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The effects of developing-countries' innovation support programs: evidence from Ecuador

Juan Fernández-Sastre* and Fernando Martín-Mayoral

Departamento de Desarrollo, Ambiente y Territorio, Facultad Latinoamericana de Ciencias Sociales (FLACSO-Ecuador), La Pradera E7-174 y Av. Diego de Almagro, Quito, Ecuador

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This paper evaluates the impact of Ecuadorian innovation support programs, which are intended to enhance firms' technological and managerial capabilities, on firms' innovative behavior and performance. In order to estimate the causal effects, we employ different Propensity Score Matching procedures. Results indicate that participating in a program increases firms' internal R&D and innovation effort, the qualification of the workforce, the likelihood of introducing product, process and organizational innovations and the probability of establishing linkages with research partners. However, participants do not show greater external R&D intensity or a higher propensity to patent, nor are they more likely to cooperate with suppliers, customer or competitors.

Keywords: innovation support programs; technological capabilities; emerging innovation systems; impact assessment

1. Introduction

In developing countries, firms lack sufficient capabilities, resources, complementary assets, knowledge and skills required to perform R&D activities (Chaminade, Lundvall, Vang, & Joseph, 2010; Hall, 2005; Perez, 1986; Teece, 1986). Furthermore, the infrastructures, networks and institutions that support and control such activities are in the early stages of development (Arocena & Sutz, 2000; Chaminade, Lundvall, Vang, & Joseph, 2009; Chaminade & Vang, 2008; Intarakumnerd & Chaminade, 2011). As a result, most firms do not have the ability to interpret the current state of the art in order to absorb, process, repair and change a given technology (Chaminade et al., 2010). In addition, technological change largely occurs through imports of intermediate capital goods from more advanced economies (Blakney, 1987; Keller, 2004; Piva, 2004; Vivarelli, 2014) which are not necessarily the most up-to-date technologies in the world, but nevertheless are more sophisticated than those traditionally adopted by local firms (Vivarelli, 2014).

In this context, innovation policy should prioritize the fostering of firms' technological and management capabilities (Bell & Pavitt, 1995; Chaminade et al., 2009; Lall, 1992), instead of exploiting firms' R&D capabilities through subsidies or tax incentives, as firms are unlikely to perform formal R&D activities until they have sufficient capabilities to absorb technology (Chaminade et al., 2010). Accordingly, in many developing countries innovation policy consists of a set of programs designed to enhance the

*Corresponding author. Email: jfernandez@flacso.edu.ec

technological and managerial capabilities of participating firms whereby no reasonable incentive structure would be sufficient to motivate private actors to overcome major technological lags (Cimoli, Dosi, Nelson, & Stiglitz, 2009).

Empirical innovation policy studies are mainly centered on developed countries (see Zúñiga-Vicente, Alonso-Borrego, Forcadell, and Galán [2014] for a recent survey) and focus on the evaluation of R&D subsidies and tax incentives, as they are the most common innovation policy instruments of these countries. More recently, demand-side technology policies such as public procurement have also been evaluated (Guerzoni & Raiteri, 2015). However, less attention has been devoted to developing countries' innovation support programs, even though programs designed to improve technological and managerial capabilities may induce firms to invest in innovation activities as the expansion of these capabilities generates a learning process through which firms internalize new knowledge and get involved in such activities (OECD, 2005). Furthermore, these programs may also have a positive impact on R&D networks, innovation outputs and workforce composition, just as R&D subsidies and tax incentives do (David, Hall, & Toole, 2000; Koga, 2005; Zúñiga-Vicente et al., 2014). Therefore, it is relevant to examine whether developing countries' innovation support programs modify the innovative behavior and performance of participating firms. However, as many developing countries do not conduct innovation surveys, the effects of these programs have not been tested (Chaminade et al., 2010).

This paper aims to fill this gap by analyzing the impact of the Ecuadorian innovation support programs on firms' innovation inputs, workforce qualification, innovation outputs and R&D networks. Ecuador is a low to middle income country, specializing in low value-added activities, characterized as a supplier of oil and raw materials and as an importer of technology in the international market. Ecuador has relatively simple production structures, fragmented and disarticulated innovation capabilities and it specializes in static comparative advantages (Cimoli et al., 2009). In Ecuador, national spending in R&D in 2011 was \$269.47 million, which represented 0.35% of its GDP (INEC & SENESCYT, 2011). Hence, Ecuador displays limited capacity either in terms of firms' technological capabilities or in terms of public investment in R&D. However, its government aspires to change productive specialization through the commitment to incorporate technology, knowledge and R&D in the productive sector (SENPLADES, 2012). Proofs of this commitment are the various public programs created to promote private innovation and the launch of the first Ecuadorian Survey of Innovation in 2013, ENAI (Encuesta Nacional de Actividades de Innovación)[1].

Drawing on ENAI data, this paper evaluates the causal effects of participating in a support program on the innovation behavior and performance of Ecuadorian firms. A central methodological aspect in innovation policy evaluation is the issue of endogeneity, as the allocation of programs is not random (Clausen, 2009; Görg & Strobl, 2007). In reality, a firm that participates in a program has first selected itself as a candidate and afterwards it has been chosen by a public agency as a recipient of support from the program. As a result, participants are unlikely to have the same characteristics as other firms. Therefore, a regression of firms' innovation behavior and performance on program participation will not produce a causal effect but suffer from so-called selection bias.

Given the cross-sectional nature of ENAI, we adopt different Propensity Score Matching procedures in order to estimate the causal effects of program participation. This methodology creates a proper comparison group for participants, based on a set of observable characteristics. The remainder of this paper is organized as follows.

Section 2 reviews the literature background for our analysis. Section 3 follows by describing the data, variables and methods. Section 4 presents and discusses the implications of the empirical results. Finally, we conclude in Section 5.

2. Literature review

In order to understand innovation policy in developing countries, we need to take into account two considerations. First, the ability of their innovation systems to support the creation, absorption, retention, use and dissemination of economically useful knowledge through interactive learning or in-house R&D activities is limited compared with that of countries with advanced innovation systems (Arocena & Sutz, 2000; Chaminade & Vang, 2008; Chaminade et al., 2009, 2010; Intarakumnerd & Chaminade, 2011). This is mainly due to the fact that developing countries' higher education systems do not produce the managerial and labor skills that allow firms to have sufficient capabilities to innovate (Bell & Pavitt, 1995; Fleming, 2001; Kogut & Zander, 1992; Lall, 1992; Westphal, Kim, & Dahlman, 1985; Zawislak, Cherubini Alves, Tello-Gamarra, Barbieux, & Reichert, 2012). As Blakney (1987) indicates, the demands of developing countries for access to technologies and innovation are paralleled by their demands for a restructuring of the legal environment and the modernization of infrastructures such as higher educational institutions and training facilities for science and technology.

Second, we need to adopt a broad concept of innovation. Innovation does not only relate to formal R&D activities but also to the absorption of external technology (Chaminade et al., 2010) and non-R&D inputs, such as the acquisition of machinery and equipment, design, engineering development, experimentation, training and marketing, which are also fundamental for the innovation process (Smith, 2005). These inputs are especially relevant for developing countries because in these economies innovation is mostly related to the absorption of technology and competence building rather than the introduction of science-based innovations (Chaminade et al., 2010; Viotti, 2002). In emerging innovation systems, firms are not yet able to produce radical innovations, but they are accumulating the competences and capabilities that are needed to engage in different forms of interactive learning and innovation (Chaminade et al., 2009).

In developing countries, innovation is highly informal and R&D activities are not clearly articulated with firms' strategies (Arocena & Sutz, 2002). Moreover as their innovation systems are at an early stage of development, the few existing innovative firms are characterized by performing in-house innovation activities because they still consider that ideas for innovation are mainly an internal concern (Arocena & Sutz, 2002). Hence, firms give little importance to external relations and networks are frequently based on ties with foreign firms, which are not normally involved in formal R&D activities, given the weakness of technological activities in the host country (Le Bas & Sierra, 2002; Patel & Vega, 1999). As Chaminade et al. (2009) indicate, unless there is substantial indigenous competence building, multinational firms mainly locate routine activities in developing countries.

Given that the systemic problems of developing countries differ from those of the developed world, their innovation policies support several activities beyond those associated with formal R&D. In most developing countries, innovation policy instruments are actually designed to enhance firms' technological and managerial capabilities that not only allow firms to choose and use technology (Gomel & Sbragia, 2006; Rush, Bessant, & Hobday, 2007) but also to create new methods, processes, techniques and products (Afuah, 2002; Zhou & Wu, 2010). These technological capabilities, necessary in order to generate technical change, include skills, knowledge and experiences (Bell & Pavitt, 1995). Once firms have developed technological capabilities, they can build up managerial capabilities (Chaminade & Vang, 2008) that integrate and combine the productive capabilities of human and physical resources (Zawislak et al., 2012), which allow firms to adopt flexible structures that facilitate doing, using and interacting modes of learning (Jensen, Johnson, Lorenz, & Lundvall, 2007; Lundvall, 2007). Thereafter, firms can construct the R&D capabilities that are decisive for innovation, which include R&D planning, capabilities in internal R&D capability, external cooperative R&D capability, R&D coordination, and intellectual property management (Dickson & Fang, 2008).

In Ecuador, there are several programs that support firms' innovation activities through the enhancement of technological and managerial capabilities. Note that we evaluate the programs that the ENAI considers as innovation support programs[2]. These programs are intended to strengthen the technical capabilities of workers, replace obsolete machinery and equipment, give assistance in management, promote exports and support business ventures through business incubators, seed money, information services, business-consulting, the creation of environments to establish trade relations, the promotion of commercial partnerships, information about suppliers and public demand for local producers.

Although programs have different characteristics, all of them are intended to enhance the technological and management capabilities of participating firms. Moreover, as we aim to evaluate the effectiveness of the 'program environment', we evaluate the causal effect of participating in a program on firms' innovative behavior and performance. Since these programs may induce firms to invest in R&D and innovation activities, we evaluate whether program participation increases firms' internal and external R&D intensity[3] and other activities related to the innovation process, such as the acquisition of machinery and equipment, hardware, software, disembodied technology, consulting and technical assistance, engineering, industrial design, training programs and market studies. We will refer to these later investments as *Innovation intensity* in order to differentiate them from internal and external R&D intensity.

We evaluate these three different innovation inputs as innovation is not a homogeneous activity (Clausen, 2009; Diamond, 1999; Link, 1982; Nelson, 1959; Robson, 1993). Although most empirical innovation policy studies have treated innovation effort as a single activity, normally measured by R&D intensity (Aschhoff, 2009; Herrera & Martínez, 2009; Hussinger, 2008; Özçelik & Taymaz, 2008; Wolff & Reinthaler, 2008), others have differentiated between research and development expenditures (Aerts & Thorwarth, 2008; Clausen, 2009; Czarnitzki, Hottenrott, & Thorwarth, 2011; Higgins & Link, 1981). Our data do not allow us to differentiate between research and development; however, we expect that support programs may have a different impact on internal and external R&D intensity and innovation intensity, as the fostering of technological and managerial capabilities might be more related to certain innovation inputs.

Additionally, support programs, as well as R&D subsidies or tax incentives, are not only expected to change the R&D and innovation effort of participants, but they may also induce firms to hire more qualified personnel, introduce product and process innovation, establish more patents, change their organizational behavior or establish R&D networks with external partners. Empirical studies have shown that innovation policy instruments may have significant effects on firms' innovation and patenting activities (Bérubé & Mohnen, 2009; Cantner & Kösters, 2015; Huergo & Moreno, 2014), quantitative and qualitative employment change (Cantner & Kösters, 2015; Wolff & Reinthaler, 2008) and on the establishment of external R&D relationships (Broekel & Graf, 2012; Huergo & Moreno, 2014). Therefore, all these changes should also be considered when evaluating the effectiveness of innovation support programs in developing countries. Consequently, besides our three measures of innovation inputs, we consider the qualification of the workforce as an additional innovation input. We also include four types of innovation outputs (product, process, organizational innovation and patents), and three R&D cooperation variables to differentiate between vertical (suppliers and customers), horizontal (competitors) and research partners (universities, public institutions of science and technology and R&D labs)[4].

3. Data and methodology

3.1. *The data and outcome variables*

We use data from the Ecuadorian Survey of Innovation 2013 (ENAI), carried out by the Ecuadorian National Statistics Institute (INEC – Instituto Nacional de Estadística y Censos) and the Secretariat for Higher Education, Science, Technology and Innovation (SENESCYT – Secretaría de Educación Superior, Ciencia, Tecnología e Innovación) (INEC, 2013). The ENAI, similar to the European Community Innovation Survey (CIS), contains information on 2815 firms operating in all sectors of the Ecuadorian economy for the period 2009–2011. Our analysis covers all firms in the sample, although we exclude those that reported sales or a number of employees equal to zero during the three years covered by the survey. This leaves us with a total number of observations of 2811. Note that since the majority of innovation policy studies examine the impact of R&D subsidies on firms' R&D intensity, they often exclude from the analysis non-R&D investors, as R&D subsidies are only targeted at firms involved in R&D activities. However, as we evaluate programs that foster technological and managerial capabilities, we include non-R&D investors as it is possible for a firm to participate in a program while not investing in R&D or innovation activities.

From the total number of firms, 569 indicated participation in an innovation support program during 2009–2011, from which 157 were not involved in any type of innovation activity or did not introduce new products or processes. We use this information to construct our treatment variable, which is a dummy variable taking on 1 if the firm participated in an innovation support program during the abovementioned period. As we have indicated, we aim at evaluating the impact of program participation on firms' innovative behavior and performance. Therefore, we employ several outcome variables in order to test the effectiveness of the programs.

First, we use four measures of innovation inputs: *Internal R&D intensity*, *External R&D intensity*, *Innovation intensity* and *Qualification*. Internal and external R&D intensity are, respectively, defined as the natural logarithm of firms' internal or external R&D expenditures divided by the number of employees. Innovation intensity is measured as the natural logarithm of firms' expenditures on the acquisition of machinery and equipment, hardware, software, disembodied technology, and expenditures on consulting and technical assistance, engineering and industrial design, training programs and market studies, divided by the number of employees. Finally qualification is defined as firms' percentage of employees with higher education. Note that internal and external R&D intensity and innovation intensity are calculated as an average for the period 2009–2011, while qualification is only measured in 2011 due to the availability of data.

Second, we employ four innovation output variables: *Product*, *Process* and *Organizational* innovation and *Patents*. The first three are dummy variables taking on 1 if, during the period 2009–2011, the firm introduced new-to-the-market or new-to-the-firm products[5] and processes or, in the case of organizational innovation, any of the following organizational changes: new management practices in the organization of work, new methods in the organization of the workplace or new methods of managing external relations with other firms or public institutions. The patent variable is a dummy variable that takes value 1 if the firm used patents to protect its new products and processes during the same period.

Finally, we also analyze the impact of support programs on the establishment of R&D and innovation relationships with external partners. A particularity of ENAI, with respect to the CIS, is that the cooperation variables not only refer to cooperation in R&D but also in innovation-related activities such as engineering and design, training, technical assistance, information and product testing. We differentiate between vertical, horizontal and research partners. *Vertical cooperation* taking the value 1 if the firm cooperated with suppliers or customers, *Horizontal cooperation* taking the value 1 if the firm cooperated with competitors, and *Research cooperation* takes the value 1 for firms cooperating with universities, public institutions of science and technology or R&D labs. All cooperation variables refer to the period 2009–2011. Notice that in ENAI only firms that introduced new products or processes or firms involved in R&D or innovation activities responded to the question on cooperation (we will refer to this group as innovative firms). Consequently, for these variables we only have 1555 observations from which 412 stated that they participate in an innovation support program.

3.2. Methods

If innovation support programs were assigned randomly between firms, the mean difference in outcome variables between participants and non-participants would be the causal effects of the programs. However, as there are two selection mechanisms in the programs' allocation process, this approach would lead to biased estimates. Innovation policy studies have documented both sources of selection bias. First, there is self-selection as innovative firms are usually more likely to apply to programs (Alvarez, 2004; Radicic, Pugh, Hollanders, & Wintjes, 2014). Second, there is selection by the government as recipients of programs might be chosen because they represent more promising candidates or because governments support firms with less promising projects (Cantner & Kösters, 2012, 2015; Curran & Storey, 2002; Wallsten, 2000). As a result, firms that participate in programs are unlikely to have the same characteristics as other firms. Moreover, if the characteristics that influence both selection decisions also condition the outcome variables, the estimated coefficients of program participation would not only reflect the impact of the programs but also the influence of these characteristics. Under this scenario, in order to estimate the causal effect we would need to subtract from the mean of the outcome variables of the participants, the mean outcome variables of the same participants as if they had not participated in the programs. Since the latter is a counterfactual that cannot be observed we need to employ a methodology that allows us to calculate it.

A common method used to address selection bias – when panel data are not available – is the matching procedure. The basic idea of matching is to find a group of non-participants that are similar to participants in all the relevant pre-treatment characteristics and to use this group as a perfect substitute for the non-observable counterfactual

(Caliendo & Kopeinig, 2008). Once we have calculated the mean outcome variables for this group of firms, where the only relevant difference with the treated group is precisely the treatment, we can calculate the average treatment effect of the treated (ATT), i.e., the average causal effect of participating in a support program on the outcome variables. Nevertheless, for a proper identification of the ATT, matching requires the satisfaction of the *conditional independence assumption* (CIA) which implies that, conditional on the set of relevant observable pre-treatment characteristics, the assignment to treatment is independent of the outcome, and thus the selection process is random. CIA requires that all the possible variables affecting both the probability of participating in a program and the outcomes are included in the construction of the control group (Rubin & Thomas, 1996). Accordingly, we include the following covariates: *Size* (the natural logarithm of the number of employees), *Investment* (the ratio of fixed capital investment to total sales), *Exports* (firms' export percentage), *Group* (dummy variable taking the value 1 if the firm is part of a business group), *Foreign* (dummy variable which takes the value 1 for foreign subsidiaries), *Public* (dummy variable which takes the value 1 if the firm is publicly owned), *Start-up* (dummy variable taking the value 1 if the firm was created during the period 2009–2011) and *Old* (dummy variable taking the value 1 if the firm has been in business 20 years or more). Finally, we employ six sector dummies to differentiate between high-tech industries (*High*), low-tech industries (*Low*), supplies activities (*Supplies*), mining and quarrying (*Mining*), knowledge intensive business services (*KIBS*) and knowledge non-intensive business services (*KNIBS*). Note that all variables refer to the period 2009–2011 as they are constructed from the ENAI database.

Although we include a large set of relevant covariates to create the control group, CIA is nevertheless a strong assumption as it is likely that there are unobservable characteristics, affecting both the probability of participating in a program and the outcomes, which can affect the construction of the counterfactual. For instance, unobservable firms' routines may affect both program participation and the outcomes. As Heckman, Ichimura, and Todd (1997) indicate, in order to reduce the bias due to unobservable characteristics it is important to use similar observable settings for treated and untreated firms as their decision to participate in a program may be potentially affected by the same unobservable characteristics. Moreover, the bias can be substantially reduced by including contextual factors in the estimation of the propensity score. Consequently, we include the following contextual variables to construct the counterfactual: *Regional migration* (regional[6] migrants over total population), *Convergence region* (dummy variable taking the value 1 if the region has an average per capita wage lower than the national average), *Regional qualification* (share of employees with higher education over total employees by region) and *Regional labor productivity* (firms' average sales per employee by region). Note that regional qualification and regional labor productivity are calculated using ENAI data; while for regional migration and convergence region we use information from the National Survey on Employment, Unemployment and Underemployment ENEMDU (Encuesta de Empleo, Desempleo y Subempleo), conducted by the National Institute of Statistics and Census INEC.

The problem associated with the inclusion of a high number of covariates is that it is very difficult to find an exact match for each participating firm, as the greater the number of variables used in the match the lower the chances of finding a control unit. Nevertheless, as Rosenbaum and Rubin (1983) showed, it is possible to condense the vector of relevant covariates into a single scalar index, called *propensity score*, which is the probability of being treated given the set of relevant covariates. At a given value of the propensity score, the exposure to treatment should be random and thus both treated and controls should be on average observationally identical. Consequently, we employ the non-parametric Propensity Score Matching (PSM) approach, which identifies the unobserved counterfactual by creating a control group of firms that did not participate in a program but, based on the pre-treatment observable characteristics, have the same probability of participating.

The propensity score is calculated with a probit regression where the dependent variable is the treatment, i.e., a variable that takes the value 1 for firms that participated in an innovation program, while independent variables are the abovementioned pre-treatment covariates. Note that since for cooperation outcome variables we just have information for innovative firms, we need to calculate two estimations of the propensity scores: one for all firms and other for innovative firms. Results from these models can be seen in Table 1, which indicates that there are several covariates affecting the probability of participating in a support program.

Although we have calculated the propensity scores for each firm in order to match treated and controls, we might still have no appropriate matches as propensity scores might still be different between participants and non-participants. Therefore, we require the additional assumption of *common support* (CS) in order to ensure that the propensity scores of participants and non-participants overlap. Consequently, we should only use observations where their propensity scores show a positive density for both participants and non-participants.

There are several matching algorithms to construct the weighting functions and the definition of potential 'neighborhoods', which restrict the number of observations that serve as a comparison unit (see Heckman, Ichimura, and Todd [1998] for a review). The choice of a matching algorithm is a matter of a trade-off in terms of bias and the efficiency of the estimator (Caliendo & Kopeinig, 2008) and depends on the data structure. We employ kernel matching, which calculates the counterfactual outcome for each treated individual using the weighted averages of observations from all individuals in the control group and assigns higher weight to observations that are closer in terms of propensity score. Thus, the kernel matching estimator provides advantages in terms of lower variance because it uses more information than other algorithms, but at the risk of including bad matches (Cantner & Kösters, 2015). Hence, the imposition of CS is of major importance for kernel matching.

To check for CS assumption, Figures 1 and 2 depict the propensity score distributions for treated and controls, respectively, for the total sample of firms and for innovative firms. The histograms show the overlap between participants and non-participants in propensity scores.

As we can see, both histograms show that there is considerable overlap in support as we can find untreated firms that can be matched with participants in any range of propensity score values. However, the figures also warn about the quality of the overlap in the upper segment of the distributions since there are treated observations with a high propensity score that are comparable with only a few observations in the control group. For the group of innovative firms, we need to discard one participant from the analysis in order to maintain CS.

Table 2 displays the balancing test of the kernel algorithm for both samples (all firms and innovative firms). It shows the difference in pre-treatment variables between participants and non-participants before and after the matching. As we can observe, before matching, participants and non-participants show significant differences regarding several pre-treatment variables in both samples. For instance, in the sample that includes

Table 1. Probit program participation model.

	All firms	Innovative firms
	(1)	(2)
Size	0.228***	0.204***
	(0.024)	(0.030)
Investment	0.022	−0.009
	(0.030)	(0.024)
Exports	0.454***	0.567***
	(0.085)	(0.103)
Group	0.012	−0.053
	(0.081)	(0.097)
Foreign	0.118	0.013
	(0.139)	(0.170)
Public	0.087	0.170
	(0.184)	(0.227)
Start-up	0.028	−0.125
	(0.160)	(0.203)
Old	−0.032	−0.076
	(0.060)	(0.077)
High	0.906***	0.750***
	(0.123)	(0.156)
Low	0.096	−0.017
	(0.076)	(0.102)
Supplies	0.095	−0.180
	(0.206)	(0.265)
Mining	−0.084	−0.271
	(0.186)	(0.267)
KIBS	0.217***	0.109
	(0.080)	(0.106)
Regional migration	−15.090***	−13.520*
	(5.521)	(6.983)
Convergence region	−0.183**	−0.096
	(0.074)	(0.097)
Regional qualification	1.191	0.700
	(0.770)	(0.903)
Regional labor productivity	−0.031	−0.013
	(0.066)	(0.084)
Constant	−1.459**	−1.252
	(0.735)	(0.967)
Observations	2,811	1,555

***$p<0.01$; **$p<0.05$; *$p<0.1$.
Robust standard errors in parentheses.

all firms, we find that participants are more likely to be large, exporters, belong to a group, to be foreign subsidiaries, public firms, old firms, belong to high-tech industries and are less likely to belong to knowledge non-intensive business services. Moreover, participants are more likely to be embedded in a region in which firms employ more skilled labor and have greater labor productivity and are less likely to belong to a convergence region. These differences appear owing to firms' self-selection into support programs and government selection; therefore, we could not estimate the causal effects by making a direct comparison between the two groups. However, results after matching

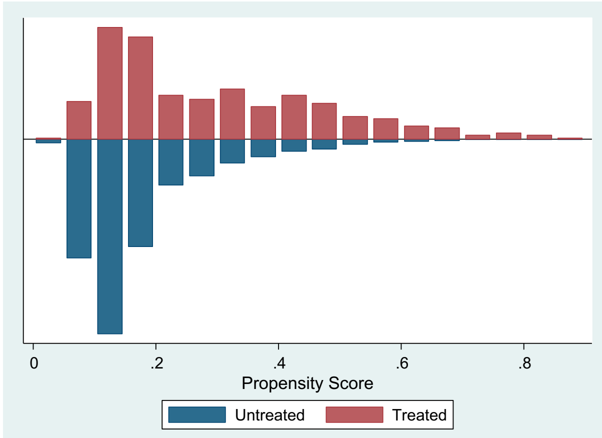

Figure 1. Common support assumption. Total firms.

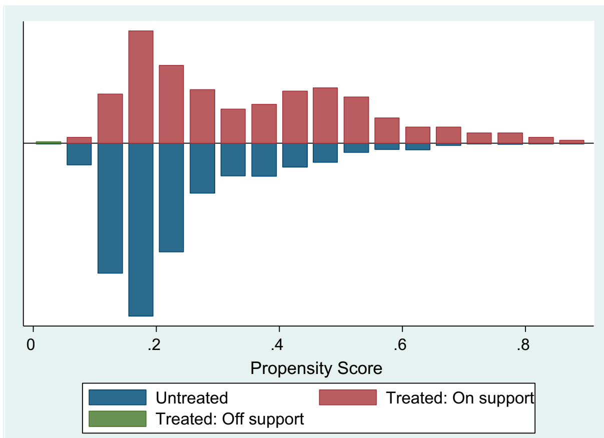

Figure 2. Common support assumption. Innovative firms.

indicate that all the pre-treatment variables are balanced for both groups, showing that PSM has generated an adequate control group, which supports the validity of the method.

To check for the robustness of the kernel results we also perform the nearest-neighbor algorithm, which uses only the closet observation in terms of propensity score as a comparison for a treated firm. Compared with the kernel, this procedure allows for smaller biases at the cost of higher variance. Furthermore, in order to increase the efficiency of the estimates, we also use up to five neighbors to build the counterfactual outcomes.[7] Additionally and following Abadie and Imbens (2008), confidence intervals for the propensity matching estimators are computed using bootstrap[8] (50 replications). Furthermore, we also present the impact of program participation using the regression version of the weighted estimator proposed by Hirano, Imbens, and Ridder (2003) which

Table 2. Differences by treatment status.

Variable	Sample	All firms Treated	All firms Control	All firms *P*-value of T-test	Innovative firms Treated	Innovative firms Control	Innovative firms *P*-value ofT-test
Size	Unmatched	4.304	3.467	0.000***	4.421	3.614	0.000***
	Matched	4.304	4.249	0.551	4.425	4.387	0.736
Investment	Unmatched	0.103	0.095	0.816	0.116	0.151	0.529
	Matched	0.103	0.108	0.918	0.116	0.100	0.682
Exports	Unmatched	0.272	0.092	0.000***	0.303	0.105	0.000***
	Matched	0.272	0.267	0.865	0.304	0.305	0.973
Group	Unmatched	0.239	0.136	0.000***	0.250	0.160	0.000***
	Matched	0.239	0.232	0.785	0.250	0.236	0.633
Foreign	Unmatched	0.075	0.030	0.000***	0.072	0.034	0.001***
	Matched	0.075	0.075	0.982	0.073	0.063	0.595
Public	Unmatched	0.033	0.021	0.080*	0.038	0.026	0.196
	Matched	0.033	0.027	0.590	0.038	0.033	0.684
Start-up	Unmatched	0.029	0.040	0.235	0.026	0.046	0.085*
	Matched	0.029	0.033	0.757	0.026	0.026	0.988
Old	Unmatched	0.514	0.436	0.001***	0.512	0.437	0.009***
	Matched	0.514	0.513	0.965	0.513	0.513	0.998
High	Unmatched	0.116	0.035	0.000***	0.121	0.042	0.000***
	Matched	0.116	0.112	0.868	0.121	0.114	0.743
Low	Unmatched	0.363	0.373	0.674	0.390	0.417	0.348
	Matched	0.363	0.357	0.832	0.391	0.388	0.915
Supplies	Unmatched	0.024	0.024	0.943	0.024	0.030	0.510
	Matched	0.024	0.023	0.923	0.021	0.021	0.965
Mining	Unmatched	0.029	0.025	0.554	0.021	0.022	0.916
	Matched	0.029	0.031	0.841	0.021	0.020	0.897
KIBS	Unmatched	0.265	0.263	0.915	0.269	0.281	0.633
	Matched	0.265	0.272	0.792	0.270	0.282	0.687
KNIBS	Unmatched	0.200	0.278	0.000***	0.172	0.205	0.146
	Matched	0.200	0.201	0.964	0.172	0.172	0.995
Regional migration	Unmatched	0.021	0.022	0.069	0.021	0.022	0.055*
	Matched	0.021	0.021	0.873	0.021	0.021	0.922
Convergence region	Unmatched	0.434	0.492	0.012**	0.427	0.448	0.449
	Matched	0.434	0.433	0.981	0.425	0.432	0.843
Regional qualification	Unmatched	0.263	0.255	0.000***	0.261	0.255	0.029**
	Matched	0.263	0.262	0.836	0.261	0.261	0.938
Regional labor productivity	Unmatched	11.424	11.339	0.000***	11.381	11.286	0.001***
	Matched	11.424	11.417	0.795	11.382	11.380	0.951
Observations	Unmatched	569	2,242		412	1,143	
	Matched	569	2,242		411	1,143	

***p<0.01; **p<0.05; *p<0.1.
The matched sample is obtained using the kernel propensity score method.

weights the observations by the inverse of the propensity score and estimates the ATT directly through ordinary least squares. Hirano et al. (2003) show that their estimator is not only more efficient than matching estimators but also leads to a fully efficient estimator since its large sample properties achieve the efficiency bound.

4. Results

Table 3 shows the ATT of program participation on the different measures of innovation inputs. The ATT is calculated as the difference between the mean outcome of participants and matched non-participants.

The ATT calculated with kernel matching indicates that participating in innovation support programs increases all our measures of innovation inputs except for external R&D intensity. Moreover, the other matching algorithms and the weighted OLS estimator of Hirano et al. (2003) show significant ATT on the range of the kernel estimators for internal R&D intensity, innovation intensity and the qualification of the workforce and also non-significant effects for external R&D intensity. Therefore, the results are robust in relation to the different methods and they indicate that programs, designed to enhance technological and management capabilities, induce firms to invest more, especially in innovation activities that are not R&D; note that the ATT for innovation intensity duplicates the one for internal R&D intensity. This is not surprising as the absorption of technology is more related to the acquisition of machinery and equipment, design, engineering development, experimentation, training and marketing rather than formal R&D (Bell & Pavitt, 1995; Chaminade et al., 2009; Lall, 1992). Nevertheless, these programs also induce firms to invest more in internal R&D, confirming that the fostering of technological and managerial capabilities generates a learning process through which firms internalize new knowledge and get involved in R&D activities (OECD, 2005). The non-significant effect for external R&D intensity suggests that the capabilities needed to make effective use of external knowledge are R&D capabilities that can only be generated when the firm is engaged in its own R&D (Cohen & Levinthal, 1989; Piga & Vivarelli, 2004). Therefore, programs designed to enhance firms' technological and management capabilities do not foster the capability of internalizing external knowledge through external R&D. However, these programs induce firms to hire more skilled labor as the absorption of technology requires qualified personnel (Bell & Pavitt, 1995).

Table 3. Results on innovation inputs.

	Internal R&D intensity (1)	External R&D intensity (2)	Innovation Intensity (3)	Qualification (4)
Kernel	0.880***	0.136	1.747***	0.038***
	(0.140)	(0.082)	(0.322)	(0.012)
Nearest neighbor	0.933***	0.193	2.191***	0.033*
	(0.153)	(0.117)	(0.401)	(0.018)
Five nearest neighbors	0.901***	0.179	1.873***	0.032**
	(0.152)	(0.130)	(0.365)	(0.013)
Weighted OLS	0.871***	0.129	1.687***	0.039***
	(0.137)	(0.088)	(0.285)	(0.010)
Observations	2,811	2,811	2,811	2,811

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$.
Standard errors for matching methods in parentheses using bootstrap with 50 repetitions. Robust standard errors for the Hirano et al. (2003) weighted OLS estimator in parentheses.

Table 4. Results on innovation outputs.

	Product	Process	Organizational	Patents
	(1)	(2)	(3)	(4)
Kernel	0.130***	0.128***	0.121***	0.013
	(0.021)	(0.028)	(0.024)	(0.014)
Nearest neighbor	0.139***	0.127***	0.128***	0.024
	(0.047)	(0.040)	(0.034)	(0.024)
Five nearest neighbors	0.145***	0.134***	0.133***	0.013
	(0.029)	(0.030)	(0.031)	(0.016)
Weighted OLS	0.127***	0.132***	0.126***	0.011
	(0.024)	(0.025)	(0.024)	(0.015)
Observations	2,811	2,811	2,811	2,811

***p<0.01; **p<0.05; *p<0.1.
Standard errors for matching methods in parentheses using bootstrap with 50 repetitions. Robust standard errors for the Hirano et al. (2003) weighted OLS estimator in parentheses.

Table 4 shows the ATT of program participation on the different measures of innovation outputs. Note that since innovation outputs are dichotomous variables, the average outcomes represent a participation rate and therefore display the share of the firms that introduce more innovation outputs both for the treated and for the control group. For this reason, the estimates have to be interpreted as the change in percentage points of the proportion of firms that introduce more innovations after participating in an innovation support program.

Again, our kernel estimators are consistent with the different methods and indicate that participating in an innovation support program increases the probability of introducing new products, processes and organizational practices. Thus, as highlighted by the literature, our results indicate that the fostering of technological capabilities allows firms to create new methods, processes and products (Afuah, 2002; Zhou & Wu, 2010). Moreover, our results show that there are no significant differences between the effects of program participation on any of these three innovation outputs. However, they show that support programs do not allow firms to introduce more patents, which is not surprising as, in order to produce patent-worthy innovations, firms require sufficient R&D capabilities such as R&D planning, internal R&D capability, external cooperative R&D capability, R&D coordination capability and, in particular, intellectual property management (Dickson & Fang, 2008), which are not intended to be fostered by the Ecuadorian programs.

Finally, Table 5 displays the results for the cooperation variables. Note that the number of observation is lower, as for this analysis we only have data for innovative firms. Thus, the matching algorithms use the propensity scores calculated in the probit regression shown in Column 2 of Table 1.

As before, kernel estimators are consistent with the different methods and indicate that participating in an innovation support program increases the probability of establishing innovation and R&D relationships with research partners, but does not affect the likelihood of cooperating with either vertical or horizontal partners. Although there is evidence showing that firms may engage in inter-organizational cooperation in order to

Table 5. Results on cooperation variables.

	(1)	(2)	(3)
Variables	Verticalcooperation	Horizontalcooperation	Research cooperation
Kernel	0.005	0.006	0.105***
	(0.025)	(0.029)	(0.021)
Nearest neighbor			
	0.004	0.019	0.065*
	(0.038)	(0.032)	(0.034)
Five nearest neighbors			
	0.006	0.017	0.085***
	(0.032)	(0.037)	(0.027)
Weighted OLS	0.003	0.013	0.107***
	(0.023)	(0.027)	(0.027)
Observations	1554	1554	1554

***$p<0.01$; **$p<0.05$; *$p<0.1$.
Standard errors for matching methods in parentheses using bootstrap with 50 repetitions. Robust standard errors for the Hirano et al. (2003) weighted OLS estimator in parentheses.

be rewarded with innovation policy instruments or that, by participating in support programs, firms become embedded into cooperation networks (Broekel & Graf, 2012; Huergo & Moreno, 2014), our results indicate that the Ecuadorian innovation support programs do not induce firms to cooperate with vertical or horizontal partners in R&D or innovation activities. Note that the establishment of R&D relationships with external partners requires external cooperative R&D capability – an aspect not directly strengthened by the Ecuadorian programs.

The industrial organization literature emphasizes the importance of knowledge spillovers in the context of collaborative research (d'Aspremont & Jacquemin, 1988; Beath, Katsoulacos, & Ulph, 1988; De Bondt & Veugelers, 1991; Kamien, Muller, & Zang, 1992; Katz, 1986; Leahy & Neary, 1997; Motta, 1992; Suzumura, 1992; Vonortas, 1994) as collaborations make it possible to internalize such spillovers and thus increase appropriability of returns within the partnership (Broekel, Schimke, & Brenner, 2011). Consequently, when spillovers are high, firms have an incentive to engage in R&D collaborations. However, as the Ecuadorian innovation programs do not foster the capability of firms to internalize knowledge spillovers, they do not increase the probability of establishing external R&D partnerships. Nevertheless, our results indicate that by participating in a support program, firms become embedded into cooperation networks with research partners, which might be explained by the fact that one aspect of the Ecuadorian innovation support programs is the promotion of partnerships with universities and public institutions of science and technology.

5. Conclusion

Innovation policy impact assessment studies focus on developed countries and they mostly evaluate the effectiveness of R&D subsidies and tax incentives. However, in developing countries, innovation policy instruments consist of several support programs designed to enhance the technological and managerial capabilities of participating firms. Although these programs may have an impact on firms' innovative behavior and performance, their efficacy has not been tested.

Drawing on data from the Ecuadorian Survey of Innovation 2013, this paper evaluates the effects of participating in an Ecuadorian innovation support program on firms' internal and external R&D intensity, innovation intensity, workforce qualification, product, process and organizational innovation, patents and vertical, horizontal and research R&D and innovation networks. Given that the Ecuadorian innovation support programs are intended to strengthen the technological and managerial capabilities of firms, it is argued that these programs may have different impacts on the innovation behavior and performance of participating firms.

In order to assess the causal effects of program participation, we deal with selection bias by using different Propensity Score Matching methodologies (kernel, nearest neighbor and five nearest neighbors) and by calculating the weighted estimator proposed by Hirano et al. (2003). Our findings, which are robust to the different methodologies applied, indicate that innovation support programs induce firms to invest more in internal R&D and innovation activities (although their effect is lower for R&D activities), to hire more skilled employees, introduce product, process and organizational innovations and to establish R&D and innovation relationships with research partners. However, results also suggest that programs do not increase firms' external R&D intensity, patents or the likelihood of establishing R&D and innovation relationships with vertical or horizontal partners.

Based on these results, it is argued that the fostering of technological and managerial capabilities through public support programs allows firms to get involved in R&D and innovation activities, as well as being more successful innovators. However, as the use of external knowledge and the internalization of knowledge spillovers require R&D capabilities and absorptive capacity, which are not enhanced by the support programs, participating firms do not increase their external R&D effort, nor they are more willing to establish linkages with suppliers, customers or competitors. Additionally, it is likely that by participating in support programs firms get embedded in networks with research partners because one aspect of the programs is the promotion of linkages with universities and public institutions of science and technology.

Our findings have important policy implications for developing countries as they suggest that innovation policies designed to enhance firms' technological and managerial capabilities can also improve the innovative behavior and performance of firms. Innovation programs tend to focus almost exclusively on science modes of learning and consequently on formal R&D. However, in developing countries, innovation policy should be more concerned with supporting on-the-job learning and easing interactions with the users (Chaminade et al., 2009). Therefore, those policies supporting competence building in engineering, design, training and managerial capabilities should be more effective (Chaminade & Vang, 2008; Chaminade et al., 2010). Once firms have developed technological and managerial capabilities and the national innovation system contains advanced R&D organizations and institutions that allow firms to establish satisfactory R&D networks, the policies designed to exploit firms' R&D capabilities may become effective (Galli & Teubal, 1997). As Chaminade et al. (2009) indicate, in mature innovation systems firms can develop R&D capabilities because they have first developed their absorptive capacity and are engaged in interactive learning with other organizations in the system.

Finally, this paper opens up future lines of research regarding the analysis of innovation policy as it indicates that other instruments besides R&D subsidies, tax incentives or public procurement should be considered when evaluating the impact of public innovation policies, especially in developing countries.

Disclosure statement

We acknowledge that there are no financial interests or benefits arising from the direct applications of this research.

Notes

1. http://anda.inec.gob.ec/anda/index.php/catalog/348
2. ENAI classifies support programs in the following categories: personal training, innovation support, technology adoption and management, production certificates, entrepreneurship support and export promotion.
3. In ENAI, internal R&D is defined as creative work undertaken on a systematic basis in order to generate new knowledge (scientific or technical), to apply or leverage existing knowledge or to use knowledge developed by others, which includes basic research and experimental development; while external R&D refers to the same activities contracted out to external agents.
4. Section 3 describes all the variables.
5. By products we mean both goods and services.
6. The regional variables refer to the Ecuadorian 24 provinces.
7. Results of group differences by treatment status from both nearest neighbor matching estimates and common support analysis are available upon request from the authors. Note that both nearest-neighbor and five-nearest-neighbors also create a control group that is balanced in pre-treatment variables and requires one treated firm to be discarded from the innovative firms subsample.
8. Standard errors for matching estimators are, in practice, generated by bootstrap resampling methods. The use of bootstrapping is backed by Abadie and Imbens (2008), who indicate that the standard bootstrap can be applied to assess the variability of kernel or local linear matching estimators. However, they show that standard bootstrap methods are not valid for assessing the variability of nearest neighbor estimators.

ORCID

Fernando Martín-Mayoral http://orcid.org/0000-0002-8553-5770

References

Abadie, A., & Imbens, G. W. (2008). On the failure of the bootstrap for matching estimators. *Econometrica, 76*, 1537–1557.

Afuah, A. (2002). Mapping technological capabilities into product markets and competitive advantage: The case of cholesterol drugs. *Strategic Management Journal, 23*, 171–179.

Alvarez, R. (2004). Sources of export success in small-and medium-sized enterprises: The impact of public programs. *International Business Review, 13*, 383–400.

Arocena, R., & Sutz, J. (2000). Looking at national systems of innovation from the South. *Industry and Innovation, 7*, 55–75.

Arocena, R., & Sutz, J. (2002). *Innovation systems and developing countries* (No. 02-05). DRUID, Copenhagen Business School, Department of Industrial Economics and Strategy/ Aalborg University, Department of Business Studies.

Aschhoff, B. (2009). *The effect of subsidies on R&D investment and success–Do subsidy history and size matter?* ZEW-Centre for European Economic Research Discussion Paper, (09-032).

d'Aspremont, C., & Jacquemin, A. (1988). Cooperative and noncooperative R & D in duopoly with spillovers. *The American Economic Review*, *7*, 1133–1137.

Beath, J., Katsoulacos, Y., & Ulph, D. (1988). R&D rivalry vs R&D cooperation under uncertainty. *Recherches Economiques de Louvain/Louvain Economic Review*, *54*, 373–384.

Bell, M., & Pavitt, K. (1995). The development of technological capabilities. *Trade, technology and international competitiveness, 22*, 69–101.

Bérubé, C., & Mohnen, P. (2009). Are firms that receive R&D subsidies more innovative? *Canadian Journal of Economics/Revue canadienne d'économique, 42*, 206–225.

Blakney, M. (1987). Transfer of technology and developing nations. *Fordham Int'l LJ, 11*, 689–723.

Broekel, T., & Graf, H. (2012). Public research intensity and the structure of German R&D networks: A comparison of 10 technologies. *Economics of Innovation and New Technology, 21*, 345–372.

Broekel, T., Schimke, A., & Brenner, T. (2011). *The effects of cooperative R&D subsidies and subsidized cooperation on employment growth* (No. 34). Working paper series in economics.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*, 31–72.

Cantner, U., & Kösters, S. (2012). Picking the winner? Empirical evidence on the targeting of R&D subsidies to start-ups. *Small Business Economics, 39*, 921–936.

Cantner, U., & Kösters, S. (2015). Public R&D support for newly founded firms–effects on patent activity and employment growth. *Journal of Innovation Economics & Management, 16*, 7–37.

Chaminade, C., Lundvall, B. Å., Vang, J., & Joseph, K. J. (2009). Designing innovation policies for development: Towards a systemic experimentation-based approach. In: B. Å. Lundvall, K. J. Joseph, C. Chaminade, & J. Vang (Eds.), (2011). *Handbook of innovation systems and developing countries: Building domestic capabilities in a global setting* (pp. 360–379). Cheltenham: Edward Elgar Publishing.

Chaminade, C., Lundvall, B. Å., Vang, J., & Joseph, K. J. (2010). *Innovation policies for development: Towards a systemic experimentation based approach*. Papers in Innovation Studies 2010/1, Lund University, CIRCLE – Center for Innovation, Research and Competences in the Learning Economy.

Chaminade, C., & Vang, J. (2008). Globalisation of knowledge production and regional innovation policy: Supporting specialized hubs in the Bangalore software industry. *Research Policy, 37*, 1684–1696.

Cimoli, M., Dosi, G., Nelson, R. R., & Stiglitz, J. E. (2009). Institutions and policies in developing economies. In B. Å. Lundvall, K. J. Joseph, C. Chaminade, & J. Vang (Eds.), (2011). *Handbook of innovation systems and developing countries: Building domestic capabilities in a global setting* (pp. 337–359). Cheltenham:Edward Elgar Publishing.

Clausen, T. H. (2009). Do subsidies have positive impacts on R&D and innovation activities at the firm level? *Structural Change and Economic Dynamics, 20*, 239–253.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: The two faces of R & D. *The Economic Journal*, *9*, 569–596.

Curran, J., & Storey, D. J. (2002). Small business policy in the United Kingdom: The inheritance of the Small Business Service and implications for its future effectiveness. *Environment and Planning C, 20*, 163–177.

Czarnitzki, D., Hottenrott, H., & Thorwarth, S. (2011). Industrial research versus development investment: The implications of financial constraints. *Cambridge Journal of Economics, 35*, 527–544.

David, P. A., Hall, B. H., & Toole, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy, 29*, 497–529.

De Bondt, R., & Veugelers, R. (1991). Strategic investment with spillovers. *European Journal of Political Economy, 7*, 345–366.

Diamond, A. M. (1999). Does federal funding "crowd in" private funding of science? *Contemporary Economic Policy, 17*, 423–431.

Dickson, K., & Fang, F. (2008, December). Management of R&D within a Dynamic Standardization Environment. In *The 5th International Conference of Innovation & Management, The Netherlands* (pp. 623–629).

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science, 47*, 117–132.

Galli, R., & Teubal, M. (1997). Paradigmatic shifts in national innovation systems. In C. Edquist (Ed.), *Systems of innovation: Technologies, institutions and organizations* (pp. 342–370). London: Printer.

Gomel, M. M., & Sbragia, R. (2006). A Capacitação Tecnológica e o Desempenho Exportador da Indústria Brasileira de Software: O Papel dos Investimentos em P&D [The technological capability and exporter performance of the Brazilian software industry: The role of R & D investments]. *Journal of Technology Management & Innovation, 1*, 60–73.

Görg, H. & Strobl, E. (2007). The effect of R&D subsidies on private R&D. *Economica, 74*, 215–234.
Guerzoni, M., & Raiteri, E. (2015). Demand-side vs. Supply-side technology policies: Hidden treatment and new empirical evidence on the policy mix. *Research Policy, 44*, 726–747.
Hall, B. (2005). *Innovation and Diffusion*. Cambridge, MA: National Bureau of Economic Research.
Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies, 64*, 605–654.
Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies, 65*, 261–294.
Herrera, L., & Martínez, A. (2009). La I+ D pública complementa o sustituye la I+ D privada? Un análisis de la insdustria manufacturera española. Paper presented to the. In XIX National Conference of ACEDE.
Higgins, R. S., & Link, A. N. (1981). Federal support of technological growth in industry: Some evidence of crowding out. *Engineering Management, IEEE Transactions on, 4*, 86–88.
Hirano, K., Imbens, G., & Ridder, G. (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica, 71*, 1161–1189.
Huergo, E., & Moreno, L. (2014). National or international public funding? Subsidies or loans? Evaluating the innovation impact of R&D support programmes. MPRA Paper 54218. Retrieved from http://mpra.ub.uni-muenchen.de/54218/
Hussinger, K. (2008). R&D and subsidies at the firm level: An application of parametric and semiparametric two-step selection models. *Journal of Applied Econometrics, 23*, 729–747.
INEC. (2013). *Encuesta Nacional de Innovación 2013: metodología del diseño muestral*. Ecuador: Instituto Nacional de Estadística y Censos.
INEC & SENESCYT. (2011). *Principales indicadores de ciencia, tecnología e innovación, periodo 2009-2011*. Instituto Nacional de Estadística y Censos, Secretaría de Educación Superior, Ciencia, Tecnología e Innovación, Ecuador. Retrieved from http://www.ecuadorencifras.gob.ec/documentos/web-inec/Estadisticas_Economicas/Ciencia_Tecnologia/Presentacion_de_principales_resultados_ACTI.pdf
Intarakumnerd, P., & Chaminade, C. (2011). Innovation policies in Thailand: Towards a system of innovation approach? *Asia Pacific Business Review, 17*, 241–256.
Jensen, M. B., Johnson, B., Lorenz, E., & Lundvall, B. Å. (2007). Forms of knowledge and modes of innovation. *Research Policy, 36*, 680–693.
Kamien, M. I., Muller, E., & Zang, I. (1992). Research joint ventures and R&D cartels. *The American Economic Review*, *82*, 1293–1306.
Katz, M. L. (1986). An analysis of cooperative research and development. *The RAND Journal of Economics*, *17*, 527–543.
Keller, W. (2004). International technology diffusion. *Journal of Economic Literature, 42*, 752–782.
Koga, T. (2005). R&D subsidy and self-financed R&D: The case of Japanese high-technology start-ups. *Small Business Economics, 24*, 53–62.
Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science, 3*, 383–397.
Lall, S. (1992). Technological capabilities and industrialization. *World Development, 20*, 165–186.
Le Bas, C., & Sierra, C. (2002). 'Location versus home country advantages' in R&D activities: Some further results on multinationals' locational strategies. *Research Policy, 31*(4), 589–609.
Leahy, D., & Neary, J. P. (1997). Public policy towards R&D in oligopolistic industries. *The American Economic Review*, *87*, 642–662.
Link, A. N. (1982). An analysis of the composition of R&D spending. *Southern Economic Journal*, *49*, 342–349.
Lundvall, B. Å. (2007). *Innovation system research and policy. Where it came from and where it might go*. Oslo: Center for Advances Studies – Norwegian Academy of Science and Letters.
Motta, M. (1992). Cooperative R&D and vertical product differentiation. *International Journal of Industrial Organization, 10*, 643–661.
Nelson, R. R. (1959). The simple economics of basic scientific research. *The Journal of Political Economy, 67*, 297–306.

OECD. (2005). *Oslo manual: Guidelines for collecting and interpreting innovation data*. Paris: Organisation for Economic Co-operation and Development: Statistical Office of the European Communities.
Özçelik, E., & Taymaz, E. (2008). R&D support programs in developing countries: The Turkish experience. *Research Policy, 37*, 258–275.
Patel, P., & Vega, M. (1999). Patterns of internationalisation of corporate technology: Location vs. Home country advantages. *Research Policy, 28*, 145–155.
Perez, C. (1986). *Catching up in technology: Entry barriers and windows of opportunity*. London: Frances Pinter.
Piga, C. A., & Vivarelli, M. (2004). Internal and external R&D: A sample selection approach*. *Oxford Bulletin of Economics and Statistics, 66*, 457–482.
Piva, M. (2004). The impact of technology transfer on employment and income distribution in developing countries: A survey of theoretical models and empirical studies. SSRN Electronic Journal SSRN Journal. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=907473
Radicic, D., Pugh, G. T., Hollanders, H., & Wintjes, R. (2014). *The impact of innovation support programmes on SME innovation in traditional manufacturing industries: An evaluation for seven EU regions*. UNU-MERIT Working Paper, (2014-033).
Robson, M. (1993). Federal funding and the level of private expenditure on basic research. *Southern Economic Journal, 60*, 63–71.
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*, 41–55.
Rubin, D. B., & Thomas, N. (1996). Matching using estimated propensity scores: Relating theory to practice. *Biometrics,* 249–264.
Rush, H., Bessant, J., & Hobday, M. (2007). Assessing the technological capabilities of firms: Developing a policy tool. *R&D Management, 37*, 221–236.
SENPLADES. (2012). *Transformación de la matriz productiva a través del conocimiento y el talento humano* [Transformation of the productive matrix through knowledge and human talent]. Secretaría Nacional de Planificación y Desarrollo.
Smith, K. (2005). Measuring innovation. In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), *The Oxford handbook of innovation* (pp. 148–177). Oxford: Oxford University Press.
Suzumura, K. (1992). Cooperative and noncooperative R&D in an oligopoly with spillovers. *The American Economic Review, 82*, 1307–1320.
Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy, 15*, 285–305.
Viotti, E. B. (2002). National learning systems: A new approach on technological change in late industrializing economies and evidences from the cases of Brazil and South Korea. *Technological Forecasting and Social Change, 69*, 653–680.
Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues, 48*, 123–154.
Vonortas, N. S. (1994). Inter-firm cooperation with imperfectly appropriable research. *International Journal of Industrial Organization, 12*, 413–435.
Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: The case of the Small Business Innovation Research program. *The RAND Journal of Economics, 31*, 82–100.
Westphal, L., Kim, L., & Dahlman, C. (1985). Reflections on the Republic of Korea's acquisition of technological capability. In N. Rosenberg & C. Frischtak (Eds.), *International technology transfer* (pp. 167–221). New York, NY: Praeger.
Wolff, G. B., & Reinthaler, V. (2008). The effectiveness of subsidies revisited: Accounting for wage and employment effects in business R&D. *Research Policy, 37*, 1403–1412.
Zawislak, P. A., Cherubini Alves, A., Tello-Gamarra, J., Barbieux, D., & Reichert, F. M. (2012). Innovation capability: From technology development to transaction capability. *Journal of technology management & innovation, 7*, 14–27.
Zhou, K. Z., & Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. *Strategic Management Journal, 31*, 547–561.
Zúñiga-Vicente, J. Á., Alonso-Borrego, C., Forcadell, F. J., & Galán, J. I. (2014). Assessing the effect of public subsidies on firm R&D investment: A survey. *Journal of Economic Surveys, 28*, 36–67.