Innovation, Employment, and Skills

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Technological innovation is expected to boost economic growth and have a sizable impact on employment. Nevertheless, economic and productivity growth can cast competing forces on labor demand with an ambiguous effect on employment which has been a major preoccupation in developing countries dealing with technical progress and trade liberalization. Furthermore, the impact on employment is likely to be mediated by the kind of innovation introduced. In this regard, the kind of shifts in employment that innovation brings matters for the definition of appropriate labor policies.

The objective of this work is to analyze the effect of innovation on labor demand, particularly, the level of employment and the skills composition of the labor force. Thus, we test whether innovation and its different types affect the demand for employment and for skilled labor.

The data for this study come from the Innovation Surveys for Uruguayan manufacturing firms over the 2000-2012 period.

Our preliminary results for ordinary least squares and instrumental variables and generalized method of moments show positive effects of innovation in the level of total employment and skilled workers. For the share of skilled labor in total employment the evidence is not clear cut, while employment and skilled labor growth seem to be affected positively by innovation. Product innovation exhibit the highest impact on employment but also productivity enhancing innovation has a beneficial effect on employment and skilled labor.

Keywords: Employment, Skilled Labor, Product Innovation, Process Innovation.

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1. Introduction

The fear of technological change conveyed by the spectrum of rising unemployment is a topic that can be easily tracked back to the first industrial revolution. Opposing the popular distress, most economists pondered the role of the compensating mechanisms triggered by technological change: increasing productivity raises the demand for new products and creates new jobs to replace the old (Vivarelli, 2014). But, are the new jobs better? And if they are, do their benefits reach all the displaced?

Technological innovation is expected to boost economic growth and to have a sizable impact on employment. Policy circles often expect growth to solve unemployment problems, but economic growth and productivity growth can cast competing forces acting on labor demand. Have innovation a dominating labor-saving impact, aggregate demand may suffer as a consequence of technological unemployment and reallocation of workers in low productivity jobs could jeopardize the productivity gains at the national level (Bogliacino, 2014). The employment intensity of growth is likely to be mediated by the kind of innovations introduced (Edquist et al., 2001). Neither economic growth always lead to more employment, nor productivity growth necessarily reduces it.

The kind of shifts in employment that innovation brings matters for the inequality debate and the definition of appropriate labor policies aimed at minimizing negative impacts of innovation and technological change. Increased inequality in developing countries has been associated with an increase in the skill premium prompted by globalization (Goldberg & Pavcnik, 2007). Employment has been a major preoccupation in developing countries dealing with technical progress and trade liberalization. These processes are often interlinked as trade liberalization increases competition forcing firms to incorporate technology to survive. Uruguay is not an exception. Trade liberalization during the 1990s was associated with increasing productivity, as firms responded to the reductions in trade barriers incorporating capital intensive technologies, but also significant job destruction and wage dispersion (Casacuberta et al. , 2004).

Uruguay provides an interesting framework to study the impact on innovation on employment and its composition for a small Latin American country. Moreover, we have a long span of data with the first years signed by the 2002 crises and the recession followed by the beginning of economic growth in the country till the last year of the sample (2012).

We aim at answering: which is the impact of innovation on employment?, does it affect differently skilled labor?, does productivity enhancing innovation has the same effects as product innovation? In this way, we contribute to the literature providing evidence for a small emerging country over a relative long time span.

We find evidence that innovation has a positive effect on the level of employment and the number of skilled workers, while the evidence for the share of skilled labor is mixed with OLS showing a positive effect but IV-GMM estimates are not significant. Further analysis is needed since innovation may affect proportionally employment and skilled workers.

2. Literature review

2.1. Theoretical aspects

Economic theory does not provide a clear prediction of the employment effect of innovation since the net result depends on; the type of innovation; and the interplay between displacement and compensation effects which at its time is mediated by market structure and institutional factors.

Consider firms that are observed through two or more consecutive periods. In the first period, firms can only produce one type of product (old products). Afterwards, firms have the choice to implement product innovation and introduce a second type of product (new products). For instance we have a production function where I indexes the firm and t the year. The parameter θ_{it} is the efficiency of the production process, K stands for capital and L for labor which can be further discriminated in skilled and unskilled labor.

$$Y_{it} = \theta_{it} F(K_{it}, L_{it})$$

In addition to the purposeful introduction of innovations there is a productivity trend that randomly increases the efficiency in the production process.

For a given level of outcome, the productivity trend and process innovations should reduce the demand for workers (displacement effect). The effect of product innovation on labor demand depends on the productivity difference between new and old products.

There is also a demand effect. Both the reduction of costs derived from process innovation and the introduction of new products may increase demand. Others things equal, higher output means higher demand for labor (compensation effect).

The net impact of innovation will depend on the relative strength of the displacement and compensation effects. Such impact can differ by type of innovation.

Suppose now that, in addition to the two types of products already presented, we can differentiate two types of labor: skilled and unskilled. The production of old and new products requires a combination of skilled and unskilled labor ($L_{it} = S_{it} + U_{it}$) that can be substitute or complementary with technology.

$$Y_{it} = \theta_{it} F(K_{it}, S_{it}, U_{it})$$

Changes in the technological parameter can have different effects according to the type of labor. Improving efficiency would still have a negative partial effect on overall labor demand for a given output, but it depends on the nature of the new technology how this is going to affect the demand for skilled and unskilled workers. If process innovation introduces skilled biased technology, the ratio of skilled to unskilled labor is expected to rise even though the impact on the absolute level of skilled labor utilized is ambiguous. For product innovation, the result may depend on the ratio of skill intensity required for old and new products.

Thus, the composition of the labor force can be altered by innovation.

The relationship between skills and technology may run in both directions. Innovators decide skill intensity of technological change. If skills are abundant, it makes sense to direct innovation towards the skilled. Hence, new technologies would be complementary to skills by design (Acemoglu, 1998). In countries where skills are not relatively abundant, it would make sense to substitute technology for skills provided that new technologies are locally produced and not imported from countries with higher skills endowment.

Moreover, increased demand for skills can be reflected on the skills premium and not in the number of workers. Due to the lack of data on wages we analyze only the impacts of innovation on the number of total workers and skilled workers (Kaplan and Verhoogen, 2004).

Summing up, productivity-enhancing innovations that improve efficiency in the production process are likely to reduce the demand for labor thereby displacing workers. Meanwhile, the introduction of new products that expands demand is expected to increase the demand for labor. Nevertheless, the relationship is not clear cut. The displacement effect of productivity-enhancing innovation can be offset by increasing demand (innovative firms get more sales and steal labor from their competitors). Also, when newer products are produced more efficiently, the replacement of the old product may result in labor reduction.

Increasing productivity while holding output constant would reduce the demand for labor; the opposite ensues when increasing sales for a given efficiency level. Productivity reduces employment per unit of output but output expansion –due to enhanced competitiveness- can overcomes this effect raising employment.

2.2. Empirical studies

Innovation can create or destroy employment depending on market structure, the type of innovation and the institutional setting. In general the introduction of new products is expected to increase employment due to an increase in demand for new goods. Nevertheless, if the innovator enjoys market power and increases prices, this may translate in a reduction of output and displacement of workers. Furthermore, new products can be designed in a way that also increases efficiency, and decreases the need of labor. Process innovation can also have an ambiguous effect on employment. Process innovation may lead to increase efficiency and lower prices. While increased efficiency may lead to contraction in the inputs used for a given level of output, a reduction in prices may lead to an increase in demand, with an expansion of the inputs needed in production. Usually, higher productivity and reduction of employment are expected as a result of process innovation. Nonetheless, as argued by Pianta (2006) if process innovation aside increasing efficiency also increases quality or decreases prices, then a rise in demand may follow with an increase in employment.

There is a group of studies on the links of innovation and employment. Nevertheless, the evidence on Latin America is scarce and results from developed countries cannot be extrapolated since innovation is mainly acquisition of knowledge from abroad (Elejalde et al., 2015).

Most studies on developed countries find a positive association between product innovation and employment but no consensus on process innovation (Lachenmaier & Rottmann, 2011). Some studies show that only product innovation generates new jobs in the sector, while process innovation generates job within the innovative firm at the expense of competitors (Greenan & Guellec, 2000). Moreover, while manufacturing is expected to receive the displacement of process innovation a positive employment impact is expected to dominate in the service sector.

Other studies in manufacturing and services in developed countries found a large increase in employment due to product innovation that more than compensates for the negative effect of process innovation (Harrison, Jaumandreu, Mairesse, & Peters, 2014). Nevertheless, contrary to theoretical expectations, for Germany, process innovation has a greater positive impact on employment than product innovation (Lachenmaier & Rottmann, 2011).

Goedhuys and Veugelers (2012) found that a large share of workers with secondary education is important for process innovation among Brazilian manufacturing firms, whilst product innovation is more skill intensive. In this particular context, product innovation appears as a more complex process requiring more knowledge and absorptive capacity than process innovation.

Studies for Latin American countries sometimes relate to the recurrent crises affecting the region. In a context of rising unemployment, innovative firms may be the better equipped to cope with the storm and preserve their working force. Indeed, innovation had a protective effect during the Argentinean crisis (Elejalde et al., 2015). The same study also concluded that product innovation creates jobs and is skilled biased, while process innovation has no effect either on skilled or unskilled jobs.

Crespi & Tacsir (2011) for Chile find that process and product innovations are important sources of employment growth at the firm level, while Benavente and Lauterbach (2008) find that product innovation increases employment and process innovation does not affect it.

Zuniga and Crespi (2013) found that Uruguayan firms that innovate generate more employment than firms that do not. The make only strategy has the largest impact. The buy only strategy has the lowest impact.

Other studies find that innovation does not lead to job losses and generates demand for qualified labor force (Aboal et al., 2011). Interviews show that process innovation is expected to have a negative impact on employment. These authors compare the make or make and buy strategy and find that the make and make or buy strategy tend to have a more positive effect on employment quantity and quality. Product innovation is complementary to labor, but process innovation displaces it.

There are some studies that analyze the level of employment and its composition (Autor, Katz and Krueger, (1998); Caroli and Van Reenen, (2001); Bresnahan, Brynjolfsson, and Hitt, (2002); and Greenan, (2003).

Other strand of the literature on developing countries has focused on skill-enhancing trade. Liberalization accelerates the flow of physical capital encouraging adaptation to skill-intensive technologies. Firms exporting to high income countries employ more skilled workers (Brambilla, Lederman, & Porto, 2012). Management is important to the success of both innovation and exporting. Skills needed to enter the exports market may differ from those required to succeed in them (Love & Roper, 2015).

The focus of this study is on the effect of innovation on labor demand. Our interest lies on the level of employment and the skill composition of the labor force. Both variables are measured at the firm level. The explanatory variable tested is innovation which is further discriminated in different types of innovations such as productivity-enhancing innovations and product innovation. Productivity-enhancing innovation is broader than the commonly used process innovation as it includes also organizational and commercialization innovation.

We expect the innovative strategies of Uruguayan firms to be dominated –not exclusively- by the adoption of technologies produced in developed countries. Such technologies are likely to be more skilled-biased than the locally developed ones (Acemoglu, 2003). Hence the adoption of new technologies may increase the relative demand of skilled workers.

Thus, we aim at answering: which is the impact of innovation on employment?, does it affect differently skilled labor?, does productivity enhancing innovation has the same effects as product innovation?

To answer these questions we use Ordinary Least Squares regressions and instrumental variables and generalized method of moments (GMM) to control for endogeneity.

3. Empirical Strategy

3.1. Data and Variables

The data for this study comes from the Innovation Activities Surveys (Encuestas de Actividades de Innovación en la Industria – EAII) collected by the National Bureau of Research and Innovation (Agencia Nacional de Investigación e Innovación – ANII). Surveys were delivered at three-year intervals. We have at our disposal the last five waves, corresponding to the years 2000, 2003, 2006, 2009, and 2012, even though information from the first wave – EAII 2000- is barely used in the following analysis due to data limitations and lack of compatibility in some important variables.

Information is collected through personal interviews that are compulsory for all the sampled firms. The questionnaire follows the guidelines of the Bogota Manual (Jaramillo, Lugones, & Salazar, 2001).

Surveys combine two inclusion criteria: (1) compulsory participation for big firms[1] until 60 percent of employment within the industry is covered –after such a quota is filled, some big firms may be exempt from the survey-; (2) representative random selection of small and medium firms stratified by industry. Two public firms and one mixed-capital firm were excluded from the analysis.[2] The remaining data contains information on 1,678 privately owned firms of whom 275 are observed throughout the full period. On the other hand, 517 firms are observed only once and therefore cannot be used for panel data analysis.

[1] Participation in EAII Surveys is mandatory for firms that either reported: (A) more than 50 employees in 2000, 2003, and 2006; or 100 employees from 2009 onwards; or (B) annual sales higher than: $U13 million (EAII2000); USD 1 million (EAII2003); $U25 million (EAII2006); $U120 million (EAII2009). Additionally, some activities are defined as mandatory inclusion regardless of size.

[2] The exclusion of ANCAP produces important changes in the composition of the sample, as it is by far the biggest firm in the universe.

3.1.1. Innovation Variables

The EAII Surveys provide binary information on whether firms have introduced or not four different types of innovation. Such types are product, process, organizational, and commercialization innovation. Product innovation implies putting in the market a new product or service whose characteristics or intended uses are either completely novel or significantly improved from previous version already offered. Process innovation is the implementation of new methods of production and can be directed to produce new goods or to increase the efficiency in producing those already existing. Organization innovation includes changes in management and administration, and may include changes that affect labor such as economic incentive systems, working groups, new ways of decision making. Finally, innovation in commercialization occurs when the firm introduces new ways of selling, delivering, or packing the products.

For the purpose of this study we differentiate between product and the other three types, which we referred to as productivity enhancing innovation based on the assumption that any of these should increase efficiency either in production or the distribution of the goods offered by the firm. Any of those forms of innovation should allow firms to provide more with the same resources because the output requires less input, workers produce more, or the consumers face less hassle to find the product.

This aggregation is not atypical. The original definition of process innovation given by Joseph Schumpeter already mentioned it: "the introduction of a new method of production or a new way of handling a commodity commercially" (Schumpeter, 1934).

Distinctions made, we can define the variables in two different ways. One is using dummies for every type of innovation, each one independent of the other. The second form is creating four mutually exclusive categories and then using the three binary variables representing three possible combinations: (1) when "only product" innovation was reported (product only), (2) when "product and other" form innovation was reported (product innovation), or (3) "any but product", when any form innovation was reported except for product (productivity enhancing innovations).

Statistical correlation between the types of innovation is high. Nevertheless, having four kinds of innovations is an asset of the data, since some previous studies have found that combining different types of innovation was crucial for exporting (Greenaway & Kneller, 2007).

3.1.2. Labor Variables

Skilled labor is defined as the sum of professionals and technicians. Workers in production activities are considered unskilled. The skills ratio is the ratio between skilled and total employment and also se define it as the ratio of skilled to unskilled workers within the firm.

Another measure of heterogeneity among the skilled workers tried is to distinguish between *literati* and *numerati* (see Bello-Pintado and Bianchi 2017). The first category includes professionals coming from the social sciences and the humanities, as well as lawyers and accountants.[3] The second is composed of professionals coming from natural and biological sciences, statistics, engineering.[4] The ratio between numerati and literati measures the balance within the workforce (Østergaard et al. , 2011).

Empirical models also include a set of control variables that basically relate to size and age of the firm; foreign ownership; industry dummies; and time dummies.

The size of the firm can be measured in terms of sales and categories of sales, in particular discriminating big firms, or medium and big firms. Some specifications include log of sales for the previous year is included in every model. In this first draft we report results with logarithm of sales as our proxy for size.

Foreign ownership is included as a dummy variable taking the value 1 whenever there is foreign capital participation in the firm and zero otherwise. It is a stylized fact that foreign-owned firms tend to be more intensive in knowledge and capital than domestic firms. Previous studies in Uruguay have shown that foreign-owned firms employ more skill labor both in absolute and relative terms, and the wage gap between skilled and skilled workers tend to be higher when compared with domestic firms (Peluffo, 2015).[5]

4.2. Econometric model

We analyze the level and the growth of total employment, skilled workers and the share of skilled workers in the labor force. First, we estimate the OLS as benchmark and then we use instrumental variable techniques in order to correct for endogeneity.

Endogeneity may be present due to omitted variables and measurement errors as a result of unobservable prices at the firm level. The omitted variable may arise due to productivity shocks included in the error term.

Our baseline equation takes the same form regardless of whether the dependent variable is total number of workers (L_{it}), number of skilled workers (SL_{it}), or the share of skilled workers in total employment in levels (SL_L_{it}) or growth rates (Y_{it}):

$$Y_{it} = \beta_0 + \beta_1 IN_{it} + \beta_2 X_{it}$$

Where i stands for firm, and t for time. IN indicates that the firm effectively innovated or the type of innovations undertaken.

The covariates included in X differ according to the various variants of the models that were tested. Basically, these include: size measured by the sales of the firm, or the rate of growth of sales, ownership of capital (foreign capital participation dummy); age of the firm, year

[3] *Literati* specifically includes: Social Sciences; Administration and Accountability; Notary and Legal Services; Humanities and others.

[4] *Numerati* specifically includes: Chemistry and Physics; Mathematics and Statistics; Natural Sciences; Medical Sciences; Architecture and Landscape Design; Software and Computer Engineering; Industrial and Public Engineering; Agricultural Sciences.

[5] At the international level, there are contrasting results on whether or not foreign ownership increases the wage gap. Studies on British firms acquired by US multinationals show reduced wage gap (Girma & Görg, 2007) while for Uruguay we find higher productivity in multinational firms but also a higher wage gap between skilled and unskilled wages.

dummies to control for macroeconomic shocks; and industry dummies to control for industry-specific effects.[6]

The presence of foreign capital indicates a certain degree of internationalization that distinguishes the firm from the nationally owned.

An important caveat to keep in mind is that we are overlooking price effects when considering the demand for skilled and unskilled workers. As the demand for a certain type of workers increases, it is likely that the price of such labor will also increase and so the demand for workers may have grown further had wages remained unchanged. This issue is in our research agenda.

4. Results

4.1. Descriptive statistics

Innovative firms are likely to be bigger in terms of sales and employees. They also tend to hire a higher proportion of skilled workers. This result verifies for developed as well as developing countries (Argentina, Chile and Uruguay).

In Table 1 to 5 we report some descriptive statistics.

In Table 1 we show the correlation between the various types of innovation. The higher correlations are among any type of innovation, productivity enhancing innovation and product innovation.

In Table 2 we present the share of firms that undertake innovations and the share by different types of innovations. Over the period 2000-2012 46 % of the firms undertake any type of innovations, with 33 % undertaking process innovations, 39 % productivity enhancing innovations and 31 % product and process innovation. Only 24 % undertake product innovations.

We can observe that innovators are bigger in terms of employment and sales, and hire a higher number of skilled workers. Moreover we discriminate for firms that introduce any type of innovation, product innovators and productivity enhancing innovations. It seems that introducing more than one type of innovation translates into a higher level of employment and skilled labor.

In Table 3 we present the rates of growth of employment, skilled labor and its share, growth in total sales and in sales of old and new products, and in labor productivity. We observe that innovators present a higher total employment growth, growth and share of skilled labor and rate of growth of total sales and sales of new products. Moreover, the rate of growth of labor productivity is higher for innovators than for non-innovators and the whole sample.

In Table 4 we present the growth in skilled and total employment. We observe that for the full sample the average number of skilled workers per firm is 9 with a growth rate of 0.1 %, while total employment grow at a rate of 16 % over the period. Nevertheless, for innovators the

[6] Greenaway and Kneller (2007) show that the potential learning from exports effect is lower for industries already exposed to high level of international competition and high intensity of R&D.

number of skilled workers is higher (14 skilled workers per firm) with a higher growth rate (18 %) which is also in line with the growth in total employment (19 %).

In Table 5 we also present the rate of growth in the share of skilled labor in total employment, the growth in total sales and in labor productivity defined roughly as sales over total employment.

4.2. Econometric results

4.2.1. Ordinary Least Squares Regressions

First we present the models estimated with Ordinary Least Squares techniques. Since it is highly likely that our innovation variables, and in particular product innovation was endogenous they are just a benchmark.

In Table 6 we present the results for OLS estimation for total number of workers per firm. We consider these results as conditional correlations and not as causal relations. Innovators have a higher number of workers. In column 1 and 2 we observe that when we introduce controls for size the magnitude of the innovation variable falls. We find that the different types of innovation have a positive and significant effect, except for process only innovation and model 5 where we test only product and only process innovation. Moreover, there is some evidence (model 6) that undertaking more than one type of innovation may act as complements to create employment.

In Table 7 we present the results for the OLS estimation when the dependent variable is skilled workers. We find similar results to those obtained for total employment. Innovators tend to hire a higher number of skilled workers. Productivity enhancing, product innovation, product only, process only and undertaking both types of innovations show positive associations with skilled labor. Product innovation only exhibits a higher coefficient than process innovation only.

Finally, in Table 8 we present the results for the share of skilled workers in total employment. Similarly to our previous results we find again that innovators have a positive association with the share of skilled workers with a higher coefficient for product innovation. Moreover product innovation only is positive and significant while process innovation only is not significant.

Age, foreign capital and size have a positive and significant effect for both total employment and skilled labor. Nevertheless, age and size have a negative effect on the share of skilled labor in total employment, implying that smaller and younger firms tend to have a higher share of skilled labor.

Regarding to the rate of growth, for the pooled sample over the period there was an increase of nearly 16 % in total employment. We should note that our sample starts in the recession period and ends with the highest growth of economic growth for the Uruguayan economy. In Table 9 we present the results. We find positive effects of any innovation, product innovation, product innovation only, enhancing innovation, and undertaking both types of innovations on employment growth. Furthermore, big firms have a positive and significant association, while old firms have a negative and significant link, so older firms tend to grow less. Process and Productivity Enhancing Innovations seem not to have an impact on employment growth.

In Table 10 we present the results for the rate of growth of skilled workers. We find positive and significant effects of any type of innovation, product innovation, product innovation only, productivity enhancing innovations, and undertaking both product and process innovation.

Finally in Table 11 we present the results for the growth of the share of skilled labor in total employment. We find positive effects of any type of innovation, product and process innovation and productivity enhancing innovations on the growth of the share of skilled labor.

In what follows we address the issue of endogeneity using instrumental variables techniques.

4.2.2. Instrumental Variable Estimation

Firstly, we analyze the variables in levels. We run instrumental variables with fixed effects and standard errors clustered by firm.

The instrument is a dummy that takes the value of one if the firm has received public funding. This instrument has been used successfully in several applied works. We assume that product innovation is endogenous and process innovation is exogenous. Since any type of innovation includes product innovation we treat it as endogenous.

The validity of the instrument relies in the correlation between the instruments and endogenous variables in the first stage regressions. Moreover we always analyze the test of under-identification proposed by Kleibergen-Paap and of weak identification supports that our instrument is good.

In Table 12 we present the models for total employment. We find that any type of innovation is significant only if we do not control for firm size. Once we control for size the impact of innovation reduces slightly. Product, process, product only, productivity enhancing and both types of innovations seems to have a positive impact on the employment level.

In Table 13 we present the results for the number of skilled workers. Except for the model 4 that is suspected as not identified all the other five models behave well according to the tests of identification and weak identification. We find that any type of innovation, product innovation, product only and process only, productivity enhancing and both types of innovations performed simultaneously translate into higher levels of skilled workers. Product only followed by product innovation show the highest coefficients.

In Table 14 we present the results for the share of skilled workers in total employment. We find positive and significant effects of product only and process only innovations as well as of productivity enhancing innovations and of undertaking both types (product and process) simultaneously. All the models seems to be well specified according to the tests.

In Table 15 we find positive effects of any type of innovation, product and product only innovations, productivity enhancing innovations and undertaking simultaneously both process and product innovation on total employment growth.

In Table 16, we find positive effects on growth in the number of skilled workers of any type of innovation, product innovation, process only, productivity enhancing innovations and undertaking simultaneously both product and process innovations.

Finally, in Table 17 we present the impact of innovations on the growth of the share of skilled labor. We do not find any significant effect of innovations, while there is a positive and significant effect of growth in total sales, age and foreign capital.

5. Concluding remarks

Our preliminary results indicate some evidence that innovation has a positive effect on the level and the rate of growth of employment and skilled labor. Product innovation seems to be the type of innovation with a higher impact on the level of total employment and skilled workers. Moreover there is also some evidence that undertaking productivity enhancing innovation, and more than one type of innovation is beneficial for employment, skill composition and the rate of growth in total employment and skilled labor. Product innovation seems to have a positive impact in particular on skilled labor, with the highest impact among the various types of innovations. On the other hand the share of skilled labor on total employment does not seem to be affected by current innovation. It shows a not significant effect for all the specifications by IV-GMM with fixed effects by firm. Thus, further analysis is needed since if employment and skilled labor increased proportionally this is to be expected. In our agenda remains also to analyze the ratio of skilled to unskilled labor and of illuminati and numerati.

We should note that these results are preliminary and further analysis is needed not only in performing some robustness checks regarding the instrumental variable estimation, as well as estimating dynamic models. Also we keep in mind the importance of analyzing wages, since increases in demand of labor may translate in higher wages. Though in the Innovation Surveys wages is lacking these analysis may be complemented with information from the Economic Surveys, so we will be able to analyze the impact on wages and also to estimate TFP and introduce it as a control variable.

Though acknowledging that there remains work to do, we can say in few words that innovation is not detrimental to labor but all the opposite, while inequality issues remain to be analyzed.

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Table 1: Correlation between different types of innovation

	Innovation	Product Inn.	Enhancing Inn.	Prod Only	Process Only
Innovation (any)	1				
Product Inn.	0.6351	1			
Enhancing Inn.	0.903	0.5146	1		
Prod. Only	0.2273	0.3579	-0.1637	1	
Process Only	0.3362	-0.1703	0.3724	-0.061	1

Table 2: Share of firms undertaking innovation activities (period 2000-2012)

Variable	Obs	Mean	Std. Dev.	Min	Max
Innovation(any type)	4150	0.4629	0.4987	0	1
Product Innovation	3390	0.2445	0.4299	0	1
Process Innovation	3390	0.3327	0.4713	0	1
Product Innovation Only	4176	0.0333	0.1794	0	1
Process Innovation Only	4176	0.0670	0.2501	0	1
Organizational Innovation	3385	0.1894	0.3919	0	1
Commercialization Innovation	3385	0.1188	0.3236	0	1
Enhancing Productivity Innovation	3390	0.3935	0.4886	0	1
Product and Process Innovation	4176	0.3144	0.4643	0	1

Notes: Own elaboration based on surveys information provided by ANII.

Table 3: Some features by innovation status and type

	Sales	Workers	Skilled (SL)	Share SL
Non-innovators				
Mean	10.2108	52	5	0.1685
sd	45.4311	99	12	0.6009
No. Obs.	1883	1883	1883	1882
Innovators				
Mean	31.9100	121	14	0.2581
sd	85.8161	205	21	0.6674
No. Obs.	1502	1502	1502	1502
Product Innovation Only				
Mean	19.5886	95	12	0.2538
sd	38.7027	124	16	0.5939
No. Obs.	134	134	134	134
Productivity Inn.				
Mean	33.3647	125	14	0.2617
sd	89.6831	212	22	0.6819
No. Obs.	1334	1334	1334	1334
Non-innovators	Sales	Workers	Skilled (SL)	Share SL
Mean	10.2108	52	5	0.1685
sd	45.4311	99	12	0.6009
No. Obs.	1883	1883	1883	1882
Innovators				
Mean	31.9100	121	14	0.2581
sd	85.8161	205	21	0.6674
No. Obs.	1502	1502	1502	1502
Product Innovation Only				
Mean	19.5886	95	12	0.2538
sd	38.7027	124	16	0.5939
No. Obs.	134	134	134	134
Productivity Inn.				
Mean	33.3647	125	14	0.2617
sd	89.6831	212	22	0.6819
No. Obs.	1334	1334	1334	1334
Total				
Mean	19.8392	83	9	0.2083
sd	67.3103	159	17	0.6327
No. Obs.	3385	3385	3385	3384

Notes: Own elaboration based on surveys information provided by ANII.

Table 4: Some characteristics of employment by innovation status

Whole Sample	Mean	Median	sd	min	max
Number of Skilled	8.802954	3	17.3703	0	279
Growth in Skilled	0.001615	-0.3182	1.4495	-1	14
Growth in total emp	0.155649	0.0909	0.6376	-0.9944	11.492
Innovators					
Number of Skilled	13.751	8	21.15598	0	279
Growth in Skilled	0.1826	-0.1639	1.5193	-1	14
Growth in total emp	0.1970	0.1364	0.4599	-0.9714	7.5938
Non-innovators					
Number of Skilled	4.8561	1	12.26527	0	228
Growth in Skilled	-0.2035	-0.55	1.3379	-1	12
Growth in total emp	0.1203	0.0423	0.7556	-0.994	11.492

Notes: Own elaboration based on surveys provided by the ANII

Table 5: Growth in employment by innovation status

	Growth in Employment	Growth in SL	Growth in the share of SL	Growth in total sales	Growth in Labor Productivity
Non-innovators					
Mean	0.1197	-0.2047	-0.2106	0.5114	0.4898
sd	0.7538	1.3373	1.3039	2.2114	2.2704
Min	-0.9944	-1	-1	-0.9999	-0.9999
Max	11.4921	12	11.66667	54.19729	56.597
Innovators					
Mean	0.1970	0.1826	0.0925	2.3511	1.7481
sd	0.4599	1.5193	1.5861	51.7622	38.4570
Min	-0.9714	-1	-1	-0.9367	-0.9497
Max	7.5938	14	17.10667	1528.11	1134.249
Total					
Mean	0.1552	0.0009	-0.0496	1.3575	1.0685
sd	0.6368	1.4493	1.4679	35.1423	26.1331
Min	-0.9944	-1	-1	-1.0000	-0.9999
Max	11.4921	14	17.1067	1528.11	1134.249

Notes: Own elaboration based on surveys information provided by ANII.

Table 6: Effects of innovation on total employment (in number of workers), OLS

VARIABLES	(1) Employment	(2) Employment	(3) Employment	(4) Employment	(5) Employment	(6) Employment
Innovation dummy	0.712***	0.186***				
	(0.0463)	(0.0319)				
Product Innov.			0.171***			
			(0.0338)			
Process Only innov.			0.0580		0.00859	
			(0.0446)		(0.0423)	
Product Only innov.				0.179***	0.0869	
				(0.0620)	(0.0588)	
Enhancing Innov.				0.194***		
				(0.0328)		
Prod. & Proc innov						0.183***
						(0.0325)
Age	0.0141***	0.00455***	0.00454***	0.00455***	0.00461***	0.00451***
	(0.00138)	(0.000940)	(0.000954)	(0.000940)	(0.000969)	(0.000942)
Foreign Capital	0.830***	-0.0198	-0.0205	-0.0209	-0.0232	-0.0215
	(0.0840)	(0.0663)	(0.0664)	(0.0662)	(0.0672)	(0.0661)
Ln Sales		0.476***	0.483***	0.475***	0.493***	0.477***
		(0.0160)	(0.0158)	(0.0160)	(0.0157)	(0.0160)
Constant	3.076***	-1.324***	-1.359***	-1.320***	-1.410***	-1.320***
	(0.0639)	(0.155)	(0.155)	(0.155)	(0.156)	(0.156)
Observations	3,384	3,381	3,381	3,381	3,381	3,381
R-squared	0.308	0.683	0.682	0.684	0.679	0.683
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effects of innovation on the number of skilled worker, OLS

VARIABLES	(1) Skilled	(2) Skilled	(3) Skilled	(4) Skilled	(5) Skilled	(6) Skilled
Innovation dummy	0.746***	0.429***				
	(0.0400)	(0.0357)				
Product Innov.			0.424***			
			(0.0407)			
Process Only innov.			0.109*		-0.0143	
			(0.0564)		(0.0555)	
Product Only innov.				0.412***	0.201***	
				(0.0697)	(0.0676)	
Enhancing Innov.				0.436***		
				(0.0369)		
Prod. & Proc innov						0.413***
						(0.0371)
Age	0.00939***	0.00365***	0.00361***	0.00364***	0.00378***	0.00356***
	(0.00118)	(0.000987)	(0.00102)	(0.000987)	(0.00106)	(0.00101)
Foreign Capital	0.926***	0.412***	0.412***	0.410***	0.405***	0.408***
	(0.0781)	(0.0669)	(0.0669)	(0.0669)	(0.0685)	(0.0667)
Ln Sales		0.288***	0.303***	0.288***	0.327***	0.291***
		(0.0151)	(0.0151)	(0.0151)	(0.0155)	(0.0151)
Constant	0.361***	-2.305***	-2.381***	-2.301***	-2.509***	-2.301***
	(0.0477)	(0.145)	(0.147)	(0.145)	(0.152)	(0.145)
Observations	3,384	3,381	3,381	3,381	3,381	3,381
R-squared	0.376	0.534	0.527	0.535	0.506	0.531
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 8: Effects of innovation on the share of skilled labor, OLS

VARIABLES	(1) sh_sl	(2) sh_sl	(3) sh_sl	(4) sh_sl	(5) sh_sl	(6) sh_sl
Innovation dummy	0.0338***	0.0350***				
	(0.00538)	(0.00551)				
Product Innov.			0.0347***			
			(0.00670)			
Process Only innov.			0.00345		-0.00702	
			(0.00730)		(0.00721)	
Product Only innov.				0.0266**	0.00886	
				(0.0117)	(0.0116)	
Enhancing Innov.				0.0354***		
				(0.00566)		
Prod. & Proc innov						0.0307***
						(0.00570)
Age	-0.0004***	-0.0004**	-0.0003**	-0.0003**	-0.0003**	-0.0003**
	(0.000125)	(0.000136)	(0.000137)	(0.000136)	(0.000137)	(0.000138)
Foreign Capital	0.0453***	0.0471***	0.0473***	0.0468***	0.0466***	0.0467***
	(0.0120)	(0.0116)	(0.0116)	(0.0116)	(0.0115)	(0.0116)
Ln Sales		-0.00101	0.000353	-0.000984	0.00231	-0.000491
		(0.00201)	(0.00199)	(0.00200)	(0.00195)	(0.00203)
Constant	0.0349***	0.0440**	0.0370*	0.0440**	0.0262	0.0428**
	(0.00541)	(0.0193)	(0.0193)	(0.0193)	(0.0192)	(0.0196)
Observations	3,384	3,381	3,381	3,381	3,381	3,381
R-squared	0.199	0.199	0.196	0.199	0.188	0.196
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 9: Effects of innovation on growth of total employment, OLS

VARIABLES	(1) Emp Growth	(2) Emp Growth	(3) Emp Growth	(4) Emp Growth	(5) Emp Growth	(6) Emp Growth
Innovation dummy	0.129***	0.0458**				
	(0.0205)	(0.0210)				
Product Innov.			0.0370*			
			(0.0217)			
Process Only innov.			0.0277		0.0188	
			(0.0255)		(0.0239)	
Product Only innov.				0.0810**	0.0627*	
				(0.0354)	(0.0335)	
Enhancing Innov.				0.0403*		
				(0.0216)		
Prod. & Proc innov						0.0482**
						(0.0203)
Age	-0.00013	-0.0012***	-0.0012***	-0.0013***	-0.0012***	-0.0012***
	(0.000425)	(0.000432)	(0.000432)	(0.000432)	(0.000433)	(0.000431)
Foreign Capital	-0.0134	-0.129***	-0.131***	-0.128***	-0.129***	-0.129***
	(0.0313)	(0.0349)	(0.0349)	(0.0349)	(0.0349)	(0.0349)
Ln Sales		0.0722***	0.0741***	0.0724***	0.0756***	0.0721***
		(0.0107)	(0.0105)	(0.0107)	(0.0101)	(0.0108)
Constant	0.0887**	-0.613***	-0.624***	-0.613***	-0.634***	-0.610***
	(0.0353)	(0.114)	(0.113)	(0.114)	(0.111)	(0.115)
Observations	1,895	1,895	1,895	1,895	1,895	1,895
R-squared	0.053	0.115	0.114	0.115	0.113	0.115
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 10: Effects of innovation on growth of skilled labor, OLS

VARIABLES	(1) gsl	(2) gsl	(3) gsl	(4) gsl	(5) gsl	(6) gsl
Innovation dummy	0.198***	0.159***				
	(0.0484)	(0.0517)				
Product Innov.			0.0924*			
			(0.0532)			
Process Only innov.			0.0714		0.0485	
			(0.0732)		(0.0689)	
Product Only innov.				0.273***	0.197*	
				(0.103)	(0.102)	
Enhancing Innov.				0.141***		
				(0.0531)		
Prod. & Proc innov						0.126**
						(0.0499)
Age	-7.78e-05	-0.000727	-0.000718	-0.000750	-0.000695	-0.000742
	(0.000838)	(0.000864)	(0.000875)	(0.000860)	(0.000871)	(0.000872)
Foreign Capital	0.00940	-0.0583	-0.0664	-0.0563	-0.0621	-0.0614
	(0.0494)	(0.0518)	(0.0524)	(0.0518)	(0.0522)	(0.0519)
Ln Sales		0.0501***	0.0585***	0.0509***	0.0617***	0.0533***
		(0.0153)	(0.0148)	(0.0151)	(0.0143)	(0.0151)
Constant	0.273***	-0.254	-0.296*	-0.258	-0.314*	-0.263
	(0.0674)	(0.164)	(0.163)	(0.164)	(0.161)	(0.164)
Observations	1,242	1,242	1,242	1,242	1,242	1,242
R-squared	0.076	0.083	0.078	0.084	0.078	0.080
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 11: Effects of innovation on growth of the share of skilled labor in total employment, Ordinary Least Squares

(Without logs)

VARIABLES	(1) gshsl	(2) gshsl	(3) gshsl	(4) gshsl	(5) gshsl	(6) gshsl
Innovation dummy	0.312***	0.251**				
	(0.0943)	(0.101)				
Product Innov.			0.217*			
			(0.127)			
Process Only innov.			0.0210		-0.0447	
			(0.121)		(0.118)	
Product Only innov.				0.386	0.243	
				(0.276)	(0.274)	
Enhancing Innov.				0.247**		
				(0.102)		
Prod. & Proc innov						0.137
						(0.102)
Age	0.00215	0.00127	0.00123	0.00123	0.00132	0.00130
	(0.00202)	(0.00195)	(0.00195)	(0.00193)	(0.00194)	(0.00196)
Foreign Capital	-0.0637	-0.153	-0.159	-0.151	-0.155	-0.160
	(0.0845)	(0.0977)	(0.0977)	(0.0982)	(0.0972)	(0.0976)
Ln Sales		0.0635*	0.0773**	0.0628*	0.0874***	0.0752**
		(0.0350)	(0.0345)	(0.0349)	(0.0334)	(0.0358)
Constant	0.361**	-0.292	-0.373	-0.283	-0.438	-0.355
	(0.165)	(0.413)	(0.413)	(0.414)	(0.411)	(0.420)
Observations	1,420	1,420	1,420	1,420	1,420	1,420
R-squared	0.033	0.036	0.034	0.037	0.033	0.033
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 12: Instrumental Variable Estimation, fixed effects, dependent variable total employment

VARIABLES	(1) lnpo	(2) lnpo	(3) lnpo	(4) lnpo	(5) lnpo	(6) lnpo
Innovation dummy	0.470***	0.348***				
	(0.0945)	(0.0774)				
Product Innov.			0.803***			
			(0.262)			
Process Only innov.			0.274***		0.594	
			(0.0869)		(1.137)	
Product Only innov.				2.195**	12.20	
				(0.934)	(24.41)	
Enhancing Innov.				0.340***		
				(0.127)		
Prod. & Proc innov						0.397***
						(0.0932)
Age	0.0233	-0.00821	-0.0159	-0.0154	-0.0572	-0.00824
	(0.0647)	(0.0576)	(0.0646)	(0.0576)	(0.124)	(0.0485)
Foreign Capital	0.0221	-0.0172	0.0165	0.0522	0.451	-0.00480
	(0.0862)	(0.0711)	(0.0895)	(0.103)	(1.049)	(0.0732)
Ln Sales		0.236***	0.216***	0.226***	0.177	0.231***
		(0.0321)	(0.0334)	(0.0345)	(0.165)	(0.0319)
Observations	2,991	2,990	2,990	2,990	2,990	2,990
Number of id	1,096	1,096	1,096	1,096	1,096	1,096
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 13: Instrumental Variable Estimation, fixed effects, dependent variable skilled workers

VARIABLES	(1) lnsl	(2) lnsl	(3) lnsl	(4) lnsl	(5) lnsl	(6) lnsl
Innovation dummy	0.529***	0.488***				
	(0.136)	(0.139)				
Product Innov.			1.090**			
			(0.434)			
Process Only innov.			0.406***		0.840	
			(0.141)		(1.557)	
Product Only innov.				2.070*	16.55	
				(1.217)	(33.45)	
Enhancing Innov.				0.482***		
				(0.165)		
Prod. & Proc innov						0.557***
						(0.165)
Age	-0.0229	-0.0337	-0.0443	-0.0398	-0.100	-0.0337
	(0.0700)	(0.0741)	(0.0900)	(0.0740)	(0.175)	(0.0772)
Foreign Capital	0.0962	0.0769	0.120	0.132	0.711	0.0944
	(0.109)	(0.107)	(0.121)	(0.129)	(1.431)	(0.109)
Ln Sales		0.0792***	0.0523	0.0710**	-0.000483	0.0727***
		(0.0282)	(0.0323)	(0.0310)	(0.224)	(0.0282)
Observations	2,991	2,990	2,990	2,990	2,990	2,990
Number of id	1,096	1,096	1,096	1,096	1,096	1,096
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 14: Instrumental Variable Estimation, fixed effects, dependent variable skilled workers (without logs)

VARIABLES	(1) sh_sl	(2) sh_sl	(3) sh_sl	(4) sh_sl	(5) sh_sl	(6) sh_sl
Innovation dummy	0.0204	0.0247				
	(0.0180)	(0.0180)				
Product Inn.			0.0532			
			(0.0454)			
Process Only			0.0215		0.0427	
			(0.0152)		(0.0818)	
Product Only				0.0296	0.809	
				(0.128)	(1.756)	
Enhancing Inn.				0.0247		
				(0.0176)		
Prod & Proc. Inn.						0.0282
						(0.0207)
Age	-0.00672	-0.00566	-0.00618	-0.00567	-0.00891	-0.00566
	(0.0127)	(0.0124)	(0.0124)	(0.0124)	(0.0154)	(0.0126)
Foreign Capital	-0.00722	-0.00646	-0.00444	-0.00683	0.0244	-0.00558
	(0.00897)	(0.00920)	(0.00996)	(0.0106)	(0.0746)	(0.00929)
Ln Sales		-0.0081*	-0.00942*	-0.00813*	-0.012	-0.0085*
		(0.00466)	(0.00519)	(0.00477)	(0.0126)	(0.00475)
Observations	2,991	2,990	2,990	2,990	2,990	2,990
R-squared	0.008	0.011	-0.016	0.011	-2.883	0.007
Number of id	1,096	1,096	1,096	1,096	1,096	1,096
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 15: Instrumental Variable Estimation, fixed effects dependent variable growth in total employment

VARIABLES	(1) glnpo	(2) glnpo	(3) glnpo	(4) glnpo	(5) glnpo	(6) glnpo
Innovation dummy	0.304***	0.229**				
	(0.112)	(0.0956)				
Product Innov.			0.556**			
			(0.256)			
Process Only innov.			0.123		-0.539	
			(0.0813)		(1.349)	
Product Only innov.				1.934*	-11.37	
				(1.108)	(30.69)	
Enhancing Innov.				0.297*		
				(0.176)		
Prod. & Proc innov						0.265**
						(0.111)
Age	-0.0260***	-0.0301***	-0.0248**	-0.0324**	0.00280	-0.0280***
	(0.00956)	(0.00962)	(0.0115)	(0.0133)	(0.120)	(0.00985)
Foreign Capital	0.0329	0.0188	0.0510	0.115	-0.591	0.0289
	(0.110)	(0.103)	(0.113)	(0.151)	(1.632)	(0.104)
Ln Sales		0.152***	0.147***	0.136**	0.270	0.152***
		(0.0485)	(0.0478)	(0.0536)	(0.308)	(0.0484)
Observations	1,247	1,247	1,247	1,247	1,247	1,247
Number of id	448	448	448	448	448	448
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 16: Instrumental Variable Estimation, dependent variable growth in skilled workers, fixed effects

VARIABLES	(1) glsl	(2) glsl	(3) glsl	(4) glsl	(5) glsl	(6) glsl
Innovation dummy	0.637**	0.626**				
	(0.290)	(0.296)				
Product Innov.			1.245*			
			(0.718)			
Process Only innov.			0.448*		-0.804	
			(0.253)		(1.746)	
Product Only innov.				3.191	-16.83	
				(2.242)	(35.28)	
Enhancing Innov.				0.751*		
				(0.442)		
Prod. & Proc innov						0.711**
						(0.348)
Age	-0.0413	-0.0428	-0.0286	-0.0484	0.0248	-0.0372
	(0.0264)	(0.0268)	(0.0327)	(0.0319)	(0.209)	(0.0283)
Foreign Capital	0.133	0.128	0.189	0.307	-1.006	0.157
	(0.189)	(0.188)	(0.206)	(0.297)	(2.312)	(0.192)
Ln Sales		0.0332	0.0209	-0.00966	0.332	0.0395
		(0.0782)	(0.0786)	(0.107)	(0.591)	(0.0766)
Observations	928	928	928	928	928	928
Number of id	347	347	347	347	347	347
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

Table 17: Instrumental Variable Estimation, dependent variable growth in the share of skilled workers in total employment, fixed effects by firm

VARIABLES	(1) gsh_sl	(2) gsh_sl	(3) gsh_sl	(4) gsh_sl	(5) gsh_sl	(6) gsh_sl
Innovation dummy	0.307	0.385				
	(0.550)	(0.536)				
Product Innov.			0.773			
			(1.209)			
Process Only innov.			0.323		-0.602	
			(0.413)		(2.181)	
Product Only innov.				0.584	-14.58	
				(3.422)	(47.19)	
Enhancing Innov.				0.383		
				(0.638)		
Prod. & Proc innov						0.441
						(0.618)
Age	-0.0463	-0.0376	-0.0292	-0.0361	-0.00636	-0.0349
	(0.0486)	(0.0505)	(0.0587)	(0.0502)	(0.173)	(0.0527)
Foreign Capital	-0.132	-0.115	-0.0842	-0.105	-0.984	-0.0974
	(0.238)	(0.242)	(0.266)	(0.338)	(2.698)	(0.250)
Ln Sales		-0.201	-0.209	-0.204	0.120	-0.197
		(0.199)	(0.204)	(0.211)	(1.024)	(0.200)
Observations	1,019	1,019	1,019	1,019	1,019	1,019
R-squared	0.006	0.009	-0.007	0.008	-3.282	0.002
Number of id	383	383	383	383	383	383
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parenthesis, observations clustered by firm, *** p<0.01, ** p<0.05, * p<0.1