Obstacles of innovation and firm size: A quantitative study for Argentina

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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 outstanding. We use Argentinean survey data for years 2010-2012. 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. The three of them 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.

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 innovative activities, sluggish commitment or reduce the chances of success. It becomes then central for innovation studies to analyse 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

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research and development (R&D) (Bond, Harhoff, & Van Reenen, 2003; D. Czarnitzki, Hottenrott, & Thorwarth, 2010; B. H. Hall, 2002; L. A. Hall & Bagchi-Sen, 2002; Hottenrott & Peters, 2012). More recently, the wider availability of innovation surveys allowed to assess other obstacles besides financial ones (Blanchard, Huiban, Musolesi, & Sevestre, 2013). Thus, different studies analysed shortcomings in the *market* pull mechanisms (García-Quevedo, Pellegrino, & Savona, 2016), the *regulatory* constraints, or issues regarding the access to and the organization of *knowledge*. In other words, the focus has widened and empirical findings suggested that obstacles are diverse, although normally complementary. Therefore, policy making should address them in an integrative framework, rather than just focusing on ameliorating the effects of the market failures associated to 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). Actually, there are several articles on obstacles to innovation which just focus on small and medium enterprises (SMEs) (Alessandrini, Presbitero, & Zazzaro, 2010; Freel, 2000; Hadjimanolis, 1999; Mancusi & Vezzulli, 2010; OECD, 2005; Xie, Zeng, & Tam, 2010), but they did not argue on the extent to which their conclusions would be different for a sample of larger firms.

In this paper we analyse the effect of obstacles to innovation both on investment decisions and on the likelihood of success in innovation, and we identify the differential impact on SMEs.

In Argentina, SMEs account for more than 40% 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, del Castillo, Aboal, Pereyra, & Rodríguez, 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 analysed 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 follow. 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. Section 7 concludes.

2. The literature on obstacles to innovation and firm's characteristics

The academic interest on barriers to innovation dates back to the 1980s when some management scholars reflected on different organisational strategies that a firm could perform in order to accelerate innovation –mainly product innovation. Millman (1982) argued that the UK industry was short in product innovation due to miss-alignments and miss-communication 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 able to better meet the rapidly changing market demand.

Likewise, More (1985) argued that there were intra-firm 'dislocations' which severely affected innovation. He referred mainly to misalignments in functions -as the previously mentioned; in decision making and expertise -information asymmetry within the firm; and in the causes and consequences of risk-taking -since 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 critical decisions 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 different economic and innovation studies have performed quantitative analysis on the determinants and effects of the factors hampering innovation, in an attempt to draw science and technology policy implications. 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 & Guenther, 2015); cost, knowledge, market and institutional factors (Oslo Manual, 3er 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 two-fold. 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 higher number of product or process innovations tended to perceive more obstacles.[3] Similarly, other studies found that firms which engaged in internal R&D (Galia & Legros, 2004) and firms that innovate persistently in products (Wziątek-Kubiak, 2011) were more prone to perceiving several obstacles. In the same vein, Hottenrott and Peters (2012) studied the determinants of firms' financial obstacles,[4] finding that firms with larger innovative capabilities experienced more constraints than those with lower capabilities, especially if they also lacked of 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 which are interested in innovation tend to perceive more obstacles than non-innovators not-interested in innovation (e.g. Werner Hölzl and Janger (2012) using the CIS for eighteen countries)[5]. Thus, when analysing obstacles, the qualification of *'being interested in'* innovation appears as an important characteristic. In fact, D'Este, Iammarino, Savona, and Von Tunzelmann (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, which 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; Schiantarelli, 1996). Firms that systematically

[3] They also found that foreign firms perceived fewer obstacles than domestic (Italian) ones.

[4] 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.

[5] 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 (W. Hölzl & Janger, 2013). Yet in another paper they found that firms operating in countries close to the technological frontier (according to a 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 (W. Hölzl & Janger, 2014).

relied on their cash flows or internal liquidity to fund investment would arguably do so due to a 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, since according to Modigliani-Miller (1958) theorem the source of finance should be irrelevant for investment decisions.

Using this approach, Bond et al. (2003) assessed the financial constraints on both fixed assets and R&D capital stock with panel data from UK and Germany[6]. 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.[7] Ahead of time in the literature of obstacles to innovation, the authors 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). The paper analysed the effect of financial barriers on the probability of engaging in innovative activities in France. As 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 innovative activities 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.[8] 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

[6] The authors estimate GMM models using cash flows and their lags to proxy liquidity constraints.
[7] One interesting paper by Dirk Czarnitzki, Hottenrott, and Thorwarth (2011) analyses 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 harder in projects which are further away from the market than in a development project, which is clearly closer to provide a market solution and which also relies on previous visible results obtained during the research stage.
[8] Alessandrini et al. (2010) also analysed 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 headquarter- tended to introduce fewer innovations.

financing at the interest rate agreed 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 IV Tobit for R&D intensity. Like 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[9] 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 & Legros, 2004). This hints the need to follow an integrative framework in the analysis, rather than separately analysing the different factors hampering innovation. Actually, the latest studies widened the focus to adopt a more systemic approach, by jointly analysing 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 Gabriele Pellegrino and Maria 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 in regulatory obstacles, knowledge 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 to achieve both process and product innovation.[10]

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 (Wesley M Cohen, 2010). SMEs share some size-specific features which put them in a more vulnerable position

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[9] 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.

[10] Using Spanish data, García-Quevedo et al. (2016) assessed the demand pulled factors as barriers to innovation. With a similar criterion for defining the relevant sample, they analysed 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.

compared to their larger counterparts (Kaufmann & Tödtling, 2002). Actually, one fairly prevalent characteristic of SMEs is their lower productivity when compared to bigger firms (Nightingale & 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 cost-spreading advantages of R&D investment (Wesley M. Cohen & Klepper, 1996). This means that larger firms expect a greater future output to spread the R&D fixed costs over (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 to innovation, while again finds larger firms in a better position to do so.

At the same time, investment in innovation requires persistent innovative behaviour and accumulation of capabilities (Wesley M. Cohen & Levinthal, 1990) which are less likely to be grasped by SMEs. They 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, & 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 they have a better developed infrastructure. Finally, larger firms could exert their influence and lobbying capacity over the regulation related to fostering innovation.

Despite these restrictions, the malleable organizational structure of SMEs provides flexibility to the innovation processes, since it may promote faster learning. They could more quickly adapt the routines in response to changes in their environment, as they could speed up the decision making (Vossen, 1998). Also, the less hierarchical human resources relation 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 on how these obstacles affect innovative behaviour and performance. In fact, several papers analysed obstacles specifically for SMEs. We will review here only those using econometric approaches.[11]

[11] 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 west midland region in 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 et al. (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

There are two papers already cited that revealed that SMEs innovative decisions and outputs suffered from financial constraints (Alessandrini et al., 2010; Mancusi & Vezzulli, 2010). Besides those papers we could mention two additional ones. Madrid-Guijarro, Garcia, and Van Auken (2009) used data from interviews to a 294 managers sample 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.[12]

In turn, Maldonado-Guzmán, Garza-Reyes, Pinzón-Castro, and Kumar (2017) focus on SMEs in a developing country, by analysing a sample of 308 Mexican service SMEs. Using a structural equation modelling 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 former (external environment, which comprises market and infrastructure obstacles) showing the strongest effect.

It seems surprising, nevertheless, the lack of a systematic approach to study the differences on how harmful obstacles result for firms of different sizes. We could only refer to Bond et al. (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 which showed that firms of different size have different perceptions of obstacles[13]. However, to the best of our knowledge, there is no methodologically thorough study analysing systematically the effect of obstacles for firms of different sizes. This is one of the contributions of our paper.

of return' and 'high-cost and high-risk of innovation'. On a recent paper based on interviews to the executives from 49 technology German SMEs (Strobel & 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.

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

[13] For example, Jung, Kim, Suh, and Kim (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.

3. Objectives and contribution

3.1. General goal and contribution

Our general goal is to understand the effect of obstacles on 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 innovative activities? 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[14] and we claim our contribution to be two-fold.

Firstly, building from recent methodological discussions, the paper attempts to control for selection bias in the relation 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 instrumental variables (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.[15]

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.

3.2. Specific objectives and hypotheses

i) To measure the effect of obstacles to innovation on the propensity to invest in innovation activities (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 on innovation (i.e. product, process, organizational and commercial innovation).

[14] Previous contributions were mostly on a descriptive nature: Hadjimanolis (1999) for Cyprus, Xie et al. (2010) for China or used simple statistical analysis: Maldonado-Guzmán et al. (2017) for Mexico and Adeyeye, Egbetokun, Opele, Oluwatope, and Sanni (2017) for Nigeria.

[15] 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.

Hypothesis 4 (H4): SMEs are more severely affected by obstacles than larger firms.

iii) To identify the specific effect of different type of obstacles using Oslo 2005 taxonomy (knowledge, market, institutional and cost obstacles) on the probability of performing IA and its 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 type 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 organisations) 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 in Crépon, Duguet, and Mairessec (1998), Savignac (2008), Blanchard et al. (2013) and G. Pellegrino and M. 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 2010-2012 period and was carried out jointly by the Labour, Employment and Social Security Ministry (MTEySS) and the Science, Technology and Productive Innovation Ministry (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 2 digits ISIC)[16] The sample comprises 3.691 firms (expansion factors available)[17]; 79% of cases correspond to SMEs[18], 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

[16] 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 wearing apparel; Electrical machinery and apparatus, TV and radio equipment; Wood and products of wood; Leather and footwear; Other industries. For some sectors of special interest, information was disaggregated at 4 digits (Food and beverages; Chemicals; Machinery and equipment and Motor vehicles)

[17] A full descriptive report of the survey can be found on the following link: 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.

[18] 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.

has mainly affected quantitative variables such as employment, sales and different types of monetary variables, mostly for large firms. SMEs data, instead, 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 innovation activities (R&D, consultancy, acquisition of machinery and equipment, etc.). The latter contains mainly qualitative information on several issues regarding innovation and employment dynamics: organizational capability and business strategy; innovation activities; profile of human resources dedicated to innovation activities; results of the innovation efforts; sources of information and innovation objectives; sources of finance for innovation activities; obstacles to innovation; linkages; employment management capabilities and training policy; organization of labour; and knowledge management capabilities.

4.2. Sampling strategy to deal with selection bias

There is a well-documented problem of selection bias which leads to find a positive correlation between obstacles and propensity to innovate or other innovation indicators. This counterintuitive result is explained because firms which 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 *non-willing-to-innovate firms* biases the estimation of the obstacles coefficient's upwards, turning them positive.

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

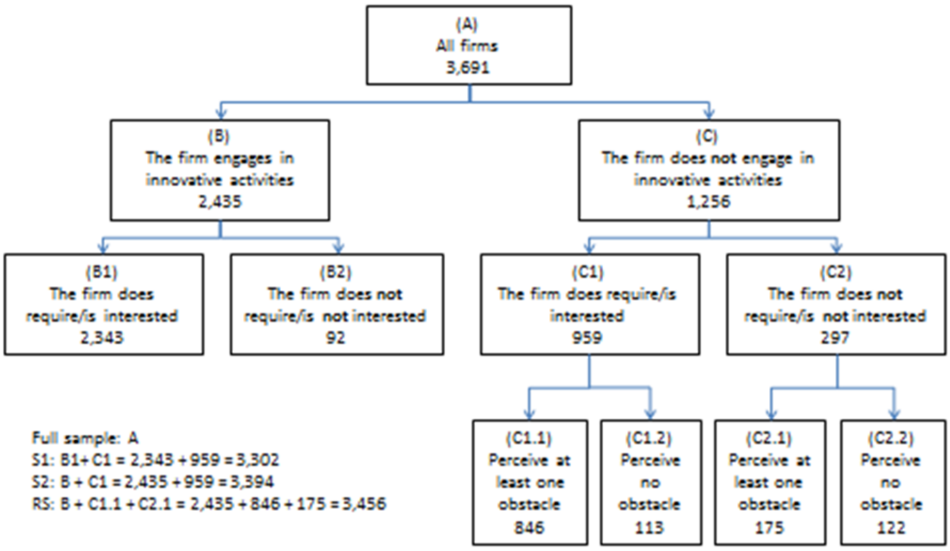
Our approach to identify the relevant sample shares the fundamentals with previous studies (i.e. we want to restrict our relevant sample to those firms that are 'interested in' innovation or 'willing to' innovate). Given the importance of the sampling methods, we compare different strategies (see Diagram 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 G. Pellegrino and M. Savona (2017): we can exclude firms that did not engage in any innovative activity and those that did not identify any obstacle (see RS in Diagram 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 innovation activities] [19]. 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 required 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 not to require/be interested in innovation (see Sample 1 or S1 in Diagram 1). Yet another definition was explored, since there were firms that reported not to be interested in innovation but still performed innovative activities. This lead us to reincorporate 92 firms (see S2 in Diagram 1).

Diagram 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 the all firms and for the RS, S1 and S2. We then select the best performing of these subsamples and show most of the remaining results just for that one 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.

Dependent variables were, alternatively, a dummy variable for investing in innovative activities (*iatot_d*), the natural logarithm of the invested amount per employee (*log_iaint_l*), and three dummies for innovation results; the first one for innovation at the national or international markets (*innova_nat*), and the second and third one for introducing technological innovations (product and/or process) (*inno_tech_nat*), and

[19]There is an ‘other’ category, which contains no valid data.

non-technological innovations (organizational and/or commercialization) (*inno_notech_nat*), at the national or international markets.

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

For goal i) and H1 we estimate two models, one for decision to engage in innovation activities (dichotomous dependent variable *iatot_d*, equation [1]), and the other one for the natural logarithm of innovation activities in relation to employment (dependent variable *log_iaint_l*; equation [2])[20] using the above mentioned explanatory variable *obst_all_p*. Our estimations comprise variations of ordinary least squares linear models (OLS) and IV linear regressions.

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

$$log\_iaint\_l_i = a_{21} + a_{22} * obst\_all\_p_i + a_{23}X_{2i} + \varepsilon_{2i} \qquad [2]$$

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 all variables definitions):

- For equation [1], X_1: *age_2001; dpull_str; spush_str; foreign; group; hcap_avg; sector_d; size_avg_imp*
- For equation [2], X_2: *age_2001; foreign; group; hcap_avg; sector_d; size_avg_imp; mkt_share_avg; mkt_share_avg_2; source_breadth_tot*

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

For goal 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.

$$innova\_nat_i = a_{31} + a_{32} * obst\_all\_p_i + a_{33}X_{3i} + \varepsilon_{3i} \qquad [3]$$

$$innova\_tech\_nat_i = a_{41} + a_{42} * obst\_all\_p_i + a_{43}X_{4i} + \varepsilon_{4i} \qquad [4]$$

$$innova\_notech\_nat_i = a_{51} + a_{52} * obst\_all\_p_i + a_{53}X_{5i} + \varepsilon_{5i} \qquad [5]$$

[20] 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.)

In this case, controls are

- For equation [3], [4] and [5], $X_3 = X_4 = X_5$: *age_2001; foreign; group; hcap_avg; sector_d; and size_avg_imp*

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

For goal iii) we build the Oslo 2005 obstacle taxonomy: knowledge, cost, market and institutional groups as explanatory variables (see Table 3)[21]. We use Tobit type 2 models, which allows to simultaneously model the decision to engage in innovation activities (*iatot_d*) and its intensity (*log_iaint_l*), controlling for the potential bias generated by the fact that not all firms decide to invest in innovation[22]. Equation [6], [7] and [8] present the general specification.

$$iatot\_d_i^* = a_{61} + a_{62} * obst\_k\_p_i + a_{63} * obst\_i\_p_i + a_{64} * obst\_c\_p_i + a_{65} * obst\_m\_p_i + a_{66}X_{6i} + \varepsilon_{6i} \quad [6]$$

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

$$log\_iaint\_l_i = a_{81} + a_{82} * obst\_k\_p_i + a_{83} * obst\_i\_p_i + a_{84} * obst\_c\_p_i + a_{85} * obst\_m\_p_i + a_{86}X_{8i} + \varepsilon_{8i} \quad [8]$$

The decision to engage in IA (*iatot_d*) is modelled in equation [6] and [7] by the latent variable *iatot_d** (unobservable), which defines that when threshold *a* is passed the firm engages in IA. As explanatory variables we consider four obstacle groups *obst_k_p, obst_i_p obst_c_p* and *obst_m_p*, accounting for the intensity of perceived obstacles in each group.

In this case, controls are:

- For equation [6], $X_6 = X_1$: *age_2001; dpull_str; spush_str; foreign; group; hcap_avg; sector_d; size_avg_imp*
- For equation [8], $X_8 = X_2$: age_2001; *foreign; group; hcap_avg; sector_d; size_avg_imp; mkt_share_avg; mkt_share_avg_2; source_breadth_tot*

[21] 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 factors so as to make clearly 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.

[22] Estimated using maximum likelihood estimators, through the Stata's command "Heckman" (StataCorp, 2013)

For the sake of completeness, equation [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 a time, as explained the paragraph just below.

Goal 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_p* being replaced alternatively by *obst_k_p, obst_i_p obst_c_p* and *obst_m_p*.[23] All these estimations include controls for intensity of the perceptions of obstacles other than those included in each group (*obst_not_group_p*). For example, when equations include *obst_k_p*, *obst_not_k_p* is also included as a variable accounting for the intensity of obstacles other than knowledge obstacles. The rest of controls are the same as in equation [6].

$$innova\_nat_i = a_{91} + a_{92} * obst\_group\_p_i + a_{93} * obst\_not\_group\_p_i + a_{96}X_{9i} + \varepsilon_{9i} \qquad [9]$$

Finally, for goal v we estimate tri-variate probit models for the propensity to innovate (*innova_nat*), the propensity to cooperate with firms (*link_firm*) and with private / public research organisations (*link_ppro*). As explanatory variable we use the index that accounts for the perception of obstacles in general (*obst_all_p*) and *link_firm* and *link_ppro* in case of equation on *innova_nat*. Other controls are the same as in equation [3]. To identify equations on *link_firm* and *link_ppro* we additionally include market share (*mkt_share_avg*), the breadth of use of sources of information (*source_breadth_tot*), a dummy variables account for openness in strategic planning (*open_strategy*) and the number of financial sources the firm reveals to know about (*k_fin_Ncon*).

Table 1 summarizes the estimations to be performed and the tables where results are shown.

Table 1: Research goals, econometric models, and organisation of results to be discussed

[23] Weak instruments test were not passed in the equation including *obst_i_p*, therefore results are not analysed.

Objective		Samples	Dep. Variable	Obstacles variable	Models	Table #
i)	Propensity of AI	Full/S1/S2/RS and for RS Big and SMEs firms	iatot_d	All together Variable: obst_all_p	LPM OLS & LPM IV (GMM)	5
i)	Intensity of AI	Full/S1/S2/RS and for RS Big and SMEs firms	log_iaint_l	All together Variable: obst_all_p	OLS & IV (GMM)	6
ii)	Propensity of innovation	Full/S1/S2/RS and for RS Big and SMEs firms	innova_nat	All together Variable: obst_all_p	LPM OLS & LPM IV (GMM)	7
ii)	Propensity of technological innovation	Full/S1/S2/RS and for RS Big and SMEs firms	innova_tech_nat	All together Variable: obst_all_p	LPM OLS & LPM IV (GMM)	8
ii)	Propensity of non-technological innovation	Full/S1/S2/RS and for RS Big and SMEs firms	innova_notech_nat	All together Variable: obst_all_p	LPM OLS & LPM IV (GMM)	9
iii)	Propensity of AI and Intensity of AI	RS for all firms and splitting in big and SMEs	iatot_d log_iaint_l	Oslo (4 groups) obst_k_p obst_i_p obst_c_p obst_m_p	Tobit type 2 (Heckman)	10
iii)	Propensity of AI	RS for all firms and splitting in big and SMEs	iatot_d	Oslo (3 groups) obst_k_p obst_c_p obst_m_p	LPM IV (GMM) Individual models for each obstacles group	11.1 and 11.2
iii)	Intensity of AI	RS for all firms and splitting in big and SMEs	log_iaint_l	Oslo (2 groups) obst_k_p obst_c_p	LPM IV (GMM) Individual models for each obstacles group	12
iv)	Propensity of innovation	RS for all firms and splitting in big and SMEs	innova_nat	Oslo (3 groups) obst_k_p obst_c_p obst_m_p	LPM IV (GMM) Individual models for each obstacles group	13.1 and 13.2

v)	Innovation propensity. Cooperation and cooperation with firms/cooperation with research organizations.	RS for all firms and splitting in SMEs and big firms.	innova_nat link_firm link_ppro	All together Variable: obst_all_p	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 labour dynamics. We may remind readers that the ENDEI was jointly implemented by two different ministries: labour (MTEySS) and science and technology (MINCyT) and therefore the questionnaire is noticeable divided in sections mostly related to innovation while others attempt to capture labour 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 abilities 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 one referred to restrictions perceived by firms that did not perform any of the above training activities (including the following options: personnel has the right competences to meet the firm's needs; the firm hires personnel with the required qualifications; the firms 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 *train_restr* 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 sceptic or less confident about the future firm performance. Therefore, they may be more prone to perceiving obstacles to innovation. Firms that cannot trust on 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 *train_restr* 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,[24] 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 together followed by cost, knowledge and market obstacles. We do not report estimation results when the instrumentation strategy failed.

5. Descriptive Statistics

The context

In 2014, 28.1% of Argentinean firms employed between 10 and 200 people. They accounted for 43.4% of total registered employment.[25] This share reaches 99.4% and 64.3%, respectively, when firms with less than 10 employees are included.

The need for improving our knowledge on 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% of the large enterprises' productivity; in Argentina they grasp just 36%. If medium-sized firms were considered, these figures would get to 85% and 47%, 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 innovation activities (Ibarrarán, Maffioli et al. 2009). As a matter of fact, in a recent revision of industrial policy in Argentina one of us identified that most policy tools, both designed and implemented by the MINCyT, 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.[26] Innovative efforts, in turn, are defined as activities performed seeking for innovative outcomes.[27] It is

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

25 Source: Observatory of Employment and Business Dynamics, Ministry of Labor and Social Security.

26 The question on innovative outputs is headed with this sentence: "You mentioned that you performed innovation activities during the period 2010-2012, have you obtained any of the following results as a result of these innovation efforts?"

27 The question on efforts is headed with this paragraph: "During the period 2010-2012: did your company perform some of the following activities searching for of innovation? This means all scientific,

worth noting that this filter question is a yes/no question, and it does not require firms to have invested positive amounts.[28]

In the full sample, 62% of firms claimed to have introduced some innovation[29] and 61% of firms introduced product or process. These percentages reduce to 31% when novelty is defined at national level at least.

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

In order 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% in the full sample. This increases to 63% for willing firms defined by S1 and S2, while it is 61% in the RS. In sum, the RS includes a higher proportion of low performant 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 yet identified some obstacles restricting innovation activities. Since this definition of relevant sample has been used in the literature, we may choose it as the relevant sample (we will discuss this further in Section 6).

(Insert Table 2 around here)

(Insert Table 3 around here)

(Insert Table 4 around here)

In terms of micro characteristics Table 3[30] shows that around 30% of firms are young (born after 2001, *age_2001*), 9% are foreign and 12% belong to a group. Indicators regarding firms' strategy show that they employ 16% of professional or technical employees (*hcap_avg*), 60% link with third parties (29% with research organisations *link_ppro* and 53% with other firms, *link_firm*), 65% invest in innovative activities (*iatot_d*) and 32% are successful in obtaining innovative outcomes that they considered novel for the national or international market (*innova_nat*). All these indicators related to firm innovative behaviour 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 behaviour, they know about fewer financial sources (*k_fin_Ncon*), they use a narrower variety of information sources (*source_breadth_tot*), they are less innovative, they have fewer links with third parties, and they perceive more obstacles.

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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)"

28 Monetary values for investment in innovative activities are informed in the self-administered form: 3% of firms that declared to have been engaged in innovative activities in the period did not inform any positive amount in self-administered form.

29 Includes new or improved products or services or organizational/commercialization innovations.

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

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%), followed by market (57%), knowledge (54%) and institutional (37%). The order is similar regardless of whether firms innovate or not. 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 (*iatot_d*), while Table 6 presents the estimates of Equation [2], with innovation activities intensity as the dependent variable (*log_iaint_l*).

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 behaviour (the *group* variable is neither significant on Table 5 nor on Table 6), while multinational corporations are not particularly likely to invest in IA (*foreign* coefficient in Table 5 is not significant) either, but when they invest they do it more intensively (Table 6). Human capital (*hcap_avg*) is positively associated to the decision to invest and to the intensity of investment, particularly for SMEs.[31] In addition, to diversify sources of information (*source_breadth_tot*) is also positively correlated with the level of investment (Table 6).

Young firms are more likely to engage in innovative activities (Table 5), especially SMEs. Interesting, young and large firms are less likely to invest in innovation.[32] 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, start-ups 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.

(Insert Tables 5 and 6 around here)

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 sub-samples. 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)[33]. 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, since it has been used elsewhere which improves the comparability of our findings.

[31] Coefficient is not significant for the sub-sample of large firm.

[32] The coefficient becomes non-significant in IV estimation

[33] Although it remains non-significant for the sub-sample of large firms (column 8)

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 (since 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 favour of H1. Results also show that this negative effect is stronger for the sub-sample of SMEs (coefficients for large firms are not significant), providing evidence for H2.

In order 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,[34] but magnitudes are much larger. This means endogeneity downplayed the role of obstacles on innovation.

Table 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 remains 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), on product and process innovation (Table 8). For non-technological innovation, the opposite is true (Table 9). Thus, our results do not support H4. [35]

(Insert Tables 7 to 9 around here)

We now turn to goal iii to analyse 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 the equations [6]-[7], on the probability to engage in investment activities are shown in columns labelled ‘selection’. In turn, results for equation [8] on intensity of investment in innovative activities are presented in columns labelled ‘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[36] and a supply push[37] strategy are more likely to engage on innovation activities.

[34] With the exception of the sub-sample of big firms on the propensity to engage in innovation activities (Table 5): coefficient for obstacles is not significant for OLS estimation and becomes significant for IV estimation.

[35] We explored including size interaction terms in IV regressions presented in column 9 of Table 7, 8 and 9, and the interaction term was never significant.

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

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

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 Table 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.[38]

Regarding obstacles, result 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 involve, knowledge barriers would determine their level of commitment to innovation. Projects that are riskier or more complex, which presumably make them more expensive, would not be chosen by firms facing knowledge obstacles.

Regarding the effect by size, cost obstacles seems to be particularly adverse for SMEs. No important size difference turns out for the effect of knowledge and market obstacles on innovation. Additionally, in graphs 1.1 and 1.2 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 is negative for smaller ones. No such effect could be found in the case of market obstacle when taking into account confidence intervals' width.

(Insert Table 10 around here)

(Insert Graph 1.1 and 1.2 around here)

For goal 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 11.1 and 11.2 show results on the probability to invest, while Table 12 on investment intensity. Only results for cost, knowledge and market obstacles are discussed in Table 11.1 and 11.2 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

[38] 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.

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 innovative activities, 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. [39]

In order to draw some conclusions for goal 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 in intensity. Size differences in the effects of obstacles on innovation, are only found for cost obstacles.

(Insert Tables 11.1, 11.2 and 12 around here)

Our goal iv was to analyse the effect of different obstacles on innovation success and to that end we estimate LPM for Equation [9]. Results are presented in Tables 13.1 and 13.2. 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.[40]

(Insert Tables 13 around here)

Finally, in Table 14 we show the results associated to goal iv. We aimed at exploring whether linking to third parties somehow work 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 organisations. Linking, in turn, is positively associated to innovation outcomes. However, obstacles remain significant and negative when explaining innovation outcomes, which could be interpreted as linking to third parties not being effective enough to overcome obstacles.[41]

[39] 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 11.1 and 12.1). Something similar turns out for the effect of knowledge obstacle on the intensity of investment in innovation (Table 12)

[40] 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

[41] In addition we ran Probit regressions with and without *link_firm* and *link_oppi* as explanatory variables, while keeping all other controls as in Table 14. If link variables are not included the coefficient for *obst_all_p* is not significant, which is what we found with OLS models (Table 7, column 6). Differences in the marginal effects of *obst_all_p* 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.

7. Conclusions

This study contributes to our understanding of how barriers to innovation affect innovation. We use survey data from Argentinean. The topic is relevant for policy purposes since innovation programmes 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 programmes in Argentina are oriented to SMEs.

The literature suggests that selection bias and endogeneity prevails in the relation between obstacles and innovation. As other 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 fact that obstacles are endogenous regressors, since firms that innovate are more likely to perceived obstacles than otherwise.

We built the instrument using information from a labour 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 sceptical 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 sub-samples: SMEs (<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 innovative activities 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 national level.

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 since 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 larger (SMEs 8.5 pp; large firms 5.1 pp). In terms of the amount invested, firms would have spent in average around 9% more (13% more for SMEs and 5% 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 56pp (SMEs, 59pp and large firms, 45pp).

In sum, the effect of obstacles is highly relevant for innovation investment and performance, and it therefore makes sense to analyse them further.

We also classified obstacles in four groups following Oslo 2005 taxonomy: knowledge, cost, market and institutional. We used several modelisation 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 or they were financially constrained or when 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 or they were too rigid or they considered technological innovation too complex or that could not rely on external knowledge partners, they did not get involve 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 two-fold. 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 recognised as 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, the cost related ones 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 which allows improving the design of policy instruments especially for SMEs.

Tables

Table 2: Sampling strategies, innovation indicators for different samples (number of firms and proportions)

	Innovation results novel at least at…				Cooperates with…			Number of firms
	firm level		national level					
	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_p	0,194	0,163	0,188	0,127	0,208	0,171	***	0,200	0,121
obst_k_p	0,117	0,107	0,115	0,141	0,126	0,113	**	0,123	0,142
obst_i_p	0,138	0,117	0,133	0,199	0,147	0,123	***	0,142	0,203
obst_c_p	0,315	0,244	0,300	0,291	0,338	0,257	***	0,321	0,290
obst_m_p	0,307	0,264	0,298	0,307	0,329	0,278	***	0,318	0,307
obst_not_k_p	0,380	0,308	0,365	0,265	0,407	0,324	***	0,389	0,255
obst_not_i_p	0,446	0,373	0,431	0,296	0,478	0,392	***	0,460	0,284
obst_not_c_p	0,307	0,269	0,299	0,241	0,329	0,283	***	0,319	0,236
obst_not_m_p	0,412	0,343	0,398	0,287	0,442	0,361	***	0,425	0,276
hcap_avg (%)	14.124	22.030	15.765	18.528	14,365	22,130	***	16,001	18,521
k_fin_Ncon	2.812	3.761	3.009	2.609	2,878	3,858	***	3,084	2,609
dpull_str	0,604	0,640	0,611	0,488	0,615	0,641		0,620	0,485
age_2001	0,341	0,093	0,292	0,455	0,339	0,093	***	0,289	0,454
foreign	0,046	0,265	0,092	0,289	0,048	0,269	***	0,094	0,292
group	0,058	0,370	0,123	0,328	0,059	0,367	***	0,124	0,329
iaint_l_avg	5522,1	20801,2	8618,7	28089,7	5924,4	21943,5	***	9214,7	28950,4
iatot_d	0,602	0,851	0,652	0,476	0,645	0,897	***	0,697	0,460
inno_tech_nat	0,272	0,481	0,315	0,465	0,292	0,507	***	0,336	0,473
inno_notech_nat	0,070	0,148	0,086	0,280	0,075	0,156	***	0,092	0,289
innova_nat	0,273	0,483	0,316	0,465	0,299	0,518	***	0,345	0,475
train_restr	2.900	1.711	2.649	1.468	2,895	1,713	***	2,642	1,476
link	0,545	0,794	0,597	0,491	0,567	0,811	***	0,619	0,486
link_firm	0,479	0,738	0,532	0,499	0,498	0,757	***	0,552	0,497
link_ppro	0,229	0,510	0,288	0,453	0,242	0,523	***	0,301	0,459
log_iaint_l	8.324	8.708	8.426	1.524	8,324	8,708	***	8,426	1,524
mkt_share_avg	0,208	2.759	0,740	1.833	0,211	2,764	***	0,750	1,852
open_strategy	0,423	0,621	0,464	0,499	0,437	0,630	***	0,477	0,500
size_avg_imp	31,2	250,5	76,7	106,5	31,5	250,5	***	77,6	107,0
source_breadth_tot	0,238	0,440	0,280	0,277	0,255	0,463	***	0,299	0,276
spush_str	0,526	0,596	0,541	0,498	0,535	0,606	***	0,550	0,498

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 innovation activities	Firms with no innovation activities	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%***

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

Table 5: LPM models for the decision to engage in any IA (iatot_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_p	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_avg_imp	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	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	-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)
hcap_avg	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)
dpull_str	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)
spush_str	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

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 (train_restr) as an instrument for obstacles

Table 6: OLS and IV models for the log of IA per employee (log_iaint_l)

	(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_p	-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_avg	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_avg_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_avg_imp	-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	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	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)
hcap_avg	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_tot	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

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 (train_restr) as an instrument for obstacles

Table 7: LPM models for innovation results at the national level (innova_nat)

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_p	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	-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	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)
hcap_avg	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_avg_imp	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

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 (train_restr) as an instrument for obstacles

Table 8: LPM models for technological innovation results (product/process) at the national level (inno_tech_nat)

	(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)	S2 - SME	S2 - Big	S2 - IV	S2 - SME - IV	S2 - Big - IV
obst_all_p	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	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	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)
hcap_avg	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_avg_imp	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

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 (train_restr) as an instrument for obstacles

Table 9: LPM models for non-technological innovation results (organization/comercialization) at the national level (inno_notech_nat)

	(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_p	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	-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	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)
hcap_avg	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_avg_imp	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

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 (train_restr) as an instrument for obstacles

Table 10: Tobit type 2 model on propensity (selection equation) and intensity (level equation) of innovation expenditures (iatot_d and log_iaint_l).

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_k_p	-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_i_p	-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_c_p	-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_m_p	-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_avg	0.496***		0.513***		1.871***		0.387***	
	(0.0651)		(0.0654)		(0.247)		(0.0721)	
mkt_share_avg_2	-0.0222***		-0.0228***		-0.273***		-0.0153***	
	(0.00326)		(0.00333)		(0.0434)		(0.00323)	
size_avg_imp	-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	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	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)
hcap_avg	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_tot	0.493***		0.500***		0.424***		0.711**	
	(0.132)		(0.132)		(0.148)		(0.277)	
dpull_str		0.0611***		0.0551***		0.0520***		0.0744***
		(0.0134)		(0.0130)		(0.0140)		(0.0244)
spush_str		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	

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.

Table 11.1: LPM models for the decision to invest in innovative activities (iatot_d). Knowledge and cost obstacles on this page; market obstacles on the next page

	(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_k_p	-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_k_p	-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_c_p							-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_c_p							-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_avg_imp	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	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	-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)
hcap_avg	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)
dpull_str	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)
spush_str	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

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 (train_restr) as an instrument for obstacles

Table 11.2: LPM models for the decision to invest in innovative activities (iatot_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_m_p	-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_m_p	-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_avg_imp	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	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	-0.0296	-0.0585	-0.0193	-0.0721	-0.0363	-0.0192
	(0.0290)	(0.102)	(0.0431)	(0.123)	(0.0353)	(0.168)
hcap_avg	0.00189***	0.00411**	0.00229***	0.00481***	0.000649	0.000230
	(0.000486)	(0.00166)	(0.000600)	(0.00180)	(0.000730)	(0.00324)
dpull_str	0.0930***	0.0915*	0.0943***	0.114**	0.0662**	-0.0759
	(0.0166)	(0.0545)	(0.0190)	(0.0573)	(0.0297)	(0.179)
spush_str	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

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 (train_restr) as an instrument for obstacles

Table 12: OLS models on the intensity of innovative activities (log_iaint_l). 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_k_p	-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_k_p	-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_c_p							-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_c_p							-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_avg	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_avg_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_avg_imp	-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	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	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)
hcap_avg	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_tot	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

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 (train_restr) as an instrument for obstacles

Table 13.1: LPM models for innovative success (innova_nat). Knowledge and cost obstacles on this page; market obstacles on the next page

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_k_p	-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_k_p	-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_c_p							-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_c_p							-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	-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	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)
hcap_avg	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_avg_imp	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

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 (train_restr) as an instrument for obstacles

Table 13.2: LPM models for innovative success (innova_nat). 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_m_p	-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_m_p	-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)
edad_2001	-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	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_avg_imp	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

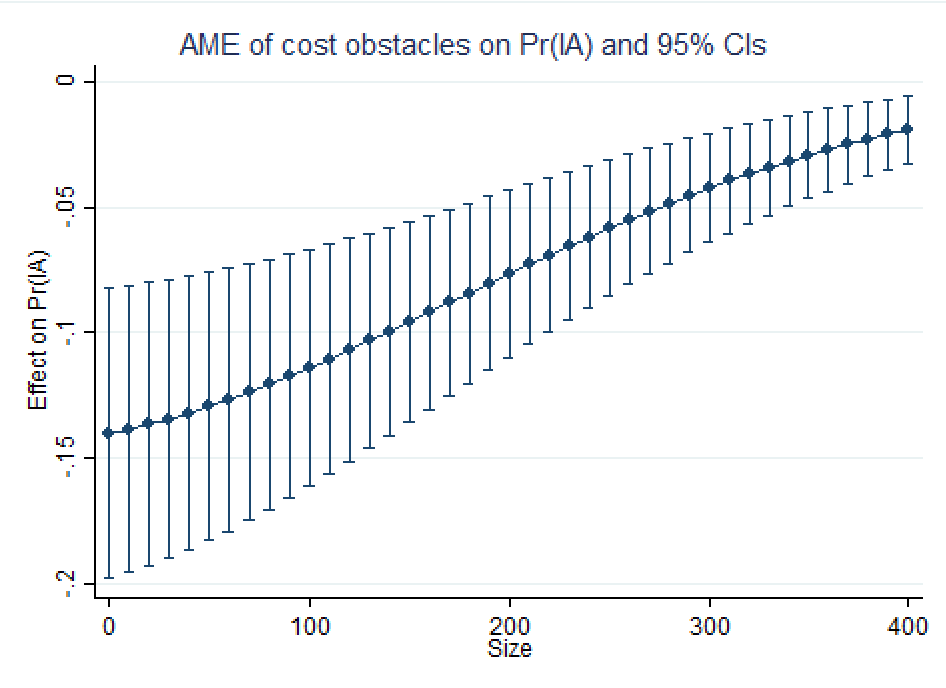
Robust standard errors in parentheses. Regressions include industry dummies not reported here.
*** p<0.01, ** p<0.05, * p<0.1
IV regressions use training limitations (train_restr) as an instrument for obstacles

Table 14: Trivariate probit models for cooperation with firms (link_firm), cooperation with private and public research organisations (link_oppi) and innovation results (innova_nat). All obstacles (obst_all_p)

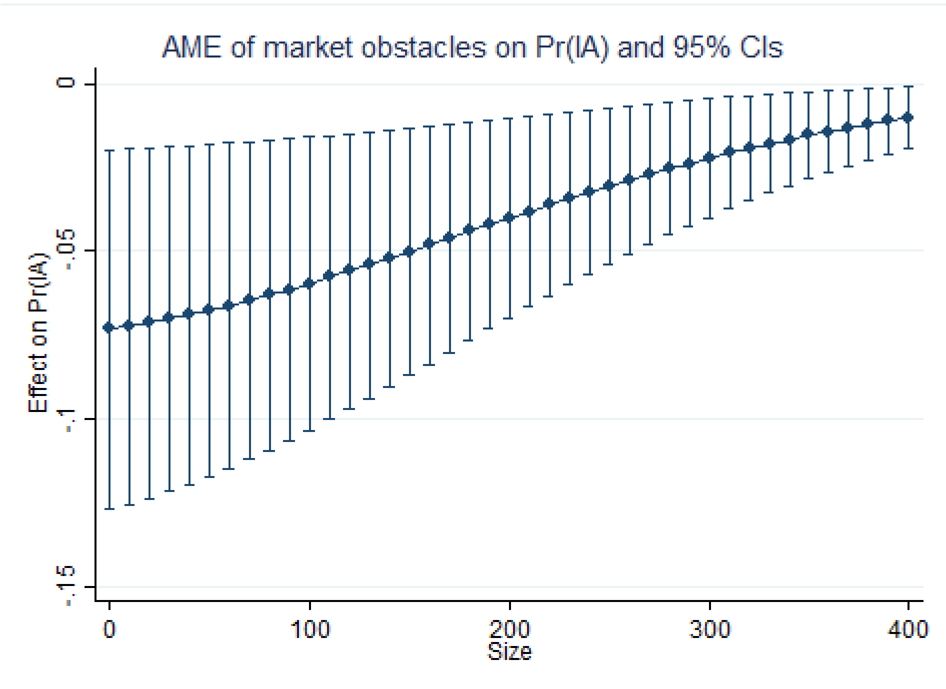
	(1) FULL RELEVANT SAMPLE			(2) SME - RELEVANT SAMPLE			(3) BIG FIRMS - RELEVANT SAMPLE		
VARIABLES	Link firm - RS full sample	Link oppi - RS full sample	Innova nat - RS full sample	Link firm - RS SME	Link oppi - RS SME	Innova nat - RS SME	Link firm - RS big	Link oppi - RS big	Innova nat- RS big
link_firm			0.415***			0.423***			0.422***
			(0.0173)			(0.0177)			(0.0813)
link_oppi			0.174***			0.141***			0.201**
			(0.0300)			(0.0373)			(0.0884)
obst_all_p	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_avg	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	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	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)
hcap_avg	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_avg_imp	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)
k_fin_Ncon	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_tot	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	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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressions include industry dummies not reported here.
Reported estimates are maginal effects

Graph 1.1. 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, column 4 Table 10)



Graph 1.2. 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, column 4 Table 10)



ANNEX

Annex A1: Variables definition and description.

Table A1: Variables definition

Variable name	Description
	Dependent variables
iaint_l_avg	Investment intensity in innovative activities: defined as the average of ratios between total expenditures in innovation activities and total employment for the 2010, 2011 and 2012 (in pesos of 2010, deflated with price indexes provided by "M&S Consultores").
iatot_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-).
inno_notech_nat	Dummy = 1 if the firm informs any innovation results which were novel for the national market, considered “no technological” (organizational or commercialization innovations).
inno_tech_nat	Dummy = 1 if the firm informs any innovation results which were novel for the national market, considered “technological” (new or improved products or processes).
innova_nat	Dummy = 1 if the firm informs any innovation results which were novel for the national market (new or improved products, processes, organizational, commercialization innovations).
log_iaint_l	Natural logarithm of iaint_l_avg
	Explanatory variables
link	Dummy = 1 if the firm cooperates with third parties to pursue different goals associated to innovative activities (excludes cooperation related to usual business activities).
link_firm	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 to innovative activities (excludes cooperation related to usual business activities)
link_ppro	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 to innovative activities (excludes cooperation related to usual business activities).
obst_all_p	Proportion of obstacles faced by the firm. Firms choose a 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_c_p	Proportion of cost obstacles faced by the firm (out of 4)
obst_i_p	Proportion of institutional obstacles faced by the firm (out of 3)
obst_k_p	Proportion of knowledge obstacles faced by the firm (out of 5)
obst_m_p	Proportion of market obstacles faced by the firm (out of 2)
obst_not_c_p	Proportion of obstacles other than cost obstacles (out of 6)
obst_not_i_p	Proportion of obstacles other than institutional obstacles (out of 6)
obst_not_k_p	Proportion of obstacles other than knowledge obstacles (out of 6)
obst_not_m_p	Proportion of obstacles other than market obstacles (out of 6)
	Control Variables
age_2001	Dummy = 1 if the firm was founded in 2001 or after.
dpull_str	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	Dummy = 1 if the firm has foreign capital participation.
group_d	Dummy = 1 if the firm is part of a conglomerate.
hcap_avg	Professional and technical personnel; average share for 2010, 2011 and 2012 - proxy for human capital or skills.
k_fin_Ncon	Number of finance sources that the firm reveals to know (out of 26)
mkt_share_avg	Average sectoral market share of the firm for 2010-2012.
mkt_share_avg_2	Squared mkt_share_avg
open_strategy	Open strategy indicator: dummy = 1 if the firm reveals to analyse routinely its environment and competition
Sector_d	Sectoral dummies (27 economic sectors).
size_avg_imp	Average number of employees of the firm 2010-2012
source_breadth_tot	Proportion of internal and external information sources for innovation used by the firm (out of 14 options).
spush_str	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
Instrument	
train_restr	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 inform 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 one limiting factor from a list of six t
	= 3 if the firm did not train its employees during 2012 and it 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 constraints from a list of eight

Annex A2: 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_p (*index for all obstacles) was the endogenous regressor.

For group obstacles as endogenous regressors:

- The test passed for all regressions including *obst_c_p* (cost obstacles)
- It passed for regressions which include *obst_k_p* (knowledge obstacles) estimated for the sub-sample of SMEs and all firms regardless of size.
- It passed for *obst_m_p* (market obstacles) for the sub-sample of SMEs and all size firms in the case where dependent variable was the probability of investing in innovative activities (Table 11.2) and also for the probability of success in innovative activities (Table 13.2). This means that IV results on the sub-sample of large firms should not be trusted in this case.
- It did not pass when *obst_m_p* (market obstacles) was the endogenous regressor and the dependent variable was the intensity of investment on innovative activities. Results are not discussed.
- It did not pass when *obst_i_p* (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 *iatot_d* and independent variable *obst_all_p* using as instrument *train_restr*

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

Table A2.2. First stage statistics of linear IV regression with dependent variable *log_iaint_l* and independent variable *obst_all_p* using as instrument *train_restr*

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

Table A2.3. First stage statistics of linear IV regression with dependent variable *innova_nat* and independent variable *obst_all_p* using as instrument *train_restr*

Instrument Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(1,2998)	Prob > F
obst_all_p	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[42] (exogeneity), indicating that IV estimation was preferred (results skipped for space reasons).

[42] Some few exceptions when estimations performed with the subsample of large firms.

Annex A3: List of 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: Technology and Productive Innovation Ministry (abbreviation in Spanish)

MTEySS: Labour, Employment and Social Security Ministry (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, sub-sample version 1

S2: 'willing-to-innovate' firms, sub-sample version 2

SMEs: small and medium enterprises

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