Working Paper Series

#2021-025

The effectiveness of innovation policy and the moderating role of market competition: Evidence from Latin American firms

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Published 19 May 2021

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UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology UNU-MERIT

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THE EFFECTIVENESS OF INNOVATION POLICY AND THE MODERATING ROLE OF MARKET COMPETITION: EVIDENCE FROM LATIN AMERICAN FIRMS[1]

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Acknowledgements: The authors are thankful to Roberto Alvarez (Universidad Catolica de Chile) and Gustavo Crespi (Inter-American Development Bank) for their insightful comments and suggestions. We are also thankful to Diego Aboal and Martin Pereira for their contributions to this research project. The views expressed correspond only to authors and do not represent the views of their organizations. This research was funded by the Inter-American Development Bank, Competitiveness and Innovation Division, Washington, D.C.

ABSTRACT

The objective of this paper is to evaluate whether market competition matters for the effectiveness of innovation policies. Using data for Chilean and Peruvian manufacturing firms, we implement propensity matching techniques combined with differences-in-differences estimation to evaluate the impact of innovation subsidies on the post-treatment innovation investment effort of firms and test whether such impact differs according to the intensity of competition. We corroborate the existence of "crowding-in" effects in beneficiaries when compared to a control group of untreated firms. The subsidy impact is found either only significant in highly competitive sectors or larger in more competition-intensive industries -compared to low competition ones. Thus, we confirm that market competition plays a moderating role in the effectiveness of innovation policies to stimulate firm innovation investment. The results are robust to different matching and estimation methods. Our results therefore suggest that market contexts should be considered in the design of innovation policies.

Keywords: Innovation Subsidies, Innovation Policy, Market Competition
Latin American firms

JEL Classificiation: O38; O31; R38; H71

INTRODUCTION

Competition is a major engine of productivity growth and an intense empirical research recurrently corroborates this impact. The goal of this paper is to examine whether the impact and effectiveness of innovation policies is influenced by market competition. Although a large literature has studied the impact of market competition on business innovation (e.g. earlies studies date back to Schumpeter (1939; 1945) and Arrow (1962); see Ahn (2002) , little is known to what extent the effectiveness of innovation policy interventions -such as R&D subsidies, matching grants or R&D tax-incentives- is associated with market conditions and competition. More generally, little consideration of the interplays between productivity development policies and competition policies exists to date.

Based on firm-level data for two Latin American countries, we evaluate empirically whether market competition matters to the effectiveness of innovation subsidies (matching grants for R&D and innovation) as reflected in their capacity to stimulate private innovation investment. The main argument behind is that if competition strengthens innovation incentives by firms –the "escape competition" effects in the lines of Arow (1962), Scherer (1980), Geroski (1990), and others, we should therefore expect innovation policies to be more efficient in stimulating firm innovation (i.e. by addressing market failures in the funding of innovation activities; Hall and David (2000); Hall and Lerner, 2003) in more competitive industries and markets. As explained by Ackcigit *et al.,* (2019) policy interventions may help ensure benefits from innovation motivations raised by intensified competition, i.e. by raising defensive innovation motives (ensure market leadership) and expansive (R&D) innovation -i.e. with trade competition, see also Bloom *et al.,* (2016).

Recent empirical research suggests that, by influencing innovation incentives in firms, market competition may have a moderating role in the effectiveness of innovation policies. Research on the impact of industrial policies for Chinese firms (e.g., Aghion, Cai, Dewatripoint, Du, Harrison and Legros (2015) and innovation policies (R&D subsidies) for European firms point to this significant relationship. According to Aghion *et al.,* (2011; 2015), policy interventions can be more effective if policies target industries or areas (instead of firms) in which competition and innovation play a key role for competitiveness and growth.[2] Thus the implementation of industrial policies (targeting sectors) and competition should be regarded as complementary rather than substitute policies (Aghion *et al.,* 2019). This research also suggests that undesired effects may arise if innovation policy interventions (such as R&D tax interventions or subsidies) advantage established

[2] Policy interventions are also known to be more effective in sectors where market failures are more pronounced and innovation risk (uncertainty) are the highest and the potential for spillovers the highest, making further the case for sectoral policy interventions (e.g. climate change and green technologies).

and dominant firms to the detriment of innovative young firms (e.g., Freitas *et al.,* 2007; Bravo-Biosca *et al.,* 2015) and if they benefit industries (i.e. knowledge intensive industries) where resource allocation is rather inflexible. Policy interventions, by involuntarily benefitting relatively more oligopolistic markets would risk deepening the innovation divide within industries with negative effects on markets and resource distribution (Freitas *et al.,* 2007).

A large strand of research indicates that the competitive environment in which a firm operates affects its incentives to innovate (Aghion and Griffith, 2005; Shapiro, 2010) and this response depends on the intensity of technology rivalry (within sectors/markets) and the distance to the technology frontier, the type of innovation (product vs. process), among other factors (Acemoglou and Zilibotti, 2012; Aghion *et al.,* 2005). While some models advocate competition on the basis that firms with high market power may be disinclined to pursue innovation that may displace existing rents (Arrow, 1962; Reinganum, 1983), early Schumpeterian growth models (Aghion and Howitt, 1992) highlight that the incentives for innovation (in terms of prospective post-innovation rents) may increase at lower levels of competition -in line with Schumpeter (1942). Accordingly, in more competitive industries, R&D activities aimed at decreasing production costs reward firms with post-innovation rents and help firms to escape from competition.

Overall, however, there is little empirical support for the view that market concentration or incumbent (large) firms are more strongly associated with a higher level of innovative activity. Most of the empirical literature tends to confirm that a positive (in some cases non-linear) relationship exists between competition and innovation (e.g. Blundell et al., 1999; Gerosky, 1990; Correa and Ornagui, 2013; Hashmi, 2013; Clyde *et al.,* 2015). The work of Aghion, Bloom, Blundell, Griffith and Howit (2005) suggests that an inverse-U shaped relation exists especially in industries or markets where firms are quite symmetrical (technology rivalry is strong). Further recent research indicates that, if we consider market contestability (i.e. Federic, Morton and Shapiro, 2020) and market openness (i.e. Ackdigit *et al.,* 2018), stronger competition (greater market rivalry) in the sense of stronger contestability in future sales, unambiguously leads to more innovation. Neither of these predictions have been evaluated in the context of innovation policy.

We use firm-level data from national innovation surveys for Chilean and Peruvian manufacturing firms to analyse this question. We use two empirical strategies to circumvent the problems of selection bias into treatment by firms, and endogeneity issues related to unobservable characteristics of firms, which are assumed permanent. With the aid of propensity score matching techniques and differences-in-difference estimation, we first assess whether innovation subsidies (R&D subsidies and innovation programs) engender input additionality effects; in other words, whether they contribute to leverage additional resources in terms of private investment in innovation and R&D, instead of crowding-them out. We then look at whether this impact is conditional on market competition conditions. We use the Boone Profit Elasticity Index, which is estimated for each industry from a profitability equation (for Chilean and Mexican firms), and the Hirschman-Herfindahl index for Peruvian firms. Further, we conduct an additional analysis for Chilean firms, where we let the definition of the competition threshold to be endogenously determined in an innovation model. Finally, we also implement panel methods (differences-in-differences) to rest the robustness of our results.

Recent research on Latin American firms (e.g., Alvarez, Benavente and Crespi; 2020; Pelaez and Hurtado, 2020) shows that market competition strengthens firm innovation propensity and the intensity of innovation investment, confirming the predominance of innovation incentives from competition. Firms would invest in innovation face to stronger competition and competitive entry threats in order to "*escape competition*" and keep in the race (Arrow, 1962; Aghion and Howit, 1992; Aghion *et al.,* 2005). For firms in emerging countries, this relationship has been found to be predominantly monotonic (e.g. Pelaez and Hurtado, 2020; Alvarez *et al.,* 2020) which would mean a large potential to spur firm innovation from strengthening competition in these regions. If public support is complementary to private innovation investment, we should expect input additionality (crowding-in) effects to raise with competition, when competitive markets encourages firm innovation more than oligopolistic marketplaces (Aghion *et al.,* 2005).

There are several reasons why we should look at these questions in Latin American countries. First, the empirical evidence on the links between innovation and competition is quite scarce for these countries. A better understanding the role of market competition and how it impacts firms´ innovation behaviour is crucial given the stagnation of productivity in Latin American countries. Second, little is known about whether competition affects the impact of innovation (and productivity development) policies or how much market and sectoral differences explain the effectiveness of public policies for innovation. Filling this gap is important as innovation subsidies is now a widespread practice in the region. The multiplication of innovation programs in the region make a compelling case for conducting this research.

We know that innovation subsidies in the form of matching grants have been proven effective in fostering input additionality and behavioural effects in Latin American firms (e.g., see a survey of these studies by Hall and Maffioli (2008) and Zuniga (2019); Castillo *et al.,* (2011) for Colombian firms; Calderon (2009) and Chavez (2019) for Mexican firms; Crespi *et al.,* (2012) for Chilean firms), but little is known whether this response is equal across industries or conditional on market conditions. And third, if competition matters to policy effectiveness, this will be an additional reason to strengthen competition in the region; not only for productivity growth but also ensure public policies are effective and not in detriment of competition. Evidence on this issue would reinforce the arguments for improving policy coordination and innovation policy design (e.g. Freitas *et al.,* 2015; Aguion *et al.,* 2019).

This paper is structured as follows. In the first section, we briefly review the literature and summarise the key messages from past research. The second and third sections describe our data, our treatments and empirical strategy. Section 4 reports our results and robustness tests. The final section concludes and summarises our main findings.

I. LITERATURE INSIGHTS

A rich literature has consistently reported evidence about the importance of market competition to productivity growth (e.g., Iversen, 2011) and optimal resource allocation (e.g. see Syverson, 2010; Holmes and Schmidt, 2010; Nicoletti and Scarpetta, 2005). Yet, the interplay between productive development policies and market competition; has been barely examined. The role of industry-specific differences such as market conditions has been paid less attention since there is limited evidence about their role in the context of innovation policy. This differs with a vast literature that shows that firm size is a critical factor in what concerns innovation and managerial capacity, and access to finance (e.g. Cohen and Levin, 1989; Cohen and Kepler, 1996). Thus, acknowledging these differences, firm size is often considered in the design of innovation support programs (subsidies and grants; and direct assistance).

A large strand of the economic literature has shown that the competitive environment in which a firm operates affects its incentives to innovate (eg., Symeonidis, 1996; Ahn, 2002; Aghion and Griffith, 2005; Shapiro, 2010). Traditional arguments date back to Schumpeter (1939; 1942) and Arrow (1962). According to Schumpeter (1942), for example, innovation would require the presence of (some market power) for firms to manage to pay for the risks of innovation and weak appropriability of returns (see also Romer, 1990; Aghion and Howitt, 1992) as ideas are costly to produce and knowledge is non-rival and can be appropriated by others.[3] In contrast, Arrow (1962) sustained that firms in monopolistic situations would only innovate to replace a rent (*"replacement"*) that already have while firms under a regime of competition would gain the full return of innovation as they would not lose any monopoly profit. Thus, competition will promote innovation especially if entails the entry of more efficient firms (e.g. Aghion *et al.,* 2009; 2012).

[3] Early models of endogenous technological change (e.g. Romer, 1986; Aghion e Howitt, 1992; Grossman and Helpman, 1991) also assumed that some market power is needed to ensure continuous innovation.

Research by Aghion, Bloom, Blundell, Griffith and Howit (2005) conciliated these two opposing views; the two scenarios can exist depending on the initial level of competition, and firms' (and industries) technology distance to the frontier and rivalry, which would make the competition-innovation relation non-monotonic. This shape which arises due to the heterogeneity of industry contexts distributed across the curve, which is also endogenous determined. Accordingly, increasing competition would reinforce innovation incentives moving firms to "*escape-competition*", especially when technology rivalry among firms increases because competition reduces firms' pre-innovation rents by more than it reduces post-innovation rents.[4] In contrast, the farther firms are from the technology frontier and the more asymmetrical sectors are, the more likely discouraging effects will prevail because ex-post rents from innovation are eroded by new entrants. Beyond a certain competition threshold, incentives to innovate will decrease; a profit margin above the competitive price is needed to foster innovation investment.

These ideas were proven empirically with a panel data from British companies with the aid of semi-parametric methods and instrumental variables (e.g., European market reforms) to correct for the endogeneity of market competition. Aghion *et al.,* (2005) corroborated that more symmetrical industries (where cross-firm disparity is low) showed stronger responses and a steeper (inverse U-shaped) course. In a follow-up work, Aghion *et al.,* (2009), authors find that the threat of technologically advanced entry (proxied by foreign entry greenfield) spurs innovation by incumbent firms in sectors close to the technology frontier but discourses it in laggard industries.

More recently, Aghion *et al. (*2019) shows that higher market concentration can be associated with lower innovation activities. The authors calibrated a model that partially replicates stylised facts of the US economy related to firm concentration, labor share, and growth, since the mid-90s. Accordingly, firms with higher costs have less incentives to innovate when competition increases, which leads to contraction in the rate of innovation

Overall, however, there is little empirical support for the view that market concentration or incumbent (large) firms are more strongly associated with a higher level of innovative activity. On the contrary, most of the empirical literature tends to confirm that a positive linear (in some cases non-linear) relationship exists between competition and innovation (e.g. Blundell *et al.,* 1999; Gerosky, 1990). A non-linear response has been detected for Canadian firms (Berube *et al.,* 2012); Swedish firms (Clyde *et al.,* 2015), among others; but the hypothesis non-linearity has increasingly been questioned and rejected in recent studies (e.g. Correa and Ornagui, 2013; Hashmi, 2013).

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[4] In this setting, technological progress by leaders and followers takes place step-by-step and not through automatic leap-frogging -as defined in previous research. Innovation incentives for incumbents are driven by the difference between post-innovation and pre-innovation profits.

Some recent works suggest that the competitive environment in which firms operate are a key element to the success of industrial policies, and productivity growth. For instance, Aghion, Cai, Dewatripoint, Du, Harrison and Legros (2015) examined the effect of a group of industrial policies -subsidies, loans, tariffs, and tax incentives- on productivity growth for medium and large enterprises in China between 1998 and 2007. Using a firm level productivity equation, they looked at the impact of the interplays between product market competition (industry-city level initial degree of competition) and the allocation of subsidies (or credits) at the sector-city level.

They find evidence that industrial policies are effective in fostering firm productivity growth only if instruments (e.g., subsidies, tax exemptions or tariffs) are allocated to competitive sectors (classified by the Lerner index) or allocated in such a way as to preserve or increase competition; only in these cases the impact of these policies becomes significant.[5] In their model, competition-friendly policies are defined as "*targeting*" that is more dispersed across firms or measures that encourage (*entry of*) younger and more productive enterprises. Accordingly, by inducing firms to operate in the same sector, *industrial ("sectoral") policy* induces firms to innovate "vertically" rather than differentiate "horizontally" to escape competition, reinforcing innovation incentives, and this response increases with more intense competition. Effectiveness depends upon the design of industrial policy, of course, which should target sectors, not particular firms.

This is in line with previous findings reported by Lee (2011) who explored differential effects of public R&D support using firm-level data for nine industries across six countries (Canada, China, India, Japan, Korea, and Taiwan). He finds that public support tends to have a complementarity effect on private R&D for firms with low technological competence, firms in industries with high technological opportunities and firms facing intense market competition. Accordingly, complementarity between public and private investment only arise in industries with high levels of competition, whereas in the rest of industries the impact is non-significant.

In contrast, a very different result was reported by Kilponen and Santavirta (2007) for Finnish firms, and by Freitas, Castellacci, Fontana, Malerba and Vezulli (2015) for Italian, Norwegian and French firms, and by Xiang (2019) for Chinese companies. Based on a Schumpeterian endogenous growth model, Kilponen and Santavirta (2007) show that a proportional R&D subsidy accelerates innovation activity at all degrees of competition model, but less so at high degrees of competition: in line with the inverse-U shaped preconised by Aghion *et al.,* (2005). They confirmed these predictions on a sample of Finnish firms for the period 1990-2001 and find that the impact of the

[5] They calculated correlations between the two variables obtaining a time-varying change correlation matrix linking initial competition (year zero) and the patterns of interventions (sector-region) across different cities in China.

R&D subsidy on firm innovation activity is positive and significant at all levels of competition excepting at the highest levels. Accordingly, the R&D grant reinforces the Schumpeterian effect: an increase in the R&D subsidy steepens the inverted U relationship when competition is fierce.

Furthermore, a recent study points out to the important complementarities that may arise between trade competition and innovation subsidies. According to Ackdigit, Ates and Impulliti (2018), R&D subsidies help domestic firms compete globally by strengthening innovation-enhancing effects of trade competition (see also, Impulliti , 2012).[6] This has been confirmed empirically for US firms where the introduction of the Research and Experimentation Tax Credit in 1981 was found an effective instrument to restore technological competitiveness face to increased global competition by Japanese and European firms. Subsidies contributed to generating substantial welfare gains in the medium and long run, maximising welfare impact of trade.

Empirical research by OECD tend to confirm the critical role of framework conditions such as trade openness and market competition (e.g., proxied by product market regulation scores or PMR index) in the impact of innovation policies (e.g. Criscuolo *et al.,* 2014; Andrews, Criscuolo and Gal, 2015). Accordingly, dynamic efficiency gains from market competition can hardly be achieved without well-functioning factor markets, which allow the reallocation of labor and capital of shrinking/exiting firms to entering/growing firm. However, some recent studies highlight out that innovation policies may also have detrimental effects on resource allocation and business dynamics (e.g., Bravo-Biosca *et al.,* 2013; Andrews *et al.,* (2015).

According to Freitas *et al.,* (2015) and Bravo-Biosca *et al., (*2013), innovation policy schemes such as tax incentives risk deepen the innovation divide across firms and industries in European countries, leading to more concentrated markets over time. Thus, the analysis of these trade-offs and interplays between competition and innovation is thus a major policy question. In a study on European manufacturing firms (Norwegian, Italian, and French), Freitas *et al.,* (2015) find that firms in sectors with high market concentration are on average more responsive to fiscal incentives for R&D than firms on more competitive sectors; larger additionality effects were detected in less competitive industries. Accordingly, face to competition, oligopolistic producers would like to reinforce their market leadership by investing in innovation. Bravo-Biosca, Menon and Criscuolo (2013) also highlight the risk for R&D tax incentives to stifle efficient resource allocation away from young firms and mature sectors (see also Acemoglou *et al.,* 2013). They show that R&D

[6] Their theoretical model, which is a step-by-step innovation based dynamic growth model takes into account three different innovation incentives that emanate in open economies; "*defensive innovation"* motivation, the "*market expansion"* effect, and "*technology spillovers*".

fiscal incentives might benefit relatively more established incumbents to the detriment of potential entrants, thereby slowing down the reallocation of resources towards entrants. They were also found to benefit disproportionally more R&D intensive industries; where R&D is deemed more critical for competitiveness and lead markets in established firms.[7]

In this paper, we investigate the role of market competition in fostering the effectiveness of innovation subsidies for the case of Latin American firms. This is the first exercise of this sort for the case of firms in emerging countries. In linen with the recent literature, we expect the impact of innovation subsidies to be more effective in spurring firm innovation efforts in more competitive sectors, i.e., in industries where products are more competitively priced and market dominance is less pronounced. We use several methods to tests this hypothesis.

II. THE DATA AND OUTCOME VARIABLES

We use firm-level data from manufacturing industries from Chile and Peru. Our main data come from the national innovation surveys, which follow the definitions and methodology defined in the OECD Oslo Manual for the Measurement of Innovation Activities (OECD and Eurostat, 2015). For Chile, we use three innovation survey waves (8th, 9th, and the 10th Survey), which combined cover the years 2011-2016. For Peru, we also use three waves of the National Innovation Survey for the period 2009-2017. In the two country cases, each innovation survey has a different sample design; as a result, the analysis of panel data is substantially constrained. In the case of Peru, even though we have information from three editions of the survey, we cannot build a panel, since we cannot identify firms across waves. However, for Chile we were able to conduct panel analysis (over four years) and implement panel regressions on the sub-set of firms that are surveyed every edition (200 firms).

We look at the impact of innovation subsidies in the form of matching grants for private innovation investment. Matching grants are a form of public subsidies that require a financial participation from the beneficiaries; in some cases, such financial part might be covered with in-kind and assets contributions from participants. The allocation of public support to innovation through matching grants (where a firm commits to match, in each proportion, the direct support received) is an increasingly common feature of government funding programs worldwide (see Blanco Armas *et al*., 2006; Hall and Maffioli, 2008). In Latin American countries, matching

[7] Other disadvantages related to R&D fiscal incentive are: a greater risk of dead weight loss (supporting projects which would have been performed anyway); less additionality in the case of very large companies; limited incentives for technology transfer, and risk of tax competition (and tax evasion) and rent-seeking.

programs for R&D or innovation investment have proliferated over the last two decades, with some evolving towards more targeted interventions (sectorial funds) and collaborative schemes.

For Peru, the innovation surveys ask firms whether they participated in a list of public policy programs, before or during the span of each wave. Most of these programs refer to subsidy programs. Given that the use of innovation programs is quite recent in Peru; the number of firms participating in each are low and this is reflected in the data. We then adopt a more wide-ranging approach and define treatment if a firm participated in any of the innovation programs listed in the questionnaire that involved support either to innovation activities, firm creation and technology transfer activities, -which are all related to firm innovation. We consider a firm as having an innovation support if she participated in the following support programs: *Innóvate Perú,* the *Start-up Peru* program, the CITES program, the 5-S Kaizen program, the *Ciencia-Activa program*, and the *AgroIDeas* and *TuEmpresa* programs (see Aboal *et al.,* 2020). Firms that report to be recipients of any policy instrument before the wave are not considered when estimating the impact of innovation policies. This implies dropping firms that were beneficiaries of the referred programs 3 or 4 years ago. The wording of the question does not allow us to ascertain the time of the previous participation, and we therefore drop them from our sample.[8]

The questionnaire asks about participation in these programs (whether they received a subsidy or grant or technical assistance) but no exact year of concession is provided. It is therefore understood that a subsidy was received during any of the two years covered by the surveys. We define the treatment variable as a dummy taking the value 1 in the last year of each wave (2011, 2014, and 2017) and 0 otherwise for firms that report being beneficiaries of at least one program during the wave period. Despite the possible limitations of this procedure, this has been a common practice in the first waves of studies conducted for European firms with the Community Innovation Surveys - e.g. Czarnitzki and Licht (2006); Aerts and Schmidt (2008)- in which the questions about innovation grants or subsidies are formulated in the same way.

We used a similar approach for the Chilean data. We considered a firm being a beneficiary if she declared receiving financial support for innovation from innovation programs operated from CORFO *(Corporación de Fomento a la Producción)*, the Chilean Innovation Agency which is the main agency in charge of the promotion and support for private sector innovation. These innovation programs mostly consist of matching grant programs (subsidies) for innovation activities. These mostly target R&D activities, product, or process innovation projects, and/or technology

[8] Unfortunately, this could not be done for the last wave because that information was not retrieved, so it is not possible to remove from the database firms that received support in some year prior to 2015.

upgrading. We must acknowledge that this identification is rather broad and may include other types of innovation programs.

We should note that the question on the use of public funding programs has evolved over time and it is not the same across the different waves. In the 8th Innovation Survey -which covers the years 2011-12, the question refers to whether the firm was beneficiary of *any* of the following innovation support programs: Innova Chile de CORFO, FONDEF (*Fondo de Fomento al Desarrollo Científico y Tecnológic*o) from CONICYT (National Commission for S&T), the FIA (*Fondo de Investigacion Agropecuaria* or Agriculture research Fund), and Innova BíoBío and "other" similar programs. In the 10th Enterprise Innovation Survey (for the years 2015-16), the question is broken down into individual programs, but we only consider for treatment those firms that declared receiving financial support from the innovation programs operated by CORFO (matching grants).[9] In these group of "treated" firms, we excluded those that declared being beneficiary of the R&D Fiscal Incentives program (Ley N° 20.570 (Ex Ley N° 20.241); therefore we drop firms that were receiving support from two different types of policy instruments (fiscal incentives and matching grants).

III. THE ESTIMATION STRATEGY

A significant hurdle in the identification of the causal relationship between R&D (or other innovation) grants and the performance of participating firms is the possibility of endogeneity and selectivity bias. Selection into programs is not an exogenous and randomised treatment but is very likely to be affected by other endogenous factors influencing allocation decisions and self-selection (see Czarnitzki and Licht, 2006; Guerzoni and Raiteri, 2014; Crespi *et al.,* 2014).

In this paper, we use two alternative methods to evaluate the impact of innovation support programs on innovation outcomes: (1) Differences-in-Differences combined with Propensity Score Matching (PSM-DID) and (2) fixed effects (DID) regression with PSM. In the three approaches, we evaluate the impact of the program in double differences, reducing the potential endogeneity of treatment due to un-observables -which are assumed constant. In the former, the matching helps reduce the selection bias based on observables characteristics by comparing treated with the most similar un-treated (within non-beneficiaries) based on an ex-ante participation probability score. At the same time, it also considers unobserved heterogeneity by comparing differences in

[9] In the 10th Innovation Survey, the following categories of financial support programs for innovation are considered: (i) Innovation programs from CORFO; ii) CONICYT; (iii) FIA (Agriculture Research Fund); (iv)) ICM (*Iniciativa Científica Milenio*); (v) FIP (Fishing Research Fund), and (vi) PROCHILE, which refers to a set of financial programs for the support of upgrading activities for exporting.

performance change -before and after treatment (Heckman *et al.,* 1997; Imbens, 2004). In addition to this, the second method - fixed effects (DID) regression with PSM- employs PSM techniques with panel regression removing thereby the two types of biases; selection and endogeneity due to non-observable time-invariant differences among firms (e.g. see Blundell & Costa-Dia, 2002).

An additional empirical challenge is the weak exogeneity of market competition, as previously discussed. Since competition and innovation are mutually dependent, competition may change because of firm innovation decisions, so reverse causality can exist (from innovation on industry competition). Endogeneity could result in biased regression estimates. A practical way to lead with the endogeneity problem of competition is to use lagged values of the indicators (t-1 or t-2) and exclude firms´ market sales from calculations, to reinforce orthogonality (see Aghion *et al.,* (2016). To circumvent the problem of weak exogeneity of competition, we therefore use competition indicators in t-1 in our innovation equations.

Another way consists in splitting the sample in high and low competition using a threshold value for market competition that designates which sectors have low market competition and which are high-competition industries. We use competition indicators (Boone and the Lerner Indexes) one period-lagged to create these categories. For Chilean firms, we estimate the profit elasticity coefficient, commonly known as the Boone index (Boone, 2006; Boone et al., 2007) from a profitability equation. These estimations were run per industry (3-digit level ISIC 4) data using the National Annual Survey for Manufacturing Industries (ENIA), which cover most of the population of Manufacturing firms. **Annex 1** describes in detail this procedure. Given that Chilean Innovation Surveys, for purposes of international comparability only report data at the 2-digit level (ISIC Rev. 4), we transform our ENIA competition indicators from 3-digit levels to 2-digit of ISIC Rev. 4.

For Peruvian firms, we use the Hirschman-Herfindahl Index which has computed with data from the innovation surveys. As an alternative competition indicator, we compute industry-level profit margin ratios (PCM) or so called the Lerner index. For Peru, these are computed at the 3-digit level of ISIC Rev. 4; whereas for Chilean enterprises, this computation was only possible at the 2-digit level -as previously mentioned. We split samples into low and high competition sectors. A high competition is considered if the Boone or the inverse of the Lerner index are strictly superior to the median value of this indicator for the whole manufacturing industry.

For Peru, we compute our competition indicators (HHI and Lerner) with data from the Innovation Surveys and we acknowledge the limitation of this approach. We compute these indicators at the ISIC 3 2-digit and 3-digit level. To reinforce our analysis and have an additional market competition indicator for comparison, we also compute Lerner (PCM) Indicators with the aid of an external survey, the World Bank Enterprise Survey (ES).[10] We then matched these competition indicators to our Innovation Surveys (ISIC. Rev.4, 2-digit level).

Our outcome variables are Innovation Expenditure per employee (in natural logarithm). Our measures of R&D and Innovation Expenditures are net of public subsidies. Our definition of innovation expenditures follows exactly the definition of the Oslo Manual (OECD and Eurostat, 2015) and covers all forms of firm activity dedicated to innovation (cf. the creation of a new product or process or service innovation, or with the goals of creating or adopting new organisation or managerial practices or business models). This definitions categorise as innovation-related all expenses related to internal and external R&D activities, technology acquisition (i.e. payments of royalties or fees concerning technology licensing and other forms of technology purchasing); royalty payments concerning the licensing of intellectual property or know-how, the acquisition of new machinery and equipment related to R&D and innovation; the acquisition of software or hardware supporting R&D and innovation activities; plus training associated to innovation or technology adoption activities (ibid).

For Peruvian firms, we define the growth rates in innovation investment as the difference between the pre-treatment log levels of our outcome measures (i.e. R&D expenditure or Innovation Expenditures per employee) in t-1 (t=treatment) and the log levels in short term (t+1 after treatment), and we compare this difference with the one computed for comparator firms. This is what is known as "double differences" of Differences-in-Differences (DID). In the analysis of Peruvian firms, we use the total original sample because we take into account firms' innovation status in order to evaluate the inducement effect of subsidies on firms that do not conduct innovation activities (Aerts and Czarnitzki, 2005; González and Pazó, 2008). If we judged only those that did, we could underestimate the treatment effect because we could not test whether a firm would have invested in innovation activities without the incentives.

IV.1. IDENTIFICATION AND THE PSM-DID APPROACH

For the two-period, two-groups case, the Difference-in-differences Matching estimator combined with PSM originally proposed by Heckman, Ichimura and Todd (1997), basically consists of applying the standard PSM estimator using the change in the outcome instead of the outcome in levels, which makes us rid-off fixed unobservable characteristics of firms that could

[10] We resort to the three available waves of the World Bank Enterprise Surveys (number of observations in parentheses): 2006 (632), 2010 (1,000) and 2017 (1,003). They all have national representativity (non-agricultural sectors) and were conducted between April and October 2006, May 2010, and March 2011, and between March 2017 and March 2018, respectively.

potentially influence participation and outcomes. This technique allows us to control for unobserved heterogeneity (assumed constant) while reconstructing the counterfactual outcome using only the most similar observations from the pool of untreated units (identification strategy). This is a more efficient strategy than the two estimators separately applied (Blundell and Costa-Dias, 2002). Under this configuration, the estimator of the average impact on the treated is:

$$\tau_{ATT}^{DID-PSM} = E[Y_{t+1}^{1} - Y_{t-1}^{1} | D_t = 1, P(X)] - E[Y_{t+1}^{0} - Y_{t-1}^{0} | D_t = 0, P(X)] \quad (1)$$

which is the difference of the interest variable (innovation outcome) before (t-1) and after the treatment (t+1), among the treated (y^1) and the control group (y^0), compared on the common support using PSM techniques. This is a more robust estimator compared to simple PSM estimators. We are aware that previous research has shown that the impact of innovation policies happens almost immediately (contemporaneously or one year after), although public policy would expect the impact to last over a span of years. Crespi *et al.,* (2014) suggest that the impact of innovation subsidies mostly takes place within the 3 years after intervention. We focus here on the very short run impact of innovation subsidies, one year after intervention. The evaluation of larger time spans (before and after intervention) severely reduces the number of firms with treatment.

Through the construction of a valid control group based on observable differences between the two groups, our matching approach should control for endogeneity bias. The second step is to assess the average treatment effect (ATT) by estimating the difference in outcome variables between the two types of firms (treated vs untreated) using linear regression as suggested by Leuven and Sianesi (2006). To build the control group we use propensity score matching to select suitable controls from the very large group of untreated firms, matching observed characteristics as closely as possible to those of treated firms before the start of the research project (Rosenbaum and Rubin, 1983; Heckman *et al.,* 1997; Becker and Ichino, 2002; Lechner, 2002). We estimate the probability that any firm participates in the innovation matching grant program(s) using a probit model (Mexico and Peru); a logit model is used for the Chilean data. Once done, we predict the propensity score for each firm, and we compare the propensity score distribution for firms before and after matching.

We use Kernel matching and Nearest-Neighbor matching with 1 (N-1) and 5 neighbors (N-5). The differences between the two matching methods lie in the number of untreated firms that are used in the control group and how untreated firms are weighted. In the first method (kernel matching), a 'synthetic' counterfactual is created for each treated firm, based on the kernel-weighted average of the characteristics of all matched untreated firms. The second method (calliper matching) only matches a treated firm with up to n- nearest untreated firms (where n is set at 5 in this study) but weights all matched firms in each match equally. Kernel matching maximises precision by retaining sample size without compromising bias as it gives larger weights to better matches. For Nearest-Neighbor matching we use a calliper of 0.05 to ensure quality of matches. We also used a calliper of 0.08 for comparison and the results were pretty much similar. In the kernel matching estimation (Epachinikov Kernel matching) we use a bandwidth of 0.08. For nearest neighbor matching, we use heteroskedasticity-consistent analytical standard errors proposed by Abadie and Imbens (2006) whereas for kernel matching (Epanechnikov Kernel) we bootstrapped standard errors (100 boostrapp estimation replications).

If the explanatory variables used for the estimation of the propensity score equation do a good job predicting which firms receive the treatment, then it is plausible that selection bias due to observables and non-observables is minimised -since we employ differences riding out firm specific non-observables. This would then mean that the estimated effect can be interpreted as causal (Antonioli *et al.* (2014), Chang *et al.* (2013) and Wamser (2013).

Our explanatory variables for the selection equation (Logit for Mexico and Chile; Probits for Peruvian firms) are all pre-treatment variables and refer to characteristics of the firm and industry one year before intervention**.** We control for industry and time effects and cluster standard errors at the firm level to deal with firm serial correlation in the error term. We include a set of firm-level variables such as employment, employment squared, firm age and firm age squared, the level of productivity (sales per employee), export intensity of the firm, the innovation intensity of the firm in the previous period (log of innovation expenditures per employee) as well as affiliation to a group (dummy equal to one). In the regressions of Chilean firms, we also include a dummy reflecting firm experience in the use of public policy programs in the past (e.g., Xing *et al.,* 2017).

In line with previous research (e.g., Gorodichenko *et al.,* 2001), we include two measures of global insertion. We use the percentage of foreign ownership in capital (or alternatively a dummy indicating whether the firm has foreign ownership in capital) and the intensity of exporting in the previous period.[11] Firms participating in global markets are expected to have stronger innovation incentives given that global competition puts additional pressures on product quality and innovation (e.g., Bustos, 2011), and facilitates knowledge transfer from abroad (i.e., Crespi *et al.,* 2006). We expect for this type of firms a higher likelihood to apply and compete in R&D and innovation support programs.

[11] In Mexico, the PEI program, as many other firm support programs of CONACYT and the Ministry of Economy were open to both national and multinational firms, with the expectation to have inter-firm collaboration and cross-sectoral R&D collaboration taking place.

Lastly, as in Aerts and Schmidt (2008), we control for the importance of financial stress (or market failures in the funding of innovation) firms perceive in the funding of innovation. We include two dummies referring to level of severity (very high, or high) firms assign to the lack of finance as barrier to innovation activities. The first is a dummy equal to one when firms declared the "lack of financial resources to innovation" as a very important or important barrier to business innovation; the second designates moderate level of importance, whereas the baseline refers to firms declaring not considering such factor as important or relevant for innovation.

IV.2 FIXED EFFECTS PANEL REGRESSION AND MATCHING

Following Angrist and Pischke (2009), Freitas *et al.,* (2016) and Crespi *et al.,* (2011), we can make use of the difference in difference (DD) approach to estimate the impact of innovation subsidies (or tax credits) on firms´ innovation effort. The fixed-effects approach is helpful in avoiding potential endogeneity problems, which arise when we deal with firms with non-observable heterogeneous characteristics, which could be correlated with program participation and outcomes. Further, the Fixed Effects (FE) model controls all the unobservable factors if they do not vary in time. The identifying assumption of DID and the fixed effects model states that there are no unobserved time-varying factors affecting both the outcome and treatment status, which means that all unobserved relevant factors must be constant (i.e. Angrist and Pischke, 2009).:

$$E(Y_{0it}|i, X_{it}, t, D_{it}) = E(Y_{0it}|i, X_{it}, t)$$

This assumption implies that in the absence of the program, the trends in the control group and the counterfactual (beneficiary firms without treatment) would have been the same (common trends).[12] Kim and Imai (2017), however, highlight two causal identification assumptions required under the fixed effects model which are often overlooked: (1) past treatments do not directly influence current outcome, and (2) past outcomes do not affect current treatment.

To estimate the effects of innovation subsidies (R&D or Innovation Support Matching Grants) we then use the following empirical specification:

$$Y_{it} = \alpha_i + \mu_t + \beta D_{it} + \delta X_{it} + \varepsilon_{it} \tag{3}$$

[12] If data for several pre-treatment periods is available, a straightforward way to provide evidence to support this assumption is to show that trends were equal between groups before the program.

where Y_{it} represents the outcome variable considered for firm i in the year t, α_i is the firm fixed effect, μ_t represents the yearly shocks that affects all firms, $D_{it}$is a binary variable that takes value one from the year following the subsidy approval for firm i, and X_{it} is a vector of control variables that vary over time, and ε_{it} is a error term that is assumed non-correlated with D_{it}. We extend equation (3) and include the market competition (Boone or Lerner index) variable and its interaction with the D_{it},

$$Y_{it} = \alpha_i + \mu_t + \beta D_{it} + \rho MC_{ijt} + \delta\left(MC_{ijt} * D_{it}\right) + \varphi X_{it} + \varepsilon_{it} \qquad (4)$$

We estimate the previous equation with Fixed Effects and adjust standard errors clustered at the firm level so that the statistical inference be robust regarding serial (firm) correlation in the error term. The model consistently estimates the parameter β which captures the average effect of the innovation support on the considered outcome variable. One feasible approach to try to correct for differences in ex-ante trends is to combine the DD estimator with Propensity Score Matching (PSM) techniques. Furthermore, the main problem dealing with this type of examination (FE regression) is that the allocation of funds is not random. As this is not an experimental design, selection of firms into treatment groups should be based on some observable characteristic that must be controlled for. We then combine PSM (matching) with FE regression and restrict samples to the most comparable observations (weighting by similarity); and conduct estimation within the common support provided by the propensity score. For Chile and Peru, we have pooled data from three innovation surveys, and overall, we have a very small number of firms reporting subsidy program participation; pooling over the years allow us to maximise the number of treated firms.

IV. THE RESULTS

Table 1 and 2 report the results from the estimation with DID-PSM (Panel A) and PSM methods to evaluate the impact of innovation subsidies on the innovation investment effort of firms proxied by the total of innovation expenditures (Oslo Manual) expenditure per employee discounted off innovation subsidies. We estimate the ATT for the total samples and sub-samples (high and low competition industries). The industry classification for Peruvian industries uses the Herfindahl Hirschman index as indicator of market competition at the 3-digit level of ISIC-4 whereas in the analysis of Chilean firms, we use the Boone index (profit elasticity index) computed at the 2-digit level of ISIC-4. Regressions are run using the three innovation surveys pooled for each country. Since we have very extreme low percentages of program participation in each wave, we prefer to pool the survey data and evaluate the average impact across the whole survey data. As expected, for DID estimation the analysis was restricted to firms reporting at least three consecutive years of data (included in two innovation waves). In the case of Chile, this resulted in a sub-sample of 334 firms, of which 164 received an innovation subsidy from CORFO over this period. Matchings were restricted to firms in the same industry-year.

V.I. SELECTION EQUATION AND BALANCING TESTS

We start with the estimation of the propensity score which is subsequently used in the matching algorithm to obtain the average treatment effect on the treated. For Chilean and Mexican firms, covariates are all pre-treatment firm and industry characteristics. **Tables 6 and 7** (**Annex 2**) shows the estimation results of the probit model on the receipt of subsidies for the three firm samples. We used probit regression for Peruvian firms, and logit estimation for Chilean firms.

These results indicate that the factors explaining firm selection into treatment are not the same across countries, reflecting differences in program selection and design. The propensity to be beneficiary is positively related to firm size and age and exporting performance of Chilean firms; but only size appears a significant determinant of selection.[13] Large firms are more likely to be considered in national innovation programs. Large firms conduct presumably more R&D projects than smaller firms and are more able to apply for public R&D support with several proposals; they might also be advantages in dealing with the bureaucratic requirements of the application process. In Peru, small and large firms are significantly more often beneficiaries than medium-size enterprises. In Chilean firms, firm program participation is significantly and non-monotonically associated with age with a decreasing probability for younger firms. In addition, past innovation effort is positively related to program participation.

In contrast, neither exporting status or multinationalism (foreign ownership) have a role in explaining firm selection into the subsidy programs in any of the three country datasets. The dummy reflecting foreign ownership is only significant in the sample of Chilean firms, for the total sample only. Consistent with past research, firm experience in other productivity support programs (e.g. value chain programs, exporting programs, etc.), is strongly associated with firm participation in innovation subsidy programs; this is the case in Chilean firms. Finally, the analysis for Chilean firms (not reported in the Table for sake of space), also showed that firms that consider (lack of) finance as a very important obstacle to innovation are significantly more likely to participate in

[13] It must be noted that, in the case of Mexico, there are three sub-components of the PEI program, one of which specifically targets SMEs; the two other sub-programs are open to any size. In this sample, all PEI programs are covered.

innovation programs -which confirm the importance of policy intervention in addressing market failures in finance.

Figures 1 (a-f) (Annex 2) report evidence of the quality of our matching on observable characteristics of firms in the control and treated groups for the Chilean data and with PSM estimation and Nearest Neighbor-1 and for the total pooled data and the two groups of industries - e.g., with low and high competition. The equivalent charts for Peruvian firms are reported in the **figures 2 (a-c)** (Annex 2). Table 3 and Table 5 report the covariate imbalance testing (Tables 5-6 for Peruvian firms) and assess the comparability of the two groups, treated and untreated and the extent of balancing between the two samples before and after having performed matching with Kernel Epanechnikov. The balancing property is satisfied with the three different methods in the total samples and sub-samples (High and Low Competition); although in both cases (Peru and Chile), balancing properties appear less strong for the sub-samples of low competitions sectors. The reduction in bias is about 92% on average for the Chilean sample, and 62% for the Peruvian.

Table 4 summarises the balancing statistics for the matched Chilean sample, which are pretty much in line with the critical threshold recommended (Rubin, 2001) for samples to be considered sufficiently balanced; the Rubin-B (Bias)<25% and Rubin-R statistics fall within the interval [0.5; 2], in the total samples, and sub-samples (High competition and low competition sectors -according to the Boone Index).[14] As required, the Pseudo-R^2s decrease significantly after matching (Sianesi, 2004); suggesting that covariates weakly explain selection into treatment with the matched sample As recommended by Sianesi (2004), we also compute the likelihood-ratio (LR) test of the joint insignificance of all the regressors before and after matching. As required, the tests are not rejected after matching. Similar conclusions are provided in Tables 5 and 6 for the Peruvian data. For Chilean firms, the ratio of the variances (Treaded versus control group) becomes non-significant in most of the covariates after matching; excepting in the case of size variables and foreign ownership which were already non-significant before matching. In the Peruvian data, after matching, covariates such as size, age, exporting intensity and labor productivity all become non-significant between treated and untreated in the sample of Chilean firms, which indicates that our control group is a good counterfactual group.

[14] Rubins' B is the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group) and Rubin's R (the ratio of treated to (matched) non-treated variances of the propensity score index).

V.II. DID-PSM AND PSM ESTIMATES

Table 1 here below reports the ATT estimates with DID-PSM methods for the two country datasets. The impact of the innovation subsidies largely differs across the three country cases, probably reflecting differences in program design. In Chilean firms, there is no significant impact of subsidies when we consider the total sample in any of the matching methods. However, subsidies do have a significant impact in terms of innovation investment differential before and after treatment, compared to the change in the control group, but this effect only occurs in highly competitive industries -those reporting a Boone profit elasticity superior to median of manufacturing. The ATT is significant with the three matching methods for these industries, with an ATT oscillating between 1.5 (kernel) and 2.3 with N-1 Nearest Neighbor matching. Yet, the standard errors for the latter are relatively larger than the total sample, and this is due to the small number of treated firms. These have been however adjusted for heteroscedasticity in nearest neighbor matching (N-1 and N-5) (Abadie and Imbens, 2006).

A similar finding is reported for Peruvian firms. The DID-PSM estimates suggest that treated firms display larger innovation investment growth than the control group, within the common support and keeping all other covariates constant. Firms receiving innovation subsidies report on average an ATT of 0.65 (Kernel) and 0.88 (NN-1), significant at the 5 and 10% probability level respectively. No significant effects emerge with Nearest N-5. Consistent with the previous findings, the estimations per type of competition shows that this additionality effect comes mainly from the high competition industries; no significant effects are found in the group of low-competition industries. In high competition industries, firms receiving an innovation subsidy (a subsidy or direct support for innovation in the case of Peru) expanded their innovation investment at a 90-95% larger rate than non-beneficiaries in the control group. This is the case with the N-5 and Kernel matching methods.

The **table 2** next reports ATT estimations with PSM only, where we compare the differences in logs between levels of innovation investment (t+1 after intervention) between treated firms and the control group. In general, under the three matching methods, the ATTs are positive and significant. The impact (ATT) of innovation subsidies is significant in the two types of competition settings. However, the size of the impact is much larger in more competitive industries than less competitive sectors; about 120% larger in the case of Peruvian beneficiaries (Kernel estimation). This result is consistent across the three matching methods.

Table 1: DID-PSM ESTIMATION OF THE AVERAGE TREATMENT ON TREATED, TOTAL AND BY INTENSITY OF COMPETITION IN MANUFACTURING FIRMS

A. CHILEAN FIRMS (POOLED SURVEYS, 2011-2016)				
	METHOD	TOTAL	LOW COMPETITION	HIGH COMPETITION
Innovation Expenditure Intensity (logarithm natural of the expenditure per employee)	NN-1	-0.183 (0.78)	-0.746 (0.828)	**2.322**** **(1.324)**
	NN-5	-0.304 (0.66)	-1.036 (0.865)	**1.870**** **(1.105)**
	Kernel	-0.045 (0.61)	-0.795 (0.72)	**1.49*** **(1.040)**
	N	N=747 T=98	N=472 T=63	N=268 T=35
B. PERUVIAN COMPANIES (POOLED SURVEYS, 2011-2017)				
Innovation Expenditure Intensity (logarithm natural of the expenditure per employee)	NN-1	**0.88*** **(0.48)**	0.19 (0.98)	0.87 (0.56)
	NN-5	0.66 (0.46)	0.44 (0.63)	**0.95***** **(0.36)**
	Kernel	**0.65**** **(0.32)**	0.50 (0.41)	**0.90***** **(0.35)**
	N	3701	1599	2102

Note: Standard errors in parentheses. Bootstrapped standard errors reported in Kernel estimation. Heteroskedasticity-consistent analytical standard errors in Neighbor (N-1 and N-5) matching (Abadie and Imbens, 2006). Matchings were restricted to firms in the same industry-year. Kernel estimation uses a bandwidth of 0.10 in the estimation for Chilean and Mexican firms; and Neighbor Matching uses a caliper of 0.05. *** p<0.01, ** p<0.05, * p<0.1 for P>|z|.

The size of the impact is relatively large. For Peruvian beneficiaries, receiving a subsidy invest about 2 and 2.5 times the amount in innovation investment reported by untreated firms. With nearest-5 neighbor estimation the ATT is 2.37 in high competition industries, compared to 1.54 in low competition sectors. In contrast, for Chilean enterprises, although the innovation subsidy is significant in the total sample; this effect only exists from beneficiaries in high-competitive sectors; no effects arise in less competitive industries. This finding is consistent across the three matching methods.

For Peruvian firms, we also ran additional regressions using the probability of engagement in innovation activities as innovation outcome measure also confirm crowding-in effects, and effects (ATTs) were found also larger in high competition industries.[15] These results are available upon request (see Aboal *et al.,* 2021). Treated firms exhibit an increase in their probability of spending in innovation activities in the order of 8 percentage points, with respect to their non-treated counterparts (across all levels of product market competition), with DID-PSM estimation and

[15] No significant effects were found with nearest-neighbor matching techniques; neither on the total sample nor a significant impact emerged in each of the two group of industries.

Kernel matching. Restricting the sample to high competition levels increases this estimate to 11 percentage points (significant at 10% level).

Table 2: PSM ESTIMATION OF THE AVERAGE TREATMENT ON TREATED (ATT), TOTAL AND BY INTENSITY OF COMPETITION IN MANUFACTURING FIRMS

A. CHILEAN ENTERPRISES (POOLED SURVEYS, 2011-2016)				
	METHOD	TOTAL	LOW COMPETITION	HIGH COMPETITION
Innovation Expenditure Intensity (logarithm natural of the expenditure per employee)	NN-1	**1.145**** **(0.637)**	1.129 (1.027)	**1.45**** **(0.785)**
	NN-5	**1.198**** **(0.519)**	0.629 (0.890)	**1.62**** **(0.698)**
	Kernel	**1.220***** **(0.503)**	0.401 (0.813)	**1.371**** **(0.643)**
	N	**N=744** **T=89**	N= 376 T=63	N= 268 T=26
B. MEXICAN COMPANIES (2017 INNOVATION SURVEY)				
Innovation Expenditure Intensity (logarithm natural of the expenditure per employee)	NN-5	**1.798***** **(0.3001)**	1.092** (0.558)	**1.775***** **(0.431)**
	Kernel	**1.800***** **(0.254)**	1.117** (0.461)	**1.807***** **(0.373)**
	N	**617** **T=85**	302 T=35	**315** **T=55**
C. PERUVIAN COMPANIES (POOLED SURVEYS, 2011-2017)				
Innovation Expenditure Intensity (expenditure per employee)	NN-1	**2.47***** **(0.42)**	1.56** (0.92)	**2.67***** **(0.35)**
	NN-5	**2.03***** **(0.33)**	1.54*** (0.56)	**2.37***** **(0.46)**
	Kernel	**2.11***** **(0.25)**	1.82*** (0.62)	**2.18***** **(0.38)**
	N	3727	1611	2116

Note: Outcome variables refer to innovation expenditures discounted off subsidies amounts. In the Chilean and Mexican estimations, the outcome variable refers to the logarithm of innovation expenditures per employee (discounted off subsidies) in t+1; one year after the subsidy was received. The estimation on Peruvian firms uses the Herfindahl Hirschman index (HHI) as indicator of market competition; whereas in the Mexican and Chilean firms we use the Boone index computed at the 2-digit level of ISIC-4. Standard errors are bootstrapped in Kernel estimation. Heteroskedasticity-consistent analytical standard errors in Neighbor (N-1 and N-5) matching (Abadie and Imbens, 2006). Kernel estimation uses a bandwidth of 0.10 in the estimation for Chilean and Mexican firms; and Neighbor Matching uses a caliper of 0.05. *** p<0.01, ** p<0.05, * p<0.1.

V. SAMPLE SPLIT WITH THRESHOLD ESTIMATION

Up to this point, we estimated ATTs and ran regressions for sub-samples based on an arbitrary criterion, above or below the median of the market competition indicators. In this section, we follow a different approach and formally test for non-linearities in the relationship competition-innovation investment. We follow Hansen (1999; 2000) and Wang (2015) and estimate a threshold panel model with firm fixed effects for the Chilean data. This method will allow us to determine endogenously whether a structural break exists and the value of this coefficient, and split samples accordingly. This sample splitting will then reflect sector-differences in the degree of firm responsiveness to market competition. Following Hansen (1999; 2000), we use bootstrapping to test the null hypothesis of no-threshold vs. single threshold, and the double threshold vs. single threshold and calculate the confidence intervals for such models. Hansen (1999) proved that this modelling provides a consistent estimator for the threshold and that the best way to test it is to compute the confidence interval using the non-rejection region method based on a likelihood-ratio rest. We apply this regression method to the Chilean data.

Table 9 in Annex 2 reports the threshold estimates obtained and their confidence intervals for the single and double threshold models. **Table 8** report the threshold regressions for the panel group of firms with the total innovation expenditure per employee (logarithm) as dependent variable (columns (1)-(3); and with innovation expenditure discounted off innovation subsidies (columns (4)-(6). There is evidence of a single threshold in the impact of market competition on firm innovation investment; with a large impact of competition before the threshold (and significant at 10% level). This would mean that in less competitive industries, innovation responses are stronger, in line with the Schumpeterian hypothesis (1949). The results are quite similar for the two sets of regressions. According to regression (1), below this threshold, a one standard deviation in the Boone index is associated with a 18% increase in innovation intensity (exp., per employee), and beyond it, the impact of competition is still positive and prominent, but with less impact. A one standard deviation increase in market competition leads to a 12% increase in innovation efforts.

The single-threshold model's estimator is 1.58 with 95% confidence interval [0.0141, 0.0167]. The F statistic is highly significant. Therefore, we reject the linear model and fit a double- or triple-threshold model. The existence of single threshold model cannot be rejected according to the F-statistics, which is significant at the 10% probability level: and slightly superior to the critical value of the F-statistic (11.52). The double threshold model is rejected (the F-statistic falls below the critical values) and given that Null hypothesis is the validity of one threshold model over the double threshold model; the former cannot be rejected. The single threshold is accepted at 0.52 probability, when testing the double threshold model.

Figure 3 in Annex reports the distribution in the values of the Boone index vis-à-vis the Likelihood-Ratio Statistic (LR), whose critical value is 7.5. The validity of the single threshold model is confirmed given the significance of observations above the critical value, and the observation denoting the structural break below that LR threshold. In contrast, the LR statistic shows that there is no additional break point that justifies a double threshold model.

The estimated threshold is a Boone index with value of 1.585, in absolute terms. We then split the sample according to this threshold (see **Table 3**). This estimated threshold corresponds to the 66th percentile of the distribution. It is much larger than the median and the mean values of the Boone Index for this sample; 1.32 and 1.33, respectively. It must be noted that the threshold regressions here reported were conducted on a sub-set of firms declaring positive innovation investment at least once over the period of analysis and reporting at least 4 years of data availability.[16] This gave us a dataset of 199 firms (798 observations) for 18 two-digit sectors over the years 2013-16. In the DID-PSM estimations, we also restricted the dataset for analysis to firms having invested at least once in innovation activities and declaring at least three years of data.[17]

Table 3 below reports the DID-PSM and PSM estimates with the sample split based on the estimated threshold for market competition. The findings are to some extent like those reported previously. In principle, there is no significant difference between beneficiaries and non-treated firms in terms of investment growth, under DID-PSM estimation. For highly competitive sectors, the ATT is positive and significant, although at 10 and 15% levels of probability, with kernel and nearest N-1 methods, respectively. Interestingly, the coefficients in both total samples and less competitive industries are all negative (but not significant), which indicates that the variation in investment is smaller in beneficiaries, as opposed to the variation (innovation investment growth) in untreated firms. This effect, however, is only significant (at 10% level) under 5-nearest neighbor matching in the less competitive industries.

With PSM estimation, the coefficients and results are pretty much as before, with significance effects only present in competitive industries, above the estimated threshold. With PSM estimation -which allow us to have more observations-, the estimate ATT is between 1.14-1.22 for the total samples; and this increases up to 2.00-2.4 in highly competitive sectors and is significant across the three matching methods. Thus, our findings prevail under endogenous definition of the market threshold. The impact of innovation subsidies seems to only work in competitive sectors.

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[16]An additional reason for restricting the analysis to four years is because that the threshold estimation with fixed effects based on the algorithm proposed by Wang (2019) is only possible with perfect balanced data.

[17] Restricting the sample to firms with at least four years available - regardless of investing or not-, gives us a sample of 464 firms with 1864 observations, for the same period. We run threshold regressions for this sample as well and the threshold estimate was the same but less significant (12% probability); no-second threshold was found according to the LR test.

TABLE 3: PSM AND DID-PSM ESTIMATION WITH SAMPLE SPLIT BASED ON THRESHOLD ESTIMATION, CHILEAN FIRMS

DID-PSM				
	METHOD	TOTAL	Industries below (α<=1.58)	Industries above (α>1.58)
Innovation Expenditure Intensity (logarithm natural of the expenditure per employee)	1-N	-0.183 (0.78)	-1.056 (0.972)	**1.50* (1.270)**
	5-N	-0.304 (0.66)	**-1.131* (0.713)**	1.287 (1.116)
	Kernel	-0.045 (0.61)	-1.056 (0.972)	**1.295* (0.948)**
	N treated	N=741 T=85	436 T=57	308 T=33
PSM (t+1)				
Innovation Expenditure Intensity (logarithm natural of the expenditure per employee)	1-N	**1.145** (0.637)**	0.900 (0.701)	**2.385** (1.022)**
	5-N	**1.198** (0.519)**	1.00 (0.741)	**2.244** (0.941)**
	Kernel	**1.220*** (0.503)**	0.7898 (0.536)	**2.009** (0.952)**
	N	**N=744 T=89**	N=517 T=49	N=611 T=83

Note: Outcome variables refer to innovation expenditures discounted off subsidies amounts. Standard errors are bootstrapped in Kernel estimation. Kernel estimation uses a bandwidth of 0.10 in the estimation for Chilean and Mexican firms; and Neighbor Matching uses a caliper of 0.05. Heteroskedasticity-consistent analytical standard errors in Neighbor (N-1 and N-5) matching (Abadie and Imbens, 2006). *** p<0.01, ** p<0.05, * p<0.1.

VI. FIXED EFFECTS PANEL REGRESSION AND MATCHING

Table 4 here below displays the fixed effect (firm) panel regressions for the sample of Chilean firms. We implement this alternative methodology as a way of robustness test. Implementing this approach, also allow us to include further controls (e.g. entry dynamics and import competition). As before, the original sample was restricted to firms investing at least once in innovation activities over the period (2011-16) and reporting at least two years of data. We used Kernel matching (Bandwidth of 0.6) to restrict the total sample to the common support where untreated firms are weighted according to their propensity score. Balancing statistics, discussed previously, are reported in tables 4 and 6, and confirmed the quality of the matching for the Chilean sample.

The coefficient on the variable **Treated_Post** refers to the differences-in-difference estimate and reflects the average impact of the innovation subsidy for the whole period. In the unmatched sample, on average, treated firms invested 107% more than untreated firms, after intervention (column 1). This is quite a large impact, but we need to recall that we have firms in the sample that in some years did not engage in any innovation investment. In column (2) we test whether this impact of subsidies varies with market competition intensity. The coefficient on the interaction term is no significant which suggests that there is no moderating role of competition in the impact of innovation subsidies. Nevertheless, in column (3) we present an alternative specification and let the treatment effect have a different intercept, for low and high competition sectors separately.[18] Three categorical groups are included, with the baseline reference being Non-treatment-Low Competition Industries (Treated-Post=0 in Low competition Sectors (HC=0). The effect of subsidies (Treated_Post =1) is only significant in highly competitive sectors, according to our sample split based on the Boone Index. This impact is larger than the overall average effect estimated in column (1); firms within this group will deploy on average a 1.22 (122%) percent increase compared to untreated firms in the comparison group (low competition sectors).

When we restrict the sample to similar (non-treated) firms with Kernel matching, these results remain pretty much like the unmatched sample. This similarity suggests that the problem of selection bias was not too severe. We did the same exercise using nearest neighbor matching N-5 and the results were also quite close, with the difference that the size of coefficients diminished. The average impact of subsidies is almost the same as in the total sample and significant at the 10% probability level. The interaction term to test the moderating effect of competition on subsidised firms is non-significant, as before. In column (6), however, we find again that the significance of the average effect comes basically from firms that received subsidies in high-competitive sectors.

As in the total sample, the coefficient on the other categorical groups are not significant. Column (7) tests the assumption of equal trends before intervention; we include two dummies for treated firms denoting two years and three years before intervention (τ). The coefficients are not significant, which confirms that assumption of parallel trends between treated and the control group. Furthermore, the inclusion of such patterns in the equation, raises the coefficient of subsidy intervention for high competition sectors to 1.43 (143%) and its significance level, while all the three other categories remain non-significant. These results are the same when we use the threshold estimate for splitting samples, and when using the Hirschman-Herfindahl index (see table 10 in Annex 2). Finally, we also ran regressions using an alternative indicator of market competition.

We also used import penetration from China using data from COMTRADE UN, as an alternative indicator of competition, in this case international product competition. With this

[18] We should note that we run individual regressions for high and low competition sectors, separately, but given that we have a low number of treated firms, we could not evaluate pre-intervention (dummies) trends in sub-samples. We are constrained therefore to follow this approach; we evaluate competition effects by introducing interaction effects with the industry groups (sample splits).

indicator and splitting samples in low and high competition sectors according to the median, the impact is positive in both high and low competition sectors; but the effects of intervention are about twice larger in highly competitive sectors. This suggests that global competition (from a low-skilled country such as China) would further raises innovation incentives in already competitive sectors, helping improve the effectiveness of innovation policy interventions in these industries. In line with Aghion *et al.,* (2015) and Acemoglu *et al.,* (2013), that market competition helps improve the allocation of resources and raises the effectiveness of innovation policies such as innovation subsidies.

TABLE 4: FIXED EFFECT PANEL REGRESSION, TOTAL AND MATCHED SAMPLE

	TOTAL SAMPLE			COMMON SUPPORT (KERNEL MATCHING)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market Competition$_{(t-1)}$	0.10	0.08		0.17	0.16		
	(0.190)	(0.198)		(0.190)	(0.198)		
Treated Post (D=1 since τ)	**1.07***	0.89		**1.08***	0.95		
	(0.601)	(0.828)		**(0.600)**	(0.832)		
Treated Post X Competition$_{(t-1)}$		0.17			0.13		
		(0.561)			(0.565)		
Treated Post X HC Sectors (HC=1)			**1.22***			**1.28***	**1.43****
			(0.712)			**(0.72)**	**(0.780)**
Treated Post X Low Competition Sectors (HC=0)			0.96			0.99	1.12
			(0.627)			(0.62)	(0.714)
Non-Treated (Treated Post (D)=0) X HC Sectors (HC=1)			-0.07			0.01	-0.01
			(0.223)			(0.23)	(0.231)
Treated firms two years before τ (τ -2)							2.31
							(1.673)
Treated firms three years before τ (τ-3)							-0.25
							(1.135)
Constant	3.12***	3.14***	3.26***	2.79**	2.81**	2.96**	2.99**
	(1.190)	(1.191)	(1.181)	(1.190)	(1.191)	(1.18)	(1.181)
Observations	2,434	2,434	2,434	2,286	2,286	2,286	2,286
R-squared	0.29	0.28	0.29	0.28	0.28	0.28	0.28
Number of ID_Act	1,561	1,561	1,561	1,441	1,441	1,441	1,441

Note: The sample consists of firms inventing at least once in innovation activities over the period of analysis and with at least two years of data availability; the average number of years available per firm is 3.5 years. The matching used Kernel matching with a bandwidth of 0.06. competition categorical dummies were computed with the Boone Profit Elasticity Index. Robust standard errors in parentheses clustered at the firm level.
*** p<0.01, ** p<0.05, * p<0.1.

VII. CONCLUSIONS

The objective of this paper was to evaluate whether market competition matters for the effectiveness of innovation policies. With this purpose, we use data from innovation surveys for two Latin American countries. Using propensity matching techniques combined with differences-in-differences, we evaluate first the impact of innovation subsidies on the innovation investment effort of firms, and test whether such impact differs according to the level of market competition.

Our findings differ across countries in terms of size impact but are pretty much conclusive. We find strong evidence that innovation policy has a positive impact on innovation investment of beneficiary firms, when compared to a control group of untreated firms. Furthermore, our analysis provides strong evidence that this effect is either only significant in highly competitive sectors, or larger effects are reported in such sectors. Thus, we confirm that competition plays a moderating role in the effectiveness of innovation policies to encourage firm innovation investment. The results are robust to different matching methods and when using an alternative indicator of market competition. These results therefore suggest that market contexts should be considered in the design of innovation policies. They also make the case for the need to improve interplays with competition policy.

This research is a first attempt to provide new evidence on the role of market competition to the effectiveness of innovation policies in Latin American firms. Our analysis is subject to several drawbacks and we attempt to address these issues in the future with improved data on both policy interventions and panel data. One important point to stress is that this is mostly a short run impact evaluation of the program since we are analysing impacts after one year after intervention; or differences in investment rates before and after intervention. Further research should consider evaluating these interplays (competition and subsidies) with larger panel data and compare effects between R&D subsidies and tax incentives. Another important issue that we must keep in mind that we have a small number of observations and treatment (firms receiving subsidies) and we only use information on beneficiaries from the innovation surveys. It is very likely that we are missing beneficiaries. These constraints handicap our efforts in testing additional heterogeneity tests or sector-by sector analysis, and therefore our findings should be taken with care.

Lastly, the traditional shortcomings for this type of analysis apply. A more comprehensive analysis of efficiency should also consider the indirect impact of policy interventions and its benefits to other un-treated firms through spillovers (knowledge or market spillovers); i.e. surrounding companies or untreated firms with productive links with beneficiaries; etc. Further research finally should also look at the types of firms within sectors (incumbent/dominant firms vs. young/new ones for instance) and their response to competition, which are expected to be different within sectors, according to the literature (Aghion *et al.,* 2015; Reinganum, 1989). Finally, possible extension of this research includes looking at specific indicators of market competition such as entry intensity (or regulatory reforms regarding business entry or trade reforms), import competition (e.g. China import penetration), and the interplay of innovation policies with other forms of competition-enhancing policies (e.g. antitrust and product regulations). We will look at these questions in our future research.

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ANNEX 1: MEASUREMENT OF COMPETITION

Empirically, the Boone Index (the profit-costs elasticity) and can be recovered by coefficient β_1 for each sector *j* and year *t* in the following regression:

$$log\pi_{ijt} = \alpha_{ijt} + \beta_1 \log\left(\frac{TVC_{ijt}}{sales_{ijt}}\right) + \beta_2 \log\left(size_{ijt}\right) + \epsilon_{ijt} \qquad (1)$$

where, $log\pi_{ijt}$ corresponds to the natural logarithm of operating profits of the firm *i* in sector *j* at year *t*, TVC_{ijt} to total variable cost relative to sales, a measure of firm size (sales per employee) and ϵ_{ijt} to a robust standard error. The econometric strategy consists in estimation the logarithm of the operating profits as a function of the logarithm of variable costs over total sales. For each sub-sector (proxy for market) at the 2 digit-level in the ISIC classification for Chilean firms, we estimate equation (1). Profits on the left-hand side of the equation are computed as sales – total costs (administration expenditures + labour cost + raw materials + depreciation + opportunity cost). Each of these variables is individually observed in the survey, except for the opportunity cost which is calculated as assets book value times the interbank interest rate. To the extent that the measurement errors are time invariant they will be picked up by the firm fixed effects.

As total variable cost is negatively related to with profits, the Boone Index is always negative -although positive values can appear (e.g. perfect collusion). For this analysis, we will use the absolute value of this index for amore interpretable estimator. Thus, a higher value for the Boone index indicates a greater sensitivity of firm profits to cost and therefore higher competition intensity. In other words, in competitive markets, firms are punished --to a greater extent-- for their inefficiencies (i.e. increasing their variable costs). As in Alvarez and Camnpusano (2014), to ensure robust Boone index estimates, industries with less than 20 firms are dropped from the dataset. The Boone does not allow for the perfect identification of extreme cases such as monopoly and perfect competition. Nevertheless, in theory, Boone index near infinity could be related to perfect competition and near zero to more uncompetitive conditions.

We also use the Lerner Index (price-cost margin) as alternative market competition indicator. The Lerner index is the commonly used ratio of profitability. It is computed at the firm level as follows: $LI_{ijt} = \left(\frac{sales_{itj} - variable\ costs_{ijt}}{sales_{ijt}}\right)$, where we proxy variable costs with total annual cost of labour, electricity, raw materials and intermediate goods used in production, plus fuel (only for the 2006 and 2010 waves) expenses and other costs. We then compute the average within each sector and year, and proxy market competition in sectors as the inverse of this index:

$$C_{jt} = 1 - \frac{1}{N_{jt}} \sum_{i \in j} LI_{it}$$

The competition index at industry level is defined as 1 minus the LI, since the LI is an inverse measure of competition. Thus, when the index is 1 there is perfect competition, and values below 1 indicate some degree of market power.

ANNEX 2

TABLE 1: SUMMARY STATISTICS, CHILEAN FIRMS (8-10th Innovation Surveys)

1.A. UNMATCHED SAMPLE, CHILEAN MANUFACTURING FIRMS

	TREATED			NON TREATED		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Beneficiaries	1,264	0	0	245	1	0
Firm Size	1,264	4.557	1.571	245	5.204	1.614
Age (log years)	1,263	3.063	0.691	243	3.117	0.842
skills_1	1,248	0.251	0.258	241	0.330	0.284
Exporting_1	1,264	0.117	0.251	241	0.209	0.309
Innovation Intensityt-1	1,248	4.146	4.171	241	5.902	4.543
Technological Innovation t-1	1,264	0.459	0.498	241	0.591	0.493
Multinational Firm	1,841	0.331	0.470	241	0.506	0.500
% of Foreign Capital	1,264	8.805	26.77	241	12.45	29.35
Firm Gap_1	1,248	0.051	0.676	241	0.020	0.639
Group Appartenance	1,841	0.359	0.479	245	0.534	0.499
Financial Obs. (high)	1,841	0.261	0.439	245	0.269	0.444
Financial Obs. (Med.)	1,841	0.282	0.450	245	0.355	0.479

1.B MATCHED SAMPLE (NEAREST-5), CHILEAN MANUFACTURING FIRMS

	TREATED			NON-TREAETD		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Beneficiaries	949	0	0	159	1	0
Firm Size	949	4.5139	1.462	159	5.204	1.614
Age (log years)	949	3.0442	0.691	159	3.117	0.842
skills_1	949	0.2441	0.260	159	0.330	0.284
Exporting_1	949	0.1191	0.2546	159	0.209	0.309
Innovation Intensityt-1	949	4.155	4.190	159	5.905	4.54
Technological Innovation t-1	949	0.4415	0.496	159	0.591	0.493
Multinational Firm	949	0.2613	0.4398	159	0.459	0.499
% of Foreign Capital	949	7.880	25.29	159	12.45	29.35
Firm Gap_1	949	0.0701	0.677	159	0.020	0.639
Group Appartenance	949	0.348	0.476	159	0.547	0.499
Financial Obs. (high)	949	0.3140	0.464	159	0.264	0.442
Financial Obs. (Med.)	949	0.3708	0.483	159	0.345	0.477

Note: The sample of reference (unmatched) consists of firms who reported innovation investment (any type of activity) superior to zero at least once across the different years covered. This group of firms represent about 35% of the total sample in each innovation survey; and 27% in the pooled survey data. Our original data is composed of the pooling of three innovation surveys: the 8th, 9th and 10th Enterprise Innovation Surveys.

TABLE 3: BALANCING TEST, CHILEAN FIRMS (KERNEL MATCHING, BANDWIDTH: 0.10)

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct bias	t-test t	p>t	V(C)	V(T)/V(C)
$Size_{t-1}$	U	5.2859	4.812	29.9		3.37	0.001		1.13

	M	5.2859	5.3039	-1.1	96.2	-0.09	0.925	1
Size $_{t-1}^2$	U	30.589	25.519	30.6		3.51	0.001	1.23
	M	30.589	30.783	-1.2	96.2	-0.09	0.925	0.97
Age	U	3.1231	3.0963	3.4		0.4	0.691	1.39*
	M	3.1231	3.126	-0.4	89.4	-0.03	0.977	1.04
Age^2	U	10.476	10.109	7.7		0.89	0.371	1.34*
	M	10.476	10.467	0.2	97.8	0.01	0.989	1.06
agesize_1	U	17.061	15.368	21.9		2.54	0.011	1.32*
	M	17.061	17.131	-0.9	95.9	-0.07	0.941	1.09
Skills$_{t-1}$	U	0.33515	0.24015	36.3		4.28	0.000	1.41*
	M	0.33515	0.32728	3	91.7	0.24	0.807	1.16
Exporting $_{-1}$	U	0.22292	0.12891	32.8		3.89	0.001	1.47*
	M	0.22292	0.20616	5.8	82.2	0.45	0.650	1
Innovation Intensity $_{t-1}$	U	6.3143	5.1219	28.1		3.22	0.001	1.21*
	M	6.3143	6.2046	2.6	90.8	0.21	0.831	1.07
Market Competition $_{t-1}$ (Boone Index)	U	1.3514	1.2893	11.9		1.74	0.081	0.68*
	M	1.2947	1.2947	0	100	0	1	1
Foreign Ownership (%)	U	13.754	10.881	9.6		1.08	0.281	1.09
	M	13.754	14.866	-3.7	61.3	-0.3	0.767	0.85

Note: * if variance ratio outside [0.78; 1.29] for U and [0.73; 1.37] for M.

TABLE 4: SUMMARY STATISTICS OF BALANCING PROPERTIES, CHILEAN FIRMS

	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Kernel Estimation (Bwidth= 0.10)								
Unmatched	0.059	47.54	0	20	25	62.9*	1.280	50
Matched	0.001	0.55	1.000	2.1	1.8	8.7	1.170	0
Nearest Neighbor, N-5 (Caliper=0.05)								
Unmatched	0.064	63.55	0	25	30.1	68.2*	1.220	50
Matched	0.002	0.69	1.000	1.7	1.6	9.3	1.210	0
Nearest Neighbor, N-1 (Caliper=0.05)								
Unmatched	0.064	63.55	0.000	25.0	30.1	68.2*	1.22	50
Matched	0.021	9.07	0.726	4.5	3.3	23.7*	0.87	10
High Competition Sectors (Boone Index>= Median)								
Nearest Neighbor, N-5 (Caliper=0.05)								
Unmatched	0.064	63.55	0.000	25.0	30.1	68.2*	1.22	50
Matched	0.005	1.14	1.000	3.8	4.0	17.1	0.71	0
Low Competition Sectors (Boone Index< Median)								
Unmatched	0.064	63.55	0.000	25.0	30.1	68.2*	1.22	50
Matched	0.035	3.54	0.966	8.6	6.4	32.8*	0.54*	10

Note: * if B>25%, R outside [0.5; 2].

TABLE 5: BALANCING TEST, PERUVIAN FIRMS (KERNEL, BANDWIDTH: 0.10)

	Unmatched	Mean			%reduct	t-test		
Variable	Matched	Treated	Control	%bias	bias	t	p>t V(C)	V(T)/V(C)
$Size_{t-1}$	U	465.29	284.25	15.1		2.15	0.032	2.51*
	M	465.29	450.51	1.2	91.8	0.09	0.93	1.02
$Size_{t-1}^2$	U	2.3e+06	9.0e+05	9.3		1.47	0.14	3.74*
	M	2.3e+06	2.2e+05	0.4	95.6	0.03	0.97	1.46
Age	U	20.937	20.896	0.2		0.03	0.97	0.97
	M	724.23	740.77	-1.2	-102.5	-0.11	0.91	1.13
Exports	U	5.06e+07	2.4e+07	16.2		2.00	0.046	1.40*
	M	5.06e+07	3.2e+07	10.8	33.6	0.87	0.38	1.13
Labor Productivity	U	4.1e+05	6.9e+05	-7.2		-0.63	0.52	0.08*
	M	4.1e+05	4.0e+05	0.2	97.5	0.04	0.97	1.13
Sales	U	2.2e+08	1.2e+08	11.8		1.69	0.09	2.56*
	M	2.2e+08	1.5e+08	7.6	35.4	0.64	0.52	2.44*
Market Competition (HHI)	U	0.1439	0.1311	10.5		1.17	0.24	0.90
	M	0.1439	0.1361	6.4	39.0	0.55	0.57	1.01

Note: * if variance ratio outside [0.78; 1.29] for U and [0.73; 1.37] for M

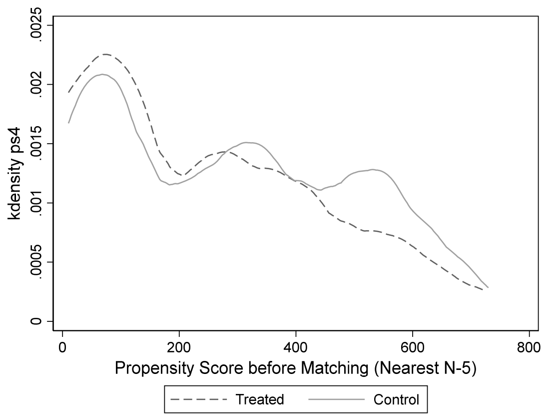
TABLE 6: SUMMARY STATISTICS OF BALANCING PROPERTIES
PERUVIAN FIRMS

	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Kernel Estimation (Bwidth= 0.10)								
Unmatched	0.038	36.670	0.346	7.1	7.5	40,3*	0,21*	56
Matched	0.011	4.490	1.000	3.1	2.2	17.6	0,44*	22
Nearest Neighbor, N-5 (Caliper=0.05)								
Unmatched	0.038	36.67	0.346	7.1	7.5	40,3*	0,21*	56
Matched	0.015	5.73	1.000	3.4	2.8	28,2*	1.44	44
Nearest Neighbor, N-1 (Caliper=0.05)								
Unmatched	0.038	36.67	0.346	7.1	7.5	40,3*	0,21*	56
Matched	0.035	13.73	0.999	5.4	4.5	44,1*	0.94	56
High Competition Sectors (HHI<= Median)								
Nearest Neighbor, N-5 (Caliper=0.05)								
Unmatched	0.075	33.62	0.214	8.8	8.8	41.9*	0.06*	44
Matched	0.021	3.88	1.00	4.7	4.4	33.3*	1.19	33
Low Competition Sectors (HHI> Median)								
Unmatched	0.114	55.93	0.002	13.4	11.4	30.7*	0.03*	78
Matched	0.024	4.71	1.000	4.5	3.0	36.0*	0.63	11

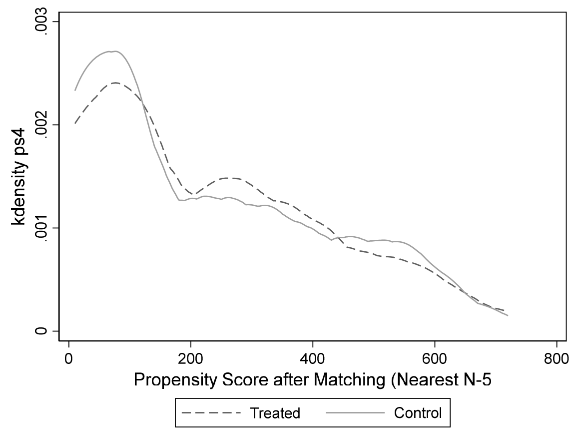
Note: * if B>25%, R outside [0.5; 2].

FIGURE 1: PROPENSITY SCORE DISTRIBUTION, BEFORE AND AFTER MATCHING (CHILEAN FIRMS)

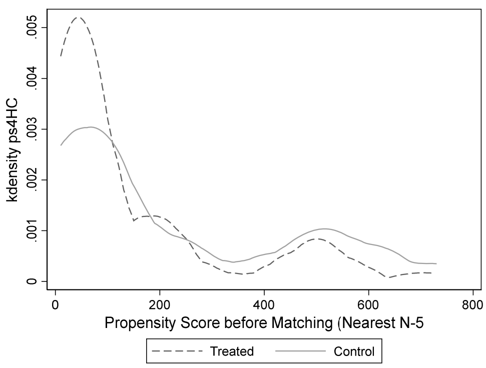
1.A: Before Matching, Chilean Enterprises



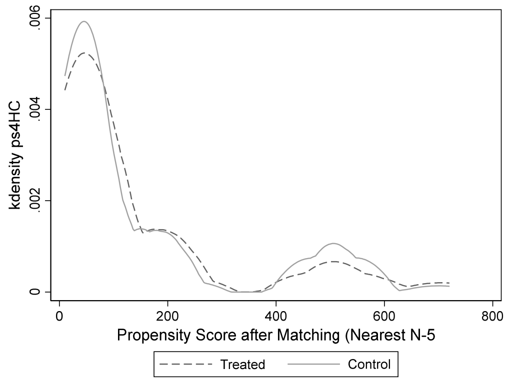
1.B: After Matching (N-5), Chilean Enterprises, Kernel Matching



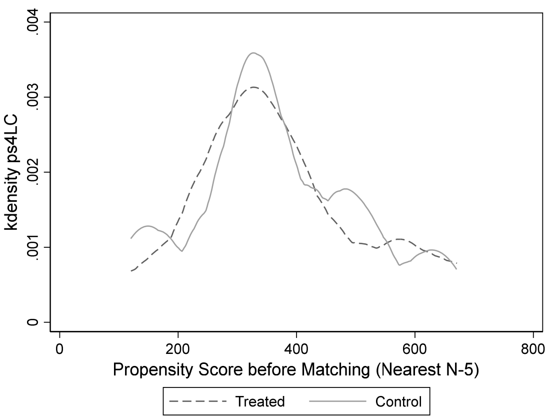
1.C: Before Matching, High Competition Sectors



1.D: After Matching (N-5), High Competition Sectors



1.E. Before Matching, Low Competition Sectors



1.F. Before Matching (N-5), Low Competition Sectors

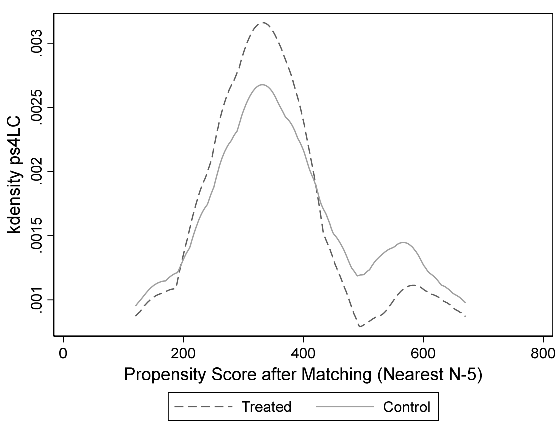


FIGURE 2: PROPENSITY SCORE DISTRIBUTION, BEFORE AND AFTER MATCHING (PERUVIAN)

Figure 2.A: Total Sample, Kernel Matching

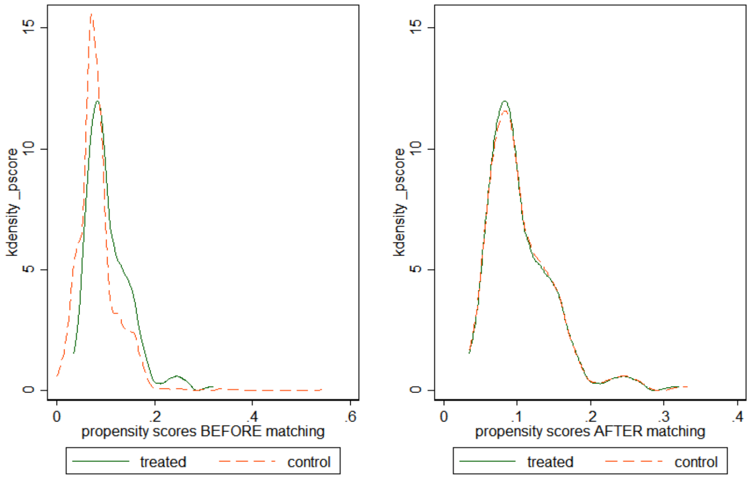


Figure 2.B: High-Competition Sectors, Kernel

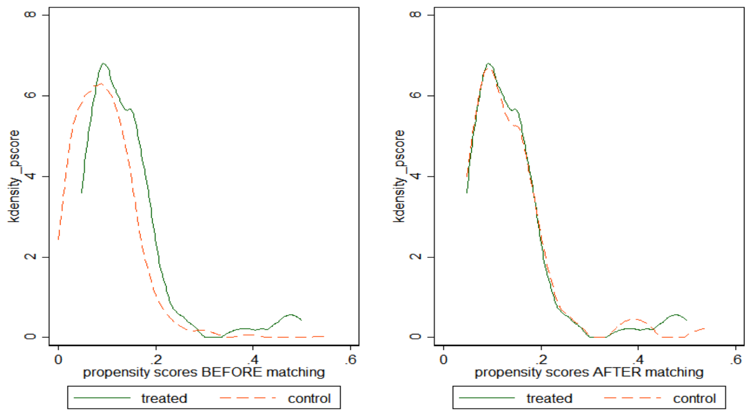


Figure 2.C: Low-Competition Sectors, Kernel

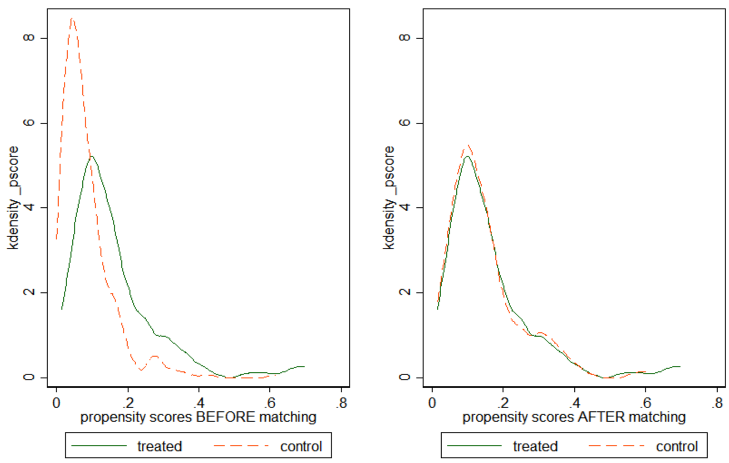


TABLE 6: LOGIT AND PROBIT ESTIMATIONS, MEXICAN AND CHILEAN SAMPLES

	CHILEAN FIRMS		
	(1)	(2)	(3)
	LOGIT	LOGIT HC	LOGIT LC
Size (log of labor) $_{t-1}$	-0.162	-0.408	0.488
	(0.457)	(0.568)	(0.824)
Size $_{t-1}$^2	0.059	0.067	0.057
	(0.045)	(0.053)	(0.089)
Skills$_{t-1}$	1.466***	1.340**	1.406
	(0.488)	(0.628)	(0.858)
Age (log of years)	-1.331**	-2.558***	0.443
	(0.596)	(0.859)	(1.221)
Age^2	0.266*	0.433**	0.085
	(0.142)	(0.195)	(0.282)
Age*Size	-0.070	-0.018	-0.250
	(0.127)	(0.156)	(0.247)
Innovation Intensity $_{t-1}$	0.054*	0.055	0.049
	(0.028)	(0.036)	(0.048)
Exporting Firm$_{t-1}$	0.492	0.680	0.678
	(0.414)	(0.435)	(1.115)
Group (D=1)	0.318	0.346	0.283
	(0.260)	(0.311)	(0.416)
Multinational Firm (D=1)	0.951*	0.903	1.344
	(0.567)	(0.659)	(1.299)
Constant	-2.12	0.81	-4.30
	(1.77)	(2.19)	(2.78)
Industry Effects	YES	YES	YES
Time Effects	YES	YES	YES
Observations	1,111	629	467
Pseudo-R2	0.125	0.134	0.166
Wald Test $\chi2$	91.94***	60.25***	54.52**

Note: Coefficients in the Mexican regressions are marginal effects. Robust standard errors in parentheses, clustered at the firm level (Chilean and Peruvian firms) and at the industry level (2-digit ISIC-4) in the regressions for Mexican firms.

*** p<0.01, ** p<0.05, * p<0.1.

Table 7: PROBIT ESTIMATION (SELECTION EQUATION), PERUVIAN SAMPLE

	PERUVIAN FIRMS		
	(7)	(8)	(9)
	PROBIT	PROBIT HC	PROBIT LC
Age (log of years)	0.007	-0.012	0.023*
	(0.007)	(0.010)	(0.012)
Age^2	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)
Exporting Firm$_{t-1}$	0.001*	0.000	0.001
	(0.001)	(0.001)	(0.001)
Multinational Firm (D=1)	-0.042	0.199	-0.247
	(0.159)	(0.249)	(0.225)
Small Size		0.485*	0.511
		(0.258)	(0.356)
Medium Size		0.457	0.838*
		(0.317)	(0.428)
Large Size		0.661**	0.642*
		(0.267)	(0.381)
Constant	-1.73**	-1.73**	-1.58**
	(0.42)	(0.56)	(0.74)
Industry Effects	YES	YES	YES
Time Effects	YES	YES	YES
Observations	4054	1611	2116
Pseudo-R2	0.11	0.12	0.16
Wald Test $\chi 2$	176.8***	86.7***	139.8***

Note: Coefficients in the Mexican regressions are marginal effects. Robust standard errors in parentheses, clustered at the firm level (Chilean and Peruvian firms) and at the industry level (2-digit ISIC-4) in the regressions for Mexican firms.

*** p<0.01, ** p<0.05, * p<0.1.

TABLE 8: THRESHOLD ESTIMATION WITH FIRM FIXED EFFECTS

CHILEAN FIRMS: INNOVATION INVESTMENT INTENSITY (EX. PER EMPLOYEE)

	Restricted Panel (Firms with N==4 years)			
	(1)	(2)	(3)	(4)
Edad	0.17	0.14	0.11	0.15
	(0.485)	(0.490)	(0.486)	(0.486)
Skills	1.39**	1.29**	1.41**	1.50**
	(0.588)	(0.592)	(0.590)	(0.591)
Exporting Firm	1.18*	1.21*	1.21*	1.13*
	(0.638)	(0.642)	(0.640)	(0.640)
Firm gap	0.36	0.48	0.37	0.43
	(0.371)	(0.372)	(0.372)	(0.373)
Size	0.99**	1.03**	1.00**	0.98**
	(0.436)	(0.439)	(0.437)	(0.436)
I(Competition<=α_1)	**1.44*** **	-10.58	**1.34*** **	**1.59*** **
	(0.432)	(7.129)	**(0.433)**	**(0.452)**
I(Competition>α_1)	0.75**		0.69**	
	(0.321)		(0.322)	
I(a_1<Competition<=α_2)		0.17		**1.72*** **
		(0.873)		**(0.357)**
I(Competition>α_2)		0.35		0.36
		(0.388)		(0.364)
Constant	-2.48	-1.58	-2.31	-2.53
	(2.488)	(2.537)	(2.494)	(2.491)
Observations	796	796	796	796
R-squared	0.11	0.10	0.11	0.11
Number of IDs (firms)	199	199	199	199
R-squared	0.07	0.06	0.06	0.07
sigma u	2.35	2.39	2.36	2.34
rho	0.38	0.39	0.38	0.38

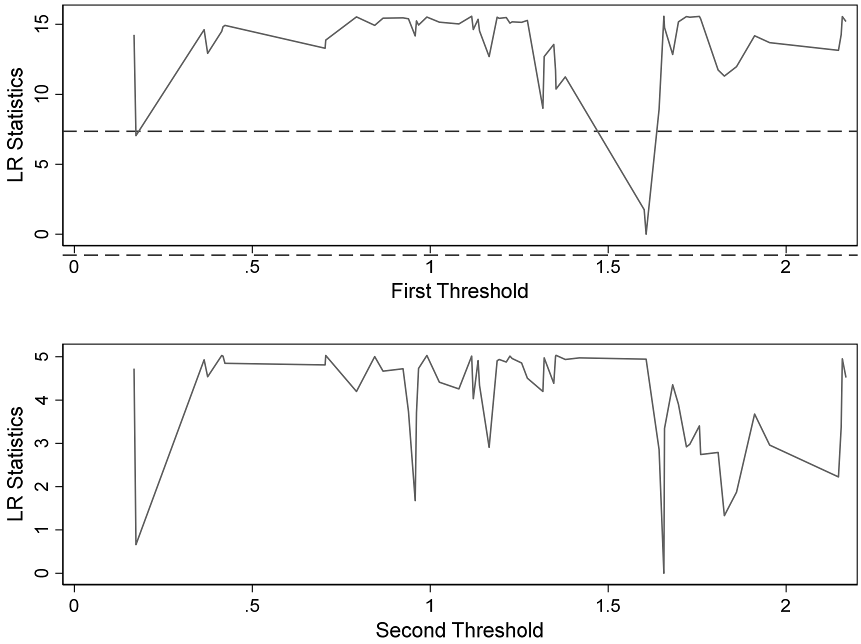
Note: Models (1) and (2) refer to the logarithm of innovation expenditure per employee, while models (3) and (4) refer to the logarithm of innovation expenditure per employee discounted off innovation subsidies. Robust standard errors in parentheses, clustered at the industry-level (two digit). *** p<0.01, ** p<0.05, * p<0.1

TABLE 9: THRESHOLD SPECIFICATION TESTS

Columns	Model		Threshold (C.I.)	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
(1)	Single	Th-1	1.58 (1.43; 1.58)	5173.85	6.53	12.17*	0.10	12.28	15.44	19.87
(2)	Single	Th-	1.58 (1.43; 1.58)	5173.85	6.53	12.17*	0.10	11.85	14.01	17.45
	Double	Th-21	0.96 (0.96; 0.99)	5133.94	6.48	6.15	0.34	9.60	11.17	13.46
		Th-22	0.17 (0.16; 0.36)							
(3)	Single	Th-1	1.58 (1.43; 1.59)	5201.30	6.56	10.67	0.12	11.55	13.10	17.84
(4)	Single	Th-	1.58 (1.39;1.58)	5201.30	6.56	10.67	0.12	11.63	13.40	17.98
	Double	Th-21	1.58 (1.39, 1.59)	5168.35	6.52	5.05	0.5	10.83	12.99	22.92
		Th-22	1.82 (1.81; 1.86)							

Note: Models (1) and (2) refer to the logarithm of innovation expenditure per employee, while models (3) and (4) refer to the logarithm of innovation expenditure discounted of innovation subsidies, per employee. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 3: THESHOLD DETECTION: LIKELIHOOD RATIO STATISTIC



Note: The X-axis reports the values for the market competition index (Boone Index) while the y-axis displays the LR statistic distribution. The dashed horizontal line in the "First Threshold" figure denotes the critical value of the LR statistic. In the bottom figure (Second Threshold), all competition values are above the LR critical value; no second thresholds exist.

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