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Obstacles to Innovation and Firm Size

A Quantitative Study for Argentina

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Competitiveness, Technology, and Innovation Division

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Abstract[*]

This study contributes to our understanding of how barriers to innovation affect firms of different size. We review the literature on obstacles to innovation. We found that there is a gap regarding the systematic appraisal of firms' size as an important characteristic mediating the effect that obstacles have on innovative investment and performance. The relevance of this topic lies in the important role that small and medium enterprises (SMEs) play in the economic structure. In developing countries, in addition, SMEs lag further behind average productivity, so the need for innovation is greater. We use Argentinean survey data for years 2010–12. We use different econometric techniques suitable for our data. We found that obstacles have a negative impact on innovation investment and performance. In terms of size, SMEs' investment is particularly affected. When the analysis is done by type of obstacles, we found that cost and market obstacles are important barriers for pursuing innovation activities. Knowledge obstacles seem to hamper the intensity of investment in innovation. Cost, market, and knowledge obstacles all limit performance in innovation. In turn, while cost obstacles are generally more deterrent for SMEs, we could not find systematic size difference regarding the effect of other obstacles.

JEL Codes: L2, O32, O54, O25

Keywords: Argentina, innovation policy, obstacles to innovation, small and medium enterprises

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Acronyms and Abbreviations

ENDEI: Employment and Innovation Dynamics National Survey (acronym in Spanish)

GMM: generalized method of moments

IA: innovation activities

IV: instrumental variables

LPM: linear probability model

MINCyT: Ministry of Science, Technology, and Productive Innovation (abbreviation in Spanish)

MTEySS: Ministry of Labor, Employment, and Social Security (abbreviation in Spanish)

OLS: ordinary least squares

R&D: research and development

RS: relevant sample of “willing-to-innovate” firms

S1: “willing-to-innovate” firms, subsample version 1

S2: “willing-to-innovate” firms, subsample version 2

SMEs: small and medium enterprises

Contents

1. Introduction

The importance of innovation as an engine for economic growth has been extensively studied in the specialized literature. Yet there are several factors that prevent firms from starting innovation activities (IA), lead to a sluggish commitment, or reduce the chances of success. It then becomes central for innovation studies to analyze the determinants, consequences, and characteristics of the factors hampering innovation, so as to be able to design accurate strategies in order to remove them.

The first quantitative studies on obstacles to innovation relied on established discussions and methodologies to assess the financial constraints to investment in fixed assets that were consecutively extended towards the analysis of investment in research and development (R&D) (Bond, Harhoff, and Van Reenen, 2003; Czarnitzki, Hottenrott, and Thorwarth, 2011; B. H. Hall, 2002; L. A. Hall and Bagchi-Sen, 2002; Hottenrott and Peters, 2012). More recently, the wider availability of innovation surveys allowed for the assessment of other obstacles besides financial ones (Blanchard et al., 2013). Innovation surveys capture firms' perception of obstacles of different types, so the literature has aggregated them using different taxonomy and assessed whether they actually had an effect on innovative investment and performance.

Thus, different studies analyzed the effect of *market* obstacles, interpreted as shortcomings in market pull mechanisms (García-Quevedo, Pellegrino, and Savona, 2016), *regulatory* obstacles, and *knowledge* obstacles. In other words, the focus has widened, and empirical findings suggested that obstacles are diverse, although normally complementary. Therefore, policymaking should address the obstacles in an integrative framework, rather than just focusing on ameliorating the effects of the market failures associated with the information asymmetries and technology uncertainty which presumably cause financial constraints.

Surprisingly, although the literature has opened the spectrum to capture a wider variety of obstacles, it has not assessed yet how micro-heterogeneity interacts with them. There is a wide agreement that heterogeneity prevails in innovation; nevertheless, very few studies have evaluated empirically whether obstacles affecting innovation differ for firms with different profiles in terms of ownership, size, age, and production activities.

We aim at bridging this gap specifically for size. Some arguments have been raised about the liability of smallness (e.g., regarding shortage of resources, experiences, and managerial skills) both in relation to pursuing internal tasks and/or to dealing with third parties or regulation (Hadjimanolis, 2003). In fact, there are several articles on obstacles to innovation that just focus on small and medium enterprises (SMEs) (Alessandrini, Presbitero, and Zazzaro, 2010; Freel, 2000; Hadjimanolis, 1999; Mancusi and Vezzulli, 2010; OECD, 2005; Xie, Zeng, and Tam, 2010), but they did not present an argument regarding the extent to which their conclusions would be different for a sample of larger firms.

In this paper we analyze the effect of obstacles to innovation both on investment decisions and on the likelihood of success in innovation. We identify whether such effect is higher for the subsample of SMEs.

In Argentina, SMEs account for more than 40 percent of registered employment, they show larger productivity gaps than in other parts of the world, and they are a main focus of public policy instruments within industrial policy programs (Arza et al., 2017). Thus, identifying how obstacles affect innovation and their interaction with firm size becomes essential for contributing to accuracy in policy design and the effectiveness of its implementation.

Following the Oslo Manual produced by the OECD (2005), hereafter referred as Oslo 2005, we classify factors hampering innovation in four groups—cost barriers, market barriers, institutional barriers, and knowledge barriers—in order to assess their effect on firms' investment decisions and on the likelihood of success in innovation.

This paper makes a twofold contribution to the literature on innovation studies. Firstly, it addresses a research problem barely analyzed in the empirical literature: how obstacles affect innovation differently for small and large firms. Secondly, it aims to overcome the different biases to be faced when studying the relationship between obstacles and innovation. Through sample sub-setting we aim at controlling for selection bias while we use instruments to control for endogeneity in the relationship between obstacles and innovation. Finding the right instrument constitutes an important challenge for which we could not find precedents in the literature.

The rest of the paper is organized as follows: Section 2 reviews the literature on obstacles to innovation, Section 3 presents the specific objectives and hypotheses, Section 4 discusses the methodological strategy, Section 5 presents some descriptive statistics regarding sampling strategy and the main variables, in Section 6 the main analytical results are presented, and Section 7 concludes.

2. The Literature on Obstacles to Innovation and Firm Characteristics

The academic interest in barriers to innovation dates back to the 1980s when some management scholars reflected on different organizational strategies that a firm could perform in order to accelerate innovation, mainly product innovation. Millman (1982) argued that the UK industry was short on product innovation due to misalignments and miscommunication between the R&D and marketing departments. He suggested that functions of these departments should be extended so that they partially overlap. Consequently, the innovative product would be better able to meet the rapidly changing market demand.

Likewise, More (1985) argued that there were intra-firm "dislocations" that severely affected innovation. He referred mainly to misalignments in functions, similar to Millman (1982); in decision making and expertise, or information asymmetry within the firm; and in the causes and consequences of risk-taking, because those who take risks were neither accountable for their decisions nor properly rewarded. He claimed that these dislocations could be solved with a better reward system that tied together the resources, the inputs, and the decisions that are critical to the success of new products.

In a similar vein, Myers (1984) argued that the most important barrier to innovation was the lack of financial capital available for financing highly risky projects. The proposed solution was again of a managerial kind: creating a special funding division within the company to finance highly risky, radically innovative projects and changing the reward incentives to promote risk-taking activities, so as to encourage the emergence of entrepreneurs within the organization.

Since the early 2000s, in an attempt to draw science and technology policy implications, different economic and innovation studies have performed quantitative analysis on the determinants and effects of the factors hampering innovation. These factors were classified using different taxonomies: internal and external (Oslo Manual, 2nd edition, see OECD [1997]); economic, entrepreneurial, and other factors (Bogotá Manual, see Jaramillo, Lugones, and Salazar [2001]); external, organizational, and attitudinal factors (Hueske and Guenther, 2015); cost, knowledge, market, and institutional factors (Oslo Manual, 3rd edition, see OECD [2005]).

The wide diffusion of innovation surveys, such as the Community Innovation Survey (CIS) in European countries, further pushed the research in this area. The literature is twofold: a first group of studies characterized the obstacles and their main determinants, while a second group assessed the impact of obstacles on innovative performance.

2.1. The Characteristics of Obstacles

The first group of literature inquired about the characteristics of firms' perceptions regarding obstacles to innovation. The early literature found that innovativeness was positively associated to the perception of obstacles. For example, Iammarino, Sanna-Randaccio, and Savona (2009) found that firms with a higher number of product or process innovations tended to perceive more obstacles.[1] Similarly, other studies found that firms that engaged in internal R&D (Galia and Legros, 2004) and firms that innovate persistently in products (Wziątek-Kubiak and Pęczkowski, 2011) were more prone to perceiving several obstacles. In the same vein, Hottenrott and Peters (2012) studied the determinants of firms' financial obstacles,[2] finding that firms with larger innovative capabilities experienced more constraints than those with lower capabilities, especially if they also lacked internal funds.

Clearly, firms that have initiated innovative projects are more likely to be aware of the factors hampering the process than firms that have not been involved in innovation. Thus, later studies attempted to distinguish between innovators, potential innovators, and non-innovators and found that non-innovators that are interested in innovation tend to perceive more obstacles than non-innovators that are not interested in innovation (e.g., Hölzl and Janger [2012] using the Community Innovation Survey, or CIS, for eighteen countries).[3] Thus, when analyzing obstacles, the qualification of *being*

[1] They also found that foreign firms perceived fewer obstacles than domestic (Italian) ones.
[2] The constraints were measured as a dummy variable that identifies firms that would have invested more in innovative projects if they had had additional funds.
[3] Using the same database, in a different paper the authors assessed whether high-growing firms were more likely to perceive obstacles, without achieving robust results (Hölzl and Janger, 2013). Yet in another paper they found that firms operating in countries close to the technological frontier (according to a

interested in innovation appears as an important characteristic. In fact, D'Este et al. (2012) argued that firms faced two types of barriers. On the one hand, *revealed* barriers were those which firms perceived due to the complexity of the innovation and the associated learning efforts. In other words, the inevitable hampering factors needed to be overcome by *any* innovator, which did not really slow down or stop innovation. In contrast, *deterring* barriers were those that prevented firms from engaging in innovation, and these are the ones that should be targeted by innovation policy.

2.2. Obstacles Affecting Innovation

Financial obstacles have been by far the most investigated factor hampering innovation. Several papers used the availability of internal funds as an explanatory variable for investment in R&D, as the literature had been doing for investment in fixed assets (for a review see Hubbard [1998] and Schiantarelli [1996]). Firms that systematically relied on their cash flows or internal liquidity to fund investment would arguably do so based on more costly access to external sources, information asymmetries, or other market failures. Thus, if firms' internal liquidity positively affects investment, it could be concluded that these firms are financially constrained, because according to Modigliani and Miller's (1958) theorem, the source of financing should be irrelevant for investment decisions.

Using this approach, Bond, Harhoff, and Van Reenen (2003) assessed the financial constraints on both fixed assets and R&D capital stock with panel data from UK and Germany.[4] The authors found that firms were constrained to invest in fixed capital but not in R&D, and only in the UK, while they were unconstrained in Germany. Moreover, non-R&D performers in the UK were more constrained to invest in fixed assets than R&D performers, implying that financial constraints may be mainly affecting the decision to engage in R&D, rather than how much to spend in existing R&D programs.[5] Ahead of their time in the literature on obstacles to innovation, Bond, Harhoff, and Van Reenen (2003) interpreted their findings as a problem of selection. They argue that "the R&D performing firms in the UK are a self-selected group who choose to make long term commitments to R&D programs, partly on the basis that they do not expect to be seriously affected by financial constraints—this is why cash flow tends to matter less for these firms' investment decisions than for other UK companies" (p. 26). Later papers dealt with the issue of self-selection by redefining the "relevant sample" and including only those firms *interested in* innovation.

One of the first studies that attempted to better identify the sample of firms interested in innovation was Savignac (2008), which analyzed the effect of financial barriers on the

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country-level taxonomy based on direct and indirect R&D intensity) are more likely to suffer from knowledge obstacles, while those further away faced primarily financial obstacles (Hölzl and Janger, 2014).

[4] The authors estimate generalized method of moments (GMM) models using cash flows and their lags to proxy liquidity constraints.

[5] One interesting paper by Czarnitzki, Hottenrott, and Thorwarth (2011) analyzes the effects of financial constraints (using the firms' stock of working capital as a proxy for liquidity) on R&D for Belgian firms. They found that there were financial constraints to investments in research, while there were not to investments in development. The information asymmetries may be operating more strongly in projects that are further away from the market than in a development project, which is clearly closer to providing a market solution and which also relies on previous visible results obtained during the research stage.

probability of engaging in IA in France. Like most papers following this approach, it assessed financial factors hampering innovation by using information from innovation surveys rather than internal liquidity. The proxy for the barrier was a dummy taking the value of one for firms that claimed either that the interest rate was too high, that there were not enough financial sources available, or that the procedures to access the funds were too slow. The paper dealt with sample selection by restricting the relevant sample to firms that either performed IA or that identified at least one obstacle to innovation. The coefficient for financial obstacles turned then to be negative. It also tackled endogeneity by estimating the bivariate recursive Probit; the negative effect was then further intensified.

With a very similar approach, Mancusi and Vezzulli (2010) estimated the effects of financial constraints on the probability to engage in R&D and on R&D intensity using Italian data for SMEs only.[6] The proxy for the financial constraint was a dummy variable adopting the value of one when firms claimed that they wished to have additional bank financing at the interest rate agreed upon with the main partner bank. The sample was restricted to "innovative firms" by excluding those that did not perform R&D and claimed not to be constrained—as was previously defined—and those that had not finished any innovative project in the recent past. Endogeneity was tackled using a recursive bi-variate Probit for the probability of performing R&D and an instrumental variable (IV) Tobit for R&D intensity. As in the previously cited paper, the coefficient on financial obstacles turned negative for the restrictive sample, and the effect was intensified when controlling for endogeneity.

Similarly, Blanchard et al. (2013) excluded from their analysis two groups of firms: (i) those that did not innovate and claimed that "there was no market conditions for innovation" and (ii) those that did not innovate and did not identify any barrier to innovation either. The authors carefully showed that the effects of obstacles[7] on innovation were sensitive to sampling decisions, with the coefficient turning negative only when the relevant sample was identified. When controlling for endogeneity by using a bivariate Probit model, the coefficient remained negative and of similar size.

A relevant aspect of obstacles to innovation that must be taken into account is that they tend to be complementary (Galia and Legros, 2004). This hints at the need to follow an integrative framework in the analysis, rather than separately analyzing the different factors hampering innovation. In fact, the latest studies widened the focus to adopt a more systemic approach by jointly analyzing several factors. However, only a few of them followed the taxonomy suggested by Oslo 2005.

An important precedent for this paper is the study by Pellegrino and Savona (2017). Using the innovation survey data from the UK, they estimated a panel data model on the probability to obtain innovative outputs, either product or process innovations. Factors hampering innovation were grouped into regulatory obstacles, knowledge

[6] Alessandrini, Presbitero, and Zazzaro (2010) also analyzed financial constraints for Italian SMEs, although using the region as the unit of analysis. They found that SMEs located in regions where banks were functionally distant—defined as an algorithm considering the quantity of branches per region and their distance to their headquarters—tended to introduce fewer innovations.

[7] Obstacles were measured with a dummy variable identifying any factor hampering innovation, split in further specifications of the model into financial and non-financial obstacles.

obstacles, market obstacles, and cost obstacles, following Oslo 2005. They defined the relevant sample by excluding firms that did not innovate as a deliberate choice and those that claimed not to have experienced any obstacle to innovation. As in the previous studies, their results were sensitive to sampling definition. Using fixed and random effects Probit models they found that, once the relevant sample was identified, the costs, regulation, and market obstacles negatively affected the probability of achieving both process and product innovation.[8]

2.3. Obstacles Hampering Innovation and Firm Size

Firm size is considered one of the most important sources of micro-heterogeneity and it has been largely studied in the innovation literature (Cohen, 2010). SMEs share some size-specific features that put them in a more vulnerable position compared to their larger counterparts (Kaufmann and Tödtling, 2002). In fact, one fairly prevalent characteristic of SMEs is their lower productivity when compared to bigger firms (Nightingale and Coad, 2013), which can be related to the low levels of investment in general and particularly in innovation.

Investment in innovation entails large initial disbursements and high levels of uncertainty about results and benefits. This may not constitute an obstacle for larger companies with more internal liquidity and better capacity to offer collateral warranty, while smaller firms do normally suffer from financial constraints. Furthermore, big firms are arguably more capable of exploiting economies of scale. In turn, they can also rely on the cost-spreading advantages of R&D investment (Cohen and Klepper, 1996). This means that larger firms expect a greater future output over which to spread the fixed R&D costs (i.e., they expect a higher return for a unit invested in R&D), which consequently pushes them to invest more than SMEs. This assumes that firms manage to appropriate the future returns on innovation, while again finding larger firms in a better position to do so.

At the same time, investment in innovation requires persistent innovative behavior and accumulation of capabilities (Cohen and Levinthal, 1990), which are less likely to be grasped by SMEs. SMEs usually have less skilled human resources and a lack of training and capability-building activities (Vossen, 1998). Consequently, in SMEs the linkages with other economic actors and public institutions become essential to encourage and facilitate the learning and knowledge incorporation needed to innovate (Dini, Stumpo, and Italiana, 2011). However, SMEs also have limited knowledge regarding external sources of information and scarce links with the institutions responsible for the creation and dissemination of scientific and technical knowledge (Hewitt-Dundas, 2006). Larger firms can instead exploit new technologies more quickly because of their accumulated absorptive capacity and better-developed infrastructure. Finally, larger firms could exert their influence and lobbying capacity over the regulation related to fostering innovation.

[8] Using Spanish data, García-Quevedo, Pellegrino, and Savona (2016) assessed the demand-pull factors as barriers to innovation. With a similar criterion for defining the relevant sample, they analyzed the effect of the perception of lack of demand and the demand uncertainty on the probability and intensity of R&D investment. Using Heckman models and controlling for other possible obstacles, they found that lack of demand was restricting R&D investment while uncertainty was not. Furthermore, uncertainty even pushed R&D intensity further in some model specifications.

Despite these restrictions, the malleable organizational structure of SMEs provides flexibility to the innovation processes because it may promote faster learning. SMEs could more quickly adapt routines in response to changes in their environment, and they could also speed up the decision making (Vossen, 1998). Also, the less hierarchical human resources structure may imply a better attitudinal response to innovation and more motivated personnel.

The differences between SMEs and larger firms concerning resources, capabilities, motivations, and strategies are expressed in their perception of obstacles, arguably playing an important role in how these obstacles affect innovative behavior and performance. In fact, several papers analyzed obstacles specifically for SMEs. We will review here only those using econometric approaches.[9]

There are two papers already cited that revealed that SMEs' innovative decisions and outputs suffered from financial constraints (Alessandrini, Presbitero, and Zazzaro, 2010; Mancusi and Vezzulli, 2010). Besides those papers, we could mention two additional ones. Madrid-Guijarro, Garcia, and Van Auken (2009) used interview data from a sample of 294 managers within a Spanish region and grouped obstacles to innovation using factor analysis. They identified three main types of barriers: (i) the external environment, which includes a mixed set of obstacles related to the market characteristics and infrastructure, (ii) human resources, including qualification and attitudinal issues, and (iii) economic risks, which are related to market obstacles as defined by Oslo 2005. In addition, they included a dummy variable for the financial position of the firm, which adopted the value of one when the firm was highly constrained. They used the barriers and the financial position as explanatory variables for product, process, and management innovation. The only variable that showed a negative and highly significantly coefficient affecting all types of innovation measures was the financial position, while the human resources obstacles affected primarily process innovation. The economic risks barriers rendered insignificant coefficients and the external environment showed the wrong sign for process innovation.[10]

In turn, Maldonado-Guzmán et al. (2017) focus on SMEs in a developing country by analyzing a sample of 308 Mexican service SMEs. Using a structural equation modeling for three types of barriers—external environment, human resources, and finance, which were defined using factor analysis—on innovative outcomes, they found a negative association in all cases, with the first (external environment, which comprises market and infrastructure obstacles) showing the strongest effect.

[9] There are other fairly descriptive papers using interviews or low scale data. For example, Freel (2000) documented the perception of financial obstacles and knowledge obstacles for a group of 238 SMEs from the West Midlands region in the UK. In turn, Hadjimanolis (1999) used data for 140 SMEs from Cyprus and found that the perception of obstacles was positively correlated with innovativeness. Besides, Xie, Zeng, and Tam (2010) used a sample of 188 Chinese manufacturing SMEs and identified the most often perceived barriers were the "lack of technical experts" followed by "lack of financial capital," "lack of technical information," "low rate of return," and "high-cost and high-risk of innovation." In a recent paper based on interviews with executives from 49 German technology SMEs (Strobel and Kratzer, 2017), three perceived measures of innovative success—related to firm efficiency, firm market share, and innovative potential—were correlated with eleven obstacles using latent class analysis. Results were not robust enough and no single obstacle remained significant for the different measures of performance, although lack of know-how seemed to be the single most important factor affecting perceived firm efficiency.

[10] Dependent variables were ordinal data using a 5-point Likert scale and a semiparametric approach known as censored least absolute deviations (CLAD) was used.

Nevertheless, the lack of a systematic approach to studying the differences on how harmful obstacles result for firms of different sizes seems surprising. We could only refer to Bond, Harhoff, and Van Reenen (2003), already mentioned in Section 2.1, which although not being particularly interested in SMEs interacted the effect of cash flows with size, without finding any significant effect. There are some previous works using mainly descriptive statistics that showed that firms of different size have different perceptions of obstacles.[11] However, to the best of our knowledge, there is no methodologically thorough study systematically analyzing the effect of obstacles for firms of different sizes. This is one of the contributions of our paper.

3. Objectives and Contribution

3.1. General Goal and Contribution

Our general goal is to understand the effect of obstacles to innovation in the Argentinean manufacturing sectors. We are particularly interested in disentangling how these effects vary with firm size. Our research questions are: To what extent are firms affected by perceived obstacles in terms of investment in IA? And, to what extent are they affected in their likelihood of achieving innovative outcomes? We answer these questions using survey data for Argentinean manufacturing firms. The paper provides evidence on the scarce literature on obstacles to innovation in developing countries[12] and we claim our contribution to be twofold.

Firstly, building from recent methodological discussions, the paper attempts to control for selection bias in the relationship between obstacles and innovation by restricting the sample to "firms willing to innovate." We do so in an integrative framework that accounts for four types of obstacles simultaneously, using Oslo 2005 taxonomy on both investment decisions and innovative outputs. We also tackle endogeneity using IV rather than simultaneous or recursive models used in previous papers, to provide a general solution to the problem of endogenous explanatory variables (Wooldridge, 2010). This implies an important effort to find a good instrument for obstacles.[13]

Secondly, we estimate our models for two subsamples: SMEs (defined as firms with less than 100 employees) and large firms, and we discuss the differential effect of obstacles on innovation.

[11] For example, Jung et al. (2016) found a positive association between some obstacles and innovativeness—although without restricting the sample to the relevant one—varying according to firm size. They found that lack of funding was more important for smaller firms and lack of capability was so for larger ones. In turn, Hewitt-Dundas (2006) estimated the impact of obstacles on the probability to innovate in products and the share of innovative sales, splitting the sample according to size with data for 348 Irish plants. Neither correction for selection bias nor for endogeneity was made. The variables included in the regressions for the different subsamples were not the same, so the comparison across size is not straight forward and it is not actually discussed in the paper.

[12] Previous contributions were mostly of a descriptive nature—Hadjimanolis (1999) for Cyprus and Xie, Zeng, and Tam (2010) for China—or used simple statistical analysis, such as Maldonado-Guzmán et al. (2017) for Mexico and Adeyeye et al. (2017) for Nigeria.

[13] Instruments must be exogenous to the equation on innovative efforts and performance, and they must be partially correlated to obstacles once the other independent variables in the regression on innovation efforts and performance have been netted out.

3.2. Specific Objectives and Hypotheses

(i) To measure the effect of obstacles to innovation on the propensity to invest in IA and IA investment intensity. How is this different for SMEs?

> Hypothesis 1 (H1): Obstacles negatively affect investment in innovation (propensity and/or magnitude).
>
> Hypothesis 2 (H2): SMEs are more affected by obstacles than large firms.

(ii) To measure the effect of obstacles to innovation on the probability of success in innovation. How is this different for SMEs?

> Hypothesis 3 (H3): Obstacles negatively affect the probability of success in innovation (i.e., product, process, organizational, and commercial innovation).
>
> Hypothesis 4 (H4): SMEs are more severely affected by obstacles than larger firms.

(iii) To identify the specific effect of different types of obstacles using Oslo 2005 taxonomy (knowledge, market, institutional, and cost obstacles) on the probability of performing IA and IA intensity. How is this different for SMEs?

> This is an exploratory question; no hypotheses could be derived from the literature other than SMEs being more largely affected by all obstacles.

(iv) To identify the specific effect of different types of obstacles using Oslo 2005 taxonomy (knowledge, market, institutional, and cost obstacles) on the probability of success in innovation. How is this different for SMEs?

> This is an exploratory question; no hypotheses could be derived from the literature other than SMEs being more largely affected by all obstacles.

(v) To identify whether firms rely on external partners (other firms or knowledge organizations) to overcome obstacles, and how it is different for SMEs.

> This is an exploratory question; no hypotheses could be derived from the literature.

4. Methodology

We develop an original research design inspired by Crépon, Duguet, and Mairessec (1998), Savignac (2008), Blanchard et al. (2013), and Pellegrino and Savona (2017).

4.1. Data

Our analysis is based on data from the Employment and Innovation Dynamics National Survey (ENDEI, for its acronym in Spanish). This survey covers the 2010–12 period and was carried out jointly by the Ministry of Labor, Employment, and Social Security (MTEySS) and the Ministry of Science, Technology, and Productive Innovation (MINCyT). The sample was drawn so as to be representative of manufacturing firms with at least 10 employees, in terms of size (small, medium, and large) and sector (mostly two-digit ISIC).[14] The sample comprises 3,691 firms (expansion factors

[14] Sectors included are: food, beverages, and tobacco; chemicals and petrochemicals; pharmaceutical; basic metals; motor vehicles, ships, and other transport equipment; paper and publishing; rubber and plastic; machinery and equipment; textiles and clothing; electrical machinery and equipment; TV and radio

available);[15] 79 percent of cases correspond to SMEs,[16] giving us sufficient data to explore the context of this subsample of firms.

It is important to mention that data was anonymized, meaning that some variables have been censored, recoded, or collapsed in order to ensure confidentiality. This process has mainly affected quantitative variables such as employment, sales, and different types of monetary variables, mostly for large firms. SMEs' data, on the other hand, seems to be more precise.

The ENDEI has two structured questionnaires, one self-administered and one that requires a face-to-face interview. The former contains questions that require inputs from different areas of the firm: income, expenses (wages and salaries, intermediate consumptions, purchase of machinery and equipment, etc.), employment (according to hierarchies and qualification), remuneration, and spending in IA (R&D, consultancy, acquisition of machinery and equipment related to innovation, etc.). The latter contains mainly qualitative information on several issues regarding innovation and employment dynamics: organizational capability and business strategy; IA; profile of human resources dedicated to IA; results of the innovation efforts; sources of information and innovation objectives; sources of financing for IA; obstacles to innovation; linkages; employment management capabilities and training policy; organization of labor; and knowledge management capabilities.

4.2. Sampling Strategy to Deal with Selection Bias

There is a well-documented problem of selection bias that leads to finding a positive correlation between obstacles and propensity to innovate or other innovation indicators. This counterintuitive result is explained because firms that are not interested in innovation perceive no obstacles. On the contrary, firms interested in innovation are better able to identify hampering factors. Thus, the inclusion of firms that are *not willing to innovate* biases the estimation of the obstacles coefficients upwards, turning them positive.

Following the line of work of Savignac (2008), Blanchard et al. (2013), and Pellegrino and Savona (2017), we generate an appropriate subset of *firms willing to innovate* to be used in all of our estimations.

Our approach to identify the relevant sample shares the fundamentals with previous studies (i.e., we want to restrict our relevant sample to those firms that are "interested in" innovation or "willing to" innovate). Given the importance of the sampling methods, we compare different strategies (see Figure 1).

The more straightforward strategy was to opt for definitions of relevant sample (RS) used previously in the literature. Our data structure allowed us to use the one by

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equipment; wood and wood products; leather and footwear; other industries. For some sectors of special interest, information was disaggregated at four digits (food and beverages; chemicals; machinery and equipment; and motor vehicles).

[15] A full descriptive report of the survey can be found at http://www.mincyt.gob.ar/estudios/encuesta-nacional-de-dinamica-de-empleo-e-innovacion-resultados-globales-2010-2012-11493. We have not used expansion factors in this version of the paper.

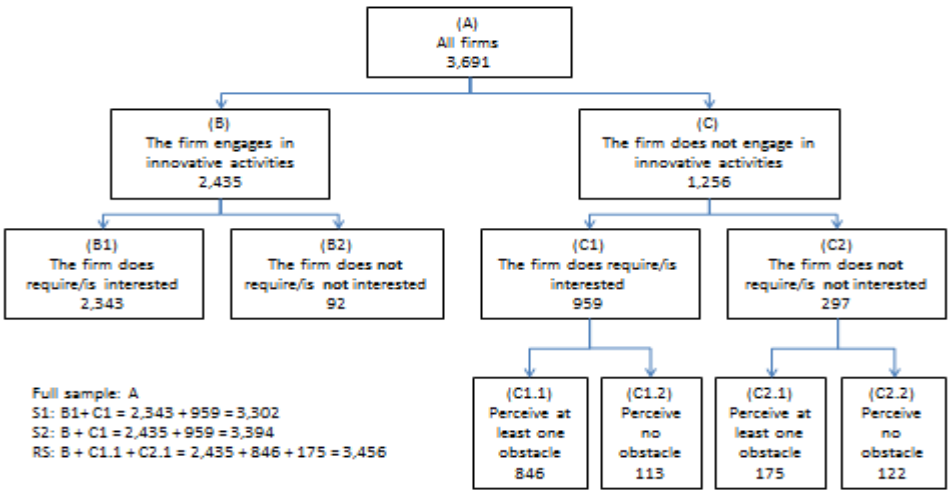
[16] The ENDEI uses the number of employees to classify firms by size: "small-sized firms" are those with 10 to 25 employees, and "medium-sized firms" are those with 26 to 99 employees.

Pellegrino and Savona (2017): we can exclude firms that did not engage in any IA and those that did not identify any obstacle (see RS in Figure 1).

The ENDEI questionnaire does not strictly follow suggestions from Bogota or Oslo Manuals, thus some questions are differently reported than those used in the literature. That is the case of obstacles. In the section of "barriers to innovation," 19 factors hampering innovation are informed, split in 10 internal and 9 external factors. Firms are requested to choose the most important factors from those lists (a maximum of three from each). In addition, there is one option that states, "The firm does not face any obstacle" and one more option stating, "The company does not require/is not interested" [in IA].[17] These latter options do not really involve obstacles, thus they were ignored when defining the RS.

However, if the firm marked that it did not require any innovation or that it was not interested in innovation, it may be considered a non-willing firm. So another definition for the sample of willing-to-innovate firms was to exclude those firms that declared they did not require/were not interested in innovation (see Sample 1 or S1 in Figure 1). Yet another definition was explored because there were firms that reported not to be interested in innovation but still performed IA. This led us to reincorporate 92 firms (see S2 in Figure 1).

Figure 1: Sampling Strategy to Account for Willing-to-Innovate Firms



4.3. Econometric Models

We estimate different econometric models to comply with objectives (i) and (ii) for all firms and for RS, S1, and S2. We then select the best performing of these subsamples and show most of the remaining results just for that subsample to save space. All estimations are divided in subsamples by size (SMEs and large firms). All variables used in the analysis are reported in Table A1 in the Annex.

[17] There is an "other" category, which contains no valid data.

Dependent variables were, alternatively, a dummy variable for investing in IA (*innoact_d*), the natural logarithm of the invested amount per employee (*log_innoact_intensity*), and three dummies for innovation results: the first for innovation in national or international markets (*innoresult_d*), and the second and third for introducing technological innovations (product and/or process) (*innoresult_tech_d*) and non-technological innovations (organizational and/or commercialization) (*innoresult_nontech_d*) in national or international markets.

The main explanatory variable was an index that measures the intensity of perceived obstacles in total (*obst_all*).

For objective (i) and H1 we estimate two models, one for decision to engage in IA (dichotomous dependent variable *innoact_d*, equation [1]), and the other for the natural logarithm of IA in relation to employment (dependent variable *log_innoact_intensity*; equation [2])[18] using the above-mentioned explanatory variable *obst_all*. Our estimations comprise variations of ordinary least squares (OLS) linear models and IV linear regressions.

$$innoact\_d_i = a_{11} + a_{12} * obst\_all_i + a_{13}X_{1i} + \varepsilon_{1i} \qquad [1]$$

$$log\_innoact\_intensity_i = a_{21} + a_{22} * obst\_all_i + a_{23}X_{2i} + \varepsilon_{2i} \qquad [2]$$

Subscript *i* represent the observational unit (the firm in our case). Meanwhile, the first subscript in coefficients, explanatory variables, and error terms account for the equation number. The *X* represents a set of control variables defined as follows (see Annex A1 for definitions of all variables):

- For equation [1], X_1: *age_2001_d; demand_pull_d; supply_push_d; foreign_d; group_d; humancapital; sector_d; size_employees*
- For equation [2], X_2: *age_2001_d; foreign_d; group_d; humancapital; sector_d; size_employees; mkt_share; mkt_share_2; source_breadth*

The main interest lies in the estimated values of parameters a_{12} and a_{22}, which reflect the impact of obstacles on the decision to engage in IA and on their intensity, allowing one to gain insight for H1. H2 in turn implies to re-estimate equation [1] and equation [2] but separately for the subsample of SMEs and large firms.

For objective (ii) and H3, we estimate a similar equation to [1] but using as the dependent variable a dichotomous one that identifies firms that succeed in obtaining innovative results. As mentioned before, we distinguish between technological innovation (product and/or process) and non-technological innovation (organizational/commercialization) in order to uncover heterogeneities in the way obstacles work.

$$innoresult\_d_i = a_{31} + a_{32} * obst\_all_i + a_{33}X_{3i} + \varepsilon_{3i} \qquad [3]$$

[18] We also conducted Probit estimations for the cases where the dependent variable was binary. Given that results were almost identical to OLS regressions, we preferred this latter option, which is more parsimonious. This is in line with several comments in econometrics texts, provided that the interest lays in the average partial effect of the explanatory variable rather than prediction (see for example Wooldridge [2010], p. 455).

$$innoresult\_tech\_d_i = a_{41} + a_{42} * obst\_all_i + a_{43}X_{4i} + \varepsilon_{4i} \quad [4]$$

$$innoresult\_nontech\_d_i = a_{51} + a_{52} * obst\_all_i + a_{53}X_{5i} + \varepsilon_{5i} \quad [5]$$

In this case, controls are:

- For equation [3], [4], and [5], $X_3 = X_4 = X_5$: *age_2001_d; foreign_d; group_d; humancapital; sector_d; and size_employees*

For H4 we re-estimate equations [3], [4], and [5] for the SMEs and big firms subsamples.

For objective (iii) we build the Oslo 2005 obstacle taxonomy: knowledge, cost, market, and institutional groups as explanatory variables (see Table 3).[19] We use Tobit type 2 models, which allows us to simultaneously model the decision to engage in IA (*innoact_d*) and its intensity (*log_innoact_intensity*), controlling for the potential bias generated by the fact that not all firms decide to invest in innovation.[20] Equations [6], [7], and [8] present the general specification.

$$innoact\_d_i^* = a_{61} + a_{62} * obst\_know_i + a_{63} * obst\_inst_i + a_{64} * obst\_cost_i + a_{65} * obst\_mrkt_i + a_{66}X_{6i} + \varepsilon_{6i} \quad [6]$$

$$innoact\_d_i = \begin{cases} 1 \; if \; innoact\_d_i^* > a \\ 0 \; if \; innoact\_d_i^* \leq a \end{cases} \quad [7]$$

$$log\_innoact\_intensity_i = a_{81} + a_{82} * obst\_know_i + a_{83} * obst\_inst_i + a_{84} * obst\_cost_i + a_{85} * obst\_mrkt_i + a_{86}X_{8i} + \varepsilon_{8i} \quad [8]$$

The decision to engage in IA (*innoact_d*) is modelled in equations [6] and [7] by the latent variable *innoact_d** (unobservable), which defines that when threshold *a* is passed the firm engages in IA. As explanatory variables we consider four obstacle groups—*obst_know, obst_inst, obst_cost,* and *obst_mrkt*—accounting for the intensity of perceived obstacles in each group.

In this case, controls are:

- For equation [6], $X_6 = X_1$: *age_2001_d; demand_pull_d; supply_push_d; foreign_d; group_d; humancapital; sector_d; size_employees*
- For equation [8], $X_8 = X_2$: *age_2001_d; foreign_d; group_d; humancapital; sector_d; size_employees; mkt_share; mkt_share_2; source_breadth*

[19] Two factors were eliminated from the analyses because they could not be matched with Oslo 2005 taxonomy: "limited productive capacity" or "difficulties in importing key inputs for innovation." This latter obstacle could have been included as a regulatory obstacle, if one interpreted it as import restriction measures. However, since it is not clear from the definition and since imports restrictions were a highly political subject (i.e., firms could choose this factor so as to make clear they did not agree with national politics of the time) during the period of data collected, we decided to exclude it from the analysis to avoid noise in our data.

[20] Estimated using maximum likelihood estimators, through the Stata command "Heckman" (StataCorp, 2013).

For the sake of completeness, equations [6] and [8] were also estimated using OLS and IV regressions. In order to be able to instrument all types of obstacles, they were included one at a time, as explained the paragraph just below.

Objective (iv) is attained using a linear probability model (LPM) to explain innovation success in terms of the different Oslo 2005 groups of obstacles. In order to be able to do IV estimations, each obstacle group is included separately in equation [9]. The equations are estimated four times, with the generic variable *obst_group* being replaced alternatively by *obst_know, obst_inst, obst_cost,* and *obst_mrkt*.[21] All these estimations include controls for intensity of the perceptions of obstacles other than those included in each group (*obst_not_group*). For example, when equations include *obst_know*, *obst_not_know* is also included as a variable accounting for the intensity of obstacles other than knowledge obstacles. The rest of the controls are the same as in equation [6].

$$innoresult\_d_i = a_{91} + a_{92} * obst\_group_i + a_{93} * obst\_not\_group_i + a_{96}X_{9} + \varepsilon_{9i} \quad [9]$$

Finally, for objective (v) we estimate tri-variate Probit models for the propensity to innovate (*innoresult_d*), the propensity to cooperate with firms (*link_firm_d*) and with private/public research organizations (*link_ppro_d*). As explanatory variable we use the index that accounts for the perception of obstacles in general (*obst_all*) and *link_firm_d* and *link_ppro_d* in case of equation on *innoresult_d*. Other controls are the same as in equation [3]. To identify equations on *link_firm_d* and *link_ppro_d* we additionally include market share (*mkt_share*), the breadth of use of sources of information (*source_breadth*), a dummy variable accounts for openness in strategic planning (*open_strategy_d*), and the number of financial sources the firm reveals to know about (*know_fin_sources*). Table 1 summarizes the estimations to be performed and the tables where results are shown.

[21] Weak instruments tests were not passed in the equation including *obst_inst*; therefore results are not analyzed.

Table 1: Research Goals, Econometric Models, and Organization of Results to Be Discussed

Objective		Samples	Dep. Variable	Obstacles variable	Models	Table #
(i)	Propensity of IA	Full/S1/S2/RS and for RS Big and SME firms	innoact_d	All together Variable: obst_all	LPM OLS & LPM IV (GMM)	5
(i)	Intensity of IA	Full/S1/S2/RS and for RS Big and SME firms	log_innoact_intensity	All together Variable: obst_all	OLS & IV (GMM)	6
(ii)	Propensity of innovation	Full/S1/S2/RS and for RS Big and SME firms	innoresult_d	All together Variable: obst_all	LPM OLS & LPM IV (GMM)	7
(ii)	Propensity of technological innovation	Full/S1/S2/RS and for RS Big and SME firms	innoresult_tech_d	All together Variable: obst_all	LPM OLS & LPM IV (GMM)	8
(ii)	Propensity of non-technological innovation	Full/S1/S2/RS and for RS Big and SME firms	innoresult_nontech_d	All together Variable: obst_all	LPM OLS & LPM IV (GMM)	9
(iii)	Propensity of IA and Intensity of IA	RS for all firms and splitting in Big and SMEs	innoact_d log_innoact_intensity	Oslo (4 groups) obst_know obst_inst obst_cost obst_mrkt	Tobit type 2 (Heckman)	10

(iii)	Propensity of IA	RS for all firms and splitting in Big and SMEs	innoact_d	Oslo (3 groups) obst_know obst_cost obst_mrkt	LPM IV (GMM) Individual models for each obstacles group	11a and 11b
(iii)	Intensity of IA	RS for all firms and splitting in Big and SMEs	log_innoact_intensity	Oslo (2 groups) obst_know obst_cost	LPM IV (GMM) Individual models for each obstacles group	12
(iv)	Propensity of innovation	RS for all firms and splitting in Big and SMEs	innoresult_d	Oslo (3 groups) obst_know obst_cost obst_mrkt	LPM IV (GMM) Individual models for each obstacles group	13a and 13b
(v)	Innovation propensity; Cooperation and cooperation with firms/cooperation with research organizations	RS for all firms and splitting in SMEs and Big firms.	innoresult_d link_firm_d link_ppro_d	All together Variable: obst_all	Tri-variate Probit model	14

4.3.1. Instrumentation strategy

We use IV estimations to control for the endogeneity in the relation between obstacles and innovation. The instrument was constructed using variables from a section of ENDEI devoted to human resources and labor dynamics. We may remind readers that the ENDEI was jointly implemented by two different ministries—labor (MTEySS) and science and technology (MINCyT)—and therefore the questionnaire is noticeably divided in sections mostly related to innovation while others attempt to capture labor dynamics. The instrument was built mixing questions on firms' restrictions in ordinary training activities. These training activities were chosen and funded at least partially by the firm with the aim to train workers in general on specific tasks related to the use of materials, machinery operation, and ability to change roles within the company.

Restrictions were in turn grouped in two lists: one accounting for limiting factors in training for firms that did perform some training activities during the period (these were related to budget constraints; lack of relevant courses; lack of capacity to identify firms' needs; lack of instructors; lack of time for training during working time; and lack of interest by the workforce). The other list referred to restrictions perceived by firms that did not perform any of the above training activities (including the following options: personnel has the right competencies to meet the firm's needs; the firm hires personnel with the required qualifications; the firm has difficulties in identifying and assessing the training needs; budget constraints; lack of relevant courses; lack of time for training during working time; lack of interest by the workforce; the firm plans to train workers the following year; and other reasons). Details of construction of *training_rest* can be seen in Annex A1.

Since training activities may affect the normal operation of the firm, we claim that firms suffering restrictions in training their employees may be more skeptical or less confident about future firm performance. Therefore, they may be more prone to perceiving obstacles to innovation. Firms that cannot trust the competence of their workforce may be more sensitive in identifying restrictions on the possibility of benefiting from innovation whose results will only materialize if the performance of the workforce is reasonably acceptable. Thus we claim *training_rest* is a good instrument for obstacles because firms facing those restrictions are also more sensitive in the identification of barriers and obstacles. Moreover, since training activities are not directly related to innovation,[22] we claim that restrictions to training only affect innovation through their effect on obstacles to innovation.

In other words, we propose that training restrictions is a relevant instrument given that both requisites for identifying a good instrument are met: it is exogenous to the equation on innovation and it is correlated with obstacles to innovation. While the assumption of exogeneity cannot be tested, we could test for the latter (i.e., that the instrument is not weak). Most IV estimations presented in this paper passed the tests for weak instruments (see Annex A2). In contrast, the instrument was found to be weak for institutional obstacles. This is to be expected because the instrument is constructed on restrictions to training, which are likely to be related to internal obstacles rather than external. In fact, the instrument works better for, in order, the index of all obstacles

[22] In one of the innovation sections from ENDEI there is another question on "training for the introduction of innovation."

together followed by cost, knowledge, and market obstacles. We do not report estimation results when the instrumentation strategy failed.

5. Descriptive Statistics

5.1 The Context

In 2014, 28.1 percent of Argentinean firms employed between 10 and 200 people. They accounted for 43.4 percent of total registered employment.[23] This share reaches 99.4 percent and 64.3 percent, respectively, when firms with less than 10 employees are included.

The need to improve our knowledge of the obstacles faced by SMEs in the innovation process is justified by the crucial role these agents play in the economic structure, particularly in relation to employment. The focus on SMEs is also justified by the deep gap in their productivity in contrast to bigger firms, especially in the context of developing countries. While in the European Union small firms reach 74 percent of the large enterprises' productivity, in Argentina they grasp just 36 percent. If medium-sized firms were considered, these figures would reach 85 percent and 47 percent respectively (CEPAL/AL-INVEST, 2013). This motivated governments to devote a growing amount of resources in public policies to support SMEs, including the promotion of their IA (Ibarrarán et al., 2009). As a matter of fact, in a recent review of industrial policy in Argentina, one of us identified that most policy tools, both designed and implemented by the MINCyT and aimed at fostering innovation, technological modernization, or the acquisition of capital goods, were mainly oriented towards SMEs (Arza et al., 2017).

Table 2 shows main innovative indicators in the first four columns. Innovation in ENDEI is defined as innovative outcomes resulting from innovative efforts.[24] Innovative efforts, in turn, are defined as activities performed seeking innovative outcomes.[25] It is worth noting that this filter question is a yes/no question, and it does not require firms to have invested positive amounts.[26]

In the full sample, 62 percent of firms claimed to have introduced some innovation[27] and 61 percent of firms introduced product or process. These percentages reduce to 31 percent when novelty is defined at national level at least.

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[23] Data comes from statistics produced by the Observatory of Employment and Business Dynamics, Ministry of Labor, Employment, and Social Security: http://www.trabajo.gob.ar/left/estadisticas/oede/estadisticas_nacionales.asp, last access February 2018.

[24] The question on innovative outputs is headed with this sentence: "You mentioned that you performed innovation activities during the period 2010–12, have you obtained any of the following results as a result of these innovation efforts?"

[25] The question on efforts is headed with this paragraph: "During the period 2010–12: did your company perform some of the following activities in search of innovation? This means all scientific, technological, organizational, financial and commercial operations that are intended to lead to the introduction of a new or significantly improved product, process, new method of marketing or organization in internal company practices, workplace organization or external relations (even though these goals have not been achieved yet)."

[26] Monetary values for investment in IA are informed on the self-administered form: 3 percent of firms that declared to have been engaged in IA in the period did not inform any positive amount on the self-administered form.

[27] Includes new or improved products or services or organizational/commercialization innovations.

If we considered just willing-to-innovate firms, following sampling definition S1 or S2, these figures increase to around 67 percent, 66 percent, and 34 percent respectively. For the RS the figures are a bit lower: 64 percent, 63 percent, and 32.5 percent respectively.

To assess the sampling strategy, we compare information on cooperation, which is a variable not affected by filters. The proportion of firms linking with third parties is 60 percent in the full sample. This increases to 63 percent for willing firms defined by S1 and S2, while it is 61 percent in the RS. In sum, the RS includes a higher proportion of low-performing firms, in terms of innovation (although that is driven by sampling definition) and in terms of linking to third parties for knowledge-related issues. These firms still identified some obstacles restricting IA. Because this definition of RS has been used in the literature, we may choose it as the RS (we will discuss this further in Section 6).

Table 2: Sampling Strategies, Innovation Indicators for Different Samples
(number of firms and proportions)

	Innovation results novel at least at…				Cooperates with…			
	firm level		national level					Number of firms
	All results	Product or process only	All results	Product or process only	Third parties	Public or private research organizations	Other firms	
Full sample	2.286	2.251	1.185	1.156	2.205	1.064	1.965	3.691
	61,93%	60,99%	31,43%	31,29%	59,74%	28,83%	53,24%	
Willing-to-innovate S1	2.213	2.182	1.166	1.138	2.078	1.022	1.857	3.302
	67,02%	66,08%	34,55%	34,40%	62,93%	30,95%	56,24%	
Willing-to-innovate S2	2.286	2.251	1.185	1.156	2.134	1.042	1.908	3.394
	67,35%	66,32%	34,18%	34,03%	62,88%	30,7%	56,22%	
Willing-to-innovate RS	2.286	2.251	1.185	1.156	2.140	1.044	1.910	3.456
	64,05%	63,07%	32,50%	32,36%	60,83%	29,50%	54,30%	

Table 3: Descriptive Statistics

	Full Sample				Willing-to-Innovate Firms (RS)				
	Mean			sd	Mean				sd
	SME	Big	Total	Total	SME	Big	Diff. Sig.	Total	Total
obst_all	0.194	0.163	0.188	0.127	0.208	0.171	***	0.200	0.121
obst_know	0.117	0.107	0.115	0.141	0.126	0.113	**	0.123	0.142
obst_inst	0.138	0.117	0.133	0.199	0.147	0.123	***	0.142	0.203
obst_cost	0.315	0.244	0.300	0.291	0.338	0.257	***	0.321	0.290
obst_mrkt	0.307	0.264	0.298	0.307	0.329	0.278	***	0.318	0.307
obst_not_know	0.380	0.308	0.365	0.265	0.407	0.324	***	0.389	0.255
obst_not_inst	0.446	0.373	0.431	0.296	0.478	0.392	***	0.460	0.284
obst_not_cost	0.307	0.269	0.299	0.241	0.329	0.283	***	0.319	0.236
obst_not_mrkt	0.412	0.343	0.398	0.287	0.442	0.361	***	0.425	0.276
humancapital (%)	14.124	22.030	15.765	18.528	14.365	22.130	***	16.001	18.521
know_fin_sources	2.812	3.761	3.009	2.609	2.878	3.858	***	3.084	2.609
demand_pull_d	0.604	0.640	0.611	0.488	0.615	0.641		0.620	0.485
age_2001_d	0.341	0.093	0.292	0.455	0.339	0.093	***	0.289	0.454
foreign_d	0.046	0.265	0.092	0.289	0.048	0.269	***	0.094	0.292
group_d	0.058	0.370	0.123	0.328	0.059	0.367	***	0.124	0.329
innoact_intensity	5522.1	20801.2	8618.7	28089.7	5924.4	21943.5	***	9214.7	28950.4
innoact_d	0.602	0.851	0.652	0.476	0.645	0.897	***	0.697	0.460
innoresult_tech_d	0.272	0.481	0.315	0.465	0.292	0.507	***	0.336	0.473
innoresult_nontech_d	0.070	0.148	0.086	0.280	0.075	0.156	***	0.092	0.289
innoresult_d	0.273	0.483	0.316	0.465	0.299	0.518	***	0.345	0.475
training_rest	2.900	1.711	2.649	1.468	2.895	1.713	***	2.642	1.476
link_d	0.545	0.794	0.597	0.491	0.567	0.811	***	0.619	0.486
link_firm_d	0.479	0.738	0.532	0.499	0.498	0.757	***	0.552	0.497
link_ppro_d	0.229	0.510	0.288	0.453	0.242	0.523	***	0.301	0.459
log_innoact_intensity	8.324	8.708	8.426	1.524	8.324	8.708	***	8.426	1.524
mkt_share	0.208	2.759	0.740	1.833	0.211	2.764	***	0.750	1.852
open_strategy_d	0.423	0.621	0.464	0.499	0.437	0.630	***	0.477	0.500
size_employees	31.2	250.5	76.7	106.5	31.5	250.5	***	77.6	107.0
source_breadth	0.238	0.440	0.280	0.277	0.255	0.463	***	0.299	0.276
supply_push_d	0.526	0.596	0.541	0.498	0.535	0.606	***	0.550	0.498

Note: The column "Diff. Sig." indicates the level of significance for a t-test for the mean difference between SMEs and big firms for each variable. Outliers are excluded in all cases.

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

Table 4: Descriptive Statistics for Obstacles (for the RS, Excluding Outliers)

Obstacle definitions	Firms with IA	Firms with no IA	Firms with innovation results	Firms with no innovation results	Number of firms
Knowledge obstacles	1237	593	607	1213	1830
	68%	***32%***	***33%***	***66%***	***100%***
Company organizational rigidities	279	148	127	297	427
Employees' reluctance to change	508	152	247	409	660
Lack of qualified personnel to boost IA	544	253	257	536	797
Difficulty to retain qualified personnel	266	102	137	228	368
Impossibility or difficulty to develop innovations because of its complexity	174	150	79	241	324
Lack of technical assistance to develop IA	209	92	107	193	301
Lack of matching between the supply of knowledge and the firm demand	59	26	32	52	85
Institutional obstacles	842	417	430	822	1259
	67%	***33%***	***34%***	***65%***	***100%***
Impossibility or difficulty to protect innovations	77	28	45	57	105
Bureaucracy in sector's regulations	397	146	222	319	543
Law/labor uncertainty	523	298	248	569	821
Cost obstacles	1557	754	769	1529	2311
	67%	***33%***	***33%***	***66%***	***100%***
High costs for product or process development or management changes	921	471	453	929	1392
The period of return on investments is too long	572	247	296	519	819
Difficulty in access to financing sources to develop IA	635	322	330	627	957
High costs for IA financing	817	433	391	855	1250
Market obstacles	1296	645	631	1298	1941
	67%	***33%***	***33%***	***67%***	***100%***
Economic/financial uncertainty	1113	574	519	1158	1687
Unfair competition	341	163	192	307	504
Number of firms	2423	1020	1178	2238	3416
	71%	***30%***	***34%***	***66%***	***100%***

Note: Innovation results include new or improved products or services or organizational/commercialization innovations, novel in the national market.

In terms of micro-characteristics, Table 3[28] shows that around 30 percent of firms are young (started after 2001, *age_2001_d*), 9 percent are foreign, and 12 percent belong to a group. Indicators regarding firms' strategy show that they employ 16 percent of professional or technical employees (*humancapital*), 60 percent link with third parties (29 percent with research organizations, *link_ppro_d,* and 53 percent with other firms, *link_firm_d*), 65 percent invest in IA (*innoact_d*), and 32 percent are successful in obtaining innovative outcomes that they considered novel for the national or

[28] From this table on, all results exclude outlier cases. The ENDEI dataset comes with a User Manual where they inform about firms that may be considered outliers in *investment in IA* and in *income*. All of them, in total 15 firms, were excluded.

international market (*innoresult_d*). All these indicators related to firm innovative behavior are bigger when the RS is considered. In this table we also show the t-test for the mean differences between SME and large firms. We found that SMEs are younger, employ less skilled personnel, and are less likely to be foreign or to belong to a group. In terms of behavior, they know about fewer financial sources (*know_fin_sources*), they use a narrower variety of information sources (*source_breadth*), they are less innovative, they have fewer links with third parties, and they perceive more obstacles.

Table 4 shows descriptive statistics for obstacles, considering firms in the RS of willing-to-innovate firms. From this table it is possible to see that firms face primarily obstacles related to costs (68 percent), followed by market (57 percent), knowledge (54 percent), and institutional (37 percent). The order is similar regardless of whether firms innovate. A key fact that can be seen from the table, which suggests the existence of selection bias, is that firms that invest in innovation are more likely to perceive obstacles, but once firms have invested, those perceiving obstacles are less likely to obtain results.

6. Econometric Findings

Table 5 shows results of Equation [1] on the decision to engage in IA (*innoact_d*), while Table 6 presents the estimates of Equation [2], with IA intensity as the dependent variable (*log_innoact_intensity*).

Estimations are successful and robust. The control variables show the expected signs. Size correlates positively with the probability of engaging in IA (Table 5) but negatively with IA intensity (Table 6), in line with observed results in the literature. Market share affects investment intensity in a non-linear way. It adopts an inverted U-shaped form, given the negative and statistically significant estimates for the quadratic term (Table 6). This result is also expected from the literature.

Belonging to a conglomerate does not seem to make a difference on innovation behavior (the *group_d* variable is not significant on Table 5 nor on Table 6), while multinational corporations are not particularly likely to invest in IA (*foreign_d* coefficient in Table 5 is not significant) either, but when they invest they do it more intensively (Table 6). Human capital (*humancapital*) is positively associated to the decision to invest and to the intensity of investment, particularly for SMEs.[29] In addition, to diversify sources of information (*source_breadth*) is also positively correlated with the level of investment (Table 6).

Young firms are more likely to engage in IA (Table 5), especially SMEs. It is interesting that young and large firms are less likely to invest in innovation.[30] Young firms also invest more intensively, but result is not significant for the sample of large firms (Table 6). In sum, results on age suggest that among small firms, startups are more likely to invest in innovation, which is also an expected result from the literature, and large and young firms, to say the least, are not particularly innovative.

[29] Coefficient is not significant for the subsample of large firm.
[30] The coefficient becomes non-significant in IV estimation.

Table 5: LPM Models for the Decision to Engage in Any IA (innoact_d)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	Full sample	Full sample - SME	Full sample - Big	S1	S2	Relevant Sample (RS)	RS - SME	RS - Big	RS - IV	RS - SME - IV	RS - Big - IV
obst_all	0.0693***	0.0477*	0.174***	-0.0737***	-0.0856***	-0.157***	-0.182***	-0.0247	-1.624***	-1.593***	-1.078***
	(0.0245)	(0.0278)	(0.0460)	(0.0253)	(0.0248)	(0.0239)	(0.0281)	(0.0364)	(0.187)	(0.213)	(0.325)
size_employees	0.00106***	0.00448***	0.000511***	0.000946***	0.000925***	0.00102***	0.00427***	0.000503***	0.000608***	0.00350***	0.000390**
	(7.01e-05)	(0.000373)	(0.000119)	(6.59e-05)	(6.42e-05)	(6.36e-05)	(0.000369)	(0.000103)	(0.000127)	(0.000553)	(0.000159)
group_d	-0.000614	0.0152	-0.00582	0.00666	0.00353	0.00972	0.0114	0.0179	-0.0558	-0.0854	-0.00434
	(0.0267)	(0.0378)	(0.0359)	(0.0257)	(0.0251)	(0.0252)	(0.0367)	(0.0311)	(0.0433)	(0.0582)	(0.0480)
age_2001_d	0.0286	0.0635***	-0.103*	0.0163	0.0160	0.0382**	0.0738***	-0.116**	0.0623**	0.0934***	-0.102
	(0.0179)	(0.0188)	(0.0595)	(0.0185)	(0.0182)	(0.0180)	(0.0190)	(0.0558)	(0.0252)	(0.0265)	(0.0649)
foreign_d	-0.0104	-0.0149	0.00880	-0.00444	-0.00119	-0.0288	-0.0179	-0.0368	-0.0329	-0.00697	-0.0530
	(0.0305)	(0.0446)	(0.0419)	(0.0289)	(0.0283)	(0.0289)	(0.0430)	(0.0352)	(0.0451)	(0.0590)	(0.0558)
humancapital	0.00209***	0.00243***	0.000869	0.00194***	0.00186***	0.00185***	0.00225***	0.000637	0.000824	0.00139*	-0.000200
	(0.000496)	(0.000601)	(0.000812)	(0.000501)	(0.000492)	(0.000486)	(0.000600)	(0.000726)	(0.000708)	(0.000816)	(0.00112)
demand_pull_d	0.108***	0.110***	0.0712**	0.0871***	0.0853***	0.0931***	0.0943***	0.0677**	0.113***	0.121***	0.0466
	(0.0164)	(0.0187)	(0.0318)	(0.0170)	(0.0167)	(0.0166)	(0.0190)	(0.0296)	(0.0239)	(0.0265)	(0.0418)
supply_push_d	0.129***	0.121***	0.110***	0.122***	0.117***	0.118***	0.117***	0.0774***	0.151***	0.169***	0.0454
	(0.0160)	(0.0182)	(0.0315)	(0.0165)	(0.0162)	(0.0160)	(0.0184)	(0.0290)	(0.0229)	(0.0260)	(0.0401)
Constant	0.341***	0.174***	0.578***	0.498***	0.521***	0.525***	0.379***	0.699***	1.350***	1.213***	1.216***
	(0.0324)	(0.0398)	(0.0665)	(0.0349)	(0.0341)	(0.0338)	(0.0427)	(0.0635)	(0.111)	(0.134)	(0.175)
Observations	3,435	2,766	669	3,062	3,143	3,209	2,575	634	3,095	2,474	621
R-squared	0.124	0.120	0.128	0.113	0.109	0.128	0.122	0.123			
Adj.R-squared	0.115	0.109	0.0813	0.103	0.0993	0.119	0.110	0.0729			
F test	19.63	12.99	2.771	15.81	15.70	19.50	12.77	2.140			
Prob> F	0	0	5.86e-07	0	0	0	0	0.000237			
Log-likelihood	-2101	-1770	-218.9	-1760	-1789	-1838	-1583	-110.3			
Wald chi2									294.4	233.4	49.42
Prob> chi2									0	0	0.0425

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

Table 6: OLS and IV Models for the Log of IA Per Employee (log_innoact_intensity)

VARIABLES	(1) Full sample	(2) Full sample - SME	(3) Full sample - Big	(4) S1	(5) S2	(6) Relevant Sample (RS)	(7) RS - SME	(8) RS - Big	(9) RS - IV	(10) RS - SME - IV	(11) RS - Big - IV
obst_all	-0.339***	-0.350***	-0.209	-0.348***	-0.339***	-0.339***	-0.350***	-0.209	-1.262***	-1.660***	0.423
	(0.0983)	(0.106)	(0.225)	(0.0999)	(0.0983)	(0.0983)	(0.106)	(0.225)	(0.485)	(0.569)	(1.139)
mkt_share	0.368***	1.310***	0.388***	0.358***	0.368***	0.368***	1.310***	0.388***	0.326***	1.129***	0.416***
	(0.0590)	(0.261)	(0.0751)	(0.0601)	(0.0590)	(0.0590)	(0.261)	(0.0751)	(0.0630)	(0.271)	(0.0905)
mkt_share_2	-0.0164***	-0.196***	-0.0152***	-0.0160***	-0.0164***	-0.0164***	-0.196***	-0.0152***	-0.0147***	-0.173***	-0.0161***
	(0.00314)	(0.0611)	(0.00338)	(0.00316)	(0.00314)	(0.00314)	(0.0611)	(0.00338)	(0.00328)	(0.0559)	(0.00374)
size_employees	-0.00277***	-0.0132***	-0.00272***	-0.00262***	-0.00277***	-0.00277***	-0.0132***	-0.00272***	-0.00268***	-0.0125***	-0.00303***
	(0.000569)	(0.00194)	(0.000902)	(0.000589)	(0.000569)	(0.000569)	(0.00194)	(0.000902)	(0.000585)	(0.00198)	(0.000977)
group_d	0.0643	0.107	-0.0583	0.0340	0.0643	0.0643	0.107	-0.0583	0.0263	0.0310	-0.0508
	(0.116)	(0.144)	(0.193)	(0.119)	(0.116)	(0.116)	(0.144)	(0.193)	(0.119)	(0.151)	(0.193)
age_2001_d	0.217***	0.195***	0.0828	0.214***	0.217***	0.217***	0.195***	0.0828	0.237***	0.215***	0.0868
	(0.0653)	(0.0662)	(0.276)	(0.0664)	(0.0653)	(0.0653)	(0.0662)	(0.276)	(0.0678)	(0.0701)	(0.269)
foreign_d	0.612***	0.400***	0.810***	0.606***	0.612***	0.612***	0.400***	0.810***	0.608***	0.410***	0.764***
	(0.122)	(0.150)	(0.216)	(0.124)	(0.122)	(0.122)	(0.150)	(0.216)	(0.123)	(0.156)	(0.215)
humancapital	0.00746***	0.00527***	0.00583	0.00756***	0.00746***	0.00746***	0.00527***	0.00583	0.00660***	0.00404*	0.00581
	(0.00187)	(0.00202)	(0.00450)	(0.00190)	(0.00187)	(0.00187)	(0.00202)	(0.00450)	(0.00197)	(0.00216)	(0.00451)
source_breadth	0.773***	0.792***	0.677**	0.787***	0.773***	0.773***	0.792***	0.677**	1.041***	1.190***	0.652**
	(0.146)	(0.167)	(0.287)	(0.150)	(0.146)	(0.146)	(0.167)	(0.287)	(0.187)	(0.240)	(0.328)
Constant	8.210***	8.482***	8.448***	8.218***	8.210***	8.210***	8.482***	8.448***	8.563***	9.044***	8.200***
	(0.118)	(0.142)	(0.288)	(0.123)	(0.118)	(0.118)	(0.142)	(0.288)	(0.243)	(0.301)	(0.470)
Observations	2,225	1,660	565	2,144	2,225	2,225	1,660	565	2,161	1,608	553
R-squared	0.138	0.127	0.236	0.135	0.138	0.138	0.127	0.236	0.105	0.047	0.223
Adj.R-squared	0.124	0.109	0.185	0.121	0.124	0.124	0.109	0.185	0.0906	0.0257	0.170
F test	8.977	6.132	5.293	8.519	8.977	8.977	6.132	5.293			
Prob> F	0	0	0	0	0	0	0	0			
Log-likelihood	-3888	-2791	-1038	-3748	-3888	-3888	-2791	-1038			
Wald chi2									306.6	206.1	188.8
Prob> chi2									0	0	0

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

Regarding sampling strategy, the effect of obstacles on the probability to engage in IA is different when comparing the full sample and willing-to-innovate subsamples. The coefficients for obstacles change from positive and significant in the full sample (Table 5, columns 1 to 3) to negative and significant in the willing-to-innovate S1, S2, and RS (columns 4 to 8).[31] The sampling strategy seems to have worked. As said before, to save space we opted to show most results, including estimation by size, only for the RS because it has been used elsewhere, which improves the comparability of our findings.

For IA intensity (Table 6) obstacles coefficients are negative and significant for all samples that do not discriminate by size. Coefficient on obstacles is the same for S2 and RS (because both capture all investing firms) and also similar to the one in S1.

All in all, results from Tables 5 and 6 provide evidence in favor of H1. Results also show that this negative effect is stronger for the subsample of SMEs (coefficients for large firms are not significant), providing evidence for H2.

To control for endogeneity, we conducted the IV estimations presented in columns 9 to 11 of Tables 5 and 6. Signs and significance are similar to OLS estimations,[32] but magnitudes are much larger. This means endogeneity downplayed the role of obstacles on innovation.

Tables 7 to 9 present estimates for equations [3] to [5] on innovation outputs. On micro-determinants, reading from Table 7, only size and human capital remain significant (and positive). The sampling strategy also seems to work well here; the coefficient for obstacle is significant and positive for the full sample (columns 1 to 3) and turns to be non-significant for willing-to-innovate subsamples (columns 4 to 8). The results become negative and significant when controlling for endogeneity. This pattern repeated for technological (Table 8) and non-technological innovations (Tables 9). In sum, results provide evidence to validate H3: obstacles negatively affect success in innovation.

In terms of whether such effects were different for firms of different size, in OLS estimations all coefficients are not significant for SMEs and for large firms. In IV regressions, the negative coefficient of obstacles is only marginally higher for SMEs on innovation outcomes in general (Table 7), and on product and process innovation (Table 8). For non-technological innovation, the opposite is true (Table 9). Thus, our results do not support H4.[33]

[31] Although it remains non-significant for the subsample of large firms (column 8).
[32] With the exception of the subsample of big firms on the propensity to engage in IA (Table 5): coefficient for obstacles is not significant for OLS estimation and becomes significant for IV estimation.
[33] We explored including size interaction terms in IV regressions presented in column 9 of Tables 7, 8, and 9, and the interaction term was never significant.

Table 7: LPM Models for Innovation Results at the National Level (innoresult_d)

VARIABLES	(1) Full sample	(2) Full sample - SME	(3) Full sample - Big	(4) S1	(5) S2	(6) Relevant Sample (RS)	(7) RS - SME	(8) RS - Big	(9) RS - IV	(10) RS - SME - IV	(11) RS - Big - IV
obst_all	0.0708***	0.0483*	0.162***	-0.00392	0.00356	-0.0272	-0.0454	0.0556	-1.195***	-1.165***	-1.036***
	(0.0235)	(0.0253)	(0.0607)	(0.0265)	(0.0260)	(0.0271)	(0.0298)	(0.0646)	(0.181)	(0.204)	(0.387)
group_d	-0.0125	-0.0448	0.0230	-0.00167	-0.00872	-0.00490	-0.0481	0.0393	-0.0529	-0.132**	0.0375
	(0.0320)	(0.0430)	(0.0504)	(0.0336)	(0.0332)	(0.0331)	(0.0451)	(0.0514)	(0.0438)	(0.0605)	(0.0615)
age_2001_d	-0.00154	0.0114	-0.0457	-0.00631	-0.00933	9.39e-05	0.0128	-0.0519	0.0159	0.0265	-0.0573
	(0.0168)	(0.0175)	(0.0611)	(0.0184)	(0.0181)	(0.0179)	(0.0187)	(0.0650)	(0.0233)	(0.0240)	(0.0817)
foreign_d	0.0307	-0.0118	0.0934	0.0322	0.0379	0.0213	-0.0101	0.0656	0.0175	0.00780	0.0284
	(0.0359)	(0.0486)	(0.0577)	(0.0374)	(0.0369)	(0.0365)	(0.0494)	(0.0593)	(0.0449)	(0.0588)	(0.0709)
humancapital	0.00301***	0.00333***	0.00213**	0.00303***	0.00303***	0.00300***	0.00339***	0.00207*	0.00204***	0.00264***	0.000836
	(0.000510)	(0.000594)	(0.00108)	(0.000551)	(0.000542)	(0.000535)	(0.000626)	(0.00113)	(0.000665)	(0.000758)	(0.00136)
size_employees	0.000968***	0.00260***	0.000728***	0.000940***	0.000933***	0.000976***	0.00252***	0.000761***	0.000666***	0.00193***	0.000562**
	(9.24e-05)	(0.000404)	(0.000169)	(9.73e-05)	(9.56e-05)	(9.55e-05)	(0.000420)	(0.000175)	(0.000133)	(0.000523)	(0.000224)
Constant	0.108***	0.0435	0.150**	0.179***	0.169***	0.175***	0.120***	0.192**	0.847***	0.808***	0.714***
	(0.0274)	(0.0328)	(0.0719)	(0.0322)	(0.0314)	(0.0312)	(0.0375)	(0.0747)	(0.109)	(0.131)	(0.201)
Observations	3,456	2,777	679	3,086	3,164	3,230	2,586	644	3,119	2,486	633
R-squared	0.104	0.077	0.134	0.098	0.098	0.103	0.074	0.134			
Adj.R-squared	0.0953	0.0662	0.0911	0.0886	0.0889	0.0936	0.0619	0.0886			
F test	13.50	8.015	4.314	11.39	11.79	12.41	6.996	4.159			
Prob> F	0	0	0	0	0	0	0	0			
Log-likelihood	-2082	-1599	-444	-1942	-1985	-2003	-1549	-420.4			
Wald chi2									281.5	163.8	107.2
Prob> chi2									0	0	4.81e-10

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

Table 8: LPM Models for Technological Innovation Results (Product/Process) at the National Level (innoresult_tech_d)

VARIABLES	(1) Full sample	(2) Full sample - SME	(3) Full sample - Big	(4) S1	(5) S2	(6) Relevant Sample (RS)	(7) S2 - SME	(8) S2 - Big	(9) S2 - IV	(10) S2 - SME - IV	(11) S2 - Big - IV
obst_all	0.0672***	0.0454*	0.149**	-0.00688	0.00109	-0.0291	-0.0463	0.0448	-1.192***	-1.161***	-1.013***
	(0.0234)	(0.0252)	(0.0611)	(0.0264)	(0.0260)	(0.0271)	(0.0297)	(0.0652)	(0.180)	(0.203)	(0.383)
group_d	0.00397	-0.0354	0.0502	0.0134	0.00860	0.0123	-0.0380	0.0672	-0.0352	-0.122**	0.0668
	(0.0322)	(0.0430)	(0.0510)	(0.0338)	(0.0335)	(0.0334)	(0.0452)	(0.0522)	(0.0441)	(0.0604)	(0.0622)
age_2001_d	0.000730	0.0131	-0.0392	-0.00352	-0.00640	0.00261	0.0147	-0.0437	0.0181	0.0280	-0.0485
	(0.0167)	(0.0174)	(0.0614)	(0.0183)	(0.0180)	(0.0178)	(0.0186)	(0.0653)	(0.0232)	(0.0239)	(0.0815)
foreign_d	0.0183	-0.00398	0.0520	0.0241	0.0247	0.00892	-0.00160	0.0229	0.00480	0.0164	-0.0142
	(0.0361)	(0.0485)	(0.0588)	(0.0378)	(0.0373)	(0.0369)	(0.0493)	(0.0605)	(0.0453)	(0.0586)	(0.0714)
humancapital	0.00297***	0.00331***	0.00220**	0.00300***	0.00300***	0.00297***	0.00337***	0.00216*	0.00202***	0.00264***	0.000964
	(0.000510)	(0.000592)	(0.00110)	(0.000550)	(0.000542)	(0.000535)	(0.000624)	(0.00115)	(0.000664)	(0.000754)	(0.00134)
size_employees	0.000936***	0.00251***	0.000705***	0.000908***	0.000901***	0.000942***	0.00244***	0.000736***	0.000633***	0.00185***	0.000542**
	(9.27e-05)	(0.000400)	(0.000168)	(9.77e-05)	(9.60e-05)	(9.58e-05)	(0.000416)	(0.000175)	(0.000133)	(0.000528)	(0.000222)
Constant	0.105***	0.0428	0.145**	0.175***	0.164***	0.170***	0.118***	0.186**	0.839***	0.802***	0.691***
	(0.0274)	(0.0326)	(0.0719)	(0.0322)	(0.0314)	(0.0312)	(0.0374)	(0.0749)	(0.109)	(0.130)	(0.200)
Observations	3,455	2,776	679	3,085	3,163	3,229	2,585	644	3,118	2,485	633
R-squared	0.100	0.075	0.129	0.096	0.095	0.099	0.072	0.128			
Adj.R-squared	0.0918	0.0646	0.0854	0.0861	0.0858	0.0904	0.0606	0.0828			
F test	12.84	8.100	4.063	10.93	11.21	11.85	7.085	3.873			
Prob> F	0	0	0	0	0	0	0	0			
Log-likelihood	-2064	-1579	-445.8	-1928	-1971	-1988	-1531	-423			
Wald chi2									271.4	161.3	102.3
Prob> chi2									0	0	2.84e-09

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

Table 9: LPM Models for Non-Technological Innovation Results (Organization/Commercialization) at the National Level (innoresult_nontech_d)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	Full sample	Full sample - SME	Full sample - Big	S1	S2	Relevant Sample (RS)	RS - SME	RS - Big	RS - IV	RS - SME - IV	RS - Big - IV
obst_all	0.0225	0.0224	0.0197	0.00128	0.00618	-0.00173	0.000861	-0.0154	-0.438***	-0.438***	-0.526**
	(0.0144)	(0.0149)	(0.0428)	(0.0168)	(0.0164)	(0.0172)	(0.0181)	(0.0470)	(0.102)	(0.116)	(0.240)
group_d	0.0158	-0.00909	0.0359	0.0208	0.0177	0.0194	-0.0102	0.0433	-0.000827	-0.0466	0.0389
	(0.0210)	(0.0244)	(0.0376)	(0.0226)	(0.0223)	(0.0222)	(0.0259)	(0.0395)	(0.0248)	(0.0309)	(0.0424)
age_2001_d	-0.00929	-0.000225	-0.0870***	-0.0132	-0.0126	-0.00999	-0.000258	-0.0953***	-0.00168	0.00768	-0.0968**
	(0.00993)	(0.0105)	(0.0302)	(0.0110)	(0.0108)	(0.0107)	(0.0113)	(0.0328)	(0.0123)	(0.0130)	(0.0401)
foreign_d	0.0193	-0.0262	0.0810*	0.0141	0.0222	0.0166	-0.0267	0.0739	0.0187	-0.0156	0.0616
	(0.0242)	(0.0266)	(0.0459)	(0.0256)	(0.0257)	(0.0251)	(0.0276)	(0.0486)	(0.0277)	(0.0329)	(0.0515)
humancapital	0.000489	0.000604*	0.000138	0.000429	0.000477	0.000464	0.000597*	-4.67e-05	3.64e-05	0.000215	-0.000607
	(0.000316)	(0.000327)	(0.000832)	(0.000347)	(0.000343)	(0.000339)	(0.000352)	(0.000884)	(0.000381)	(0.000404)	(0.000964)
size_employees	0.000326***	0.000628**	0.000244**	0.000322***	0.000321***	0.000334***	0.000614**	0.000264**	0.000225***	0.000385	0.000190
	(6.52e-05)	(0.000253)	(0.000122)	(7.02e-05)	(6.86e-05)	(6.86e-05)	(0.000264)	(0.000131)	(8.11e-05)	(0.000289)	(0.000153)
Constant	0.0463***	0.0136	0.129**	0.0681***	0.0640***	0.0646***	0.0319	0.144**	0.316***	0.299***	0.390***
	(0.0177)	(0.0192)	(0.0554)	(0.0209)	(0.0205)	(0.0203)	(0.0221)	(0.0580)	(0.0630)	(0.0746)	(0.133)
Observations	3,456	2,777	679	3,086	3,164	3,230	2,586	644	3,119	2,486	633
R-squared	0.036	0.020	0.087	0.035	0.035	0.036	0.018	0.092			
Adj.R-squared	0.0273	0.00862	0.0418	0.0252	0.0253	0.0264	0.00610	0.0441			
F test	3.128	4.408	2.978	4.804	2.898	2.995	4.847	3.061			
Prob> F	8.81e-09	0	1.49e-07	0	1.09e-07	3.85e-08	0	7.23e-08			
Log-likelihood	-438.7	-136.2	-225.3	-527.1	-529.4	-509	-213.9	-226.1			
Wald chi2									99.04	64.75	69.12
Prob> chi2									8.92e-09	0.000536	0.000153

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

We now turn to objective (iii) to analyze the effect of different types of obstacles on investment in innovation. Results on the Tobit type 2 models are presented in Table 10. Results for equation [6], on the probability to engage in investment activities, are shown in columns labeled "selection." In turn, results for equation [8] on intensity of investment in IA are presented in columns labeled "level."

The variables we chose for the correct identification of the selection equations are both significant and positive. Firms that follow a demand-pull strategy[34] and a supply-push[35] strategy are more likely to engage in IA.

We read results for the micro-determinants for the RS (columns 3 and 4). They are similar to those found for OLS models presented in Tables 5 and 6, which enhance the robustness of our results: size has a positive effect on the probability to invest, but negative for the intensity; foreign firms invest more intensively when they do (but the coefficient is not significant for the *selection* equation); younger firms are more likely to invest as well as firms that hire more skilled personnel; and the use of a large diversity of information sources intensifies investment.[36]

Regarding obstacles, results show that cost and market obstacles deter investment in innovation, while knowledge obstacles limit its intensity. This would imply that cost and market barriers simply discourage firms from making decisions to embark on innovation projects. These projects are risky and long term by nature; firms that are constrained financially or are not financially relaxed prefer to look away. Slack innovation will definitely not occur when facing cost and market obstacles.

However, for firms that do get involved, knowledge barriers would determine their level of commitment to innovation. Projects that are riskier or more complex—which presumably makes them more expensive—would not be chosen by firms facing knowledge obstacles.

Regarding the effect by size, cost obstacles seem to be particularly adverse for SMEs. No important size difference turns out for the effect of knowledge and market obstacles on innovation. Additionally, in Figures 2a and 2b we show how the marginal effect from the selection equation of significant obstacles groups (cost and market) vary by firm size. For cost obstacles we could see that the marginal effect becomes closer to zero for larger firms, while it is negative for smaller ones. No such effect could be found in the case of market obstacle when taking into account confidence intervals' width.

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[34] See Annex A1 for definition; it basically accounts for firms that reveal that for their performance it was particularly important to always be ready to offer something new to the market.

[35] See Annex A1 for definition; it basically accounts for firms that reveal that for their performance it was particularly important to be updated about the existence of new equipment and to link to science and technology organizations.

[36] The only difference we found is on the *level* equation for age and skills; these variables are not significant in Table 10 and they are positive and significant in Table 6.

Table 10: Tobit Type 2 Model on Propensity (Selection Equation) and Intensity (Level Equation) of Innovation Expenditures (innoact_d and log_innoact_intensity)

VARIABLES	(1) Full sample - Level	(2) Full sample - Selection	(3) RS - Level	(4) RS- Selection	(5) RS - SME - Level	(6) RS - SME - Selection	(7) RS - Big - Level	(8) RS - Big - Selection
obst_know	-0.793***	0.135***	-0.418**	0.00567	-0.194	-0.0128	-0.526	0.00678
	(0.180)	(0.0380)	(0.178)	(0.0375)	(0.201)	(0.0435)	(0.364)	(0.0590)
obst_inst	-0.00945	0.0253	0.246	-0.0575	0.270	-0.0663	0.0901	0.0437
	(0.167)	(0.0369)	(0.166)	(0.0360)	(0.184)	(0.0412)	(0.332)	(0.0621)
obst_cost	-0.146	-0.00283	0.185	-0.120***	0.206	-0.126***	0.126	-0.0512
	(0.121)	(0.0261)	(0.121)	(0.0253)	(0.133)	(0.0297)	(0.245)	(0.0367)
obst_mrkt	-0.233**	0.0300	0.0297	-0.0629***	0.0256	-0.0581**	-0.355	-0.0625*
	(0.116)	(0.0242)	(0.116)	(0.0235)	(0.126)	(0.0272)	(0.257)	(0.0369)
mkt_share	0.496***		0.513***		1.871***		0.387***	
	(0.0651)		(0.0654)		(0.247)		(0.0721)	
mkt_share_2	-0.0222***		-0.0228***		-0.273***		-0.0153***	
	(0.00326)		(0.00333)		(0.0434)		(0.00323)	
size_employees	-0.00626***	0.00133***	-0.00630***	0.00145***	-0.0261***	0.00430***	-0.00248***	0.000542***
	(0.000667)	(0.000112)	(0.000667)	(0.000126)	(0.00223)	(0.000398)	(0.000879)	(0.000111)
group_d	0.0802	0.00700	0.0425	0.0232	0.0476	0.0210	-0.0567	0.00729
	(0.132)	(0.0300)	(0.130)	(0.0298)	(0.168)	(0.0393)	(0.186)	(0.0310)
age_2001_d	0.132*	0.0264	0.119	0.0375**	0.00122	0.0658***	0.0320	-0.0707**
	(0.0762)	(0.0163)	(0.0752)	(0.0161)	(0.0785)	(0.0180)	(0.275)	(0.0295)
foreign_d	0.595***	-0.0257	0.646***	-0.0560	0.428**	-0.0300	0.787***	-0.0421
	(0.142)	(0.0346)	(0.139)	(0.0346)	(0.177)	(0.0457)	(0.208)	(0.0364)
humancapital	0.00263	0.00209***	0.00333	0.00192***	-0.000287	0.00236***	0.00595	0.000454
	(0.00215)	(0.000510)	(0.00213)	(0.000515)	(0.00242)	(0.000607)	(0.00432)	(0.000787)
source_breadth	0.493***		0.500***		0.424***		0.711**	
	(0.132)		(0.132)		(0.148)		(0.277)	
demand_pull_d		0.0611***		0.0551***		0.0520***		0.0744***
		(0.0134)		(0.0130)		(0.0140)		(0.0244)

supply_push_d		0.0973***		0.0889***		0.0843***		0.0654***
		(0.0127)		(0.0126)		(0.0140)		(0.0251)
Constant	9.651***		9.227***		9.880***		8.355***	
	(0.151)		(0.144)		(0.182)		(0.287)	
atrho		-1.513***		-1.530***		-1.712***		0.247
		(0.0864)		(0.0912)		(0.111)		(0.170)
lnsigma		0.572***		0.547***		0.539***		0.422***
		(0.0241)		(0.0233)		(0.0275)		(0.0342)
Observations	3,423	3,408	3,197	3,185	2,565	2,554	632	631
Cens. Obs	1198		972		905		67	
Wald chi2	218.7		219		206.8		198.9	
Wald-p	0		0		0		0	

Note: Robust standard errors in parentheses.

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

Regressions include industry dummies not reported here.

Reported coefficients for the selection equation are marginal effects.

Figure 2a: Marginal Effects of Cost Obstacles on the Decision to Engage in IA by Firm Size (Marginal Effects from Selection Equation of Tobit Type 2 Model, Table 10 Column 4)

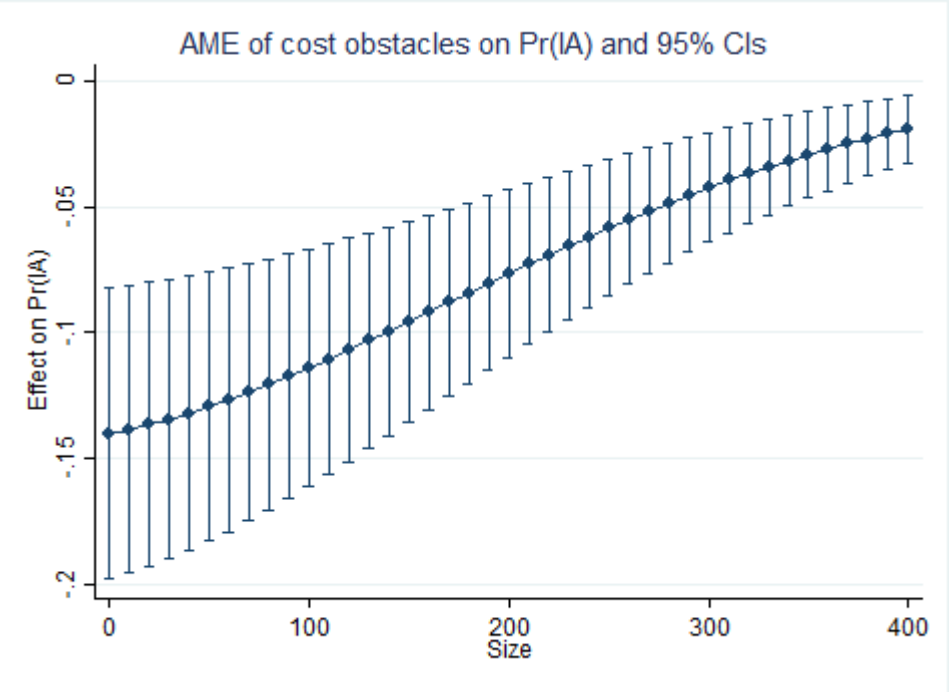
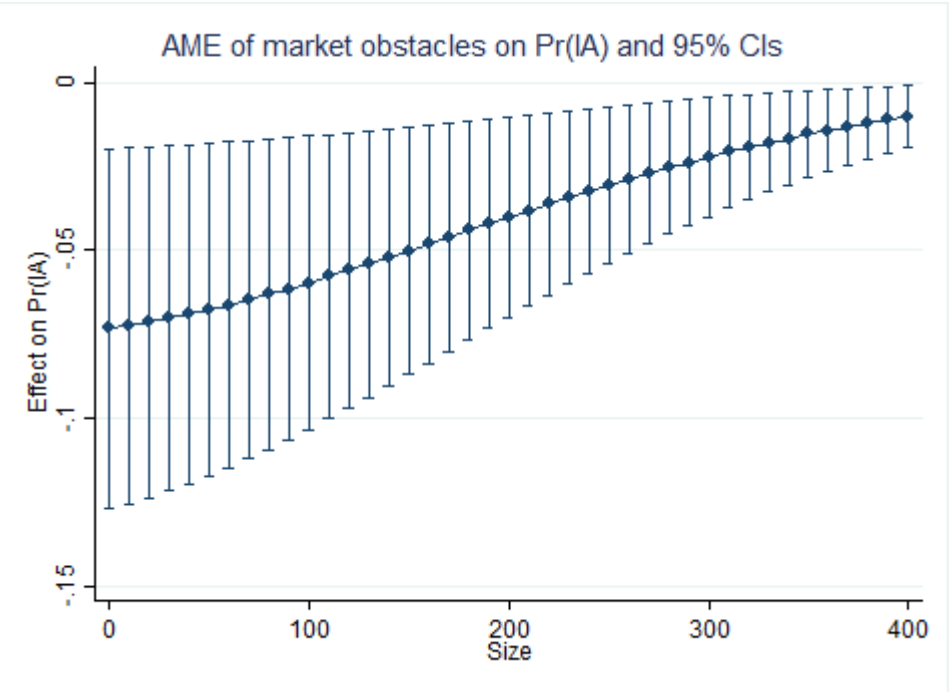


Figure 2b: Marginal Effects of Market Obstacles on the Decision to Engage in IA by Firm Size (Marginal Effects from Selection Equation of Tobit Type 2 Model, Table 10 Column 4)



For objective (iii), as a robustness check, we also estimate equations [6] and [8] using OLS. To be able to use IV regressions, obstacles were included separately. Tables 11a and 11b show results on the probability to invest, while Table 12 shows the results on investment intensity. Only results for cost, knowledge, and market obstacles are discussed in Table 11a and 11b and only those for cost and knowledge in Table 12. Instruments did not work for not-shown obstacle groups (see Annex A2).

Results for OLS regressions are very similar to those discussed from Table 10: cost and market obstacles matter for the probability to invest, while knowledge obstacles do so for investment intensity. IV results are also interesting. As in previous models, the effect of obstacles is intensified when endogeneity is controlled for. Signs and significance remain, but the magnitude of coefficients increases largely in all cases. In addition, knowledge obstacles become significant to explain the decision to invest in IA, while cost obstacles become marginally significant to explain investment intensity. Conclusions regarding the effect of obstacles on innovation investment by firms of different size are similar to those already mentioned for Table 10.[37]

In order to draw some conclusions for objective (iii), we choose the more conservative results discussed from Table 10: cost and market obstacles affect the decision to invest, while knowledge obstacles affect investment intensity. Size differences in the effects of obstacles to innovation are only found for cost obstacles.

[37] While SMEs are affected by cost obstacles in their decisions to invest and on the intensity of such investment, the coefficient is not significant for the subsample of large firms (Tables 11a and 12a). Something similar turns out for the effect of knowledge obstacles on the intensity of investment in innovation (Table 12).

Table 11a: LPM Models for the Decision to Invest in IA (innoact_d) *(knowledge and cost obstacles)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	RS - Obst know	RS - Obst know - IV	RS - SME - Obst know	RS - SME - Obst know - IV	RS - Big - Obst know	RS - Big - Obst know - IV	RS - Obst cost	RS - Obst cost - IV	RS - SME - Obst cost	RS - SME - Obst cost - IV	RS - Big - Obst cost	RS - Big - Obst cost - IV
obst_know	-0.0130	-3.934***	-0.0409	-3.378***	0.0294	-3.812*						
	(0.0391)	(0.708)	(0.0456)	(0.633)	(0.0632)	(2.233)						
obst_not_know	-0.194***	0.0637	-0.209***	-0.00562	-0.0544	0.257						
	(0.0294)	(0.0823)	(0.0344)	(0.0768)	(0.0488)	(0.236)						
obst_cost							-0.128***	-2.795***	-0.140***	-3.180***	-0.0458	-1.215***
							(0.0270)	(0.473)	(0.0312)	(0.724)	(0.0471)	(0.364)
obst_not_cost							-0.0989***	0.142*	-0.119***	0.112	0.00115	0.165**
							(0.0321)	(0.0807)	(0.0378)	(0.105)	(0.0482)	(0.0821)
size_employees	0.00102***	0.000736***	0.00423***	0.00468***	0.000505***	0.000201	0.00102***	0.000602***	0.00428***	0.00324***	0.000504***	0.000502***
	(6.35e-05)	(0.000181)	(0.000370)	(0.000714)	(0.000103)	(0.000331)	(6.34e-05)	(0.000185)	(0.000369)	(0.000913)	(0.000103)	(0.000159)
group_d	0.00753	0.0395	0.00959	0.0307	0.0167	0.0683	0.00908	-0.135**	0.0122	-0.161*	0.0164	-0.0458
	(0.0251)	(0.0624)	(0.0366)	(0.0749)	(0.0311)	(0.0937)	(0.0251)	(0.0626)	(0.0365)	(0.0975)	(0.0308)	(0.0476)
age_2001_d	0.0396**	0.0295	0.0750***	0.0707**	-0.117**	-0.0739	0.0400**	0.150***	0.0758***	0.205***	-0.117**	-0.127*
	(0.0180)	(0.0371)	(0.0190)	(0.0346)	(0.0557)	(0.133)	(0.0180)	(0.0413)	(0.0191)	(0.0528)	(0.0558)	(0.0684)
foreign_d	-0.0293	-0.0567	-0.0208	6.30e-05	-0.0354	-0.156	-0.0288	0.00389	-0.0190	0.0276	-0.0356	-0.00435
	(0.0289)	(0.0659)	(0.0430)	(0.0806)	(0.0353)	(0.121)	(0.0289)	(0.0628)	(0.0430)	(0.0960)	(0.0352)	(0.0530)
humancapital	0.00188***	0.000633	0.00228***	0.00146	0.000655	-0.00125	0.00186***	0.000471	0.00227***	0.000656	0.000633	0.000208
	(0.000486)	(0.000965)	(0.000601)	(0.00100)	(0.000728)	(0.00210)	(0.000486)	(0.00102)	(0.000602)	(0.00137)	(0.000724)	(0.00103)
demand_pull_d	0.0952***	0.0652*	0.0960***	0.0877***	0.0694**	-0.0650	0.0944***	0.181***	0.0953***	0.188***	0.0694**	0.115***
	(0.0166)	(0.0339)	(0.0190)	(0.0333)	(0.0295)	(0.107)	(0.0166)	(0.0375)	(0.0190)	(0.0485)	(0.0295)	(0.0432)
supply_push_d	0.118***	0.117***	0.118***	0.121***	0.0768***	0.0478	0.119***	0.213***	0.118***	0.262***	0.0774***	0.0665*
	(0.0160)	(0.0325)	(0.0184)	(0.0324)	(0.0290)	(0.0733)	(0.0160)	(0.0367)	(0.0184)	(0.0532)	(0.0290)	(0.0386)
Constant	0.517***	1.217***	0.370***	0.969***	0.700***	1.336***	0.513***	1.261***	0.364***	1.287***	0.698***	0.930***
	(0.0337)	(0.137)	(0.0426)	(0.132)	(0.0634)	(0.387)	(0.0337)	(0.142)	(0.0426)	(0.230)	(0.0632)	(0.0991)
Observations	3,209	3,095	2,575	2,474	634	621	3,209	3,095	2,575	2,474	634	621
R-squared	0.129		0.122		0.124		0.127		0.120		0.124	
Adj.R-squared	0.119		0.110		0.0729		0.118		0.108		0.0724	
F test	19.15		12.44		2.099		18.94		12.20		2.089	
Prob> F	0		0		0.000289		0		0		0.000318	
Log-likelihood	-1836		-1583		-109.8		-1840		-1585		-109.9	
Wald chi2		152.3		147.3		16.61		147.3		89.87		43.16

Prob> chi2	0	0	0.996	0	1.03e-06	0.162

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

Table 11b: LPM Models for the Decision to Invest in IA (innoact_d) *(market obstacles)*

VARIABLES	(13) RS - Obst mrkt	(14) RS - Obst mrkt - IV	(15) RS - SME - Obst mrkt	(16) RS - SME - Obst mrkt - IV	(17) RS - Big - Obst mrkt	(18) RS - Big - Obst mrkt - IV
obst_mrkt	-0.0813***	-4.641***	-0.0765**	-4.192***	-0.0785*	-4.968
	(0.0262)	(1.333)	(0.0298)	(1.336)	(0.0431)	(4.431)
obst_not_mrkt	-0.123***	0.744***	-0.151***	0.571**	0.0151	1.140
	(0.0275)	(0.273)	(0.0321)	(0.257)	(0.0411)	(1.053)
size_employees	0.00102***	0.000292	0.00426***	0.00172	0.000492***	-0.000250
	(6.37e-05)	(0.000335)	(0.000370)	(0.00149)	(0.000102)	(0.000836)
group_d	0.00940	-0.143	0.0113	-0.228	0.0173	-0.0656
	(0.0252)	(0.108)	(0.0368)	(0.148)	(0.0312)	(0.163)
age_2001_d	0.0369**	-0.0751	0.0729***	-0.0421	-0.117**	-0.161
	(0.0180)	(0.0667)	(0.0191)	(0.0675)	(0.0553)	(0.211)
foreign_d	-0.0296	-0.0585	-0.0193	-0.0721	-0.0363	-0.0192
	(0.0290)	(0.102)	(0.0431)	(0.123)	(0.0353)	(0.168)
humancapital	0.00189***	0.00411**	0.00229***	0.00481***	0.000649	0.000230
	(0.000486)	(0.00166)	(0.000600)	(0.00180)	(0.000730)	(0.00324)
demand_pull_d	0.0930***	0.0915*	0.0943***	0.114**	0.0662**	-0.0759
	(0.0166)	(0.0545)	(0.0190)	(0.0573)	(0.0297)	(0.179)
supply_push_d	0.117***	0.0414	0.116***	0.0912	0.0736**	-0.221
	(0.0160)	(0.0579)	(0.0184)	(0.0560)	(0.0291)	(0.300)
Constant	0.520***	1.721***	0.372***	1.544***	0.711***	2.109
	(0.0338)	(0.358)	(0.0427)	(0.389)	(0.0631)	(1.304)
Observations	3,209	3,095	2,575	2,474	634	621
R-squared	0.127		0.120		0.127	
Adj.R-squared	0.118		0.108		0.0756	
F test	18.78		12.18		2.142	
Prob> F	0		0		0.000197	
Log-likelihood	-1840		-1585		-108.8	
Wald chi2		54.80		49.07		5.315
Prob> chi2		0.0177		0.0576		1

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

*** p<0.01, ** p<0.05, * p<0.1
IV regressions use training limitations (training_rest) as an instrument for obstacles.

Table 12: OLS Models on the Intensity of IA (log_innoact_intensity) *(knowledge and cost obstacles)*

VARIABLES	(1) RS - Obst know	(2) RS - Obst know - IV	(3) RS - SME - Obst know	(4) RS - SME - Obst know - IV	(5) RS - Big - Obst know	(6) RS - Big - Obst know - IV	(7) RS - Obst cost	(8) RS - Obst cost - IV	(9) RS - SME - Obst cost	(10) RS - SME - Obst cost - IV	(11) RS - Big - Obst cost	(12) RS - Big - Obst cost - IV
obst_know	-0.507***	-3.423**	-0.390**	-4.007**	-0.574	1.857						
	(0.162)	(1.557)	(0.179)	(1.634)	(0.369)	(4.546)						
obst_not_know	-0.174	0.121	-0.225*	0.136	-0.0280	-0.225						
	(0.120)	(0.194)	(0.128)	(0.214)	(0.280)	(0.468)						
obst_cost							-0.0935	-1.728**	-0.149	-2.870**	0.146	0.669
							(0.106)	(0.830)	(0.112)	(1.236)	(0.252)	(1.266)
obst_not_cost							-0.412***	-0.196	-0.345**	0.0168	-0.500*	-0.594*
							(0.129)	(0.175)	(0.143)	(0.235)	(0.282)	(0.319)
mkt_share	0.370***	0.337***	1.311***	1.071***	0.392***	0.402***	0.372***	0.309***	1.316***	1.034***	0.395***	0.414***
	(0.0587)	(0.0621)	(0.261)	(0.288)	(0.0746)	(0.0798)	(0.0588)	(0.0685)	(0.262)	(0.300)	(0.0749)	(0.0890)
mkt_share_2	-0.0165***	-0.0156***	-0.195***	-0.160***	-0.0154***	-0.0152***	-0.0166***	-0.0136***	-0.196***	-0.157***	-0.0156***	-0.0164***
	(0.00311)	(0.00304)	(0.0613)	(0.0590)	(0.00335)	(0.00342)	(0.00313)	(0.00363)	(0.0614)	(0.0583)	(0.00337)	(0.00396)
size_employees	-0.00278***	-0.00271***	-0.0131***	-0.0114***	-0.00276***	-0.00283***	-0.00280***	-0.00255***	-0.0132***	-0.0121***	-0.00278***	-0.00306***
	(0.000567)	(0.000597)	(0.00195)	(0.00220)	(0.000899)	(0.000938)	(0.000567)	(0.000614)	(0.00194)	(0.00216)	(0.000899)	(0.000982)
group_d	0.0725	0.106	0.116	0.178	-0.0561	-0.0709	0.0702	-0.0205	0.112	-0.0653	-0.0533	-0.0397
	(0.116)	(0.128)	(0.146)	(0.172)	(0.193)	(0.200)	(0.116)	(0.128)	(0.145)	(0.172)	(0.192)	(0.193)
age_2001_d	0.217***	0.239***	0.195***	0.218***	0.0921	0.0487	0.211***	0.273***	0.192***	0.288***	0.0844	0.0865
	(0.0654)	(0.0736)	(0.0663)	(0.0775)	(0.280)	(0.272)	(0.0654)	(0.0743)	(0.0662)	(0.0879)	(0.279)	(0.276)
foreign_d	0.607***	0.568***	0.399***	0.411***	0.799***	0.812***	0.607***	0.639***	0.397***	0.456**	0.795***	0.740***
	(0.121)	(0.125)	(0.149)	(0.157)	(0.216)	(0.235)	(0.122)	(0.132)	(0.150)	(0.188)	(0.216)	(0.219)
humancapital	0.00740***	0.00579***	0.00526***	0.00365	0.00561	0.00672	0.00750***	0.00669***	0.00531***	0.00361	0.00577	0.00537
	(0.00187)	(0.00221)	(0.00202)	(0.00242)	(0.00449)	(0.00539)	(0.00187)	(0.00203)	(0.00202)	(0.00250)	(0.00451)	(0.00443)
source_breadth	0.772***	1.061***	0.786***	1.174***	0.682**	0.638*	0.769***	1.045***	0.784***	1.279***	0.690**	0.729**
	(0.146)	(0.205)	(0.167)	(0.254)	(0.289)	(0.350)	(0.146)	(0.191)	(0.167)	(0.292)	(0.288)	(0.295)
Constant	8.190***	8.471***	8.454***	8.811***	8.458***	8.152***	8.197***	8.499***	8.459***	9.051***	8.463***	8.357***
	(0.118)	(0.226)	(0.142)	(0.255)	(0.289)	(0.580)	(0.118)	(0.219)	(0.141)	(0.332)	(0.289)	(0.338)
Observations	2,225	2,161	1,660	1,608	565	553	2,225	2,161	1,660	1,608	565	553
R-squared	0.139		0.127		0.239	0.164	0.138	0.045	0.126		0.239	0.233
Adj.R-squared	0.125		0.107		0.187		0.124		0.107		0.187	
F test	8.786		5.935		5.197		8.723		5.906		5.197	
Prob> F	0		0		0		0		0		0	
Log-likelihood	-3886		-2792		-1037		-3887		-2792		-1037	
Wald chi2		287.8		185.1		178.7		294		163.3		193
Prob> chi2		0		0		0		0		0		0

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

Objective (iv) was to analyze the effect of different obstacles on innovation success; to that end, we estimate LPM for Equation [9]. Results are presented in Tables 13a and 13b. Only results for cost, knowledge, and market obstacles are discussed because the instrument did not work for institutional obstacles (see Annex A2). Estimated coefficients for control variables are very similar to those reported for Equation [3], presented in Table 7. Moreover, as in those estimations, only IV regressions render significant coefficients. Cost, market, and knowledge obstacles seem to negatively affect success in innovation. In terms of differences between large and small firms, as for investment in innovation (Table 10), cost obstacles seem to be particularly more pronounced for SMEs.[38]

[38] However, it was not possible to find significance for interactive terms when running IV regressions including interactions between obstacles and size, so this finding should be taken with caution.

Table 13a: LPM Models for Innovative Success (innoresult_d) *(knowledge and cost obstacles)*

VARIABLES	(1) RS - Obst know	(2) RS - Obst know - IV	(3) RS - SME - Obst know	(4) RS - SME - Obst know - IV	(5) RS - Big - Obst know	(6) RS - Big - Obst know - IV	(7) RS - Obst cost	(8) RS - Obst cost - IV	(9) RS - SME - Obst cost	(10) RS - SME - Obst cost - IV	(11) RS - Big - Obst cost	(12) RS - Big - Obst cost - IV
obst_know	-0.0151	-3.064***	-0.0131	-2.622***	-0.0469	-3.431*						
	(0.0406)	(0.613)	(0.0445)	(0.565)	(0.0988)	(1.814)						
obst_not_know	-0.0131	0.186***	-0.0354	0.123*	0.106	0.373*						
	(0.0321)	(0.0708)	(0.0354)	(0.0674)	(0.0777)	(0.211)						
obst_cost							-0.0111	-2.169***	-0.0287	-2.429***	0.0855	-1.304**
							(0.0280)	(0.431)	(0.0307)	(0.617)	(0.0694)	(0.512)
obst_not_cost							-0.0113	0.182**	-0.0169	0.179**	0.0102	0.150
							(0.0346)	(0.0726)	(0.0382)	(0.0912)	(0.0834)	(0.119)
group_d	-0.00423	0.0344	-0.0474	-0.0258	0.0408	0.0929	-0.00440	-0.119**	-0.0471	-0.183**	0.0418	-0.00958
	(0.0331)	(0.0558)	(0.0451)	(0.0730)	(0.0513)	(0.0837)	(0.0331)	(0.0578)	(0.0450)	(0.0851)	(0.0516)	(0.0677)
age_2001_d	-0.000148	-0.0162	0.0128	0.00329	-0.0505	-0.0411	-2.04e-05	0.0863**	0.0132	0.116***	-0.0505	-0.0779
	(0.0180)	(0.0312)	(0.0187)	(0.0296)	(0.0655)	(0.128)	(0.0180)	(0.0359)	(0.0188)	(0.0447)	(0.0654)	(0.0821)
foreign_d	0.0211	0.000705	-0.0108	0.00996	0.0641	-0.0364	0.0212	0.0460	-0.0106	0.0370	0.0640	0.0711
	(0.0365)	(0.0579)	(0.0494)	(0.0768)	(0.0591)	(0.0982)	(0.0365)	(0.0564)	(0.0494)	(0.0807)	(0.0593)	(0.0748)
humancapital	0.00301***	0.00186**	0.00340***	0.00260***	0.00204*	0.000430	0.00301***	0.00169*	0.00340***	0.00208*	0.00208*	0.000993
	(0.000536)	(0.000850)	(0.000627)	(0.000904)	(0.00113)	(0.00190)	(0.000535)	(0.000900)	(0.000627)	(0.00116)	(0.00113)	(0.00138)
size_employees	0.000979***	0.000750***	0.00253***	0.00289***	0.000755***	0.000360	0.000979***	0.000694***	0.00253***	0.00184**	0.000758***	0.000702***
	(9.54e-05)	(0.000163)	(0.000420)	(0.000650)	(0.000176)	(0.000355)	(9.54e-05)	(0.000170)	(0.000420)	(0.000772)	(0.000175)	(0.000223)
Constant	0.168***	0.703***	0.112***	0.579***	0.192***	0.711**	0.167***	0.839***	0.110***	0.920***	0.193***	0.519***
	(0.0309)	(0.115)	(0.0373)	(0.114)	(0.0736)	(0.284)	(0.0309)	(0.142)	(0.0372)	(0.216)	(0.0741)	(0.147)
Observations	3,230	3,119	2,586	2,486	644	633	3,230	3,119	2,586	2,486	644	633
R-squared	0.102		0.073		0.136		0.102		0.073		0.135	
Adj.R-squared	0.0931		0.0611		0.0889		0.0931		0.0611		0.0882	
F test	12.03		6.751		4.137		12.02		6.746		4.116	
Prob> F	0		0		0		0		0		0	
Log-likelihood	-2003		-1550		-419.8		-2003		-1550		-420	
Wald chi2		170.5		108.4		50.46		166.7		76.82		87.56
Prob> chi2		0		5.86e-10		0.0265		0		2.38e-05		7.82e-07

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

Table 13b: LPM Models for Innovative Success (innoresult_d) *(market obstacles)*

	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	RS - Obst mrkt	RS - Obst mrkt - IV	RS - SME - Obst mrkt	RS - SME - Obst mrkt - IV	RS - Big - Obst mrkt	RS - Big - Obst mrkt - IV
obst_mrkt	-0.0267	-3.479***	-0.0229	-3.384***	-0.0442	-2.972*
	(0.0267)	(0.989)	(0.0291)	(1.142)	(0.0695)	(1.627)
obst_not_mrkt	-0.00671	0.639***	-0.0277	0.561**	0.0888	0.737*
	(0.0299)	(0.202)	(0.0329)	(0.218)	(0.0711)	(0.411)
group_d	-0.00507	-0.135	-0.0480	-0.293**	0.0394	0.0220
	(0.0331)	(0.0885)	(0.0452)	(0.137)	(0.0515)	(0.102)
age_2001_d	-0.000703	-0.0794	0.0123	-0.0738	-0.0527	-0.0992
	(0.0179)	(0.0505)	(0.0187)	(0.0548)	(0.0651)	(0.145)
foreign_d	0.0209	-0.00828	-0.0107	-0.0370	0.0652	0.0124
	(0.0366)	(0.0828)	(0.0495)	(0.105)	(0.0594)	(0.116)
cap_h_avg	0.00302***	0.00455***	0.00341***	0.00546***	0.00206*	0.00145
	(0.000535)	(0.00128)	(0.000626)	(0.00151)	(0.00113)	(0.00212)
size_employees	0.000976***	0.000402	0.00252***	0.000358	0.000751***	0.000266
	(9.54e-05)	(0.000266)	(0.000420)	(0.00125)	(0.000175)	(0.000422)
Constant	0.171***	1.036***	0.115***	1.047***	0.200***	0.908**
	(0.0311)	(0.254)	(0.0374)	(0.324)	(0.0750)	(0.414)
Observations	3,230	3,119	2,586	2,486	644	633
R-squared	0.103		0.073		0.135	
Adj.R-squared	0.0933		0.0613		0.0884	
F test	12.08		6.795		4.148	
Prob> F	0		0		0	
Log-likelihood	-2003		-1549		-419.9	
Wald chi2		75.49		41.25		34.74
Prob> chi2		3.56e-05		0.153		0.385

Note: Robust standard errors in parentheses. Regressions include industry dummies not reported here.

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

IV regressions use training limitations (training_rest) as an instrument for obstacles.

Table 14: Trivariate Probit Models for Cooperation with Firms (link_firm_d), Cooperation with Private and Public Research Organizations (link_ppro_d) and Innovation Results (innoresult_d); All Obstacles (obst_all)

	(1) FULL RELEVANT SAMPLE			(2) SME - RELEVANT SAMPLE			(3) BIG FIRMS - RELEVANT SAMPLE		
VARIABLES	Link firm - RS full sample	Link ppro - RS full sample	Innova nat - RS full sample	Link firm - RS SME	Link ppro - RS SME	Innova nat - RS SME	Link firm - RS big	Link ppro - RS big	Innova nat- RS big
link_firm_d			0.415***			0.423***			0.422***
			(0.0173)			(0.0177)			(0.0813)
link_ppro_d			0.174***			0.141***			0.201**
			(0.0300)			(0.0373)			(0.0884)
obst_all	0.0441*	0.0525**	-0.0708***	0.0537*	0.0512**	-0.0804***	0.0174	0.0412	-0.0194
	(0.0251)	(0.0237)	(0.0201)	(0.0286)	(0.0255)	(0.0218)	(0.0493)	(0.0583)	(0.0504)
mkt_share	0.0287**	0.00194		0.0315	0.00844		0.0310**	0.0201	
	(0.0134)	(0.0164)		(0.0393)	(0.0401)		(0.0128)	(0.0193)	
group_d	0.0756**	0.0178	-0.0714***	0.0930**	0.0286	-0.103***	0.0284	-0.00863	-0.0249
	(0.0318)	(0.0263)	(0.0231)	(0.0418)	(0.0335)	(0.0309)	(0.0413)	(0.0460)	(0.0384)
age_2001_d	0.0150	-0.00411	-0.00986	0.0208	0.00876	-0.0154	0.0234	-0.0549	-0.0112
	(0.0163)	(0.0161)	(0.0133)	(0.0178)	(0.0164)	(0.0137)	(0.0470)	(0.0609)	(0.0512)
foreign_d	0.0444	-0.0254	0.0134	0.0181	-0.0339	-0.00235	0.0677	0.00612	0.0219
	(0.0342)	(0.0289)	(0.0249)	(0.0435)	(0.0373)	(0.0329)	(0.0502)	(0.0520)	(0.0453)
humancapital	0.00146***	0.00109**	0.000203	0.00159***	0.00118**	2.02e-05	0.00110	0.000424	0.000682
	(0.000490)	(0.000440)	(0.000401)	(0.000557)	(0.000474)	(0.000439)	(0.00103)	(0.00110)	(0.00100)
size_employees	6.15e-06	0.000291**	3.27e-05	0.000329	0.00144***	-0.000105	-0.000145	-0.000109	0.000191
	(0.000137)	(0.000133)	(7.30e-05)	(0.000441)	(0.000391)	(0.000307)	(0.000176)	(0.000231)	(0.000144)
know_fin_sources	0.0116***	0.0115***		0.0107***	0.0160***		0.0103**	0.000414	
	(0.00266)	(0.00269)		(0.00323)	(0.00325)		(0.00410)	(0.00527)	
source_breadth	0.646***	0.483***		0.698***	0.421***		0.434***	0.578***	
	(0.0241)	(0.0253)		(0.0264)	(0.0299)		(0.0549)	(0.0556)	
open_strategy_d	0.0479***	0.0266*		0.0471***	0.0270*		0.0365	-0.00698	
	(0.0128)	(0.0142)		(0.0143)	(0.0154)		(0.0283)	(0.0348)	
Observations	3,222	3,222	3,222	2,573	2,573	2,573	649	649	649

Note: Robust standard errors in parentheses.

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

Regressions include industry dummies not reported here.

Reported estimates are marginal effects.

Finally, in Table 14 we show the results associated with objective (iv). We aimed at exploring whether linking to third parties somehow works as a palliative strategy for obstacles. We found that, in fact, when firms face obstacles, they are more likely to connect for knowledge-related reasons to both other firms and public or private research organizations. Linking, in turn, is positively associated to innovation outcomes. However, obstacles remain significant and negative when explaining innovation outcomes, which could be interpreted to mean that linking to third parties is not effective enough to overcome obstacles.[39]

7. Conclusions

This study contributes to our understanding of how barriers to innovation affect innovation. We use survey data from Argentina. The topic is relevant for policy purposes because innovation programs could be better designed if more information is provided about what makes firms more reluctant or less successful in terms of innovation. Our interest is also to disentangle how obstacles affect firms of different size, inspired primarily by the fact that most innovation programs in Argentina are oriented to SMEs.

The literature suggests that selection bias and endogeneity prevail in the relation between obstacles and innovation. As others have done before, we selected a relevant sample of willing-to-innovate firms defined as those that either performed some innovative activity or recalled some obstacle to innovation. We also use instrumental variables to control for the fact that obstacles are endogenous regressors, because firms that innovate are more likely to perceive obstacles than those that do not innovate.

We built the instrument using information from a labor dynamic section within the survey. It accounts for restrictions to ordinary training activities. We argued that firms experiencing problems in training their staff may be more skeptical about their future, and therefore more prone to identifying obstacles to long-term investment in innovation. The instrumentation strategy was successful in all estimations discussed in the paper. In addition, we estimate our models for two subsamples: SMEs (less than 100 employees) and large firms.

We constructed different indexes for obstacles. The most parsimonious specifications used a single index to capture intensity in the perception of obstacles and a series of control variables used in the innovation literature.

For OLS regressions we found that obstacles severely affected the decision to invest in IA and the intensity of such investment. IV regression intensified such negative effects, and, in addition, obstacles also seemed to affect the probability of obtaining technological and non-technological innovation defined as novel at least at the national level.

[39] In addition we ran Probit regressions with and without *link_firm_d* and *link_ppro_d* as explanatory variables, while keeping all other controls as in Table 14. If link variables are not included the coefficient for *obst_all* is not significant, which is what we found with OLS models (Table 7, column 6). Differences in the marginal effects of *obst_all* for both Probit estimations, with and without link variables, are not significant. Thus, we interpret that linking does not work as a palliative strategy for obstacles.

With the purpose to illustrate our results with some order of magnitude, counterfactual analysis was performed. We compared the predicted values on different dependent variables obtained from our estimations with the predicted values that would have been obtained had the firms faced no obstacles.

For OLS estimations, which is the conservative scenario because IV coefficients are larger, we found that if firms had not experienced obstacles the probability of engaging in IA would have been almost 7.9 pp (percentage points) larger (SMEs 8.5 pp and large firms 5.1 pp). In terms of the amount invested, firms would have spent on average around 9 percent more (13 percent more for SMEs and 5 percent more for large firms). Finally, in terms of innovation success (considering IV estimations in this case given that OLS results are not significant), in the absence of obstacles the chance of obtaining innovative outcomes would have increased by 56 pp (SMEs 59 pp and large firms 45 pp). In sum, the effect of obstacles is highly relevant for innovation investment and performance, and it therefore makes sense to analyze them further.

We also classified obstacles in four groups following Oslo 2005 taxonomy: knowledge, cost, market, and institutional. We used several modelization strategies, including OLS, IV OLS, and Tobit type 2 models. We found robust results on the effect of cost, market, and knowledge obstacles on investment in innovation. Cost and market obstacles primarily affected the decision to invest, while knowledge obstacles limited the invested amount. Firms were discouraged from innovation when they believed it was too expensive, they were financially constrained, or they felt uncertain about their potential market success. In turn, among IA-performing firms, those that perceived that their technical and organizational capabilities were low, that were too rigid, that considered technological innovation too complex, or that could not rely on external knowledge partners did not get involved in ambitious IA projects.

For innovative success, only IV estimations rendered significant and negative coefficients for cost, market, and knowledge obstacles. We believe our contribution is twofold. Methodologically, we controlled for both selection and endogeneity biases in an integrating framework assessing for all and different types of obstacles. We found no precedent of this approach in the literature, although endogeneity has been recognized as an important methodological challenge. Moreover, empirically, we compared the effect of obstacles on firms of different size. There is consensus in the literature about size heterogeneity regarding all different aspects of innovation. However, we did not find a systematic analysis that empirically compared the effect of obstacles for firms of different size.

Our results showed that SMEs' investment in innovation suffered from obstacles more intensively. Among different types of obstacles, cost-related obstacles affect primarily SMEs. We believe that these contributions make this study interesting for science and technology policy literature. In addition, it may be found relevant for the design of innovation policies, particularly for Argentina. It provides novel information that allows for improving the design of policy instruments, especially for SMEs.

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ANNEX

Annex 1: Variables Definitions and Descriptions

Table A1: Variables Definitions

Variable name	Description
Dependent variables	
innoact_intensity	Investment intensity in IA: defined as the average of ratios between total expenditures in IA and total employment for 2010, 2011, and 2012 (in pesos of 2010, deflated with price indexes provided by M&S Consultores)
innoact_d	Dummy = 1 if the firm engages in any innovative effort/activity (internal R&D, external R&D outsourcing, acquisition of machinery and equipment, knowledge transfer, training for the introduction of innovations, consultancies and industrial design and engineering [internal])
innoresult_nontech_d	Dummy = 1 if the firm reports any innovation results that were novel for the national market, considered “non-technological” (organizational or commercialization innovations)
innoresult_tech_d	Dummy = 1 if the firm reports any innovation results that were novel for the national market, considered “technological” (new or improved products or processes)
innoresult_d	Dummy = 1 if the firm reports any innovation results that were novel for the national market (new or improved products, processes, organizational, commercialization innovations)
log_innoact_intensity	Natural logarithm of innoact_intensity
Explanatory variables	
link_d	Dummy = 1 if the firm cooperates with third parties to pursue different goals associated with IA (excludes cooperation related to usual business activities)
link_firm_d	Dummy = 1 if firm cooperates with other firms (three options: (i) firms within its group; (ii) other firms; (iii) consultants and business chambers) to pursue different goals associated with IA (excludes cooperation related to usual business activities)
link_ppro_d	Dummy = 1 if the firm cooperates with public or private research organizations (two options: (i) public and private universities and (ii) public institutes in science and technology) to pursue different goals associated with IA (excludes cooperation related to usual business activities)
obst_all	Proportion of obstacles faced by the firm; firms choose at most 3 internal and 3 external obstacles, so we consider proportion out of 6 (cases of more than 6 reported obstacles are considered errors and censored at 6)
obst_cost	Proportion of cost obstacles faced by the firm (out of 4)
obst_inst	Proportion of institutional obstacles faced by the firm (out of 3)
obst_know	Proportion of knowledge obstacles faced by the firm (out of 5)
obst_mkt	Proportion of market obstacles faced by the firm (out of 2)
obst_not_cost	Proportion of obstacles other than cost obstacles (out of 6)
obst_not_inst	Proportion of obstacles other than institutional obstacles (out of 6)
obst_not_know	Proportion of obstacles other than knowledge obstacles (out of 6)
obst_not_mrkt	Proportion of obstacles other than market obstacles (out of 6)
Control variables	
age_2001_d	Dummy = 1 if the firm was founded in 2001 or after
demand_pull_d	Demand-pull indicator: dummy = 1 if the firm reveals as key factors for its performance a) to look and develop new markets; or b) always develop and supply new products for the market
foreign_d	Dummy = 1 if the firm has foreign capital participation
group_d	Dummy = 1 if the firm is part of a conglomerate

humancapital	Professional and technical personnel; average share for 2010, 2011, and 2012—proxy for human capital or skills
know_fin_sources	Number of finance sources that the firm reveals to know (out of 26)
mkt_share	Average sectoral market share of the firm for 2010–12
mkt_share_2	Squared mkt_share
open_strategy_d	Open strategy indicator: dummy = 1 if the firm reveals to analyze routinely its environment and competition
sector_d	Sectoral dummies (27 economic sectors)
size_employees	Average number of employees of the firm 2010–12
source_breadth	Proportion of internal and external information sources for innovation used by the firm (out of 14 options)
supply_push_d	Supply-push indicator: dummy = 1 if the firm reveals as key factors for its performance a) to collaborate and cooperate with science & technology organizations; or b) to count on technologically adequate machinery and equipment
Instrumental variable	
training_rest	Ordinal variable reflecting firm's restrictions/limitations for training activities, with values as follows:
	= 0 if the firm trained its employees during 2012 and did not report any restriction
	= 1 if the firm trained its employees during 2012 and experienced one limiting factor from a list of six
	= 2 if the firm trained its employees during 2012 and experienced two or more limiting factors from a list of six
	= 3 if the firm did not train its employees during 2012 and claimed it was not necessary
	= 4 if the firm did not train its employees during 2012 and revealed to have experienced one constraint from a list of eight
	= 5 if the firm did not train its employees during 2012 and revealed to have experienced two or more constraints from a list of eight

Annex 2: Instrumentation Strategy, First Stage Regressions Statistics

We calculate the partial R-sq and the F statistic which evaluates the correlation and significance of the instrument in explaining the endogenous variable after considering the effect of the controls. This is a test for weak instruments. We rejected the null hypothesis on weak instruments when F-statistic was significantly different from zero and higher than 10, following Wooldridge (2016, p. 478).

The test passed for all IV estimations when *obst_all* (index for all obstacles) was the endogenous regressor.

For group obstacles as endogenous regressors:

- The test passed for all regressions including *obst_cost* (cost obstacles)
- It passed for regressions which include *obst_know* (knowledge obstacles) estimated for the subsample of SMEs and all firms regardless of size.
- It passed for *obst_mrkt* (market obstacles) for the subsample of SMEs and all size firms in the case where dependent variable was the probability of investing in IA (Table 11b) and also for the probability of success in IA (Table 13b). This means that IV results on the subsample of large firms should not be trusted in this case.
- It did not pass when *obst_mrkt* (market obstacles) was the endogenous regressor and the dependent variable was the intensity of investment on IA. Results are not discussed.
- It did not pass when *obst_inst* (institutional obstacles) was the endogenous regressor. Results are not discussed.

We also performed the Stock and Yogo's test (see StataCorp [2017], p. 1204) on weak instruments. In this case, the partial F-statistics resulting from 2SLS estimation is compared with tabulated critical values to reject the null hypotheses of instruments are weak. The test outcome is similar to the one already described.

In order to save space, we only present the F-statistics of IV regressions when the index of all obstacles was the endogenous regressions (Tables 5, 6, and 7) for firms of all size (column 9 of those tables).

Table A2.1: First Stage Statistics of Linear IV Regression with Dependent Variable *innoact_d* and Independent Variable *obst_all* Using As Instrument *training_rest*

Instrument Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(1,3060)	Prob > F
obst_all	0.0665	0.0561	0.0365	111.677	0.000

Table A2.2: First Stage Statistics of Linear IV Regression with Dependent Variable *log_innoact_intensity* and Independent Variable *obst_all* Using As Instrument *training_rest*

Instrument Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(1,2998)	Prob > F
obst_all	0.0925	0.0775	0.0399	87.0386	0.000

Table A2.3: First Stage Statistics of Linear IV Regression with Dependent Variable *innoresult_d* and Independent Variable *obst_all* Using As Instrument *training_rest*

Instrument Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(1,2998)	Prob > F
obst_all	0.0647	0.0550	0.0364	112.551	0.000

We also performed the C statistic (differences-in-Sargan statistic) in order to check if obstacles could be considered exogenous. For most IV estimations discussed in the paper the test rejected the null hypothesis[40] (exogeneity), indicating that IV estimation was preferred (results omitted for space reasons).

[40] A few exceptions when estimations performed with the subsample of large firms.