Impacts of the Brazilian science and technology sector funds on industrial firms' R&D inputs and outputs: new perspectives using a dose-response function

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Resumo

Este estudo tem o objetivo de avaliar o impacto dos Fundos Setoriais em relação à quantidade de recursos fornecidos às empresas entre 2001 e 2006. Avaliou-se o impacto do investimento governamental sobre os indicadores de esforços tecnológicos e de resultados (tamanho da firma e exportações de alta intensidade tecnológica). Para isso, foi utilizada uma técnica que avalia a resposta dos investimentos privados às diferentes quantias de incentivo público, usando o escore de propensão generalizado. Este é o primeiro estudo no Brasil que utiliza esta técnica de tratamento contínuo para avaliar o impacto de incentivos públicos à inovação. Estimativas para o efeito médio indicam que se o governo aumentasse os recursos disponibilizados para os Fundos Setoriais em 1%, as empresas aumentariam seu investimento em P&D em 1,5% no ano de acesso e em 1,8% quatro anos após o acesso, em relação às firmas que não acessaram. Ademais, os impactos dos fundos setoriais sobre o nível dos tratamentos indicam uma relação quadrática em forma de "U", o que sugere que esses recursos têm mais impacto nas extremidades da distribuição, ou seja, têm um impacto relativo maior para firmas muito pequenas ou para firmas de tamanhos médios e grandes. Todos esses resultados permitem rejeitar a hipótese de *crowding-out*.

Abstract

This study aims to assess the impact of Brazilian Sector Funds from the standpoint of the amount of resources provided to industrial companies between 2001 and 2006. We evaluate the impact of government investment on firms' indicators of technological efforts and outcomes (size and high-technology exports). To this end, we use a technique that evaluates private investments' response to different amounts of public incentive, using the generalized propensity score. This is the first study in Brazil that uses a continuous treatment technique to assess the impact of public incentives for innovation. Estimates for the average effects indicate that, compared to those which have not received incentives, if the government had increased the resources provided by Sector Funds by 1%, firms would have increased their R&D investments by 1.5% in the year that they received those resources and 1.8% four years after access. Furthermore, the impacts of the Sector Funds on treatment level indicate a quadratic "U"-shaped relationship, suggesting that these resources have more impact on the extremes of the distribution, that is, they have stronger relative impact for very small firms and for medium-sized or large firms. All of these results allow us to reject the crowding-out hypothesis.

Palavras-chave: inovação/ P&D / avaliação de impacto/ tratamento contínuo/ escore de propensão generalizado.

Keywords*: innovation / R&D / impact evaluation / continuous treatment / generalized propensity score.*

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1 INTRODUCTION

Innovation is the transformation process that takes place at the core of firms, which changes the existing state of the economy or of consumer demand. The innovative process not only provides a high social rate of return, but is important both in the context of firm survival in competitive markets and in the economic development of nations.

Usually, because innovation provides a high degree of social return and has positive externalities, the State provides this support through actions that alter firm's opportunity costs of capital and/or their marginal rate of return to R&D.

There are basically three ways to support firms' innovation activities: (i) basic infrastructure for research and training of manpower, mainly through universities, (ii) indirect support via tax incentives that reduce R&D costs and (iii) direct support, via credit on more favorable terms, non-repayable grants and financial incentives for university-industry partnerships. There is no hierarchy among these forms: each has a purpose and a specific target that outlines the innovation support system according to the productive structure, institutions and national objectives.

Since 1999 the Brazilian Sector Funds have directly supported innovation and provided consistency for public incentives towards science, technology, and innovation (ST&I). By linking the resources allocated to the funds to a wide set of sources, the legislation that created them intended to prevent fiscal constraints from causing discontinuities in ST&I policies adopted by the Federal Government. The context that marked its institutionalization was also characterized by the growing recognition of the importance of establishing incentives for firms' technological development. This explains why these resources have been a major instrument of ST&I's national policy to support the spread of innovation in the productive sector.

Sector funds' resources are used to create more favorable conditions for innovation by subsidizing loans for innovative projects, encouraging partnerships between universities and companies and also by giving non-refundable grants. As a partnership between FINEP (*Financiadora de Estudos e Projetos* – Research and Projects Financing Institution) and CNPq (*Conselho Nacional de Pesquisa Científica e Tecnológica* - National Council for Scientific and Technological Development), the Sector Funds are currently the main mechanism of direct support for innovation in Brazil.

The possible positive impact on firms' R&D isn't the only concern of methods that assess the impact of direct support mechanisms. Researchers are also concerned about the cost-effectiveness of innovation support, for example, taking into account possible crowding-out effects – to what extent government support displaces private investment in innovation. Overall, throughout the literature the "one-to-one" rule prevails: $1.00 of public innovation support induces a $1.00 increase in R&D investments by the private sector. A summary of prior international literature on the impact of innovation support is provided in Table 1 below.

TABLE 1

Summary table of reviewed papers

Approach	Method	Author	Country	Time span	Specification	Dependent variable	Findings
Structural	Instrumental variables	Wallsten (2000)	USA	1992	Multi-equation model with potentially available resources for innovation as instrumental variable.	Private R&D spending.	Crowding-out
		Aerts and Thorwarth (2008)	Belgium	2004 and 2006	Instrumental variables: i) Total amount of incentives received through the last 5 years over total projects' value; ii) Total number of projects submitted to IWT in the last five years.	i) Private R&D spending; ii) Expenditure in research only; iii) Expenditure in development only.	Additionality
	Selection models	Busom (2000)	Spain	1988	Probit model to assess the decision-making behavior of firms and the government agency.	i) Private R&D spending; ii) Employees in R&D activities; ii) Expenditure in R&D per employee; iv) Employees in R&D activities over total employees.	Additionality, but for 30% of the sample the full crowding-out hypothesis cannot be ruled out.

		González et. al. (2005)	Spain	1990 to 1999	Estimate the expected value of R&D investments that will be supported and its profitability thresholds.	Private R&D spending.	Additionality.
		Takalo et. al. (2008)	Finland	2000 to 2002	The process of granting incentives is modeled as a game of imperfect information in four stages between two players (firms and government). Estimate ex-ante effects.	How much firms intend to invest in R&D.	Inconclusive regarding additionality;
		Garcia and Mohnen (2010)	Austria	1998 to 2000	Estimation of governmental behavior via probit model and firm behavior via tobit model.	i) Private R&D spending; ii) Revenue of new products to the firm; iii) Revenue of new products to the market.	Additionality.
Program Evaluation	Dif-in-Dif	Lach (2002)	Israel	1990 to 1995	Fixed and dynamic effects panel.	Private R&D spending.	Inconclusive
	PSM	Almus and Czarnitzki (2003)	"Eastern" Germany	1996	Caliper matching on PSM's second step.	R&D spending over revenue	Additionality.
		Duguet (2004)	France	1985 to 1997	Nadaraya-Watson estimator on PSM's second step. Estimates ATE, ATT and ATU.	i) Growth rate of R&D investment in relation to firms' revenues; ii) Indicator variable in case of positive growth rate.	ATE: Crowding-out only in 1987. ATT: Inconclusive.
		Aschhoff (2009)	Germany	1994 to 2005	Mahalanobis Distance on PSM's second step. Evaluates the continuity and amount of incentives, by separating firms into categories according to each of these variables.	i) Total (private + incentives) R&D spending; ii) Private R&D spending.	Additionality on overall outcome.

Source: Elaborated by the authors.

In Brazil there are three studies, all based on the program evaluation approach, that evaluated the impact of *Financiadora de Estudos e Projetos*' (FINEP) direct support through the SF on innovative efforts and firms performance. These papers, summarized in Table 2, modeled the access to FINEP's mechanisms as binary variables (0 or 1, or "not accessed vs. accessed"), evaluated its impact and rejected the null hypothesis that the Sector Funds don't have impacts on firms' innovative efforts.

TABLE 2

Summary of papers that evaluate the impact of FINEP's direct support mechanisms

Method	Author	Time span	Specification	Dependent variable	Findings
PSM with tests for differences in means	De Negri, De Negri and Lemos (2008)	1996-2003	Compairson of matching results to several case-control cases	R&D spending	Firms that had access to ADTEN invested 60% more that those who hadn't. Firms' growth (revenue and total employees) also had positive impacts, although productivity and patenting hadn't.
PSM with tests for differences in means	Avellar and Kupfer (2008)	2000-2003	Evaluation of three different incentive schemes: i) PDTI (fiscal incentives); ii) ADTEN (refundable direct support); iii) Cooperative FNDCT (non-refundable).	i) R&D spending; ii) R&D spending over revenue	PDTI and ADTEN induce higher R&D spending but they don't change the fraction of R&D over revenues. Inconclusive results for the Cooperative FNDCT.
PSM with tests for differences in means and dif-in-dif	Araújo et al. (2010)	2001-2006	Evaluation of the access to Sector Funds using employees in R&D activities as proxy to R&D spending.	i) Employees in R&D activities; ii) Total employees (as proxy to firms' size); iii) high-tech exports.	Access to Sector Funds induces higher innovative efforts (crowding-out is ruled out) and higher growth (in the first 2 years after the access). No impacts on high-tech exports.

Source: Elaborated by the authors.

This paper is a contribution to the Brazilian literature that aims to assess the possible effects of crowding-in or crowding-out of the Brazilian Sector Funds, that is, whether the Government, by allocating \$1.00 to private firms' R&D, can induce them to invest more or less than \$1.00 in R&D on their own. An assessment of the impacts of Sector Funds' evaluation becomes even more important due to the steady increase in the volume of public resources during the past 10 years.

As shown in Tables 1 and 2, most impact evaluations consider only the dichotomous aspect of policies. In order to go beyond this assessment, we used a method which evaluates the response of private investment to different amounts ("doses") of public support and is a direct extension of Araújo et al's (2010) work, where the authors used a dichotomous variable to indicate access to the Sector Funds to evaluate their performance. Here, the assessment is performed using the approach proposed by Imai and van Dyk (2004) and complemented by Adorno et al (2007). It should be noted that this is the first time that this methodology is employed for Brazil.

Following this introduction, the paper is organized as follows. In Section 2 a brief explanation of the Sector Funds' operation is presented. Subsequently, in Section 3, we define the data and explain the econometric approach used here. Section 4 presents and discusses the results and provides material for the conclusions presented in Section 5.

2 FINEP AND THE SECTORAL FUNDS

FINEP is the most important innovation agency in Brazil. FINEP was established in 1967 during a wave of institutional building of innovation support in Brazil. Most of FINEP's funding comes from the Sector Funds, by special taxation on some economic activities such as electricity, telecommunications, oil exploration and others. They're intended to provide stable R&D funding to 14 strategic sectors and have two special funds aimed at promoting university-enterprise interactions and upgrading research infra-structure in universities and public research institutions, respectively. The novelty of the initiative was that R&D funding would no longer be subject to budgetary cuts and administrative preferences.

FINEP's total budget in 2010 was US\$ 2.25 billion. This budget more than doubled compared to 2009 and 2008, in national currency. Over the decade, there was an eight-fold increase in FINEP's budget, according to Figure 1. From the 2010 amount, the largest share (US\$ 1.26 billion) went to the National Fund to S&T Development (FNDCT), which is a fund targeted at research infrastructure. US\$ 690 million went to credit operations and US\$ 299 million went to direct subsidies. Since 2003, FINEP has managed to raise its budget execution rate to almost 100%. The Sector Funds' funding has risen steadily over the last years and nowadays is one of the most important sources of innovation funding in Brazil.

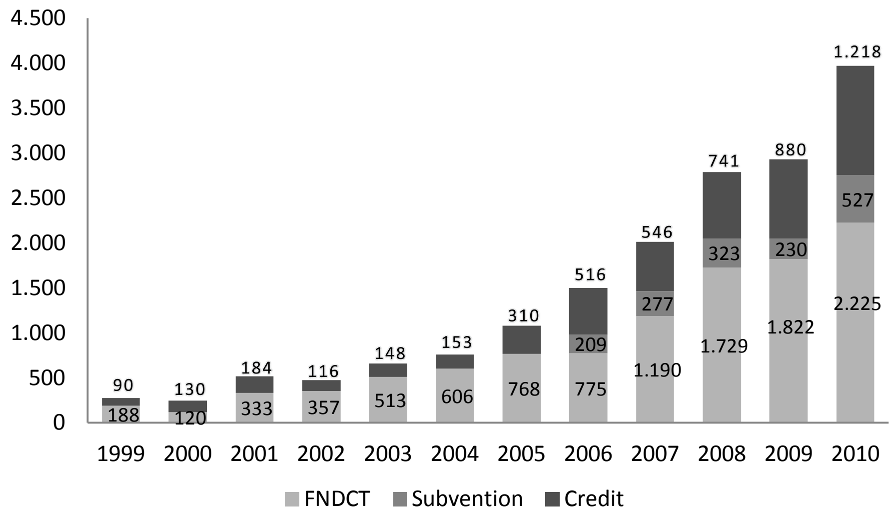
From 2010's budget, most (around 60%) went to the National Fund for Scientific and Technological Development (FNDCT), which is focused on the development of research infrastructure in Brazil, mainly in universities. Private firms access 40% of the budget, through credit or non-reimbursable (subvention) channels.

Indeed, firms may access FINEP's support in three ways. The first is through a cooperative project with a research institution. The second is through subsidized credit towards innovation. The funding for this kind of operation doesn't come exclusively from the Sector Funds, but the implicit subsidy to lower interest rates does. The third method of access – made possible by the Innovation Act of 2004 – is through economic subvention or direct subsidy. Support is project-based, and firms and research institutions must participate in public calls for proposals. A council composed of scholars, bureaucrats and entrepreneurs decides which projects are approved.

Therefore, data on FINEP's direct support measures come from administrative records of cooperative projects with universities (a kind of grant), credit in special conditions and economic subvention or non-reimbursable subsidies. The first two will be analyzed here.

FIGURE 1

FINEP's Disbursements, by support modality (in local currency - BRL millions).



Source: FINEP.

3 RESEARCH METHODS

3.1 Data and variables

The database analyzed comes from the administrative records of more than 13.000 projects supported by the Sector Funds between 2000 and 2007 restricted to industrial firms with five or more employees. This database was merged with the RAIS (*Relação Anual de Informações Sociais*, or Annual List of Social Information, from the Ministry of Labor), an administrative record of the labor force profile which is mandatory in Brazil for all firms in all sectors. Technically speaking, the RAIS is a matched employer-employee database comprised of information on every formal worker in Brazil, including his/her gender, age, occupation (according to the Brazilian Occupations Classification), wages, tenure at the company, and educational level, among others. The final database also contains information on exports and imports from the administrative records of the Secretary of Foreign Trade (SECEX) of the Ministry of Development, Industry and Foreign Trade (MDIC).

The access to the Sector Funds considered here involves cooperative projects with universities and research centers (both as project leader or participant) and credit at favorable conditions[1].

In this paper, the focus is on general access to the funds, without making a distinction amongst access types. Implicitly, it is assumed that when firms take part in cooperative projects supported by sector funds, they benefit from research activities carried out by universities and research centers (although this modality of support is obviously less direct than credit or grants[2]).

We are interested in the impacts on innovation inputs – measured by firms' technical scientific personnel – and outputs – measured by high-tech exports (classified by the Ministry of Development, Industry and Foreign Trade and in accordance with OCDE criteria) and firms' size (proxied by the number of employees). Although this proxy presents evident limitations (for example, in the

[1] Even if the credit resources do not originate directly from the Sectoral Funds, the firms which benefited from these resources were included in the treatment group because interest rates are subsidized by the funds.

[2] There are many more firms engaged in this kind of cooperative project than firms accessing credit and grants. However, it can be argued that cooperative projects might, in some cases, induce some sort of outsourcing of R&D activities, as these activities would be performed in universities and research centers. In any case, it may be interesting to distinguish impacts of each instrument in our empirical strategy, in order to seek for complementarities or substitution effects between the modalities.

circumstances in which innovation activities lead to the increase of labor productivity), it is assumed here that on average there is a positive correlation between revenue growth and the increase of the total number of employees.

R&D inputs (or technological efforts) were measured by the number of technical-scientific employees (PoTec). This proxy for technological efforts was suggested by Araújo et al. (2009) in order to overcome some practical problems in relying on Innovation Survey data, such as the Brazilian PINTEC, to measure innovation inputs. The first problem is related to timing: the innovation surveys' results are usually released with some delay, and they typically only collect quantitative information for the surveys' last year of reference.[3] The second problem is related to the sampling scheme. Innovation surveys are sample surveys; when one matches administrative registers from support programs to sample surveys, much information may be lost because beneficiaries were not sampled. Moreover, in Brazil it is not possible to form a panel of firms from the PINTEC, except for those very large – and very few – firms which are interviewed in every round of the innovation survey (those firms with 500 or more employees).

The use of PoTec as a proxy for technological efforts follows the pioneering study by Blank and Stigler (1957) and is related to the fact that most of R&D expenditures are comprised by researchers' wages. Hence, PoTec is simply defined as the sum of the number of researchers, engineers[4], R&D directors and managers, and "scientific professionals"[5] for each firm (Araújo et al., 2009).

Originally proposed by Gusso (2006) and adjusted afterwards by Araújo et al. (2009), the typology indicated above presented, according to these authors, a correlation coefficient greater than 90% with internal and external R&D expenditures. Therefore, there is robust evidence that PoTec is an appropriate proxy of technological efforts. Since PoTec can be calculated based on data from the Annual List of Social Information (RAIS), it is possible to follow its yearly evolution during the period considered in this work.

The methodology used here requires a lag period, thus only those firms who have accessed these mechanisms between 2001 and 2006 were considered for the treatment group. Therefore, the final database contains 344 treated firms and 113,000 (113 thousand) untreated firms. Some descriptive statistics on treated firms' most important variables are reported in Table 3.

TABLE 3

Features of firms supported by the Sector Funds, 2000-2007.

Measure	Amount of incentives (BRL thousands)	Total employees	Technical-scientific employees	Average wage (BRL)	High-tech exports (US$)
Mean	2,367.11	1,047	50	1,626	4,623,738
Standard-deviation	7,871.08	3,027	350	1,190	31,879,408
Median	271.14	212	3	1,260	-

Source: Elaborated by the authors.

Table 4 shows the distribution of the number of firms by their year of debut in the sector funds and access type. The majority (70.6%) access the resources only through cooperative projects and few companies access both cooperative projects and subsidized credit (2.6%). After a fall in 2003, there is an increase in the number of firms who have accessed these resources. Among other reasons, it is likely that

[3] Hence, in Brazil, R&D expenditures from the PINTEC are only available for 2000, 2003, 2005 and 2008.
[4] Which aggregate: mechanical and electrical engineers; civil engineers, among others; agronomists and fishing engineers.
[5] Composed of: biotechnologists, geneticists, metrology researchers, and specialists in meteorological calibrations; mathematicians, statisticians, among others; IT and computer professionals; physicists, chemists, among others; biologists and other professionals.

this recovery is linked to changes in innovations' legal framework that took place in 2004.

TABLE 4

Number of firms by year of debut in the sector funds different modalities of support, 2001 – 2006.

Year	Cooperative projects only	Credit only	Both	Total
2001	-	17	-	17
2002	47	13	3	63
2003	13	5	-	18
2004	79	-	-	79
2005	56	25	2	83
2006	48	32	4	84
Total	243	92	9	344

Source: Elaborated by the authors.

3.2 The generalized propensity score and the dose-response function

In many studies, particularly those that investigate public policies' impacts, treatment does not occur in a binary manner. When it comes to R&D incentives, different firms receive distinct amounts that may have different impacts on their private investment.

In the last decade, several methodologies were developed to estimate dose-response functions (Imbens, 2000; Lechner, 2001; Lechner, 2004; Hirano and Imbens, 2005; Flores, 2005). One of the most used is Hirano and Imbens' (2005) parametric estimator. In this paper, we chose the estimator proposed by Imai and van Dyk (2004) since it is non-parametric, which is appropriate since we cannot always rely on Gaussian data.

This method works as follows: consider a random sample indexed by $i = 1, \dots, \mathrm{N}$. For each unit i, let $\mathrm{Y_i}(t^{\mathrm{p}})$ be a random variable that maps a possible treatment $t^{\mathrm{p}} \in \mathcal{T}$ to a potential outcome Y_i, where $\mathcal{T}$ is a set of possible treatment (or direct support) values. There's also a vector $\mathbf{X}_\mathrm{i}$ of pretreatment covariates and a random variable of the treatment assigned, T^A.

The purpose of this method is to evaluate the average dose-response $\mathrm{E}[Y_i(t^p)]$ and to assess the treatment effect on this function. To this end, the authors rely on two assumptions:

A.1 – SUTVA (stable unit treatment value assumption):
$p\left[Y_i\left(t_i^p\right) \middle| T_j^A = t_j^p, \mathbf{X}_i\right] = p\left[Y_i\left(t_i^p\right) \middle| \mathbf{X}_i\right], \ \forall\, i \neq j$ and $\forall \left[t_i^p, t_j^p\right] \in \mathcal{T}$; and

A.2 – Strong ignorability of treatment assignment:
$p(T^A | Y(t^p), \mathbf{X}) = p(T^A | \mathbf{X}), \ \forall \ t^p \in \mathcal{T}$. For all $\mathbf{X} \in \mathcal{X}$ and positive measurable sets $\mathcal{A} \subset \mathcal{T}$, we also have $p(T^A \in \mathcal{A} | \mathbf{X}) > 0$.

From these assumptions, with $t_1^p \neq t_2^p$, the average causal effect is:

$$E\left[Y\left(t_1^p\right) \middle| T^A = t_1^p, X\right] - E\left[Y\left(t_2^p\right) \middle| T^A = t_2^p, \mathbf{X}\right] = E\left[Y\left(t_1^p\right) - Y\left(t_2^p\right) \middle| \mathbf{X}\right] \quad \text{(Eq.1)}$$

In the case of continuous treatments, Imai and van Dyk (2004) generalize the propensity score and define a propensity function to facilitate matching. This function is the conditional probability of the actual treatment given the covariates, $p_\psi(T^A | \mathbf{X})$. Because we cannot directly observe this probability, the propensity function $p_\psi(\cdot\, | \mathbf{X})$ is estimated as $e_\psi(\cdot\, | \mathbf{X})$, where ψ is estimated via maximum likelihood and parameterizes this distribution. Regarding this parameterization, the authors make a third assumption to simplify the notation:

A.3 – Uniquely Parameterized Propensity Function:

For all $\mathbf{X} \in \mathcal{X}$, there exists a unique finite-dimensional parameter $\theta \in \mathbf{\Theta}$, such that $e_{\psi}(\cdot\,|\mathbf{X}) = e_{\psi}\left[\cdot\,\middle|\theta_{\psi}(\mathbf{X})\right]$. Besides, $\int_{\mathcal{A}} e_{\psi}(\mathrm{t}|\theta)dt = \int_{\mathcal{A}} e_{\psi}(\mathrm{t}|\theta')dt$ implies that $\theta = \theta'$, for all measurable sets $\mathcal{A} \subset \mathcal{T}$. That is, θ uniquely represents $e_{\psi}\left[\cdot\,\middle|\theta_{\psi}(X)\right]$, so we may write the propensity function as $e(\cdot\,|\theta)$.

To perform inference based on propensity function, the authors define two important theoretical results (Imai and van Dyk, 2004, p. 856):

T.1 – Propensity function as a balancing score:

$$p(T^A|\mathbf{X}) = p[T^A|\mathbf{X}, e(\cdot\,|\mathbf{X})] = p[T^A\,|e(\cdot\,|X)] \qquad \text{(Eq.2)}$$

T.2 – Strong ignorability of treatment assignment given the propensity function:

$$p[Y(t)|T, e(\cdot\,|X)] = p[Y(t)|e(\cdot\,|X)], \qquad \forall t \in \mathcal{T} \qquad \text{(Eq.3)}$$

The first theorem shows that the conditional distribution of the actual treatment, given the propensity function, doesn't depend on the covariates. The second theorem is the key result of Imai and van Dyk's work, which states that the possible outcomes and the allocated treatment are conditionally independent, given the propensity function. According to T.2, to obtain the dose-response function, $p[Y(t^p)]$, one must integrate $p[Y(t^p)|e(\cdot\,|\mathbf{X})]$ over the propensity function's distribution. In practice, this integration can be approximated by subclassifying units on K similar groups depending on the percentiles of θ and calculating the average effect, $E[Y(t^p)]$, as a weighted mean from the effect on each k, $E\left[Y(t^p)\middle|T^A = t^p, \hat{\theta}_{\mathrm{k}}\right]$, with weights, W_k, equal to the relative size of each group:

$$E[Y(t^p)] \approx \sum_{k=1}^{K} E\left[Y(t^p)\middle|T^A = t^p, \hat{\theta}_{\mathrm{k}}\right] W_k \qquad \text{(Eq.4)}$$

It should be noted that this analysis is restricted to treated firms and the matching is done to evaluate differences between firms that received more or less treatment. However, we'd like to assess the differences between firms that were treated and firms that weren't. Thus, together with this methodology it is necessary to use a mechanism that deals with the self-selection problem. This is the approach proposed by Adorno et al. (2007).

In the first stage of this approach, a probit model for treatment is estimated to define the propensity score. The second stage is the estimation of the propensity function following Imai and van Dyk(2004). In this stage, the propensity score calculated in the first stage is taken into account. Hence, $\theta = e[\cdot\,|\mathbf{X}, \hat{p}(D=1)]$, where $\hat{p}(D=1)$ is the predicted value of the binary treatment D from the first stage. After the propensity function is estimated, the average dose-response function is evaluated in each percentile group of $\hat{\theta}$ as:

$$E\left[\hat{Y}(t)\right] = \frac{1}{n_t} \sum_{i|t_i=t} \left\{Y_i(t_i) - \sum_{j\epsilon\mathcal{C}} m_{ij} Y_j(0)\right\}. \qquad \text{(Eq.5)}$$

In Eq. (5) $\mathcal{C}$ is the set of firms defined as "controls", j indexes the firms in this group, and the number of observations on which $t_i^p = t^p$ is n_t. Therefore, this estimator can only be calculated for the observed treatment levels t (Adorno et al., 2007, p. 77). The weight m_{ij} is the weight of firm j as a control for firm i from the first and second stages (w_{ij}^1 and w_{ij}^2, respectively) relative to the weights of all controls for firm i and is given by

$$m_{ij} = \frac{w_{ij}^1 w_{ij}^2}{\sum_{k \in C} w_{ik}^1 w_{ik}^2}\,. \qquad \text{(Eq.6)}$$

3.3 Empirical strategy

In this paper, we follow the two-stage strategy depicted in the previous section. In the first stage, the following probit model was estimated via maximum likelihood to predict the probability of access to the SF by a given firm:

$$Pr(SF_i = 1|\mathbf{X}_i) = G(\mathbf{X}_i'\,\boldsymbol{\beta}) \equiv\ p(\mathbf{X}_i) \qquad \text{(Eq.7)}$$

Where G is the Gaussian cumulative distribution function, $\Phi(\mathbf{X}'\boldsymbol{\beta})$, and $\mathbf{X}$ includes: log of lag of technical-scientific employees (and interaction with year of first time access), log of lag of total employees (and interaction with year of first time access), and dummies for multinational, corporation, industrial sector, region, and year of first time access. With these results, a kernel matching was performed. In this type of matching each treated firm is compared to a weighted average of all controlled firms. This is the weight w_{ij}^1 from Eq. (6).

In the second stage, the following Gaussian model was fit to estimate the amount of support received by each firm and obtain the propensity function:

$$T_i^A = \gamma Z_i + \mathbf{X}_i'\boldsymbol{\beta} +\ \hat{p}_i(\mathbf{X}) + \varepsilon_i. \qquad \text{(Eq.8)}$$

In Eq. (8), T_i^A is the observed value of the direct support to firm i (in log), $\hat{p}(\cdot)$ is the estimated propensity score and Z is the average workers' wage (in log).

Following this stage, the deciles of the propensity function were calculated and firms were classified into groups based on these deciles. The weights W_k were defined by the number of treated firms in each group. This is w_{ij}^2 from Eq. (6).

With the weights in hand, Eq. (5) was used to compare supported and unsupported firms and estimate the impacts of incentives on each treatment level. To estimate the dose-response function, a linear model to explain firms' inputs and output as a function of the treatment and the propensity function was estimated in each percentile range of $\hat{e}(\cdot\ |\mathrm{X})$. The idea is to compare the trajectories, relative to the control group, of firms that received a certain amount of resources from the sector funds to those of firms that received smaller (or larger) quantities. Mathematically, we've estimated:

$$Y_{i,m} = \beta \log\,(T_{i,m}^A) + \gamma \hat{e}(\cdot\ |\theta_{i,m}) + \varepsilon_{i,m} \qquad \text{(Eq.9)}$$

$$\Delta Y_{i,m+s} = \alpha \log\left(T_{i,m}^A\right) + \eta \hat{e}(\cdot\ |\theta_{i,m}) + \upsilon_{i,m+s} \qquad \text{(Eq.10)}$$

Where m indicates the year of debut in the sector funds (t_0) and $s = 1,2,3,4$ is the period after this access. Since R&D investments do not normally mature in the same period where the firms received the support, we chose to assess the response variables in the periods $m + s$. Values of α and β, estimated in each percentile range of $\hat{e}\left(\cdot\ |\theta_{i,m}\right)$, are the average effect of each "dose" of support. Using the weights of each group, we used these estimates to calculate the average dose-response function as depicted in (Eq.5).

We also estimated first difference equations to evaluate the growth rates of variables of interest. We chose to use this dif-in-dif (DID) estimator to capture changes in firms' R&D inputs and outputs caused by the SF, assuming that unobserved differences among firms are stable over the years. Hence:

$$\hat{\alpha}(t) = \Delta\overline{Y}^{\,treat}(t_h < t_i < t_k) - \Delta\overline{Y}^{untreat}(0) \qquad \text{(Eq.11)}$$

Where $\Delta\overline{Y}^{\,treat}(t_h < t_i < t_k)$ is the average change in performance from before to after access for those firms that received support $[t_h, t_k]$. With this strategy, "the idea is to use the information on the treatment level to select a group of subsidized firms (homogenous by grant amount) and to estimate their average treatment effects with respect to the whole control group" (Adorno et al., 2007, p. 80).

The method used in this paper also allows for the identification of the impact of incentives on treatment level. This can be done by simply applying an OLS with a quadratic specification on the propensity function for treated firms:

$$Y_i = \beta_1\hat{\theta} + \beta_2\hat{\theta}^2 + \mu_i\ . \qquad \text{(Eq.12)}$$

4 RESULTS

Initially, we estimate a probit model to predict the probability of access to the SF by a given firm, considering its characteristics. Since few companies have accessed this mechanism relative to the total number of Brazilian industrial firms, we used a bootstrap process to reduce the bias of the fit. Hence, 450 replications were made to determine the parameters $\boldsymbol{\beta}$ of Eq. (7). The results indicate that the specification used in this first step is satisfactory since all the parameters' confidence intervals do not include zero. (Table 5).

TABLE 5

Distribution of probit coefficients after 450 repetitions.

Variable	Median	[Confidence interval - 95%]	
Log of technical-scientific employees (t_{-1})	0.156	0.104	0.238
Log of total employees (t_{-1})	0.213	0.127	0.255
Multinational (dummy)	-0.505	-0.679	-0.305
Business corporation (dummy)	0.432	0.279	0.585
Log-likelihood	-2116.5	-2342.7	-1931.4

Obs.: sector dummies, year dummies and interactions not shown.

Source: Elaborated by the authors.

As expected, the fact that the company employs technical-scientific staff increases their likelihood of being supported by the sector funds. The favoring of national industry is also clear, since the coefficient was negative for multinationals. This result is consistent with the purpose of this instrument, since the goal is to stimulate investment in R&D for Brazilian firms. On the other hand, this instrument may not be suitable for small companies, since the coefficient of total employees indicates that larger companies have greater access chances. It should be noted that the mechanism designed to support small and medium companies was not included in this study since it was only introduced in 2006.

After the bootstrap, we used the median of each parameter to calculate the propensity score. Because of the common support restriction, the number of controlled firms dropped from 113,000 (113 thousand) to about 1,800 (one thousand eight hundred) and the treated group went from 344 to 330 firms.

Once those groups were defined, an assessment of the mean differences between them in the year prior to fund access was made. Table 6 shows that the unmatched groups have statistically different means (p-value<0,05). On the other hand, after the matching there are no significant differences between firms. This result indicates that the propensity score balancing conditions were satisfied. This condition is essential to eliminate selection bias and also indicates that pre-treatment firms' characteristics are similar in both groups. The elimination of bias is contingent on all variables that affect firm participation in the sector funds having been included in the probabilistic model.

TABLE 6

Average differences between matched and unmatched groups.

Variable	Sample	Mean		t-test p-value
		Treated	Controls	
PoTec (scientific emplyees)	Unmatched	49.5	0.6	0.0
	Matched	47.0	22.9	0.2
Po (employees)	Unmatched	979.6	188.0	0.0
	Matched	965.6	671.3	0.06
High-tech exports	Unmatched	1.1E+07	3.0E+06	0.0
	Matched	4.5E+06	2.2E+06	0.2

Source: Elaborated by the authors.

Since firms are similar before receiving incentives, we can assess the trajectory of their indicators from the moment in which the treated firms were supported and attribute any differences to treatment. However, firms can have different paths because of the distinct amount of funds received and therefore it is necessary to perform a second matching, which takes into account the different levels of incentives by generalizing the propensity score.

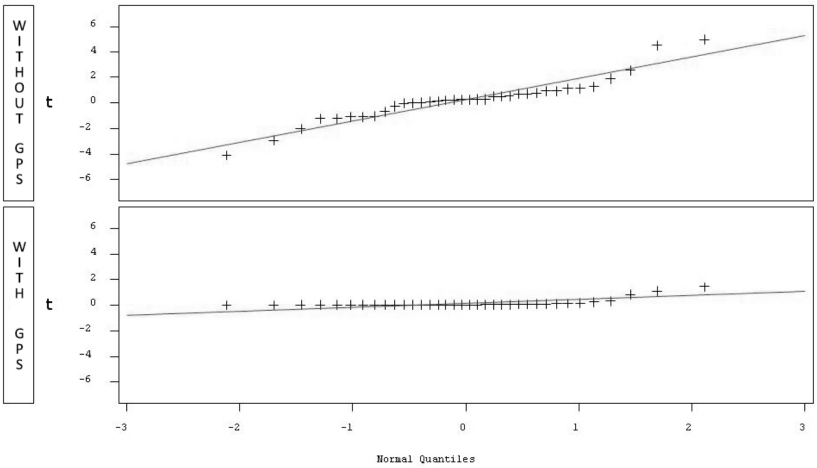
This was done by adjusting a Gaussian model according to Eq. (8). Balance (or a check of Theorem 1) was verified by examining the t-statistics for the coefficient of T^A in a model that uses each Z and **X** as independent variables while controlling for the estimated propensity function. Once balance is verified, any differences in outcome trajectories can be attributed to differences in the amounts of incentive since bias associated with different incentive levels has been eliminated. Again, the bias elimination is contingent on the inclusion of all relevant variables in the regression that could affect funding levels.

Although this diagnosis of balance isn't a perfect way to detect all deviations from independence of treatment levels from covariates, values of the t-statistic close to zero for T^A may indicate a good balancing (Imai and van Dyk, 2004, p. 856). The upper part of FIGURE 3 shows that the value of the t-statistic ranges from -5 to 6 when there's no control for the propensity function. When it's added to the regression, $T^{A\prime}$s t-values drop to almost zero for every covariate and the balancing is satisfied (lower part of Figure 2).

Using the estimated values of the propensity function, we separated the treated firms into classes of the same size. Each treated firm has a set of controlled firms (defined in the first stage – kernel matching) so that the comparison depicted in Eq. (5) can be performed. The impact evaluation is done by comparing the average difference between treated and untreated firms' R&D inputs and outputs. If this difference is positive and statistically significant, then there is additionality and the policy does indeed stimulate private investment.

FIGURE 2

Propensity function balancing result.



Source: Elaborated by the authors.

We can see these differences for firms' size in Table 7. The results indicate that the average causal effect was approximately, 5.2%. This means that a 1% increase in SF's resources would lead to 5% more growth in firm size. The 4.7% effect of SF on firms in the 8th decile (those that received incentives between $521,000 and $807,000 BRL) is positive and significant for the year that they accessed the funds. The effects on deciles 2 and 6 occur later on, with significant values of about 5% only three years after access. Also, firms that accessed the SF grew at larger annual rates (in relation to the year of debut) than those that didn't (something close to 1%). The combination of both results tells us that firms that had access to SF grew more and faster than those who didn't.

TABLE 7

Estimates of log of firms' size.

Amount of incentives (BRL)	Decile	Treated	Untreated	Level					Differences			
				t_0	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4
Total average effect	-	330	1753	5.24*	5.32*	5.38*	5.86*	5.72*	0.09*	0.1*	0.1*	0.18*
-| 4.838	1	33	160	5.31	5.56	5.65	5.76	5.59	0.25	0.35*	0.45*	0.56*
4.839 |-| 16.527	2	33	107	5.43	5.45	5.52	5.65*	5.57*	0.02	0.08	0.22*	0.28*
16.528 |-| 56.406	3	33	122	6.25	6.28	6.31	6.56	6.52	0.04*	0.07*	0	0.15*
56.407 |-| 112.473	4	33	254	4.03	4.2	4.16	2.75	3.21	0.12	0.08	0.91	1.37
112.474 |-| 222.222	5	33	245	4.92	4.96	5.17	0	0	0.19	0.3	0	0
222.223 |-| 349.816	6	33	141	5.05	5.43	6.04	5.3*	5.36*	0.11*	0.05	0.2*	0.34*
349.817 |-| 521.362	7	33	249	4.73	4.81	5.18	0	0	0.21	0.14	0	0
521.363 |-| 807.915	8	33	138	4.73*	5	4.66	0	0	0.15	0.83	0	0
807.916 |-| 1.417.064	9	33	142	5.35	5.46	6.77	0	0	0.18	0.68	0	0
1.417.064 |-	10	33	195	6.66	6.82	5.75*	0	0	0.36	0.04*	0	0

Obs.: * significant at 5%.

Source: Elaborated by the authors.

Among high-tech exporters, the total average effect was positive and increases over the years (Table 8). Furthermore, the effect in the year of access is statistically significant for deciles 1, 5 and 9. In the latter, firms that received funds ranging from $807,000 to $1.4 million BRL exported 8% more compared to similar companies that have not.

TABLE 8

Estimates of log of high-tech exports.

Amount of incentives (BRL)	Decile	Treated	Untreated	Level					Differences			
				t_0	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4
Total average effect	-	330	1753	4.15*	4.22*	4.61*	5*	5.68*	0.22*	0.58*	0.63*	1.11*
-| 4.838	1	33	160	5.08*	4.7*	5.67*	6.23*	5.41*	0	0.59	1.15	1.12
4.839 |-| 16.527	2	33	107	4.01	4.67	4.47	4.6	5.79*	0.66	0.46	0.59	1.34
16.528 |-| 56.406	3	33	122	6.43	6.85	7.85*	6.95	10.53*	0.49	1.49	0	2.38
56.407 |-| 112.473	4	33	254	2.63	2.97	4.26*	0	0	0.26	1.27	0	0
112.474 |-| 222.222	5	33	245	4.57*	4.62	7.09*	0	0	0	0.57	0	0
222.223 |-| 349.816	6	33	141	4.7	5.73	6.82	9.16*	9.31*	0.66*	0.47*	0.36*	0.66*
349.817 |-| 521.362	7	33	249	3.74	4.83	6.5	0	0	1.58	2.88	0	0
521.363 |-| 807.915	8	33	138	4.63	5.38	5.45	0	0	0.82	0	0	0
807.916 |-| 1.417.064	9	33	142	7.88*	5.53	5.17	0	0	0	0	0	0
1.417.064 |-	10	33	195	6.38	6.56	0	0	0	0.85	0	0	0

Obs.: * significant at 5%.

Source: Elaborated by the authors.

Estimates for the growth rate of exports shows a result which is, in some ways, expected (Table 8). Treated firms should export relatively more high-tech products over the years. However, requirements for competitive insertion, not captured by the model, make the impact on differences lower in the first years compared to later years (total effect of 0,22% in the first year and 1,1% four years after the access).

When it comes to technological efforts, only the total average effect in the year of access was statistically significant (Table 9). Treated firms had an average increase of 1.5% in their R&D investment in the year of access. This positive impact increases over the years (with the exception of t_4, which is slightly smaller than t_3) and suggests additionality. This additionality gets more evident when analyzing the differences estimates, as the relative growth rate of investment in the year following the access was positive and significant (0,03%), meaning that not only treated firms invested more, but at a higher pace. Although it wasn't possible to observe significant differences for every group in every year, the average effect is always positive, thus excluding a crowding-out hypothesis.

By analyzing groups based on the amount of incentives received, significant impacts are only seen after long periods and for firms that received between $222,000 and $349,000 BRL. If those firms had received 1% more resources, they would've invested, on average, 4.5% more in t3 and 4.6% in t4 (Table 9). This may indicate the creation of an innovation culture, at least for those companies in this group.

TABLE 9

Estimates of log of technological efforts.

Amount of incentives (BRL)	Decile	Treated	Untreated	Level					Differences			
				t_0	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4
Total average effect	-	330	1753	1.53*	1.6*	1.63*	1.84*	1.83*	0.03*	0.02	0.03	0.12*
-| 4.838	1	33	160	1.4	1.71	1.74	1.76	1.87	0.31*	0.34*	0.36*	0.57*
4.839 |-| 16.527	2	33	107	1.27	1.15	1.18	1.33	1.29	0	0	0.07	0.19
16.528 |-| 56.406	3	33	122	2.61	2.56	2.67	3.02	3.03	0	0	0	0.07
56.407 |-| 112.473	4	33	254	0.82	0.95	0.94	0	0	0.1*	0	0	0
112.474 |-| 222.222	5	33	245	1.34	1.37	1.64	0	0	0.03	0	0	0
222.223 |-| 349.816	6	33	141	1.36	1.72	2.72	4.55*	4.61*	0.09	0.15	0.35*	0.48*
349.817 |-| 521.362	7	33	249	1.3	1.48	2.29	0	0	0.14	0.31	0	0
521.363 |-| 807.915	8	33	138	1.32	1.47	1.68	0	0	0.05	0.07	0	0
807.916 |-| 1.417.064	9	33	142	1.59	2.11	4	0	0	0.14	0.16	0	0
1.417.064 |-	10	33	195	2.95	3.2	0	0	0	0.44	0	0	0

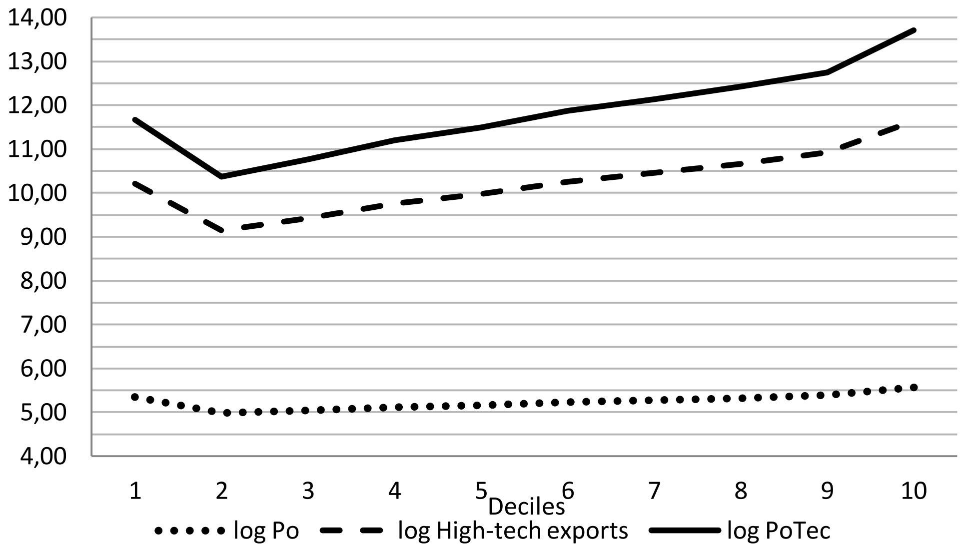
Obs.: * significant at 5%.

Source: Elaborated by the authors.

Finally, the methodology used in this paper allows the identification of the impact of the SF on the treatment level for firms' R&D inputs and output. All curves in Figure 3 decrease when moving from the 1st decile (incentives up to $4,838 BRL) to the 2nd decile (incentives varying from $4,839 to $16,527 BRL). But, after that initial decrease, all variables have an always increasing response with a positive slope shift at the last decile (more than $1.4 million BRL). Thus, the impacts of sector funds indicate a quadratic "U"-shaped relationship, suggesting that these resources have a important impact at the beginning of the distribution and a stronger impact at the end of the distribution (Figure 3).

FIGURE 3

Sector Funds' impacts on treatment level.



Source: Elaborated by the authors.

5 FINAL REMARKS

The Sector Funds are instruments that are designed to provide a source of comprehensive and continuous investment in S&T, since they bind revenues from specific sectors to expenditures in the same sectors. Currently, they are considered the most important instruments to promote innovation, either through partnerships between universities, the private sector and institutions of science and technology, or through incentives for private investment in R&D.

Because of the magnitude of the resources offered to firms through the sector funds (about $1 billion BRL in recent years, including the values of Grants and Loans), it is important to evaluate the effectiveness of this instrument. Several studies have been performed in recent years to evaluate this mechanism, and one of the most recent ones is from Araújo et al. (2010), in which the authors study the effect of the presence of incentives. The authors evaluated the effect of sector funds on companies that have accessed them, compared to those who haven't.

Although this type of evaluation is very important, some information about the amount invested may be lost. A natural evolution of these methods considers the different amounts of incentives that companies receive, because such differences may have distinct impacts on private investment. With the aim of evaluating whether different amounts stimulate more (or less) private investment in R&D and to complement Araújo et al.'s (2010) work, we chose to use a methodology that also considers the volume of resources, not just its presence. By using these techniques, we believe that more accurate estimates of the effects of different amounts of resources can be obtained.

Generally speaking (i.e., considering the whole set of firms), the effect of sector funds on firm size is positive and significant. On average, if the government provided 1% more resources to firms that accessed this instrument, they would be 5% larger than firms that did not access the funds. In particular, for firms that received incentives from $4.8 thousand to $16.5 thousand and between $222,000 and $349,000 this effect was only observed three years after access, with significant values on the order of 5%. For these firms, this may mean a lower marginal cost of capital. If firms can lower their R&D expenses, they can use this "saved" capital to hire more employees and increase in size. However, this size increase isn't substantial, since the *DID* estimator that measures firms' growth rates indicated a positive and significant effect of less than 0,2%.

The overall impact of incentives on high-tech exports was also positive, and is strictly increasing over time, starting at 4% in the year of access and growing to 5.7% after four years. The *DID* estimates show that the supported firms' export growth rate is higher than the rates of those who did not receive funds. This result suggests that companies gain when they invest in innovation, because the return of these investments provides technologies that enable them to become more competitive in the international market.

There was a significant total average effect of technological efforts, measured by the variable *Potec* (number of scientific employees, as a proxy for private investment in R&D), of 1.5%. This means that if the government had increased the volume of resources available by 1%, companies would have invested 1.5% more in the year they had access to such resources. Moreover, this effect is increasing over time with firms investing about 1.8% more after 4 years. This additionality effect, although small, was significant and allows the rejection of the crowding-out hypothesis and supports the hypothesis that the sector funds create a culture of innovation in these firms.

In addition to these results, the method used here allows the assessment of the impacts that the sector funds had on treatment levels for each response variables. In all cases, the results show a quadratic "U"-shapped relationship, which suggests that such features have more impact on the extremes of the distribution, that is, they have stronger relative impact for very small firms (which participate in very low value projects, being small the relative impact is increased) and for medium or large firms (which participate in higher valued projects). However, we should also consider that the last decile - for which the impacts are supposedly higher - does not mean more expensive projects, but it means that FINEP's incentive distribution is so skewed to the left that an innovation project that costs $1.5 million BRL is already in the last decile.

Finally, we point out some limitations regarding the databases and methodological issues in this paper. The indicators used in this paper for firms' technological efforts and size are not the most suitable. It is known that an assessment of firms' growth by increasing the number of employees does not take into account the productivity gains provided by technological innovations.

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