 (0.24)
Number in Engineering	1.23 (3.75)	0.87 (3.01)	-0.36 (0.23)
Number in Health	0.06 (0.55)	0.25 (2.89)	0.19 (0.36)
Number in Agronomy	0.04 (0.43)	0.09 (0.54)	0.05 (0.26)
Number in Humanities	0.03 (0.19)	0.12 (0.91)	0.09 (0.15)
Number in Hard Sciences	0.28 (2.14)	0.18 (1.75)	-0.10 (0.53)
Number in Electromechanics	0.15 (0.52)	0.10 (0.48)	-0.05 (0.24)
R&D Workforce Summary			
Total R&D Workers	4.88 (7.24)	5.38 (17.66)	0.50 (0.81)
Wage Bill (R&D)	17,326.84 (48,246.22)	15,688.59 (71,210.39)	-1,638.25 (0.77)
Number of HS Dropout (R&D)	0.27 (0.72)	0.48 (2.77)	0.21 (0.51)
Number of HS Complete (R&D)	0.55 (2.14)	0.26 (1.12)	-0.29** (0.04)
Number of More than HS (R&D)	1.57 (3.75)	1.75 (9.05)	0.18 (0.78)
Observations	208	324	532

Notes: 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. Columns 1 and 2 have the standard deviation in parentheses, and column 3 has the p-value of the difference. Wages and wage bill are in 2010 R\$. 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.

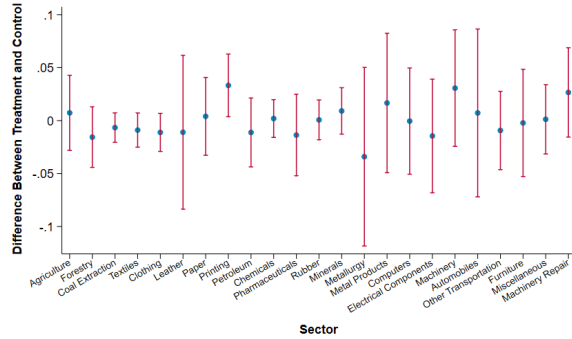
Table C5: Balance Test on Additional Variables of Firm Size

	(1)	(2)	(3)
	<i>Treatment</i>	<i>Control</i>	<i>(2) - (1)</i>
Firm Characteristics and Performance			
Number of Establishments	4.69 (15.28)	3.16 (6.50)	-1.53 (0.11)
Wage Bill	1,527,504.00 (2,649,805.50)	1,774,265.25 (9,025,110.00)	246,761.25 (0.70)
Firm Age	24.84 (13.20)	22.76 (13.77)	-2.08* (0.09)
Export Value	7,402,968.50 (22,160,010.00)	13,259,297.00 (121,059,288.00)	5,856,328.00 (0.57)
Import Value	3,273,902.50 (16,147,409.00)	6,816,790.00 (36,773,748.00)	3,542,887.50 (0.28)
Observations	208	324	532

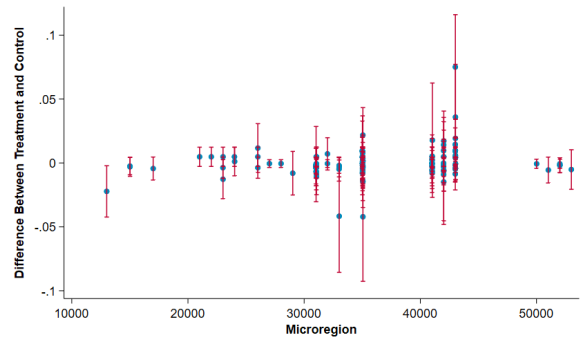
Description: This table shows statistics of matched treatment and control firms. Column 1 has the average for different variables for the treatment group and column 2 for the control. Columns 1 and 2 have the standard deviation in parentheses, and column 3 has the p-value of the difference. Wage bill are in 2010 R\$. Exports and imports are in current dollars. 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 C4: 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 C4a 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 C4b 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 C6: **Balance Test on Innovation and Tariff Exposure**

	(1) <i>Treatment</i>	(2) <i>Control</i>	(3) <i>(2) - (1)</i>
	Patent and Export Tariff Exposure		
Citations to High-Tariff Patents (Q4)	1.02 (10.15)	0.25 (1.73)	-0.77 (0.18)
Citations to Low-Tariff Patents (Q1)	2.00 (26.23)	0.51 (5.38)	-1.49 (0.32)
Patents Linked to High-Tariff Products (Q4)	0.65 (3.70)	0.42 (2.00)	-0.23 (0.35)
Patents Linked to Low-Tariff Products (Q1)	0.44 (1.64)	1.15 (11.00)	0.71 (0.35)
Avg. Tariff on Exported Products	11.90 (4.92)	11.91 (5.81)	0.01 (0.99)
Observations	208	324	532

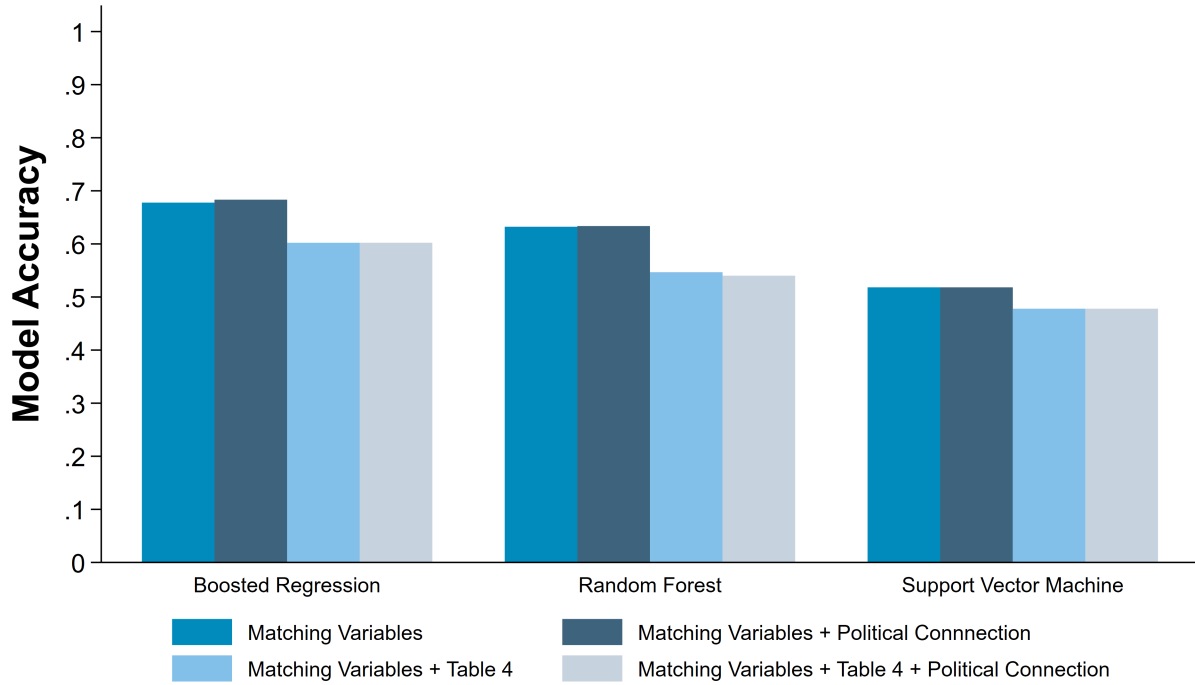
Description: This table shows statistics of matched treatment and control firms. Column 1 has the average for different variables for the treatment group and column 2 for the control. Columns 1 and 2 have the standard deviation in parentheses, and column 3 has the p-value of the difference. The last 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.

Table C7: Comparison Between Matched and Unmatched Firms

	(1) <i>Matched</i>	(2) <i>Unmatched</i>	(3) <i>(2) - (1)</i>
N. Firms on Call for Projects	82.94 (18.94)	62.36 (30.96)	-20.58*** (0.00)
N. Workers	632.22 (3244.05)	516.59 (2035.75)	-115.63 (0.44)
N. Patents	0.01 (0.11)	0.01 (0.15)	0.00 (0.45)
Citations	0.07 (1.09)	0.43 (4.98)	0.36* (0.10)
Value Requested	7314560.50 (12633071.00)	7195543.50 (19732724.00)	-119017 (0.90)
Avg. Wage	2291.72 (2056.77)	2283.35 (1993.58)	-8.37 (0.94)
Avg. Yrs. of Education	11.61 (2.01)	12.34 (2.11)	0.73*** (0.00)
Avg. Wage of Researchers	7528.64 (5161.48)	8496.86 (6261.14)	968.22** (0.02)
Avg. Yrs. of Educ. of Researchers	14.88 (1.70)	15.52 (1.71)	0.64*** (0.00)
Flesh-Kincaid Index	-0.81 (50.89)	-0.36 (51.64)	0.45 (0.87)
Implied Project Market Value	1.12 (0.45)	1.11 (0.52)	-0.01 (0.78)
Implied Project Scientific Value	0.59 (0.24)	0.59 (0.25)	0.00 (0.56)
Similarity with Past Patents	0.05 (0.09)	0.06 (0.13)	0.01 (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 C.2 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 C5: Predicting Subsidy using Different Machine Learning Methods



Description: This figure reports out-of-sample accuracy for alternative algorithms predicting subsidy reciprocity. The sample is randomly split into training and test sets; models are fitted on the training set and accuracy is evaluated on the held-out test set. The “matching variables” are the pre-application number of workers, number of patents, total citations, and the requested subsidy amount. The “political-connection variables” add indicators for firms’ campaign contributions, prior borrowing from the state development bank (BNDES), and revolving-door ties to the funding agency. The “Table 4 variables” in augments covariates with additional pre-treatment firm characteristics used in the balance exercises: average worker and researcher wages and years of education, Flesch–Kincaid readability index, implied scientific and market value, AI evaluator score, and similarity to past patents.

C.2 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 reciprocity 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.³⁸

$$citation_j = \frac{\text{average number of citations on patents containing word } j}{\text{average number of words on the title of patents containing word } j} \quad (5)$$

$citation_j$ 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:

$$Scientific\ Value_p = \sum_j \frac{\mathbb{I}\{Project\ p\ has\ word\ j\} \times citation_j}{Number\ of\ Words\ on\ the\ Project\ Title} \quad (6)$$

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 5 and 6 using the patent value, we can infer the value of a patent using

$$value_j = \frac{\text{average market value of patents containing word } j}{\text{average number of words on the title of patents containing word } j} \quad (7)$$

$$Economic\ Value_p = \sum_j \frac{\mathbb{I}\{Project\ p\ has\ word\ j\} \times value_j}{Number\ of\ Words\ on\ the\ Project\ Title} \quad (8)$$

Inferred scientific value predict R&D subsidy reciprocity. Table C8 shows the correlation between receiving the subsidy and the scientific and economic value of projects.

³⁸To 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).

Table C8 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 C8 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 C8: Correlation Between Scientific and Economic Value with Subsidy Recipiency

	(1)	(2)	(3)
	$\mathbb{I}(\textit{Subsidy})$	$\mathbb{I}(\textit{Subsidy})$	$\mathbb{I}(\textit{Subsidy})$
$\log(\textit{Scientific Value}_p)$	0.0552** (0.0238)	0.0552** (0.0236)	0.248*** (0.0931)
$\log(\textit{Economic Value}_p)$	-0.0344 (0.0218)	-0.0344 (0.0216)	-0.137* (0.0832)
Method	OLS	Probit	Tobit
N	4,388	4,388	4,388
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

C.3 Using a Large Language Model to Infer the Quality of Innovation Projects

In this section, we describe how we use Google’s Gemini 1.5 Flash to infer the quality of each research project. We then show that the LLM-generated scores can predict which proposals receive subsidies. The prompt applies two established prompt engineering techniques known to improve LLM performance. First, it uses role prompting, instructing the model to assume the role of a human evaluator, which is a strategy shown to enhance accuracy in Zhang and Soh (2023). Second, it incorporates a small number of illustrative examples, applying n-shot prompting (Brown et al. 2020), which improves prediction quality even with limited training instances.

For each project, we provide the LLM with the following prompt:

You are an evaluator in a call for projects at the Brazilian agency Funding Authority for Studies and Projects. You are an specialist in the field of {CALL TOPIC} and was selected to participate due to your contributions to this field.

Context: Finep is an Portuguese acronym for a Brazilian government agency known as Financiadora de Estudos e Projects or, in English, the Funding Authority for Studies and Projects. The goal of this government agency is to award subsidies to Brazilian firms to help support the development of products, services, or processes. In order to receive this subsidy, firms must provide a variety of documents including a technical proposal, a business, plan, a history of balance sheets, and compliance certifications. Each application is then reviewed by an unbiased board of experts and applications scoring the highest on a pre-determined set of criteria win the subsidy.

About you: You are a member of this review board working for FINEP in Brazil. Your goal is to score projects based on its degree of inventiveness.

The following application appears in front of you. The year is {YEAR} and the firm's name is {FIRM NAME}. The title of the project is {RESEARCH TITLE} and the firm is asking for R\${VALUE REQUESTED} in 2010 Brazilian Reais to implement the project. The firm has {NUMBER OF WORKERS} employees, created {NUMBER OF PATENTS} patents, and in total its patents have received {CITATIONS} citations. The average wage of its research team is R\${AVG. WAGE OF SCIENTISTS} in 2010 Brazilian Reais, the average years of education of the research team is AVG. YEARS OF EDUCATION OF SCIENTISTS, the CEO of the firm makes R\${CEO WAGE} in 2010 Brazilian reais, and the name of the CEO is {CEO NAME}. The age of the firm is FIRM AGE, the sector of the firm is {SECTOR NAME}, and the corresponding Brazilian CNAE sector code is {SECTOR CODE}.

About the task: Your task is to provide a score from 0 (worst) to 5 (best) based on the degree of inventiveness of the project. Remember that Brazil is a developing

country that does not have as much advanced technology compared to the United States. You should not be harsh and give scores relative to the US, instead you should give scores relative to the technological status of Brazil. To calculate these scores use only data prior to {YEAR}.

Give higher scores to technologies that are associated with a step forward in Brazilian innovation or that are new to Brazil in the time period. The projects that are most innovative to Brazil should be given the top score (5) while work that is not as inventive should be given a lower score. Impressive sounding projects should be given a score of 5. Applications in higher-tech and more innovative sectors should be given a score of 5. This score should be relative to the technologies that existed in Brazil at the time and not compared to the United States or other developed countries.

For instance, a project by a large firm, with reputable scientists, that has multiple citations, and aims to create a biotechnology lab is likely highly innovative in Brazil because Brazilian firms do not have a history of biotechnology research. In the other hand, projects in technologies already adopted in Brazil should have lower scores.

Output: To calculate these scores use only data prior to {YEAR}. Your output should be a score taking the value of 1, 2, 3, 4 or 5. Do not write any other words or text besides the scores.

Table C9 shows the correlation between the AI-generated score and a dummy indicating whether the application received the subsidy. Higher scores are associated with a greater likelihood of subsidy approval, suggesting that the AI is capturing features of the proposal that are correlated with the technical criteria used by the Funding Authority.

Table C9: Relationship Between Innovation Score and Treatment Status

	(1)	(2)	(3)
	$\mathbb{I}\{Subsidy\}$	$\mathbb{I}\{Subsidy\}$	$\mathbb{I}\{Subsidy\}$
<i>Score by AI</i>	0.0263*** (0.00500)	0.0965*** (0.0181)	0.0263*** (0.00497)
<i>Method</i>	OLS	Probit	Tobit
<i>N</i>	5421	4191	5423

Description: This table shows the relationship between the AI generated innovation score of projects and an indicator for treatment status. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

C.4 Validation: Placebo and Exogeneity Tests

C.4.1 Placebo Tests

Table C10: Random Placebo Regressions

	(1)	(2)	(3)	(4)
	$\log(Citations)$	$\log(Wage\ Bill)$	$\log(Exports)$	$\log(Product\ Patent)$
$\mathbb{I}(Subsidy)$	-0.0138 (0.0133)	-0.0216 (0.0864)	0.325 (0.332)	0.00965 (0.0303)
<i>N</i>	12,133	12,133	6,842	12,133

	(5)	(6)	(7)	(8)
	$\log(Process\ Patent)$	$\log(\# Export\ Products)$	$\log(N. Patent\ High\ Tariff\ Prod.)$	$\log(N. Patent\ Low\ Tariff\ Prod.)$
$\mathbb{I}(Subsidy)$	-0.000510 (0.00806)	0.0548 (0.0663)	0.0282 (0.0209)	0.00479 (0.0160)
<i>N</i>	12,133	6,842	12,133	12,133

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 log of citations that will be received by the firm during the next 3 years plus one; in column 2 it is the log of the wage bill; in column 3 it is the log of exports plus one; in column 4 it is the log of product patents plus one; in column 5 it is the log of process patents plus one; in column 6 it is the number of different export products plus one; in column 7 it is the number of patents during the next three years associated with products that have a tariff on the top quartile plus one; and in column 8 it is the number of patents that during the next three years will be associated with products that have tariff in the bottom quartile plus one. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table C11: Matched Placebo Regressions

	(1) <i>log(Citations)</i>	(2) <i>log(Wage Bill)</i>	(3) <i>log(Exports)</i>	(4) <i>log(Product Patents)</i>
$\mathbb{I}(\text{Subsidy})$	0.0173 (0.0143)	0.0328 (0.135)	-0.668 (0.506)	0.00219 (0.0371)
N	6,405	4,889	3,965	6,405
R^2	0.496	0.887	0.822	0.647
	(5) <i>log(Process Patents)</i>	(6) <i>log(# Export Products)</i>	(7) <i>log(Patents High Tariff)</i>	(8) <i>log(Patents Low Tariff)</i>
$\mathbb{I}(\text{Subsidy})$	-0.00270 (0.0107)	-0.0954 (0.0749)	0.00250 (0.0212)	0.00267 (0.0156)
N	6,405	3,965	6,405	6,405
R^2	0.360	0.868	0.544	0.772

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 log of citations that will be received by the firm during the next three years plus one; in column 2 it is the log of the wage bill; in column 3 it is the log of exports plus one; in column 4 it is the log of product patents plus one; in column 5 it is the log of process patents plus one; in column 6 it is the number of different export products; in column 7 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 8 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. Because these outcomes can be zero for many firms, we add one before taking the logarithm. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

C.4.2 Exogeneity Tests

Table C12: Innovation Subsidy and Political Connections

	(1) $\mathbb{I}(\text{Subsidize Loan})$	(2) $\mathbb{I}(\text{Campaign Contribution})$	(3) $\mathbb{I}(\text{Subsidize Loan Nxt. 3})$	(4) $\mathbb{I}(\text{Campaign Contribution Nxt. 3})$
$\mathbb{I}(\text{Subsidy})$	0.00022 (0.00843)	0.00130 (0.00982)	-0.00960 (0.0251)	-0.0196 (0.0323)
N	7,602	7,602	7,059	7,059
R^2	0.250	0.288	0.504	0.507
	(5) $\mathbb{IHS}(\text{Subsidize Loan})$	(6) $\mathbb{IHS}(\text{Campaign Contribution})$	(7) $\mathbb{IHS}(\text{Subsidize Loan Nxt. 3})$	(8) $\mathbb{IHS}(\text{Campaign Contribution Nxt. 3})$
$\mathbb{I}(\text{Subsidy})$	0.0144 (0.150)	-0.0226 (0.103)	-0.114 (0.441)	-0.285 (0.341)
N	7,602	7,602	7,059	7,059
R^2	0.262	0.281	0.528	0.511

Description: This table shows the effect of the innovation subsidy on the political connection of firms. 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 2 is a dummy if the firm made a campaign contribution in the last election; in column 3 is a dummy if the firm will receive a subsidized loan during the next 3 years; and in column 4 is a dummy if the firm will make a campaign contribution during the next 3 years. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table C13: Innovation Subsidy and Political Capture

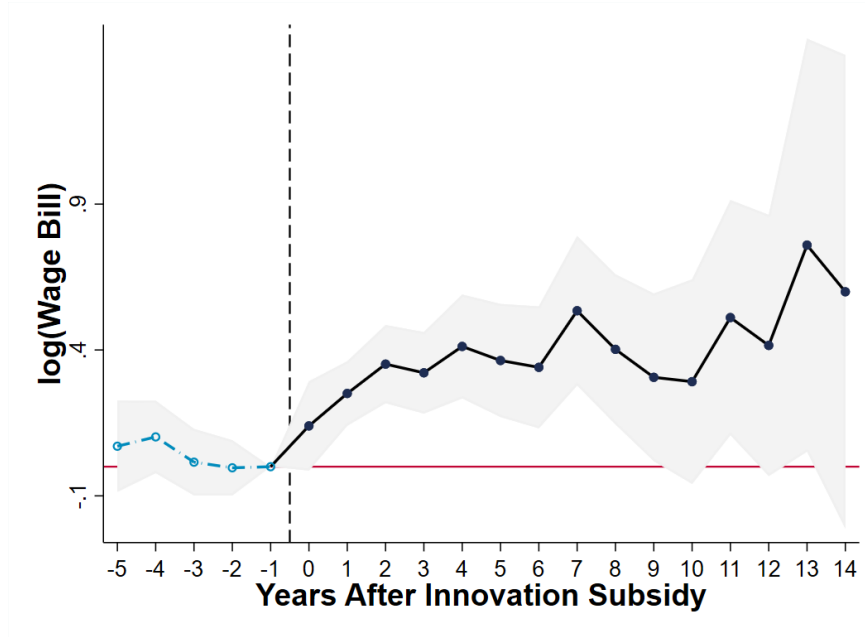
	(1)	(2)	(3)
	$\mathbb{I}(\text{Subsidy})$	$\mathbb{I}(\text{Subsidy})$	$\mathbb{I}(\text{Subsidy})$
$\mathbb{I}(\text{Revolving Door Connection})$	0.0153 (0.0297)	-0.0541* (0.0317)	-0.0624* (0.0321)
N	5,421	4,535	4,388
R^2	0.312	0.322	0.316

Description: This table shows the correlation between receiving an innovation subsidy and revolving door connection to the Funding Authority, i.e., a dummy that takes the value of one if the firm has ever hired a former Funding Authority employee or it has a previous worker at the Funding Authority. Column 2 also includes among the controls the log of the number of workers at the firm, the total number of patent applications that the firm has ever made, and the total number of citations received by the firm. All controls are calculated on the year before the application. Column 3 add to the controls the scientific and economic value of the project, as described in C.2. All columns include a call for project fixed effect. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

D Results

D.1 Additional Results

Figure D6: Innovation Subsidy led to Persistent Increase in Wage Bill



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

Table D14: **Effect of Innovation Subsidy on Loan Types**

	(1) <i>IHS(Collateralized Loans)</i>	(2) <i>IHS(Uncollateralized Loans)</i>
<i>Panel A: Simple DD</i>		
$\mathbb{I}\{\text{Subsidy}\}$	0.244 (0.579)	0.963* (0.503)
<i>Panel B: Extended DD</i>		
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0420 (0.572)	0.437 (0.491)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.586 (0.646)	1.362** (0.556)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0345 (0.759)	1.368** (0.630)
<i>N</i>	6,516	6,516

Description: This table reports the effect of the innovation subsidy on different loan types. The dependent variables are the inverse hyperbolic sine (IHS) of the firm's outstanding bank loans: column 1 shows collateralized loans and column 2 shows uncollateralized loans. Coefficients are from model 1 in Panel A and model 2 in Panel B. Standard errors are clustered at the firm level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table D15: **Innovation Subsidy and Innovation Effort**

	(1) $\log(\text{Patents}$ <i>Nxt. 5)</i>	(2) $\log(\text{Patents}$ <i>Nxt. 5)</i>	(3) $\log(\text{Trademarks}$ <i>Nxt. 5)</i>
$\mathbb{I}(\text{Subsidy})$	0.103** (0.0486)	0.0964*** (0.0313)	0.120 (0.0846)
<i>N</i>	9,358	9,358	9,358
<i>R</i> ²	0.700	0.605	0.754

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 log of the number of patent applications made by the firm during the next five years plus one; 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 in column 3 it is the log of the number of trademarks in the next five years plus one. Because these outcomes can be zero for many firms, we add one before taking the logarithm. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table D16: Innovation Subsidy and Scientists Field

	(1) log(<i>Engineering</i>)	(2) log(<i>Biology</i>)	(3) log(<i>Meteorology</i>)	(4) log(<i>Automation</i>)	(5) log(<i>Health</i>)
$\mathbb{I}(\textit{Subsidy})$	0.112*** (0.0419)	0.00207 (0.0237)	0.0258 (0.0200)	0.0144 (0.0192)	0.00417 (0.0167)
N	9,358	9,358	9,358	9,358	9,358
R^2	0.750	0.804	0.734	0.615	0.842

	(6) log(<i>Agronomy</i>)	(7) log(<i>Humanities</i>)	(8) log(<i>Hard Sciences</i>)	(9) log(<i>Electro-mechanics</i>)
$\mathbb{I}(\textit{Subsidy})$	-0.000846 (0.00979)	0.00150 (0.00988)	0.0319 (0.0258)	0.0144 (0.0192)
N	9,358	9,358	9,358	9,358
R^2	0.817	0.810	0.732	0.615

Description: This table shows the estimates of model 1 on the log of the number of scientists in different fields plus one. 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. Because the number of scientists can be zero for many firms, we add one before taking the logarithm. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table D17: Effect of Innovation Subsidy on the Direction of Innovation within Sector

	(1) log(<i>High Tariff Prod.</i>)	(2) log(<i>Low Tariff Prod.</i>)	(3) log(<i>High Tariff Prod.</i>)	(4) log(<i>Low Tariff Prod.</i>)	(5) log(<i>High Tariff Prod.</i>)	(6) log(<i>Low Tariff Prod.</i>)
$\mathbb{I}(\textit{Subsidy})$	0.0449** (0.0223)	0.0189 (0.0206)	0.0400** (0.0187)	0.0152 (0.0235)	0.0521** (0.0207)	0.0143 (0.0251)
Quartile at	<i>1-digit sector</i>	<i>1-digit sector</i>	<i>2-digit sector</i>	<i>2-digit sector</i>	<i>3-digit sector</i>	<i>3-digit sector</i>
N	9,358	9,358	9,358	9,358	9,358	9,358
R^2	0.611	0.718	0.520	0.695	0.607	0.667

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 D18: **Effect of Subsidy on Imports is Larger for Countries in which the Effect of the Subsidy on Citations is Also Large**

	(1)	(2)	(3)
	<i>Effect of Subsidy on Imports of Machines</i>	<i>Effect of Subsidy on Imports of Machines</i>	<i>Effect of Subsidy on Imports of Machines</i>
Effect of Subsidy on Citations	8.835** (3.234)	7.848** (3.107)	9.191** (3.917)
$\log(\text{GDP Capita})$		0.0649 (0.0395)	0.0915 (0.0588)
$\log(\text{Distance})$		0.156 (0.0981)	0.255 (0.418)
N	31	31	28
R^2	0.205	0.347	0.421

Description: This table reports the correlation between the effect of the innovation subsidy on imports of machines from the different countries and the effect of the innovation subsidy on citations to different countries. Each observation represents a different country. Column 2 adds as control the log of per capita GDP in 2000 and the distance to Brazil. Column 3 add as controls dummies for continent and income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table D19: **Effect of Subsidy on Exports is Larger for Destinations with Higher Import Tariff Against Developed Countries**

	(1)	(2)	(3)
	<i>Effect of Subsidy on Exports</i>	<i>Effect of Subsidy on Exports</i>	<i>Effect of Subsidy on Exports</i>
<i>Tariff on Developed Countries</i>	0.0544*** (0.0115)	0.0341** (0.0147)	0.0280* (0.0156)
$\log(\text{GDP Capita})$		-0.0200 (0.0670)	0.0161 (0.0549)
$\log(\text{Distance})$		-0.308*** (0.0891)	0.379** (0.149)
N	40	40	38
R^2	0.372	0.530	0.755

Description: This table reports the correlation between the effect of the innovation subsidy on exports to different countries and the tariff that those countries impose against developed countries. Each observation represents a different country. Column 2 adds as control the log of per capita GDP in 2000 and the distance to Brazil. Column 3 add as controls dummies for continent and income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

D.2 Heterogeneous Treatment Effects are Consistent with the Subsidy Alleviating Financial Constraints

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 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 at the year prior to the subsidy application. In this section we discuss the results from applying this method. We leave to Section D.3 a detailed discussion of the implementation.

Table D20 shows statistics of the distribution of the treatment effect of the innovation subsidy on the number of workers, number of scientists, and number of patents in a 5 year horizon. 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 D20: **Distribution of the Effect of the Innovation Subsidy**

	$\theta^{\log(N. Workers)}$	$\theta^{\text{IHS}(N. Researchers)}$	$\theta^{\text{IHS}(N. Pat. Nxt. 3)}$
Mean	0.389	0.373	0.106
Standard Deviation	0.071	0.185	0.086
10th Percentile	0.295	0.112	-0.018
25th Percentile	0.332	0.229	0.054
Median (50th Percentile)	0.388	0.371	0.107
75th Percentile	0.441	0.524	0.164
90th Percentile	0.475	0.618	0.221
N	355	388	388

Description: This table describes the distribution of treatment effects. The treatment effect is calculated using a long difference and causal forest (Wager and Athey (2018)). Appendix D.3 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 D21 shows that financial constraints is an important determinant of the effect of the innovation subsidy. Table D21 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. Table D21 shows that conditional on subsidy value, the banking credit spreads that firms were facing are the most relevant characteristic. This is consistent with the idea that the innovation subsidy alleviates tight financial constraints.

Table D21: Correlation Between Treatment Effect and Firm Characteristics

	(1) $\rho^{\log(N. Workers)}$	(2) $\rho^{\mathbb{IHS}(N. Researchers)}$	(3) $\rho^{\mathbb{IHS}(N. Pat. Nxt. 3)}$
$\log(Subsidy Value)$	0.0347*** (0.00261)	0.0850*** (0.00649)	0.0153*** (0.00356)
$\log(Credit Spread_{t=-1})$	0.0215*** (0.00232)	0.0305*** (0.00591)	0.0163*** (0.00324)
$\log(N. Workers_{t=-1})$	-0.00970*** (0.00237)	0.00763 (0.00592)	-0.0152*** (0.00325)
$\log(Age_{t=-1})$	-0.00535 (0.00457)	0.00797 (0.0112)	-0.00758 (0.00616)
N	330	359	359
R^2	0.438	0.428	0.193

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 interest rate on bank loans before applying for the innovation subsidy. *Age_{t=-1}* is firm's age. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

D.3 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): $E[Y_{1,i} - Y_{0,i} | X_i = x]$, 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)):

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

where Δy_i is the difference in outcome y_i one year before and 5 years after the innovation subsidy, $\mathbb{I}_i \{Innovation Subsidy\}$ 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

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

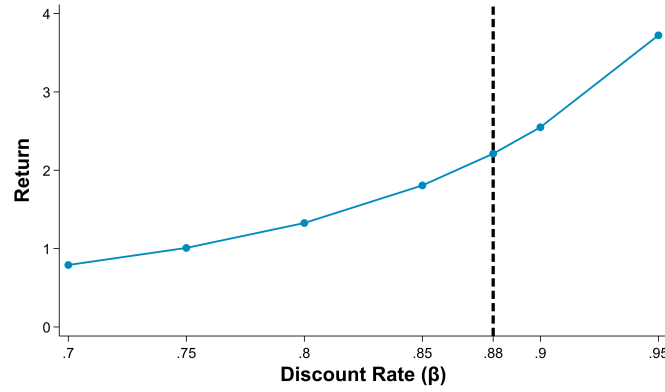
where $\theta(X_i)$ is the conditional average treatment effect of the innovation subsidy on a firm with covariates X_i . X_i contains the subsidy value, interest rate spreads on bank loans, employment, and firm age in the year prior to the subsidy application. As the name suggests, in a causal forest 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, ensuring 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.

D.4 Robustness on the Subsidy Tax Return

In this section, we present alternative calibrations and formulas for estimating the tax return of the innovation subsidy. Depending on the specification, the estimated return ranges from \$0.9 to \$6 per dollar spent. Most estimates exceed \$1, with only one falling below that threshold.

Alternative discount rate. Figure D7 shows how the return on each dollar of R&D subsidy changes with different discount rate calibrations. For Brazil, standard values range from 0.96 to 0.98 (Cavalcanti et al. 2021, Delalibera et al. 2025, de Castro et al. 2011), and within that range, the estimated return exceeds \$3.8. A return below \$1 emerges only if the discount rate falls to an implausibly low level of 0.7.

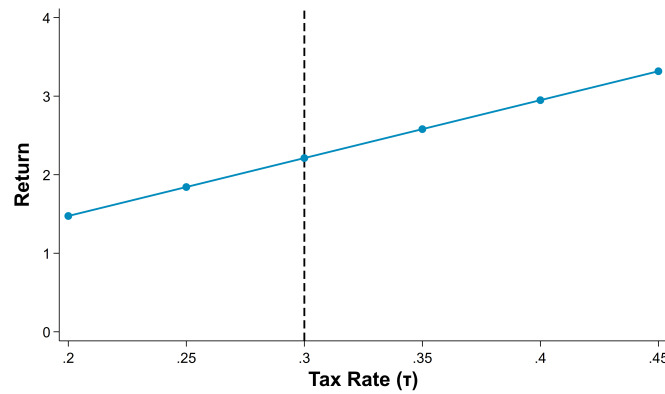
Figure D7: **Return with Different Discount Rates**



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 reciprocity 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.

Alternative marginal tax. Figure D8 shows the inferred return under different calibrations of the marginal tax rate τ . Payroll taxes in Brazil range from 28% to 34%, depending on the worker's salary. Assuming a marginal tax rate of 20%, the fiscal return on the R&D subsidy would be \$1.5 for every dollar invested. This is a conservative lower bound on the tax because it doesn't take into account that profits, sales, and imports are also taxed by the subsidy.

Figure D8: **Return with Different Tax Rates**



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 reciprocity 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.

Take into account recurring subsidies. As noted in Section E.2, receiving a subsidy today raises a firm’s chances of obtaining another in the future. This is expected because subsidies build research experience, a key criterion used by the Funding Authority in evaluating applications. However, ignoring this dynamic risks understating the cost of the program. To account for the impact on future subsidies, we use the following expression:

$$return = \tau \frac{\sum_t \beta^t (e^{\theta_t} - 1) \overline{Wage\ Bill}}{\sum_t \beta^t P_t^S \overline{Subsidy}} \quad (9)$$

where P_t^S is the effect of receiving the innovation subsidy at $t = 0$ on the probability that the firm receives another subsidy t years later. Thus, $\sum_t \beta^t P_t^S, \overline{Subsidy}$ represents the present value of all future subsidies received by a firm initially treated at time $t = 0$. The P_t^S coefficients are estimated in Figure E9. As with the wage bill calculation, we assume $P_t^S = 0$ for all $t \geq 14$. Using the same baseline calibration for other parameters, this yields a return of \$1.01 per dollar invested.

Alternative long-run effects. In the baseline return calibration, we adopted the strict assumption that the effect of the subsidy drops to zero in the long run. The first line of Table D22 relaxes this assumption. Column 1 presents the baseline case, assuming zero effect beyond year 14. Column 2 assumes the return after year 14 equals the long-run estimate from Table D22. Column 3 sets the post-year-14 effect to 0.259, the average wage bill effect from Table 4. Column 4 holds the effect constant at its year-14 level, so $\theta_t = 0.59, \forall t > 14$. Column 5 assumes a constant effect of 0.259 over the entire sample period. Across these specifications, the fiscal return ranges from \$1.8 to \$2.9 per dollar invested.

The second row of Table D22 shows returns that include the likelihood of firms receiving additional subsidies later on. In that case, the fiscal return ranges from 1.01 to 1.2.

Alternative functional form. We also test the following functional form for calculating the return

$$return = \tau \sum_t \beta^t (e^{\theta_t} - 1) E \left[\frac{Wage\ Bill_i}{Subsidy_i} \right] \quad (10)$$

Table D22: **Back-of-the-Envelope Estimates of Subsidy Returns**

Return Formula	Long-Run Effect Assumption				
	(1) Zero	(2) Long-Run	(3) Average	(4) Last Effect	(5) Uniform Effect
$PV(E[\text{Wage Bill}]) / E[\text{Subsidy}]$	2.21	2.60	2.48	2.95	1.81
$PV(E[\text{Wage Bill}]) / PV(E[\text{Subsidy}])$	1.01	1.14	1.02	1.29	1.14
$PV(E[\text{Wage Bill}/\text{Subsidy}])$	4.69	5.50	5.25	6.25	3.83

Description: This table presents alternative approximations of the return on the R&D subsidy program. Each row uses a different return formula, and each column represents a different assumption about the persistence of the subsidy's effect. "Last Effect" assumes the effect remains constant at its last observed value. "Uniform Effect" assumes constant treatment effects from year one.

In this equation, instead of dividing the average wage bill by the average subsidy, we use the average of the firm-level ratio between wage bill and subsidy, which captures the joint distribution of the two variables. The last line of Table D22 reports the fiscal return under different assumptions about the continuation value. Depending on the specification, the return ranges from \$3.8 to \$5.5 per dollar invested.

Conclusion: return ranges from \$1 to \$6. Across the different methods used to estimate the return of the innovation subsidy, we find values ranging from approximately 1 to 5.5 per dollar invested. This implies that, even under the most conservative assumptions, the subsidy more than pays for itself.

E Alternative Explanations

E.1 Knowledge Spillover and Market Rivalry Effect

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 $T_i = (T_{i,1}, \dots, T_{i,132})$ 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

$$spilltech_{i,j} = \frac{(T_i T'_j)}{(T_i T'_i)^{1/2} (T_j T'_j)^{1/2}}$$

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

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

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

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

We calculate the market rivalry effect using sectors. Let $S_i = (S_{i,1}, \dots, S_{i,527})$ 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:

$$SIC_{ij} = \frac{(S_i S'_j)}{(S_i S'_i)^{1/2} (S_j S'_j)^{1/2}}$$

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

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

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

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

model:³⁹

$$y_{i,t} = \lambda^{spill} \log(Spilltech_{i,t} + 1) + \lambda^{SIC} \log(SpillSIC_{ij} + 1) + X'_{i,t}\Lambda + \mu_i + \mu_t + \epsilon_{i,t} \quad (11)$$

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

According to Table E23, the subsidy did not generate a spillover or market rivalry effect, which is consistent with the mechanics of the innovation subsidy discussed before. Table E23 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.

³⁹One 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, and other general equilibrium effects. Therefore, regional effects are not informative about knowledge spillovers.

Table E23: **Spillover and Market Rivalry of Innovation Subsidy**

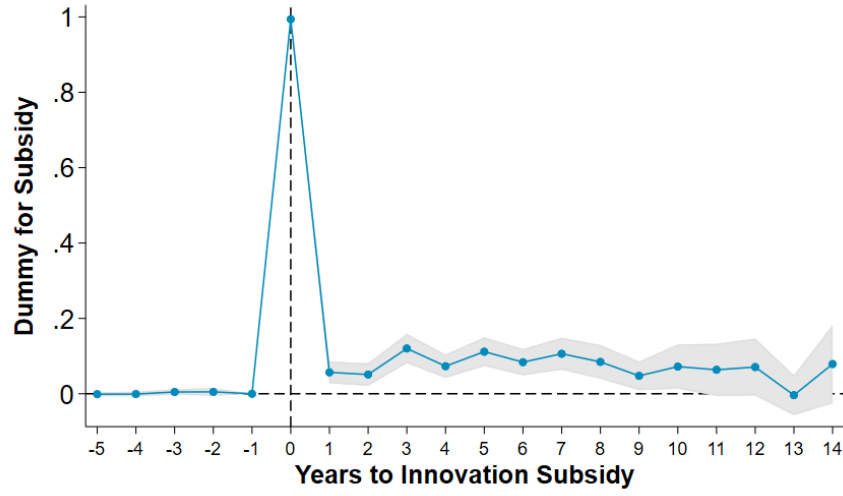
	(1) <i>log(Workers)</i>	(2) <i>log(Branches)</i>	(3) <i>log(Payroll)</i>	(4) <i>IHS(Payroll Scientists)</i>	(5) <i>IHS(Patents)</i>
<i>log(Spilltech_{i,t} + 1)</i>	-0.0157 (0.0268)	-0.00485 (0.0134)	-0.0149 (0.0284)	-0.0408 (0.0674)	-0.00389 (0.0147)
<i>log(SpillSIC_{ij} + 1)</i>	-0.0407 (0.0451)	-0.00105 (0.0190)	-0.0687 (0.0482)	-0.0501 (0.120)	-0.0468* (0.0252)
<i>N</i>	85,748	85,745	85,748	85,748	85,748
<i>R</i> 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 11. 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.

E.2 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 E9 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 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.

Figure E9: **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.

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

$$y_{i,t} = \sum_j \theta_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} \times \log(\text{Subsidy Value}_{i,t}) + \quad (12)$$

$$\sum_j \alpha_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t}$$

where $\text{Subsidy Value}_{i,t}$ is the sum in Brazilian reais of all R&D subsidy received by firm i up to year t . If the firm did not receive any innovation subsidy, we set $\text{Subsidy Value}_{i,t}$ 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.

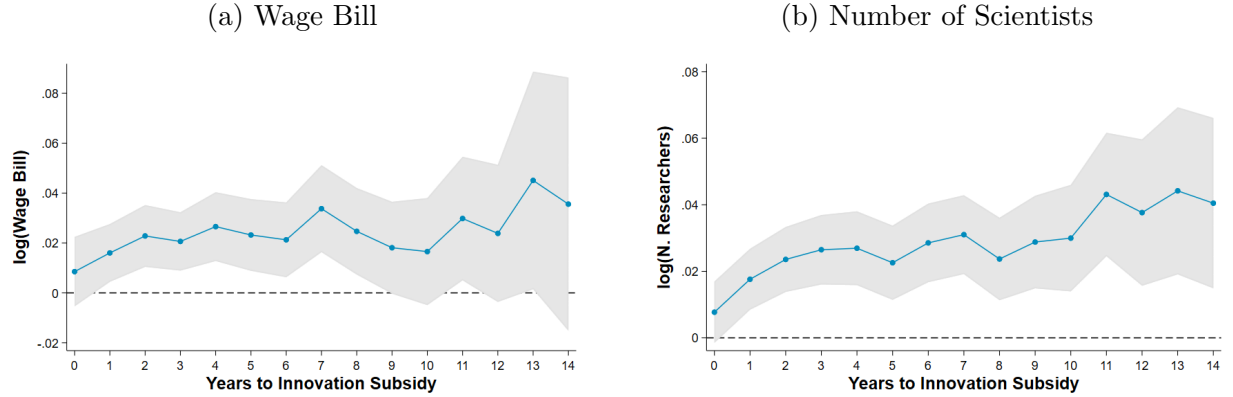
After the first subsidy application, increases in innovation subsidy are endogenous. To deal with that, we instrument the subsidy with a dummy if the firm was successful on its first application, as in the baseline model:

$$\log(\text{Subsidy Value}_{i,t}) = \sum_j \theta_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} \times \mathbb{I}_i\{\text{Treatment}\} +$$

$$\sum_j \alpha_j \times \mathbb{I}_{i,t}\{j \text{ Yrs to Subsidy Application}\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t}$$
(13)

Results. Figures E10a and E10b 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.

Figure E10: **Effect of Innovation Subsidy on the Long-Run**



Description: This figure shows the dynamic effect of the innovation subsidy on firms' wage bill and number of researchers according to model 12. 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 E10a, or on the number of researchers, in Figure E10b. The first stage is given by 13. Standard errors are clustered at the firm level.

E.3 Marginal Subsidy Recipients

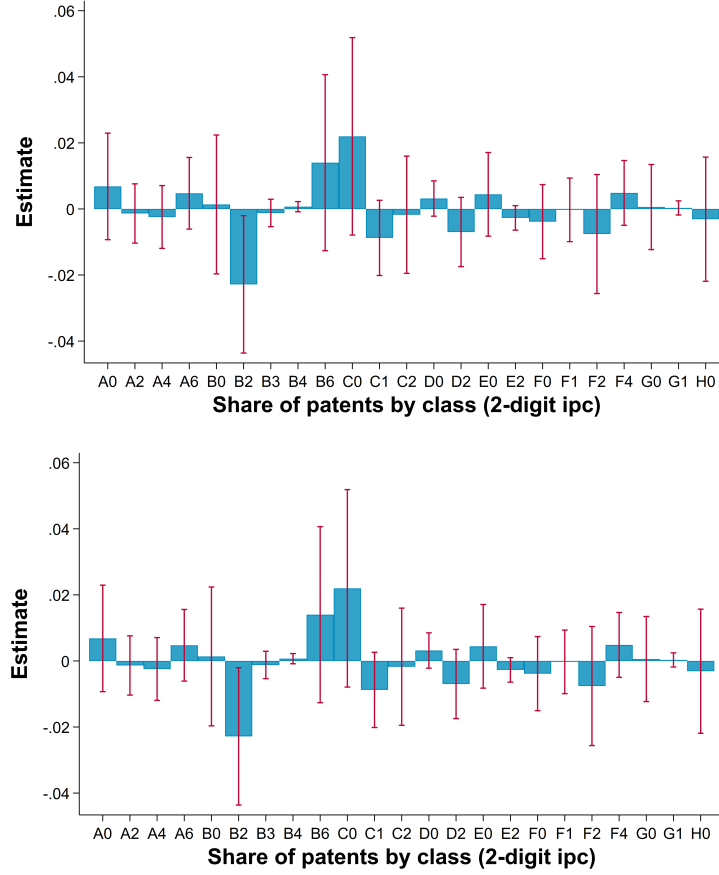
Table E24: Main Results Interacting for Dummy for High Budget Call

	(1) $\mathbb{I}(N. Patent$ $Nxt. 3)$	(2) $\log(Citations)$	(3) $\log(Wage$ $Bill)$	(4) $\log(Exports)$	(5) $\log(Prod$ $Pat)$	(6) $\log(Proc$ $Pat)$	(7) $\log(\#$ $Export$ $Products)$	(8) $\log(N. Pat$ $High Tar$ $Prod.)$	(9) $\log(N. Pat$ $Low Tar$ $Prod.)$
$\mathbb{I}\{Subsidy\}$	0.0709** (0.0325)	0.0190 (0.0177)	0.239** (0.108)	1.302*** (0.443)	0.0787* (0.0475)	0.0168 (0.0149)	0.393*** (0.0872)	0.0504** (0.0251)	0.0124 (0.0235)
$\mathbb{I}\{Subsidy in High$ $Budget Call\}$	0.00775 (0.0522)	-0.0101 (0.0224)	0.0586 (0.158)	1.069 (1.798)	-0.0229 (0.0711)	-0.0265 (0.0227)	-0.177 (0.272)	0.0128 (0.0380)	-0.0265 (0.0361)
N	9,358	9,358	9,358	5,600	9,358	9,358	5,600	9,358	9,358
R^2	0.532	0.512	0.865	0.836	0.647	0.400	0.866	0.585	0.731

Description: This table shows the effect of the subsidy, allowing it to be different in large call for projects. The table plots the parameters θ_1 and θ_2 of the following model: $y_{i,t} = \theta_1 \mathbb{I}_{i,t} \{Subsidy\} + \theta_2 \mathbb{I}_{i,t} \{Subsidy in High Budget Call\} + \mu_i + \mu_{g(i),t} + \epsilon_{i,t}$. A call for project is defined as high budget if the total subsidy awarded is on the top quartile. The left-hand side in column 1 is the log of the number of patent applications made by the firm during the next three years plus one; in column 2 it is the log of citations received by the firm during the next three years plus one; in column 3 the log of wage bill; in column 4 the log of exports plus one; in column 5 the log of product patents plus one; in column 6 the log of process patents plus one; in column 7 the number of different export products; in column 8 the number of patents in the next three years associated with products with tariffs in 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. Because these outcomes can be zero for many firms, we add one before taking the logarithm. Standard errors are clustered at the firm level.

E.4 Direction of Innovation

Figure E11: Effect on Share of Patents in Different Patent Classes



Description: This figure shows the estimated effect of the innovation subsidy on the distribution of patents across technological classes. The y-axis reports the estimated coefficients of the subsidy effect on the share of patents in each class. The x-axis contain the different patent classes. The figure illustrates whether firms shifted the composition of their patenting activity toward particular categories following receipt of the subsidy. Standard errors are clustered at the firm level.

E.5 Robustness Appendix

E.5.1 Control-Function with all subsidy applicants

In the main analysis, we estimate the effect of the R&D subsidy using a matched difference-in-differences design that compares near-winners and near-losers within the same call for projects. This matching strategy ensures that treatment and control firms are comparable in observed characteristics and evaluated under the same selection criteria. However, it necessarily restricts the analysis to a narrow set of marginal applicants. In this section, we complement that design with a control-function approach that expands the sample to include

all firms that applied to the subsidy program. This strategy delivers the same conclusions as in the baseline identification strategy, which suggests that our conclusion is not only valid to a narrow set of firms near the eligibility cut off.

We use the following model:

$$y_{i,t} = \theta \mathbb{I}_{i,t} \{Innovation\ Subsidy\} + \mu_i + X_{i,t} + \epsilon_{i,t} \quad (14)$$

where $y_{i,t}$ is the outcome of interest for firm i in year t , such as wage bill, exports, or employment. The indicator $\mathbb{I}_{i,t} \{Innovation\ Subsidy\}$ equals one if firm i received the subsidy by year t , and zero otherwise. Firm fixed effects μ_i absorb all time-invariant firm characteristics, and $X_{i,t}$ includes the vector of firm-year-level controls. The coefficient of interest, θ , captures the average effect of receiving the subsidy, conditional on observed characteristics. We cluster standard errors at the firm level to account for serial correlation.

We consider three sets of continuous controls in the specification. First, we include the number of workers, number of patents, number of citations received, and the value of the subsidy requested—all measured in the year prior to the first subsidy application—and interact them with year fixed effects. Second, we augment this set by adding the average wage of the research team, also measured in the pre-application year and interacted with year dummies. Third, we consider a specification without any controls.

In addition, we explore three sets of fixed effects. First, we include project call-year fixed effects, which compare firms that applied to the same call for projects in the same year. Second, we use sector-by-project call-year fixed effects to restrict comparisons to firms in the same sector and project call. Finally, we consider a baseline specification that omits fixed effects entirely.

The identifying assumption in this setting is that, conditional on the controls, the only difference between a firm that received the subsidy and another that didn't is the subsidy itself. This is a stronger assumption than in the matched design, which only compare firms that are similar in several characteristics. However, the benefit of this approach is that it allows us to recover the average treatment effect across a much broader population of firms.

Tables E25 and E26 report the effects of the innovation subsidy under various controls.

Across all models, we find a positive effect on patenting, wage bill, and exports, although some coefficients lose statistical significance due to the large number of controls. Column 2 shows no effect on citations, reinforcing the conclusion that the subsidy did not produce high-impact innovations. Columns 7, 8, and 9 indicate that the subsidy drove an expansion in product variety toward high-tariff goods. Taken together, the results confirm the main findings.

Table E25: Main Results using Control Function with Project Call FE

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
Baseline									
$\mathbb{I}\{Subsidy\}$	0.0629** (0.0237)	0.00393 (0.0185)	0.217*** (0.0836)	0.917** (0.382)	0.0667* (0.0363)	0.00642 (0.0115)	0.275*** (0.0804)	0.0516** (0.0222)	-0.00744 (0.0201)
N	19,779	19,779	19,779	11,203	19,779	19,779	11,203	19,779	19,779
R^2	0.550	0.820	0.890	0.843	0.676	0.537	0.871	0.624	0.643
Baseline + Scientists' Wage									
$\mathbb{I}\{Subsidy\}$	0.0893*** (0.0299)	0.0105 (0.0230)	0.177* (0.0966)	0.905* (0.470)	0.120*** (0.0463)	0.00804 (0.0142)	0.263*** (0.0924)	0.0792*** (0.0282)	0.0132 (0.0255)
N	12,295	12,295	12,295	7,271	12,295	12,295	7,271	12,295	12,295
R^2	0.571	0.830	0.871	0.853	0.695	0.549	0.880	0.643	0.665

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 log of the number of patent applications the firm will make during the next three years plus one; in column 2 it is the log of citations the firm will receive during the next three years plus one; in column 3 it is the log of the wage bill; in column 4 it is the log of exports plus one; in column 5 it is the log of product patents plus one; in column 6 it is the log of process patents plus one; 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 log of the number of patents plus one, the log of the total number of citations received plus one, and the log of the subsidy grant requested. The "Baseline + Scientists' Wage" adds as control the log of the wage of the scientists plus one. Because these outcomes can be zero for many firms, we add one before taking the logarithm. Standard errors are clustered at the firm level.

Table E26: Main Results using Control Function with Project Call and Sector FEs

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
Baseline									
$\mathbb{I}\{Subsidy\}$	0.0605** (0.0283)	0.00399 (0.0221)	0.150 (0.0957)	0.836* (0.440)	0.0760* (0.0434)	0.0170 (0.0131)	0.287*** (0.0922)	0.0541* (0.0277)	-0.00356 (0.0222)
N	16,808	16,808	16,808	9,218	16,808	16,808	9,218	16,808	16,808
R^2	0.612	0.840	0.913	0.872	0.720	0.580	0.885	0.682	0.685
Baseline + Scientists' Wage									
$\mathbb{I}\{Subsidy\}$	0.0458 (0.0397)	-0.000396 (0.0312)	0.142 (0.127)	0.817 (0.581)	0.0962 (0.0630)	0.00964 (0.0176)	0.275** (0.118)	0.0833** (0.0392)	-0.00861 (0.0317)
N	9,823	9,823	9,823	5,652	9,823	9,823	5,652	9,823	9,823
R^2	0.643	0.856	0.904	0.880	0.746	0.605	0.894	0.720	0.710

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 hyperbolic 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.

E.5.2 Empirical Model using Subsidy Size Variation

The main specification in Section 1 estimates the average effect of receiving an R&D subsidy, treating all recipients the same regardless of how much funding they received. This approach ensures that the identification comes from comparing treatment to control firms and identify the effect of the average subsidy. In this section, we augment this strategy by exploiting variation from subsidy size.

The empirical model is:

$$y_{i,t} = \theta \log(\text{Subsidy Value}_i) \times \mathbb{I}_{i,t} \{ \text{Innovation Subsidy} \} + \mu_{g(i),t} + \mu_i + \epsilon_{i,t} \quad (15)$$

where Subsidy Value_i is the value of the subsidy requested by firm i .

Table E27 shows that our main conclusions remain unchanged. The subsidy increased innovation and firm size, with effects persisting in the long run. Columns 5 to 7 show that firms expanded the variety of exported products and patent classes. Columns 8 and 9 confirm that this expansion was concentrated in high-tariff products, consistent with the import-substitution mechanism.

Table E27: Main Results using Variation from Subsidy Value

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
<i>log{ VI Subsidy }</i>	0.00452** (0.00190)	0.000956 (0.00190)	0.0163** (0.00644)	0.0964*** (0.0311)	0.00570* (0.00341)	0.000725 (0.00115)	0.0309*** (0.00691)	0.00430** (0.00183)	0.000415 (0.00173)
<i>Panel B: Extended DD</i>									
<i>log{ VI Subsidy 0-2 Yrs }</i>	0.00357* (0.00215)	-0.000231 (0.00172)	0.0123** (0.00589)	0.0873*** (0.0324)	0.00483 (0.00358)	0.000992 (0.00144)	0.0287*** (0.00709)	0.00412** (0.00202)	0.000663 (0.00195)
<i>log{ VI Subsidy 3-5 Yrs }</i>	0.00720*** (0.00228)	0.00382 (0.00375)	0.0185*** (0.00699)	0.120** (0.0465)	0.00949** (0.00404)	0.00168 (0.00140)	0.0376*** (0.0106)	0.00481** (0.00232)	0.00171 (0.00228)
<i>log{ VI Subsidy 6+ Yrs }</i>	0.00321 (0.00291)	-0.00101 (0.00265)	0.0223** (0.00989)	0.112* (0.0651)	0.00333 (0.00496)	-0.000550 (0.00180)	0.0386** (0.0174)	0.00412 (0.00276)	-0.000784 (0.00288)
<i>N</i>	9,197	9,197	9,197	5,510	9,197	9,197	5,510	9,197	9,197

Description: This table shows the effect of the innovation subsidy on the main firm outcomes. Each column displays the coefficient of model $y_{i,t} = \theta \log(VI \text{ Subsidy}) \mathbb{I}_{i,t} \{ \text{Innovation Subsidy} \} + \mu_{g(i),t} + \mu_i + \epsilon_{i,t}$, where $VI \text{ Subsidy}$ is the value requested for the grant. The left-hand side in column 1 is a dummy if the firm made any patent application in the next three years; in column 2 it is the log of citations that will be received by the firm during the next three years plus one; in column 3 it is the log of the wage bill; in column 4 it is the log of exports plus one; in column 5 it is the log of product patents plus one; in column 6 it is the log of process patents plus one; 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 are in the bottom quartile. Because these outcomes can be zero for many firms, we add one before taking the logarithm. Standard errors are clustered at the firm level.

E.5.3 Alternative Matching Strategies

Table E28: Main Results Matching on CEO Wage

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
$\mathbb{I}\{\text{Subsidy}\}$	0.0665** (0.0333)	-0.00582 (0.0240)	0.267** (0.105)	1.122*** (0.429)	0.0806 (0.0570)	0.00998 (0.0164)	0.365*** (0.0940)	0.0568* (0.0342)	0.0165 (0.0254)
<i>Panel B: Extended DD</i>									
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0542 (0.0369)	-0.00277 (0.0196)	0.193** (0.0907)	0.925** (0.432)	0.0446 (0.0516)	0.00736 (0.0158)	0.326*** (0.0941)	0.0414 (0.0321)	-0.000312 (0.0241)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.0960** (0.0410)	0.00918 (0.0223)	0.289*** (0.109)	1.740** (0.678)	0.115* (0.0639)	0.0212 (0.0169)	0.499*** (0.147)	0.0610 (0.0393)	0.0256 (0.0296)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0511 (0.0507)	-0.0276 (0.0563)	0.353** (0.168)	1.236 (1.090)	0.0897 (0.0834)	0.00128 (0.0370)	0.369 (0.230)	0.0725 (0.0470)	0.0284 (0.0467)
<i>N</i>	7,772	7,772	7,772	4,633	7,772	7,772	4,633	7,772	7,772
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 a dummy if the firm made any patent application in the next three years; in column 2 it is the log of citations that will be received by the firm during the next three years plus one; in column 3 it is the log of wage bill; in column 4 it is the log of exports plus one; in column 5 it is the log of product patents plus one; in column 6 it is the log of process patents plus one; 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 E29: Main Results Matching on Sector

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
$\mathbb{I}\{\text{Subsidy}\}$	0.0756* (0.0401)	0.0351** (0.0177)	0.326** (0.127)	1.202** (0.511)	0.0561 (0.0568)	0.00221 (0.0205)	0.438*** (0.103)	0.0587* (0.0310)	0.00134 (0.0259)
<i>Panel B: Extended DD</i>									
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0592 (0.0449)	0.0285* (0.0160)	0.327*** (0.112)	1.243** (0.563)	0.0475 (0.0600)	-0.00379 (0.0247)	0.424*** (0.106)	0.0562* (0.0330)	-0.00705 (0.0268)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.117** (0.0500)	0.0424 (0.0260)	0.312** (0.143)	0.818 (0.754)	0.0971 (0.0690)	0.0134 (0.0248)	0.492*** (0.166)	0.0710* (0.0411)	0.0145 (0.0354)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0539 (0.0578)	0.0351 (0.0238)	0.360* (0.200)	1.009 (1.156)	0.0257 (0.0743)	-0.00150 (0.0201)	0.266 (0.265)	0.0484 (0.0418)	0.00126 (0.0394)
<i>N</i>	6,151	6,151	6,151	3,657	6,151	6,151	3,657	6,151	6,151
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 a dummy if the firm made any patent application in the next three years; in column 2 it is the log of citations that the firm will receive during the next three years plus one; in column 3 it is the log of the wage bill; in column 4 it is the log of exports plus one; in column 5 it is the log of product patents plus one; in column 6 it is the log of process patents plus one; 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. Standard errors are clustered at the firm level.									

Table E30: Main Results Matching on Quality of Research Team

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
$\mathbb{I}\{\text{Subsidy}\}$	0.106*** (0.0294)	0.0101 (0.0101)	0.312*** (0.103)	1.272** (0.494)	0.0781* (0.0401)	0.00949 (0.00782)	0.409*** (0.0976)	0.0473* (0.0240)	0.00829 (0.0141)
<i>Panel B: Extended DD</i>									
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0689** (0.0344)	-0.00483 (0.0135)	0.280*** (0.0897)	1.203** (0.510)	0.0462 (0.0422)	0.000417 (0.0120)	0.390*** (0.101)	0.0313 (0.0252)	-0.0242 (0.0157)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.147*** (0.0369)	0.0143 (0.0122)	0.358*** (0.110)	1.521** (0.742)	0.102** (0.0506)	0.0194* (0.0111)	0.477*** (0.148)	0.0543* (0.0324)	-0.00918 (0.0209)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.127*** (0.0401)	0.0258* (0.0156)	0.427*** (0.161)	1.654 (1.127)	0.107* (0.0571)	0.0158 (0.0117)	0.395 (0.265)	0.0609* (0.0345)	0.0242 (0.0206)
<i>N</i>	7,583	7,583	7,583	4,516	7,583	7,583	4,516	7,583	7,583
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 a dummy if the firm made any patent application in the next three years; in column 2 it is the log of citations that will be received by the firm during the next three years plus one; in column 3 it is the log of the wage bill; in column 4 it is the log of exports plus one; in column 5 it is the log of product patents plus one; in column 6 it is the log of process patents plus one; 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. Standard errors are clustered at the firm level.									

Table E31: Main Results Matching on Project Quality

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
$\mathbb{I}\{\text{Subsidy}\}$	0.106*** (0.0313)	-0.00690 (0.0171)	0.285*** (0.107)	1.385*** (0.447)	0.103** (0.0483)	0.00347 (0.0122)	0.427*** (0.0944)	0.0567** (0.0281)	0.0220 (0.0230)
<i>Panel B: Extended DD</i>									
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0835** (0.0343)	-0.0117 (0.0197)	0.232** (0.0908)	1.279*** (0.469)	0.0810* (0.0480)	0.000767 (0.0161)	0.400*** (0.0945)	0.0554* (0.0282)	0.00244 (0.0230)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.142*** (0.0402)	0.00795 (0.0212)	0.309*** (0.113)	1.641** (0.670)	0.120** (0.0582)	0.0154 (0.0152)	0.528*** (0.162)	0.0528 (0.0354)	0.0264 (0.0286)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0984** (0.0420)	-0.0206 (0.0334)	0.349* (0.181)	1.496 (1.063)	0.118* (0.0643)	-0.00327 (0.0202)	0.401 (0.259)	0.0638* (0.0386)	0.0455 (0.0337)
<i>N</i>	7,432	7,432	7,432	4,428	7,432	7,432	4,428	7,432	7,432

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 a dummy if the firm made any patent application in the next three years; in column 2 it is the log of citations that will be received by the firm during the next three years plus one; in column 3 it is the log of the wage bill; in column 4 it is the log of exports plus one; in column 5 it is the log of product patents plus one; in column 6 it is the log of process patents plus one; 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 E32: Main Results Matching on 2 Years Leading to the Subsidy Application

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>log(Cit.)</i>	(3) <i>log(Wage Bill)</i>	(4) <i>log(Exports)</i>	(5) <i>log(Prod. Pat.)</i>	(6) <i>log(Proc. Pat.)</i>	(7) <i>log(# Exp. Prod.)</i>	(8) <i>log(N. Pat. High Tariff Prod.)</i>	(9) <i>log(N. Pat. Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
$\mathbb{I}\{\text{Subsidy}\}$	0.0678** (0.0336)	0.0275* (0.0156)	0.270** (0.107)	1.461 *** (0.480)	0.0358 (0.0472)	-0.00647 (0.0205)	0.348*** (0.0877)	0.0511** (0.0257)	-0.00989 (0.0245)
<i>Panel B: Extended DD</i>									
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0605 (0.0373)	0.00762 (0.0186)	0.169* (0.0960)	1.376*** (0.483)	0.0248 (0.0483)	0.0127 (0.0193)	0.339*** (0.0924)	0.0457* (0.0269)	0.00125 (0.0234)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.0933** (0.0402)	0.0439** (0.0192)	0.265** (0.111)	1.641** (0.760)	0.0509 (0.0548)	0.000602 (0.0215)	0.375*** (0.136)	0.0404 (0.0319)	0.000643 (0.0299)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0532 (0.0476)	0.0330 (0.0227)	0.422** (0.183)	1.985* (1.147)	0.0384 (0.0652)	-0.0366 (0.0363)	0.400* (0.229)	0.0707* (0.0390)	-0.0319 (0.0450)
<i>N</i>	6,669	6,669	6,669	4,066	6,669	6,669	4,066	6,669	6,669

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 two years before the subsidy application. The left-hand side in column 1 is a dummy if the firm made any patent application in the next three years; in column 2 it is the log of citations that will be received by the firm during the next three years plus one; in column 3 it is the log of the wage bill; in column 4 it is the log of exports plus one; in column 5 it is the log of product patents plus one; in column 6 it is the log of process patents plus one; 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.

E.5.4 Indirect Evidence of the Effect of the Innovation Subsidy on Informality

Table E33: Effect of Innovation Subsidy on Labor Market Inspections

	(1) <i>log(N. Inspection)</i>	(2) <i>log(N. Informal Infraction)</i>	(3) <i>log(N. Inspection with Infraction)</i>	(4) <i>log(N. Inspection without Infraction)</i>
$\mathbb{I}\{\text{Subsidy}\}$	0.107** (0.0535)	0.00525 (0.00555)	0.118*** (0.0398)	0.0405 (0.0462)
<i>N</i>	11,403	11,403	11,403	11,403
<i>R</i> ²	0.566	0.249	0.563	0.408

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 the log of the number of labor inspections that the firm received in a year plus one; in column 2 it is the log of the number of infractions for hiring informal workers plus one; in column 3 it is the number of inspections that did not find any infraction; and in column 4 it is the number of inspections that found any labor market infraction. Standard errors are clustered at the firm level.

E.5.5 Dealing with Zeros According to Suggestion of Chen and Roth (2023)

Table E34: Main Results using Percentile Transformation

	(1) <i>Per(N. Pat Nxt. 3)</i>	(2) <i>Per(Cit.)</i>	(3) <i>Per(Citation Weighted Patents)</i>	(4) <i>Per(Exports)</i>	(5) <i>Per(Prod Pat)</i>	(6) <i>Per(Proc Pat)</i>	(7) <i>Per(# Export Products)</i>	(8) <i>Per(N. Pat High Tariff Prod.)</i>	(9) <i>Per(N. Pat Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
$\mathbb{I}\{\text{Subsidy}\}$	6.799** (2.670)	0.937 (0.979)	0.228 (0.217)	7.312** (2.902)	5.529** (2.624)	0.960 (1.378)	7.484*** (2.877)	5.559*** (1.959)	-0.432 (1.743)
<i>Panel B: Extended DD</i>									
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	5.523* (3.004)	0.270 (1.446)	0.387 (0.455)	6.202** (3.054)	4.140 (2.795)	0.610 (1.857)	6.199** (3.030)	5.079** (2.148)	-0.990 (2.042)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	10.43*** (3.205)	1.245 (1.455)	0.361 (0.450)	9.954** (4.404)	8.985*** (3.134)	2.423 (1.826)	10.58** (4.330)	6.502*** (2.404)	0.477 (2.271)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	5.240 (3.979)	1.165 (0.996)	-0.158 (0.132)	10.78* (5.661)	4.204 (3.961)	0.0458 (1.901)	12.24** (5.819)	5.310* (3.058)	-0.136 (2.633)
<i>N</i>	9,358	9,358	9,358	5,600	9,358	9,358	5,600	9,358	9,358

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 three 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 E35: Main Results using Inverse Hyperbolic Sine

	(1) <i>IHS(N. Patent Nxt. 3)</i>	(2) <i>IHS(Cit.)</i>	(3) <i>IHS(Citation Weighted Patents)</i>	(4) <i>IHS(Exports)</i>	(5) <i>IHS(Product Patent)</i>	(6) <i>IHS(Process Patent)</i>	(7) <i>IHS(# Export Products)</i>	(8) <i>IHS(N. Patent High Tariff Prod.)</i>	(9) <i>IHS(N. Patent Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>									
$\mathbb{I}\{\text{Subsidy}\}$	0.112** (0.0536)	0.0192 (0.148)	0.00300 (0.00277)	1.379*** (0.457)	0.0893* (0.0508)	0.00953 (0.0168)	0.443*** (0.101)	0.0718*** (0.0276)	0.00229 (0.0250)
<i>Panel B: Extended DD</i>									
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0968* (0.0571)	0.00194 (0.0194)	0.00599 (0.00658)	1.222** (0.479)	0.0716 (0.0535)	0.0123 (0.0209)	0.406*** (0.104)	0.0668** (0.0302)	0.00166 (0.0283)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.177*** (0.0638)	0.0288 (0.0268)	0.00315 (0.00405)	1.797*** (0.690)	0.145** (0.0593)	0.0242 (0.0207)	0.550*** (0.155)	0.0844** (0.0350)	0.0209 (0.0328)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0734 (0.0758)	0.0253 (0.0254)	-0.00137 (0.00119)	1.701* (0.958)	0.0643 (0.0721)	-0.00796 (0.0258)	0.574** (0.252)	0.0670 (0.0410)	-0.00840 (0.0398)
<i>N</i>	9,358	9,358	9,358	5,600	9,358	9,358	5,600	9,358	9,358

Description: This table shows the effect of the innovation subsidy on the main variables of interest using the inverse hyperbolic sine transformation. The inverse hyperbolic sine approximates the log while preserving zeros (Bellemare and Wichman 2020). 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 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 three years; in column 3 it is the inverse hyperbolic sine of citation weighted patents; 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 inverse hyperbolic sine of the number of different export products; in column 8 it is the inverse hyperbolic sine of 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 inverse hyperbolic sine of 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 E36: Main Results using a Dummy

	(1) <i>I(N. Patent Nxt. 3)</i>	(2) <i>I(Cit.)</i>	(3) <i>I(Exports)</i>	(4) <i>I(Product Patent)</i>	(5) <i>I(Process Patent)</i>	(6) <i>I(N. Patent High Tariff Prod.)</i>	(7) <i>I(N. Patent Low Tariff Prod.)</i>
<i>Panel A: Simple DD</i>							
$\mathbb{I}\{\text{Subsidy}\}$	0.0736*** (0.0285)	0.00946 (0.00989)	0.0722** (0.0332)	0.0601** (0.0282)	0.00980 (0.0140)	0.0574*** (0.0203)	-0.00438 (0.0180)
<i>Panel B: Extended DD</i>							
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0598* (0.0322)	0.00273 (0.0146)	0.0571 (0.0351)	0.0449 (0.0301)	0.00615 (0.0189)	0.0524** (0.0222)	-0.0104 (0.0211)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.112*** (0.0343)	0.0126 (0.0147)	0.107** (0.0498)	0.0974*** (0.0339)	0.0247 (0.0186)	0.0671*** (0.0249)	0.00489 (0.0234)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0576 (0.0427)	0.0118 (0.0101)	0.130** (0.0641)	0.0463 (0.0429)	0.000553 (0.0193)	0.0549* (0.0318)	0.000849 (0.0270)
<i>N</i>	9,358	9,358	5,600	9,358	9,358	9,358	9,358

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E37: Subsidy Caused Wide and Sustained Firm Expansion

	(1) <i>I(Exports)</i>	(2) <i>IHS(Exports)</i>
<i>Panel A: Simple DD</i>		
$\mathbb{I}\{\text{Subsidy}\}$	0.0722*** (0.0332)	1.379*** (0.457)
<i>Panel B: Extended DD</i>		
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Yrs}\}$	0.0571 (0.0351)	1.222** (0.479)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Yrs}\}$	0.107** (0.0498)	1.797*** (0.690)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.130** (0.0641)	1.701* (958)
<i>N</i>	5,600	5,600

Description: This table presents the effect of the innovation subsidy on firm exports. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The dependent variable in column 1 is a dummy equal to one if the firm exports at least once in a given year, and in column 2 the inverse hyperbolic sine of exports, which approximates the log while preserving observations with zero exports. Standard errors are clustered at the firm level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E38: Subsidy Does Not Crowd Out Bank Lending

	(1) <i>IHS(Loans)</i>	(2) <i>IHS(Invest. Loans)</i>	(3) <i>IHS(Working Cap. Loans)</i>
<i>Panel A: Simple DD</i>			
$\mathbb{I}\{\text{Subsidy}\}$	0.887* (0.493)	-0.158 (0.603)	0.908* (0.518)
<i>Panel B: Extended DD</i>			
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.439 (0.488)	-0.344 (0.600)	0.407 (0.511)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	1.262** (0.539)	-0.0194 (0.678)	1.328** (0.568)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	1.166* (0.621)	-0.00775 (0.785)	1.219* (0.640)
<i>N</i>	6,516	6,516	6,516

Description: This robustness table shows the effect of the innovation subsidy on access to credit using the inverse hyperbolic sine (IHS) transformation. The IHS approximates the log while preserving zeros (Bellemare and Wichman 2020). Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The dependent variable in column 1 is the inverse hyperbolic sine of the firm's outstanding bank loans in Brazilian reais; in column 2 the inverse hyperbolic sine of outstanding investment-related loans; and in column 3 the inverse hyperbolic sine of outstanding working-capital loans. These results serve as robustness to Table 6, which uses the log of the variables plus one to preserve zero values, and to Table E39, which uses dummies equal to one if the firm has any loans in each category. Standard errors, in parentheses, are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E39: Effect of Subsidy on Bank Loans

	(1) <i>I(Loans)</i>	(2) <i>I(Invest. Loans)</i>	(3) <i>I(Working Cap. Loans)</i>
<i>Panel A: Simple DD</i>			
$\mathbb{I}\{\text{Subsidy}\}$	0.0449* (0.0271)	-0.00118 (0.0440)	0.0461 (0.0285)
<i>Panel B: Extended DD</i>			
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.0220 (0.0271)	-0.0133 (0.0447)	0.0219 (0.0283)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.0650** (0.0294)	0.0101 (0.0490)	0.0678** (0.0309)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0572* (0.0343)	0.00409 (0.0560)	0.0584* (0.0354)
<i>N</i>	6,516	6,516	6,516
<i>R</i> ²	0.536	0.543	0.550

Description: This table shows the effect of the innovation subsidy on firms' access to bank loans using dummy outcomes as robustness. Panel A reports the coefficients from the simple DD specification (model 1), and Panel B from the extended DD specification (model 2). The dependent variable in column 1 is a dummy equal to one if the firm holds any bank loan; in column 2 it is a dummy for having at least one investment loan; and in column 3 it is a dummy for having at least one working capital loan. Tables 6 and E38 confirm the robustness of these results by, respectively, using the log of loan amounts plus one and the inverse hyperbolic sine transformation, which approximates the log while preserving zeros (Bellemare and Wichman 2020). Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E40: Subsidy Increased Innovation Effort

	(1) <i>IHS(N. Patents)</i>	(2) <i>IHS(N. Scientists)</i>	(3) <i>I (N. Trademarks)</i>	(4) <i>IHS(N. Trademarks)</i>
<i>Panel A: Simple DD</i>				
$\mathbb{I}\{\text{Subsidy}\}$	0.112** (0.0536)	0.189** (0.0831)	0.0163 (0.0342)	0.162* (0.0898)
<i>Panel B: Extended DD</i>				
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.0968* (0.0571)	0.126* (0.0750)	0.0268 (0.0364)	0.211** (0.0903)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.177*** (0.0638)	0.187* (0.0959)	0.0303 (0.0413)	0.190* (0.104)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0734 (0.0758)	0.296** (0.122)	-0.00829 (0.0523)	0.0862 (0.132)
<i>N</i>	9,358	9,358	9,358	9,358

Description: This table presents robustness checks of the effect of the innovation subsidy on firm innovation measures using alternative functional forms to handle zeros. 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 the inverse hyperbolic sine of the number of scientists; in column 3 it is a dummy if the firm registers at least one trademark; and in column 4 it is the inverse hyperbolic sine of the number of trademarks. The inverse hyperbolic sine approximates the log while preserving zeros (Bellemare and Wichman 2020). These results serve as robustness to Table 7, which uses the log of the variables plus one. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E41: Subsidy Did Not Increase Quality-Weighted Innovation

	(1) <i>I(Citations)</i>	(2) <i>IHS(Citations)</i>	(3) <i>IHS(Citation Weighted Patents)</i>	(4) <i>IHS(Inventor Wage Weighted Patents)</i>	(5) <i>IHS(Inventor Educ. Weighted Patents)</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	0.0115 (0.0114)	0.0192 (0.0187)	0.00300 (0.00277)	0.242 (0.183)	0.141 (0.103)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.00366 (0.0147)	0.00194 (0.0194)	0.00599 (0.00658)	0.115 (0.196)	0.0644 (0.108)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.0164 (0.0156)	0.0288 (0.0268)	0.00315 (0.00405)	0.313 (0.229)	0.179 (0.129)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0132 (0.0145)	0.0253 (0.0254)	-0.00137 (0.00119)	0.340 (0.256)	0.204 (0.145)
<i>N</i>	9,358	9,358	9,358	9,358	9,358

Description: This table shows the effect of the innovation subsidy on firm innovation measures using both dummy and inverse hyperbolic sine transformations. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. The dependent variable in column 1 is a dummy equal to one if the firm receives at least one citation; in column 2 it is the inverse hyperbolic sine of the number of citations; in column 3 the inverse hyperbolic sine of citation-weighted patent counts; in column 4 the inverse hyperbolic sine of patents weighted by the wages of inventors; and in column 5 the inverse hyperbolic sine of patents weighted by the years of education of inventors. The inverse hyperbolic sine approximates the log while preserving zeros (Bellemare and Wichman 2020). These results serve as robustness to Table 8, which uses the log of the variables plus one. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E42: R&D Hires Don't Have Experience in Research

	(1) <i>IHS(Scient. Bfr.)</i>	(2) <i>IHS(Engineer Bfr.)</i>	(3) <i>IHS(Health Bfr.)</i>	(4) <i>IHS(Technician Bfr.)</i>	(5) <i>IHS(Operation Bfr.)</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	-0.00168 (0.00926)	0.00797 (0.0240)	0.0280* (0.0158)	0.0755*** (0.0281)	0.0491*** (0.0141)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Years}\}$	-0.00718 (0.00557)	-0.00315 (0.0199)	0.0200 (0.0124)	0.0575** (0.0251)	0.0357** (0.0138)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Years}\}$	-0.00281 (0.0110)	0.0121 (0.0299)	0.0329* (0.0182)	0.0776** (0.0345)	0.0472*** (0.0159)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	0.00950 (0.0177)	0.0205 (0.0352)	0.0312 (0.0232)	0.107*** (0.0393)	0.0789*** (0.0195)
<i>N</i>	7,059	7,059	7,059	7,059	7,059

Description: This table presents robustness checks of the effect of the innovation subsidy on the hiring of scientists from different sectors and occupations using the inverse hyperbolic sine transformation to handle zeros. 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. Column 1 contains the inverse hyperbolic sine of the number of scientists that, before joining the firm, were employed as scientists as well. Column 2 contains the inverse hyperbolic sine of the number of scientists that, before joining the firm, were employed as engineers. Column 3 contains the inverse hyperbolic sine of the number of scientists that, before joining the firm, were employed as health professionals such as biologists or medical doctors. Column 4 contains the inverse hyperbolic sine of the number of scientists that, before joining the firm, were employed as technicians (CBO 2002 code 3), such as mechatronics, chemical, and laboratory technicians. Column 5 contains the inverse hyperbolic sine of the number of scientists that, before joining the firm, were employed as operation workers (CBO 2002 code 7), such as plant operation supervisors and machinery operators. The inverse hyperbolic sine approximates the log while preserving zeros (Bellemare and Wichman 2020). These results serve as robustness to Table 9, which uses the log of the variables plus one. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E43: R&D Hires Don't Have Experience in Research

	(1) <i>I{Scient. Bfr.}</i>	(2) <i>I{Engineer Bfr.}</i>	(3) <i>I{Health Bfr.}</i>	(4) <i>I{Technician Bfr.}</i>	(5) <i>I{Operation Bfr.}</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	-0.000262 (0.00867)	0.0179 (0.0168)	0.0148 (0.0111)	0.0653*** (0.0187)	0.0519*** (0.0131)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Years}\}$	-0.00541 (0.00759)	0.00107 (0.0166)	0.0152 (0.0101)	0.0605*** (0.0190)	0.0367*** (0.0128)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Years}\}$	-0.00194 (0.0106)	0.0152 (0.0208)	0.0176 (0.0122)	0.0567** (0.0225)	0.0489*** (0.0148)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	0.00682 (0.0112)	0.0374 (0.0258)	0.00997 (0.0146)	0.0790*** (0.0264)	0.0714*** (0.0177)
<i>N</i>	11,403	11,403	11,403	11,403	11,403

Description: This table presents robustness checks of the effect of the innovation subsidy on the hiring of scientists from different sectors and occupations using dummy variables as the left-hand side. 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. Each column indicates whether the firm hired at least one scientist from a given prior occupation. Column 1 is a dummy for whether the firm hired at least one scientist who was previously employed as a scientist. Column 2 is a dummy for whether the firm hired at least one scientist who was previously employed as an engineer. Column 3 is a dummy for whether the firm hired at least one scientist who was previously employed as a health professional, such as a biologist or medical doctor. Column 4 is a dummy for whether the firm hired at least one scientist who was previously employed as a technician (CBO 2002 code 3), such as mechatronics, chemical, and laboratory technicians. Column 5 is a dummy for whether the firm hired at least one scientist who was previously employed as an operation worker (CBO 2002 code 7), such as plant operation supervisors and machinery operators. These results serve as robustness to Table 9, which uses the log of the number of hires plus one, and Table E42, which uses the inverse hyperbolic sine transformation (Bellemare and Wichman 2020). Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E44: Subsidy Increased Product Variety

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

Description: This table presents robustness checks of the effect of the innovation subsidy on product variety using the inverse hyperbolic sine transformation to handle zeros. 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 applications 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 patent claims. Because claims are not available for patents in Brazil, we classify patents as process if, on average, USPTO patents with the same 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 inverse hyperbolic sine of the number of different trademark classes; in column 5 it is the inverse hyperbolic sine of the number of different products exported; and in column 6 it is the inverse hyperbolic sine of the number of different imported products. The inverse hyperbolic sine approximates the log while preserving zeros (Bellemare and Wichman 2020). These results serve as robustness to Table 10, which uses the log of the variables plus one, and Table E45, which uses dummy variables for whether the firm introduced at least one product, process, trademark class, export product, or import input. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E45: Subsidy Increased Product Variety

	(1) <i>I{Product Patents}</i>	(2) <i>I{Process Patents}</i>
<i>Panel A: Simple DD</i>		
$\mathbb{I}\{\text{Subsidy}\}$	0.0601** (0.0282)	0.00980 (0.0140)
<i>Panel B: Extended DD</i>		
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Years}\}$	0.0449 (0.0301)	0.00615 (0.0189)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Years}\}$	0.0974*** (0.0339)	0.0247 (0.0186)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	0.0463 (0.0429)	0.000553 (0.0193)
<i>N</i>	9358	9358

Description: This table presents robustness checks of the effect of the innovation subsidy on product variety using dummy variables as the left-hand side. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. Column 1 is a dummy for whether the firm applied for at least one product patent 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 patent claims. Because claims are not available for patents in Brazil, we classify patents as process if, on average, USPTO patents with the same class are more likely to be process than product. Column 2 is a dummy for whether the firm applied for at least one process patent in the next three years. These results serve as robustness to Table 10, which uses the log of the variables plus one, and Table E44, which uses the inverse hyperbolic sine transformation (Bellemare and Wichman 2020). All results point to similar conclusions. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E46: Innovation and Export are Concentrated in High-Tariff Products

	(1) <i>IHS{Patent High Tariff Prod.}</i>	(2) <i>IHS{Patent Low Tariff Prod.}</i>	(3) <i>IHS{Citations High Tariff Pat.}</i>	(4) <i>IHS{Citations Low Tariff Pat.}</i>	(5) <i>IHS{Exports High Tariff Prod.}</i>	(6) <i>IHS{Exports Low Tariff Prod.}</i>
<i>Panel A: Simple DD</i>						
$\mathbb{I}\{\text{Subsidy}\}$	0.0718*** (0.0276)	0.00229 (0.0250)	0.0822*** (0.0296)	0.0214 (0.0314)	1.183** (0.458)	0.200 (0.123)
<i>Panel B: Extended DD</i>						
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.0668** (0.0302)	0.00166 (0.0283)	0.0647** (0.0326)	-0.00586 (0.0392)	1.048** (0.463)	0.193 (0.140)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.0844** (0.0350)	0.0209 (0.0328)	0.115*** (0.0394)	0.0503 (0.0362)	1.613** (0.740)	0.195 (0.153)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0670 (0.0410)	-0.00840 (0.0398)	0.0597 (0.0435)	0.0182 (0.0392)	1.309 (0.903)	0.379 (0.445)
<i>N</i>	9,358	9,358	9,358	9,358	5,600	5,600

Description: This table presents robustness checks of the effect of the innovation subsidy on the direction of innovation and exports using the inverse hyperbolic sine (IHS) transformation. The inverse hyperbolic sine approximates the log while preserving zeros (Bellemare and Wichman 2020). 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 in the next three years in high import tariff patent classes. To estimate the tariff of each patent, we use the concordance by Lybbert and Zolas (2014) to map IPC classes to HS product codes, compute a patent-specific average tariff, and classify patents in the top quartile as high tariff. Column 2 is the inverse hyperbolic sine of the number of patent applications in the bottom quartile of import tariffs; column 3 is the inverse hyperbolic sine of the number of citations made to patents in the top quartile of import tariffs; column 4 is the inverse hyperbolic sine of the number of citations made to patents in the bottom quartile; column 5 is the inverse hyperbolic sine of exports of high-tariff products; and column 6 is the inverse hyperbolic sine of exports of low-tariff products. These results serve as robustness to Table 11, which uses the log of the variables plus one. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E47: Innovation and Export are Concentrated in High-Tariff Products

	(1) <i>I{Patent High Tariff Prod.}</i>	(2) <i>I{Patent Low Tariff Prod.}</i>	(3) <i>I{Citations High Tariff Pat.}</i>	(4) <i>I{Citations Low Tariff Pat.}</i>	(5) <i>I{Exports High Tariff Prod.}</i>	(6) <i>I{Exports Low Tariff Prod.}</i>
<i>Panel A: Simple DD</i>						
$\mathbb{I}\{\text{Subsidy}\}$	0.0574*** (0.0203)	-0.00438 (0.0180)	0.0286*** (0.00977)	0.0113 (0.00924)	0.0569* (0.0340)	0.0206 (0.0126)
<i>Panel B: Extended DD</i>						
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.0524** (0.0222)	-0.0104 (0.0211)	0.0207* (0.0130)	0.00425 (0.0128)	0.0435 (0.0341)	0.0234 (0.0152)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.0671*** (0.0249)	0.00489 (0.0234)	0.0393*** (0.0123)	0.0158* (0.00945)	0.0953* (0.0563)	0.00821 (0.0130)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.0549* (0.0318)	-0.000849 (0.0270)	0.0243* (0.0141)	0.0127 (0.0137)	0.0910 (0.0667)	0.0295 (0.0508)
<i>N</i>	9,358	9,358	9,358	9,358	5,600	5,600

Description: This table presents robustness checks of the effect of the innovation subsidy on the direction of innovation and exports using dummy variables as the dependent variables. Each column displays the coefficient of model 1 in the first panel and model 2 in the second panel. Column 1 is a dummy for whether the firm applied for at least one patent in a high-tariff class in the next three years. To estimate the tariff of each patent, we use the concordance by Lybbert and Zolas (2014) to map IPC classes to HS product codes, compute a patent-specific average tariff, and classify patents in the top quartile as high tariff. Column 2 is a dummy for whether the firm applied for at least one patent in the bottom quartile of import tariffs; column 3 is a dummy for whether the firm cited at least one patent in the top quartile of import tariffs; column 4 is a dummy for whether the firm cited at least one patent in the bottom quartile; column 5 is a dummy for whether the firm exported at least one high-tariff product; and column 6 is a dummy for whether the firm exported at least one low-tariff product. These results serve as robustness to Table 11, which uses the log of the variables plus one, and Table E46, which uses the inverse hyperbolic sine transformation. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E48: Subsidy Increased Imports of Machines

	(1) <i>I(Imp. Capital Goods)</i>	(2) <i>I(Imp. Intermediate Goods)</i>	(3) <i>I(Imports of Machines)</i>	(4) <i>I(Imports of Adv. Tech.)</i>	(5) <i>I(Imp. of Adv. Tech. Machines)</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	0.0744* (0.0405)	0.0393 (0.0329)	0.104*** (0.0363)	0.0810** (0.0398)	0.106*** (0.0383)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Years}\}$	0.0873** (0.0437)	0.0439 (0.0332)	0.103*** (0.0380)	0.0593 (0.0415)	0.0894** (0.0390)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Years}\}$	0.0221 (0.0615)	0.0180 (0.0474)	0.113* (0.0579)	0.130** (0.0597)	0.142** (0.0587)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	0.0859 (0.117)	0.00863 (0.0903)	0.000602 (0.0978)	0.257** (0.114)	0.287** (0.119)
<i>N</i>	5,600	5,600	5,600	5,600	5,600

Description: This robustness table measures the effect of the innovation subsidy on the probability of importing in each category. Each column reports the coefficient of model 1 in Panel A and model 2 in Panel B. The dependent variable is a dummy equal to one if the firm has any imports in: column 1 capital goods, column 2 intermediate goods, column 3 machinery within capital goods, column 4 advanced technology products, and column 5 advanced technology machinery (advanced technology products follow the U.S. Census ATP list). The classification of goods comes from SECEX, and machines are defined as HS codes 8401–9209. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E49: Subsidy Increased Imports of Machines

	(1) <i>IHS(Imp. Capital Goods)</i>	(2) <i>IHS(Imp. Intermediate Goods)</i>	(3) <i>IHS(Imports of Machines)</i>	(4) <i>IHS(Imports of Adv. Tech.)</i>	(5) <i>IHS(Imp. of Adv. Tech. Machines)</i>
<i>Panel A: Simple DD</i>					
$\mathbb{I}\{\text{Subsidy}\}$	1.176** (0.502)	0.779* (0.441)	1.614*** (0.457)	1.198** (0.480)	1.406*** (0.446)
<i>Panel B: Extended DD</i>					
$\mathbb{I}\{\text{Subsidy } 0-2 \text{ Years}\}$	1.312** (0.529)	0.849** (0.427)	1.589*** (0.462)	0.928* (0.492)	1.240*** (0.453)
$\mathbb{I}\{\text{Subsidy } 3-5 \text{ Years}\}$	0.565 (0.803)	0.562 (0.663)	1.743** (0.741)	1.726** (0.727)	1.664** (0.691)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Years}\}$	1.568 (1.481)	−0.121 (1.346)	0.834 (1.442)	4.043*** (1.381)	3.801*** (1.423)
<i>N</i>	5,600	5,600	5,600	5,600	5,600

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E50: Subsidy Increased Imports and Citations from Europe and N. America

	(1) <i>I{Imp. Mercosur}</i>	(2) <i>I{Imp. S. America}</i>	(3) <i>I{Imp. Europe}</i>	(4) <i>I{Imp. N. America}</i>	(5) <i>I{Citation to BR}</i>	(6) <i>I{Citation to foreign}</i>
<i>Panel A: Simple DD</i>						
<i>II{Subsidy}</i>	0.0271 (0.0375)	0.0331 (0.0377)	0.0983*** (0.0351)	0.0687* (0.0365)	0.0159** (0.00704)	0.0320*** (0.0110)
<i>Panel B: Extended DD</i>						
<i>II{Subsidy 0-2 Yrs}</i>	0.0391** (0.0397)	0.0383 (0.0394)	0.0975*** (0.0377)	0.0814** (0.0381)	0.00770 (0.00779)	0.0264* (0.0157)
<i>II{Subsidy 3-5 Yrs}</i>	0.0127** (0.0530)	0.0459 (0.0571)	0.1000** (0.0461)	0.0443 (0.0554)	0.0215** (0.0102)	0.0510*** (0.0140)
<i>II{Subsidy 6+ Yrs}</i>	-0.146 (0.134)	-0.154 (0.140)	0.0500 (0.0966)	-0.0708 (0.100)	0.0184* (0.0104)	0.0164 (0.0128)
<i>N</i>	5,600	5,600	5,600	5,600	9,358	9,358

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E51: Subsidy Increased Imports and Citations from Europe and N. America

	(1) <i>IHS{Imp. Mercosur}</i>	(2) <i>IHS{Imp. S. America}</i>	(3) <i>IHS{Imp. Europe}</i>	(4) <i>IHS{Imp. N. America}</i>	(5) <i>IHS{Citation to BR}</i>	(6) <i>IHS{Citation to foreign}</i>
<i>Panel A: Simple DD</i>						
<i>II{Subsidy}</i>	0.329 (0.469)	0.474 (0.478)	1.416*** (0.444)	0.976** (0.459)	0.0480* (0.0245)	0.126** (0.0535)
<i>Panel B: Extended DD</i>						
<i>II{Subsidy 0-2 Yrs}</i>	0.409 (0.487)	0.475 (0.496)	1.419*** (0.466)	1.179** (0.461)	0.0302 (0.0281)	0.108 (0.0753)
<i>II{Subsidy 3-5 Yrs}</i>	0.326** (0.687)	0.759 (0.709)	1.436** (0.604)	0.597 (0.712)	0.0689** (0.0346)	0.195*** (0.0616)
<i>II{Subsidy 6+ Yrs}</i>	-1.315 (1.695)	-1.226 (1.692)	0.559 (1.292)	-1.308 (1.358)	0.0413 (0.0357)	0.0631 (0.0637)
<i>N</i>	5,600	5,600	5,600	5,600	9,358	9,358

Description: This table reports robustness checks of the effect of the innovation subsidy on imports and citations using the inverse hyperbolic sine (IHS) transformation, which approximates the logarithm while preserving zeros (Bellemare and Wichman 2020). Each column reports the coefficient of model 1 in Panel A and model 2 in Panel B. The dependent variable in column 1 is the IHS of imports from Mercosur countries (Argentina, Paraguay, Venezuela, and Uruguay); column 2 is the IHS of imports from other South American countries; column 3 is the IHS of imports from Europe; column 4 is the IHS of imports from North America; column 5 is the IHS of citations to Brazilian patents; and column 6 is the IHS of citations to foreign patents. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E52: Firms Export to South America but not to Developed Countries

	(1) <i>I{Exp. Mercosur}</i>	(2) <i>I{Exp. S. America}</i>	(3) <i>I{Exp. Europe}</i>	(4) <i>I{Exp. N. America}</i>
<i>Panel A: Simple DD</i>				
$\mathbb{I}\{\text{Subsidy}\}$	0.106*** (0.0344)	0.0820** (0.0338)	0.0149 (0.0381)	0.0173 (0.0386)
<i>Panel B: Extended DD</i>				
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	0.0784** (0.0372)	0.0591 (0.0374)	0.0801** (0.0360)	0.0522 (0.0391)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	0.190*** (0.0463)	0.151*** (0.0443)	-0.188*** (0.0696)	-0.0711 (0.0574)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	0.143* (0.0869)	0.128 (0.0859)	-0.184** (0.0908)	-0.162 (0.137)
<i>N</i>	5,600	5,600	5,600	5,600

Description: This table reports robustness checks of the effect of the innovation subsidy on exports by destination using dummy variables as the dependent variable. Each column displays the coefficient of model 1 in Panel A and model 2 in Panel B. The dependent variable in column 1 is a dummy for whether the firm exports to Mercosur countries (Argentina, Paraguay, Venezuela, and Uruguay); in column 2 it is a dummy for whether the firm exports to other South American countries; in column 3 it is a dummy for whether the firm exports to Europe; and in column 4 it is a dummy for whether the firm exports to North America. These results provide robustness to the baseline specification in Table 14, which uses the log of exports plus one, and Table E53, which uses the inverse hyperbolic sine transformation. Standard errors are clustered at the firm level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table E53: Firms Export to South America but not to Developed Countries

	(1) <i>IHS{Exp. Mercosur}</i>	(2) <i>IHS{Exp. S. America}</i>	(3) <i>IHS{Exp. Europe}</i>	(4) <i>IHS{Exp. N. America}</i>
<i>Panel A: Simple DD</i>				
$\mathbb{I}\{\text{Subsidy}\}$	1.671*** (0.439)	1.583*** (0.443)	0.400 (0.491)	0.351 (0.497)
<i>Panel B: Extended DD</i>				
$\mathbb{I}\{\text{Subsidy } 0\text{--}2 \text{ Yrs}\}$	1.385*** (0.470)	1.294*** (0.483)	1.178** (0.458)	0.757 (0.510)
$\mathbb{I}\{\text{Subsidy } 3\text{--}5 \text{ Yrs}\}$	2.586*** (0.617)	2.468*** (0.595)	-1.937** (0.884)	-0.573 (0.745)
$\mathbb{I}\{\text{Subsidy } 6+ \text{ Yrs}\}$	1.999* (1.197)	2.158* (1.176)	-2.414* (1.353)	-2.436 (1.696)
<i>N</i>	5,600	5,600	5,600	5,600

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.