The Productivity Impact of Innovation on Industry in Argentina

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ABSTRACT

This paper assesses the innovative process of Argentinian manufacturing firms and its impact on labour productivity. Applying a CDM model, we combined firms' innovative decisions with innovation results and their impacts on labour productivity. We used recent data from Argentina's National Survey on Employment and Innovation Dynamics (ENDEI in Spanish) from 2010-2012 and 2014-2016. Our findings verify the innovative process which links innovation with productivity regardless of prevailing macroeconomic and industrial conditions.

Keywords: innovation; productivity; CDM model; manufacturing industry; Argentina.

Subject classification codes: J24, O12, O14, O33.

I. Introduction

Since the mid-2000s, after a general socioeconomic crisis, industry in Argentina has experienced significant recomposition following the abolishment of the Convertibility Plan which was implemented in 1991 (Arza & López, 2010). From a need to increase their competitive advantage, many firms have implemented technological innovation processes, yielding various results for their productive performance while facing challenges to innovation typical of any peripheral economy (Bernat, 2017; Chudnovsky et al., 2004). In the 21st century, some historical problems with development in Latin American persist, such as different obstacles to innovation, the limited scope of innovation policies and low productivity levels prevailing in most industrial sectors (CEPAL, 2017; Grazzi et al., 2016).

It is reasonable to attribute this poor performance to a large extent to the historically low productivity of the national economy, particularly of the manufacturing sector, within the framework of the absence or weakness of innovation diffusion at levels capable of stimulating structural change. Structural technological heterogeneity and activities of low technological complexity remain widely prevalent and there are persistent macroeconomic restrictions as well as productive disarticulation (Abeles & Amar, 2017).

According to this scenario, the study assesses innovation processes in Argentinian manufacturing firms and how they impact labour productivity. Our underlying hypothesis was that, in recent decades, firms that have undertaken innovative processes have achieved significant innovation outputs, which have positively affected their labour productivity levels. This can be verified irrespective of general industry conditions.

In macroeconomic terms, the difficulties pointed out are associated with the dampening of economic growth in the country since the second half of the 20th century. While Argentina is considered an 'upper-middle income' country, the last six decades have witnessed different stop-go cycles that have critically affected long-term output trends. Between 1960 and 2019, the GDP per capita reported average annual growth of less than 1%. Considering decades in particular, this performance was not better. The GPD per capita saw rates of 2.3% in the 1960s and 1.1% in the 1970s but decreased by 2.3% annually during the 1980s. In the 1990s, data indicated an average growth rate of almost 2% and a negative rate of 0.7% in 2000s (see Table A1 in the Appendix Section). Above all, recurrent crises have revealed marked declines of growth in the late 1980s, 1990s and from 2017 onwards[1]. In relative terms, the GDP per

[1] Source: WDI Indicators. GDP per capita at constant LCU. Accessed: April 2021 https://data.worldbank.org/indicator/NY.GDP.PCAP.KN?locations=AR.

capita during this long period remained at levels significantly lower than the average for OECD countries, the US and Australia and was generally less than the output of Germany, France and even Italy (except for the period of decline in these countries during the World War II)[2].

The most notable positive leap in GDP per capita in Argentina occurred during the post-convertibility period, excepting a slight decline from 2008-2009. The data for the periods covered by this research indicate similar fluctuations: it grew by 4.8% in 2011, achieving the highest historical level and then falling by 2.1% in 2012. In 2014, its level was slightly lower than that of 2012. Then, the output data indicate a slight rise of 1.6% in 2015 followed by a decline of 3.1% in 2016. Taking Australia as a parameter, Argentina's GDP per capita has grown almost uninterruptedly since 1960, indicating a long-term trend that has contributed to its current development level.

Most of the background regarding the relationship between innovation and productivity in local industry has used data from the first few years of the 20th century, before the economic recovery that was experienced at the macroeconomic and sectoral levels (Chudnovsky et al., 2004; Katz, 2000). Thus, it is relevant to identify and quantify problems through an application exercise using more recently available data (collected after the period of local industrial expansion) (Pereira & Tacsir, 2017)[3]. Consequently, focusing on recent decades, this paper proposes a structural recursive model, known as CDM, which links the different

[2] See data from Maddison Project Database, available at https://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/

[3] According to data from the Industrial Monthly Estimator (base 2012 = 100, trend-cycle), manufacturing production averaged for the 2010-2012 period a maximum level, surpassing by 62% what was recorded at the beginning of the series (1994). After that, manufacturing production decreased by 5% in 2014 (this is the last available estimate).

stages of innovation in firms and their impacts on different performance variables (Crépon et al., 1998). We used data from the National Survey on Employment and Innovation Dynamics (ENDEI in Spanish), implemented by the Ministry of Labour and the Ministry of Science and Technology of Argentina (MTEySS and MINCyT in Spanish). We analysed data from the first two rounds of this survey, which covers the periods 2010-2012 and 2014-2016. This novel database has not previously been utilised extensively and presents advantages in terms of coverage, specificity, sample size and available innovation indicators (MINCyT & MTEySS, 2015).

There are three main contributions of this study. First, in terms of novelty, we have applied a recent database related to the manufacturing industry in a country with experience in this relevant sector. Also, related to our findings, we identified diverse limitations and the innovative potential of local industries. Among the former: we found a relative disparity between the innovation efforts of manufacturing firms and the innovation outputs they achieve; also, microeconomic determinants did not influence innovative decisions. Regarding potentialities, we observed a significant and positive link between innovation and firm productivity, including in idiosyncratic conditions associated with innovation processes, which has been verified across different innovation outputs. Our findings contribute to a broadening of the regional literature on the subject and to the review and formulation of specific policies. Our paper is organised as follows. In the next section, we present our literature review and theoretical framework. Section III describes the methodology of the CDM model. Section IV reports the status and performance of the firms studied and section V presents our empirical results. The final section discusses these results and proposes areas for future research.

II. Literature review

Increasing the productivity of enterprises is one of the most significant economic challenges faced by Latin American countries. Low productivity is the root cause of Latin America's poor economic growth (Pagés, 2010). Productivity begins at the firm level and is related to how efficiently firms convert input into output. The reallocation of economic activity from lower to higher productivity firms also largely explains aggregate economic growth (Foster, Haltiwanger & Krizan, 2001).

There has long been a consensus on the relevance of technological innovation to productivity growth and development (Nelson & Winter, 1982; Jorgenson, 2011). Innovation is fundamental to economic catching up and raising living standards. There is evidence demonstrating a virtuous cycle in which R&D spending, innovation, productivity and per capita income mutually reinforce each other, lead to long-term, sustained growth (Hall & Jones, 1999; Guloglu & Tekin, 2012) and potentially foster job creation (Vivarelli, 2013). Additionally, in most countries, the productivity effect of product innovation is more significant in manufacturing than in service industries (OECD, 2009). Various studies specifically based on innovation surveys have repeatedly demonstrated that product and/or process innovation leads to improved economic performance in European companies (Lööf et al., 2001; Mohnen et al., 2006). Studies conducted in peripheral economies have obtained similar results (Arza & López, 2010; Chudnovsky et al., 2004; Gómez & Borrastero, 2018;[4]

[4] Concerning the decision to innovate and their links with certain performance variables of firms, in a previous study, the authors - using methods of quantile regression and ordinary least squares - concluded that the innovation activities of Argentinian firms are significantly associated with higher levels of productivity, wages and job skills, in a magnitude that differs at the sectoral and firm levels due to the structural heterogeneity of the industry.

Raffo et al., 2008), highlighting the importance of innovation in continuing catching up processes and the challenges to these economies regarding investment in innovation.

Generally, but particularly for Latin American economies, investing in innovation can result in substantial economic payoffs.[5] Firms that invest in innovation are better equipped to introduce technological advances and tend to have higher levels of labour productivity than those that do not.[6] Hence, strengthening in-house technological capabilities induces knowledge spillovers by acquiring machinery and equipment and interacting with other firms. However, even in developed economies, not all firms are equally productive. In developing countries, firms are too far from the technological frontier and incentives to invest in innovation are weak or absent (Acemoglu et al., 2006). Thus, the current evidence on the ability of these firms to obtain innovations from their innovative activities is inconclusive (Crespi, Tacsir & Vargas, 2016).

Firms' innovations in many Latin American countries generally consist of incremental changes with little or no impact on international markets and are mostly based on imitation and technology transfer, such as the acquisition of machinery and equipment and disembodied technology (Anlló & Suárez, 2009; Navarro et al., 2010). In many cases, R&D is financially prohibitive and, considering the human capital required, its materialisation could require long-term planning (Navarro et al., 2010). However, this does not mean that

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[5] Among the newly industrialised countries, a positive association between R&D, innovation and productivity has been found for South Korea (Lee & Kang, 2007), Malaysia (Hegde & Shapira, 2007), Taiwan (Aw et al., 2008) and China (Jefferson et al., 2006). By investing in R&D and human capital, these countries have managed to narrow their distance from the best practices.

[6] Crespi and Zúñiga (2012) reported that productivity gaps in the manufacturing sector between innovative and non-innovative firms are much higher in Latin America than in industrialised countries. For a typical country in the European Union, the productivity gap is 20%, while it is 70% in a typical Latin American country. Thus, Latin America has great potential to benefit from investment and policies that foster innovation.

innovation is non-existent or not profitable (Crespi, Tacsir & Vargas, 2016). Additionally, Crespi and Zuniga (2012) have shown that determinants of innovation investments are still more heterogeneous in Latin America than in OECD countries: cooperation, foreign ownership and exporting increased the propensity to invest in innovation in only half of Latin American countries. Thus, it is necessary and beneficial to study the innovation processes of firms and their impact on industry productivity. The general conceptual framework that informs the current innovation survey in Argentina (ENDEI) assumes this set of theoretical and empirical assumptions and takes as a reference several of the background reviewed here (CEPAL, 2017).

Historically, there have been many challenges to measuring the effects of innovation activities on productivity. Following the seminal contributions of Griliches (1979) and Pakes and Griliches (1980), a widely accepted approach is to model this link in an innovation function and the contribution of innovation to productivity in a production function. Crépon et al. (1998) were the first to empirically integrate these relationships into a structured model (hence the acronym CDM with which it is commonly referred to). This paper is grounded in the general CDM approach and its adaptations to Latin America and Argentina.

III. Methodology

Data

For this analysis, we used data from the ENDEI. This survey was recently implemented following an agreement between the Ministry of Labour, Employment and Social Security and the Ministry of Science and Technology of Argentina (MTEySS and MINCyT in Spanish acronyms). Two survey rounds are available for registered users, which cover the periods

2010-2012 and 2014-2016. To the best of our knowledge, few studies have used this data as a basis for research. Yet, the ENDEI survey presents advantages in terms of coverage, specificity, sample size and available innovation indicators (MINCyT & MTEySS, 2015).

First published in 2015, the ENDEI took up the path of industry-specific innovation surveys (previously discontinued) to open the possibility for research using more up-to-date data, particularly regarding labour and productive dimensions. Both editions of the survey were non-mandatory. Data were collected via interviews and self-administered forms completed by CEOs and firm managers.[7] Consistency was reinforced through new calls to enterprises already surveyed, which made it possible to generate better quality data and recover a significant number of missing surveys. The number of firms present in the initial data frame was 3691 for ENDEI I (2010-2012), with a response rate of 92% (3691 effective responses out of 3995 administered surveys) and 4068 for ENDEI II (2014-2016), with a response rate of 97% (3944 effective responses out of 4068 administered surveys). Argentinian manufacturing firms were selected with a stratified sampling by size and sector. Manufacturing sectors appeared disaggregated at 2-digit ISIC-Rev. 3 and at 4-digit in the food and beverages sector, while the firm size was classified by the level of employment, grouping firms into categories of 10-25, 26-99, 100-399 or over 400 or more employees. As all firms surveyed were registered in the Argentine Pension System (SIPA in Spanish), this

[7] The data collection method for the ENDEI II consisted of the application of two forms: an online self-administered questionnaire and a questionnaire in the form of a face-to-face interview with an official surveyor. The web-based questionnaire collected balance sheet information from enterprises and was completed autonomously by the respondent. It had automated consistency criteria that allowed the respondent to review the information uploaded and rectify it if necessary. The face-to-face questionnaire was designed to be completed through a notebook application. The information it collected was qualitative and structured and was completed by the interviewer through face-to-face interviews. Therefore, the design of the questionnaire was directed and participatory. Both questionnaires were semi-structured as they featured both pre-coded and open-ended responses.

data included information for firms working under formal labour conditions only (with registered workers). Due to the sample stratification (which is consistent between both rounds), this data represents almost 19,000 companies in the manufacturing sector.

One issue to consider is related to the ENDEI as a short-term sample. While the data covers 3 years (a relatively short period), there are several examples in the literature where this model has been applied using similarly short periods (e.g. Cozzarin, 2016; Crespi et al., 2016; Raffo et al., 2008). Likewise, Crespi and Zuniga (2012) followed the CDM methodology for both Argentinian firms and firms from five other countries in the region, using analysis periods that did not exceed 3 years. These studies are the most direct references for our empirical strategy due to their use of national innovation surveys and deep understanding of the challenges to innovation in Latin America.

Empirical strategy

The ENDEI presents some advantages associated with measuring innovation in developing countries (See Table A2, including the definitions of the variables). In particular, innovation expenditure is measured as the aggregate innovation expenditure per employee in 2010 (for 2010-2012) and 2014 (for 2014-2016). For innovation expenditure, we referred to the expenses in all categories of innovation activities outlined in the ENDEI data (in-house and external R&D, expenditure on machinery and equipment and hardware and software, technology transfer, design and engineering, consultancy and training).[8] Among these categories, the expenditure on machinery and equipment and in-house R&D had the highest

[8] The inclusion of the acquisition of machinery and equipment could potentially present bias towards the innovation intensity variable. As an embodied innovation effort, it is not possible to disaggregate and discount the annual depreciation rate.

shares of total innovation expenditure (See Table A3 and the discussion in the descriptive results section). We used natural logarithms of the variable in the regressions. Innovation expenditure per employee was chosen as the indicator of innovation efforts for several reasons. R&D efforts are significantly lower in developing than in developed economies. In generic enterprise surveys (such as the World Business Enterprise Survey from the World Bank), the data only cover R&D expenditures, which is less correlated with innovation and performance indicators in Latin American countries (Acemoglu et al., 2006; Arza & López, 2010; Hall & Mairesse, 2006).[9]

The CDM framework consists of a structural recursive model which considers three phases of innovation processes: 1) the decision to innovate (i.e. investing in innovation activities) and the intensity of innovation (measured by innovation expenditure per employee), 2) innovation results, modelled by a knowledge production function and 3) the impacts of innovation on the firm's performance, in this case, labour productivity. Concerning firms, we followed Griffith et al. (2006), Raffo et al. (2008) and Crespi and Zuniga (2012), as we estimated this model from the full sample, including both innovative (which invest in innovative activities) and non-innovative firms.

The model was defined under the assumption of the absence of feedback effects between equations. As a result, a selection bias arises among firms since only those that can invest in

[9] It is necessary to link innovative activity in developing countries with the reconversion efforts that firms face in response to the new conditions generated by openness and globalisation, where the organisational dimension is an essential activity (Jaramillo et al., 2000). It is possible to regard decisions to innovate as investment decisions with objectives focused on productivity and competitiveness. In the Frascatti Manual, the most common measure of input (R&D) has limitations as a measure of innovation effort, ignoring other relevant innovative activities. Kline and Rosemberg (1986) and Albornoz (2009) have discussed this in relation to the political implications of these methodological issues.
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innovation can also develop an innovation output and achieve higher levels of labour productivity. Hence, in the first stage, the empirical strategy consisted of modelling in the first stage, a selection equation that describes whether the firm invests in innovation or not jointly with an equation for the amount invested (reflecting the intensity of innovation efforts). The endogeneity problems associated with the inclusion of variables in different stages of the innovative process were addressed through the use of latent variables in the knowledge production equation (using predicted values of the innovation expenditure per employee) and productivity equation (using alternating, predicted values of product/process innovation, commercial/organisation innovation and the innovation category that combined both areas). Finally, considering the need to correct standard errors and the kind of variability that this data often reveals, we estimated each equation using robust standard errors in clusters that combined sector and size.

The decision to innovate and the intensity of innovation

The first phase of the innovative process was estimated with a generalised two-stage Tobit model (Tobit II), which combines two equations. The first one modelled the decision to innovate and the second one modelled the intensity of innovation. For firm i=1…n (n=3072, 2589); and period t=2010 and 2014, the equations were as follows:[10]

$$Inno_{it} = \{1 \; if \;\; Inno^{*}_{it} = X'_{it}\alpha_t + e_{it} > 0 \; 0 \; otherwise\} \qquad (1)$$

$$I\_exp_{it} = \{I\_exp^{*}_{it} = W'_{it}\beta_t + v_{it} \; if \; Inno_{it} = 1 \; 0 \; otherwise\}, \qquad (2)$$

[10] All equations included control variables of unobserved heterogeneity, described at the end of this section.

Where $Inno_{it}$ is the indicator vector that captures the decision of the firm i to engage in innovation activities. This dummy variable took a value of 1 if the firm reported innovation expenditures *(I_exp)* during the period *t* (see the variable description in Table A2), following Brown and Guzmán (2014), Mairesse and Mohnen (2010) and Raffo et al. (2008). *I_exp* is the intensity of the innovation expenditures, measured by (log of) the innovation expenditure per employee at constant values. As mentioned above, we referred to the expenses in all categories of innovation activities defined in the database (R&D, machinery and equipment expenditure for innovation and five other items).

To model the decision to innovate, we considered several determinants (included in vectors X and W) associated with both the firm and its environment. Crespi et al. (2016) organised these determinants into four groups.[11] The first group captures the internal capabilities of the firm. Related to productive, organisational or knowledge dimensions, capabilities are a central internal element both for innovation and assessing a firm's likelihood of overcoming obstacles (Arza & López, 2021). The variables included in this group were firm age, human capital, foreign capital composition and knowledge stock (associated with previous experience in conducting innovation processes).

- With Age, we aimed to capture the tacit knowledge accumulated from the experience itself and its impact on innovation plans, according to Arrow (1971). It was included as a dummy that indicated whether the firm was 10 years old or more.[12]

[11] Certain variables intervened both in the stages of innovation efforts and innovation output stages, as indicated in the following section.
[12] In this period (2014-2016), this condition was defined as 9 years or more.

- Human capital (*H_cap*) is intended to measure the degree of cognitive skills required to absorb new knowledge and develop new technologies (Acemoglu et al., 2006). To avoid potential endogeneity issues, we did not include the percentage of professional skills reported by firms. Instead, we computed the average percentage of firms with professional skills in the same sector and the same size as firm *i*.[13]

- Foreign capital refers to the condition of multinational firms that can be linked to higher levels of human capital and access to finance (Girma & Gorg, 2007). This indicator is especially relevant in the context of Argentina, as the concentration of the sector in multinational firms is inherited from the 1990s (Azpiazu, Manzanelli & Schorr, 2011). The dummy variable was *F_cap*, which took a value of 1 if the firm had a foreign capital composition).[14]

- With knowledge stock, defined by the condition of firms that had patents abroad (*Pat*), we seek to measure the capacity of firms to manage intellectual property, protect their innovations and obtain innovation outputs with a significant degree of novelty (Crespi et al., 2016).[15]

The second group of determinants considered the access to external knowledge as an important driver of innovation. It included the policy of cooperation with other firms and the variety of external sources of information:

[13] This strategy was equivalent for human capital, cooperation and access to financing variables, following Crespi and Zuniga (2012) and Crespi et al. (2016).

[14] We could argue that the variable considers an excessively low threshold to define whether the firm is integrated with foreign capital (1% of total capital). However, previous studies share this type of construction for other analyses on innovation data from Argentina (Lugones, Suárez & Gregorini, 2007; Arza & López, 2021)

[15] As patents stand both as a determinant of innovation efforts and an indicator of outputs – although, more frequently in developed countries - their presence may have generated an endogeneity bias due to their high correlation with innovation efforts. As in Crespi and Zuniga (2012), we assumed exogeneity, considering that bureaucratic processes for obtaining a patent are lengthy and it is likely that innovations patented by the firm are older than the coverage period of the ENDEI.

- The variable *Coop* is intended to capture the degree of cooperation with other firms for the purpose of innovation. In theory, firms that cooperate with others can share costs and internalise spillovers, boosting productivity and allowing for further innovation investments. Evidence reports positive effects of cooperation on productivity levels (Goya & Vayá-Valcarce, 2012). With the same strategy applied to human capital (see footnote 11) it measures the average share of firms that cooperate with others in the same sector and of the same size.
- Regarding the information used as an input for innovation, *S_info* indicated the variety of the external sources of information used by the firm. Considering suppliers, customers, competitors, institutions from the national system of innovation and alternative sources, it reports the share of sources employed over nine information channels. One of the most relevant conditions that affects innovation plans is that innovation is strongly demand-driven. We conceived the exporting condition of the firm as its exposure to international markets. As in Crespi et al. (2016), we expected that firms that reported exports fostered innovation efforts.

The final category to consider as a determinant of innovation links the financial dimension of the firm with the public policies designed to foster innovation and the likelihood to innovate. The rationale behind the inclusion of access to public support programmes for innovation (*P_sup)* is that they lead to additional innovation efforts and exclude any potential crowding-out effect with private financing (Mairesse & Mohnen, 2010). The literature considers this condition due to its potential relevance in underdeveloped economies (Brown & Guzmán, 2014; Petelski et al., 2017; Silva, 2009).[16]

We included other control variables as *Size* (measured by the natural logarithm of employment) as we considered various advantages of large firms, for example, economies of scale related to innovation, greater possibilities to diversify innovation expenditures and better appropriation of external knowledge spillovers (Crespi & Zúñiga, 2010). Vectors α and e represent the coefficients for X and the error vector, respectively.

The second equation defined the intensity of the innovation effort (I_exp_{it}), conditional on the firm engaging in innovation activities. In this case, W_{it}, β_t and v_{it} represent the covariates, the parameters and the error term, respectively, which jointly determine the latent variable $I\_exp_{it}*$ of innovation expenditure per employee. The underlying rationale is that, when deciding to increase innovation efforts, firms determine the amount to be invested in innovation activities. The first expression estimated the average marginal effects of different covariates on the probability to innovate, while the second equation estimated the effects of determinants on the expected value of innovation expenditure.[17] Our analysis featured a slight departure from the CDM model as we included the same set of control variables, except for *S_info* and *Size*. Implicitly, this indicated that size and variety of information sources can influence the decision to innovate but not the intensity of innovation efforts. This condition

[16] It is assumed that this kind of support has a strong impact on both the probability to innovate and the amount invested. Such high correlation may generate an upward bias on the effects of this factor if the observed variable is considered - whether the firm assessed public financial support or not - (Raffo et al., 2008: 236). Thus, the strategy was to measure *P_sup* using the percentage of firms of the same size and in the same sector to avoid potential endogeneity with the dependent variable (Tello, 2017).

[17] In the innovation intensity expression, while the expected value may be estimated both conditionally on reporting positive values (as an innovative firm) and non-conditionally, we adopted the latter, as this reflects the dependent variable prediction considering the innovative status of firms.

follows previous evidence from Crespi and Peirano (2007), Raffo et al. (2008) and Crespi and Zuniga (2012), among others.

Innovation results

The process to generate innovation results was modelled by an innovation production function for each firm i, which was estimated through a probit model with instrumental variables (equation no. 3):

$$IR_{ijt} = I\_exp_{it}^{*\prime}\,\gamma_{jt} + Z_{it}^{\prime}\delta_{jt} + \tau_{ijt}\ . \qquad (3)$$

This knowledge output equation models the innovation result j for firm i= 1…n; at the period t = (2010-2012) and (2014-2016). The index interval for j was composed of three categories of innovation results IR_j, expressed in three alternative equations with the following dependent variables: product and/or process, commercial and/or organisational and all types of innovation. We considered the category 'all innovations' to combine the different innovation outputs reported by firms, including both previous categories of innovation. In Argentina, innovation of products and process were not only independent but both appeared to correlate with the process of obtaining commercial and organisational innovations. From the ENDEI data, across the periods estimated, 97% of firms that declared innovations in commercial and/or organisational areas also declared to have innovated products/processes.

As can be seen, the main explanatory variable is the latent innovation expenditure I_exp^*, which was estimated using predicted values from the previous equation. Vectors Z and δ were incorporated as other covariates of interest with their respective coefficients and τ was included as the error term. Following Raffo et al. (2008) and Arza and López (2010), some internal variables concerning the firms were included, for example, exporter, foreign capital, age, human capital and size, considering the impact of these indicators alongside the innovation process.

Productivity impacts

To measure the impact of innovation on the productive performance of firms, we estimated a Cobb-Douglas function with constant returns to scale the output per employee (Eq. no. 4), which was estimated by least squares in two stages (2SLS):

$$L_{prod_{it}} = IR^{*}_{ijt}{}'\vartheta + T'_{it}\pi_t + s_i. \quad (4)$$

The dependent variable, labour productivity, was measured for each firm i, considering the period *t*=2012 and 2016 for both periods estimated. The production function included capital, human capital, labour and knowledge. The latter was represented by the three categories of innovation results, obtaining three alternative expressions, according to each of the *j* categories of innovations estimated by the knowledge production function. These were instrumented by the predicted likelihood of obtaining these innovations from the previous stage to avoid the effects of a circular relationship between the observed variables and the firm's higher level of productivity. Concerning capital per employee, since data for this variable were not available, it was replaced by a proxy, adapting the criteria followed by Crespi and Zuniga (2012) and Moncaut et al. (2017). Finally, human capital was included, as in Crespi, Tacsir and Vagas (2016), as well as size.

Sample definition and controls

The final samples that were the basis for the estimations consisted of 3072 and 2589 firms for the 2010-2012 and 2014-2016 periods, respectively. These subsamples were the result of a series of filters of outliers identified in the following variables: current income, value-added, innovation activities, innovation expenditure and declared workforce, and of harmonising variables that reported few differences between periods.[18] Likewise, to control these estimates for the unobserved variability at the sectoral level, we controlled the industrial dummy variables. Finally, all nominal information was deflated using an Argentinian producer price index - net of taxes - for each of the periods estimated, with a level of disaggregation adapted to that proposed by ENDEI.

IV. Descriptive Results

This section analyses the descriptive statistics for the firms included in each econometric analysis. Table 1 presents descriptive statistics for the variables included in our estimations, considering the first period as 2010-2012 and the second as 2014-2016. All results reported are related to subsets of each sample to harmonise certain differences between both surveys (see Table A2 and the variable definitions).

The data shows that the share of innovative firms grew between periods. While 60% of the firms reported innovation expenditures in the first period, this share rose to 70% in the second period. This is reflected in Table A3 (Annex) which indicates the increasing shares of firms that engaged in each kind of innovation activity (excepting technology transfers). In many of

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[18] Outliers on value-added and innovation activities were eliminated and firms which reported growth in real sales higher than 500% in the period were filtered, along with those that reported innovation expenditure to be higher than 50% of their sales and those that did not declare personnel.

these categories, the increase was significant. Additionally, the acquisition of machinery and equipment (43% of the firms invested in this activity in 2010 and 48% in 2014) and in-house R&D (23% and 29% of firms invested in this in 2010 and 2014, respectively) were the most frequent innovation activities among firms.

For innovation results, although the data indicate a rising share of firms that introduced innovations between the analysed periods, these indicators did not grow as significantly as the share of innovative firms. Firms that obtained product and/or process innovations accounted for 60% of the sample in the first period and 66% in the second period. In terms of commercial and/or organisational innovations, 30% and 36% of the firms registered these kinds of innovations, respectively.[19] Regarding firms' performance, less than 40% of firms registered exports in both periods (with a little decrease between the two periods). Additionally, for 6.3% of firms in the first period and 7.9% in the second, the patent indicator in both periods reflected a poor performance of Argentinian firms in obtaining intellectual property instruments.

One important aspect was the financial support system for innovation. The data indicated that 22% of the firms in 2010-2012 and 18% in 2014-2016 obtained financing from public institutions. This is higher than other studies for Argentina, yet methodological issues may have arisen in the comparison.[20,21]

[19] There are two reasons why innovation results reported statistics similar to those of innovation efforts in certain cases. The first one is that over 90% of the innovative firms obtained at least one innovative result. The other is related to the construction of the innovation results variables, which were constructed in the database for the entire periods (2010-2014), while the innovation expenditure only accounted for 2010 and 2014, respectively. See the variable definitions in Table A2.

[20] Raffo et al. (2008), Arza and López (2010) and Crespi, et al. (2016).

[21] The differences in firms' age may be related to the different construction of the variable (see the variable definition in Table A2).

Finally, the labour productivity reported by firms rose between the estimated periods. As is usual for Latin American countries, productivity measures reflected high dispersion (from the standard deviation measures and their comparison with respective means). However, this dispersion was not as high as that for innovation expenditures, reflecting that heterogeneity in the technological dimension was much stronger than in the productive one.

Table 1. Descriptive statistics

Periods	2010-2012				2014-2016			
Continuous variables	mean	sd	Min	Max	mean	sd	Min	Max
Innovation expenditure (1)	7.50	31.86	0.00	1246.29	19.71	56.09	0.00	866.17
Human capital (2)	6.37	3.53	1.76	21.57	8.06	3.54	2.54	19.79
Cooperation	33.48	11.84	8.33	78.57	39.01	12.04	15.15	75.00
Public support	22.09	11.29	5.80	72.73	17.90	8.95	2.63	44.12
Sources of information	25.73	27.85	0.00	100.00	24.90	25.64	0.00	100.00
Size	73.32	102.54	2.00	400.00	74.01	101.44	2.00	400.00
Labour productivity (1)	244.83	294.20	2.32	3454.99	476.66	614.65	2.81	8614.46
Capital (3)	35.30	148.00	0.00	3960.00	30.06	169.00	0.00	4890.00
Dummy variables (frequencies) (2)	2010-2012				2014-2016			
Innovative	60.1				70.1			
Exporter	38.4				32.8			
Foreign capital	7.9				5.3			
Patent	6.3				7.9			
Age	7.5				15.5			
Product/ process innovation	60.0				66.6			
Commercial/ organisational innovation	30.0				36.1			
All innovations	61.0				67.8			

Note: Estimation sample (2010-2012): 3072; (2014-2016): 2589. Descriptive statistics correspond to 2010 and 2014 for innovation expenditure, human capital and size, respectively. For labour productivity, reports are for 2012 and 2016. These measures are reported according to the variable definitions (except for innovation results that account for entire periods). See Table A1. Due to space constraints variables are expressed in scales: (1) in thousands of LCU; (2) in percentages; (3) in millions of LCU. See definitions of variables in Table 1. All data is not weighted

Source: own elaboration on ENDEI data.

V. Econometric Results

The results of the CDM model, estimated separately for 2010-2012 and 2014-2016, are discussed below.

The decision to innovate

Table 2 shows the econometric results for equations 1 & 2 and reports average marginal effects (AME) on the likelihood of investing in innovation and the expected innovation expenditure.[22] As expected, firms that exported increased their probabilities of engaging in innovation activities and also reported higher innovation expenditures. This result has been verified for both periods. Concerning the ownership nature of firms, this condition did not appear to influence innovative decisions, while it stands as a significant determinant of innovation expenditure in both periods.[23] Accessing public funding did not have a significant impact on the likelihood to innovate or the intensity of innovation in the period from 2010-2012. This is consistent with the findings of Crespi and Zuniga (2012) on Argentina. Yet, in 2014-2016, this indicator reflected a positive effect on the likelihood to innovate. Further research is required to assess whether this effect remains steady over time.

One important issue relates to firms that patented their innovations. The data report positive effects of patents both on the decision to innovate and on the intensity of innovation, which were significant in both periods but increased markedly for 2014-2016 in magnitude (also in

[22] Williams (2012) expressed the average marginal effects (AME) as a proper alternative when computing predicted values, particularly when the objective is to compare two hypothetical populations that differ in the specific values of the variable of interest and have the same values of the other independent variables in the model. As AME uses all of the data instead of just the mean values, a majority of authors prefer this method to measure impacts.

[23] Previous studies have reported mixed results. Raffo et al. (2008) did not find a significant effect over the decision to engage in R&D activities nor the intensity of innovation. However, significant and positive effects were reported by Crespi and Zuniga (2012).

statistical significance, as shown in the table). Yet, there are very few firms that have obtained patents in Argentina. One plausible interpretation indicates that the knowledge acquired by firms in the process of developing innovation outputs and patenting them represents a value-added for further innovation activities. Other determinants such as age, cooperation with other firms and human capital do not influence firms' innovation efforts. Conversely, those firms that diversified their information sources also increased their likelihood of investing in innovations. This result has been verified for the second period by Arza and López (2021). Finally, size appeared to modify the likelihood of innovating in the period from 2010-2012.

Table 2. Decision to invest in innovation and innovation intensity				
Periods	2010-2012		2014-2016	
Variables	Probability to invest in innovation (1)	Expected innovation expenditure (2)	Probability to invest in innovation (1)	Expected innovation expenditure (2)
Exporter (Exp)	0.044***	0.380***	0.043***	0.623***
	(0.016)	(0.145)	(0.015)	(0.152)
Foreign capital (F_cap)	0.040	0.826***	0.044*	0.829***
	(0.034)	(0.318)	(0.026)	(0.279)
Patent (Pat)	0.096**	0.876**	0.299***	2.968***
	(0.045)	(0.387)	(0.004)	(0.097)
Age	-0.016	-0.206	-0.009	-0.044
	(0.016)	(0.138)	(0.012)	(0.136)
Human capital (H_cap)	0.034	1.733	0.057	0.658
	(0.402)	(3.623)	(0.153)	(1.779)
Cooperation (Coop)	0.131	1.215	0.017	0.073
	(0.130)	(1.130)	(0.059)	(0.623)
Public support (Pub_s)	0.115	0.935	0.096**	0.354
	(0.086)	(0.789)	(0.045)	(0.476)
Sources of information (S_info	0.009***	-	0.049***	-
	(0.002)		(0.002)	
Size	0.030***	-	0.007	-
	(0.009)		(0.007)	
Sector dummies	Yes		Yes	
ln sigma	0.362***		0.384***	
	(0.003)		(0.000)	
athrho	-0.140*		-0.169***	
	(0.008)		(0.005)	
Log pseudo likelihood	-4,431.30		-3,658.65	
Rho	-0.139		-0.167	
Adjusted R2	0.480		0.746	
Consored observations	1325		764	
Uncensored observations	1747		1825	

Notes: *p<0.01, ** p<0.01, *** p<0.01. Reported estimates are (1) Average marginal effect on the probability to invest in innovation; (2) Average marginal effect on the unconditional expected value of innovation. Clustered standard errors in parentheses (at sector and size levels). Sector dummies (not reported) were included in the estimation.
Source: own elaboration on ENDEI data.

The innovation results

This section discusses the estimates of equation 3, corresponding to the knowledge production function. Table 3 shows the marginal effects on the likelihood of introducing innovations. In three alternative IV probit regressions, we considered the following categories of innovation outputs: product and/or process innovations, commercial and/or organisational innovations and a category that included all kinds of innovation results.[24]

Innovation expenditure is confirmed as a significant determinant of completing innovations, both in 2010-2012 and 2014-2016.[25] However, while the AME had the expected sign and were statistically different from zero, the magnitude of the reported effect was moderate in every category of innovation estimated, revealing a weak connection between innovation efforts and results. By doubling innovation expenditure per employee, the likelihood of innovating (for any innovation category) increased by less than 4%.

Across the different equations and periods, the exporting condition did not have any significant effect on the likelihood to introduce innovation outputs, except for the AME reported regarding commercial/organisational innovations. In these particular cases, it should be noted that the original probit coefficient was not significant (see Table A4 with IV probit coefficients), which is, in this case, a more relevant indicator in probit specifications, according to Williams (2016, 2017).[26]

The ownership nature of firms - conversely to the results reported in the previous section - influenced the likelihood of obtaining innovations in both periods estimated, considering

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[24] Both in innovation results and productivity equations, the instruments used to control endogeneity were tested, rejecting the null hypothesis of a weak instrument.

[25] As in previous studies for Argentina, we assume that all kinds of innovative activities exert an influence on innovation outputs. As in this study, in Crespi and Zuniga (2012) and Crespi, Tacsir and Vargas (2016) the innovation efforts are estimated by the aggregate innovation expenditure. In Arza and López (2010), innovation expenditures are classified according to certain activity categories, though they are all inserted in the knowledge production function.

[26] Williams (2016, 2017) and other authors in the Statalist forum stated that the differences that could arise between the original and the marginal effect coefficients in terms of statistical significance is related to the fact that they are the result of testing different hypotheses and the non-linearity of these models produces these seemingly ‘paradoxical’ results. The consensus is - when these differences are reported - to follow the sign and p-value of the original coefficients.

products/process and the category that combined all types of innovations. As in Crespi and Zuniga (2012), these effects imply that firms with foreign capital composition are less likely to develop innovation outputs than domestic enterprises.[27] One plausible explanation for this is that foreign firms in developing countries focus on achieving products or process innovations, leaving those tasks to their headquarters.

Of the remaining control variables, firms' age and human capital (skilled labour) did not significantly influence the likelihood of completing innovations. Finally, the size of the firm had a positive but limited effect on innovation outputs when they were broadly considered.

[27] As in the exporting condition, we followed the original probit coefficient for product/process innovation in the 2014-2016 period.

Table 3. Innovation results

Periods	2010-2012			2014-2016		
Variables	Product/ process innovation	Commercial/ organisational innovation	All innovations	Product/ process innovation	Commercial/ organisational innovation	All innovations
Predict (I_exp)	0.025***	0.019***	0.025***	0.027***	0.039***	0.023***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Exporter (Exp)	-0.003	-0.036***	-0.008	0.020*	0.024	0.013
	(0.012)	(0.012)	(0.011)	(0.012)	(0.020)	(0.009)
Foreign capital (F_cap)	-0.095***	-0.051*	-0.090***	-0.057*	0.033	-0.062**
	(0.023)	(0.027)	(0.026)	(0.030)	(0.033)	(0.026)
Age	0.009	-0.020	0.002	-0.001	0.018	0.003
	(0.014)	(0.019)	(0.013)	(0.013)	(0.024)	(0.010)
Human capital (H_cap)	-0.541*	-0.496	-0.316	-0.081	0.211	-0.042
	(0.302)	(0.343)	(0.291)	(0.145)	(0.320)	(0.147)
Size	-0.005	0.000	-0.004	0.006	0.014*	0.008**
	(0.007)	(0.008)	(0.007)	(0.004)	(0.008)	(0.004)
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudo likelihood	-8635.00	-9373.57	-8579.83	-6136.99	-6994.97	-6038.08
Wald-chi2	2621.58***	2050.14***	3293.27***	2668.35***	1709.42***	2543.65***
Wald (exogeneity)	354.06***	267.36***	364.4***	68.81***	52.23***	59.75***
Correct classification	93.33%	73.50%	94.01%	95.52%	69.49%	96.87%
Observations	3072	3072	3072	2589	2589	2589

Notes: *p<0.01, ** p<0.01, *** p<0.01. (1) Each column represents a different IV probit estimation, considering the innovation result categories (see data section). Reported estimates are average marginal effects on the probability to obtain innovation results. Clustered standard errors in parentheses (at sector and size levels). Sector dummies (not reported) were included in the estimation. Probit coefficients reported in Annex Table A3.
Source: own elaboration on ENDEI data.

The productivity impacts

Table 4 reports the estimates for the last stage of the CDM model (the impacts of innovation on labour productivity).

The impacts of innovation on firms' labour productivity in both periods appeared much stronger than the link between the first two stages of the innovation process. The data indicate that introducing innovations has a positive, significant and strong impact on the value-added per employee and this has been verified for every kind of innovation output.

Another issue is that, in the 2014-2016 period, the effects reported were more significant than in the previous period. The AME from 2010-2012 in product/process (commercial/organisational) innovations rose from 13% (31%) to 21% (58%) from 2014-2016. As expected, the combination of these categories indicates a growing effect. These semi-elasticity coefficients reveal that the achievement of any type of innovation significantly influenced the productive performance of firms.

The control variables associated with human capital and fixed investment did not significantly influence labour productivity. Conversely, as expected, they did positively affect productive performance across both periods. This indicates that larger firms achieve higher productivity levels. Additionally, to test the robustness of the measures, we estimated the impact of innovation expenditure on productivity and found a positive but limited impact, similar to its impact on innovation outputs. These estimates are not included in this study but are available upon a request made to the authors.

Table 4. Innovation impacts on labour productivity

Periods	2010-2012			2014-2016		
Variables	From product/ process innovation	From commercial/ organizational innovation	From all innovations	From product/ process innovation	From commercial/ organizational innovation	From all innovations
Predict (Pr_pr)	0.138***	-	-	0.199***	-	-
	(0.041)			(0.043)		
Predict (Com_org)	-	0.319***	-	-	0.562***	-
		(0.075)			(0.085)	
Predict (All_I)	-	-	0.130***	-	-	0.184***
			(0.041)			(0.041)
Capital (Cap)	0.002	0.001	0.002	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Human capital (H_cap)	1.212	1.169	1.194	1.494*	1.165	1.500*
	(1.008)	(1.017)	(1.006)	(0.852)	(0.905)	(0.855)
Size	0.106***	0.101***	0.106***	0.135***	0.114***	0.137***
	(0.018)	(0.019)	(0.018)	(0.020)	(0.021)	(0.020)
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes
F	15.39***	14.89***	15.18***	28.87***	33.73***	28.75***
Adjusted R2	0.065	0.039	0.062	0.095	0.0420	0.096
Endogeneity test	9.89***	12.09***	9.89***	8.19***	25.59***	6.77***
Heteroskedasticity test	61.73***	65.71***	62.76***	33.31***	24.88*	33.77**
Observations	3072	3072	3072	2589	2589	2589

Notes: *p<0.01, ** p<0.01, *** p<0.01. (1) Each columm represents a different IV regression, considering as alternative covariates the innovation result categories (see data section). Reported estimates are average marginal effects of innovation results on (log) labour productivity. Clustered standard errors in parentheses (at sector and size levels). Sector dummies (not reported) were included in the estimation.

Source: own elaboration on ENDEI data.

VI - Discussion and Conclusion

This study explored the innovation dynamics of manufacturing firms in Argentina, considering two periods where macroeconomic and sectoral conditions could potentially affect how these enterprises engaged in innovation plans, achieved certain results and promoted productivity. The main contribution of this research is the focus on the connection between innovation and productive performance during recent periods in Argentina. We applied the CDM model to Argentinian manufacturing firms using a novel database that combined the innovation variables with labour, productive, market, institutional and other relevant dimensions. We identified diverse shortcomings related to the first two stages of the process. In particular, we found a relative disconnection between the innovation efforts of manufacturing firms and innovation outputs they achieved, besides a lack of influence of certain microeconomic determinants that theoretically affect the decisions to innovate.

Regarding strengths, we observed a significant and positive link between every kind of innovation and firm productivity, including in idiosyncratic conditions associated with innovation processes. This connection has been verified across different innovation outputs.

Throughout innovation processes, the presence (absence) of certain conditions can foster (restrain) the underlying dynamics that connect innovative decisions with firms' productive performance. The exporting condition, in particular, significantly and positively influenced decisions to innovate and the intensity of innovations in both periods analysed. Yet, according to our findings, the exporter status does not affect the likelihood of achieving innovation outputs. While the complementarity between innovation efforts and the exporting condition has been documented in different contexts (Lugones, Suárez & Le Clech, 2007; Brambilla & Pacheco, 2018), the exact impact of this variable on innovation outputs remains unconfirmed.

The capital composition indicator also reported mixed results. On the one hand, firms with foreign capital did not show a greater likelihood to invest in innovation (yet, these findings indicate higher innovation expenditures for these firms on average). On the other hand, firms with foreign capital are associated with being less likely to achieve innovation results (particularly for product/process innovations or the category that combined all types of innovation outputs); these findings are consistent with Crespi and Zuniga (2012). Additionally, firms' size had few significant effects on the probability of investing (with a significant but reduced impact on the decision to innovate in 2010-2012 that decreased years after) and the likelihood of completing an innovation (for the composite innovation category and only for the period 2014-2016). Conversely, larger firms showed higher productivity than smaller ones and this has been verified in both estimated periods. Findings from Raffo et al. (2008) support this result for Argentina. As in the previous stages, size does not appear to foster innovation investment nor innovation outputs. Productive performance had a positive impact, likely the result of the existence of economies of scale.

One aspect that deserves attention is the changing nature of the impact of public funding on the likelihood to invest in innovation. From 2010-2012, public funding did not have any significant impact, for the recent period (2014-2016) the access to financing innovation projects is a plausible condition to promote these investments. Considering the relevance of this variable as an instrument of public policy for innovation, further in-depth analysis should focus on these issues. Along with the contributions, certain methodological limitations of this work should be stated. First, there may be additional potential sources of endogeneity that we did not contemplate. Furthermore, it is critical to incorporate other determinants into the analysis that are linked to the innovation capabilities of firms. Finally, future research should assess what conditions the structural heterogeneity of industry in Argentina may impose on the results using this type of measurement and how these influence innovative and productive dimensions across different periods.

VII - References

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Appendix

Table A1. Argentina's GDP per cápita anual growth between decades

1960	2.3%
1970	1.1%
1980	-2.3%
1990	2.8%
2000	2.4%
2010	-0.7%

Note: Constant LCU.

Source: WDI. The World Bank. Access: April 2021.

Table A2. Variable definitions

I_exp	*Innovation expenditure*	Innovation expenditure per worker at constant values in 2010 (2010-2012 estimation) or in 2014 (2014-2016 estimation). For this variable we include the categories of innovation activities defined in ENDEI data (in-house and external R&D, expenditure in machinery & equipment and hardware & software, technology transfer, design & engineering, consultancy, training). This expenditure is estimated for all the innovation outputs. We use natural logarithms of the variable in the regressions.
Pr(I_exp)	*Predict (I_exp)*	Predicted values for the variable *I_exp* when estimating equation (1)
Innov	*Innovative*	Innovative firm. Dummy equal to 1 if the firm invested in at least one kind of innovation in 2010 (for estimation 2010-2012) or in 2014 (estimation 2014-2016) .
Exp	*Exporter*	Dummy equal to 1 if the firm exports (in each estimation period).
F_cap	*Foreign capital*	Dummy equal to 1 if the firm has a foreign participation of 1 percent or above (in each estimation period).
Pat	*Patent*	Dummy equal to 1 if the firm has been granted with at least one patent (in each estimation period).
Age	*Age*	Dummy equals to 1 if the firm has 10 years old or more in the market (2010-2012 estimation). Due to changes in the variable coding in ENDEI data, for the estimation of 2014-2016 period, corresponds 9 years old or more.
H_cap	*Human capital (1)*	Percentage of workers with professional skills. Average of firms for the same sector and the same size categories (in each estimation period). We use this average ratio instead of including the share of professional skills reported by the firm to deal with potential endogeneity issues.
Coop	*Cooperation (1)*	Percentage of firms that cooperate with others for innovation activities, estimated for the same sector and the same size categories (in each estimation period). We use this average ratio instead of including the collaboration activities reported by the firm to deal with potential endogeneity issues.
Pub_s	*Public support (1)*	Percentage of firms that received public support programs for innovation, estimated for the same sector and the same size categories (in each estimation period). We use this average ratio instead of including the financial support status reported by the firm to deal with potential endogeneity issues.
S_info	*Sources of information (2)*	Percentage of external sources of information that the firm uses to develop its innovation activities. The survey includes nine alternative sources that represent 100 percent (suppliers/ customers; competitors/ other firms; consultants; public and/or private universities; public institutions of science and technology; Internet and industry forums; chambers and business associations; trade fairs, conferences, exhibitions, congresses; technical publications, catalogs, and academic journals).
Size	*Size (1)*	Firm size. Total employment in 2010 (estimation 2010-2012) or in 2014 (estimation 2014-2016). We use natural logarithms in the regressions.
Pr_pr	*Product/ process innovation*	Dummy equal to 1 if the firm reported that it introduced and/or significantly improved products and/or processs. Due to the construction of the variable in the database, this indicator accounts for innovation results over the entire periods (2010-2012 and 2014-2016).
Pr(Pr_pr)	*Predict (Pr_pr)*	Predicted values for the variable *Pr_pr* when estimating equation (2)
Com_org	*Commercial/ organisational innovation (3)*	Dummy equal to 1 if the firm reported that has introduced a new commercial channel and/or implemented signifficant organizational changes. This indicator accounts for innovation results over the entire periods (2010-2012 and 2014-2016).
Pr(Com_org)	*Predict (Com_org)*	Predicted values for the variable *Com_org* when estimating equation (2)
All_I	*All innovations*	Dummy equal to 1 if the firm reported that has introduced at least one innovation result (i.e. product/ process/ commercial/ organisational innovation). This indicator accounts for innovation results over the entire periods (2010-2012 and 2014-2016)
p_All_I	*Predict (All_I)*	Predicted values for the variable *All_I* when estimating equation (2)
L_prod	*Labour productivity*	Labour productivity. Value added per worker at constant values in 2012 (for estimation 2010-2012) or in 2016 (estimation 2014-2016). We use natural logarithms in the regressions.
Cap	*Capital (3)*	Fixed investment per worker at constant vaues. For 2010-2012 estimation we use investment in machinery and equipment per worker during 2010-2011. Due to data restrictions for 2014-2016 we use other noncurrent expenditures during 2014-2015. We replace 0 values with 0.00001 to avoid missing observations and we use natural logarithms in the regressions.

Note: definitions based on ENDEI data. (1) Definition adapted from Crespi, Tacsir and Vargas (2016); (2) adapted from Arza and López (2010); (3) adapted from Raffo, Lhuillery, and Miotti (2008).

Table A3. Innovation efforts by categories

Periods	2010-2012		2014-2016	
Innovation activities	Firms that reported innovation expenditures	Average share on total innovation expenditure (1)	Firms that reported innovation expenditures	Average share on total innovation expenditure
In-house R&D	0.229	39.79	0.293	41.12
External R&D	0.072	25.05	0.077	22.13
Machinery & equipment	0.428	74.59	0.479	71.70
Hardware & software	0.197	17.77	0.245	19.14
Technology transfer	0.032	28.73	0.029	17.65
Design & engineering	0.164	27.92	0.281	37.45
Consultancy	0.140	24.92	0.192	26.17
Training	0.147	10.23	0.155	10.72

Note: Estimation sample (2010-2012): 3072; (2014-2019): 2589. (1) Average shares should not be added.

Source: own elaboration on ENDEI data.

Table A4. Innovation results. IV probit coefficients

Periods	2010-2012			2014-2016		
Variables	Product/ process	Commercial/ organisational	All innovations	Product/ process	Commercial/ organisational	All innovations
Predict (I_exp)	0.363***	0.227***	0.372***	0.436***	0.246***	0.473***
	(0.008)	(0.006)	(0.009)	(0.011)	(0.007)	(0.012)
Exporter (Exp)	0.031	-0.086*	0.003	0.217	0.081	0.185
	(0.067)	(0.046)	(0.068)	(0.141)	(0.070)	(0.143)
Foreign capital (F_cap)	-0.465***	-0.159	-0.464***	-0.500**	0.118	-0.658***
	(0.129)	(0.115)	(0.146)	(0.226)	(0.125)	(0.211)
Age	0.025	-0.080	-0.012	-0.013	0.063	0.046
	(0.071)	(0.064)	(0.073)	(0.139)	(0.087)	(0.155)
Human capital (H_cap)	-2.593*	-1.496	-1.521	-0.886	0.740	-0.606
	(1.507)	(1.177)	(1.459)	(1.634)	(1.199)	(2.142)
Size	0.011	0.027	0.016	0.064	0.050*	0.116**
	(0.035)	(0.030)	(0.037)	(0.049)	(0.027)	(0.055)
Constant	-1.139***	-1.483***	-1.121***	-2.402***	-2.431***	-2.744***
	(0.152)	(0.124)	(0.147)	(0.276)	(0.169)	(0.300)
Obs.	3072	3072	3072	2589	2589	2589

Notes: *p<0.01, ** p<0.01, *** p<0.01. Reported estimates are probit coefficients for each innovation results equation. Clustered standard errors in parentheses (at sector and size levels). Sector dummies (not reported) were included in the estimation.
Source: own elaboration on ENDEI data.