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Evidence from Chile

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Innovation, Productivity, and Spillover Effects: Evidence from Chile

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Abstract

This paper estimates the direct and spillover effects of two matching grants schemes designed to promote firm-level research and development (R&D) investment in Chile on firm productivity. Because the two programs target different kinds of projects—the National Productivity and Technological Development Fund (FONTEC) subsidizes intramural R&D, while the Science and Technology Development Fund (FONDEF) finances extramural R&D carried out in collaboration with research institutes—analyzing their effects can shed light on the process of knowledge creation and diffusion. The paper applies fixed-effects techniques to a novel dataset that merges several waves of Chile's National Manufacturing Surveys collected by the National Institute of Statistics with register data on the beneficiaries of both programs. The results suggest that while both programs have had a positive impact on participants' productivity, only FONDEF-funded projects have generated positive spillovers on firms' productivity. The analysis reveals that the spillover effects on productivity display an inverted-U relationship with the intensity of public support. Spillover effects were found to occur only if firms were both geographically and technologically close.

JEL Codes: D24, D62, H43, L60, O32, O38

Keywords: innovation, productivity, spillover effects, R&D subsidies, policy evaluation, Chile

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1. Introduction

The research and development (R&D) undertaken by one firm can affect the performance of other firms operating in the same or in other industries, either locally or abroad. A discovery in one firm, sector, or country can trigger new avenues of research, inspire new research projects, lead to new applications, or simply be imitated by other firms, sectors, or countries (Hall and Lerner, 2010). It is well established that knowledge is a non-rival, and only partially excludable, good (Nelson, 1959; Arrow, 1962). Because of weak or incomplete intellectual property protection, the difficulty of keeping innovations secret, and the possibility of reverse engineering and imitation, some of the knowledge and benefits from R&D spill over to other firms.

Different types of R&D may vary in their potential to generate spillovers. Firms conducting intramural R&D—that is, R&D activities that are developed within the firm—may find it easier to protect the knowledge generated internally, and thus be able to limit diffusion and corresponding knowledge spillovers. By contrast, knowledge generated via extramural R&D—that is, R&D activities that are undertaken in collaboration with (or by) an external partner such as a firm, consortium, university, or another institute—may be more generic and/or easier to codify, and its benefits more difficult to appropriate. Thus, extramural R&D could be expected to produce more knowledge spillovers (Cassiman and Veugelers, 2002).

R&D may also produce different types of spillover effects, depending on the technological, spatial, and other economic distances between firms (Jaffe, 1986). The two most common spillover effects have opposite outcomes. The first type is the *knowledge spillover effect*, which may increase the productivity of other firms. The second is the *business-stealing effect*, in which productivity gains in an innovating firm decrease the value of competing firms.[1]

Knowledge spillovers are at the heart of growth and development because they lay the foundation for further knowledge creation and diffusion (Aghion and Howitt, 1990; Romer, 1990; Grossman and Helpman, 1991).[2] These spillovers create a wedge between private and social returns and generate disincentives for private investment in knowledge production. While granting intellectual property rights (IPR) can help safeguard and thus stimulate such investments, this approach usually offers limited legal coverage, particularly in developing countries, where very few firms are able to produce knowledge that is novel enough to be eligible for IPR protection.

[1] For example, Bloom, Schankerman, and Van Reenen (2013) show that R&D conducted by neighbors that are close in the technology space is associated with a higher firm market value, patenting, and total factor productivity (TFP) (i.e., the knowledge spillover effect), while R&D by neighbors that are close in the product market space exacerbates the rivalry effect, lowering the firm's market value without affecting patents or TFP.
[2] For a survey of the literature on growth and spillovers, see Jones (2005).

Policy interventions are therefore a plausible way to close this gap, for example through targeted subsidies.

Although knowledge spillovers are the main rationale for public subsidies to support business R&D, most previous impact evaluations of innovation programs have focused on their impact on direct beneficiaries (Cerulli, 2010; Crespi, Maffioli and Rastelletti, 2014; Zúñiga-Vicente, et al., 2014; Figal Garone and Maffioli, 2016). Yet this approach is not informative enough to assess whether such subsidies are justified. For example, a subsidy would not be justified if all the benefits from the R&D investment are concentrated in one firm. While such an investment would be socially desirable, the private firm would be motivated to undertake it without the need for public incentives. In such cases, a traditional impact evaluation would indicate that the intervention increased investment and productivity, even if it failed to generate knowledge spillovers.[3] If the justification for such a policy intervention is indeed the potential to trigger knowledge spillovers, it is important to assess whether such spillovers have occurred.

This paper contributes to the literature in three main ways. First, it evaluates the long-term direct and indirect (spillover) effects of public support to R&D on firm performance in Chile. Rather than focusing only on direct beneficiaries, it assesses the extent to which R&D subsidies have also indirectly affected untreated firms—that is, the occurrence of spillover effects—using an indicator of spatial and technological (sectorial) proximity between treated and untreated firms. Spatial and technological distances have been shown to be important mechanisms for transmitting knowledge between firms (Jaffe, 1986; Bernstein and Nadiri, 1989; Audretsch and Feldman, 1996; Anselin, Varga and Acs, 1997; Aw, 2002; Fosfuri and Ronde, 2004; Paz, 2014). In addition, rather than looking at the impact of the subsidies on R&D efforts, we focus on the impact on firm performance, that is, productivity.[4]

Second, to further explore the source of the spillover effects and the mechanisms that generate them, we compare the effect of two R&D subsidy schemes that target different kinds of R&D projects: the National Productivity and Technological Development Fund (FONTEC), which subsidizes intramural R&D, and the Science and Technology Development Fund (FONDEF),

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[3] Even worse, in the absence of spillovers, the subsidy could lead to an increase in R&D investment in projects that are socially undesirable but for which the private returns exceed private (after subsidy) costs, for example, a project with a private return of $5, no spillovers, and a cost of $6, $3 of which is paid by the subsidy. Note that this investment would be undesirable even if there were spillovers, if they are small enough (in this example, smaller than $1).

[4] Although we recognize that R&D and productivity have an indirect relationship mediated by the success (or lack thereof) of innovation outcomes (such as new products or processes), data availability forces us to focus on firm performance. We believe that productivity is a valid outcome indicator for our main concern, as a knowledge-augmented production function model provides the right setting in which to assess the importance of knowledge spillovers (for a review, see Hall and Lerner, 2010; Keller, 2010).

which finances extramural R&D carried out in collaboration with research institutes. This unique Chilean setting allows us to determine which type of policy design could more effectively address market failures due to the lack of knowledge appropriability.

Finally, we characterize the nature of spillover effects by studying how they change with differences in policy intensity, that is, when more (or fewer) firms are supported. This analysis allows us to understand how the two countervailing spillover effects operate: positive effects from knowledge spillovers vs. negative business-stealing effects from product market rivals.

To identify these effects, we use an index number method to measure firm-level (total factor) productivity and apply fixed-effects techniques to a novel dataset. This dataset merges several waves of Chile's National Manufacturing Surveys collected by the National Institute of Statistics (Instituto Nacional de Estadística, or INE) with register data containing information on the beneficiaries of both programs. Our final dataset is a 17-year panel covering almost 9,000 firms and 600 program beneficiaries.

Our findings show that R&D subsidies in Chile do generate spillover effects. Indeed, when considering both programs together, we find that policy intervention increases the productivity of both treated firms (direct beneficiaries) and untreated firms located in the same region and sector (indirect beneficiaries). Directly participating in an innovation program (either FONTEC or FONDEF) increases a firm's total factor productivity (TFP) by around 4 percent. In terms of spillover effects, a one-standard-deviation increase in the share of supported firms increases TFP of firms that are close in both the geographic and technology spaces by around 1 percent.

When looking at each program separately, the direct effect remains quite similar. However, our results suggest that spillover effects are contingent on program design: while both programs increase productivity for direct beneficiaries, only FONDEF-funded projects (i.e., extramural R&D) generate positive spillover effects.

When we analyze the spillover effects in more depth, the results are striking in two respects. First, we find an inverted-U relationship between the intensity of the support, captured by the share of firms receiving R&D subsidies in the same sector and location, and the spillover effects on productivity. This suggests that two countervailing spillover effects may be in play: positive knowledge spillover effects dominate if the share of treated firms in the sector-location is relatively low; by contrast, if the program supports a larger fraction of a firm's rivals, business-stealing may produce decreasing spillover effects on productivity. The inverted-U shaped curve may be generated, for example, if there are decreasing returns on knowledge spillovers as more firms adopt a technology—that is, firms can learn most of what there is to learn from early adopters—but the negative business-stealing effects may be linear based on the number of adopters.

Second, we find that proximity in both geographic and technology spaces is necessary for spillovers to occur. That is, knowledge flows more easily among geographically proximate firms that belong to the same sector.

The paper is structured as follows. Section 2 summarizes the relevant literature, focusing on the rationale behind innovation policy and evidence of the effectiveness of R&D support programs. It also describes the main features of the two subsidy programs. Section 3 presents the empirical strategy used to measure the programs' direct and spillover effects. Section 4 describes the data and analyzes some descriptive statistics. Section 5 presents the results, and Section 6 concludes.

2. Background

2.1. The Rationale behind R&D Subsidies

The fundamental premise underlying R&D subsidies is that government intervention can be beneficial if profit-driven actors underinvest in R&D from a social welfare perspective due to the presence of spillover effects associated with the 'public good' nature of knowledge (Steinmueller, 2010). If knowledge is a non-rival and non-excludable good,[5] then a firm's rivals may be able to free-ride on its investments. These spillovers may create a gap between private and social returns, and a disincentive to privately invest in knowledge production.

Spillovers are not automatic, however, and should not be taken for granted, since not all knowledge is considered a public good to the same extent. Certainly, the public good rationale of knowledge applies more strongly to generic or scientific knowledge than to technological knowledge, which tends to be more applicable and specific to the firm. Furthermore, for the public good rationale to be valid, there should be some possibility of free-riding. If the originator can protect the results of the knowledge generated (through entry barriers or the use of strategic mechanisms, for example), then the potential for market failure declines. In this regard, knowledge generated through collaboration among different parties might be more difficult to protect, and

[5] The seminal work by Nelson (1959) and Arrow (1962) maintains that, once produced, new knowledge is a non-rival good: it can be used simultaneously by many different firms. This characteristic represents an extreme form of decreasing marginal costs as the scale of use increases: although the costs of the first use of new knowledge may be large since they include the costs of its generation, further use incurs negligible incremental costs (Aghion, David, and Foray, 2009). Knowledge is said to be non-excludable due to the difficulty and cost of trying to retain exclusive possession of it while using it.

therefore might be more prone to spillovers than knowledge generated by individual entities based on their internal capabilities.[6]

Other market failures, including asymmetric information and uncertainty, affect the financing of innovation activities. R&D projects are different from other investments in three main ways (Hall and Lerner, 2010): (i) the returns on R&D investments are more uncertain and take longer to materialize; (ii) innovators may be reluctant to disclose information about their projects due to the risk of spillovers; and (iii) R&D investments normally involve intangible assets that have very limited use as collateral. For these reasons, firms without deep pockets may find it difficult to access financing for innovation projects, even when these have positive expected private rates of return. Thus, some potentially profitable projects will never be carried out. However, it is important to establish that, in the absence of spillovers, R&D subsidies are not the solution to these problems. Rather, the best remedies for a lack of financing are financial instruments such as long-term credit lines or guarantees for intangible assets (IDB, 2014).

R&D projects might also be affected by pervasive coordination failures. Knowledge has important tacit components that cannot be embodied in a set of artifacts, such as machines, manuals, or blueprints. Thus, firms can benefit from networking with one another and with other actors, because they need to learn from the knowledge bases of other organizations. However, these knowledge networks are less effective if private and public agents fail to coordinate their knowledge investment plans to create mutual positive externalities (Aghion, David, and Foray, 2009). For example, coordination failures could occur in the process of accessing technological infrastructure. Firms that cannot afford infrastructure on their own can gain access to it if they collaborate with others.

Solving coordination problems requires paying special attention to institutional settings that can affect the linkages between different actors in the innovation system. What policy tools can help remedy coordination failures? In most cases, this requires institutional reforms that provide appropriate incentives for innovation actors to collaborate with each other. R&D subsidies might also help align the parties' incentives, particularly during the preliminary learning phases of a joint venture. By making support contingent on collaboration, these subsidy schemes may help shift collaborating partners to a better equilibrium.

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[6] Under specific circumstances, private R&D investments might even be higher than socially optimal if, for example, firms must invest in R&D to build sufficient absorptive capacity to benefit from spillovers. Thus, environments with strong spillovers could induce more, rather than less, R&D investment. "Patent race" models, in which a pool of companies invests in R&D to obtain a patent that gives them monopoly control over the knowledge generated, may also inadvertently increase private investment. In such cases, cooperative arrangements for R&D might be better from a welfare perspective than simple R&D subsidies (Cerulli, 2010).

In summary, R&D subsidies are primarily justified by the presence of knowledge spillovers, which are more likely to occur when the knowledge generated is more generic and when it is developed within a collaborative joint venture.

2.2. Public Support to Innovation, Knowledge Spillovers, and the Missing Link

There is no guarantee that R&D subsidies will solve the problem of business R&D underinvestment. Their effectiveness will depend on several complex considerations that policymakers will not have advance knowledge of, including the actual presence of knowledge spillovers, the type of knowledge targeted by the intervention, and the reaction to the intervention by supported and unsupported firms (Toivanen, 2009). The need to learn which policies are most beneficial has motivated a growing empirical literature analyzing the impact of R&D subsidies.[7]

Most of the empirical literature has measured the results of R&D subsidies in terms of input additionality, or the extent to which subsidies crowd in or out private R&D investment. The implicit assumption underlying this approach is that, to the extent that subsidies are rightly targeting the market failure (e.g., knowledge spillovers), they will allow firms to pursue projects that they would not have implemented otherwise. The problem with this approach is that input additionality is not sufficient to justify the subsidy, as firms may respond by increasing their investment due to other sorts of market failures (such as liquidity constraints) or, even worse, investing in projects that are socially unprofitable.

Zúñiga-Vicente et al. (2014) conducted one of the most comprehensive reviews of the impact of R&D subsidies on private R&D investments around the world. They document the results of 76 studies carried out at the firm level since the early 1960s, most of which were published in the 2000s. Although the studies are not fully comparable a general pattern clearly emerges: in 60 percent of the cases, the crowding-in hypothesis cannot be ruled out. The rest of the studies find either crowding out or non-significant effects (20 percent each). More recently, Dimos and Pugh (2016) provides a Meta-Regresion Analysis (MRA) of micro-level studies published since 2000 on the impact of public subsidy for R&D on either input or output R&D. Their MRA findings reject crowding-out of private investment by public subsidy but reveal no evidence of substantial additionality.

As in other regions, the most common approach of assessing the effectiveness of R&D subsidies in Latin America and the Caribbean has been to evaluate their effects on private R&D investment. Crespi, Maffioli, and Rastelletti (2014) and Figal Garone and Maffioli (2016)

[7] For a detailed review of the pros and cons of different approaches to assessing the impact of R&D subsidies, see Cerulli (2010). Regarding science and technology programs, see also Crespi et al. (2011).

summarize the results of 16 impact evaluations undertaken in the region. Their analysis shows that in most cases, subsidies do stimulate R&D investments, and there is evidence of a crowding-in effect. Interestingly, the effects tend to be larger when subsidies target projects that involve collaboration between firms and research institutes.

In summary, the empirical evidence tends to confirm that R&D subsidies are an effective way to increase private R&D investment. But what are the actual returns on these investments? To the extent that knowledge is a production input, the right setting in which to assess the impact on outputs is a knowledge-augmented production function model. In other words, properly assessing the effectiveness of R&D subsidies requires evaluating their impact in terms of their output (i.e., innovation or productivity). The main difficulty associated with this type of study is that a longer time horizon is required to detect the effects. While R&D expenditure effects can be detected almost immediately after the receipt of public financing, productivity effects can only be assessed after an innovation has taken place. Rigorous impact evaluation of these effects therefore requires panel data to track firms' progress after receiving the subsidy.[8]

More importantly, are R&D subsidies targeting projects that generate knowledge spillovers and hence are less likely to be implemented without the subsidy? Although a growing empirical literature seeks to identify knowledge spillovers, far fewer studies have sought to link these spillovers to public support for R&D and integrate them into an empirical impact evaluation framework (see, for example, Branstetter and Sakakibara, 1998, and Møen, 2004).

Although they do not evaluate policy impacts, two empirical papers on knowledge spillovers are highly relevant to our study. First, Bloom (2007) shows that the relationship between a firm's R&D and that of rival companies operating in the same sector depends on the degree of complementarity/substitutability of innovative outputs (patents). Indeed, when products are complements, companies can take advantage of other firms' inventions (and hence, others' R&D efforts), which gives them an incentive to increase their own R&D investment. The opposite occurs when products are substitutes. In a second important paper, Bloom, Schankerman, and Van Reenen (2013) emphasize that two different types of spillover effects might be present: a positive effect from knowledge spillovers and a negative, business-stealing effect from product market rivals. Using different measures of firm proximity to analyze panel data on U.S. firms, their

[8] See, for example, Crespi et al. (2015).

results suggest that positive knowledge spillovers quantitatively dominate, so R&D gross social returns are likely twice as high as R&D private returns.[9]

For developing countries, most empirical assessments have also focused on the performance of direct beneficiaries. Perhaps the only two exceptions are Castillo et al.'s (2019) study on Argentina and USP Research Group's (2013)[10] research on Brazil. These studies focus on R&D subsidy programs and find positive knowledge spillovers through labor mobility. Although neither of these papers directly assesses the impact of R&D subsidies on productivity, mostly due to a lack of data, their results might indicate productivity increases due to spillover effects through labor mobility.

2.3. Chilean Business Innovation Policy: 20 Years of Experimentation

Since the early 1990s, the Chilean government has implemented several programs designed to support innovation and productivity in private firms. This paper focuses on two of such programs, FONTEC and FONDEF.

FONTEC, managed by the Chilean National Development Agency (CORFO), provides financing for innovation projects carried out by private firms. It has supported more than 2,200 business innovation projects since its creation in 1991. FONTEC uses a matching grant approach, subsidizing 40–65 percent of the total costs of private projects with private co-funding in the form of ex post reimbursement of approved eligible expenditures (Benavente, Crespi, and Maffioli, 2007). Providing only partial funding helps align the goals of the public agency and the firm and eases the potential moral hazard problem. While FONTEC can allocate resources in different ways, the most important instrument consists of direct business R&D subsidies, which finance innovation projects carried out by individual firms.

FONTEC grants are allocated under an open window system, on a rolling first-in-first-out basis. External peer reviewers technically assess innovation projects submitted by firms, and an adjudicatory committee with representatives from both the public and the private sectors makes the final allocation decision. Although this approach is more flexible in response to firms' demands for support, it may be less competitive than a system based on a call for proposals. FONTEC is designed to help closing the gap between social and private returns to business R&D. In principle,

[9] Although in the paper Bloom, Schankerman, and Van Reenen (2013) find that business-stealing effects are relatively minor, this might not be the case when subsidies are provided. When companies are receiving innovation subsidies, they usually accept a higher risk and seek to obtain higher returns (e.g., gain market share). In these cases, business-stealing effects are more likely to occur. Thus, we believe that considering such effects is relevant for a proper assessment of innovation policies.

[10] A program promoting cooperation between firms and universities was found to produce the largest spillover effects.

its subsidies should be targeting knowledge spillovers generated by R&D projects implemented by individual firms based on their internal capabilities.

FONDEF, managed by the National Science and Technology Council (CONICYT), provides funding for pre-competitive R&D and technology projects executed jointly by universities, technology institutes, and the private sector. The government subsidy also entails a matching grant covering a portion of the total costs of the project (up to a maximum of 55 percent). Universities and non-profit R&D institutions are the main beneficiaries, but private sector participation is required. The research institution (executor) involved in the project is required to contribute the equivalent of 20 percent of the total cost of the project, while associates and companies must contribute a minimum of 25 percent of the total project cost. The grants are awarded through an annual public bidding process after a review of project proposals.

FONDEF's economic justification seems to involve internalizing R&D spillovers by forming joint ventures and facilitating collaboration among R&D innovation system actors. In other words, the program seeks to align the interests of public research organizations with those of the productive sector. These incentives also give private firms access to a large set of complementary knowledge assets (external capabilities) and technological infrastructure to help implement their R&D projects.

In sum, although FONDEF and FONTEC are designed to increase private R&D investment and productivity at the firm level, they use very different mechanisms to achieve this goal. While FONTEC focuses on alleviating the lack of appropriability that harms business R&D by providing support to individual firms to implement their projects based on their internal capabilities, FONDEF addresses the same problem by fostering collaboration and interaction between public research organizations and firms. Given the different designs of these programs, it is important from a policy perspective to compare their performance. To the extent that FONDEF is more likely to produce more generic knowledge and that firms executing (intramural) FONTEC projects are more likely to be able to protect their acquired knowledge, we expect FONDEF projects to have a greater potential to produce externalities. The involvement of multiple parties could also increase the likelihood of major knowledge spillovers.

3. Empirical Strategy and Expected Impacts

3.1 Direct Impact: Linking R&D and Productivity

As mentioned in Section 2.3, FONTEC and FONDEF support different types of R&D projects, which could produce different impacts on private vs. social returns. A conceptual framework is thus necessary to differentiate the (private and social) returns of both programs on firm productivity.

We build on the R&D capital model laid out, for example, in Griliches (1973, 1979, and 2016). Variations of this framework are widely used in studies of the returns to R&D.[11] We follow Moretti (2004) to specify the following basic model:

$$Y_{irjt} = A_{irjt} H_{irjt}^{\alpha H} L_{itjt}^{\alpha L} M_{irjt}^{\alpha M} K_{irjt}^{\alpha K} \ , \qquad (1)$$

where Y_{irjt} is output, H_{irjt} is skilled labor, L_{irjt} unskilled labor, M_{irjt} is raw materials, K_{irjt} is capital stock, and A_{irst} is TFP, for firm *i*, region *r*, sector *j*, and period *t*.

We assume that an R&D subsidy operates by shifting the TFP parameter. We estimate TFP under the following assumptions: (i) technology is Cobb-Douglas; (ii) factor prices equal marginal products; and (iii) there are constant returns on scale to capital, materials and labor. Our main measure of productivity is estimated using an index number where the elasticities are the factor shares measured at the 2-digit sector and region levels using the mean of plant-specific ratios of input costs over total costs.[12]

Since the subsidies are not granted randomly, beneficiaries may differ from non-beneficiaries due to selection bias: beneficiaries are likely to be more productive than non-beneficiaries. Therefore, beneficiaries would show different outcomes than non-beneficiaries even in the absence of program support.

A major advantage of using longitudinal firm-level datasets is that they allow us to account for constant unobservable factors that may affect both the outcome of interest and participation in the innovation program. We estimate the program effects on direct beneficiaries using the following fixed-effects log-linear regression model:[13]

$$\ln\left(\mathrm{A}_{\mathrm{irjt}}\right) = \rho \mathrm{D}_{\mathrm{irjt\text{-}1}} + \beta \mathrm{X}_{\mathrm{irjt}} + \epsilon_{\mathrm{i}} + \epsilon_{\mathrm{t}} + \epsilon_{\mathrm{rt}} + \epsilon_{\mathrm{jt}} + \varepsilon_{\mathrm{irjt}} \quad (2)$$

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[11] See Mairesse and Sassenou (1991) and Wieser (2005) for good reviews on this methodological and empirical literature.

[12] We replicate the results for two alternative measures of productivity. The first is estimated from the residual of a production function estimated at the 2-digit industry level using the Levinshon-Petrin approach (for details, see Alvarez and Crespi, 2007). The second measure is similar to the main one but uses factor shares measured at the 2-digit sector level. The results, available upon request, are identical to those presented in the paper.

[13] See Bertrand, Duflo, and Mullainathan (2002) for a formal discussion of DID estimates.

Firm fixed effects ϵ_i fully absorb any permanent heterogeneity at the firm level, and ϵ_t represents yearly shocks that affect all firms. Regarding the interaction terms, ϵ_{rt} denote region-year effects such as the construction of a freeway or airport, or the implementation of new local policies, and ϵ_{jt} fully absorb industry-year effects—time-specific shocks that affect the productivity of all firms in industry *j*. D_{irst-1} is a binary variable that takes a value of 1 the year after firm *i* enters the innovation program and thereafter. Therefore, ρ represents the parameter of interest, which captures the causal effect of D_{irjt-1} on productivity.[14] In other words, ρ is the innovation program's average impact on participating firms in the post-treatment period. X_{irjt} are time-varying firm characteristics such as the log of the firm's age and age squared, and ε_{irjt} is the usual error term assumed to be uncorrelated with D_{irjt-1}. In this case, the identifying assumption is independence of treatment status and potential outcomes, conditional on time-invariant unobservable and observable factors as well as time-varying observable confounders. Since we are evaluating two programs, we extend the empirical model in equation (2) to obtain different impact parameters for each program:

$$ln(A_{irjt}) = \rho_C D_{C,irjt-1} + \rho_F D_{F,irjt-1} + \beta X_{irjt} + \epsilon_i + \epsilon_t + \epsilon_{rt} + \epsilon_{jt} + \varepsilon_{irjt}\,, \quad (3)$$

where $D_{C,irjt-1}$ and $D_{F,irjt-1}$ correspond to FONTEC or FONDEF, respectively.

3.2 Indirect Impact: Spillover Measure and Effects

The presence of knowledge spillovers in a production function setting has implications for both how to estimate the impact of R&D subsidies on participant firms (direct beneficiaries) and how to identify the knowledge spillovers. Regarding the former, using non-supported firms to evaluate what would have happened to supported firms if they had not been supported assumes that R&D subsidies have no spillover effects on non-supported firms, which is clearly problematic. The question is whether the performance of non-supported firms can be considered independently of the support given to supported firms (Klette, Møen, and Griliches, 2000). If knowledge spillovers are present, this might lead us to underestimate the impact of R&D subsidies on treated firms. Therefore, to obtain proper estimates of the impact of R&D subsidies on treated firms' economic performance, it is important to control for spillover effects in the empirical approach.

[14] It is worth emphasizing that we are using a two-step approach to measure the impact of R&D subsidies on productivity. We first measure productivity using different methodologies. In the second step we correlate the resulting TFP index with the R&D variables. To the extent that the methodology used to measure TFP in the first step does not include R&D variables (in other words, it assumed that productivity is exogenous), any estimated impact in the second step will be underestimated (see Doraszelski and Jamandreu, 2013).

Most empirical approaches to controlling for spillovers within a production function framework augment the production function with a variable capturing the "pool" of outside knowledge relevant to each firm. This pool is normally constructed using a weighted average of other firms' knowledge, where the weights capture the degree of (technological, geographic, vertical, etc.) proximity among firms. However, one important methodological challenge associated with identifying knowledge spillovers—in addition to measuring them—is avoiding spurious correlation due to correlated unobservables across technologically related firms (Griliches, 1998). Equation (2) can then be augmented to assess the presence of geographic-technological spillover effects:

$$\ln\left(\mathrm{A_{irjt}}\right) = \rho \mathrm{D_{irjt\text{-}1}} + \rho_{\mathrm{S}} \mathrm{S_{irjt\text{-}1}} + \beta \mathrm{X_{irjt}} + \epsilon_{\mathrm{i}} + \epsilon_{\mathrm{t}} + \epsilon_{\mathrm{rt}} + \epsilon_{\mathrm{jt}} + \varepsilon_{\mathrm{irjt}}, \quad (4)$$

where S_{irjt-1} measures exposure to spillovers within a region within 2-digit sectors. The parameter ρ_S captures the spillover effects of the innovation programs. Therefore, a beneficiary firm receives a direct impact of the program (ρ) and an indirect impact (ρ_S). Equation (4) captures spillovers that occur within a region across the 2-digit sector.[15]

To estimate Equation (4), the measurement of S_{irjt-1} is critical.[16] For this, let *T* be the universe of firms directly supported by FONTEC or FONDEF and *N* the universe of firms. We then construct the share of treated firms other than firm *i* in the region and industry of firm *i*, that is:

$$S_{irjt-1} = \begin{cases} \dfrac{T_{rjt-1} - 1}{N_{rjt-1} - 1} & if\ D_{irjt-1} = 1 \\ \dfrac{T_{rjt-1}}{N_{rjt-1} - 1} & if\ D_{irjt-1} = 0 \end{cases} \qquad (5)$$

The numerators of S_{irjt-1} are the number of treated firms other than firm *i* in the region-sector, and the denominators are the number of all firms other than firm *i* in the region-sector (or "*rj*" cluster). Thus, we assume that the size of the spillover is proportional to the share of other firms in the region-sector that receive treatment.

Assigning a constant S_{irjt-1} to each *rj* cluster implies that we assume that each treated firm equally affects all its neighbors' TFP. Assigning a linear growth on S_{irjt-1} implies that we assume there is no complementarity between individual firms' spillovers (we will relax this later). We also assume there are no spillovers between clusters (i.e., we assume that there are only

[15] We construct the spillovers at the 2-digit sector level to ensure we have a reasonable number of treated firms within the region-sector. This improves the statistical power of the estimations.

[16] Bloom, Schankerman, and Van Reenen (2013) made the first attempt to provide an "axiomatic" basis for evaluating different measures of technology proximity and spillovers by proposing seven desirable properties. Since none of their measures dominates all the others, they conclude that the relative weight of these properties should be the choice of the empirical researcher depending on the research question.

within-cluster spillovers and we will test for that). All these assumptions are included in the broader assumption that $E[\,(S_{irjt-1}, \varepsilon_{irjt}\,)|X_{irjt}, \epsilon_i, \epsilon_t, \epsilon_{rt}, \epsilon_{jt}\,] = 0$. We can then define geographic-technological spillover as the change in A_{irjt} caused by the change in the share of treated neighbors S_{irjt-1}.

In a similar fashion, we can estimate the presence of spillovers for the different treatments as follows:

$$\ln\left(A_{irjt}\right) = \rho_C D_{C,irjt-1} + \rho_F D_{F,irjt-1} + \rho_{S,C} S_{C,irjt-1} + \rho_{S,F} S_{F,irjt-1} + \beta X_{irjt} + \epsilon_i + \epsilon_t + \epsilon_{rt} + \epsilon_{jt} + \varepsilon_{irjt} \quad (6)$$

where $\rho_{S,C}$ and $\rho_{S,F}$ capture the FONTEC and FONDEF spillover effects, respectively.

As mentioned in Section 2.3, FONTEC and FONDEF are expected to have different spillover effects on productivity. Given that FONTEC finances intramural R&D, a project submitted by a firm to this program is likely to be more closely related to the firm's internal capabilities. Since this type of project is more appropriable, the firm may have carried it out anyway. By contrast, FONDEF finances extramural R&D, which almost by definition involves knowledge that is more generic or further away from firms' internal capabilities. The knowledge generated in such projects is less likely to be appropriable. Thus, we expect spillover effects to be higher for FONDEF than for FONTEC projects. That is $\rho_{S,C} < \rho_{S,F}$.

4. Data and Preliminary Statistics

We use two datasets for our analysis. The first is the National Annual Manufacturing Survey (Encuesta Nacional Industrial Annual, or ENIA) of all manufacturing firms with 10 or more employees (n = 5,000) every year from 1990 to 2006. Second, we use administrative data provided by CORFO and CONICYT with the collaboration of INE to identify which firms in the ENIA data received FONTEC or FONDEF funding during this period.

Table 1 presents the number of firms by cohort of entry to FONTEC or FONDEF and the breakdown by program. The number of treated firms started to grow gradually in 1995 until reaching a typical flow of about 50 per year.[17]

[17] It is important to note that both programs are demand driven in the sense that the firm must submit a proposal to the funding agency. Volatility due to business cycles is also expected. Both programs are horizontal, since they support innovation activity regardless of the firm's sector or region. However, given that the ENIA is a manufacturing survey, the figures for treated firms are for manufacturing firms.

Table 1: Number of Firms by Cohort of Entry to the Program, 1990–2006

Year	Any treatment	FONTEC	FONDEF
1990	0	0	0
1991	0	0	0
1992	0	0	0
1993	0	0	0
1994	0	0	0
1995	11	11	0
1996	29	29	0
1997	105	31	74
1998	61	30	31
1999	68	42	26
2000	44	29	15
2001	39	24	15
2002	58	27	31
2003	55	29	26
2004	31	22	9
2005	20	8	12
2006	46	23	23
Total	**567**	**305**	**262**

Source: Authors' calculations based on CORFO and CONICYT administrative register data.

Table 2a describes the universe of manufacturing firms between 1990 and 2006. It shows separate statistics for firms participating in either program and non-participant firms (control group). We exclude the small number of firms that participated in both programs from our estimations. Table 2a highlights that treated firms generally score 28 percent higher than the control group on our main performance variable, TFP.

Treated firms also outperform control firms across various firm characteristics. Treated firms are slightly older and considerably larger than control firms (treated firms have an average of 192 employees, while the typical control firm has only 68 employees). Treated firms also have a more highly skilled workforce. We use the number of white-collar employees to proxy for skilled labor, and find that treated firms have an average of 70 skilled employees, while control firms average just 21. Treated firms also have a higher relative number of white-collar workers reflected on a mean skill intensity of 39 percent, compared to 35 percent for control firms. Finally, treated firms are more outward oriented, with a higher participation of foreign direct investment ownership and export intensity. While significant, the differences are smaller with regards to the firms' sector distribution. Treated firms have a higher participation in food, chemicals, basic metals, and machinery, while controls have greater participation in sectors such as textiles and wood processing. Finally, treated firms are dispersed throughout Chile, while control firms are more densely concentrated in Santiago.

Table 2b summarizes the descriptive statistics for the beneficiaries of each program. In general, the differences across the programs are relatively small, particularly when compared with the control group. Perhaps the most striking difference is that firms that received FONTEC benefits tend to be smaller and less highly skilled than those that received FONDEF subsidies. Firms participating in the FONTEC program seem to be over-represented in the chemicals and machinery sectors, while FONDEF participants are biased toward the foodstuff sector. Finally, FONTEC firms are more often located in Santiago, while FONDEF tends to mostly support firms in other regions of the country. Despite these differences across firm characteristics, there are no striking differences in performance or productivity.

As discussed above, the differences in performance between the control and treatment groups cannot be automatically attributed to the programs, since the participating firms were not chosen at random. To identify the direct and spillover effects of the innovation programs, we follow the empirical strategy described in Section 3 to properly account for potential selection bias.

Table 2a: Preliminary Statistics, 1990–2006

	Control group			Treatment group (FONTEC+FONDEF)		
	Obs	Firms	Mean	Obs	Firms	Mean
TFP	66,484	8,036	-0.02	5,930	540	0.25
Age	77,529	8,436	11.44	6,952	567	13.07
Sales (log)	74,618	8,436	12.66	6,794	567	14.57
Employment	74,617	8,436	67.66	6,794	567	191.73
Skilled	74,618	8,436	20.84	6,794	567	69.88
Skill Intensity	74,616	8,436	0.35	6,794	567	0.39
Export	77,529	8,436	0.15	6,953	567	0.48
FDI	77,529	8,436	0.07	6,953	567	0.22
Size						
Small	77,529	8,436	0.67	6,953	567	0.34
Medium	77,529	8,436	0.23	6,953	567	0.36
Large	77,529	8,436	0.11	6,953	567	0.29
Sector						
Food	77,529	8,436	0.30	6,953	567	0.33
Textile	77,529	8,436	0.16	6,953	567	0.03
Wood	77,529	8,436	0.10	6,953	567	0.05
Paper	77,529	8,436	0.07	6,953	567	0.04
Chemicals	77,529	8,436	0.11	6,953	567	0.21
Non-Metallic	77,529	8,436	0.04	6,953	567	0.04
Basic Metal	77,529	8,436	0.01	6,953	567	0.08
Machinery	77,529	8,436	0.18	6,953	567	0.22
Other	77,529	8,436	0.01	6,953	567	0.00
Region						
Tarapacá	77,529	8,436	0.03	6,953	567	0.03
Antofagasta	77,529	8,436	0.02	6,953	567	0.07
Atacama	77,529	8,436	0.01	6,953	567	0.05
Coquimbo	77,529	8,436	0.02	6,953	567	0.01
Valparaiso	77,529	8,436	0.08	6,953	567	0.06
O´Higgins	77,529	8,436	0.03	6,953	567	0.05
Maule	77,529	8,436	0.04	6,953	567	0.03
Biobio	77,529	8,436	0.11	6,953	567	0.12
La Araucanía	77,529	8,436	0.03	6,953	567	0.02
Los Lagos	77,529	8,436	0.04	6,953	567	0.07
Aisén	77,529	8,436	0.00	6,953	567	0.01
Antártica	77,529	8,436	0.01	6,953	567	0.01
Santiago	77,529	8,436	0.58	6,953	567	0.45

Source: Authors’ calculations based on CORFO and CONICYT administrative register data and INE.

Table 2b: Preliminary Statistics, 1990–2006

	FONDEF			FONTEC		
	Obs	Firms	Mean	Obs	Firms	Mean
TFP	2,608	247	0.26	3,322	293	0.25
Age	3,211	262	13.39	3,741	305	12.80
Sales (log)	3,157	262	15.53	3,637	305	13.74
Employment	3,157	262	280.15	3,637	305	114.99
Skilled	3,157	262	111.82	3,637	305	33.48
Skill Intensity	3,157	262	0.43	3,637	305	0.35
Export	3,212	262	0.56	3,741	305	0.42
FDI	3,212	262	0.28	3,741	305	0.17
Size						
Small	3,212	262	0.23	3,741	305	0.44
Medium	3,212	262	0.34	3,741	305	0.38
Large	3,212	262	0.43	3,741	305	0.18
Sector						
Food	3,212	262	0.38	3,741	305	0.29
Textile	3,212	262	0.01	3,741	305	0.05
Wood	3,212	262	0.08	3,741	305	0.03
Paper	3,212	262	0.05	3,741	305	0.03
Chemicals	3,212	262	0.16	3,741	305	0.24
Non-Metallic	3,212	262	0.05	3,741	305	0.03
Basic Metal	3,212	262	0.15	3,741	305	0.02
Machinery	3,212	262	0.11	3,741	305	0.31
Other	3,212	262	0.01	3,741	305	0.00
Region						
Tarapacá	3,212	262	0.02	3,741	305	0.04
Antofagasta	3,212	262	0.11	3,741	305	0.03
Atacama	3,212	262	0.08	3,741	305	0.02
Coquimbo	3,212	262	0.01	3,741	305	0.02
Valparaiso	3,212	262	0.08	3,741	305	0.04
O´Higgins	3,212	262	0.08	3,741	305	0.03
Maule	3,212	262	0.03	3,741	305	0.03
Biobio	3,212	262	0.19	3,741	305	0.06
La Araucanía	3,212	262	0.01	3,741	305	0.03
Los Lagos	3,212	262	0.12	3,741	305	0.04
Aisén	3,212	262	0.02	3,741	305	0.01
Antártica	3,212	262	0.03	3,741	305	0.00
Santiago	3,212	262	0.22	3,741	305	0.65

Source: Authors' calculations based on CORFO and CONICYT administrative register data and INE.

5. Results

5.1. Direct and Spillover Effects

We first estimate the direct effect on total factor productivity (TFP) of a global measure of the R&D subsidies program (i.e., having participated in any treatment). Table 3, Column 1 presents fixed-effects estimates of Equation (2). The estimated coefficient of interest (ρ) is positive and statistically significant, indicating that R&D subsidy programs have a positive direct effect on beneficiary firms' productivity. In general, participating in an innovation program in Chile increases a firm's TFP by an average of 4.3 percent in the post-treatment period (Table 3, Column 1). Looking at each program separately, the direct effects remain statistically significant and are similar in magnitude (Column 2).

A key identifying assumption of the model is that outcome trends between treated and control groups are the same. Although it is not possible to test for this during the treatment period, we can explore whether both groups exhibit similar productivity trends during the pre-treatment period. In Appendix Table 6 we show that this is indeed the case.

In Table 3, Column 3 we augment the model by introducing a global (for both programs) spillover variable, as defined in Equation (5). The results show that the estimated coefficient for S_{irst-1} is positive and statistically significant, while the direct treatment effect remains the same. These results imply that the subsidy programs, taken together, have positive spillover effects on non-treated firms. The existence of these positive spillovers suggests that the social returns from R&D are greater than the private returns, thus justifying the provision of R&D subsidies. Given the paucity of evidence on spillovers from R&D subsidies onto productivity, we think this is an important result. It means that a one-standard-deviation increase in the share of supported (innovative) firms increases TFP of firms that are close in both the geographic and technology spaces by around 1 percent.

To examine whether the programs differ in the likelihood of generating spillovers, our next estimate untangles the spillover effect based on the type of innovation support program. For this, in Equation (6) we extend the basic model to include different spillover parameters, as well as different direct effect parameters, for each program.

Table 3, Column 4 summarizes the results of these estimates. Our findings show that only FONDEF, which finances collaborative R&D that is expected to be less appropriable than that financed by FONTEC, has positive spillover effects on the productivity of other firms in the same region-sector. The spillover effects generated by FONDEF are also economically relevant: a one-standard-deviation increase in the spillover's variable increases TFP by 1.1 percent.

These results could be criticized on the grounds that FONDEF simply generates more spillovers since it includes more cooperating partners. We believe this is not the case, because the nature of the cooperating partners is different. FONDEF promotes firm-level innovation through encouraging collaboration between firms and universities or research institutes. Knowledge generated by these organizations is normally more generic and thus more likely to leak to other actors through publications, presentations, or the movement of researchers.

Table 3: Direct and Spillover Effects of Innovation Programs on Productivity

	Total factor productivity			
	(1)	(2)	(3)	(4)
Treatment	0.0435**		0.0423**	
	(0.017)		(0.017)	
FONTEC		0.0412*		0.0416*
		(0.023)		(0.023)
FONDEF		0.0467*		0.0429*
		(0.029)		(0.029)
Spillover share			0.1733***	
			(0.060)	
Spillover share FONTEC				-0.0192
				(0.181)
Spillover share FONDEF				0.2230***
				(0.062)
Age & age^2	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Sector-year effect	Yes	Yes	Yes	Yes
Region-year effect	Yes	Yes	Yes	Yes
Number of firms	8,576	8,576	8,576	8,576
Observations	63,863	63,863	63,863	63,863
R-squared	0.937	0.937	0.937	0.937

Notes: (a) Estimates of fixed-effects model. (b) Clustered standard errors at 2-digit sector-region in parentheses. (c) ***, **, * statistically significant at 1%, 5%, and 10%.

5.2. Intensity of Spillovers and Countervailing Effects

The discussion above suggests that there are theoretical reasons to expect that a non-linear specification might be needed to properly characterize the impact of spillovers. Indeed, as mentioned before two countervailing spillovers might affect firm performance: a positive effect from knowledge spillovers and a negative, business-stealing effect from product market rivals.

To capture the non-linear effects in the spillover term, we specify a polynomial function for the spillover term in Equation (4). This allows us to directly search for the right functional form of the relationship between the intensity of the treatment and the spillover effect.

$$\ln(A_{irjt}) = \rho D_{irjt-1} + \rho_S S_{irjt-1} + \rho_{S,sq} S^2_{irjt-1} + \rho_{S,cu} S^3_{irjt-1} + \beta X_{irjt} + \epsilon_i + \epsilon_t + \epsilon_{rt} + \epsilon_{jt} + \varepsilon_{irjt} \quad (7)$$

The results (presented in Table 4, Columns 2 and 4) show that the squared terms are strongly positive and significant, while the cubic terms are strongly negative and significant for both the global measure of spillovers and the FONDEF spillover measure. To understand what this means, we predict spillover effects on TFP by the intensity of the treatment and plot the results. In the case of FONTEC, the coefficients have similar signs, but are not significant.

Figure 1 illustrates the spillover effects by the intensity of support (i.e., the share of treated firms other than firm *i* in the region and industry of firm *i*). There is an inverted-U relationship between spillover effects on productivity and the intensity of public support (innovation). Thus, the positive knowledge spillover effects generated by FONDEF dominate when the share of treated firms in the region-sector is relatively low. If the program supports a larger fraction of a firm's rivals, however, business-stealing effects produce decreasing total spillover effects on TFP.

In order to provide a rationale for this non-linear result, let's assume that the program facilitates one obvious innovation in a particular region-sector (e.g., adoption of numerical control machinery). Most of what a firm has to learn from observing others can be learned from the first adopter/s. When the proportion of supported firms is low, knowledge spillovers might be important and dominate market-stealing effects. However, knowledge spillovers might have decreasing returns as more supported firms adopt the technology (not much is left to be learned after the few early adopters adopted the innovation). In contrast, when the program supports a greater share of a firm's rivals (which in turn incorporate the technology and hence they become more efficient), the negative business-stealing effect on laggards may be assumed to be linear. As firms adopt the new technology, the negative impact on the remaining firms will be greater. The combination of these two effects would be consistent with an inverted-U curve as the one simulated in Figure 2).[18]

[18] Let T be the number of supported firms and N the universe of firms. For our simulation, we define:

- Knowledge spillovers $KS = \frac{T/N}{0.05 + T/N}$;
- Business-steling effect $BS = -T/N$; and
- Total spillover effect $TS = KS + BS$.

Table 4: The Intensity of Spillover Effects

	Total factor productivity			
	(1)	(2)	(3)	(4)
Treatment	0.0423**	0.0421**		
	(0.017)	(0.017)		
Spillover share	0.1733***	-0.0370		
	(0.060)	(0.179)		
Spillover share^2		1.2934**		
		(0.579)		
Spillover share^3		-1.2861***		
		(0.472)		
FONTEC			0.0416*	0.0417*
			(0.023)	(0.023)
Spillover share FONTEC			-0.0192	-0.2891
			(0.181)	(0.304)
Spillover share FONTEC^2				1.7462
				(1.391)
Spillover share FONTEC^3				-1.3835
				(1.215)
FONDEF			0.0429*	0.0408*
			(0.025)	(0.029)
Spillover share FONDEF			0.2230***	0.2020
			(0.062)	(0.177)
Spillover share FONDEF^2				0.9782*
				(0.626)
Spillover share FONDEF^3				-1.3900**
				(0.542)
Age & age^2	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Sector-year effect	Yes	Yes	Yes	Yes
Region-year effect	Yes	Yes	Yes	Yes
Number of firms	8,576	8,576	8,576	8,576
Observations	63,863	63,863	63,863	63,863
R-squared	0.937	0.937	0.937	0.937

Notes: (a) Estimates of fixed-effects model. (b) Clustered standard errors at 2-digit sector-region in parentheses. (c) ***, **, * statistically significant at 1%, 5%, and 10%.

Figure 1. Spillover Share and Effect on TFP (Total + FONDEF)

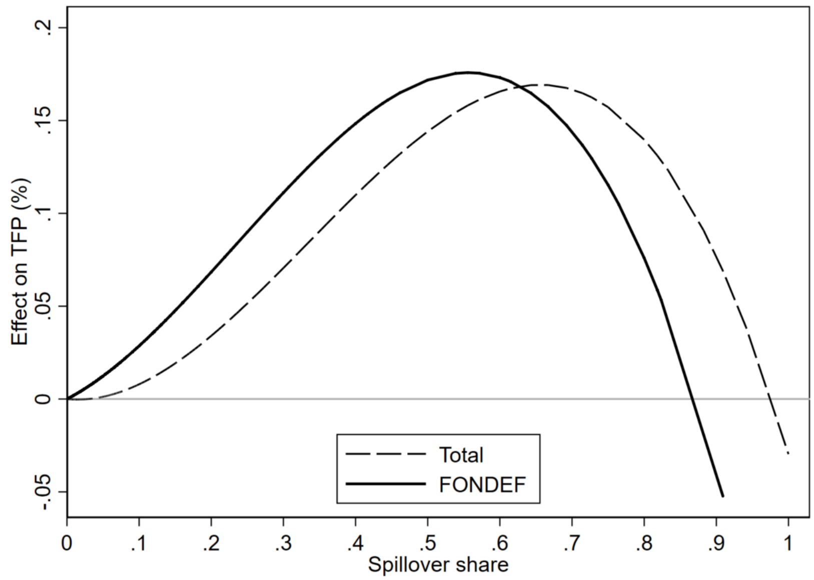
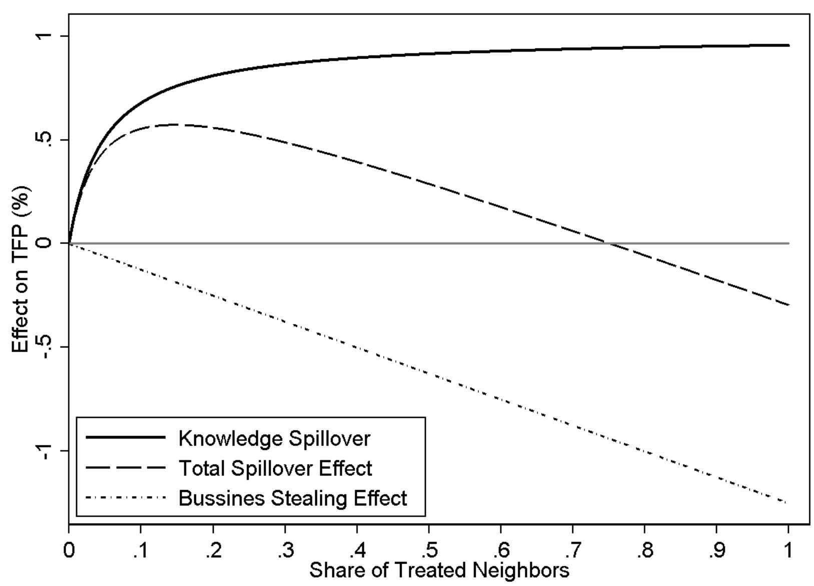


Figure 2. Simulation: Knowledge Spillover Effects vs. Business-stealing Effects



6. Robustness Checks

6.1. Falsification Tests: Changes in Geographic and Technological Distances

The key assumption of our spillover measure is that knowledge flows more easily among geographically proximate firms that belong to the same sector. That is, proximity in both geographic and technology spaces is necessary for spillovers to occur.

To show that the results obtained in Section 5 are not spurious correlations, and to validate our assumption, we explore how the spillover effect varies with changes in geographic and technological distances. The idea behind these falsification tests is that the inherent validity of the results would be limited if we obtain similar or larger spillover effects with more distance in the geographic and/or technological spaces.

First, we compared within-region/within-sector spillover estimates from Table 3, Columns 3 and 4 (and reproduced here in Table 5, Columns 1 and 2) with the effect of the share of treated firms from other sectors and other regions (across-region/across-sector spillover effect, shown in Table 5, Columns 3 and 4). Finding similar effects would cast doubt on the validity of our hypothesis and main results, as they would imply that geographic and technological proximity do not affect spillovers. As shown in Table 4, the spillover effects disappear when looking across regions and sectors.

Second, we construct the share of treated firms within the sector but outside the region, as well as the share of treated firms outside the sector but within the region. The lack of significant results in Columns 5–8 suggests that both geographic and technological proximity are needed for spillovers to occur. Spillovers do not seem to travel well on either the geographic or technological dimensions alone.

6.2. Random Treatment: Disregarding Agglomeration Effects

Our spillover measure, by construction, could be correlated with the size and productivity of a sector in a region, and therefore, capture agglomeration effects. To discard this hyphotesis, we create random treatment variables with the same mean by year as the original ones (general treatment, FONTEC and FONDEF). For this, we use uniformly distributed random variates on the interval [0,1) and replicate the share of supported firms by entry year for each treatment.

Table 6 shows the results of estimating Equation (5) and (6) using the random variables of the general treatment, FONTEC and FONDEF, and the resulting spillover variables. As shown in this table, neither the direct effects nor the spillover effects are statistically different from zero.

Table 5: Falsification Tests: Changes in Geographic and Technological Distances

	Total factor productivity							
	Within region - Within sector		Across region - Across sector		Across region - Within sector		Within region - Across sector	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.0423**		0.0433***		0.0425***		0.0415***	
	(0.017)		(0.016)		(0.017)		(0.016)	
FONTEC		0.0416*		0.0402**		0.0401*		0.0401*
		(0.023)		(0.024)		(0.023)		(0.022)
FONDEF		0.0429*		0.0465*		0.0459*		0.0439*
		(0.029)		(0.027)		(0.029)		(0.027)
Spillover share	0.1733***		-0.0252		-0.0065		-0.1234	
	(0.060)		(0.105)		(0.040)		(0.145)	
Spillover share FONTEC		-0.0192		0.2180		-0.0056		0.0059
		(0.181)		(0.503)		(0.095)		(0.313)
Spillover share FONDEF		0.2230***		-0.1241		-0.0074		-0.1443
		(0.062)		(0.208)		(0.044)		(0.138)
Age & Age^2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	-	-	Yes	Yes	Yes	Yes
Sector-Year effect	Yes	Yes	-	-	Yes	Yes	-	-
Region-Year effect	Yes	Yes	-	-	-	-	Yes	Yes
Number of firms	8,576	8,576	8,576	8,576	8,576	8,576	8,576	8,576
Observations	63,863	63,863	63,863	63,863	63,863	63,863	63,863	63,863
R-squared	0.937	0.937	0.937	0.937	0.937	0.937	0.958	0.958

Notes: (a) Estimates of fixed-effects model. (b) Clustered standard errors at 2-digit sector-region in parentheses. (c) ***, **, * statistically significant at 1%, 5%, and 10%. (d) “-“ means omitted because of collinearity with the spillover variable.

Table 6: Random Treatment and Agglomeration Effects

	TFP	
	(1)	(2)
Random Treatment	-0.0081	
	(0.011)	
Random FONTEC		0.0127
		(0.028)
Random FONDEF		-0.0413
		(0.030)
Spillover share (Random Treatment)	0.0876	
	(0.073)	
Spillover share Random FONTEC		0.0081
		(0.121)
Spillover share Random FONDEF		-0.0514
		(0.109)
Age & age^2	Yes	Yes
Firm effect	Yes	Yes
Time effect	Yes	Yes
Sector-year effect	Yes	Yes
Region-year effect	Yes	Yes
Number of firms	8,576	8,576
Observations	63,863	63,863
R-squared	0.937	0.937

Notes: (a) Estimates of fixed-effects model. (b) Clustered standard errors at 2-digit sector-region in parentheses. (c) ***, **, * statistically significant at 1%, 5%, and 10%.

6.3. Common Support of Firms

To strengthen the validity of our results, we run regressions (5) and (6) on a common support sample created by selecting from the universe of firms those firms that are similar to beneficiaries in terms of pretreatment observed characteristics, including the trends of relevant variables. This strategy involves three steps: (i) estimate the probability of participating in the programs (i.e., the propensity score) with a probit model using two-year lagged information –excluding from the pool all post-treatment observations of beneficiary firms;[23] (ii) restrict the sample to a common support area based on the propensity score;[24] and, (iii) estimate using FE.

[23] We include in the probit model: TFP, sales, employment, skilled labor, export status, age and age squared, dummies for years, whether the firm has foreign direct investment, size, sector and region. We also include two-year lagged information on TFP, sales, employment, skilled labor and export status.

[24] We adopt a min-max criterion and eliminate control group firms that present a higher or lower average propensity score than the maximum or minimum propensity score of the treatment group, respectively.

Table 7 shows that the effects of our variables of interest are robust. The coefficients show very similar values compared to the main results. While both programs have a direct impact on productivity, only FONDEF positively affects the productivity of other firms in the same region-sector.

6.4. Similarity Control Variable

Another problem with the estimation of the spillover effects is that firms in the region-sector with more treated firms can increase their productivity not because there are more treated firms but because there are more firms with similar characteristics to the treated ones. To test this hyphotesis, we use the propensity score obtained in the previous exercise and add to Equations (5) and (6) a variable that measure the share of non-treated firms in the sector-region that are very similar to the treated firms.[25] Columns 5 and 6 in Table 7 shows the results of this robustness test. Our results remains equal after controlling for the degree of similarity between treated and non-treated firms in a region-sector.

7. Conclusions

There is increasing interest in Latin American and Caribbean countries in granting fiscal incentives to encourage private investment in R&D. This interest has inspired a diverse set of policy experiments, ranging from the provision of matching grants to tax incentives. There is a need to assess the extent to which these interventions have corrected the various market failures that hinder private sector investment in R&D. However, many of the impact evaluations that have been carried out so far focus on the subsidies' impacts on direct beneficiaries (treated firms). Although much of this evidence suggests that these interventions have succeeded in increasing firm-level innovation investment (and sometimes productive performance), these findings are neither necessary nor sufficient to claim that the policy interventions have been effective. To the extent that innovation subsidies are justified by the presence of knowledge leakages and spillovers, an informative impact evaluation should also look at the programs' impact on the performance of indirect beneficiaries.

This paper aims to narrow this knowledge gap by focusing on the effects of two matching grant schemes to promote firm-level R&D investment in Chile. The analysis applies fixed-effects techniques to a novel dataset that merges several waves of Chile's National Manufacturing Surveys with register data on the beneficiaries of both programs. The differences in the structure

[25] Similar non-treated firms are defined as firms with a propensity score that satisfied this condition:

$$\overline{pscore}_{treated} - SD(pscore_{i,treated}) \leq pscore_i \leq \overline{pscore}_{treated} + SD(pscore_{i,treated})$$

of the two programs enable a further level of analysis. While one program subsidizes intramural R&D projects (FONTEC), the other (FONDEF) finances extramural R&D projects conducted by firms in collaboration with research institutes. This difference is important since, due to their collaborative nature, FONDEF projects may be more generic and more prone to knowledge leakages than the intramural R&D promoted by FONTEC.

The results suggest that only FONDEF-funded projects generate positive spillover effects on non-beneficiary firms. We find that while FONTEC-supported projects have a positive, significant impact on the direct beneficiaries, they have no effect on indirect beneficiaries. In other words, FONTEC subsidies would not be justified based on our analysis.

Are there potential alternative explanations? After all, FONDEF and FONTEC also differ in other dimensions. First, FONDEF allocates resources based on a call-for-proposals system, which promotes direct competition for resources across projects, and thus may fund higher-quality projects. Second, FONDEF might address a coordination failure by giving firms access to sophisticated technological infrastructure that is available only in universities or research centers, thus allowing them to implement more complex R&D projects. Both alternative explanations would be expected to result in larger treatment effects for direct beneficiaries of FONDEF. This is not the case in our empirical results, which suggests that the direct effects of both treatments are broadly the same.

Our findings also generate complementary evidence on two important underlying mechanisms that might trigger these spillovers. First, spillovers have non-linear effects on productivity, which may be due to a combination of pure knowledge spillover effects and business-stealing mechanisms. These non-linear effects ha two important implications for policy design: (1) there may be a critical mass in the number of treated firms that must be reached in order to generate these spillovers (i.e., pilot programs or small programs might not induce any spillovers at all) and (2) there are saturation points (i.e., programs that are too large will dilute the true knowledge spillovers through business-stealing effects).

Second, we implement several falsification tests, changing the location and technology distances in the measurement of spillovers. The results show that both geographic and technological proximity are required for the occurrence of spillovers. However, we also show that these spillovers are not the results of simply agglomeration effects or due to the presence in the cluster of untreated firms that are similar in terms of observable characteristics as treated firms. In other words, a treatment (a subsidy) must present in order to generate spillover effects.

An important policy implication of our results is that innovation policy designs that encourage research collaboration among different actors, particularly firms and universities or technological institutes, should be preferred over those that simply subsidize intramural R&D. Thus, Chile should expand FONDEF's coverage by re-allocating FONTEC resources to it. However, we acknowledge that collaborative schemes such as those encouraged by FONDEF require collaborative partners with sufficient human capital and technological infrastructure to address the technological challenges faced by the firms, as well as firms with enough absorptive capacity to adopt the solutions developed. So, although collaborative schemes might work for a middle-income country such as Chile, they might not be the best solution for less developed countries.

Table 7: Direct and Spillover Effects on Productivity – Common Support

	Total factor productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0571***		0.0567***		0.0565***	
	(0.013)		(0.013)		(0.013)	
FONTEC		0.0596***		0.0599***		0.0603***
		(0.018)		(0.017)		(0.017)
FONDEF		0.0535*		0.0508*		0.0500*
		(0.030)		(0.030)		(0.030)
Spillover share			0.1601**		0.1590**	
			(0.072)		(0.072)	
Spillover share FONTEC				-0.1207		-0.1021
				(0.207)		(0.208)
Spillover share FONDEF				0.2263***		0.2184***
				(0.076)		(0.074)
Share of similar FDT firms					0.0091	
					(0.015)	
Share of similar FONTEC firms						-0.0118
						(0.012)
Share of similar FONDEF firms						0.0202
						(0.016)
Age & age^2	Yes	Yes	Yes	Yes	Yes	Yes
Pscore & pscore^2	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-year effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	6,959	6,959	6,959	6,959	6,959	6,959
Observations	40,880	40,880	40,880	40,880	40,880	40,880
R-squared	0.947	0.947	0.947	0.947	0.947	0.947

Notes: (a) Estimates of fixed-effects model. (b) Clustered standard errors at 2-digit sector-region in parentheses. (c) ***, **, * statistically significant at 1%, 5%, and 10%.

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Annex I. Pre-treatment Trends Equality Test

The key assumption of the fixed-effects model is that the performance of the control group (firms that did not participate in the program) is an unbiased estimator of what would have happened to the treated group in the absence of the program. Although this assumption cannot be tested directly, we can test whether the time trends in the control and treatment firms were the same during the pre-intervention periods. If they were, then it is likely that they would have been the same in the post-intervention period if the treated firms had not received support.

To test the similarity of the previous trends, we estimated a modified version of equation (2) using only observations for the pre-intervention period,[26] which instead of the treatment variable includes interactions between treatment and time:

$$\ln(A_{irst}) = \gamma_1 \overline{D}_{irjt} * Year + \gamma_2 \overline{D}_{irjt} * Year^2 + \gamma_3 Year + \gamma_4 Year^2 + \beta X_{irjt} + \epsilon_i + \epsilon_t + \epsilon_{rt} + \epsilon_{jt} + \varepsilon_{irjt} ,$$

where $\overline{D}_{irjt}$ is a dummy variable that takes a value of 1 if the firm was eventually treated and 0 if the firm was never treated (i.e., treatment status), $Year$ represents a linear trend and $Year^2$ a quadratic trend.

Table A1 presents the results for this equation. We test whether the treated and control groups had different trends before the intervention. We find that the null hypothesis (that the pre-intervention quadratic trends are the same for the treated and control firms) cannot be rejected.

[26] Since we have different treatment cohorts, we delete all the observations for the eventually treated firms after they were treated to construct the pre-intervention period.

Table A1: Pre-treatment Trend Equality Tests

	Total factor productivity			
	(1)	(2)	(3)	(4)
Treatment_status*Year	-2.9302			
	(2.115)			
Treatment_status*Year^2	0.0007			
	(0.001)			
FONTEC_status*Year		-2.5064		-2.5272
		(2.893)		(2.898)
FONTEC_status*Year^2		0.0006		0.0006
		(0.001)		(0.001)
FONDEF_status*Year			-3.5337	-3.6017
			(2.499)	(2.509)
FONDEF_status*Year^2			0.0009	0.0009
			(0.001)	(0.001)
Year & year^2	Yes	Yes	Yes	Yes
Age & age^2	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes
Sector-Year effect	Yes	Yes	Yes	Yes
Region-Year effect	Yes	Yes	Yes	Yes
Number of firms	8,576	8,576	8,576	8,576
Observations	70,269	70,269	70,269	70,269
R-squared	0.934	0.934	0.934	0.934

Notes: (a) Estimates of fixed-effects model. (b) Clustered standard errors at 2-digit sector-region in parentheses. (c) ***, **, * statistically significant at 1%, 5%, and 10%.