Received: 23 December 2022 | Revised: 3 July 2023 | Accepted: 22 July 2023

DOI: 10.1111/rode.13038

REGULAR ARTICLE

WILEY

A possible mechanism for partial crowding-out of R&D subsidies in developing countries

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Funding information
"ERDF A way of making Europe", Grant/Award Number: PID2021-124266OB-I00; European Union NextGenerationEU/PRTR, Grant/Award Number: TED2021-130232B-I00; Ministerio de Ciencia e Innovación, Grant/Award Numbers: PID2021-124266OB-I00, TED2021-130232B-I00; Universidad del Río, Ecuador, Grant/Award Number: research funds 2019-2023

Abstract

We analyze the effectiveness of R&D subsidies on firms' R&D efforts in a developing country like Ecuador. We use the National Survey of Innovation Activities. Methodologically, we employ a structural framework that considers simultaneity and selection issues. Our results indicate that subsidies have an extensive margin effect, as they encourage firms to carry out R&D activities, and an intensive margin effect, as they increase firms' total innovation effort. However, this is compatible with partial crowding-out of private efforts by public funds. One possible mechanism to explain this result is that, in developing countries with less developed capital markets, firms with financial constraints may divert part of the subsidy to invest in fixed capital. We find some support for this hypothesis, as the most financially constrained firms both explain the crowding-out effect and increase their fixed capital investment when receiving a subsidy. For other firms, we observe crowding-in, and their fixed capital investment remains insensitive to the subsidy.

KEYWORDS

crowding-in, financially constrained firms, investment in fixed capital, partial crowding-out, R&D subsidies

1 | INTRODUCTION

Most of the existing literature on the effectiveness of public R&D subsidies on R&D efforts is focused on developed countries. Regarding the intensive margin effects of R&D (i.e., whether subsidies increase or not the R&D efforts of firms), it is common to distinguish between crowding-in (additionality) and crowding-out (or substitutability). Crowding-in occurs when R&D subsidies stimulate private R&D efforts, while crowding-out occurs when subsidies displace private efforts. However, complete crowding-out is not always observed. In fact, most studies that find crowding-out identify partial crowding-out, indicating that firms' total R&D effort increases but to a lesser extent than the subsidy. In other words, private effort is lower with the subsidy than it would have been without it. Conversely, when the increase in private effort exceeds the subsidy, we refer to it as crowding-in or additionality.

The literature on R&D subsidies has identified various mechanisms that can result in either complete or partial crowding out of private R&D by public funding. In an early paper by David and Hall (2000), one relevant factor in explaining the impact of public R&D expenditures on private R&D is the elasticity of scientific labor supply in research-input markets with limited supply. The public R&D sector does not generally act in these markets as a wage-taker because it influences the wages of R&D workers. When this happens, crowding-out may occur through the competition of public R&D for R&D workers, which puts pressure on their wages and makes private R&D projects more expensive. Researchers are specialized inputs with a low elasticity of substitution due to their long training periods. Consequently, higher R&D costs, including wages, would reduce the expected rate of return on private-sector R&D investments.

A more recent paper discussing the role of the allocation of scientific and business talent in explaining the crowding-out effects of public R&D on private R&D is Damrich et al. (2022). In their model, as public research expands, attractive conditions are offered to the most talented scientists, incentivizing their transition from the private to the public sector. Their work goes beyond wage differentials and adds the concept of "prestige," which encompasses nonmonetary factors that serve as an incentive for researchers to opt for the public sector. These factors include greater flexibility and freedom in determining research priorities. If the most talented scientists prioritize these advantages over income, they are likely to choose the public sector. As a result, researchers with relatively lower capabilities may opt for the private sector. However, if the concept of "prestige" holds less significance for talented scientists, they may be more drawn to the private sector, where the potential for higher innovation rents exists through the commercial success of their ideas. In such scenarios, researchers with comparatively lower skills may find opportunities for employment in the public sector.

Both papers primarily focus on the allocation of limited scientific resources between the private and public sectors. The second paper expands upon this by examining differences in research and business talent to shed light on the allocation of higher and lower-quality researchers. The relative significance of monetary factors and prestige, as well as the distribution of scientific and business skills, play a role in researchers' decisions to work in either the public or private sectors. For instance, in countries where entrepreneurial talent is highly valued, this can mitigate the tendency for scientists to shift from the private sector to the public sector. Similarly, scientists possessing strong entrepreneurial skills may find less motivation to transition to the public sector if they prioritize monetary rewards over prestige.

In our paper, our primary objective is to provide an explanation for the phenomenon of crowding-out (or partial crowding-out) of private R&D by public R&D in developing countries. With this objective in mind, our paper aims to make a valuable contribution to the existing literature by introducing a distinct mechanism that emphasizes the impact of financial constraints associated with underdeveloped capital markets. In this regard, we provide evidence suggesting that one possible mechanism to explain crowding-out is that in developing countries, where funds are often limited, financially constrained firms may allocate a portion of the subsidy towards investing in fixed capital. As highlighted by Lach (2002), firms facing credit constraints may find it easier and more cost-effective to obtain financing through R&D subsidies. In this case, "the firm views the R&D subsidy as a substitute source of financing and not necessarily as a stimulating force to do more R&D" (Lach, 2002). The acquisition of technology embodied in capital goods (machinery and equipment) remains significant in developing countries, as it can foster innovation and drive firms' innovative outputs (Dabla-Norris et al., 2012; Goedhuys & Veugelers, 2012; Navarro et al., 2010). As countries develop, firms' R&D investments capable of creating new technologies are expected to replace a more supply-dominated process, which operates through the acquisition of available technology embodied in fixed capital (Goedhuys & Veugelers, 2012). In particular, for the Ecuadorian economy, it has been found that one of the drivers of firms' innovative outputs is investment in capital goods (Rochina-Barrachina & Rodríguez, 2019). Therefore, if partial crowding-out is accompanied by increased investment in capital goods by financially constrained firms, it could indicate a more effective allocation of funds towards innovation strategies commonly observed in developing countries, involving the assimilation of new technologies embedded in capital goods.

For our analysis, we rely on the two available waves of the Ecuadorian National Survey of Innovation Activities (NIAS: 2013 and 2015), which provide us with firm-level data. The survey is similar in nature to the European CIS (Community Innovation Surveys). Ecuadorian firms are an interesting subject for our research because the country faces a significant deficit in terms of innovation, which deserves attention. According to the Global Innovation Index (Cornell University, INSEAD, and WIPO, 2022), Ecuador is ranked 98th out of 132 countries. Additionally, the total gross expenditure on R&D in Ecuador was 0.4% of the GDP in 2014, which is the most recent available data.

Methodologically, our analysis is based on a behavioral model that provides a structural description of firms' optimal decisions regarding R&D. This framework takes into account issues of simultaneity and selection. In this model, firms consider expected subsidies when determining their optimal R&D choices.

During the study period, the leadership in science, technology, and innovation policy was held by the MCPEC (Ministry of Coordination of Production, Employment, and Competitiveness), which since the beginning of 2009 promoted the implementation of instruments to support innovation and entrepreneurship. This organization sought direct transfers of public resources to private firms with innovation projects considered to be of direct benefit to the community. In other words, the spirit of public aid was to finance firms willing to participate in innovation activities that could generate positive externalities.

Our results indicate that subsidies have an extensive margin effect, as they encourage firms to carry out R&D activities, and an intensive margin effect, as they increase firms' *total* innovation effort. However, this is compatible with our finding of partial crowding-out of *private* efforts by *public* funds. Moreover, we find some support in the paper for our hypothesized mechanism that may underlie this result. It is the most financially constrained firms that explain the crowding-out effect and that simultaneously increase their fixed capital investment when they receive a subsidy. For the remaining firms, we find crowding-in and that their fixed capital investment is insensitive to the subsidy. These results for a developing country like Ecuador differ from those generally found for developed countries, where R&D subsidies are particularly effective in increasing private R&D by financially constrained firms (Becker, 2015; Zúñiga-Vicente et al., 2014).

Our study contributes to the existing literature in several ways. First, while most papers on the effects of public R&D subsidies on private R&D focus on developed countries, our research extends to developing countries as well.

Second, we offer fresh insights into the influence of firm characteristics as a potential explanation for the divergent findings found in previous empirical studies (Dimos & Pugh, 2016; Heijs et al., 2022; Marino et al., 2016; Steinmo et al., 2022; Szücs, 2020). Earlier research has presented mixed results regarding the presence of crowding-in, crowding-out, or even nonsignificant effects (Dimos & Pugh, 2016), and the heterogeneity in firm characteristics has been suggested as a possible explanation. For example, Steinmo et al. (2022) distinguish between science-based firms and engineering-based firms. Additionally, Szücs (2020) and Marino et al. (2016) discover, in their examination of different sectors based on R&D intensity, that firms in low R&D sectors experience some degree of crowding-out. Furthermore, Heijs et al. (2022) focus on the heterogeneous additionality effects of R&D subsidy programs at different government levels. Their study, which covers the period 2007–2016 for Spanish R&D performers, reveals that firms participating in multiple programs corresponding to various government levels (regional, national, and/or European) exhibit higher crowding-in effects.

In contrast to previously existing studies, our empirical analysis aims to explore the possibility of an alternative mechanism contributing to crowding-out, specifically the incentives faced by financially constrained firms in developing countries, where financial markets are less developed, to utilize subsidized R&D funds for other investments. To the best of our knowledge, there are only two very recent papers that find out heterogeneous effects of R&D subsidies depending on firms' financial obstacles. One of them is Heijs et al. (2022), who despite focusing on the heterogeneous effects of participating in programs coming from different levels of government, obtain an interesting accompanying result for Spanish innovative firms related to their financial difficulties. Specifically, they find that firms reporting financial obstacles show a lower level of subsidy additionality. They explain this result as follows. Subsidized firms with financial constraints find it more difficult to cope with the "self-financing" part of their R&D projects than firms without such constraints. In the conclusions of their paper, these authors highlight the need for further research to investigate why the presence of financial constraints may weaken the impact of R&D subsidies in promoting private R&D investment. The other is Acebo et al. (2022). Using data from Spanish R&D performing firms during the period 2010–2017, the authors find that subsidies lead to a decrease in R&D intensity. However, when distinguishing between financially constrained and unconstrained firms, they observe that this effect is driven by financially constrained firms, as for unconstrained firms the subsidy has a positive effect. However, the paper lacks an economic interpretation of these results and does not establish a connection to the literature on crowding-in or crowding-out. Neither of these two papers has explored the mechanisms behind the reduction of crowding-in effects for financially constrained firms, and both papers focus exclusively on a developed country. This underscores the gap in the current literature and emphasizes the novel contribution of our paper in addressing this gap.

Third, our result on the diversion of funds to fixed capital investment by financially constrained firms contributes to the ongoing debate on the broader economic effects that public R&D subsidies can have, providing valuable insights into the additional channels through which these subsidies are transmitted to the economy.

The rest of the paper is organized as follows. Section 2 presents the data. Section 3 presents the analytical framework. Section 4 presents the econometric modeling. Section 5 presents the empirical specifications and estimation results. Section 6 presents the interpretation of the results. Finally, Section 7 concludes.

2 | DATA

We utilize the two available waves of the Ecuador's National Survey of Innovation Activities (NIAS), namely the 2013 wave covering the period 2009–2011 and the 2015 wave covering the period 2012–2014. This survey is sponsored by the National Institute of Statistics and Census (INEC) and the Secretariat of Higher Education, Science, Technology, and Innovation (SENESCYT). The survey sample is representative in terms of geographical location, sector of activity, and size. Similar to the European CIS, the NIAS provides firm-level information on characteristics related to innovation activities, following the guidelines outlined in the Frascati Manual and the Oslo Manual (OECD, 2002; OECD & Eurostat, 2005). Additionally, it includes more general firm characteristics such as sector of activity, sales, and employment.

The NIAS sample was derived from the universe of firms obtained by processing primary sources such as the National Economic Census and the Directory of Firms and Economic Establishments (DIEE). These sources provide coverage across all regions of the country and ensure representation of industry-size strata and sectoral composition. NIAS excludes firms operating in the agriculture sector and adheres to the United Nations ISIC Rev. 4 classification. Additionally, it excludes firms with fewer than 10 employees. Participation in the survey is mandatory, resulting in a total of 9090 firm observations. Among these, 169 firms reported receiving subsidies as a source of funding for their R&D activities. Consequently, it can be inferred that public R&D subsidies are not widely prevalent among Ecuadorian firms.

In the NIAS dataset, it is observed that 43% of the firms engage in R&D activities. However, among the firms that receive subsidies, this percentage increases significantly to 98%. Furthermore, when examining the R&D effort as a proportion of sales, nonsubsidized firms exhibit an average R&D effort of 2.74%, whereas subsidized firms display a much higher average of 39.70%. These descriptive findings indicate a positive association between the provision of subsidies and the overall R&D effort of firms.

3 | ANALYTICAL FRAMEWORK

We employ a behavioral framework that provides a structural description of how public subsidies impact firms' optimal decisions regarding R&D activities, considering the presence of set-up costs (Arqué-Castells & Mohnen, 2015; González et al., 2005; Takalo et al., 2013). The summarized structural model outlined below incorporates both the decision-making process of whether to engage in R&D and the determination of the optimal investment level.

Firm i must decide whether to invest in R&D and determine the appropriate level of investment. If it chooses not to invest in R&D, its profits will be $\pi_{it}^{\text{No RD}}$. However, if it decides to invest in R&D, it incurs a variable cost $\text{RD}_{it} > 0$ and a set-up cost $F_{it} > 0$. It is assumed that the public sector provides a subsidy equal to a fraction ρ_{it} of the firm's variable R&D expenditure, as subsidies are modeled as a share of to-be-incurred R&D expenditures.[i] This approach aligns with the typical structure of R&D subsidy programs, as highlighted by Arqué-Castells and Mohnen (2015). In addition, the survey used in this study collects information on R&D subsidies in the form of the percentage of a firm's R&D expenditures that have been subsidized during the period in question. This measure is in line with the modeling approach adopted in our work.

The expected profits of the firm from engaging in R&D activities are as follows:

$$\pi_{it}^{\mathrm{RD}} = \exp(Z_{it}\theta + \nu_{it})\mathrm{RD}_{it}^{\phi} - (1-\rho_{it})\mathrm{RD}_{it} - F_{it} \tag{1}$$

where $\exp(Z_{it}\theta + \nu_{it})\mathrm{RD}_{it}^{\phi}$ is firm's revenue determined by several components: (i) $\exp(Z_{it}\theta + \nu_{it})$ that captures the productivity of R&D investments as a function of firm's observable characteristics Z_{it}, a vector of parameters θ, and a random R&D productivity shock ν_{it} observed by the firm but not by the econometrician; and (ii) also depends on R&D expenditure itself with a lower (null) to higher intensity depending on the value of the parameter $\phi \in [0,1)$, which reflects the elasticity of the firm's revenue to R&D.

From the profit expression in (1), with a little algebra (see Appendix) we can obtain the mathematical expressions of two crucial R&D measures in our analysis: the optimal R&D investment and the R&D threshold. The former comes from the profit maximization with respect to R&D and the latter corresponds to the R&D investment that makes the firm indifferent, in terms of profit, between investing or not in R&D[ii]:

$$\mathrm{RD}_{it}^{\mathrm{optimal}^*} = \left[\frac{\phi \exp(Z_{it}\theta + \nu_{it})}{(1-\rho_{it})}\right]^{\frac{1}{1-\phi}} \tag{2}$$

$$\mathrm{RD}_{it}^{\mathrm{threshold}} = \left[\frac{F_{it} + \pi_{it}^{\mathrm{No\ RD}}}{(1-\phi)\exp(Z_{it}\theta + \nu_{it})}\right]^{\frac{1}{\phi}} \tag{3}$$

One firm optimally invests in R&D when its optimal nonzero R&D according to (2) is higher than its threshold R&D in (3). This observability rule that emerges from this comparison implies that the extensive margin effect of R&D subsidies operates through their influence on the endogenous optimal R&D variable that is compared to the threshold value. Conditional on firms performing R&D according to the outcome of this observability rule, the intensive margin effect of R&D subsidies operates exclusively through the endogenous optimal R&D variable. Note that the subsidy ρ_{it} affects the optimal R&D expenditure, but not the threshold R&D expenditure. This will be very important in the empirical analysis to recover the parameters of the threshold R&D equation, as it provides a natural exclusion restriction that allows for identification. It is safe to exclude subsidies from the determinants of the R&D threshold equation because, as reported in González et al. (2005), thresholds for determining the feasibility of profitable technological activities are defined in terms of the total expenditure required, regardless of whether the financing comes from public or private sources. Hence, the subsidy share ρ_{it} is not only excluded from the threshold equation by the maths in the model but also on theoretical grounds.

4 | ECONOMETRIC MODELING

4.1 | Optimal and threshold R&D efforts

In the empirical specification, we work with R&D effort (as González et al., 2005). R&D effort is defined as the ratio of R&D expenditure to firm sales. Let $rde_{it}^{\text{optimal}^*}$ and $rde_{it}^{\text{threshold}}$denote optimal and threshold R&D efforts in logarithms. The optimal R&D effort is only observed if $rde_{it}^{\text{optimal}^*} - rde_{it}^{\text{threshold}} > 0$. The model is originally defined by equations:

$$rde_{it}^{\text{optimal}^*} = -\beta \ln(1-\rho_{it}) + X_{1,it}\beta_1 + \varepsilon_{1,it} \tag{4}$$

$$rde_{it}^{\text{threshold}} = X_{2,it}\beta_2 + \varepsilon_{2,it} \tag{5}$$

where $\beta = \frac{1}{1-\phi}$, $\varepsilon_{1,it} = \frac{v_{it}}{1-\phi}$, and $\varepsilon_{2,it} = \frac{v_{it}}{\phi}$. Expression (4) incorporates the reduced form determinants of $\ln\phi$ and Z_{it} in the vector of regressors $X_{1,it}$. Differently, the $rde_{it}^{\text{threshold}}$ equation has reduced form determinants for $\ln\left(F_{it} + \pi_{it}^{\text{No RD}}\right)$, $\ln(1-\phi)$ and Z_{it} incorporated in the vector of regressors $X_{2,it}$. Therefore, beyond ρ_{it} the model also provides as natural exclusion restrictions in the $rde_{it}^{\text{optimal}^*}$ equation with respect to the $rde_{it}^{\text{threshold}}$ equation, the reduced form determinants for $\ln\left(F_{it} + \pi_{it}^{\text{No RD}}\right)$.[iii]

For the estimation of β and β_1 in (4), we combine (4) and (5) in a type-II Tobit model that includes the equation of interest $rde_{it}^{\text{optimal}^*}$ and its observability rule (selection equation):

$$rde_{it}^{\text{optimal}} = \begin{cases} rde_{it}^{\text{optimal}^*} = -\beta \ln(1-\rho_{it}) + X_{1,it}\beta_1 + \varepsilon_{1,it} & \text{if } d_{it} = 1 \\ = 0 & \text{if } d_{it} = 0 \end{cases} \tag{6}$$

$$\begin{aligned} d_{it} &= 1\left[rde_{it}^{\text{optimal}^*} - rde_{it}^{\text{threshold}} > 0\right] \\ &= 1\left[-\beta \ln(1-\rho_{it}) + X_{1,it}\beta_0^{no\_exc.rest} + X_{2,it}^{exc.rest}\beta_0^{exc.rest} + \varepsilon_{0,it} > 0\right] \end{aligned} \tag{7}$$

where $1[\cdot]$ is the indicator function that takes value 1 when the condition in brackets is true and 0 otherwise, $X_{1,it}$ are the common regressors in the optimal and threshold R&D equations and $X_{2,it}^{exc.rest}$ are the regressors in the threshold equation that are excluded from the optimal equation (exclusion restrictions).[iv] Assuming that $\varepsilon_{1,it}$ and $\varepsilon_{0,it}$ have a bivariate normal distribution, the parameters of (6)–(7) are estimated by maximum likelihood.

On the other hand, the parameters of the R&D effort threshold equation (β_2 in (5)) cannot be estimated directly, since $rde_{it}^{\text{threshold}}$ is unobservable. However, we can recover them as follows from the estimates in (6) and (7)[v]:

$$\begin{aligned} \widehat{\beta}_2^{no\_exc.rest} &= \widehat{\beta}_1 - \widehat{\sigma}\widehat{\beta}_0^{scaled\_no\_exc.rest} \\ \widehat{\beta}_2^{exc.rest} &= 0 - \widehat{\sigma}\widehat{\beta}_0^{scaled\_exc.rest} \end{aligned} \tag{8}$$

where $\widehat{\beta}_1$ comes from estimation of the $rde_{it}^{\text{optimal}^*}$ equation and $\widehat{\beta}_0^{\text{scaled}}$ comes from estimation of the *probit* Equation (7). Since in *probit* models, we estimate parameters "up to scale", the scale parameter (σ) being the standard deviation of the error term of the *probit* equation ($\varepsilon_{0,it}$), $\widehat{\beta}_0^{scaled\_no\_exc.rest} = \left(\beta_0^{no\_exc.rest}/\sigma\right)$ and $\widehat{\beta}_0^{scaled\_exc.rest} = \left(\beta_0^{exc.rest}/\sigma\right)$. From these, to have estimates of $\beta_0^{no\_exc.rest}$ and $\beta_0^{exc.rest}$ we need an estimate of σ. For this, although *probit* models do not identify σ, since we estimate the same parameter β (for the subsidy variable $-\ln(1-\rho_{it})$) scale-free in (6) and "up to scale" in (7), we recover an estimate of σ with the ratio of $\widehat{\beta}$ estimated in (6) over $\widehat{\beta}^{scaled}$ estimated in (7).[vi] Next, the parameters of the threshold equation in (5), β_2, are recovered by applying (8).

4.2 | Expected subsidy share

Before estimating (6) and (7), two problems must be solved. On the one hand, there may be a nonrandom selection of subsidy recipients. On the other hand, subsidies may suffer from endogeneity problems in the R&D equations if agencies selecting recipients take into account the R&D effort and performance of firms. This will cause "observed" subsidy rates to be correlated with R&D productivity shocks. To solve both problems we consider, like González et al. (2005), Takalo et al. (2013), and Arqué-Castells and Mohnen (2015), that when firms decide whether or not to invest in R&D and how much, they base their decisions on "expected" subsidies. Therefore, we need to estimate the fraction of R&D that firms expect to be funded by the public sector.

Let ρ_{it}^* denote the firm's latent (expected) subsidy share, which is formally modeled as

$$\rho_{it}^* = \gamma_1' w_{1,it} + u_{1,it} \tag{9}$$

where γ_1' captures the effects of explanatory variables on the potential firm's subsidy share and $u_{1,it}$ is the idiosyncratic error that affects ρ_{it}^*. The observed counterpart to ρ_{it}^* is defined as

$$\rho_{it} = \mathbf{1}\left[d_{\rho,it}^* > 0\right]\rho_{it}^* \equiv d_{\rho,it} \cdot \rho_{it}^*, \tag{10}$$

where $\mathbf{1}[]$ is the indicator function. This notation indicates that firm *i*'s subsidy share is observed to be positive only if firm *i* has a subsidy, that is, if the observed dichotomous variable $d_{\rho,it}$ is equal to *1* or, equivalently, $d_{\rho,it}^* > 0$, where $d_{\rho,it}^*$ is a latent variable underlying firm *i*'s propensity to have a subsidy given firm characteristics $w_{2,it}$. Formally,

$$\begin{aligned} d_{\rho,it}^* &= \gamma_2' w_{2,it} + u_{2,it} \\ d_{\rho,it} &= \mathbf{1}\left[d_{\rho,it}^* > 0\right], \end{aligned} \tag{11}$$

where γ_2' captures the effects of explanatory variables on the propensity to have a subsidy and $u_{2,it}$ is the idiosyncratic error that affects $d_{\rho,it}^*$. $\mathbf{1}[]$ is the indicator function. Unfortunately, as with CIS data, we do not have information on firm applications and agency adjudication. Therefore, with $w_{2,it}$ we capture both the likelihood of firm applications and agency eligibility rules.

For the estimation of γ_1' and γ_2', we combine (10) and (11) in a type-II Tobit model. Assuming that $u_{1,it}$ and $u_{2,it}$ have a bivariate normal distribution, the parameters involved are estimated by maximum likelihood.

5 | EMPIRICAL SPECIFICATIONS AND RESULTS

In this study, we obtain the parameters of five equations: (1) The yes/no subsidy equation in (11) with parameters γ_2'; (2) the "expected" subsidy share equation in (9) with parameters γ_1'; (3) the yes/no R&D equation in (7), with parameters β, $\beta_0^{no\_exc.rest}$ and $\beta_0^{exc.rest}$; (4) the firm's optimal R&D effort equation in (6) with parameters β and β_1; and finally, (5) the threshold equation in (5) with parameters β_2. Next, we specify them empirically and present estimation results.

5.1 | Public support: Expected subsidy share and yes/no subsidy equations

The vector of explanatory variables for the likelihood of getting a subsidy should include variables that explain firms' willingness to apply and/or the eligibility rules of the agency. The vector of variables $w_{2,it}$ in (11) has been selected based on previous empirical literature on this topic (see, for instance, Arqué-Castells & Mohnen, 2015; Busom et al., 2014, 2017; González et al., 2005). As in NIAS the subsidy share corresponds to the fraction of R&D expenditure subsidized during the period from $t-2$ to t, as long as there is information in the survey on the regressors in vector $w_{2,it}$ (or $w_{1,it}$ in (9)) for the period $t-2$, they will be used with that lag. This is the case for variables such as firm size (the logarithm of the number of employees), an export dummy variable, the logarithm of export intensity (over sales), market share (capturing market power), a dummy variable for fixed capital investment (which approximates capital growth and demand expectations) and the logarithm of the firm's labor productivity relative to its industry average (which captures both the distance to the technological frontier and that returns to innovation may be higher for more productive firms). For other variables, the survey information corresponds to period t. This is the case for the foreign capital dummy variable (more than 50% ownership), the dummy for firms belonging to a business group and for the ICT dummy variable for firms with a formal Information and Communication Technologies department. Foreign-owned, group-affiliated or more productive firms might be more likely to finance R&D from their group's internal capital market or from their own funds, rather than from public subsidies. Regressions also include industry, location and survey wave dummy variables.[vii,viii] Variables such as ICT, or even industry classification, can capture the technological sophistication of firms and the quality of projects, which agencies are likely to take into account for eligibility.

In our data, at a descriptive level, firms with public subsidies are larger, more likely to have a formal ICT department, more likely to export, less likely to have foreign capital participation, less likely to belong to a business group, more likely to have a larger market share and more likely to invest in fixed capital.

Table 1 shows the results of the joint maximum likelihood estimation of the yes/no subsidy equation (column 1) and the "expected" subsidy share equation (column 2). In the lower part of the table, the Wald test on the null hypothesis of independent errors allows for the rejection of this hypothesis and thus supports the joint estimation.

In the yes/no equation, certain variables, such as the presence of foreign capital, belonging to a business group, or relative productivity, exhibit statistically significant negative coefficients. These findings may indicate that firms with these characteristics face fewer financial constraints when it comes to investing in R&D. Furthermore, it is observed that firms located in the three provinces with the highest concentration of economic activity are less likely to receive subsidies.

TABLE 1 Public support estimation: Type-II Tobit model.

Variables	(1) *d*_Subsidy (Yes/No)	(2) *Log* subsidy share
Size $t-2$	0.102*** (0.028)	−0.423 (0.367)
*d*_ICT	0.276*** (0.076)	2.814*** (1.058)
Export intensity $t-2$	0.060* (0.036)	−0.144 (0.514)
*d*_export $t-2$	0.179 (0.131)	0.873 (1.618)
*d*_foreign	−0.384** (0.151)	−1.493 (1.830)
*d*_group	−0.261** (0.113)	−1.570 (1.170)
Market share $t-2$	0.613* (0.350)	0.608 (5.109)
*d*_fixed investment $t-2$	0.394*** (0.075)	2.776*** (1.063)
$d\_\text{geographical}_{\text{Guayas, Pichincha, Azuay}}$	−0.171** (0.075)	2.273** (0.947)
$d\_\text{time}_{\text{second wave of the survey}}$	−0.128* (0.074)	−2.283*** (0.855)
Relative productivity $t-2$	−0.453*** (0.156)	−0.810 (2.221)
Med-Low tech manufacturing	0.279** (0.113)	
Med-High tech manufacturing	0.186 (0.167)	
High tech manufacturing	0.519** (0.254)	
Med-High and High tech manufacturing		2.815** (1.142)
Knowledge-intensive services	−0.280*** (0.101)	0.216 (1.202)
Other sectors	0.442*** (0.088)	0.394 (1.164)
Constant	−2.172*** (0.165)	−11.066*** (3.943)
Observations	9090	169

Note: Standard errors are shown in parentheses. Rho = 0.54; Wald test of independent equations (Rho = 0): $\text{Chi}^2(1) = 9.90$ and p-value = .0017. Log pseudolikelihood = −1259.039. In column (1), the reference category for the technological classification of sectors is the aggregated category of Low tech manufacturing plus non-Knowledge intensive services. In column (2), it is the aggregated category of Low and Med-Low tech manufacturing plus non-Knowledge intensive services.
$^*p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Conversely, several other variables are positively associated with a higher probability of firms receiving subsidies. These variables include size, the existence of an ICT department, export intensity, market share, and capital growth. It could be that both technological sophistication (captured by the ICT variable) and the higher risk associated with export markets encourage government agencies to grant subsidies. The role of size may be related to the fact that only firms of a certain size can cope with the administrative process of applying for a subsidy. It is also possible that government agencies tend to grant subsidies to large firms, with a high market share and with expectations of demand growth (captured by fixed capital investment). If this is the case, agencies may not be selecting firms subject to market failures that prevent them from investing in R&D, but rather firms that are fairly well established in terms of turnover, market power, and business prospects.

Regarding the subsidy equation, there are several variables that positively influence the proportion of subsidized R&D. These variables include the presence of an ICT department, investment in fixed capital, belonging to a high- or medium-tech manufacturing sector, and being located in a province that is central to the country's economic activity. It is important to note that in this equation, the dependent variable is expressed in logarithms, and the statistically significant regressors are represented by dummy variables. As a result, the estimated parameters are semi-elasticities.

5.2 | Optimal R&D effort equation

The optimal R&D effort equation in (6) depends on the “expected” subsidy share through the regressor $-\ln\left(1-\rho_{it}^{*}\right)$ and on the vector of regressors $X_{1,it}$. This vector includes variables that represent different types of elasticities, which play a crucial role in assessing the profitability of a firm's R&D expenditure.[ix] Specifically, the elasticity of demand to R&D, which is expected to be positive and to have a positive effect on the firm's optimal R&D effort. Conversely, the elasticity of demand to price, which is expected to be negative and to have a negative effect on the firm's optimal R&D effort (if an increase in competition discourages innovation). The elasticity of demand to R&D can be further expressed as the product of the elasticity of demand to innovation (related to demand conditions) and the elasticity of innovation to R&D (related to technological opportunities). Although all these elasticities are unobservable, NIAS provides reduced form indicators to control for them.

To approximate firms' expected demand response to innovation, we include four variables. The first variable, *unsatisfied demand*, is calculated as the proportion of innovative firms in the same industry wave of the survey that states the detection of unsatisfied demand in the product market as a reason for undertaking innovation activities. The second variable, *quality improvement*, represents the relative importance of improving product quality within an industry-wave. A higher value of this variable indicates a greater emphasis placed on the objective of enhancing product quality during the pursuit of innovations. This variable is constructed using a survey question where firms indicate the relevance of a set of objectives to the development of their innovation activities. Each objective is assigned a value from 1 to 4, with 4 indicating greater relevance. It is worth noting that the values have been recoded in the opposite direction from how they appear in the survey. We calculate the average value that a firm assigns to all the objectives considered in the survey, including the improvement of product quality. Then, we determine the relative value that the firm assigns to the product quality improvement objective in relation to its average value across all objectives. Finally, to assess the relative importance of this objective within the industry-wave to which the firm belongs, we calculate the average of the relative ratings assigned to this objective. The third variable considered is the fixed capital investment dummy, which may reflect positive demand expectations (Busom et al., 2014). The fourth variable, *environmental concern*, is constructed using the same methodology as the *quality improvement* variable. A higher value of this variable indicates a greater emphasis placed on the objective of reducing environmental damage within an industry-wave when pursuing innovation. We expect these four variables to have a positive effect on the firm's optimal R&D effort. The reason is that the existence of unsatisfied demand in the market, firms' perceptions of the relevance of product quality improvement, good expectations about demand conditions, and that environmental issues are relevant to consumers can create incentives to innovate, as firms' demand is expected to react positively to innovation.

To approximate the firms' response to R&D expenditure in terms of innovation, we construct two variables while also controlling for dummy variables based on the OECD technological classification of industries. All of these variables aim to capture the technological opportunities available to firms. Greater technological opportunities make it easier for firms to achieve innovation outcomes from their R&D investments. The first variable, *scientific-technical opportunities*, is calculated as the proportion of innovative firms in the same industry-wave of the survey that indicate the utilization of scientific-technical ideas and/or novelties as a driving force behind their innovation activities. The second variable, *lack of technological information*, is constructed similarly to *quality improvement*. However, it is derived from a survey question where firms report the significance of various obstacles to innovation. A higher value indicates a greater relative importance of the obstacle of lacking technological knowledge and information within a particular industry-wave.

As for the demand-price elasticity, we searched the survey for variables related to competition and market power. We selected four types of variables. First, *prices by demand and discounts*. This is a dummy variable that identifies firms that introduce new pricing methods for the first time, such as demand-related pricing or customer discount schemes. These changes in the pricing system may be a reaction of the firm to increased competition in the product market. Second, *market share*. Firms with a higher market share are generally considered to face less competition. Third, the dummy variable for the firm's export status and *export intensity* (in logarithms). If export markets are more competitive, exporters will face more competition. Finally, (novel) *marketing intensity* is defined as spending on marketing innovation over sales (in logarithms). This includes such things as spending on a new type of advertising campaign, a new brand image, the introduction of customer loyalty cards, a new product positioning in the market, and so on. These firm strategies may be in response to increased competition, but they may also aim to better position its products and thus reduce the competition it faces.

5.3 | Observability rule for the optimal R&D effort equation: The yes/no decision

The explanatory variables in Equation (7) are the same as those in Equation (6) plus some additional variables. The latter are intended to capture the set-up costs of innovative activities that determine the firm's R&D decision, but they do not influence the firm's R&D effort. The reason why they appear in the R&D decision is their presence in the threshold R&D effort equation (which is affected by set-up costs F_{it}). For this purpose, we use variables related to the technological sophistication of the firm and the employment of skilled workers, such as the existence of an ICT department and the presence of employees with a PhD, a Master's degree, or a university degree (dummy variable *d_skill*). Better human capital may be related to a greater ability to generate ideas and higher-quality R&D projects. In addition, we also include a dummy variable for appropriability and protection of innovative ideas and products that can incentivize R&D, *d_protection*, which takes value 1 if the firm uses at least one appropriability instrument or protection mechanism (trademarks, patents, utility models, industrial design, copyrights, designations of origin, confidentiality clauses for employees, or confidentiality contracts with suppliers and customers). Finally, the relative productivity of the firm in its sector (and its squared value).[x,xi] This variable may reflect not only that more productive firms are better able to overcome set-up costs, but also that returns to R&D may be higher for more productive firms. Similarly, it may also reflect that more productive firms in a sector, when undertaking more ambitious or radical projects, may face higher set-up costs.

5.4 | Results for the yes/no R&D decision and the optimal and threshold R&D effort equations

Table 2 shows the results of the joint maximum likelihood estimation of the yes/no R&D equation (column 2) and the optimal R&D effort equation (column 1). In the lower part of the table, the Wald test on the null hypothesis of independent errors allows for rejection of this hypothesis and thus supports the joint estimation. Column 3 shows the parameters of the threshold R&D effort equation obtained by applying the transformation of (8) to the parameters in columns 1 and 2 (i.e., $\beta_2 = \beta_1 - \sigma\beta_0$, with $\beta_1 = 0$ for variables acting as exclusion restrictions in column 1).

The results indicate, both for the yes/no R&D decision equation and for the optimal R&D effort equation, that the higher the "expected" subsidy for a firm, the higher its probability of doing R&D and the higher its R&D effort. As for the four variables capturing the elasticity of demand to innovation (related to demand conditions), we obtain that all of them are statistically significant and have the expected positive sign on the R&D decision. In the R&D effort equation, they still have a positive sign, but only two of them are statistically significant (the fixed capital investment dummy variable, which may reflect positive expectations about demand, and the environmental concern in pursuing innovation, which may be valuable for consumers). Consumer demand seems to respond positively to innovation intentions that aim to satisfy unsatisfied demands, improve product quality or care about the environment. If the firm is also in an expansionary phase in the product market, this also contributes to a better acceptance of innovations by consumers.

The variables that capture the elasticity of innovation to R&D investment (*scientific-technical opportunities* and *lack of technological information*, both related to technological opportunities), are not statistically significant in the yes/no R&D decision, but they are and with the expected signs (positive and negative, respectively) in the optimal R&D effort equation. Therefore, on the one hand, if it is believed that there is a relevant possibility in the market to exploit new ideas and/or new scientific and technical opportunities, firms will increase their R&D effort. On the other hand, the opposite will occur when the lack or difficulty of access to technological information is perceived as a major obstacle to innovation.

Finally, for the four price-demand elasticity variables, we find that market share, although not significant in the yes/no R&D decision, is significant with a negative sign in the optimal R&D effort equation, indicating that market power discourages firms' R&D effort (Schumpeterian effect). Conversely, if firms change their prices in a more demand-sensitive way, the positive sign we obtain for the *prices by demand and discounts* variable, both in the yes/no R&D equation and in the R&D effort equation, suggests that greater competition encourages R&D activities (scape competition effect, Arrow, 1962). Furthermore, the implementation of new marketing campaigns and the firm's export intensity have negative and statistically significant effects on the yes/no R&D decision. This may suggest that these business strategies are substitutes (and not complements) to R&D activity. However, novel marketing campaigns increase the firm's R&D effort once the firm already invests in R&D. They may appear as a reaction to increased competition in the product market and thus be related to the above-mentioned "scape competition effect" (Arrow, 1962).

Among controls, firm size positively affects R&D decision but not R&D effort, firm age reduces R&D effort, and firms in the provinces of Guayas, Pichincha, and Azuay are less likely to perform R&D.

The results for the exclusion restriction variables that appear in column 2 but not in column 1 of Table 2 are discussed with the results in the last column of this table, column 3, where the

TABLE 2 The effect of public funding on R&D decisions.

	(1) (log of) Optimal R&D effort β, β_1	(2) d_R&D (Yes/No) $\beta^{\text{scaled}} = (\beta/\sigma), \beta_0$	(3) (log of) R&D effort threshold β_2
$-\ln(1-\rho_{it}^{*})$	0.159* (0.085)	10.504* (5.754)	
To proxy elasticity of demand w.r.t. innovation (demand conditions)			
Unsatisfied demand	0.029 (0.175)	0.217** (0.087)	0.026 (0.175)
Quality improvement	0.062 (0.240)	0.276*** (0.096)	0.057 (0.239)
*d*_fixed investment $t-2$	0.203* (0.112)	0.875*** (0.030)	0.189* (0.112)
Environmental concern	0.825*** (0.217)	0.418*** (0.101)	0.818*** (0.217)
To proxy elasticity of innovation w.r.t. R&D (technological opportunities)			
Scientific-technical opportunities	0.519*** (0.178)	−0.042 (0.090)	0.519*** (0.178)
Lack of technological information	−0.553** (0.256)	−0.019 (0.114)	−0.552** (0.256)
Med-Low tech manufacturing	0.064 (0.096)	0.059 (0.055)	0.063 (0.096)
Med-High tech manufacturing	−0.239* (0.143)	0.155* (0.080)	−0.240* (0.143)
High tech manufacturing	0.258 (0.229)	0.144 (0.180)	0.256 (0.266)
Knowledge-intensive services	−0.700*** (0.092)	−0.440*** (0.037)	−0.693*** (0.092)
Other sectors	0.287** (0.119)	−0.269*** (0.054)	0.291** (0.119)
To proxy elasticity of demand w.r.t. prices (competition and market power)			
Prices by demand and discounts	0.401*** (0.110)	0.263*** (0.076)	0.397*** (0.110)
Market share $t-2$	−1.765*** (0.594)	0.417 (0.299)	−1.771*** (0.595)
Export intensity t – 2	−0.011 (0.036)	−0.036* (0.021)	−0.010 (0.361)
*d*_export $t-2$	−0.125 (0.135)	−0.076 (0.066)	−0.124 (0.135)
(novel) Marketing intensity $t-2$	0.074*** (0.011)	−0.055*** (0.006)	0.075*** (0.115)
Controls			
*d*_foreign	−0.116 (0.105)	0.045 (0.054)	−0.116 (0.105)
*d*_group	−0.019 (0.086)	−0.013 (0.044)	−0.018 (0.086)
Size $t-2$	−0.216*** (0.027)	0.025* (0.015)	0.216*** (0.027)
Age	−0.123*** (0.043)	−0.010 (0.021)	−0.122*** (0.042)
*d*_geographical$_{\text{Guayas, Pichincha, Azuay}}$	0.008 (0.068)	−0.167*** (0.034)	0.010 (0.682)
*d*_time$_{\text{second wave of the survey}}$	−0.546*** (0.069)	−0.259*** (0.036)	−0.541*** (0.069)
Exclusion restrictions			
*d*_skill		0.181*** (0.055)	−0.002*** (0.000)

TABLE 2 (Continued)

	(1) (log of) Optimal R&D effort β, β_1	(2) d_R&D (Yes/No) $\beta^{\text{scaled}} = (\beta/\sigma), \beta_0$	(3) (log of) R&D effort threshold β_2
*d*_protection		0.761*** (0.035)	−0.011*** (0.000)
*d*_ICT		0.213*** (0.036)	−0.003*** (0.000)
Relative productivity $t-2$		0.252 (0.207)	−0.003 (0.003)
(Relative productivity $t-2)^2$		−0.448*** (0.145)	0.006*** (0.002)
Constant	−2.684*** (0.579)	−1.280*** (0.192)	−2.664 (0.579)
Observations	4024	9090	9090

Note: (β,β_1), $(\beta^{\text{scaled}} = (\beta/\sigma),\beta_0)$ and β_2 refer to the parameters of Equations (6), (7), and (5), respectively. The coefficients of the threshold equation have been calculated as $\beta_2 = \beta_1 - \sigma\beta_0$ (see (8) in the main text), making $\beta_1 = 0$ for the variables acting as exclusion restrictions. Standard errors are shown in parentheses. Rho = −0.51; Wald test of independent equations (Rho = 0): $\text{Chi}^2(1) = 35.49$ and *p*-value = .0000. Log-pseudolikelihood = −12,891.83.
$^*p < .1$, $^{**}p < .05$, $^{***}p < .01$.

results for the R&D effort threshold equation are presented. Note that these variables appear in the yes/no R&D decision in expression (7) only because they are regressors of the threshold equation in the model, as they do not appear in the optimal R&D effort equation. In the threshold equation (as written in expression (3)), these variables are to capture the set-up costs of conducting R&D. According to the results in column 3 for these variables, higher productivity is associated with higher set-up costs (probably because more ambitious and radical R&D projects are pursued) and thus with higher R&D effort thresholds and, consequently, a lower probability of performing R&D (see the decision rule in expression (7)). However, the existence of a skilled workforce, an ICT department, and mechanisms for the protection and appropriability of ideas and innovation results are associated with lower set-up costs and/or a greater ability to overcome them, and thus with lower R&D effort thresholds and, consequently, a higher probability of doing R&D.

As for the other variables in the threshold equation in column 3 (also included in the optimal R&D effort equation in column 1 and in the yes/no R&D decision in column 2), those that are statistically significant for the optimal R&D effort are statistically significant (with the same sign and very similar magnitude) for the R&D effort thresholds. The similarity in the magnitude of the common regressors in the threshold and optimal R&D effort equations is due to a small σ (standard deviation of the error term $\varepsilon_{0,it}$ in the *probit* equation for the yes/no R&D decision). As $\sigma = 0.014$, when we calculate $\beta_2 = \beta_1 - \sigma\beta_0$ the effect of β_0 is reduced and, therefore, β_2 is very similar to β_1.[xii]

6 | INTERPRETATION OF RESULTS IN TERMS OF CROWDING-IN OR CROWDING-OUT OF PRIVATE R&D EFFORT: A POSSIBLE MECHANISM FOR PARTIAL CROWDING-OUT OF R&D SUBSIDIES

Once the optimal and threshold R&D effort equations have been estimated, we proceed to assess the crowding-in or crowding-out effect of subsidies on private R&D efforts. To do so, we use a proxy measure of the change in private effort as a consequence of subsidies (as in González et al., 2005):

$$\frac{\left(1-\rho_{it}^{*}\right)\varepsilon\left(\rho_{it}^{*}\right)-\varepsilon(0)}{\varepsilon(0)}=\frac{\left(1-\rho_{it}^{*}\right)\varepsilon\left(\rho_{it}^{*}\right)}{\varepsilon(0)}-1=\left[\left(1-\rho_{it}^{*}\right)^{-(\beta-1)}-1\right] \tag{12}$$

where ε is "effort" as measured by the ratio of R&D over sales, $\varepsilon\left(\rho_{it}^{*}\right)$ is *total* effort with subsidy (*total* means publicly and privately financed R&D), $\varepsilon(0)$ is *total* effort with zero subsidy (here *total* means only private funding) and, finally, $\left(1-\rho_{it}^{*}\right)\varepsilon\left(\rho_{it}^{*}\right)$ corresponds to private effort when R&D is subsidized. Both $\varepsilon\left(\rho_{it}^{*}\right)$ and $\varepsilon(0)$ are determined by the optimal R&D effort equation in (4).[xiii] Therefore, β is the estimated coefficient in this equation for the subsidy variable $-\ln\left(1-\rho_{it}^{*}\right)$. Depending on the value of the subsidy efficiency β, the expression in (12) is equal to 0, greater than 0 or less than 0:

- *The subsidy is neutral for private R&D efforts*: If $\beta=1$, (12) is equal to 0. This means that private effort does not change with the subsidy compared to what it would have been without the subsidy.
- *Crowding-in*: If $\beta>1$, (12) is greater than 0. This means that private effort is greater with the subsidy than it would have been without it. The subsidy increases private effort, and the *total* effort will be greater than the sum of the public share and the private effort without subsidy.
- *Crowding-out*: If $\beta<1$, (12) is less than 0. This means that private effort is less with the subsidy than it would have been without it. The subsidy reduces private effort, and the *total* effort will be less than the sum of the public share and the private effort without subsidy.

However, crowding-out does not have to be complete. A typical result when crowding-out is found is partial crowding-out. This means that firms' total R&D effort increases, but less than the subsidy, as part of the subsidy is used to substitute part of private effort. The estimate of β (the coefficient equal to 0.159 of the subsidy variable in the optimal R&D effort equation; see column 1 of Table 2) indicates partial crowding-out. The change in private effort from no subsidy to subsidy is calculated with $\left[\left(1-\rho_{it}\right)^{-(\beta-1)}-1\right]*100$. Evaluating this expression with subsidy values of 1%, 10%, and 20%, the percentage decrease in private effort due to the subsidy is −0.84%, −8.48%, and −17.11%, respectively. Therefore, the crowding-out effect increases with the amount of the subsidy.

As anticipated in the Introduction, one possible mechanism to explain the partial crowding-out effect is that in developing countries, where the availability of funds is often restricted, financially constrained firms may divert part of the subsidy to invest in fixed capital. If one wants to find some support for this hypothesis, one would have to check, first, that it is the more financially constrained firms that explain the crowding-out effect and that they simultaneously increase their investment in fixed capital when receiving a subsidy. Second, for other firms, there is crowding-in (or neutrality) and their investment in fixed capital is insensitive to the subsidy. To do so, we first re-estimate the optimal R&D effort equation by allowing the coefficient associated with the subsidy regressor to differ between financially constrained and non-financially constrained firms. Second, we estimate a new regression in which the dependent variable is the firm's investment in fixed capital and in which we also allow the regressor associated with the subsidy to have different effects for the two types of firms.

Unfortunately, firms' financial information is not available in CIS-type databases. Instead, we first use information on whether or not firms belong to a business group. Group membership, by providing access to intra-group resources, can partially substitute for an external capital market (Beneito et al., 2015, finds that group membership alleviates the role of credit constraints for firms' R&D investments).

Other variables among regressors that could, in principle, also be related to firms' financial constraints or their ability to raise finance are foreign capital participation, firm size, productivity, and market share. Nevertheless, these variables are also strongly related to group membership. In particular, 95% of firms that do not belong to a group do not have foreign capital either and, in turn, 60% of firms with foreign capital belong to a group. Furthermore, 93% of nongroup firms are SMEs (firms with less than 250 employees). On the other hand, around 70% of firms belonging to a group have high productivity within their sector.[xiv] Finally, around 68% of firms belonging to a group have a high market share.[xv] For these reasons, we believe that an appropriate variable in the survey to classify firms according to their financial constraints is whether or not they belong to a group, as it at least facilitates access to an internal capital market.

The results of the two aforementioned regressions are shown in Table 3. For the sake of comparability of the results of the two regressions, the new regression introduced (with fixed capital investment in logarithms as a dependent variable) keeps the same regressors as the optimal R&D effort equation and is estimated in the same way. When subsidized, financially constrained firms increase their fixed capital investment (column 2) and partially reduce their private R&D effort (partial crowding out, see column 1). In contrast, the fixed capital investment of nonfinancially constrained firms does not respond to the subsidy and, in addition, crowding-in is obtained for them. Consequently, financially constrained firms explain the partial crowding-out we have found in this paper for the whole sample of firms.

Although, as argued, firms belonging to a business group may be less likely to be financially constrained, the Group variable may capture other effects as well. In our estimates in Table 3, since the Group variable in addition to interacting with the subsidy is also included without interaction, we consider that we are somehow controlling for the possibility that group membership may have other direct effects (beyond better access to finance) on optimal R&D and fixed capital investment. However, as a robustness check, we also repeat the estimates in columns 1 and 2 of Table 3 with a synthetic measure of firms' financial constraints that we construct using factor analysis. Factor analysis is a statistical technique that reduces the number of variables in an analysis by finding a few common factors that linearly reconstruct the original set of variables. Each extracted factor is associated with a set of linear coefficients called factor loadings. Factor loadings indicate the weight of each factor on the observed variables. High loadings suggest a higher contribution of the factors to those variables. Factor analysis can be used, as mentioned above, not only to represent a set of original variables in a parsimonious way, but also to provide measures (factors) that approximate a given concept. The key idea of factor analysis is that multiple observed variables have similar patterns because they are all associated with a latent (i.e., not directly measured) variable. In this article, we use factor analysis for this second purpose, and try to determine whether any of the extracted factors can be interpreted as an indicator of firms' financial constraints (with low values of this indicator for firms with more financial constraints and high values for firms with less financial constraints). We will consider that we have found such a factor if there is a factor with positive loading on all of the following variables: the dummy variables of group and foreign capital, and the continuous variables firm size (in logarithms), (relative) productivity, and market share. The values of these variables are expected to be associated with the latent variable "firm financial constraints".

TABLE 3 The effect of public funding on R&D and fixed capital investments: financially constrained versus nonfinancially constrained firms.

	(1) (log of) Optimal R&D effort β,β_1	(2) (log of) fixed investment		(3) (log of) Optimal R&D effort β,β_1	(4) (log of) Fixed investment
$-\ln\left(1-\rho_{it}^{*}\right) \times d\_group$	1.769** (0.880)	0.651 (0.624)	$-\ln\left(1-\rho_{it}^{*}\right) \times \text{factor1}$	0.235 (0.250)	−0.208 (0.171)
$-\ln\left(1-\rho_{it}^{*}\right) \times d\_No\_group$	0.148* (0.085)	0.251*** (0.086)	$-\ln\left(1-\rho_{it}^{*}\right)$	0.184*** (0.065)	0.212*** (0.062)
To proxy elasticity of demand w.r.t. innovation (demand conditions)					
Unsatisfied demand	0.033 (0.175)	0.167 (0.189)		0.021 (0.177)	0.172 (0.168)
Quality improvement	0.069 (0.240)	0.014 (0.234)		0.030 (0.239)	−0.015 (0.216)
d_fixed investment $t-2$	0.224** (0.111)	−0.975*** (0.112)		0.134 (0.104)	0.058 (0.595)
Environmental concern	0.824*** (0.217)	0.829*** (0.222)		0.835*** (0.216)	0.836*** (0.203)
To proxy elasticity of innovation w.r.t. R&D (technological opportunities)					
Scientific-technical opportunities	0.523*** (0.178)	0.338* (0.202)		0.518*** (0.180)	0.265 (0.179)
Lack of technological information	−0.556** (0.256)	0.453* (0.262)		−0.513** (0.261)	0.409* (0.238)
Med-Low tech manufacturing	0.066 (0.096)	0.009 (0.105)		0.057 (0.097)	0.057 (0.093)
Med-High tech manufacturing	−0.229 (0.143)	−0.224 (0.157)		−0.277* (0.143)	−0.106 (0.149)
High tech manufacturing	0.236 (0.228)	0.085 (0.257)		0.267 (0.220)	0.345 (0.248)
Knowledge-intensive services	−0.712*** (0.092)	0.036 (0.077)		−0.670*** (0.089)	−0.019 (0.086)
Other sectors	0.278** (0.119)	0.528*** (0.124)		0.358*** (0.120)	0.274* (0.145)
To proxy elasticity of demand w.r.t. prices (competition and market power)					
Prices by demand and discounts	0.410*** (0.110)	−0.178 (0.127)		0.331*** (0.111)	−0.033 (0.129)
Market share $t-2$	−1.757*** (0.593)	3.098*** (0.704)		2.875*** (0.887)	−7.340*** (1.622)

TABLE 3 (Continued)

	(1) (log of) Optimal R&D effort β,β_1	(2) (log of) fixed investment	(3) (log of) Optimal R&D effort β,β_1	(4) (log of) Fixed investment
Export intensity $t-2$	−0.010 (0.036)	−0.074* (0.040)	−0.006 (0.038)	−0.086** (0.036)
d_export $t-2$	−0.126 (0.135)	0.140 (0.133)	−0.068 (0.138)	−0.005 (0.129)
(novel) Marketing intensity $t-2$	0.073*** (0.011)	0.003 (0.011)	0.071*** (0.011)	−0.008 (0.014)
Controls				
d_foreign	−0.107 (0.105)	0.534*** (0.112)	1.364*** (0.239)	−2.861*** (0.461)
d_group	−0.033 (0.086)	0.422*** (0.092)	1.367*** (0.217)	−2.843*** (0.464)
Size $t-2$	−0.215*** (0.027)	0.613*** (0.031)	−0.001 (0.042)	0.139** (0.058)
Age	−0.125*** (0.043)	−0.072 (0.045)	−0.150*** (0.043)	−0.011 (0.042)
d_geographical$_{\text{Guayas, Pichincha, Azuay}}$	0.007 (0.068)	0.237*** (0.069)	0.089 (0.069)	0.021 (0.079)
d_time$_{\text{second wave of the survey}}$	−0.548*** (0.069)	0.410*** (0.074)	−0.550*** (0.069)	0.411*** (0.067)
Factor1			−1.370*** (0.199)	3.206*** (0.441)
Constant	−2.728*** (0.580)	8.527*** (0.492)	−3.729*** (0.593)	9.871*** (0.712)
Observations	4024	4707	4024	4707

Note: (β,β_1) refer to the parameters of Equation (6). Standard errors are shown in parentheses.
$^*p<.1$, $^{**}p<.05$, $^{***}p<.01$.

TABLE 4 Factor 1: Factor loadings and scoring coefficients.

Variables	Factor loadings	Scoring coefficients
*d*_group	0.596	0.366
*d*_foreign	0.557	0.316
Size (log number of employees)	0.505	0.269
Relative productivity	0.296	0.137
Market share	0.355	0.191

Note: % of variance accounted for by factor 1, 72.27%.

Our (iterated principal) factor analysis method provides a factor with positive loadings for all variables included. The method does not provide any other factor showing such positive loadings. Moreover, this factor (factor 1) coincides with the factor that explains most of the overall variance of the observed variables (72.27%). Table 4 presents the so-called factor loadings (the relationship of each variable to the underlying factor 1) and the regression scoring coefficients used to create this factor, showing that the factor is obtained as a weighted sum of the variables listed therein, with all scoring coefficients also being positive.[xvi] The variable with the strongest association with the underlying latent variable represented by factor 1 is the group dummy variable, with a factor loading of 0.596. Since factor loadings can be interpreted as standardized regression coefficients, it can be said that the group dummy variable has a correlation of 0.596 with factor 1. This would be considered a strong association for a factor analysis in most research fields.

The results obtained using our synthetic indicator of financial constraints are presented in columns 3 and 4 of Table 3. Once again, we find supporting evidence for our hypothesis. When considering the subsidy variable alone and in conjunction with factor1, a continuous variable where higher values indicate fewer financial constraints, we observe that firms with lower financial constraints (higher values of factor1) show less sensitivity in their R&D and fixed capital investments towards the subsidy. Conversely, firms facing greater financial constraints (lower values of factor1) exhibit a stronger impact of the subsidy variable, with a statistically significant coefficient of 0.184, indicating partial crowding-out (refer to column 3 of Table 3). Regarding investment in fixed capital (column 4 of Table 3), our findings reveal that firms with higher values of factor 1 (indicating lower financial constraints) show a lack of sensitivity to the subsidy. Conversely, firms with lower values of factor 1 (indicating higher financial constraints) demonstrate an increase in their fixed capital investment when they receive a subsidy. This effect is supported by a highly significant coefficient of the subsidy variable, with a value of 0.212.

7 | CONCLUDING REMARKS

In this article, we examine the effectiveness of R&D subsidies on firm-level R&D efforts in a developing country, specifically Ecuador. We utilize data from the National Survey of Innovation Activities and employ a structural framework that addresses simultaneity and selection issues. Our results indicate that subsidies have both an extensive margin effect, encouraging firms to engage in R&D, and an intensive margin effect, increasing the overall R&D effort. However, these effects are accompanied by a partial crowding-out of private efforts by public funds. Additionally, we propose a potential mechanism to explain these findings in developing countries, where limited availability of funds is a concern. We suggest that financially constrained firms may allocate a portion of the subsidy towards fixed capital investment. Our estimates provide some support for this hypothesis, showing that the crowding-out effect is driven by financially constrained firms, which simultaneously increase their fixed capital investment upon receiving a subsidy. On the contrary, for other firms, we find a crowding-in effect and that their investment in fixed capital is not sensitive to the subsidy.

From the point of view of policy recommendations, is the presence of partial crowding-out good or bad for a developing country? On the one hand, public agencies in developing countries may be interested in the long-term spillover effects of R&D-induced performers. That is, as Takalo et al. (2013) state, public agencies "may be willing to encourage the firm to invest more even if there were some crowding-out. Thus it might be possible that no evidence for additionality can be found in a country where R&D projects create large spillovers (and where the support is therefore optimally extensive)". In a country like Ecuador, which still has room for improvement in terms of innovation (Rodríguez-Moreno & Rochina-Barrachina, 2019; Cornell University, INSEAD, and WIPO, 2018), it may be optimal for the public agency to increase the base of R&D performers despite the partial crowding-out of private R&D by public funding. The rationale is to encourage future positive spillovers through the expansion of the number of R&D performing firms (R&D extensive margin), which may offset the short-term partial crowding-out effect on the R&D intensive margin. In this regard, Crespi et al. (2020) state that "it is the existence of spillovers—and not the potential impact of grants on grant recipients—that is the main rationale for government intervention in these programs." They empirically corroborate this by showing that R&D subsidies to Chilean firms increase the productivity of direct beneficiaries and indirect beneficiaries located in the same region and sector.

On the other hand, our work presents an alternative perspective that challenges the prevailing notion that R&D crowding-out is universally negative. The results of our study reveal a phenomenon of partial crowding-out, where financially constrained firms allocate some R&D public subsidies toward investment in capital goods. This finding could even point to a potential improvement in the allocation of innovative efforts in developing countries, with a focus on capital investment. The notion that embodied technology in capital goods is significant for developing countries and can contribute to fostering future innovation is well-supported by studies such as Navarro et al. (2010), Dabla-Norris et al. (2012), Goedhuys and Veugelers (2012), and Rochina-Barrachina & Rodríguez (2019). Furthermore, this idea is also evident in more recent papers. In this regard, Elkomy et al. (2021) highlight that many developing countries have acquired technology embodied in imports of capital equipment, serving as a channel for the technology transfer of foreign innovations and technologies from developed to developing countries. Empirically, they find, for Egyptian industries, that new foreign machinery and equipment have a positive effect on productivity. They argue that developing countries can enhance their domestic technology stock without incurring higher costs of innovation and save time by assimilating and imitating foreign innovations. Notably, as mentioned by Almeida and Fernandes (2008), industrializing economies can narrow the technological gap with more advanced economies through imitation and reverse engineering. While this innovation strategy is particularly relevant for developing countries, it can also play a role in developed ones. For instance, Wang et al. (2021) demonstrate that German firms that combine R&D investment with the acquisition of new technologies embodied in machinery and equipment exhibit higher innovation performance in terms of product and process innovation.

In recent literature using Chinese provincial data for the period 2000–2010, we find further support for the idea that fixed capital investment may be the result of the partial crowding-out of private R&D by public R&D and that it may also indicate a more efficient allocation of innovative efforts in developing countries when R&D subsidies alleviate firms' financial constraints. For example, Eberle and Boeing (2019) examine R&D subsidies in Chinese provinces and observe an increase in physical capital investment as a positive spillover effect of R&D subsidies. The authors argue that these investments can complement R&D activities and do not necessarily imply a misallocation of R&D subsidies. Another relevant study is conducted by Boeing et al. (2022), who analyze the same panel database of Chinese provinces for the same time period. They find that R&D subsidies stimulate total R&D but lead to a reduction in private R&D, indicating partial crowding-out. However, they argue that focusing solely on the effect of R&D subsidies on R&D itself overlooks broader positive effects on the economy, such as capital deepening through physical capital investments. Interestingly, at a descriptive level, the least developed Chinese provinces exhibit the highest growth in physical capital investment, suggesting potentially higher marginal returns to physical capital in these regions. In contrast, more developed provinces may prioritize innovation over physical capital. Furthermore, the estimation results of Boeing et al. (2022) indicate that an increase in the intensity of R&D subsidies has a positive impact on provincial investment in physical capital, suggesting that R&D subsidies indirectly influence fixed asset investment. This broader impact of subsidies is expected to have a positive economic effect on Chinese provinces, as capital deepening is crucial for growth, particularly in emerging and developing economies.

In summary, previous literature commonly suggests that public R&D subsidies are implemented to stimulate private R&D investment by fostering a crowding-in effect. It is generally anticipated that firms facing financial constraints will increase their R&D expenditure when receiving public support. However, our research reveals that providing subsidies to financially constrained firms may not necessarily result in an increase in private R&D incentives. It is important to note that the absence of a crowding-in effect does not automatically imply that public intervention is negative or unnecessary. Our study argues that even in cases where a partial crowding-out effect exists the positive influence of R&D subsidies on capital investment can outweigh the negative aspects. This can be particularly advantageous for developing countries, as innovation can also occur through the adoption of technology embedded in capital goods imported from technologically advanced countries.

We believe that the debate raised by our work is relevant because one of the main justifications for public intervention through R&D subsidies is the presence of financial constraints in firms. The findings of this article indicate that in developing countries with weak financial markets, it may not be advisable to eliminate subsidies for financially constrained firms when there are crowding-out effects associated with capital deepening. The convergence of these two factors may suggest an innovation strategy that relies more on imitation and assimilation of technology embedded in capital goods. Over the medium to long term, this strategy could enable the firm to develop absorptive capacity, facilitating a transition toward a more proactive innovation strategy where the firm generates its own knowledge through dedicated R&D efforts. To expedite this process, it would be desirable for governments to proactively foster a domestic environment that encourages more favorable returns on R&D investments. The findings of our paper suggest that achieving this objective can be facilitated through various policies and initiatives, including enhancing demand conditions, improving access to information and knowledge regarding technological opportunities, and promoting greater competitiveness within markets.

For developing countries, where the availability of funds is often restricted and the technological system is underdeveloped, a study like ours is relevant so that policy makers can better manage and assess the end use and impact of R&D subsidies.

Finally, we recognize as a limitation of our study that the results are based on a case study of a country with a small proportion of R&D subsidy recipients. Nevertheless, we believe that we contribute to the debate on the effects of R&D subsidies to the extent that our results suggest that the financial situation of firms may be an important factor in understanding how R&D subsidies incentivize private investment. There is a clear need for further research in this area with richer and more extensive data from other developing countries. The problem is that many of them do not conduct innovation surveys or do so without continuity over time.

ACKNOWLEDGMENTS

María Engracia Rochina Barrachina acknowledges financial support from Grant PID2021-124266OB-I00 funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe" and from Grant TED2021-130232B-I00 funded by MCIN/AEI/10.13039/501100011033 and by the "European Union NextGenerationEU/PRTR". Jorge Antonio Rodríguez Moreno gratefully acknowledges financial support from research funds from the Universidad del Río-Ecuador period 2019–2023.

CONFLICT OF INTEREST STATEMENT

On behalf of all authors, the corresponding author states that there is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the open access survey https://www.ecuadorencifras.gob.ec/encuesta-nacional-de-actividades-de-ciencia-tecnologia-e-innovacion-acti/.

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ENDNOTES

[i] The approach of modeling R&D subsidies as a share of to-be-incurred R&D expenditures is widely used in the literature that utilizes structural models to analyse R&D choices and investments (Arqué-Castells & Mohnen, 2015; González et al., 2005; Takalo et al., 2013).

[ii] Two of the reasons why governments subsidise firms' R&D are precisely that, when there are positive externalities of R&D investment and there is uncertainty about R&D outcomes, firms tend to under-invest in R&D. The above reasons create a gap between private and social returns to R&D that leads firms to decide their private R&D investment optimally through profit maximization, but below the social optimum. The objective of the subsidy is precisely to lower firms' R&D unit costs and in this way bring the private optimum of R&D investment closer to the social optimum. Hence, this underinvestment is compatible with profit-driven firms in the presence of "public goods" or other market failures such as asymmetric information and uncertainty.

[iii] In empirical specifications we proxy for F_{it} and normalize $\pi_{it}^{No\ RD}$ to zero.

[iv] Since coefficients and the error term in (7) come from (4) minus (5): $\beta_0^{no\_exc.rest} = \left(\beta_1 - \beta_2^{no\_exc.rest}\right)$, $\beta_0^{exc.rest} = \left(0 - \beta_2^{exc.rest}\right)$, and $\varepsilon_{0,it} = (\varepsilon_{1,it} - \varepsilon_{2,it})$. Moreover, β_2 in (5) is equal to $\beta_2^{no\_exc.rest}$ and $\beta_2^{exc.rest}$.

[v] See footnote 4.

[vi] $\beta^{\text{scaled}} = (\beta/\sigma)$.

vii In manufacturing, sectors are grouped into low-tech, medium-low-tech, medium-high-tech, and high-tech. In services, they are grouped into knowledge-intensive and nonknowledge-intensive. OECD classifications are applied. In terms of location, a dummy is included that identifies firms in the provinces of Guayas, Pichincha, or Azuay. These three provinces alone account for 64.27% of firms in Ecuador.

viii The regressors in $w_{1,it}$ for the latent equation of the "expected" subsidy share in (9) are similar, with the difference that manufactures are split between "high" (which aggregates the medium-high and high categories) or low-tech.

ix In addition, it includes controls such as firm age and size (in logarithms), and foreign, group, location, and wave dummies.

x Again, most firm-level regressors in vectors $X_{1,it}$ and $X_{2,it}$ in (7) are included with a two-period lag (i.e., at $t-2$).

xi The additional set of variables in (7) compared to (6) is not statistically significant when included in the optimal R&D effort equation (Equation (6)).

xii The estimate of σ is obtained as $\sigma = \beta / \beta^{\text{scaled}}$, where β and β^{scaled} are, respectively, the estimated coefficients for the variable $-\ln\left(1-\rho_{it}^{*}\right)$ that appears as a regressor in both the optimal R&D effort equation (column 1) and the yes/no R&D decision (column 2).

xiii To obtain different R&D efforts, we simply need to substitute the different values of the subsidy variable ρ_{it} into $rde_{it}^{\text{optimal}^*} = -\beta \ln(1-\rho_{it}) + X_{1,it}\beta_1 + \varepsilon_{1,it}$ (expression 4).

xiv To classify firms as high or low productivity within their sector, we use the firm's relative productivity variable. The median and mean of this variable is 1 and, therefore, firms are classified as high productivity within a sector if their relative productivity is above 1 and low productivity otherwise.

xv Firms are classified as having a high market share if their market share is above the median of this variable and as having a low market share otherwise.

xvi Factor scores are composites of the variables that are used to make the latent factor into an observed variable and to give it a scale. One would use factor scores, for example, when the factor was of interest to use as a predictor, as it is our case.

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How to cite this article: Rochina Barrachina, M. E., & Rodríguez Moreno, J. A. (2024). A possible mechanism for partial crowding-out of R&D subsidies in developing countries. *Review of Development Economics*, *28*(1), 71–96. https://doi.org/10.1111/rode.13038

APPENDIX: ALGEBRAIC ANALYSIS

R&D optimal and threshold expressions.

Starting with the firm's expected profit from doing R&D:

$$\pi_{it}^{\mathrm{RD}} = \exp(Z_{it}\theta + v_{it})\mathrm{RD}_{it}^{\phi} - (1-\rho_{it})\mathrm{RD}_{it} - F_{it} \tag{A1}$$

The first order conditions (FOC) with respect to R&D give the optimal R&D investment:

$$\mathrm{RD}_{it}^{\mathrm{optimal}^*} = \left[\frac{\phi \exp(Z_{it}\theta + v_{it})}{(1-\rho_{it})}\right]^{\frac{1}{1-\phi}} \tag{A2}$$

Then, introducing (A2) into (A1) we get as optimal profit:

$$\pi_{it}^{\mathrm{RD}} = \frac{1-\phi}{\phi}(1-\rho_{it})^{\frac{\phi}{\phi-1}}(\phi \exp(Z_{it}\theta + v_{it}))^{\frac{1}{1-\phi}} - F_{it} \tag{A3}$$

Therefore, firm i performs R&D when (A3) is greater than the nonperforming R&D profit:

$$\frac{1-\phi}{\phi}(1-\rho_{it})^{\frac{\phi}{\phi-1}}(\phi \exp(Z_{it}\theta + v_{it}))^{\frac{1}{1-\phi}} > F_{it} + \pi_{it}^{\mathrm{No\ RD}}, \tag{A4}$$

Using this expression as an equality, we can isolate the fraction of total firm R&D that should be subsidized to make the firm indifferent between investing or not in R&D (threshold subsidy):

$$\rho_{it}^{\mathrm{threshold}} = 1 - \phi^{\frac{\phi-1}{\phi}}(\phi \exp(Z_{it}\theta + v_{it}))^{\frac{1}{\phi}}\left(\frac{1-\phi}{F_{it} + \pi_{it}^{\mathrm{No\ RD}}}\right)^{\frac{1-\phi}{\phi}} \tag{A5}$$

Substituting (A5) into (A2), we get the R&D threshold expression:

$$\mathrm{RD}_{it}^{\mathrm{threshold}} = \left[\frac{F_{it} + \pi_{it}^{\mathrm{No\ RD}}}{(1-\phi)\exp(Z_{it}\theta + v_{it})}\right]^{\frac{1}{\phi}} \tag{A6}$$