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Supply-side versus Demand-side Innovation Policies in Peru:

The Impacts of Public Procurement of Innovation

Gustavo Crespi
Rafael Castillo

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Inter-American Development Bank
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Washington, D.C. 20577
www.iadb.org

Abstract

This paper exploits new data on the participation of Peruvian firms on public tenders to shed light on the potential for public procurement to encourage innovation. Many industrialized countries have gradually enlarged their innovation policy mix to include demand-side interventions, among them the use of public procurement to stimulate innovation investment at the firm level. Latin America, though, exhibits an unbalanced policy mix with little deployment of policy interventions that tackle the conditions that affect the demand for innovation. Using nonexperimental impact evaluation techniques, this research not only assesses the impacts of participating in public procurement projects on firm-level innovation efforts and outcomes but also compares these impacts with traditional supply-side approaches. The findings suggest that public procurement has a significant impact on innovation outcomes, but the results only hold when public procurement requires the development of new solutions. Regular or noninnovative public procurement does not show any impact on firm-level innovation.

JEL Classifications: L1, L2, L5, H4, O3
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CONTENTS

Introduction

The contribution of innovation to economic growth is increasingly recognized. Indeed, in the case of the United States, almost two-thirds of productivity growth during the post-World War II period is explained by research and development (R&D) efforts and the diffusion of information and communication technologies.[1] It is not surprising that most industrialized countries have implemented various policy schemes to promote private investment in innovation. Overall, it can be said that support to private innovation includes both supply-side and demand-side approaches. Supply-side interventions focus on those failures that affect business as originators of innovation, while demand-side interventions focus on those ones that affect both private and public consumers plus businesses as users of innovative solutions (Steinmueller, 2010). Although in Latin America and the Caribbean (LAC) supply-side policies have dominated innovation policies so far, demand-side interventions such as public procurement are gaining more traction as an alternative to foster firm innovation. Among the factors that underly this trend are the increasing disappointment with supply-side interventions to show impacts on market performance, the wide-spread interest in demand-side policies, in particular procurement, in Organisation for Economic Co-operation and Development (OECD) countries (Moñux and Uyarra, 2016), and the increasing fiscal constraints to push for a rollout of supply-side policies, which contrasts with the capacity of public procurement to mobilize resources due to the potential impact of a large market. For instance, in 2016, public procurement represented on average 30 percent of total government expenditure and 9 percent of gross domestic product (GDP) in Latin American and Caribbean (Izquierdo et al., 2018).

Additionally, there is a growing literature about innovation that points out different reasons to use public procurement to encourage innovation: (i) increasing attention to mission-oriented policies (Mazzucato, 2015); (ii) pressing demands to respond more effectively to societal challenges; and (iii) public procurement as a way to compensate decreasing direct government support to innovation in times of fiscal constraints (Crespi and Guarascio, 2019). In this regard, public procurement can act as a mission-oriented policy that allows governments to respond to productive, social, and environmental challenges (Edquist and Zabala-Iturriagagoitia, 2012; Kuhlmann and Rip 2014, Uyarra et al., 2020) as well as reduce regional disparities and promote economic growth (Uyarra et al., 2020). Also, public procurement might become an additional source of resources to support firm innovation in the context of limited fiscal capacity to fund supply-side innovation policies (such as subsidies or tax incentives). Although expenditures on R&D and innovation activities vary among LAC countries, on average the region spends 0.64 percent of GDP, which is substantially below the average in OECD countries (2.38 percent) (RICYT, 2020; OECD, 2020a). Catching up with the OECD figures requires a serious revamping of regional science and technology budgets; however, as a response to the COVID-19 pandemic, governments have allocated their limited resources to providing support for short-term liquidity of businesses, deploying social protection programs, and improving public health-care systems, all which puts traditional supply-side innovation support schemes under severe fiscal stress.

[1] About 1 percent of 1.5 percent per year during the period 1950–2007 (Reikard, 2011).

Industrialized countries have a long tradition of using public procurement to stimulate innovation; however most of this experience has been historically constrained to the national defense sectors. More recently, there has been a growing rollout of public procurement in other government areas, after the European Union (EU) passed new directives on public procurement in 2014. Although Latin American countries lag in these developments, there is a growing interest in including public procurement within the innovation policy mix of the region. However, policymaking should be guided by evidence, and despite the growing deployment of public procurement to promote innovation in OECD countries, there are only a few evaluations to assess its impact. Moreover, evidence based on OECD impacts should not be applied directly to LAC countries, where innovation systems are weaker, institutional capacities are incipient, and production structures are very different. So, in this research we take some steps forward to understand whether public procurement could also be a promising avenue to encourage private innovation in the LAC region. In this context, the following research questions guide this research: Do demand-side policies impact innovation in firms in Peru? And are demand-side policies more effective in promoting innovation than supply-side policies in Peru?

The purpose of this paper is to evaluate the impact of demand-side and supply-side policies on innovation in Peru. Although Peru does not have an explicit policy regarding public procurement of innovation (PPI), Peru's 2018 National Survey of Innovation of Manufacturing Sector and Knowledge-Intensive Services (INEI, 2019) included two questions regarding public procurement in its innovation survey of the manufacturing sector and knowledge-intensive services. This provided a way to gather firsthand evidence to evaluate public procurement impact on innovation efforts and results. The paper also assesses the impact of supply-side policies, mainly through matching grants and tax incentives, on innovation to determine whether there is a difference from PPI. Finally, this paper contributes to the literature about innovation by providing firm-level evidence of the impact of supply-side and demand-side policies in Peru.

1. Literature Review

There is a vast literature regarding policies that support business innovation. These policies are designed to correct market failures that harm private innovation activities. Market failures associated with innovation activities are externalities related to the public good nature of knowledge, which only allows firms to partially appropriate innovation returns; information asymmetries and uncertainty, which restrain access to financial resources to develop new technologies; and coordination problems among knowledge suppliers and users (Aghion et al., 2009). In LAC, the design of innovation policies has favored supply-side instruments such as matching grants and tax incentives, while demand-side interventions have gained greater importance for policymakers only in recent years. This is consistent with the evolution of innovation policy frameworks, which were initially led by a linear view of innovation but that later evolved into a systemic view of the innovation process (Sagasti, 2009). However, and despite this transition, supply-side policies are still predominant in the innovation policy mixes.

Innovation policy instruments can be classified based on their attempts to either increase the supply of innovation or promote the demand for innovation activities. Supply-side policies such as subsidies and tax incentives are the most well-known and widely used instruments in the innovation policy mix. These policies seek to increase private innovation investments through reducing the private cost of these investments either directly through subsidies, indirectly through tax returns, or through promoting collaboration between academia and industry (Köhler et al, 2012; Cunningham et al, 2013). There is an extensive literature on the impact of supply-side instruments on innovation performance. Zúñiga-Vicente et al. (2014) conducted one of the most comprehensive reviews of the impact of subsidies on private innovation investments around the world. They document the results of 76 studies carried out at the firm level since the early 1960s, most of which were published in the 2000s. Although the studies are not fully comparable, a general pattern clearly emerges as in 60 percent of the cases the crowding-in hypothesis of privately funded investment cannot be ruled out; in the rest of the studies, crowding out (20 percent) or nonsignificant effects (20 percent) are shown. More recently, Dimos and Pugh (2016) provide a meta-regression analysis (MRA) of micro-level studies published since 2000 on the impact of public subsidy for R&D on either input or output R&D. Their MRA findings reject crowding-out of private investment by public subsidy but reveal no evidence of substantial crowding-in. As in other regions, the most common approach to assessing the effectiveness of R&D subsidies in LAC has been to evaluate their effects on private R&D investment. Crespi et al. (2014) and Figal Garone and Maffioli (2016) summarize the results of 16 impact evaluations undertaken in the region. Their analysis shows that, in most cases, subsidies do stimulate R&D investments, and there is evidence of a crowding-in effect. Interestingly, the effects tend to be larger when subsidies target projects that involve collaboration between firms and research institutes. Thus, the empirical evidence tends to confirm that R&D subsidies are an effective way to increase private R&D investment. However, the literature presents mixed results about output additionality depending on firm size, grant amount, sector (such as high-tech), and the presence of other innovation policies (Cunningham et al, 2013; OECD, 2014). Moreover, although recent studies indicate positive input additionality, rejecting crowding-out, the effects are somehow still limited (Crespi et al., 2014; Guerzoni and Raiteri, 2015; Figal Garone et al., 2016; Radicic, 2019; OECD, 2020b).

Demand-side policies such as public procurement have been used recently to promote innovation.[2] Public procurement can be defined as regular or innovative. Regular public procurement refers to the acquisition of goods and services already available in the market. Regular public procurement is based on product specification and, most of the time, does not involve innovation activities. On the contrary, public procurement of innovation (PPI) is defined as the purchase of products or processes that previously did not exist in the market to fulfill a government function (Edquist and Zabala-Iturriagagoitia, 2012). Edquist and Zabala-Iturriagagoitia (2020) states that defining PPI in terms of product specifications is incorrect because if the product can be described in advance, then it cannot be considered an innovation. Functional procurement is an alternative concept for public procurement that fosters innovation and is defined as the purchase of "functions that provide solutions to problems" (Edquist and Zabala-Iturriagagoitia, 2020: 12).

Although regular public procurement is not deliberately aimed at supporting innovation, the literature indicates that this policy might still promote the demand for innovations (Moñux and Uyarra, 2016). Regular public procurement could induce innovation through market creation and size effects, which could encourage innovation and reduce uncertainty for firms (Georghiou et al., 2014; Uyarra et al., 2014; Moñux and Uyarra, 2016 Crespi and Guarascio, 2019). On the other hand, when public procurement explicitly requires the implementation of innovation activities, it promotes innovation by: (i) directly purchasing new goods or services, (ii) providing a space for experimentation in (real) market conditions; (iii) revealing market needs (government requirement) to suppliers; (iv) lowering the cost of learning for the suppliers; and (v) promoting learning and co-creation among innovation system actors such as government, universities, and companies (Aschhoff and Sofka, 2009; Guerzoni and Raiteri, 2015; Uyarra, 2020).[3]

There are only a few evaluations of the impact of PPI in which the evidence is not conclusive (Aschhoff and Sofka, 2009; Guerzoni and Raiteri, 2015; Georghiou et al., 2014; Edler et al., 2015; Moñux and Uyarra, 2016; Raiteri, 2018; Fernández-Sastre and Montalvo-Quizhpi, 2019; Radicic, 2019; Stojčić et al., 2020). These evaluations focus on developed economies and assess the impacts of supply-side and demand-side policies to compare their effects on innovation. One of the few studies for LAC was done by Fernández-Sastre and Montalvo-Quizhpi (2019) for Ecuador. They use the 2013 Innovation Survey and the State Suppliers database to evaluate the effect of regular public procurement and financial support programs to promote firm innovation. This study finds that financial support programs have a positive impact to foster innovation while regular public procurement contracts, no matter their size, do not have an impact on innovation input variables such as R&D expenditure. These results indicate that in

[2] Other demand-side policies are regulations and standards.

[3] For instance, Crespi and Guarascio (2019) analyze the role of public procurement in shaping innovation activities at the sectoral level. This study finds that industries characterized by relatively more-intense public procurement flows have also more-intense innovative dynamics in terms of patents, and industries displaying a relatively stronger import penetration are characterized by a significant reduction in the pro-innovative effect of public procurement.

Ecuador, where firms' innovation capabilities are rather limited, policies that increase capabilities to generate and assimilate new knowledge are more effective in promoting innovation than policies that increase the demand for innovation (Fernández-Sastre and Montalvo-Quizhpi, 2019). In another paper, Betancor, Crespi, and Robano (2019) analyze the effectiveness of regular public procurement to spur the development and expansion of innovative start-up companies in Uruguay. They analyze two mechanisms through which regular public procurement could have a positive impact on companies: (i) making it possible to reach a sufficient scale to expand in the domestic market or abroad and, (ii) complementing innovation public support programs. They do not find any evidence indicating that being a supplier of the state affects the development and expansion of companies. However, they reject the null hypothesis that there is no effect of regular public procurement on the exports growth of start-ups. Indeed, both in the case of those that have not made innovations and in the case of innovators, being a public supplier is linked to a greater orientation to the external market. Betancor, Crespi, and Robano also reject the null hypothesis that there is no impact on the interaction of demand-side policies and supply-side policies.

Finally, with regard to industrialized countries, Stojčić et al. (2020) use a quasi-experimental method for 41,623 firms of eight catching-up countries of Central and Eastern European and find that, although financial support programs and PPI have a positive effect on product and process innovation, financial support programs have a larger impact on innovative sales. Also, Radicic (2019) finds that for 6,719 innovative firms from manufacturing and services sector in the United States and EU, the treatment effect on product innovation in both goods and services is larger for PPI than public financial support in both sectors. However, this study finds no statistical difference in the treatment effect of PPI or public financial support for process innovation. Our paper further explores whether public procurement show a differential impact on innovation inputs and outputs when comparing with supply-side public support programs.

2. Conceptual Framework

This section introduces a very simple conceptual framework to guide the formulation of the main hypotheses of this paper. This conceptual framework builds on the concept of Technological Readiness Level (TRL). The TRL was originally developed at NASA (the U.S. National Aeronautics and Space Administration) during the 1970s, as a method for estimating the maturity of a given technology. A technology's TRL is determined during a Technology Readiness Assessment (TRA) that examines concepts, requirements, and demonstrated capabilities. Technologies are assessed on a scale from 1 to 9, with 9 being the most mature technology (Héder, 2017). The European Commission advised EU-funded research and innovation projects to adopt the scale in 2010. The nine levels are defined in Table 1.

Table 1: Technological Readiness Levels (TRLs) and Supply- and Demand-Side Policies

Supply-Side Policy	TRL (EU Definition)	Demand-Driven Policy
↓	(1) Basic principles observed	↑
	(2) Technology concept formulated	
	(3) Experimental proof of concept	
	(4) Technology validated in lab	
	(5) Technology validated in relevant environment	
	(6) Technology demonstrated in relevant environment	
	(7) System prototype demonstration in operational environment	
	(8) System complete and qualified	
	(9) Actual system proven in operational environment	

Source: Authors' elaboration.

As it is possible to appreciate from Table 1, the focus of supply-side policies (R&D subsidies and tax incentives) is to promote those activities with a higher level of uncertainties and where the spillovers can be the highest due to the generic nature of the knowledge being created. For these reasons, innovation projects supported by supply-side policies mostly focus on TRLs 1 to 5, which are the phases of research and technological development plus technical validation of the technology. Beyond these levels, it is the responsibility of the firm to take the innovation to the market, which requires passing through further levels of technical validation and most importantly reaching commercial validation. Given the uncertainties and potential market failures in these other steps, not all projects are expected to successfully reach the market. For this reason, the main focus of the policy is to increase private sector investment in innovation.

With PPI, the opposite happens. In this case, the focus of the policy is to solve a concrete problem so those companies that can show that they already have a validated prototype with all the qualifications needed for implementation will be given higher priority. We are mostly talking here of projects between TRLs 6 to 9. To win the competition, the company might or might not need to do R&D because it can simply rest on the stock of knowledge that it already has, and that might be the result of R&D carried out in the past. Sometimes some complementary R&D might be needed to adapt the prototypes already available to the specific functional requirements asked for by the client. For this reason, the principal focus of the policy is to reach the market with an innovative solution—something that sometimes, but not always, could be accompanied by doing R&D. Based on the previous discussion, the following two hypothesis are put forward:

Hypothesis 1: Supply-side policies outweigh demand-side policies if the policy focus is the promotion of innovation investment.

Hypothesis 2: Demand-side policies outweigh supply-side policies if the policy focus is the promotion of innovations outcomes available in the market.

The comparison between regular public procurement and innovative public procurement is also relevant. As mentioned above, regular procurement could also have a positive impact on both innovation investments and outcomes if the market is enlarged and uncertainty is reduced. However, most of the regular procurement is based on standard products with very little or nil technological opportunities. Accordingly, we should expect that innovation impacts of PPI are higher than for the case of regular procurement. This leads to our third hypothesis.

Hypothesis 3: Public procurement of innovation (PPI) should have higher impact than regular public procurement (PP), both in terms of innovation investment and outcomes.

3. Data and Variables

We use the 2018 National Survey of Innovation of Manufacturing Sector and Knowledge-Intensive Services or ENIIMESIC (INEI, 2019), which contains information for the period 2015–2017. This survey includes indicators of the characteristics of the firm, innovation activities, innovation results, financing, public procurement, human resources, sources of information and collaboration, intellectual property, and obstacles to innovate. The total number of observations of the 2018 ENIIMESIC is 2,084 firms (small, medium, and large) of which 54.9 percent (1,145) carried out innovation activities and from which 52.6 percent of those achieved innovation results. In this paper we only include for the analysis firms that carried out innovation activities during the 2015–2017 period.

By design, the ENIIMESIC included two questions regarding public procurement and which are exploited in this paper. These questions are the following: During the 2015–2017 period, has the firm been selected in any public procurement contract? If so, has the firm carried out innovation activities in the public procurement contract for which it has been selected? These questions are a novelty from the previous two national innovation surveys, and they allow us to assess the impact of public procurement on innovation inputs and outcomes.[4,5] The 2018 ENIIMESIC also included a section about public support programs for promoting innovation. This section allows us to identify if a firm applied for and accessed any public support programs for innovation for the 2015–2017 period. The public support programs included are matching grants provided by the National Innovation Program for Competitiveness and Productivity (Innovate Peru) and the National Council of Science, Technology, and Innovation (CONCYTEC-

[4] The way these two questions are phrased is very similar to the questions included in previous EU and CIS (Commonwealth of Independent States) surveys that asked firms whether they were involved in public contracts and whether such contracts required innovation. The main difference with the Peruvian survey is that this last question is about the implementation of innovation activities (that might or might not lead to innovation). This is better than asking about the achievement of innovation in the extent that it biases the question in favor to traditional supply-side policies. So, a test based on the Peruvian survey will be necessarily more demanding than a test based on the EU model.

[5] There is not a clear consensus in the literature regarding how public procurement of innovation (PPI) is defined and measured. Other studies have followed a different approach. For example, the UK Underpinn study had a similar question in relation to the nature of the contracts that firms participated in (to understand whether innovation-friendly practices were used) and whether their reported innovations were the result of bidding for or delivering public sector contracts.

FONDECYT), and the Tax Incentive Program for R&D and innovation projects. Innovate Peru and CONCYTEC-FONDECYT are the most important entities to support innovation in Peru.

As stated in the hypotheses, we aim to assess the impact of public procurement as a demand-side instrument and public support programs as a supply-side intervention. To this end, the paper defines three different policy treatments: (i) regular public procurement, or PP; (ii) public procurement of innovation, or PPI; and (iii) public financial and tax deduction support programs. If a company received both interventions (that is, participated in a public procurement contract and received financing from a public support program), the observation was dropped from the sample.[6] The fact that we only keep observations from participation in only one of the interventions allows us to isolate the effect of each policy treatment on firm innovation. Thus, the working sample is of 1,130 firms from which treatment and control groups are built. See the Appendix for definitions of the variables and descriptive statistics.

The demand-side treatment is public procurement, regular (PP) and innovative (PPI). The regular public procurement variable includes the set of firms that participated in a public procurement contract during the period 2015–2017. The PPI variable refers to the set of firms that had to perform innovation activities for the public procurement contract in which they participated during the period 2015–2017. The total number of companies that participated in regular public procurement contracts and PPI is 225 and 75, respectively. Although Peru does not have an explicit PPI policy, this survey question is a proxy for PPI because it explicitly asks whether the firm had to carry out innovation activities (R&D, licensing, training, etc.) to fulfill a government requirement. The lack of a dedicated public procurement for innovation does not preclude that some innovative procurement biddings can still be developed within the context of the regular framework. Of course, a specific innovative public procurement framework would make PPI easier and would help it while rolling out. The supply-side treatment includes the set of firms that accessed the resources provided by Innovate Peru, CONCYTEC-FONDECYT, or the tax-incentive program for R&D and innovation during the period 2015–2017. The total number of companies that received this treatment was 45.

The input and outcome additionality of the supply-side and demand-side policy instruments is evaluated on several variables: investment in R&D and innovation activities over employment, introduction of product innovation, process innovation, exports, sales, and employment. All the values of these variables are expressed for the year 2017 when available. Finally, the control group (not treated firms) includes the set of firms that did not access any of the demand-side or supply-side treatments. We used 2015 firms' characteristics and innovative behaviors to match treated and not treated firms: sales, employment, participation in an economic group and foreign capital, exports, and firm age, investment in R&D and innovation activities over employment, application to intellectual property rights, collaboration for innovation activities, and access to technology extension services before 2015. For more information, see Table A2: Descriptive Statistics.

[6] These are very few companies. The size of the sample is not large enough to explore the important question regarding the presence of complementarities among supply-side and demand-side polices.

4. Methodology

A quasi-experimental technique is used to carry out the attribution analysis of the supply-side and demand-side interventions. Inference about the impact of a treatment on the outcome of an individual involves speculation about how this individual would have performed had the individual not received the treatment. In the case of a binary treatment, the treatment indicator D_i equals one if individual *i* receives treatment and zero otherwise. The potential outcomes are then defined as $Y_i(D_i)$ for each individual *i*, where *i* = 1, ..., *N* and *N* denotes the total population. The treatment effect for an individual *i* can be written as:

$$\tau_i = Y_i(1) - Y_i(0)$$

The fundamental evaluation problem arises because only one of the potentials outcomes is observed for each individual *i*. The unobserved outcome is called a counterfactual outcome. Hence, estimating the individual treatment effect τ_i is not possible and one has to concentrate on (population) average treatment effects (Caliendo and Kopeining, 2005). The parameter of interest in this case is the "average treatment effect on the treated" (ATT) which is defined as:

$$\tau_{ATT} = E(\tau|D = 1) = E[Y(1)|D = 1] - E[Y(0)|D = 1]$$

As the counterfactual mean for those being treated—$E[Y(0)|D = 1]$—is not observed, it is necessary to choose a proper substitute for it to estimate ATT. According to the available data from the survey, the propensity score matching (PSM) method is used to analyze the impact of the different treatments on the beneficiaries and the control group. This methodology is valid under two assumptions. The first assumption is called the conditional independence assumption (CIA) and implies that, given a set of observable covariates *X* which are not affected by treatment, potential outcomes are independent of treatment assignment.

$$Y_i(0), Y_i(1) \coprod D|X, \forall\, X$$

This implies, that selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed. Clearly, this is a strong assumption; however, we have at hand a large set of observables at the baseline from the survey, including information regarding R&D and innovation investments from previous years (before treatment). These are variables that have the largest weight at the moment of allocating public subsidies. These variables also have some weight at the moment of allocating public bidding contracts, but in this case, we also include past patents as they are more heavily assessed in this case. The variable *X* is a high dimension vector, and to deal with this problem we use Rosenbaum and Rubin (1983) who show that, if potential outcomes are independent of treatment conditional on *X*, they are also independent of treatment conditional on a balancing score $b(X)$. The propensity score $P(D = 1|X) = P(X)$ is one possible balancing score. The second condition for the identification is the common support or overlap condition. That condition ensures that individuals with the same *X* values have a positive probability of being both participants and nonparticipants:

$$0 < P(D = 1|X) < 1$$

Given both assumptions, the PSM estimator for ATT can be written as:

$$\tau_{ATT}^{PSM} = E_{P(X)|D=1} = \{E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0, P(X)]\}$$

So, the estimator of ATT is the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants. To do this in our main results, we use kernel matching methods. One advantage of kernel matching is the using of weighted averages of all individuals in the control group to construct the counterfactual. This generates a lower variance because more information is used. However, a drawback of kernel matching is the possible use of observations that are bad matches, a problem that might be controlled for by the imposition of the common support assumption. However, to test for the robustness of the results, we also build the control group using the single nearest-neighbor technique with common support as a matching method. According to this technique, a subject in the control group is paired with an individual in the treatment group and chosen because their propensity score of accessing the treatment is the closest to the corresponding treated individual (Caliendo and Kopeinig, 2005). In contrast to kernel matching methods, single nearest-neighbor matching minimizes the biases at the cost of a higher variance. In the following sections we present the main results.

5. Results

Assessing the Quality of the Matching

In all the results shown below propensity scores are estimated using logit models. To assess the quality of the matching, it is important to perform tests that check whether the propensity score adequately balances characteristics between the treatment and comparison group units. Formally, the objective of these tests is to verify that treatment is independent of unit characteristics after conditioning on observed characteristics (as estimated in the propensity score model) (Heinrich et al., 2010). In other words, after the application of matching, there should be no statistically significant differences between covariate means of the treatment and comparison units.

Table 2 shows the results of the balancing tests before the matching for the three treatments. Before matching, treatment and control groups are not comparable regarding the variables used to assess the probability of accessing the treatment (demand-side and supply-side instruments). There are significant differences between treated and control groups for the three treatments defined in this study (regular public procurement, public procurement of innovation or PPI, and public support programs). For instance, when the treatments are regular public procurement and public support programs, there are statistically significant differences in variables such as intellectual property rights and sales in 2015 for the treatment and control groups. When the treatment is PPI, there are differences in variables such as innovation activities expenditure per employee in 2015, access to technology extension services, and collaboration for innovation activities.

Table 2: Balance of Treatment vs Control Groups, Unmatched Sample

Variables	Regular public procurement					Public procurement of innovation					Public support programs				
	Mean			t-test		Mean			t-test		Mean			t-test	
	Treated	Control	%bias	t	p>|t|	Treated	Control	%bias	t	p>|t|	Treated	Control	%bias	t	p>|t|
Innovation activities expenditure per employee (2015)	4,494	4,421	1,8	0,24	0,811	5,524	4,414	28,1	2,33	0,020	5,006	4,475	13,5	0,88	0,380
R&D expenditure per employee (2015)	1,211	1,131	3,0	0,39	0,694	1,696	1,178	18,2	1,60	0,111	2,985	1,162	56,8	4,45	0,000
Intellectual property	0,184	0,129	15,3	2,09	0,037	0,135	0,140	-1,5	-0,12	0,902	0,378	0,129	59,4	4,78	0,000
Technology extension services	0,014	0,028	-9,8	-1,17	0,242	0,081	0,024	25,6	2,88	0,004	0,156	0,023	47,2	5,24	0,000
Collaboration for innovation activities	0,198	0,174	6,1	0,81	0,416	0,270	0,178	22,1	1,97	0,049	0,600	0,170	97,7	7,39	0,000
Employment (2015)	0,263	0,189	17,6	2,37	0,018	0,216	0,214	0,4	0,04	0,971	0,267	0,214	12,2	0,84	0,403
Economic group (2015)	0,184	0,148	9,8	1,32	0,188	0,176	0,161	3,8	0,32	0,747	0,222	0,160	15,9	1,11	0,266
Foreign capital (2015)	16,852	16,677	9,5	1,25	0,210	16,539	16,727	-9,6	-0,84	0,399	17,478	16,712	39,1	2,76	0,006
Exports (2015)	4,233	4,290	-3,7	-0,48	0,631	4,149	4,300	-9,0	-0,79	0,431	5,301	4,269	62,0	4,31	0,000
Sales (2015)	5,788	7,005	-15,8	-2,02	0,043	5,692	6,711	-13,3	-1,08	0,280	11,968	6,603	68,1	4,51	0,000
Sector	0,576	0,771	-42,6	-5,83	0,000	0,649	0,732	-18,1	-1,56	0,119	0,911	0,719	51,0	2,84	0,005
Startup	0,152	0,179	-7,3	-0,94	0,349	0,162	0,172	-2,7	-0,22	0,823	0,044	0,175	-42,7	-2,29	0,022

Note: *P<0.10; ** P<0.05; *** P<0.01

Source: Authors' elaboration

However, after matching, all groups seemed better balanced with no statistical differences between the control variables (Table 3).

Table 3: Balance of Treatment vs Control Groups, Matched Sample (Kernel Matching)

Variables	Regular public procurement					Public procurement of innovation					Public support programs				
	Mean			t-test		Mean			t-test		Mean			t-test	
	Treated	Control	%bias	t	p>|t|	Treated	Control	%bias	t	p>|t|	Treated	Control	%bias	t	p>|t|
Innovation activities expenditure per employee (2015)	4.454	4.627	-4.4	-0.46	0.649	5.569	5.233	8.5	0.51	0.613	5.057	5.493	-11.1	-0.52	0.602
R&D expenditure per employee (2015)	1.151	1.215	-2.4	-0.25	0.803	1.743	1.620	4.3	0.24	0.811	2.963	3.052	-2.8	-0.11	0.909
Intellectual property	0.186	0.185	0.2	0.02	0.985	0.139	0.138	0.4	0.02	0.983	0.372	0.348	5.7	0.23	0.821
Technology extension services	0.014	0.014	-0.3	-0.04	0.966	0.083	0.071	5.4	0.27	0.790	0.116	0.159	-15.1	-0.57	0.573
Collaboration for innovation activities	0.200	0.198	0.4	0.04	0.966	0.264	0.254	2.3	0.13	0.897	0.581	0.540	9.3	0.38	0.706
Employment (2015)	0.260	0.246	3.4	0.34	0.737	0.222	0.211	2.7	0.16	0.874	0.279	0.370	-21.1	-0.89	0.375
Economic group (2015)	0.186	0.176	2.6	0.26	0.792	0.181	0.175	1.5	0.09	0.931	0.233	0.211	5.5	0.24	0.811
Foreign capital (2015)	16.832	16.795	2.0	0.21	0.832	16.629	16.664	-1.8	-0.10	0.918	17.455	17.477	-1.1	-0.05	0.960
Exports (2015)	4.253	4.224	1.8	0.19	0.849	4.213	4.275	-3.7	-0.22	0.826	5.332	5.225	6.4	0.28	0.781
Sales (2015)	5.842	5.873	-0.4	-0.04	0.966	5.850	6.021	-2.2	-0.13	0.893	11.769	10.770	12.7	0.58	0.565
Sector	0.577	0.578	-0.3	-0.03	0.975	0.653	0.664	-2.5	-0.14	0.885	0.907	0.850	15.0	0.80	0.426
Startup	0.153	0.147	1.7	0.18	0.855	0.153	0.158	-1.3	-0.08	0.935	0.047	0.069	-7.2	-0.44	0.665

Source: Authors' elaboration

To further verify the quality of the matching exercise, we also report different overall measures of covariate imbalance. As it is possible to see from Table 4 after matching the pseudo R2 is lower, which indicates a good matching. Table 4 also demonstrates the corresponding *P*-values of the likelihood-ratio (LR) test of the joint insignificance of all the regressors (before and after matching if option both is specified) and the mean and median bias as summary indicators of the distribution of the absolute bias.

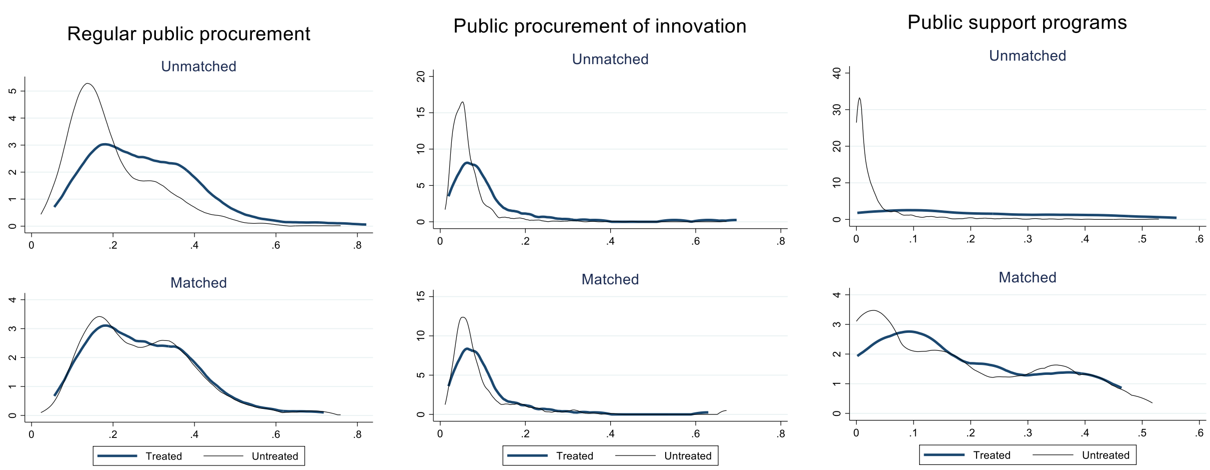
Table 4: Overall Measures of Covariate Imbalance (Kernel Matching)

	Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias
Regular public procurement	Unmatched	0.077	80.84	0.000	9.3	7.8
	Matched	0.003	1.88	1.000	1.9	1.9
Public procurement of innovation	Unmatched	0.073	39.23	0.026	12.4	11.7
	Matched	0.005	1.06	1.000	3.0	2.4
Public support programs	Unmatched	0.268	99.92	0.000	29.4	18.4
	Matched	0.033	3.90	1.000	6.9	6.3

Source: Authors' elaboration

Another important step in investigating the validity or performance of the propensity score matching estimation is to verify the common support or overlap condition. We assume that the probability of participation in an intervention, conditional on observed characteristics, lies between 0 and 1 (implying participation is not perfectly predicted, that is, $0 < P(D = 1|X) < 1$. Figure 1 allows for the visual inspection of the propensity score distributions for both the treatment and comparison groups before an and after matching, showing that the densities of the propensity scores are more similar after matching. The plots also reveal a clear overlapping of the distributions.

Figure 1: Propensity Score Distribution, Matched and Unmatched Samples



Source: Authors' elaboration

Main Results of the Matching

We first present the results for supply-side policies and compare them with PPI (see Table 5). With regards to PPI, we do find a positive and significant impact on innovation activities and R&D expenditure per employee (at 10 percent level of statistical significance), innovative products over total sales, and product innovation. Thus, firms that participate in public procurement that includes innovation activities spend more resources on R&D and are more innovative than comparable firms in the control group. Also, firms that participate in PPI are 23 percentage points more likely to introduce product innovation than comparable firms in the control group. On the other hand, although public support programs for promoting innovation show a positive impact on innovation activities expenditure per employee, these interventions do not show an impact on product innovation. Overall, our results look very consistent with our previous hypotheses to the extent that participating in public support programs has a higher impact on innovation investment, but that participating in public procurement biddings that require innovation activities show much higher impact on innovation outcomes. So, both Hypothesis 1 and Hypothesis 2 from above seem to be confirmed.

Table 5: Results of Public Procurement of Innovation and Innovation Public Support Policies, Matched Sample *(Average Treatment Effect on the Treated, Kernel Matching)*

Outcome variables	Public Procurement of Innovation	Public support programs
R&D expenditure per employee (2017)	0.678 *	1.140 *
	(0.401)	(0.643)
Innovation activities expenditure per employee (2017)	0.788 *	1.292 **
	(0.427)	(0.562)
Innovative products over total sales (2017)	0.077 **	0.021
	(0.034)	(0.047)
Product innovation	0.233 ***	0.025
	(0.053)	(0.088)
Business process innovation	-0.019	0.008
	(0.041)	(0.059)
Motivation to innovate	0.161	-0.073
	(0.061)	(0.09)
Private funding for innovation activities	0.147	-0.010
	(0.062)	(0.087)

Note: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses.

Our third hypothesis focuses on whether the request for innovation activities to perform public procurement contracts make any difference regarding innovation performance. To explore this, we compare the results of regular public procurement—which does not require the performance of innovation activities—with public procurement that requires innovation activities. Table 6 presents the results for each of these two treatments evaluated. Our study did not find any statistically significant positive impact on the outcome variables for accessing regular public procurement. This result may be a consequence of the nature of regular public procurement in Peru, which aims to purchase goods and services that already exist in the market and that values cost savings, instead of solving functional requirements. These results are consistent with the findings of Fernández-Sastre and Montalvo-Quizhpi (2019) for Ecuador. The results also confirm Hypothesis 3, to the extent that only the public procurement that requires the performance of innovation activities shows positive and significant effects on innovation outcomes. Regular procurement, on the other hand, does not show any impact at all.

Table 6: Results of Public Procurement of Innovation and Regular Public Procurement *(Average Treatment Effect on the Treated, Kernel Matching)*

Outcome variables	Public Procurement of Innovation	Regular Public Procurement
R&D expenditure per employee (2017)	0.678 *	0.085
	(0.401)	(0.237)
Innovation activities expenditure per employee (2017)	0.788 *	0.071
	(0.427)	(0.287)
Innovative products over total sales (2017)	0.077 **	-0.074 ***
	(0.034)	(0.019)
Product innovation	0.233 ***	-0.079 *
	(0.053)	(0.041)
Business process innovation	-0.019	-0.019
	(0.041)	(0.026)
Motivation to innovate	0.161	-0.007
	(0.061)	(0.041)
Private funding for innovation activities	0.147	-0.026
	(0.062)	(0.037)

Note: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses.

Robustness Analysis

For a robustness check, we explore three different sets of concerns. First, we check for potential instability of the results depending on the matching algorithm being used. This makes sure that the previous findings are not driven by the selection of a particular empirical strategy. Second, we explore the extent to which the results might be affected by the problem of choice-based sampling. And third, we study how robust the results are in the presence of unobserved heterogeneity.

With regards to the first problem mentioned above—instability of the results with respect to the empirical strategy—we replicate the analysis while checking for both instability related to the matching algorithm used and instability due to the model specification used to estimate the propensity scored. To explore for potential instability due to the matching algorithm, we replicate the analysis using for the single nearest-neighbor matching. As mentioned above, this matching algorithm shows lower bias than the previously used kernel matching, but it also has lower efficiency. Table 7 shows the results of this exercise. The findings support our previous results in which PPI outweighs public support programs in the promotion of innovations outcomes. However, this matching technique does find a positive impact on R&D investment of the demand-side policy while the supply-side policy does not have any impact on the promotion of R&D or innovation investment.

To explore for the instability of results due to the propensity score model specification, we estimate the average treatment effect on the treated using the double machine learning method proposed by Chernozhukov et al. (2018). This method combines an augmented inverse probability weighting (AIPW) regression model with a model selection technique that addresses the conflict between conditional independence and overlap assumption while maintaining a robust estimator to model misspecification. This alternative method is applied to verify that our findings are robust when examined for the model specification used to estimate the propensity scores. The results of this approach are summarized in Table 8. Table 8 suggests that our results are robust when examined for the model specification in which PPI has a positive impact on both innovation investment and outcomes. Also, these results indicate that companies that participate in public procurement contracts that required innovation activities are more likely to fund innovation activities with private funding than their control group. As found in previous models, public support programs have positive impact on R&D investment rather than on outcomes. However, this model also found that PPI has an impact on R&D investment.

Table 7: Results of Public Procurement of Innovation and Innovation Public Support Policies *(Average Treatment Effect on the Treated, Nearest-Neighbor Matching)*

Outcome variables	Public Procurement of Innovation	Public support programs
R&D expenditure per employee (2017)	1.117 **	1.186
	(0.539)	(0.846)
Innovation activities expenditure per employee (2017)	0.420	0.772
	(0.612)	(0.686)
Innovative products over total sales (2017)	0.098 **	-0.033
	(0.047)	(0.062)
Product innovation	0.288 ***	-0.023
	(0.081)	(0.116)
Business process innovation	0.014	0.000
	(0.059)	(0.085)
Motivation to innovate	0.068	-0.047
	(0.087)	-(0.163)
Private funding for innovation activities	0.151 *	0.047
	(0.084)	(0.115)

Note: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses.

Table 8: Results of Public Procurement of Innovation and Innovation Public Support Policies *(Average Treatment Effect on the Treated, Lasso+AIPW Matching)*

Outcome variables	Public Procurement of Innovation	Public support programs
R&D expenditure per employee (2017)	0.542 **	0.847 **
	(0.239)	(0.405)
Innovation activities expenditure per employee (2017)	0.754 *	0.583
	(0.392)	(0.436)
Innovative products over total sales (2017)	0.081 **	0.025
	(0.032)	(0.038)
Product innovation	0.223 ***	0.055
	(0.051)	(0.071)
Business process innovation	-0.008	-0.021
	(0.039)	(0.052)
Motivation to innovate	0.147 **	0.085
	(0.058)	(0.075)
Private funding for innovation activities	0.167 ***	0.011
	(0.058)	(0.072)

Note: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses.

In recent years, PSM has received some criticisms for matching. This is because the matching is done on the propensity score, which in turn depends on the covariates, rather than matching directly on the covariates. However, while matching on covariates guarantees the matching of the propensity score, matching the other way around is not necessarily correct. This introduces problems of model dependence (in the sense that the results change with the selection model used), inefficiency (due to loss of information), and exposure to the discretion of the researcher when "choosing" the more convenient model. All of this leads to biased results (King and Nielsen, 2018). To address this problem, we also use Mahalanobis distance matching (MDM) that directly matches on the covariates without using propensity scores. Table 9 summarizes the results when using MDM. The results are consistent with the previous findings in which PPI has an impact on the promotion of innovation outcomes while public support programs have an impact on the promotion of R&D investment (at 10 percent level of statistical significance). However, this model finds that PPI has an impact on both R&D and innovation investment.

Table 9: Results of Public Procurement of Innovation and Innovation Public Support Policies *(Average Treatment Effect on the Treated, MDM Matching)*

Outcome variables	Public Procurement of Innovation	Public support programs
R&D expenditure per employee (2017)	1.098 **	1.365 *
	(0.51)	(0.739)
Innovation activities expenditure per employee (2017)	1.171 **	0.380
	(0.566)	(0.658)
Innovative products over total sales (2017)	0.142 ***	0.012
	(0.041)	(0.057)
Product innovation	0.280 ***	0.089
	(0.081)	(0.104)
Business process innovation	-0.013	-0.022
	(0.054)	(0.071)
Motivation to innovate	0.133	0.044
	(0.085)	(0.107)
Private funding for innovation activities	0.160 *	-0.044
	(0.085)	(0.105)

Note: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses.

A second concern relates to the problem of choice-based sampling. This is a situation where program participants are oversampled relative to their frequency in the population of eligible individuals. It is important to clarify that this situation does not occur in our case because the sample is random from the industry, and within this sample, the treated and controls are identified without any special prior consideration in terms of sampling. That is, the treated in this sample have the same frequency as in the population. However, we still check the robustness of the results to a possible choice-based sampling using the approach suggested by Heckman and Smith (1995). According to these authors, under choice-based sampling, weights are required to consistently estimate the probability of program participation. Heckman and Smith (1995) show that, with weights unknown, matching methods can still be applied, because the odds ratio estimated using the incorrect weights (those that ignore the choice-based sample) is a scalar multiple of the true odds ratio, which is itself a monotonic transformation of propensity scores. Hence, matching can be done on the (misweighted) estimate of the odds ratio.[7] The results of the kernel matching on the odds ratio are summarized in Table 10. The results suggest that both PPI and public support programs have a positive impact on innovation investment. However, this model also confirmed our previous findings that PPI outweighs public support programs in the promotion of innovation outcomes.

[7] In the case of single nearest neighbor matching, it does not matter whether matching is performed on the odds ratio or the estimated propensity score (with wrong weights), since ranking of the observations is identical and therefore the same neighbors will be selected (Caliendo and Kopeining, 2005).

Table 10: Results of Public Procurement of Innovation and Innovation Public Support Policies *(Average Treatment Effect on the Treated, Kernel Matching on the Odds Ratio)*

Outcome variables	Public Procurement of Innovation	Public support programs
R&D expenditure per employee (2017)	0.669 *	1.223 *
	(0.402)	(0.631)
Innovation activities expenditure per employee (2017)	0.931 **	1.312 **
	(0.435)	(0.575)
Innovative products over total sales (2017)	0.079 **	0.017
	(0.034)	(0.046)
Product innovation	0.244 **	0.021
	(0.054)	(0.087)
Business process innovation	-0.019	-0.014
	(0.041)	(0.061)
Motivation to innovate	0.159 **	-0.070
	(0.062)	(0.091)
Private funding for innovation activities	0.158 **	0.034
	(0.063)	(0.087)

Note: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses.

The final robustness issue relates to the effects of unobserved heterogeneity. The estimation of treatment effects with matching estimators is based on the CIA—that is, selection based on observable characteristics. However, if there are unobserved variables that affect assignment into treatment and the outcome variable simultaneously, a "hidden bias" might arise. It should be clear that matching estimators are not robust against this "hidden bias."[8] Since it is not possible to estimate the magnitude of selection bias with nonexperimental data, we address this problem with the sensitivity analysis approach proposed by Ichino, Mealli, and Nannicini (2008). This approach assumes the conditional independence assumption could be satisfied if one could observe an additional binary variable. This potential confounder can be simulated in the data and used as an additional covariate in combination with the preferred matching estimator. The comparison of the estimates obtained with and without matching on the simulated confounder shows to what extent the baseline results are robust in relation to specific sources of failure of the CIA, since the distribution of the simulated variable can be constructed to capture different hypotheses on the nature of potential confounding factors. In order to do this, two probability ratios, both of them increasing in the simulated confounder, are computed (d, s). While d captures the effect of the simulated confounder on the outcome, s is the effect of the same confounder on the treatment. Increasing values of s and d will drive ATT to zero. A higher level of critical d and s is a signal of matching robustness. To carry out this analysis we assume the confounder to be calibrated to mimic the constructed variable of having an R&D laboratory (that is, having R&D greater than zero reported in 2015). The simulated

[8] The term "hidden bias" refers to the fact that two individuals with the same observed covariates X have differing chances of receiving treatment.

results of the kernel matching are summarized in Table 11. The key results in the last column of Table 11 capture the extent to which the baseline results drop due to an unobservable confounder that behaves as having or not an R&D laboratory. With regards to public procurement for innovation, the results seem to be quite robust. The effects of unobserved heterogeneity on R&D and innovation expenditures are quite small (16 percent and 12 percent respectively), while the effects of innovation outcomes are always lower than 10 percent. With regards to public support programs, the effects are relatively low in the case of R&D expenditures (10 percent) and much larger in the case of innovation expenditures (33 percent) both in comparison with PPI. The effects are larger in the case of innovation outcomes, but these were already nonsignificantly different from zero in the case of innovation public support programs. In summary, it does not seem that our previous findings are driven by unobserved heterogeneity.

Table 11. Results of Public Procurement of Innovation and Innovation Public Support Policies *(Simulated Average Treatment Effect on the Treated, Kernel Matching)*

Outcome variables	Public Procurement of Innovation						Public support programs					
	Simulated confounder	Std. Err.	Outcome effect	Selection effect	Baseline	% of the baseline estimated	Simulated confounder	Std. Err.	Outcome effect	Selection effect	Baseline	% of the baseline estimated
R&D expenditure per employee	0.711	0.073	422.9	2.171	0.843	16%	0.817	0.109	482.9	1.685	0.905	10%
Innovation activities expenditure per employee (2017)	0.880	0.095	4.738	2.004	1.004	12%	0.547	0.196	4.442	4.344	0.813	33%
Innovative products over total sales (2017)	0.079	0.006	1.910	2.019	0.087	9%	-0.004	0.019	2.002	4.282	0.011	136%
Product innovation	0.242	0.011	3.102	1.955	0.256	5%	0.052	0.032	3.212	3.919	0.096	46%
Business process innovation	-0.036	0.005	1.284	2.049	-0.037	3%	-0.052	0.019	1.215	4.437	-0.049	-6%
Motivation to innovate	0.137	0.007	1.269	2.035	0.140	2%	-0.074	0.030	1.368	3.970	-0.067	-10%
Private funding for innovation activities	0.151	0.01	1.188	1.981	0.159	5%	-0.041	0.034	1.262	4.162	-0.040	-3%

6. CONCLUSIONS

Despite the importance and recent implementation of public procurement to promote innovation, there are only few evaluations to assess its impact. This study is a first attempt to evaluate PPI using firm-level data in Peru even when there is not an explicit policy. Using alternative nonexperimental impact evaluation techniques to control for selection bias, this research uses new data on the participation of Peruvian firms on public tenders from the 2018 National Innovation Survey of Manufacturing Sector and Knowledge-Intensive Services (INEI, 2019). This research not only assesses the impacts of participating in public procurement on innovation efforts and outcomes at the firm level, but it also compares these impacts with those from traditional supply-side approaches, which are typically matching grant and tax incentive instruments.

Although innovation policies in Peru are highly concentrated in supply-side instruments, our results show a positive impact of demand-side policies to promote firm innovation. While regular public procurement (PP) does not encourage innovation, public procurement of innovation (PPI) has a positive and significant impact on product and process innovation. All the methods applied (such as kernel, nearest-neighbor, and AIPW matching) confirm this result. Our results are also sufficiently robust to address problems such as matching on propensity scores, choice-based sampling, and unobserved heterogeneity. However, with regards to the impact of accessing public support programs, the results are not so conclusive. Public support programs have positive effects on R&D and innovation activities, sometimes even larger than PPI, but they do not have any effect on innovation outcomes. Finally, our findings provide relevant information to policymakers in Peru regarding the importance of including PPI in the innovation policy mix to the extent that PPI not only encourages firms to expend more on R&D, but it also promotes the introduction of product innovation in markets. This finding suggests that, if the objective of policymakers is to encourage investment in innovation and promote innovation outcomes, the policy mix needs to be better balanced to include demand-driven interventions.

This is the first and very exploratory inspection of the impacts of PPI on the innovation performance in LAC. More research, with a larger sample size, needs to be carried out in the future to confirm these results. Also, a larger sample size would also allow exploring the potential existence of complementarities of public support of innovation and traditional supply-side funding programs. These further steps are contemplated in the future research agenda.

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Appendix

Table A1: Variable Definitions

Treatment Variables	Description
Public procurement of innovation	1 if the firm performed innovation activities for the public procurement contract in which it participated during the period 2015–2017; and 0 otherwise.
Regular public procurement	1 if the firm participated in a public procurement contract during the period 2015–2017; and 0 otherwise.
Public support programs	1 if the firm had access to grants and tax incentives for innovation activities and technology extension services during the period 2015–2017; and 0 otherwise.

Outcome Variables	Description
R&D expenditure per employee (2017)	Natural logarithm of 1 + research and development expenditure by employee in 2017.
Innovation activities expenditure per employee (2017)	Natural logarithm of 1 + innovation activities expenditure by employee in 2017.
Innovative products over total sales (2017)	Sales of new or significantly improved products in the domestic or international markets over total sales in 2017.
Product innovation	1 if the firm introduced on the market a new or improved good or service that differs significantly from the firm's previous goods or services during the period 2015–2017; and 0 otherwise.
Business process innovation	1 if the firm brought into use a new or improved business process for one or more business functions, such as production, logistics, distribution, marketing, organizational or support activities, that differs significantly from the firm's previous business processes during the period 2015–2017; and 0 otherwise.
Motivation to innovate	1 if the firm responded "high" to the question: What was the degree of significance of the economic impact of the following innovation results achieved by your company during the period 2015–2017: productivity increase and capacity improvement; and 0 otherwise.
Private funding for innovation activities	1 if the firm used private funding from banks, finance companies, angel investment or venture capital to performed innovation activities during the period 2015–2017; and 0 otherwise.

Control Variables	Description
R&D expenditure per employee (2015)	Natural logarithm of research and development expenditure by employee in 2015.
Innovation activities expenditure per employee (2015)	Natural logarithm of innovation activities expenditure by employee in 2015.
Intellectual property rights	1 if the firm applied for a patent, utility model, industrial design, trademark, and copyright during the period 2015–2017; and 0 otherwise.

Collaboration in innovation activities	1 if the firm cooperated for innovation activities with any other organization or institution.
Employment (2015)	Natural logarithm of 1 + total number of employees in 2015.
Sector	1 if the firm belongs to the manufacturing industry; 0 otherwise.
Exports (2015)	Natural logarithm of 1 + firm exports in 2015.
Sales (2015)	Natural logarithm of 1 + firm net sales in 2015.
Economic group (2015)	1 if the firm belong to an economic group in 2015; 0 otherwise.
Foreign capital (2015)	1 if the firm had foreign capital in 2015; 0 otherwise.
Start-up	1 if the firm was created in 2010 or after; 0 otherwise.
Technology extension services	1 if the firm access to technology extension services before 2015; and 0 otherwise.

Table A2: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
R&D expenditure per employee (2017)	1,125	1.558	2.923	0.0	15.5
Innovation activities expenditure per employee (2017)	1,125	5.668	3.669	0.0	17.8
Innovative products over total sales (2017)	1,130	0.257	0.371	0.0	1.0
Product innovation	1,130	0.537	0.499	0.0	1.0
Business process innovation	1,130	0.886	0.318	0.0	1.0
Motivation to innovate	1,130	0.449	0.498	0.0	1.0
Private funding for innovation activities	1,130	0.336	0.473	0.0	1.0
Innovation activities expenditure per employee (2015)	1,117	4.498	3.965	0.0	17.5
R&D expenditure per employee (2015)	1,117	1.217	2.699	0.0	15.2
Intellectual property rights	1,130	0.140	0.347	0.0	1.0
Technology extension services access (2015)	1,130	0.027	0.163	0.0	1.0
Collaboration in innovation activities	1,130	0.186	0.389	0.0	1.0
Economic group (2015)	1,130	0.212	0.409	0.0	1.0
Foreign capital (2015)	1,130	0.159	0.366	0.0	1.0
Sales (2015)	1,130	16.716	1.910	0.0	23.2
Employment (2015)	1,126	4.256	1.633	0.0	9.7
Exports (2015)	1,130	6.692	7.864	0.0	21.5
Sector	1,130	0.727	0.445	0.0	1.0
Start-up	1,130	0.172	0.377	0.0	1.0

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