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# Employment Generation, Firm Size and Innovation: Microeconometric Evidence from Argentina[1]

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**Abstract**

This paper provides evidence about the relationship between innovation and employment in Argentina. In particular, it quantifies the impact of different types of innovations (process or product innovations) on employment growth and skill composition (skilled-unskilled labor) and the impact of different innovation strategies (buy or make) on employment growth, and analyzes whether these impacts depend on firm size or technology intensity. To answer these questions a model proposed in Harrison, Jaumandreu, Mairesse, and Peters (2008) was estimated using an IV approach with data from the Innovation Surveys for Argentina for the period 1998-2001. The results suggest that product innovations have a positive impact on employment growth while process innovations have no significant impact on employment growth. In addition, there is some evidence that product innovations are skill-biased, and that a mixed innovative strategy of make and buy has a larger impact on employment growth than a buy-only strategy. Finally, similar impacts for small firms but differential impacts for low-tech and high-tech sectors were found.

**JEL Classification:** D2, J23, L1, O31, O33.
**Keywords:** Innovation, employment.

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## 1. Introduction

The effect of innovation on employment is not straightforward; innovation can create or destroy employment depending on market structure, institutional setting, and the type of innovation that the firm introduces. In general, the introduction of a new or significantly improved product increases employment via an increase in demand. However, if after the innovation the innovator enjoys market power, it can set prices that maximize its profits but imply a reduction in output. It can also be the case that new products replace old ones or are designed in such a way as to reduce costs. Therefore, the net effect of a product innovation could be a contraction in employment. The effect of process innovation can also be ambiguous. The development (or adoption) of process innovations leads to greater efficiency of production, with savings in labor and/or capital, and with a potential for price reductions. The usual outcome is higher productivity and loss of employment. However, if process innovations increase quality or reduce prices, a rise in demand may result in employment creation (Pianta, 2006).

Harrison, Jaumandreu, Mairesse, and Peters (2008) (henceforth HJMP) pose a model to study the relationship between employment growth and innovation, distinguishing between process and product innovations. Estimating the model using manufacturing and services data from France, Germany, Spain, and the United Kingdom, they show that the increase in employment due to product innovations is large enough to compensate for the negative effect of process innovations. The results are similar across countries, although some interesting differences emerge. For example, they find no evidence for a displacement effect of process innovation in Spanish manufacturing. Hall, Lotti, and Mairesse (2006) estimate the model for Italy and find similar results as HJMP. Innovation not only affects the number of employees but also the composition of employment. Indeed, innovation might change the skill composition (Autor, Katz, and Krueger, 1998; Caroli and Van Reenen, 2001; Bresnahan, Brynjolfsson, and Hitt, 2002; and Greenan, 2003) and the composition of employment according to the duration of the labor contracts (Giuliodori and Stucchi, 2010).

Evidence on the relationship between innovation and employment in Latin America is scarce. The available evidence comes from Benavente and Lauterbach (2008), who estimated the model presented in HJMP using data from Chile. They found that while product innovations increase employment, process innovations do not affect it. Further research is needed not only because there is evidence only for one country but also because the idiosyncratic nature of innovation in Latin America raises doubts about the possibility of extrapolating the evidence from European countries to Latin America. Many Latin American firms invest in innovation. Nonetheless, their financial commitment amounts to a mere 0.5 percent of gross revenue compared to 2 percent for countries in the Organization for Economic Co-operation and Development (OECD). Firms in the region spend most of their innovation dollars on assimilating technology in new equipment and machinery, while developed countries invest primarily in research and development (IDB, 2010). In addition, technological change in developed countries might respond to different objectives, incentives, and factor endowments as well as go in different directions from technological change in developing countries. So, it is not only that Latin American firms produce different types of innovations but also that the nature of the innovation process is different. As a consequence, the effects of innovation on employment growth in Latin America can be different. Furthermore, the Latin American market structure is dominated by small firms, and the innovation process in small firms shows different characteristics from that of large firms. Another reason to expect a different effect of innovation on employment in Latin America is differences in the mix of goods produced even within similar industries. If the mix of goods produced in Latin America is different from the mix produced in developed economies, the impact of innovation on employment might be different.

The aim of this paper is to provide evidence about the relationship between innovation and employment in Argentina. Specifically, we intend to answer the following research questions: (i) Do different types of innovations create or destroy employment in Argentina? In particular we will focus on the differential effect of *product and process innovations* on employment growth. ii) Does the impact of innovation vary according to firm size? iii) Does the impact of innovation vary between high- and low-tech industries? iv) Do different types of innovation affect the skill composition? and (v) Do different innovation strategies influence the capacity of innovation to generate or destroy employment? We will consider two types of innovation strategies: *make* (in-house developed innovation) and *buy* (externally acquired innovation). To answer these questions we use data from Innovation Surveys for Argentina for the period 1998-2001.

Argentina provides an interesting opportunity to estimate the effects of innovation on employment growth in a highly recessive scenario. The period 1998-2001 coincides with one of the deepest recessions in Argentine history. The gross domestic product (GDP) fell 8.4 percent between 1998 and 2001 (a negative average growth rate of 2.9 percent per year). Unemployment rose from 13.2 percent in May 1998 to 18.3 percent in October 2001. Investment plunged at an average annual rate of 12 percent. The manufacturing sector showed a significant contraction; the index of manufacturing activity fell 22 percent between 1998 and 2001. The innovation survey we use in the analysis shows a contraction in employment of 8 percent between 1998 and 2001, with small firms showing a larger contraction. Interestingly, the reduction in employment was different between innovators and non-innovators. The reduction in employment was 7 percent between those firms that reported process or product innovations and 13 percent in firms that do not introduced any innovation.[5]

From a policy perspective, understanding the relationship between innovation and employment is crucial. First, Argentina—like the rest of the Latin American economies—faces a low productivity problem that is needs attention. Policies that distort the size distribution of firms—including some employment policies—negatively affect productivity and therefore the growth rate of the economy (Pages, 2010; Guner, Ventura, and Yi, 2007). Interestingly, this is not the case of innovation policies; it is widely accepted that innovation is one of the main drivers of productivity growth. Therefore, if in addition to an indirect effect on employment—through productivity improvements and increased growth rates—innovation has a direct impact on employment, innovation policies become more attractive for policy makers. Second, the impact of innovation on skill composition can justify the implementation of compensation policies. For example, if innovation destroys mainly unskilled jobs, this would suggest the need for training programs for displaced workers. Finally, the analysis of the impact of innovation on employment by firm size and by innovation strategy would provide evidence for improving the design of innovation policies.

## 2. Innovation and Employment in Argentina

Aimed at increasing efficiency, a series of market-oriented reforms were applied in the early 1990s. These reforms included tariff reductions, market deregulation, and the privatization of public enterprises. In addition, the exchange rate was fixed to the dollar through a currency board in 1991. From 1990 to 1998, the economy grew at an annual rate of 6.3 percent. In 1995, the

[5] The statistics on employment growth are weighted means of firm employment growth for the period 1998-2001. These statistics differ from statistics reported in Table 4 because the latter are simple means of annual growth rates.

economy entered a recession due to the “Tequila crisis” and unemployment rose to 18.8 percent. The economy recovered and grew in 1996 and 1997. In 1998, the economy entered into another deep recession. Fiscal policy became inconsistent with the currency board and, after one of the most severe political and economic crises in Argentine history, Argentina defaulted on its debt and the Argentine peso was devalued in 2002. From 1998 to 2002, GDP contracted 18.3 percent. After 2002, the economy recovered and growth resumed. Since 2003, the economy has been growing approximately 7 percent a year. Unemployment fell from 23.6 percent in 2002 to 8.3 percent in 2010. However, inflation became a concern. To restrain inflation, the government applied heterodox policies that included price controls and quotas.

The post-2003 recovery also included improvements in labor productivity. Annual labor productivity growth changed from negative during the 1990s and early 2000s to positive, reaching 4 percent after 2005. The high growth rates after 2003 and the increase in labor productivity were facilitated by favorable external conditions such as improvements in the terms of trade and an expansion in international demand.

With respect to the long-run determinants of productivity, there was a considerable increase in innovation expenditures. The ratio of innovation activities to GDP in 2007 was 0.61 percent; during the 1990s this ratio had been 0.50 percent. The same applies for the ratio of research and development (R&D) to GDP. The ratio of business enterprise expenditure in R&D (BERD) to GDP increased slightly, from 0.12 percent in 1995 to 0.14 percent in 2008. Therefore, the increase in public R&D expenditures was the most important contributor to the increase in total R&D expenditure. The share of the labor force with tertiary education also rose steadily; it was 23 percent in 1995, 27 percent in 2000, and 33 percent in 2009. Table 1 summarizes the evolution of the most relevant variables for our analysis.

**Table 1: Evolution of Main Variables in Relation to Employment and Innovation**

| Indicator | 1995 | 2000 | 2005 | 2009 |
|---|---|---|---|---|
| GDP per capita (US$ PPP) | 7,839 | 9,112 | 10,819 | 14,538 |
| GDP growth (*between periods, in percentage*) | - | 13.6 | 10.4 | 26.9 |
| GDP growth (*average annual growth between periods in percentage*) | - | 2.6 | 2.0 | 6.1 |
| Labor productivity growth (*growth between period averages, in percentage*) | - | -1.0 | -2.9 | 17.1 |
| Labor productivity growth (*average annual growth between periods in percentage*) | - | -0.2 | -0.6 | 4.0 |
| Share of the population in the labor force (*in percentage*) | 41.4 | 45.1 | 46.2 | 46.1 |
| Share of tertiary educated as a proportion of the labor force (*in percentage*) | 23.0 | 27.2 | 31.0 | 33.4 |
| Unemployment (*in percentage of the labor force*) | 16.6 | 14.7 | 11.1 | 9.1 |
| Unemployment of the tertiary educated | 2.9 | 2.7 | 2.7 | 2.2 |
| Innovation expenditures/GDP (*in percentage*) | 0.50[(a)] | 0.50 | 0.53 | 0.61[(b)] |
| R&D/GDP (*in percentage*) | 0.42[(a)] | 0.44 | 0.46 | 0.52[(b)] |
| BERD/GDP (*in percentage*) | 0.12[(a)] | 0.11 | 0.15 | 0.14[(b)] |

*Source:* Authors' calculations with information from World Development Indicators 2010, INDEC, and Ministerio de Ciencia, Tecnología e Innovación Productiva.
*Notes:* Labor productivity was computed as GDP (2000 USD) divided by employment, Tertiary education includes individuals with university and tertiary (1 to 3-years degrees related to technical professions) studies, and BERD denotes Business enterprise expenditure on R&D. (a) Datum corresponding to 1997, (b) Datum corresponding to 2008.

The agency in charge of employment and training policies in Argentina is the Ministry of Labor, Employment, and Social Security. At the regional level, each province has its own Ministry of Labor, which administers employment and training policies. In terms of science and technology policies, the agency in charge is the Ministry of Science, Technology, and Productive Innovation (MINCYT). The promotion of scientific activities and firm innovation is the responsibility of the National Agency of Scientific and Technologic Promotion (*Agencia Nacional de Promoción Científica y Tecnológica*) a MINCYT agency. Other public agencies executing innovation and technology policies are the *Consejo Nacional de Investigaciones Científicas y Tecnológicas* (CONICET), national universities, and other public agencies specializing in agriculture (INTA), the manufacturing sector (INTI), and the fishing sector (INIDEP). At the regional level, provinces have Science and Technology Councils.

**Table2: Innovation and Employment Policies**

| Dimension | Responsible agencies | Level of influence | Interactions and consultation mechanisms with other considered dimensions (4 point scale [a]) | Private-public partnerships. Participation of the private sector (4 point scale[a]) | Policy assessment mechanisms (4 point scale[b]) |
|---|---|---|---|---|---|
| Innovation | Ministry of Science and Technology | National | 2 | 2 | 2 |
| Employment policies (emphasis on R&D, skilled employment) | Ministry of Labor, Employment, and Social Security | National | 2 | 1 | 2 |
| Higher education (universities, vocational education) | Ministry of Education | National | 2 | 2 | 2 |
| Training policies (on the job, lifelong learning, etc.) | Ministry of Labor, Employment, and Social Security | National | 2 | 2 | 2 |

*Source:* Authors elaboration based on key informant interviews.
*Notes*: (a) Scale: 1: Non-existent; 2: Low; 3: High; 4: Very high. (b) Scale: 1: Non-existent, 2: Some assessment (non compulsory) exist; 3: Assessments are inherent part but the results are not necessary taken into account in the (re)design of the program; 4: Assessments are made and results imply redesign/abandon of programs.

Coordination among the different ministries involved in science, technology, and innovation policy is the responsibility of GACTEC (*Gabinete Científico Tecnológico*). The interaction between innovation and employment policies is limited. The participation of the private sector in the policy dialogue is limited. (Table 2)

Historically, there has been no formal mechanism of policy assessment. Some innovation policies have been evaluated by the Inter-American Development Bank and independent researchers. Binelli and Maffioli (2007) evaluated the innovation support program FONTAR. They found evidence of its effectiveness in increasing R&D expenditures. López, Reynoso, and Rossi (2010) also evaluated FONTAR and found similar results. Cerdán-Infantes, Maffioli, and Ubfal (2008) evaluated the impact of the provision of agricultural extension services to grape producers in Mendoza, Argentina, on yield and grape quality. Castillo et al. (2010) evaluated the effects of a small and medium enterprise support program on employment, wages, and the probability of exporting. Recently, the Ministry of Labor, Employment, and Social Security has begun an evaluation of the impact of training and employment programs. These formal policy evaluations are expected to influence the design of future programs.

Interviews of representatives of firms, trade associations, and academics also confirmed what Pagés (2010) found for Latin America; i.e., innovation does not come from research and development but rather from the acquisition of new machine or licenses.

Interviews were conducted on firms of different sizes and technological intensities and from different sectors. The firms included in the survey were a multinational firm which manufactures mobile, fixed, and other telecommunication devices; a small pasta producer; a multinational consulting company; and a firm which provides customs services, accounting, tax administration, and other service to other firms in the same group.

Table 3 shows a summary of the interviews. We found some common perceptions among firms. For example, firms perceive that product innovations have a positive effect on employment while process innovations have a negative effect on employment, and that innovations tend to destroy unskilled jobs and create skilled jobs. The representatives interviewed also expressed a variety of concerns about innovation. Issues of concern to small manufacturing firms include rigidities in the labor market and restricted access to credit markets, while high-tech firms pointed to the mismatch between the skills of the labor force and the specific needs of the firm. Such concerns hint at the presence of heterogeneous effects of innovation on employment depending on size and technological intensity, an issue that we consider in the quantitative part of the paper.

The interviews also aimed at testing the implications of HJMP. The main implications were confirmed; the officials interviewed pointed out that the importance of distinguishing the effects of process and product innovation, and most of them agreed that product innovations create jobs because they tend to lead to an expansion of the firm's operations. In the case of process innovation, however, they stressed the importance of the time dimension. In the short run, process innovation might destroy jobs, as the model suggests. However, it creates jobs in the long run. Those interviewed indicated that process innovations, in general, aim to increase productivity and in so doing facilitate growth.

In terms of labor regulations, the interviews revealed that firm size matters. Only small firms identified labor regulations as an obstacle to employing workers. Small firms also complain about restricted access to credit markets. The main obstacle for employment creation according to both small and some large firms are unpredictability in regulations and high uncertainty about future regulations, inflation, and labor-management conflicts. Firms claimed that an unfavorable investment climate created a new relationship between innovation and employment. Accordingly, they introduced capital-intensive production processes that are only profitable after discounting the high uncertainty about future regulatory changes and future labor problems.

The officials interviewed also mentioned the lack of consistency in public policies as an obstacle to job creation. On the one hand, productive development policies (innovation, credit, and cluster policies) aim at supporting the growth of firms. However, trade policy imposes restrictions to import some capital goods.

In spite of the obstacles that currently might be affecting investment and job creation, there are factors that under other conditions would promote innovation. Firms pointed out that the introduction of new processes required more highly skilled workers, and it was not difficult to find those workers because the pool of skilled workers is large.

**Table 3: Summary of Interviews**

| Firm Characteristics | | | Interview Summary |
|---|---|---|---|
| Sector | Size | Technology | |
| Manufacturing, Telecommunications and technology | Large | High | • Labor market conditions: Regulations are not a barrier for hiring, but the firm subcontracts workers because it is less expensive. New workers need to be trained workers for at least a year.<br>• Innovation activity: Product innovations are more frequent; process and organizational innovations are marginal. The firm follows mostly a buy innovation strategy.<br>• Innovation and employment: Process innovations tend to destroy employment while product innovations do not affect employment.<br>• Innovation and skill composition: Process innovations tend to destroy less skilled jobs and jobs held by younger workers and those over 45. |
| Manufacturing, Food | Small | Low | • Labor market conditions: The firm prefers to hire temporary workers to avoid steep hiring costs and the likelihood of labor suits.<br>• Innovation activity: Mainly product innovations but some process innovations associated with new products. Lack of credit is the main obstacle to innovation.<br>• Innovation and employment: The effect of product innovation on employment is positive.<br>• Innovation and skill composition: When innovation destroys jobs, less skilled and temporary workers are fired. |
| Services, Strategy Consulting | Large | High | • Labor market conditions: Complaints about high labor costs, rigidity in labor regulations, social conflict, and uncertainty about future regulations. On the other hand, there is a large pool of qualified workers.<br>• Innovation activity: Mainly product innovations.<br>• Innovation and employment: Product innovations create new jobs.<br>• Skill-biased in innovation: Innovations tend to destroy unskilled jobs and generate higher skilled jobs. |
| Services, Business Administration | Large | High | • Labor market conditions: Labor market is flexible and unionization is low in the service sector.<br>• Innovation activity: It introduced an important organizational change innovation based on centralization and automation of processes.<br>• Innovation and employment: This innovation destroyed and created new jobs. No net effect on employment in the short run but positive effect in the long run.<br>• Skill-biased in innovation: Innovations tends to displace less qualified, younger workers and workers over 40. |

*Source:* Authors' elaboration based on key informant interviews.

**Table 4: Challenges, Strengths and Actions in Relation to Innovation, Employment Creation, and the Upgrading of Labor Force Skills**

| Dimension | Main challenges faced by the country | Challenges at the institutional/policy dimension | Main strengths | Actions taken/ to be taken |
|---|---|---|---|---|
| **Innovation** | Low R&D intensity | Low coordination between innovation support policy and other national public policies | High level of human capital | Instruments supporting innovation (specifically for small firms) in place. |
| | Small firms have restricted access to credit or they have access to expensive credit. | | | Instruments supporting small firms in place. |
| **Employment creation** | Weak job creation. Firms substitute labor using labor saving alternatives (even if in the short run is more expensive) | (i) Uncertainty about future public policies and regulations, (ii) High infltion, (iii) High level of conflict with employees | | Tax credits if firms do not destroy employment. |
| **Upgrading of the labor force skills** | Lack of qualified workers is some sectors (e.g. telecommunications and technology) | | High level of human capital | Several agencies offering training courses |

*Source:* Authors elaboration based on key informant interviews.

## 3. Empirical Framework

HJMP show that in order to untangle the employment displacement vs. creation effect of innovation, the distinction between product and process innovation is useful. These authors proposed a model with two types of products: existing products ($Y_1$) and new products ($Y_2$). The change in employment is then decomposed into the part due to the increased efficiency in production of old products (which could be related to process innovations) and the part due to the introduction of new products. The basic estimating equation is given by

$$l = \alpha_0 + \alpha_1 d + g_1 + \beta g_2 + v, \text{(1)}$$

where $l$ is total employment growth, $g_1$ is the nominal growth in sales of old products, $g_2$ is the nominal growth in sales of new products (product innovations) and $d$ captures the introduction of process innovations in the production of old products. In general it can be expected that process innovations displace employment ($\alpha_1 < 0$) and product innovations create employment ($\beta > 0$). The parameter $\beta$ also captures the relative efficiency in the production of old and new products: when $\beta < 1$ ($\beta > 1$) new products are produced more (less) efficiently than old products. The constant in equation (1) represents (minus) the average efficiency growth in the production of old products (for firms that have not introduced any product or process innovation).

We observe employment and total sales in 1998 and 2001 and firms report if they introduced product or process innovations between those years. This is important because it provides us with information before and after the innovation. Moreover, in 2001 it is possible to know the percentage of sales corresponding to new products. This information is crucial to estimate equation (1).

The period we analyze is a period of employment contraction due to the recession that started in 1998. If the recession affected different industries in different ways, the effect of the recession in each industry can be isolated by including industry dummies in equation (1).

The type of innovation can differ considerably by technological intensity. Therefore, the effect of innovation on employment can also differ by technological intensity. In addition, labor market regulations can have different effects depending on firm size. Large firms can circumvent labor rigidities by outsourcing part of their work, while this is more difficult for small firms. This heterogeneity can have relevant policy implications, and therefore it is important to pay attention to it. We study the heterogeneity of the impact of innovation on employment by size estimating equation (1) separately for small firms and low- and high-tech sectors.

A concern about the identification of the coefficients in equation (1) is the fact that innovation can be correlated with the error term. Therefore, OLS will produce inconsistent estimates. The possible endogeneity of innovation comes from the fact that productivity is omitted from equation (1) and it can be correlated with innovation. This is the case because innovations are the result of investment decisions, such as R&D, and those decisions depend on the firm's productivity.[6] Then, if productivity is in the error term because it is an omitted variable, the error term will be correlated with innovation, leading to the endogeneity problem.

Productivity can be thought of as an unobservable of two components: a firm's attributes that are mainly time invariant, such as managerial skills or organizational capital, and

[6] If we think in the production function of innovations, innovation can also be correlated to productivity if for the same amount of innovation inputs more productive firms obtain more innovations.

productivity shocks, which might lead the firm to reduce labor costs. Equation (1) is specified as a growth equation and the influence of the time invariant part of productivity is removed from the error term. Therefore, the remaining source of correlation between innovation outputs and productivity are the productivity shocks. The correlation between innovation outputs and productivity shocks depends on the timing of the innovation investment decisions and the presence of serial correlation in the productivity shocks. If investment decisions are taken in advance and the productivity shocks are uncorrelated, innovation variables in equation (1) will not be correlated with the error term, and equation (1) can be estimated by OLS. If, on the other hand, investment decisions are made at the same time as the productivity shocks are observed or the productivity shocks are correlated, innovation outputs might become endogenous in equation (1).

A possible source of contemporaneous correlation between innovation and productivity shocks is the relationship between these variables and the business cycle. If both innovation and productivity are related to the business cycle as some literature has found—see, for example, Barlevy (2007) for innovation and Basu and Fernald (2001) for productivity—then endogeneity is a valid concern. To avoid this source of correlation, we include a set of industry dummies in the growth equation (1). A set of industry dummies in equation (1) is equivalent to the interaction between industry dummies and a 2001 dummy in a level equation. Therefore, these variables will capture the business cycle effect.

There are good reasons to think that process innovation can in fact be exogenous.[7] First, innovation expenditures are usually made well before they result in applicable innovations. Second, as HJMP mentioned, it seems realistic to assume that firms cannot predict future labor problems, supply chain disruptions, or demand shocks when deciding their innovation expenditures. Third, we included a set of industry dummies to control for industry productivity shocks. This reinforces the finding of the absence of serial correlation in individual productivity shocks and it controls for the business cycle effect. Accordingly, the hypothesis on exogeneity of process innovations is maintained in this paper.

Another possible source of endogeneity is the presence of measurement error in $g_1$ and $g_2$. Ideally we would use growth in real production, but we only observe growth in nominal

[7] It should be noted that similar arguments can apply for product innovations. However, as we argue below, our measure of product innovation is measured with error. This additional source of endogeneity in the product innovation variable is not present in the process innovation variable..

sales. Hence the growth in prices of old and new products are left in the error term, and correlation between growth in prices and $g_2$ can create an attenuation bias in the estimation of $\beta$. To deal with this measurement error problem we follow HJMP. First, we use industry price indexes $\pi$ as a proxy for the growth in prices of old products. Second, we use instrumental variables that are correlated with real growth in the production of new products but uncorrelated with its nominal growth.

The instruments that identify the effect of interest need to satisfy two conditions. First, they have to be partially correlated with product innovation. This correlation can be tested in a reduced form regression of innovation variables on the set of exogenous variables and the list of instruments. Second, they do not have to be correlated with the error term. In other words, they need to be correlated with the growth in employment only through their relationship with innovation. The exogeneity of the instruments is a maintained hypothesis. However, when there are more instruments then endogenous variables it is possible to test for overidentification using the Sargan-Hansen test. In addition, we test whether $g_2$ is indeed endogenous using the Davidson-MacKinnon exogeneity test.[8]

## 4. Data and Descriptive Statistics

We use data from the Second National Innovation Survey (ENIT01).[9] [10] ENIT01 was conducted in 2003 by the National Institute of Statistics and Censuses (INDEC) and collected retrospective information for each year between 1998 and 2001. The firms that were surveyed are the same firms surveyed in the Annual Industrial Survey—manufacturing firms with 10 or more employees.[11] The response rate was 76 percent; questionnaires were distributed to 2,229 firms, and 1,688 responded to the questionnaire. The sampling frame includes 23 industries—22 of them correspond to industries classified according with two digits of ISIC-Rev3 and the rest include firms with special characteristics. They have linkages with the Ministry of Defense or the National Commission of Atomic Energy. The response rate within each industry was also high, between 67 and 100 percent. Therefore, after considering the non-response, the percentage of firms by industry in the sample was close to the sampling design. Moreover, the percentage of

[8] Davidson-MacKinnon test is asymptotically equivalent to the Durbin-Wu-Hausman test. We prefer to compute the Davidson-MacKinnon because a heteroskedasticity-robust version is straightforward to compute.
[9] Segunda Encuesta Nacional de Innovación y Conducta Tecnológica de las Empresas Argentinas 1998-2001.
[10] Other Innovation Surveys in Argentina do not contain the necessary information to estimate the HJMP model.
[11] The population for the sample design of the Annual Manufacturing Survey is the National Economic Census 1994 conducted by INDEC.

aggregate sales by industry in the sample is close to the percentage of sales by industry using the Annual Industrial Survey. (INDEC, 2003)

The survey contains detailed information on the firms' characteristics, innovation activity, and employment—both the number of employees and employment composition by education and length of the labor contracts. Importantly, it also has detailed information on the composition of sales that allow us to compute the percentage of sales corresponding to new products.

We classified firms in mutually exclusive categories according to their innovation status: *product innovators, process only innovators, and non-innovators*. Product innovators are firms that have introduced product innovations. Process only innovators are firms that have introduced process innovations or organizational change innovations excluding product innovators. Non-innovators are firms not classified as product or process innovators.

Following HJMP, we classify firms that have introduced both product and process innovations as product innovators. The implicit assumption is that product and process innovators are more similar to product innovators than to process innovators. We will present some evidence supporting this assumption in the next section.

Table 5 shows the descriptive statistics for the share of innovative firms, employment growth, sales growth and labor productivity.

A large number of firms (63 percent) have introduced at least one innovation in 1998-2001. Most of the innovators are product innovators (48 percent) rather than process innovators (15 percent). HJMP report a similar share of innovative firms for France, Germany, Spain, and the United Kingdom. The higher ratio of R&D expenditure to sales in developed countries suggests, however, that different innovation activities are undertaken by firms in Argentina and in developed countries. Innovative firms in Argentina aim more at assimilating foreign technology or consist of incremental, marginal innovations, while innovative firms in developed countries invest primarily in R&D.

Interestingly, the reduction in employment was different between innovators and non-innovators. The annual reduction in employment was 2.5 percent for product innovators and 4 percent for process only innovators, while it was 6 percent for non-innovators. A similar pattern is observed in sales growth, with a smaller reduction in sales for innovators than non-innovators.

The annual reduction in sales was 7 percent for product innovators, 8 percent for process innovators, and 13 percent for non-innovators.

It is important to highlight the rapid pace at which product innovators substituted old products for new products: sales of old products decreased 45 percent, while sales of new products increased 40 percent. This pace, especially the decrease in sales of old products, is significantly faster than in France, Germany, Spain, and the United Kingdom reported in HJMP. The difference might be explained by the recessive scenario in 1998-2001 in Argentina or by new products presenting only incremental, marginal innovations with respect to old products.

The decrease in labor productivity was 4 percent for innovators and 6.5 percent for non-innovators. This suggests that innovators might be able to compensate for the negative aggregate shock through the introduction of new products or processes.

**Table 5: Descriptive Statistics**

| | Mean | Median | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| **Number of observations** | 1,415 | | | | |
| **Distribution of firms (%)** | | | | | |
| Non-innovators (no process or product innovations) | 36 | 0 | 48 | 0 | 100 |
| Process only innovators (non product innovators) | 15 | 0 | 36 | 0 | 100 |
| Product innovators | 48 | 0 | 50 | 0 | 100 |
| **Number of employees at the beginning of (each) survey** | 233 | 100 | 556 | 10 | 10,865 |
| **Foreign ownership (10% or more)** | 0.20 | 0.00 | 0.40 | 0.00 | 1.00 |
| **Located in the capital of the country** | 0.64 | 1.00 | 0.48 | 0.00 | 1.00 |
| **Employment growth (%) (yearly rate)** | | | | | |
| *All firms* | -4.0 | -2.9 | 12.3 | -100.0 | 57.1 |
| Non-innovators (no process or product innovations) | -6.0 | -3.7 | 12.8 | -100.0 | 29.8 |
| Process only innovators (non product innovators) | -3.9 | -2.8 | 12.3 | -63.0 | 47.4 |
| Product innovators | -2.5 | -2.1 | 11.6 | -100.0 | 57.1 |
| **Sales growth (%)(nominal growth) (yearly rate)** | | | | | |
| *All firms* | -9.0 | -9.1 | 16.0 | -79.3 | 58.2 |
| Non-innovators (no process or product innovations) | -12.5 | -12.4 | 17.5 | -79.3 | 58.0 |
| Process only innovators (non product innovators) | -8.1 | -7.4 | 15.3 | -70.4 | 40.2 |
| Product innovators | -6.7 | -7.3 | 14.5 | -57.3 | 58.2 |
| *of which:* | | | | | |
| Old products | -45.3 | -38.5 | 36.3 | -100.0 | 37.1 |
| New products | 38.7 | 27.4 | 36.3 | 0.0 | 158.2 |
| **Labor productivity growth (%)[(a)](yearly rate)** | | | | | |
| *All firms* | -5.0 | -5.5 | 15.2 | -64.6 | 112.0 |
| Non-innovators (no process or product innovations) | -6.5 | -7-0 | 17.4 | -64.6 | 112.0 |
| Process only innovators (non product innovators) | -4.3 | -4.2 | 13.4 | -44.1 | 60.4 |
| Product innovators | -4.2 | -4.8 | 13.9 | -56.4 | 104.4 |
| **Price growth (%) [(b)]** | | | | | |
| *All firms* | -2.0 | -1.8 | 2.3 | -12.9 | 8.9 |
| Non-innovators (no process or product innovations) | -2.3 | -2.0 | 2.2 | -12.9 | 8.9 |
| Process only innovators (non product innovators) | -1.9 | -1.8 | 2.0 | -5.7 | 8.9 |
| Product innovators | -1.9 | -1.4 | 2.5 | -12.9 | 8.9 |

*Source:* ENIT01.
*Notes: Product innovators* are firms that have introduced product innovations. *Process only innovators* are firms that have introduced process innovations or organizational change innovations excluding product innovators. *Non-innovators* are firms not classified as product or process innovators. Sample: Firms with information in all the relevant variables for the empirical analysis. (a) Sales growth for each type of firm is the average of the variable g and averages for old and new products are the averages of variables g1 and g2, respectively, and (b) prices computed at the 2-digit level of the ISIC and assigned to firms according to their activity.

Table 6 shows the descriptive statistics for small firms, defined as firms with fewer than 50 employees. The sample size for small firms is 417. Since process innovators are only 12 percent of the sample, we will only comment on innovators without distinguishing between process and product innovators.

As expected, the share of innovators is smaller for small firms: 45 percent of the small firms have introduced an innovation during the period. Consistent with the results for the full sample, we also find important differences between innovators and non-innovators in terms of employment, sales, and labor productivity growth.

**Table 6: Descriptive Statistics - Small Firms**

| | Mean | Median | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| **Number of observations** | 417 | | | | |
| **Distribution of firms (%)** | | | | | |
| Non-innovators (no process or product innovations) | 56 | 100 | 50 | 0 | 100 |
| Process only innovators (non product innovators) | 12 | 0 | 32 | 0 | 100 |
| Product innovators | 32 | 0 | 47 | 0 | 100 |
| **Number of employees at the beginning of (each) survey** | 28 | 26 | 12 | 10 | 50 |
| **Foreign ownership (10% or more)** | 0.06 | 0.00 | 0.24 | 0.00 | 1.00 |
| **Located in the capital of the country** | 0.64 | 1.00 | 0.48 | 0.00 | 1.00 |
| **Employment growth (%) (yearly rate)** | | | | | |
| *All firms* | -3.5 | -2.1 | 13.4 | -100.0 | 57.1 |
| Non-innovators (no process or product innovations) | -5.8 | -3.5 | 12.9 | -100.0 | 29.8 |
| Process only innovators (non product innovators) | 1.5 | 0.0 | 11.6 | -20.6 | 47.4 |
| Product innovators | -1.2 | -0.9 | 14.0 | -100.0 | 57.1 |
| **Sales growth (%)(nominal growth) (yearly rate)** | | | | | |
| *All firms* | -9.7 | -10.3 | 17.4 | -68.5 | 58.2 |
| Non-innovators (no process or product innovations) | -12.8 | -14.0 | 17.8 | -68.5 | 58.0 |
| Process only innovators (non product innovators) | -3.0 | -5.3 | 16.5 | -47.7 | 40.2 |
| Product innovators | -6.6 | -7.8 | 15.7 | -51.6 | 58.2 |
| *of which:* | | | | | |
| Old products | -49.2 | -48.6 | 39.0 | -100.0 | 34.4 |
| New products | 42.6 | 34.1 | 39.4 | 0.0 | 158.2 |
| **Labor productivity growth (%) [(a)] (yearly rate)** | | | | | |
| *All firms* | -6.2 | -7.1 | 18.7 | -64.6 | 112.0 |
| Non-innovators (no process or product innovations) | -7.0 | -8.6 | 19.6 | -64.6 | 112.0 |
| Process only innovators (non product innovators) | -4.5 | -5.3 | 15.9 | -44.1 | 35.4 |
| Product innovators | -5.4 | -6.0 | 18.1 | -56.4 | 104.4 |
| **Price growth (%) [(b)]** | | | | | |
| *All firms* | -2.0 | -1.8 | 2.0 | -12.9 | 8.9 |
| Non-innovators (no process or product innovations) | -2.2 | -2.0 | 2.0 | -12.9 | 4.2 |
| Process only innovators (non product innovators) | -1.4 | -1.4 | 2.0 | -4.6 | 8.9 |
| Product innovators | -1.9 | -1.4 | 1.9 | -12.9 | 0.8 |

*Source:* ENIT01.
*Notes: Product innovators* are firms that have introduced product innovations. *Process only innovators* are firms that have introduced process innovations or organizational change innovations excluding product innovators. *Non-innovators* are firms not classified as product or process innovators. Sample: Firms with less than 50 employees and with information in all the relevant variables for the empirical analysis. (a) Sales growth for each type of firm is the average of the variable g and averages for old and new products are the averages of variables g1 and g2, respectively, and (b) prices computed at the 2-digit level of the ISIC and assigned to firms according to their activity.

We also studied the presence of heterogeneous effects in industries with different levels of technology intensity. Industries were classified as low-tech or high-tech based on their innovation expenditure-to-sales ratio. Industries with ratios below the median are considered low-tech industries, and industries with ratios above the median are considered high-tech industries. Table 44 in the Appendix shows the distribution of industries in high- and low-tech categories.

Table 7 summarizes descriptive statistics for low- and high-tech firms. Surprisingly, there are no differences in the distribution of non-innovators, process innovators, and product innovators between low- and high-tech firms. On the other hand, low-tech seems less affected by the recession than high-tech firms in terms of employment, sales, and labor productivity. Within each technology sector, innovators show better performance than non-innovators.

**Table 7: Descriptive Statistics – Low- and High-tech Firms**

| | Low-tech | High-tech |
|---|---|---|
| | **Mean** | **Mean** |
| **Number of observations** | 672 | 743 |
| **Distribution of firms (%)** | | |
| Non-innovators (no process or product innovations) | 36 | 36 |
| Process only innovators (non product innovators) | 15 | 15 |
| Product innovators | 48 | 49 |
| **Number of employees at the beginning of (each) survey** | 277 | 194 |
| **Foreign ownership (10% or more)** | 16 | 23 |
| **Located in the capital of the country** | 54 | 72 |
| **Employment growth (%) (yearly rate)** | | |
| *All firms* | -3.4 | -4.4 |
| Non-innovators (no process or product innovations) | -5.7 | -6.4 |
| Process only innovators (non product innovators) | -3.9 | -3.9 |
| Product innovators | -1.6 | -3.2 |
| **Sales growth (%)(nominal growth) (yearly rate)** | | |
| *All firms* | -7.6 | -10.3 |
| Non-innovators (no process or product innovations) | -10.5 | -14.3 |
| Process only innovators (non product innovators) | -7.1 | -9.1 |
| Product innovators | -5.5 | -7.7 |
| *of which:* | | |
| Old products | -44.0 | -46.6 |
| New products | 38.5 | 38.9 |
| **Labor productivity growth (%)[(a)](yearly rate)** | | |
| *All firms* | -4.1 | -5.8 |
| Non-innovators (no process or product innovations) | -4.9 | -7.9 |
| Process only innovators (non product innovators) | -3.2 | -5.3 |
| Product innovators | -3.9 | -4.4 |
| **Price growth (%) [(b)]** | | |
| *All firms* | -2.2 | -1.9 |
| Non-innovators (no process or product innovations) | -2.3 | -2.3 |
| Process only innovators (non product innovators) | -2.2 | -1.5 |
| Product innovators | -2.0 | -1.7 |

*Source:* ENIT01.

*Notes: Product innovators* are firms that have introduced product innovations*.* *Process only innovators* are firms that have introduced process innovations or organizational change innovations excluding product innovators. *Non-innovators* are firms not classified as product or process innovators. Sample: Firms with information in all the relevant variables for the empirical analysis. (a) Sales growth for each type of firm is the average of the variable g and averages for old and new products are the averages of variables g1 and g2, respectively, and (b) prices computed at the 2-digit level of the ISIC and assigned to firms according to their activity.

## 5. Innovation and Employment Growth

In this section, we present several results of the effects of innovation on employment growth at the firm level. To begin with, we present the basic results of the effects of process and product innovations on employment growth. Then, we analyze the extent to which these effects are different for small firms and for low- and high-tech industries.

***Naïve Regressions***

Tables 8 to 11 show OLS descriptive regressions of employment growth on innovation variables, real growth in sales of old products, industry dummies, and additional controls. These descriptive regressions should be interpreted as partial correlations which can be useful to describe the data set but cannot identify the effect of innovation on employment.

Table 8 shows the results for all the firms in the sample. In column (1) product innovators and process innovators are included in the same variable, while in columns (2) to (4) product innovators and process innovators are included in separate variables. Columns (2) and (4) differ in the allocation of firms that have introduced both product and process innovations. In column (2) product and process innovators are included with product innovators, in column (3) they are included with process innovators, and in column (4) they are included as a separate category.

The estimate of the constant is approximately -5 percent, and it captures the mean employment growth for non-innovators. Innovators are associated with a 4 percent higher employment growth than non-innovators. Column (4) shows significant differences in employment growth between product and process innovators and process only innovators. On the other hand, there are no significant differences between product and process innovators and product only innovators. This evidence supports including product and process innovators and product only innovators in the same category. We will follow this convention in the rest of the paper.

The estimated coefficient on real growth in sales suggests that sales are associated with marginal increase in employment: a 10 percent increase in sales growth of old products implies a 0.3-0.4 percent increase in employment growth.

Table 9 shows the results for firms with fewer than 50 employees (small firms). There are 417 small firms in our sample and only 50 process innovators. The small sample size implies an important loss in precision in the estimation, and the small number of process innovators makes it difficult to identify differences between product and process innovators. These caveats should be considered in the interpretation of the results for small firms.

The results for small firms show a pattern similar to the full sample, although with less precision. Average employment growth for non-innovators is -5 percent, and innovators have a 6 percent higher employment growth. There are no significant differences between product and process innovators. The estimated coefficient on real growth in sales suggests a negligible effect of sales of old products on employment.

Tables 10 and 11 show the results for low-tech and high-tech firms. In general, the results are similar to those for the full sample. There is, however, a relevant difference between low-tech and high-tech firms. For low-tech firms, product innovators are consistently correlated with higher employment growth. For high-tech firms, process innovators are consistently correlated with higher employment growth. These results highlight the need to run separate regressions for low-tech and high-tech firms.

**Table 8: Dependent Variable: l (Employment Growth-Yearly) - OLS Estimation**

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-OLS** | **Manufacturing**<br>**2-OLS** | **Manufacturing**<br>**3-OLS** | **Manufacturing**<br>**4-OLS** |
|---|---|---|---|---|
| Constant | -5.634*** | -5.490*** | -5.631*** | -5.473*** |
| | (0.720) | (0.715) | (0.721) | (0.715) |
| Product or process innovator | 4.088*** | | | |
| | (0.806) | | | |
| Product innovator | | 4.862*** | | |
| | | (0.880) | | |
| Process only innovator (non product innovator) | | 2.311* | | 2.323* |
| | | (1.013) | | (1.014) |
| Product only innovator (non process innovator) | | | 3.461** | 3.696** |
| | | | (1.221) | (1.231) |
| Process innovator | | | 4.157*** | |
| | | | (0.820) | |
| Product and process innovator | | | | 5.050*** |
| | | | | (0.908) |
| Real sales growth *(g1-Π)* | 0.034** | 0.040*** | 0.033** | 0.040*** |
| | (0.011) | (0.012) | (0.011) | (0.012) |
| Located in the capital | -0.060 | -0.169 | -0.068 | -0.193 |
| | (0.679) | (0.674) | (0.680) | (0.673) |
| Foreign owned (10% or more) | 0.395 | 0.426 | 0.370 | 0.381 |
| | (0.742) | (0.740) | (0.744) | (0.740) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.069 | 0.073 | 0.069 | 0.074 |
| Number of firms | 1,415 | 1,415 | 1,415 | 1,415 |

*Notes: Product innovators* are firms that have introduced product innovations*.* *Process innovators* are firms that have introduced process innovations or organizational change innovations. *Product only innovators* are firms that are product innovators but not process innovators. *Process only innovators* are firms that are process innovators but not product innovators. *Product or process innovators* are firms that are product innovators or process innovators*. Product and process innovators* are firms that are both product innovators and process innovators.
(i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 9: Dependent Variable: l (Employment Growth - Annual) - OLS Estimation Small Firms

| Sector<br>Regression | Small firms in Manufacturing<br>1-OLS | Small firms in Manufacturing<br>2-OLS | Small firms in Manufacturing<br>3-OLS | Small firms in Manufacturing<br>4-OLS |
|---|---|---|---|---|
| Constant | -5.399*** | -5.414*** | -5.386*** | -5.407*** |
| | (1.292) | (1.279) | (1.295) | (1.282) |
| Product or process innovator | 5.790** | | | |
| | (1.768) | | | |
| Product innovator | | 5.638** | | |
| | | (2.086) | | |
| Process only innovator (non product innovator) | | 6.114** | | 6.075** |
| | | (2.028) | | (2.039) |
| Product only innovator (non process innovator) | | | 6.660*** | 6.590*** |
| | | | (1.890) | (1.915) |
| Process innovator | | | 5.637** | |
| | | | (1.926) | |
| Product and process innovator | | | | 5.393* |
| | | | | (2.380) |
| Real sales growth *(g-Π)* | 0.024 | 0.023 | 0.025 | 0.023 |
| | (0.025) | (0.026) | (0.024) | (0.026) |
| Located in the capital | -0.335 | -0.336 | -0.325 | -0.323 |
| | (1.399) | (1.403) | (1.395) | (1.396) |
| Foreign owned (10% or more) | 3.469 | 3.457 | 3.487 | 3.474 |
| | (0.742) | (0.740) | (0.744) | (1.991) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.111 | 0.111 | 0.112 | 0.112 |
| Number of firms | 417 | 417 | 417 | 417 |

*Notes: Product innovators* are firms that have introduced product innovations*. Process innovators* are firms that have introduced process innovations or organizational change innovations. *Product only innovators* are firms that are product innovators but not process innovators. *Process only innovators* are firms that are process innovators but not product innovators. *Product or process innovators* are firms that are product innovators or process innovators*. Product and process innovators* are firms that are both product innovators and process innovators.
(i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 10: Dependent Variable: l (Employment Growth - Annual) - OLS Estimation Low-tech Firms

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-OLS** | **Manufacturing**<br>**2-OLS** | **Manufacturing**<br>**3-OLS** | **Manufacturing**<br>**4-OLS** |
|---|---|---|---|---|
| Constant | -5.826*** | -5.679*** | -5.831*** | -5.681*** |
| | (1.004) | (0.999) | (1.006) | (1.000) |
| Product or process innovator | 4.442*** | | | |
| | (1.228) | | | |
| Product innovator | | 5.542*** | | |
| | | (1.331) | | |
| Process only innovator (non product innovator) | | 1.936 | | 1.934 |
| | | (1.540) | | (1.542) |
| Product only innovator (non process innovator) | | | 5.419*** | 5.718*** |
| | | | (1.622) | (1.637) |
| Process innovator | | | 4.333*** | |
| | | | (1.244) | |
| Product and process innovator | | | | 5.513*** |
| | | | | (1.364) |
| Real sales growth *(g1-Π)* | 0.027 | 0.035* | 0.028 | 0.035* |
| | (0.015) | (0.016) | (0.015) | (0.016) |
| Located in the capital | 0.024 | -0.116 | 0.036 | -0.113 |
| | (0.937) | (0.934) | (0.937) | (0.934) |
| Foreign owned (10% or more) | 1.919 | 1.848 | 1.96 | 1.857 |
| | (1.195) | (1.180) | (1.204) | (1.189) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.062 | 0.071 | 0.062 | 0.071 |
| Number of firms | 672 | 672 | 672 | 672 |

*Notes: Product innovators* are firms that have introduced product innovations. *Process innovators* are firms that have introduced process innovations or organizational change innovations. *Product only innovators* are firms that are product innovators but not process innovators. *Process only innovators* are firms that are process innovators but not product innovators. *Product or process innovators* are firms that are product innovators or process innovators. *Product and process innovators* are firms that are both product innovators and process innovators.

(i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

**Table 11: Dependent Variable: l (Employment Growth - Annual) - OLS Estimation**
**High-tech Firms**

| **Sector** <br> **Regression** | **Manufacturing** <br> **1-OLS** | **Manufacturing** <br> **2-OLS** | **Manufacturing** <br> **3-OLS** | **Manufacturing** <br> **4-OLS** |
|---|---|---|---|---|
| Constant | -5.435*** | -5.324*** | -5.422*** | -5.284*** |
| | (1.084) | (1.073) | (1.085) | (1.073) |
| Product or process innovator | 3.776*** | | | |
| | (1.066) | | | |
| Product innovator | | 4.248*** | | |
| | | (1.175) | | |
| Process only innovator (non product innovator) | | 2.698* | | 2.716* |
| | | (1.335) | | (1.337) |
| Product only innovator (non process innovator) | | | 1.766 | 1.941 |
| | | | (1.780) | (1.792) |
| Process innovator | | | 3.997*** | |
| | | | (1.089) | |
| Product and process innovator | | | | 4.620*** |
| | | | | (1.221) |
| Real sales growth *(g1-Π)* | 0.039* | 0.043* | 0.038* | 0.043* |
| | (0.016) | (0.017) | (0.016) | (0.017) |
| Located in the capital | -0.121 | -0.19 | -0.152 | -0.243 |
| | (0.982) | (0.968) | (0.982) | (0.966) |
| Foreign owned (10% or more) | -0.632 | -0.575 | -0.707 | -0.652 |
| | (0.938) | (0.943) | (0.938) | (0.942) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.077 | 0.079 | 0.079 | 0.082 |
| Number of firms | 743 | 743 | 743 | 743 |

*Notes: Product innovators* are firms that have introduced product innovations. *Process innovators* are firms that have introduced process innovations or organizational change innovations. *Product only innovators* are firms that are product innovators but not process innovators. *Process only innovators* are firms that are process innovators but not product innovators. *Product or process innovators* are firms that are product innovators or process innovators. *Product and process innovators* are firms that are both product innovators and process innovators.
(i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

### *Innovation and Employment Growth*

Columns (1) and (2) in Table 12 show the OLS results for the innovation-employment model in HJMP. Column (1) presents the basic model, and column (2) presents the results after controlling for additional variables.[12]

The OLS results of the innovation-employment model show that a process innovation does not have a significant effect on employment while a product innovation has a positive and significant effect on employment. The estimated coefficient on $g_2$ is close to 1, which indicates no important differences in efficiency in the production of old and new products.

Columns (1) and (2) in Table 13 show the OLS results for the innovation-employment model for small firms. The OLS results for small firms are similar to the results for the full sample. The main difference is that a process innovation has a negative though not statistically significant effect on employment. In addition, the smaller sample size translates into a loss of precision in the estimates.

[12] The additional controls are *an indicator for foreign owned firms* and *an indicator of whether the firm is located in the capital of the country*.

Column (1) and (2) in Tables 14 and 15 show the OLS results for the innovation-employment model for low- and high-tech firms. The OLS results for low-tech and high-tech firms are similar. The estimated coefficient on $g_2$ suggests that the gain in efficiency in the production of new products is larger in high-tech sectors, a result that will be confirmed in the IV regressions.

Column (3) and (4) in table 12 show the IV results for the innovation-employment model in HJMP. There are two endogeneity problems that can bias the OLS estimation: an omitted variable problem because productivity shocks are included in the error term (with a negative sign), and a measurement error problem due to unobservability of firm prices. These endogeneity issues tend to generate a downward bias in the OLS estimate of the coefficient on $g_2$.

The only instrument used in the IV estimation is *an indicator of the firm knowledge of public support for innovation activities*. This variable is likely to be correlated with time-invariant firm attributes such managerial skills or organizational capital. However, given that the estimating equation is in growth rates, time-invariant firm attributes are not part of the error term, and correlation with productivity shocks or growth in prices of new products seems less likely.

The validity of the chosen instruments relies on significant correlation between instruments and endogenous variables in the first stage regressions. Stock, Wright, and Yogo (2002) recommend a test of excluded instruments in the first stage with an F statistic higher than 10 to avoid weak instruments concerns. Table 12 shows that this F statistic is approximately 15 for the full sample, and Table 13 shows that it is approximately 8 for small firms. In addition, the identified IV estimators are median unbiased so less prone to weak instruments criticism.

The results in Table 12 show that the IV estimate of the coefficient on $g_2$ moves upwards, consistent with a downward bias in the OLS estimate. The estimate increases from 0.96 in the OLS estimation in column (2) to 1.17 in the IV estimation in column (4). A coefficient greater than 1 offers evidence that new products are produced less efficiently than old products. However this evidence is tenuous because the estimate is not statistically different than 1. To summarize, there is no evidence that product innovations displace employment due to an increase in efficiency; there is only a creation effect due to increased demand.

The results in table 12 also show that the IV estimate of the coefficient on process innovation is corrected upwards. The estimated coefficient is positive but not significant, suggesting that process innovations have no effect on employment. There are two plausible explanations for this result. First, process innovations may not generate important productivity gains; hence, there is no displacement effect on employment. Second, process innovations may generate productivity gains (displacement effect), which increase demand through market competition (creation effect). In the end, the creation effect on employment compensates the displacement effect on employment.

Columns (3) and (4) in Table 13 show the IV results for the innovation-employment model for small firms. Again, the IV results for small firms are similar to the results for the full sample. The estimate of the coefficient on $g_2$ increases from 0.96 in the OLS estimation in column (2) to 1.14 in the IV estimation in column (4). The estimate of the coefficient on product innovation is negative but not significant.

We ran a Davidson-MacKinnon test to assess the endogeneity of $g_2$. We rejected exogeneity of $g_2$ at 10 percent for the full sample while we failed to reject it for small firms. The failure to reject exogeneity of $g_2$ for small firms is probably related to the lack of precision in the IV estimation. Thus our preferred specification for the innovation-employment model for small firms is the IV estimation where $g_2$ is endogenous.

Columns (3) and (4) in Tables 14 and 15 show the IV results for the innovation-employment model for low- and high-tech industries. We use the full set of instruments in the IV estimation because the just identified model is not identified for high-tech firms. Interestingly, we found a significantly smaller estimate for $g_2$ in high-tech firms than in low-tech firms. This finding would suggest that new products are produced relatively more efficiently than old products in high-tech firms. Moreover, the OLS results offer additional evidence that support this result.[13]

[13] It should be noted that the IV identification seems less convincing for the sample of high-tech firms. First, the IV estimate is smaller than the OLS estimate which is counterintuitive. Second, the Davidson-McKinnon exogeneity test does not reject exogeneity of g2. That said, the main conclusion that the gain in efficiency in the production of new products is larger in high-tech sectors is confirmed by the OLS results.

## Table 12: Dependent Variable: l -(g1-Π) - OLS and IV Estimation

| Sector<br>Regression | Manufacturing<br>1-OLS | Manufacturing<br>2-OLS | Manufacturing<br>3-IV | Manufacturing<br>4-IV |
|---|---|---|---|---|
| Constant | 4.143*** | 4.139*** | -0.701 | -0.994 |
| | (0.566) | (0.836) | (3.027) | (3.236) |
| Process only innovator (*d*) | -1.007 | -0.601 | 0.767 | 1.398 |
| | (1.010) | (1.004) | (1.586) | (1.673) |
| Sales growth due to new products *(g2)* | 0.955*** | 0.959*** | 1.159*** | 1.170*** |
| | (0.012) | (0.013) | (0.123) | (0.125) |
| Located in the capital | - | 0.989 | - | 1.623 |
| | - | (0.854) | - | (0.998) |
| Foreign owned (10% or more) | - | -3.962*** | - | -5.467*** |
| | - | (0.905) | - | (1.349) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *g2* equation | - | - | 14.820 | 14.320 |
| Pvalue | - | - | 0.001 | 0.002 |
| Davidson-MacKinnon test of exogeneity for *g2* | - | - | 3.213 | 3.319 |
| Pvalue | - | - | 0.073 | 0.069 |
| Test $H_0: g2 = 1$ (p-value) | - | - | 0.206 | 0.187 |
| R-squared | 0.829 | 0.830 | 0.785 | 0.785 |
| Number of firms | 1,415 | 1,415 | 1,415 | 1,415 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities*. Endogenous variables: *g2*.

## Table 13: Dependent Variable: l-(g1-Π) - OLS and IV Estimation - Small Firms

| Sector<br>Regression | Small firms in Manufacturing<br>1-OLS | Small firms in Manufacturing<br>2-OLS | Small firms in Manufacturing<br>3-IV | Small firms in Manufacturing<br>4-IV |
|---|---|---|---|---|
| Constant | 5.214*** | 2.739 | 3.579 | -0.684 |
| | (1.148) | (1.685) | (3.498) | (4.440) |
| Process only innovator (*d*) | -2.851 | -2.489 | -2.923 | -2.542 |
| | (2.433) | (2.425) | (2.512) | (2.691) |
| Sales growth due to new products (*g2*) | 0.958*** | 0.963*** | 1.052*** | 1.140*** |
| | (0.030) | (0.030) | (0.189) | (0.218) |
| Located in the capital | - | 3.990* | - | 4.690* |
| | - | (1.900) | - | (2.220) |
| Foreign owned (10% or more) | - | -3.441 | - | -5.412 |
| | - | (3.682) | - | (5.132) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, g2 equation | - | - | 7.380 | 6.200 |
| Pvalue | - | - | 0.007 | 0.013 |
| Davidson-MacKinnon test of exogeneity for *g2* | - | - | 0.248 | 0.784 |
| Pvalue | - | - | 0.618 | 0.376 |
| Test $H_0: g2 = 1$ (p-value) | - | - | 0.788 | 0.509 |
| R-squared | 0.765 | 0.767 | 0.738 | 0.724 |
| Number of firms | 417 | 417 | 417 | 417 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities*. Endogenous variables: *g2*.

**Table 14: Dependent Variable: l-(g1-Π) - OLS and IV Estimation - Low-tech Firms**

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-OLS** | **Manufacturing**<br>**2-OLS** | **Manufacturing**<br>**3-IV** | **Manufacturing**<br>**4-IV** |
|---|---|---|---|---|
| Constant | 2.743** | 3.140** | -0.266 | -0.201 |
| | (0.885) | (1.195) | (1.667) | (1.961) |
| Process only innovator *(d)* | -0.439 | -0.196 | 0.478 | 0.849 |
| | (1.526) | (1.516) | (1.865) | (1.884) |
| Sales growth due to new products *(g2)* | 0.969*** | 0.972*** | 1.098*** | 1.105*** |
| | (0.017) | (0.017) | (0.064) | (0.066) |
| Located in the capital | - | 0.491 | - | 1.088 |
| | - | (1.255) | - | (1.393) |
| Foreign owned (10% or more) | - | -4.885** | - | -5.614** |
| | - | (1.564) | - | (1.849) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *g2* equation | - | - | 9.010 | 8.650 |
| Pvalue | - | - | 0.000 | 0.000 |
| Davidson-MacKinnon test of exogeneity for *g2* | - | - | 4.691 | 4.857 |
| Pvalue | - | - | 0.031 | 0.028 |
| Sargan-Hansen test of overidentification | - | - | 2.603 | 2.451 |
| Pvalue (degrees of freedom) | - | - | 0.857 | 0.874 |
| Test $H_0: g2 = 1$ (p-value) | - | - | 0.086 | 0.072 |
| R-squared | 0.816 | 0.818 | 0.807 | 0.811 |
| Number of firms | 672 | 672 | 672 | 672 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities, continuous R&D dummy,* and *product life cycle dummies*. Endogenous variables: *g2*.

**Table 15: Dependent Variable: l-(g1-Π) - OLS and IV Estimation - High-tech Firms**

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-OLS** | **Manufacturing**<br>**2-OLS** | **Manufacturing**<br>**3-IV** | **Manufacturing**<br>**4-IV** |
|---|---|---|---|---|
| Constant | 5.443*** | 4.878*** | 6.349*** | 5.697** |
| | (0.720) | (1.169) | (1.764) | (1.946) |
| Process only innovator (d) | -1.574 | -1.059 | -1.955 | -1.45 |
| | (1.341) | (1.333) | (1.587) | (1.628) |
| Sales growth due to new products (g2) | 0.941*** | 0.945*** | 0.903*** | 0.910*** |
| | (0.018) | (0.018) | (0.070) | (0.071) |
| Located in the capital | - | 1.582 | - | 1.533 |
| | - | (1.151) | - | (1.163) |
| Foreign owned (10% or more) | - | -3.243** | - | -2.948* |
| | - | (1.086) | - | (1.386) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, g2 equation | - | - | 5.380 | 5.170 |
| Pvalue | - | - | 0.000 | 0.000 |
| Davidson-MacKinnon test of exogeneity for g2 | - | - | 0.310 | 0.261 |
| Pvalue | - | - | 0.578 | 0.610 |
| Sargan-Hansen test of overidentification | - | - | 1.686 | 1.773 |
| Pvalue (degrees of freedom) | - | - | 0.946 | 0.939 |
| Test $H_0: g2 = 1$ (p-value) | - | - | 0.127 | 0.165 |
| R-squared | 0.843 | 0.844 | 0.725 | 0.748 |
| Number of firms | 743 | 743 | 743 | 743 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities, continuous R&D dummy,* and *product life cycle dummies*. Endogenous variables: *g2*.

## 6. Robustness Checks

We ran some robustness checks to evaluate the sensitivity of the results. To simplify the exposition, we focus on the impact of innovation on employment.

First, we used a more restrictive definition for sales of new products: we excluded new goods sold by the firm that were already sold in the market by other firms. Table 16 shows the OLS and IV results for the new definition of new products. The reported results show that the new estimates are consistent with the previous results.

Second, we included additional instruments to test exogeneity of instruments using a Sargan-Hansen overidentification test. The additional instruments used are an indicator of positive R&D investment in each year *(continuous R&D dummy)* and a set of indicators related with the life cycle of the main product (*product life cycle dummies*).[14] *Continuous R&D* is likely to be correlated with time-invariant firm attributes rather than productivity shocks. *Product life cycle dummies* may capture reasons for introducing new products unrelated to productivity shocks or growth in prices for new products. Thus, both seem like sensible instrument candidates.

Columns (1) and (2) in table 17 show the results of the overidentified model. The test of excluded instruments in the first stage has an F statistic of 14, which suggests that the model is identified and weak instruments are not a concern. In addition, the Sargan-Hansen test does not reject exogeneity of the instruments. These results provide additional evidence of the validity of the chosen instrument.

Third, we estimated the innovation-employment model under the assumptions that both g2 and process innovation are endogenous. Columns (3) and (4) in Table 17 show these results. The estimate on the coefficient on process innovation experiences an important loss in precision. But, more importantly, the estimate of the coefficient on $g_2$ is similar to the estimate under exogeneity of the process innovation. Accordingly, the Davidson-MacKinnon test does not reject exogeneity of the process innovation.

Fourth, we added an interaction between $g_2$ and a *product and process innovator dummy* as an additional covariate, and used the interaction between knowledge of support for innovation activity and the product and process innovator dummy as an additional instrument. Columns (5) and (6) in Table 17 show these results. Even though the estimated coefficient on $g_2$ increases, the interaction is not significant. We conclude that there is no compelling evidence to treat product and process innovators separately from product innovators.

[14] We constructed 6 dummies related with the product life cycle: less than 1 year, 1 to 3 years, 4 to 6 years, 7 to 9 years, more than 9 years, and not possible to identify the product life cycle. We dropped the dummy of a product life cycle larger than 9 years to avoid perfect multicollinearity.

Fifth, we investigated the estimation of innovation-employment model under non-constant returns to scale in the Appendix. The main result is that joint identification of efficiency and scale parameters is quite complicated, and assuming constant returns to sale is a sensible working assumption given those constraints.

**Table 16: Dependent Variable: l–(g1-Π) - OLS and IV Estimation - New Definition for g2**

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-OLS** | **Manufacturing**<br>**2-OLS** | **Manufacturing**<br>**3-IV** | **Manufacturing**<br>**4-IV** |
|---|---|---|---|---|
| Constant | 3.652*** | 3.710*** | 0.082 | -0.107 |
| | (0.498) | (0.793) | (2.475) | (2.661) |
| Process only innovator *(d)* | -0.872 | -0.470 | 0.717 | 1.260 |
| | (1.010) | (1.003) | (1.571) | (1.620) |
| Sales growth due to new products *(g2)* | 0.944*** | 0.946*** | 1.294*** | 1.310*** |
| | (0.020) | (0.020) | (0.235) | (0.238) |
| Located in the capital | | 1.063 | | 1.395 |
| | | (0.853) | | (0.980) |
| Foreign owned (10% or more) | | -4.164*** | | -4.768*** |
| | | (0.901) | | (1.139) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *g2* equation | - | - | 10.460 | 10.258 |
| Pvalue | - | - | 0.001 | 0.001 |
| Davidson-MacKinnon test of exogeneity for *g2* | - | - | 2.757 | 2.957 |
| Pvalue | - | - | 0.097 | 0.086 |
| R-squared | 0.674 | 0.678 | 0.569 | 0.566 |
| Number of firms | 1,415 | 1,415 | 1,415 | 1,415 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities*. Endogenous variables: *g2*.

**Table 17: Dependent Variable: l-(g1-Π) - Robustness Checks**

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-IV[(a)]** | **Manufacturing**<br>**2-IV[(a)]** | **Manufacturing**<br>**3-IV[(b)]** | **Manufacturing**<br>**4-IV[(b)]** | **Manufacturing**<br>**5-IV[(c)]** | **Manufacturing**<br>**6-IV[(c)]** |
|---|---|---|---|---|---|---|
| Constant | 2.776 | 2.575 | 0.507 | -0.096 | -2.890 | -3.686 |
| | (1.206) | (1.384) | (3.187) | (4.084) | (5.164) | (5.849) |
| Process only innovator (*d*) | -0.506 | 0.008 | 9.282 | 9.840 | -4.646 | -4.034 |
| | (1.195) | (1.215) | (12.708) | (14.125) | (3.030) | (3.057) |
| Sales growth due to new products *(g2)* | 1.013*** | 1.023*** | 1.047*** | 1.061*** | 1.661*** | 1.689** |
| | (0.047) | (0.048) | (0.066) | (0.074) | (0.485) | (0.514) |
| *g2**Product and process innovator (*g2*prod&proc*) | - | - | - | - | -0.503 | -0.512 |
| | - | - | - | - | (0.342) | (0.360) |
| Located in the capital | - | 1.182 | - | 1.957 | | 1.949 |
| | - | (0.892) | - | (1.446) | | (1.433) |
| Foreign owned (10% or more) | - | -4.420*** | - | -5.299** | | -5.148** |
| | - | (1.103) | - | (1.702) | | (1.792) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| F test, *g2* equation | 13.743 | 13.295 | 14.454 | 14.121 | 28.940 | 27.975 |
| Pvalue | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| F test, *d* equation | - | - | 3.232 | 3.176 | - | - |
| Pvalue | - | - | 0.002 | 0.002 | - | - |
| F test, *g2*prod&proc* equation | - | - | | | 81.861 | 80.487 |
| Pvalue | - | - | | | 0.000 | 0.000 |
| Sargan-Hansen test of overidentification | 3.775 | 3.952 | 2.906 | 3.164 | | |
| Pvalue (degrees of freedom) | 0.707(6) | 0.683(6) | 0.714(5) | 0.675(5) | | |
| Davidson-MacKinnon test for *g2* | 1.607 | 1.938 | 2.135 | 2.251 | 2.991 | 2.989 |
| Pvalue | 0.205 | 0.164 | 0.144 | 0.134 | 0.083 | 0.084 |
| Davidson-MacKinnon test for *d* | - | - | 0.629 | 0.513 | - | - |
| Pvalue | - | - | 0.428 | 0.474 | - | - |
| Davidson-MacKinnon test for *g2*prod&proc* | - | - | - | - | 1.698 | 1.699 |
| Pvalue | - | - | - | - | 0.193 | 0.192 |
| R-squared | 0.765 | 0.776 | 0.790 | 0.802 | 0.758 | 0.796 |
| Number of firms | 1,415 | 1,415 | 1,415 | 1,415 | 1,415 | 1,415 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%,

[(a)] Instruments: *knowledge of public support for innovation activities, continuous R&D dummy,* and *product life cycle dummies*. Endogenous variables: *g2*.

[(b)] Instruments: *knowledge of public support for innovation activities, continuous R&D dummy,* and *product life cycle dummies*. Endogenous variables: *g2* and *d*.

[(c)] Instruments: *knowledge of public support for innovation activities* and (*knowledge of public support for innovation activities x product and process innovator*). Endogenous variables: *g2* and (*g2* x *product and process innovator)*.

## 7. Innovation and Skill Composition

In this section, we discuss the impact of innovation on skill composition. The effects of innovation activity on skilled and unskilled labor are central for the design of public policy. If innovation activities and skilled labor are complements, we expect that the introduction of innovations will be mainly reflected in a higher demand for skilled labor. This could justify the implementation of compensation policies or labor training programs simultaneously with pro-innovation policies.

The effect of innovation on employment composition is estimated with a version of equation (1) for employment growth of skilled and unskilled workers. Skilled workers are defined as employees with tertiary education (1 to 3-years degrees related to technical professions) or a university degree, and unskilled workers are defined as employees with primary education, or secondary education.

For the two types of workers, skilled ($s$) and unskilled ($u$), we estimate

$$l^q = \alpha_0^q + \alpha_1^q d + g_1 + \beta^q g_2 + v^q, \qquad q = s, u, \quad (2)$$

where $l^q$ is the growth rate of employment of type $q$.

Table 18 shows the descriptive statistics for skilled and unskilled labor. ENIT01 has detailed information about the number of employees in 1998 and 2001 and the composition of employment by education. As we mentioned above, after 1998 Argentina faced a deep recession. In our sample, employment contracted at an annual rate of 4 percent. However, there were important differences between skilled and unskilled labor. Skilled employment decreased 2 percent while unskilled employment decreased 5 percent. The difference between skilled and unskilled labor growth rates were greater for innovators than for non-innovators. This suggests some complementarities between innovation and skilled labor.

**Table 18: Descriptive Statistics - Employment Quality**

| | Mean | Median | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| **Share of skilled labor** | | | | | |
| *All firms* | 34 | 28 | 28 | 0 | 100 |
| Non-innovators (no process or product innovations) | 28 | 19 | 27 | 0 | 100 |
| Process only innovators (non product innovators) | 34 | 29 | 27 | 0 | 100 |
| Product innovators | 39 | 33 | 28 | 0 | 100 |
| **Employment (total) growth (%)** | | | | | |
| *All firms* | -4.0 | -2.9 | 12.3 | -100.0 | 57.1 |
| Non-innovators (no process or product innovations) | -6.0 | -3.7 | 12.8 | -100.0 | 29.8 |
| Process only innovators (non product innovators) | -3.9 | -2.8 | 12.3 | -63.0 | 47.4 |
| Product innovators | -2.5 | -2.1 | 11.6 | -100.0 | 57.1 |
| **Skilled labor growth (%)** | | | | | |
| *All firms* | -1.4 | 0.0 | 14.6 | -100.0 | 99.0 |
| Non-innovators (no process or product innovations) | -3.9 | 0.0 | 16.0 | -100.0 | 49.4 |
| Process only innovators (non product innovators) | -1.1 | 0.0 | 14.4 | -40.2 | 99.0 |
| Product innovators | 0.2 | 0.0 | 13.3 | -100.0 | 66.8 |
| **Unskilled labor growth (%)** | | | | | |
| *All firms* | -5.3 | -3.9 | 13.9 | -100.0 | 60.2 |
| Non-innovators (no process or product innovations) | -6.7 | -4.2 | 13.6 | -100.0 | 26.9 |
| Process only innovators (non product innovators) | -4.6 | -4.5 | 14.1 | -56.7 | 60.2 |
| Product innovators | -4.6 | -3.4 | 14.0 | -100.0 | 36.3 |

*Source:* ENIT01.

*Notes: Skilled workers* are employees with a university degree or tertiary education (1 to 3-year degree related to technical professions). *Unskilled workers* are employees with primary or secondary education. *Product innovators* are firms that have introduced product innovations. *Process only innovators* are firms that have introduced process innovations or organizational change innovations excluding product innovators. *Non-innovators* are firms not classified as product or process innovators. Sample: Firms with information in all the relevant variables for the empirical analysis.

Table 19 shows the OLS and IV results for the full sample. Column (3) and (4) in Table 19 show the IV results for the effect of innovations on skilled and unskilled employment. The IV estimates of the effect of process innovation and product innovation are larger than the OLS estimates in columns (1) and (2). This is consistent with a downward bias in the OLS estimation.

Interestingly, the IV results suggest that product innovations are more skill-intensive. In a one-sided test of $H_0: \beta^u = \beta^s$ vs. $H_1: \beta^u < \beta^s$ we reject the null at a significance level of 0.10 but not at 0.05. On the other hand, there is no evidence that process innovations affect the skill composition.

It should be noted that the test for endogeneity of $g_2$ does not reject exogeneity of $g_2$. We interpret this result as evidence than the loss in precision prevents us from ruling out exogeneity of $g_2$. Otherwise, this should offer a convincing explanation for the fact that $g_2$ is endogenous for skilled labor but not for unskilled labor or, as we will see below, it is endogenous for low-tech firms but not high-tech firms. We follow a more conservative approach of treating $g_2$ as endogenous in all specifications.

Table 20 shows the OLS and IV results for the effect of innovations on skilled and unskilled employment for small firms. For small firms, the IV results show some evidence that product innovations are more skilled intensive but these effects are not statistically significant. This is probably due to the small sample size. There is no evidence that process innovations affect skill composition.

Table 21 and 22 show the OLS and IV results for the effect of innovation on skilled and unskilled employment for low-tech and high-tech firms. The IV results show no evidence that process innovations or product innovations affect skill composition.

**Table 19: Quality - OLS and IV Estimation**

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-Skilled**<br>**OLS** | **Manufacturing**<br>**2-Unskilled**<br>**OLS** | **Manufacturing**<br>**3-Skilled**<br>**IV** | **Manufacturing**<br>**4-Unskilled**<br>**IV** |
|---|---|---|---|---|
| Constant | 7.184*** | 2.213* | -1.179 | -1.975 |
| | (0.947) | (1.060) | (4.353) | (3.848) |
| Process only innovator (*d*) | -0.152 | 0.845 | 3.048 | 2.448 |
| | (1.174) | (1.173) | (2.291) | (2.010) |
| Sales growth due to new products *(g2)* | 0.962*** | 0.953*** | 1.308*** | 1.126*** |
| | (0.015) | (0.015) | (0.174) | (0.153) |
| Located in the capital | -0.438 | 1.791 | 0.160 | 2.090 |
| | (1.022) | (1.101) | (1.259) | (1.197) |
| Foreign owned (10% or more) | -3.591** | -5.273*** | -5.408** | -6.183*** |
| | (1.125) | (1.134) | (1.646) | (1.369) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *g2* equation | | | 11.470 | 11.470 |
| Pvalue | | | 0.001 | 0.001 |
| Davidson-MacKinnon test of exogeneity for *g2* | | | 5.992 | 1.427 |
| Pvalue | | | 0.015 | 0.232 |
| R-squared | 0.805 | 0.795 | 0.696 | 0.761 |
| Number of firms | 1,209 | 1,209 | 1,209 | 1,209 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities*. Endogenous variables: *g2*.

**Table 20: Quality - OLS and IV Estimation - Small Firms**

| Sector<br>Regression | Manufacturing<br>1-Skilled<br>OLS | Manufacturing<br>2-Unskilled<br>OLS | Manufacturing<br>3-Skilled<br>IV | Manufacturing<br>4-Unskilled<br>IV |
|---|---|---|---|---|
| Constant | 3.652 | -1.395 | -3.184 | -3.581 |
| | (2.274) | (2.632) | (7.263) | (6.159) |
| Process only innovator (*d*) | -3.874 | 0.162 | -3.696 | 0.218 |
| | (2.988) | (2.882) | (3.887) | (3.025) |
| Sales growth due to new products *(g2)* | 0.991*** | 0.965*** | 1.346*** | 1.075*** |
| | (0.042) | (0.038) | (0.379) | (0.304) |
| Located in the capital | 1.434 | 6.408* | 1.690 | 6.488* |
| | (2.829) | (2.808) | (3.211) | (2.863) |
| Foreign owned (10% or more) | -0.548 | -1.150 | -0.597 | -1.166 |
| | (4.593) | (4.758) | (5.960) | (4.966) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *g2* equation | | | 4.486 | 4.486 |
| Pvalue | | | 0.035 | 0.035 |
| Davidson-MacKinnon test of exogeneity for *g2* | | | 1.341 | 0.141 |
| Pvalue | | | 0.247 | 0.707 |
| R-squared | 0.715 | 0.729 | 0.610 | 0.700 |
| Number of firms | 306 | 306 | 306 | 306 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%., (iii) Instruments: *knowledge of public support for innovation activities*. Endogenous variables: *g2*.

**Table 21: Quality - OLS and IV Estimation - Low-tech Firms**

| Sector<br>Regression | Manufacturing<br>1-Skilled<br>OLS | Manufacturing<br>2-Unskilled<br>OLS | Manufacturing<br>3-Skilled<br>IV | Manufacturing<br>4-Unskilled<br>IV |
|---|---|---|---|---|
| Constant | 5.545*** | 2.700* | 1.04 | -0.981 |
| | (1.357) | (1.265) | (2.342) | (2.079) |
| Process only innovator (*d*) | -0.042 | 1.585 | 1.477 | 2.662 |
| | (1.756) | (1.845) | (2.188) | (2.074) |
| Sales growth due to new products *(g2)* | 0.973*** | 0.968*** | 1.144*** | 1.118*** |
| | (0.021) | (0.019) | (0.075) | (0.070) |
| Located in the capital | -1.612 | 0.146 | -0.939 | 0.697 |
| | (1.456) | (1.479) | (1.636) | (1.548) |
| Foreign owned (10% or more) | -3.931* | -7.892*** | -4.657* | -8.309*** |
| | (1.832) | (1.885) | (2.089) | (2.072) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *g2* equation | | | 9.014 | 8.651 |
| Pvalue | | | 0.000 | 0.000 |
| Sargan-Hansen test of overidentification | | | 4.452 | 2.436 |
| Pvalue (degrees of freedom) | | | 0.616 | 0.876 |
| Davidson-MacKinnon test of exogeneity for *g2* | | | 6.449 | 5.610 |
| Pvalue | | | 0.011 | 0.018 |
| R-squared | 0.793 | 0.782 | 0.763 | 0.755 |
| Number of firms | 599 | 651 | 599 | 651 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: knowledge of public support for innovation activities, continuous R&D dummy, and product life cycle dummies. Endogenous variables: g2.

**Table 22: Quality - OLS and IV Estimation - High-tech Firms**

| Sector<br>Regression | Manufacturing<br>1-Skilled<br>OLS | Manufacturing<br>2-Unskilled<br>OLS | Manufacturing<br>3-Skilled<br>IV | Manufacturing<br>4-Unskilled<br>IV |
|---|---|---|---|---|
| Constant | 7.704*** | 2.895* | 8.487*** | 3.801 |
| | (1.353) | (1.448) | (2.362) | (2.375) |
| Process only innovator (*d*) | -1.028 | -0.585 | -1.403 | -0.996 |
| | (1.523) | (1.489) | (1.883) | (1.907) |
| Sales growth due to new products *(g2)* | 0.952*** | 0.938*** | 0.919*** | 0.899*** |
| | (0.020) | (0.020) | (0.084) | (0.089) |
| Located in the capital | 0.732 | 2.637 | 0.693 | 2.579 |
| | (1.362) | (1.444) | (1.343) | (1.359) |
| Foreign owned (10% or more) | -2.892* | -3.918** | -2.673 | -3.628* |
| | (1.310) | (1.286) | (1.525) | (1.609) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *g2* equation | | | 5.380 | 5.171 |
| Pvalue | | | 0.000 | 0.000 |
| Sargan-Hansen test of overidentification | | | 3.974 | 0.612 |
| Pvalue (degrees of freedom) | | | 0.680 | 0.996 |
| Davidson-MacKinnon test of exogeneity for *g2* | | | 0.156 | 0.206 |
| Pvalue | | | 0.693 | 0.650 |
| R-squared | 0.818 | 0.798 | 0.809 | 0.790 |
| Number of firms | 698 | 718 | 698 | 718 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: knowledge of public support for innovation activities, continuous R&D dummy, and product life cycle dummies. Endogenous variables: g2.

A modified version of the equation used by Berman, Bound, and Griliches (1994) (henceforth BBG) is also estimated. The estimating equation is given by

$$\frac{L^S}{L} = \alpha_0 + \alpha_1 \ln(Y) + \alpha_2 \frac{Y_{22}}{Y} + \alpha_3 d + v, \quad (3)$$

where $L^S/L$ is the share of skilled labor on total labor,$Y$ is total sales, $Y_{22}/Y$ is the share of sales of new products on total sales, and $d$ is an indicator of process innovation.

Table 23 shows the OLS and IV results of the BBG model. The results suggest that process and product innovation do not affect the employment composition. On the other hand, an increase in total sales has an effect on labor composition increasing the skilled labor share. A 10 percent increase in sales would increase the share of skilled labor between 0.5 and 0.6 percentage points. Table 24 shows that the OLS and IV results of the BBG are similar for small firms.

## Table 23: Effect on Quality following Berman, Bound and Griliches (1994) OLS and IV Estimation

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-OLS** | **Manufacturing**<br>**2-OLS** | **Manufacturing**<br>**3-IV** | **Manufacturing**<br>**4-IV** |
|---|---|---|---|---|
| Constant | -0.569*** | -0.442*** | -0.583*** | -0.431*** |
| | (0.063) | (0.067) | (0.087) | (0.089) |
| Ln total sales | 0.059*** | 0.050*** | 0.061*** | 0.048*** |
| | (0.004) | (0.004) | (0.008) | (0.009) |
| Share of innovative sales on total sales *(Y22/Y)* | 0.000 | 0.000 | -0.000 | 0.001 |
| | (0.000) | (0.000) | (0.002) | (0.002) |
| Process only innovator (*d*) | -0.013 | -0.018 | -0.018 | -0.014 |
| | (0.018) | (0.018) | (0.029) | (0.031) |
| Located in the capital | | -0.003 | | -0.001 |
| | | (0.015) | | (0.018) |
| Foreign owned (10% or more) | | 0.103*** | | 0.102*** |
| | | (0.020) | | (0.019) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *(Y22/Y)* equation | - | - | 12.16 | 10.670 |
| Pvalue | - | - | 0.000 | 0.001 |
| Davidson-MacKinnon test of exogeneity for *(Y22/Y)* | - | - | 0.058 | 0.033 |
| Pvalue | - | - | 0.809 | 0.855 |
| R-squared | 0.262 | 0.277 | 0.142 | 0.113 |
| Number of firms | 1,412 | 1,412 | 1,412 | 1,412 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities*. Endogenous variables: *share of innovative sales on total sales*.

## Table 24: Effect on Quality following Berman, Bound and Griliches (1994) OLS and IV Estimation, Small Firms

| **Sector**<br>**Regression** | **Small in Manufacturing**<br>**3-OLS** | **Small in Manufacturing**<br>**4-OLS** | **Small in Manufacturing**<br>**3-IV** | **Small in Manufacturing**<br>**4-IV** |
|---|---|---|---|---|
| Constant | -0.519*** | -0.446** | -0.570** | -0.533* |
| | (0.151) | (0.148) | (0.217) | (0.221) |
| Ln total sales | 0.057*** | 0.053*** | 0.062*** | 0.063** |
| | (0.011) | (0.011) | (0.019) | (0.020) |
| Share of innovative sales on total sales *(Y22/Y)* | 0.000 | 0.000 | -0.001 | -0.002 |
| | (0.000) | (0.000) | (0.003) | (0.004) |
| Process only innovator (*d*) | 0.056 | 0.053 | 0.055 | 0.049 |
| | (0.045) | (0.043) | (0.042) | (0.044) |
| Located in the capital | | -0.041 | | -0.050 |
| | | (0.030) | | (0.034) |
| Foreign owned (10% or more) | | 0.126* | | 0.137* |
| | | (0.062) | | (0.060) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| F test, *(Y22/Y)* equation | - | - | 5.41 | 4.56 |
| Pvalue | - | - | 0.020 | 0.033 |
| Davidson-MacKinnon test of exogeneity for *(Y22/Y)* | - | - | 0.120 | 0.379 |
| Pvalue | - | - | 0.729 | 0.538 |
| R-squared | 0.229 | 0.241 | 0.398 | 0.334 |
| Number of firms | 415 | 415 | 415 | 415 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%, (iii) Instruments: *knowledge of public support for innovation activities*. Endogenous variables: *share of innovative sales on total sales*.

## 8. Innovation Strategies and Employment

Both product and process innovations are the result of different innovation strategies undertaken by firms. Indeed, firms can innovate by investing in R&D, training, acquiring embodied technologies or purchasing codified knowledge (e.g., through technological licenses). Previous innovation research has broadly categorized these channels in two types of innovation strategies: make or buy (Veugelers and Cassiman, 1999).

We consider a firm to be following a *make innovation strategy* if the firm conducts R&D aimed at introducing an innovation; a firm can be said to be following a *buy innovation strategy* if it acquired technology through licensing, R&D contracting, consultancy services or the acquisition of capital goods, hardware, or software aimed at introducing an innovation. We distinguish between firms following a *make only strategy*, a *buy only strategy* and *a mix of make and buy strategies*.

We follow two approaches to estimate the impact of innovation strategies on employment growth: first, a reduced-form approach, which is an extension of the innovation-employment model allowing for different innovation strategies, and second, a structural approach modeled as a two-step process. In the first step, innovation inputs (innovation strategies) impact on innovation outputs (product and process innovations), and in the second step innovation outputs impact on employment growth.

In the reduced-form approach we estimate the econometric model

$$l-(g_1-\pi)= \alpha_0+\alpha_m make+\alpha_b\, buy+\alpha_{mnb} make\&buy+v, \quad (4)$$

where $make$ is an indicator of whether the firm follows a *make only strategy*, $buy$ is an indicator of whether the firm follows a *buy only strategy*, $make\&buy$ an indicator of whether the firm follows both *a mix of make and buy strategies*.

In the structural approach, we regress innovation strategies on product and process innovations and growth sales of old products. After that, we use the results of the innovation-employment model to decompose the impact of innovation strategies on employment growth in different channels: a product innovation effect, a process innovation effect, and sales of old products effect.

The econometric model for the first stage of the structural approach is

$$d = \delta_0 + \delta_m make + \delta_b\, buy + \delta_{mnb} make\&buy + error,$$

$$g_2 = \gamma_0 + \gamma_m make + \gamma_b\, buy + \gamma_{mnb}\, make\&buy + error,$$

$$g_1 = \rho_0 + \rho_m make + \rho_b\, buy + \rho_{mnb}\, make\&buy + error.$$

These equations measure the impact of different innovation strategies on process and product innovations, and on sales of old products.

The second stage is simply the innovation-employment model of HMJP already estimated:

$$l = \alpha_0 + \alpha_1 d + g_1 + \beta g_2 + v.$$

To decompose the impact of different innovation strategies on employment growth, we can use the estimates of the first and second stages. For example, the expected impact of a make innovation strategy (vs. no innovation strategy) on employment growth is

$$\begin{aligned} &E[l|make = 1, x] - E[l|make = 0, x] \\ &\quad = \beta\, (E[g_2|make = 1, x] - E[g_2|make = 0, x]) \\ &\quad + \alpha_1(\Pr(d = 1|make = 1, x) - \Pr(d = 1|make = 0, x)) \\ &\quad + (\mathrm{E}(g_1|make = 1, x) - \mathrm{E}(g_1|make = 0, x)) \\ &\quad = \alpha_1\delta_m + \beta\,\gamma_m + \rho_m. \end{aligned}$$

The first term measures the impact of a make strategy on employment through process innovations, the second term measures the impact through product innovations, and the third term measures the impact through the growth in sales of old products. As usual, we replace unknown parameters with their sample estimates to get an estimate of these effects.

Table 25 shows the descriptive statistics for innovation strategies. A firm follows a *make innovation strategy* if the firm does R&D aimed at introducing an innovation, and a *buy innovation strategy* if the firm acquired technology through licensing, through R&D contracting, through consultancy services, and/or through the acquisition of capital goods, hardware or software aimed at introducing an innovation. We distinguish between firms following a *make only strategy*, a *buy only strategy* and *a mix of make and buy strategies*.

Table 25 shows that most of the firms follow a buy only strategy (25 percent) or a make and buy strategy (23 percent), with only few firms following a make only strategy (5 percent). The sample statistics show that most firms that follow a buy only strategy are process innovators, and most firms that follow a make and buy strategy are product innovators.

**Table 25: Descriptive Statistics - Innovation Strategies**

| | Buy only | Make only | Make and Buy |
|---|---|---|---|
| **Share of firms pursuing each type of strategy by type of firm (%)** | | | |
| *All firms* | 25 | 5 | 23 |
| Non-innovators (no process or product innovations) | 12 | 1 | 1 |
| Process only innovators (non product innovators) | 49 | 2 | 14 |
| Product innovators | 26 | 9 | 40 |
| **Share of firms pursuing each type of strategy by type of firm (%) – Small firms** | | | |
| *All firms* | 21 | 5 | 11 |
| Non-innovators (no process or product innovations) | 11 | 1 | 1 |
| Process only innovators (non product innovators) | 43 | 3 | 10 |
| Product innovators | 29 | 12 | 28 |

*Source:* ENIT01.

*Notes: Make innovation strategy*: the firm does R&D aimed at introducing an innovation. *Buy innovation strategy:* the firm acquired technology through licensing and/or through R&D contracting and/or through consultancy services and/or through the acquisition of capital goods, hardware or software aimed at introducing an innovation. *Product innovators* are firms that have introduced product innovations. *Process only innovators* are firms that have introduced process innovations or organizational change innovations excluding product innovators. *Non-innovators* are firms not classified as product or process innovators. Sample: Firms with information in all the relevant variables for the empirical analysis.

Table 26 shows the reduced form and first-stage regressions (upper panel), and the second-stage regression (lower panel). Column (1) in the upper panel of Table 26 shows the OLS results for reduced form model. The results in column (1) suggest that the make only strategy has a larger effect on employment than both make and buy and buy only strategies. These results also suggest that a make and buy strategy has a larger effect on employment than a buy strategy.

It should be noted that only 5 percent of firms follows a make only strategy (Table 9). Thus, it is difficult to draw clear-cut conclusions from these firms. For this reason, in the following analysis we will focus only on the differences between a make and buy strategy and a buy only strategy.

Columns (2), (3), and (4) in the upper panel of Table 26 show the results of the first stage between innovation strategies and product and process innovations and sales of old products. The results suggest that a make and buy strategy accelerates the introduction of new products by 10 percentage points more than a buy only strategy. On the other hand, a make and buy strategy decreases the sales of old products by 10 percentage points more than a buy only strategy. In addition, a buy only strategy increases the probability of introducing a process innovation by 20 percentage points more than a make and buy strategy. These differences are statistically significant.

Columns (1) and (2) in the lower panel of Table 26 reproduce the results of the innovation-employment model showing that product innovation has a positive effect on employment and that process innovations have no effect on employment. Thus, given the results of the first stage, we intuitively expect that a make and buy strategy has a larger effect on employment growth than a buy only strategy if the product innovation affect dominates the sales of old products effect.

In Table 30, we quantify the total effect of different innovation strategies on employment growth. The main result is that a make and buy strategy has a larger effect on employment than a buy only strategy. In short, the larger employment growth in the product innovation effect more than compensates for the lower employment growth in the sales of old products. As expected, the process innovation effect has negligible effects on employment growth.

Table 27 shows the reduced form and the first stage regressions (upper panel), and the second stage regression (lower panel) for small firms. In summary, the results are similar than the results for the full sample with a loss in precision due to the sample size. Table 30 shows that a make and buy strategy has a larger effect on employment than a buy only strategy, and this difference is larger for small firms than for the full sample.

Table 28 and 29 show the reduced form and the first-stage regressions (upper panel), and the second-stage regression (lower panel) for low-tech and high-tech firms. The results for low-tech firms are similar than the results for the full sample: a make only strategy has a larger effect on employment than both make and buy and buy only strategies, but the results for high-tech firms do not show important differences between the effects of make and buy and buy only strategies.

## Table 26: Strategies - Reduced form and First and Second stage regressions

| **Sector**<br>**First equation** | **Manufacturing**<br>**Reduced form**<br>**l -(g1-Π)**<br>**1-OLS** | **Manufacturing**<br>**First stage**<br>**g2**<br>**2-OLS** | **Manufacturing**<br>**First stage**<br>**d**<br>**3-OLS** | **Manufacturing**<br>**First stage**<br>**g1**<br>**4-OLS** |
|---|---|---|---|---|
| Constant | 14.899*** | 11.433*** | 0.114*** | -21.462*** |
| | (1.272) | (0.743) | (0.011) | (0.696) |
| Make only (dummy) | 30.430*** | 30.833*** | -0.050 | -31.009*** |
| | (4.846) | (4.433) | (0.030) | (4.088) |
| Buy only (dummy) | 14.589*** | 15.222*** | 0.195*** | -12.943*** |
| | (2.510) | (2.123) | (0.028) | (1.966) |
| Make & Buy (dummy) | 23.972*** | 25.599*** | -0.013 | -22.456*** |
| | (2.567) | (1.970) | (0.017) | (1.719) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.128 | 0.114 | 0.058 | 0.092 |
| Number of firms | 1,209 | 1,209 | 1,209 | 1,209 |

| **Sector**<br>**Second Equation** | **Manufacturing**<br>**l -(g1-Π)** | **Manufacturing**<br>**l -(g1-Π)** |
|---|---|---|
| Constant | 2.776 | -0.701 |
| | (1.206) | (3.027) |
| Process only innovator (*d*) | -0.506 | 0.767 |
| | (1.195) | (1.586) |
| Sales growth due to new products *(g2)* | 1.013*** | 1.159*** |
| | (0.047) | (0.123) |
| 2-digit industry dummies | Yes | Yes |
| F test, *g2* equation | 14.820 | 14.454 |
| Pvalue | 0.001 | 0.000 |
| F test, d equation | - | 3.232 |
| Pvalue | - | 0.002 |
| Sargan-Hansen test of overidentification | - | 2.906 |
| Pvalue (degrees of freedom) | - | 0.714(5) |
| Davidson-MacKinnon test for g2 | 3.213 | 2.135 |
| Pvalue | 0.073 | 0.144 |
| Davidson-MacKinnon test for d | - | 0.629 |
| Pvalue | - | 0.428 |
| R-squared | 0.785 | 0.790 |
| Number of firms | 1,415 | 1,415 |

*Notes:* A firm follows a *make innovation strategy* if the firm does R&D aimed at introducing an innovation, and a firm follows a *buy innovation strategy* if the firm acquired technology through licensing and/or through R&D contracting and/or through consultancy services and/or through the acquisition of capital goods, hardware or software aimed at introducing an innovation. (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

**Table 27: Strategies - Reduced Form and First- and Second-stage Regressions**
**Small Firms**

| Sector<br>First equation | Small Manufacturing Reduced form l -(g1-Π) 1-OLS | Small Manufacturing First stage g2 2-OLS | Small Manufacturing First stage d 3-OLS | Small Manufacturing First stage g1 4-OLS |
|---|---|---|---|---|
| Constant | 12.374*** | 8.558*** | 0.101*** | -18.115*** |
| | (2.248) | (1.500) | (0.023) | (1.739) |
| Make only (dummy) | 41.504*** | 37.787** | -0.043 | -41.444** |
| | (10.847) | (11.506) | (0.083) | (12.122) |
| Buy only (dummy) | 16.693** | 17.315** | 0.157 | -15.580* |
| | (5.819) | (5.087) | (0.076) | (6.375) |
| Make & Buy (dummy) | 31.422*** | 36.880*** | -0.014 | -30.670*** |
| | (8.577) | (5.958) | (0.068) | (4.220) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.174 | 0.166 | 0.042 | 0.131 |
| Number of firms | 306 | 306 | 306 | 306 |

| Sector<br>Second Equation | Small Manufacturing l -(g1-Π) | Small Manufacturing l -(g1-Π) |
|---|---|---|
| Constant | 3.579 | 8.490** |
| | (3.498) | (3.477) |
| Process only innovator (*d*) | -2.923 | -29.023 |
| | (2.512) | (21.910) |
| Sales growth due to new products *(g2)* | 1.052*** | 0.947*** |
| | (0.189) | (0.092) |
| 2-digit industry dummies | Yes | Yes |
| F test, *g2* equation | 7.380 | 7.511 |
| Pvalue | 0.007 | 0.000 |
| F test, d equation | - | 1.295 |
| Pvalue | - | 0.251 |
| Sargan-Hansen test of overidentification | - | 3.428 |
| Pvalue (degrees of freedom) | - | 0.634(5) |
| Davidson-MacKinnon test for g2 | 0.248 | 0.023 |
| Pvalue | 0.618 | 0.879 |
| Davidson-MacKinnon test for d | - | 1.755 |
| Pvalue | - | 0.185 |
| R-squared | 0.738 | 0.695 |
| Number of firms | 417 | 417 |

*Notes:* A firm follows a *make innovation strategy* if the firm does R&D aimed at introducing an innovation, and a firm follows a *buy innovation strategy* if the firm acquired technology through licensing and/or through R&D contracting and/or through consultancy services and/or through the acquisition of capital goods, hardware or software aimed at introducing an innovation. (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 28: Strategies - Reduced Form and First- and Second-stage Regressions Low-tech Firms

| **Sector**<br><br><br>**First equation** | **Manufacturing**<br>**Reduced form**<br>**l -(g1-Π)**<br>**1-OLS** | **Manufacturing**<br>**First stage**<br>**g2**<br>**2-OLS** | **Manufacturing**<br>**First stage**<br>**d**<br>**3-OLS** | **Manufacturing**<br>**First stage**<br>**g1**<br>**4-OLS** |
|---|---|---|---|---|
| Constant | 14.582*** | 12.636*** | 0.135*** | -20.882*** |
| | (1.978) | (0.992) | (0.007) | (1.321) |
| Make only (dummy) | 28.316*** | 30.476** | -0.102*** | -29.458** |
| | (7.559) | (7.483) | (0.014) | (7.981) |
| Buy only (dummy) | 8.138* | 7.980* | 0.175*** | -6.752 |
| | (3.953) | (2.541) | (0.035) | (3.345) |
| Make & Buy (dummy) | 28.311*** | 28.451*** | -0.018 | -25.673*** |
| | (3.798) | (2.508) | (0.021) | (2.380) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.143 | 0.13 | 0.046 | 0.105 |
| Number of firms | 559 | 559 | 559 | 559 |
| **Sector**<br>**Second Equation** | **Manufacturing**<br>**l -(g1-Π)** | **Manufacturing**<br>**l -(g1-Π)** | | |
| Constant | -0.266 | -2.109 | | |
| | (1.667) | (3.572) | | |
| Process only innovator (*d*) | 0.478 | 9.351 | | |
| | (1.865) | (15.203) | | |
| Sales growth due to new products *(g2)* | 1.098*** | 1.119*** | | |
| | (0.064) | (0.075) | | |
| 2-digit industry dummies | Yes | Yes | | |
| F test, *g2* equation | 9.010 | 9.274 | | |
| Pvalue | 0.000 | 0.000 | | |
| F test, d equation | - | 1.897 | | |
| Pvalue | - | 0.068 | | |
| Sargan-Hansen test of overidentification | 2.603 | 2.109 | | |
| Pvalue (degrees of freedom) | 0.857 | 0.834(5) | | |
| Davidson-MacKinnon test for g2 | 4.691 | 4.834 | | |
| Pvalue | 0.031 | 0.028 | | |
| Davidson-MacKinnon test for d | - | 0.358 | | |
| Pvalue | - | 0.550 | | |
| R-squared | 0.807 | 0.782 | | |
| Number of firms | 672 | 672 | | |

*Notes:* A firm follows a *make innovation strategy* if the firm does R&D aimed at introducing an innovation, and a firm follows a *buy innovation strategy* if the firm acquired technology through licensing and/or through R&D contracting and/or through consultancy services and/or through the acquisition of capital goods, hardware or software aimed at introducing an innovation. (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 29: Strategies - Reduced Form and First- and Second-stage Regressions High-tech Firms

| **Sector** | **Manufacturing** | **Manufacturing** | **Manufacturing** | **Manufacturing** |
|---|---|---|---|---|
| | **Reduced form** | **First stage** | **First stage** | **First stage** |
| **First equation** | **l -(g1-Π)** | **g2** | **d** | **g1** |
| | **1-OLS** | **2-OLS** | **3-OLS** | **4-OLS** |
| Constant | 15.226*** | 10.413*** | 0.095*** | -21.988*** |
| | (1.637) | (1.135) | (0.020) | (0.815) |
| Make only (dummy) | 31.933*** | 31.115*** | -0.009 | -32.156*** |
| | (6.301) | (5.658) | (0.053) | (4.210) |
| Buy only (dummy) | 18.734*** | 20.000*** | 0.209*** | -16.987*** |
| | (3.205) | (2.275) | (0.044) | (2.040) |
| Make & Buy (dummy) | 19.444*** | 22.553*** | -0.008 | -19.068*** |
| | (3.402) | (3.215) | (0.027) | (2.628) |
| 2-digit industry dummies | Yes | Yes | Yes | Yes |
| R-squared | 0.128 | 0.116 | 0.071 | 0.095 |
| Number of firms | 650 | 650 | 650 | 650 |
| **Sector** | **Manufacturing** | **Manufacturing** | | |
| **Second Equation** | **l -(g1-Π)** | **l -(g1-Π)** | | |
| Constant | 6.349*** | 4.509 | | |
| | (1.764) | (3.800) | | |
| Process only innovator (*d*) | -1.955 | 5.061 | | |
| | (1.587) | (12.900) | | |
| Sales growth due to new products *(g2)* | 0.903*** | 0.938*** | | |
| | (0.070) | (0.095) | | |
| 2-digit industry dummies | Yes | Yes | | |
| F test, *g2* equation | 5.380 | 5.864 | | |
| Pvalue | 0.000 | 0.000 | | |
| F test, d equation | - | 2.586 | | |
| Pvalue | - | 0.012 | | |
| Sargan-Hansen test of overidentification | 1.686 | 1.348 | | |
| Pvalue (degrees of freedom) | 0.946 | 0.930(5) | | |
| Davidson-MacKinnon test for g2 | 0.310 | 0.018 | | |
| Pvalue | 0.578 | 0.892 | | |
| Davidson-MacKinnon test for d | - | 0.309 | | |
| Pvalue | - | 0.578 | | |
| R-squared | 0.725 | 0.832 | | |
| Number of firms | 743 | 743 | | |

*Notes:* A firm follows a *make innovation strategy* if the firm does R&D aimed at introducing an innovation, and a firm follows a *buy innovation strategy* if the firm acquired technology through licensing and/or through R&D contracting and/or through consultancy services and/or through the acquisition of capital goods, hardware or software aimed at introducing an innovation. (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

**Table 30: Effect of Different Innovation Strategies on Employment**

| Sector | Manufacturing | | | | Small in Manufacturing | | | |
|---|---|---|---|---|---|---|---|---|
| | Effects on employment growth | | | | Effects on employment growth | | | |
| **Strategy** | **Product innovations** | **Process innovations** | **Sales of old products** | **Total** | **Product innovations** | **Process innovations** | **Sales of old products** | **Total** |
| Make only | 35.74 | -0.04 | -31.01 | 4.69 | 39.75 | 0.13 | -41.44 | -1.57 |
| Buy only | 17.64 | 0.15 | -12.94 | 4.85 | 18.22 | -0.46 | -15.58 | 2.18 |
| Make & Buy | 29.67 | -0.01 | -22.46 | 7.20 | 38.80 | 0.04 | -30.67 | 8.17 |

*Notes:* A firm follows a *make innovation strategy* if the firm does R&D aimed at introducing an innovation, and a firm follows a *buy innovation strategy* if the firm acquired technology through licensing and/or through R&D contracting and/or through consultancy services and/or through the acquisition of capital goods, hardware or software aimed at introducing an innovation.

## 9. Employment Growth Decomposition

The results of the innovation-employment equation can be used to decompose the contribution of different factors to employment growth.

We use the employment growth decomposition proposed in HJMP. Firm's employment growth can be written as:

$$l_i = \sum_j \left(\alpha_j + \alpha_{0j}\right) industry_{ji} + \alpha_1 d_i + [1 - 1(g_{2i} > 0)](g_{1i} - \pi_1) + 1(g_{2i} >$$
$$0 g1i - \pi 1 + \beta g2i + \upsilon i,$$

where $industry_{ji}$ is an industry dummy variable. Thus, employment growth can be decomposed into four main components. The first component ($\sum_j(\alpha_j + \alpha_{0j})\, industry_{ji}$) measures the contribution of the *(industry specific) productivity trend in the production of old products*, the second component ($\alpha_1 d_i$) measures the contribution of the *productivity effect of process innovations in the production of old products*, the third component ($[1 - 1(g_{2i} > 0)](g_{1i} - \pi_1)$) measures the contribution of *output growth of old products for non-product innovators*, and the fourth component ($1(g_{2i} > 0)(g_{1i} - \pi_1 + \beta g_{2i})$) measures the *net contribution of product innovators.* In turn the net contribution of product innovators can be divided into the contribution of *output growth of old products for product innovators* and the contribution of the *production of new products for product innovators.*

Table 31 shows the contribution of the different components to employment growth. In what follows we concentrate on column (2) which shows the IV results for the full sample. The contribution of the productivity trend in the production of old products is -0.1 percent which shows a negligible increase in labor productivity in this period. This trend in productivity may be explained, at least in part, by the business cycle. Sales contracted at 9 percent per year, but firms did not transfer the full extent of the adjustment to the labor force. This can be an optimal decision the firms in the presence of labor adjustment costs or if firms have more optimistic expectations for the future.

The contribution of the effect of process innovations in the production of old products is -0.1 percent. Two factors affect this contribution. First, there are few firms which introduce only process innovations (15 percent of the sample). Second, process innovations seem to have rather small effects on employment.

The contribution of the output growth of old products for non-product innovators is -4.6 percent. This is just the effect of the business cycle, with a 10 percent decrease in sales for non-product innovators.

The net contribution of product innovators is 0.6 percent, which can be divided into the contribution of output growth of old products (-21.1 percent) and the contribution of production of new products (21.7 percent). These results show that product innovators substitute old products with new products at a rapid pace even in a recessive scenario. The result of the innovation-employment model that there are no efficiency gains in the production of new products might also suggest that product innovators are selling a similar product with small changes (incremental innovation).

Table 32 shows the decomposition for high and low technology sectors. Columns (2) and (4) show the IV results for high technology and low technology. High- and low-tech sectors have similar employment growth rates but for different reasons. Employment growth in high-tech sectors receives a positive contribution from a negative trend in productivity that it is more than compensated for by the negative contributions by non-product innovators and product innovators. Employment growth in low-tech sectors gets a positive contribution from product innovators that it is more than compensated for by the negative contributions from non-product innovators.

Tables 33 and 34 show a similar decomposition for skilled and unskilled labor. We comment on the IV results for the full sample in column (2). It is interesting to analyze the factors behind the differential growth in skilled labor (-1.4 percent) and unskilled labor (-5.3 percent). The decomposition suggests that the skill bias of product innovators more than compensates for the higher productivity trend observed in skilled workers.

**Table 31: Contributions of Innovation to Employment Growth, Manufacturing, Period 1998-2001**

| | Manufacturing<br>1-OLS | Manufacturing<br>2-IV | Small in Manufacturing<br>3-OLS | Small in Manufacturing<br>4-IV |
|---|---|---|---|---|
| Firms employment growth | -4.0 | -4.0 | -3.5 | -3.5 |
| Productivity trend in production of old products | 4.0 | -0.1 | 5.0 | 3.8 |
| Gross effect of process innovation in production of old products | -0.2 | 0.1 | -0.3 | -0.4 |
| Output growth of old products for non-product innovators | -4.6 | -4.6 | -6.1 | -6.1 |
| Net contribution of product innovation | -3.2 | 0.6 | -2.1 | -0.8 |
| Contribution of old products by product innovators | -21.1 | -21.1 | -15.1 | -15.1 |
| Contribution of new products by product innovators | 17.9 | 21.7 | 13.0 | 14.3 |

*Notes: Decomposition based on Tables 5, 6, 14 and 15. Annual rates of growth for the period 1998–2001.*

**Table 32: Contributions of Innovation to Employment Growth, Low- and High- tech Industries, Period 1998-2001**

| | High-tech<br>1-OLS | High-tech<br>2-IV | Low-tech<br>3-OLS | Low-tech<br>4-IV |
|---|---|---|---|---|
| Firms employment growth | -4.4 | -4.4 | -3.4 | -3.4 |
| Productivity trend in production of old products | 5.2 | 6.0 | 2.6 | 0.1 |
| Gross effect of process innovation in production of old products | -0.2 | -0.3 | -0.1 | 0.1 |
| Output growth of old products for non-product innovators | -5.4 | -5.4 | -3.7 | -3.7 |
| Net contribution of product innovation | -4.0 | -4.7 | -2.3 | 0.1 |
| Contribution of old products by product innovators | -21.8 | -21.8 | -20.2 | -20.2 |
| Contribution of new products by product innovators | 17.8 | 17.1 | 18.0 | 20.4 |

*Notes: Decomposition based on Tables 7, 16 and 17. Annual rates of growth for the period 1998–2001.*

## Table 33: Contributions of Innovation to Skilled Employment Growth, Manufacturing, Period 1998-2001

| | Manufacturing<br>1-OLS | Manufacturing<br>2-IV | Small in Manufacturing<br>3-OLS | Small in Manufacturing<br>4-IV |
|---|---|---|---|---|
| Firms employment growth | -1.4 | -1.4 | -2.7 | -2.7 |
| Productivity trend in production of old products | 6.3 | -2.2 | 5.1 | 1.0 |
| Gross effect of process innovation in production of old products | 0.0 | 0.6 | -0.4 | -0.3 |
| Output growth of old products for non-product innovators | -4.4 | -4.4 | -5.6 | -5.6 |
| Net contribution of product innovation | -3.2 | 4.7 | -1.8 | 2.3 |
| Contribution of old products by product innovators | -21.8 | -21.8 | -16.7 | -16.7 |
| Contribution of new products by product innovators | 18.6 | 26.5 | 14.9 | 19.0 |

*Notes: Decomposition based on Tables 5, 6, 8, 18 and 19. Annual rates of growth for the period 1998–2001.*

## Table 34: Contributions of Innovation to Unskilled Employment Growth, Manufacturing, Period 1998-2001

| | Manufacturing<br>1-OLS | Manufacturing<br>2-IV | Small in Manufacturing<br>3-OLS | Small in Manufacturing<br>4-IV |
|---|---|---|---|---|
| Firms employment growth | -5.3 | -5.3 | -4.3 | -4.3 |
| Productivity trend in production of old products | 2.7 | -0.5 | 3.8 | 2.9 |
| Gross effect of process innovation in production of old products | 0.0 | 0.1 | -0.2 | -0.2 |
| Output growth of old products for non-product innovators | -4.4 | -4.4 | -5.6 | -5.6 |
| Net contribution of product innovation | -3.5 | -0.5 | -2.3 | -1.4 |
| Contribution of old products by product innovators | -21.8 | -21.8 | -16.7 | -16.7 |
| Contribution of new products by product innovators | 18.3 | 21.3 | 14.4 | 15.3 |

*Notes: Decomposition based on Tables 5, 6, 9, 18 and 19. Annual rates of growth for the period 1998–2001.*

## 10. Conclusions

This paper presented evidence about the relationship between innovation and employment in Argentina. More precisely, we attempted to answer the following research questions: (i) Do different types of innovation create or destroy employment? In particular, we focused on the differential effect of *product and process innovations* on employment growth. ii) Does the impact of innovation vary according to firm size? iii) Does the impact of innovation vary between high- and low-tech industries? iv) Do different types of innovations affect skill composition? (v) Do different innovation strategies influence the capacity of innovation to generate or destroy employment? We considered two types of innovation strategies: *make* (in-house developed innovation) and *buy* (externally acquired innovation).

We answered these questions estimating the structural model proposed in HJMP using an IV approach with data from the Innovation Surveys for Argentina for the period 1998-2001.

The estimation of the effect of the different types of innovation on employment suggests that while product innovations generate employment, process innovation has no effect on employment. In the case of product innovations, we find no evidence that new products are produced more efficiently than old products. Therefore, the displacement effect of product innovation on employment has no empirical support. These findings allow us to conclude that there is only a job creation effect due to increased demand. In the case of process innovation, there are two plausible explanations for its lack of effect on employment. First, a process innovation may not generate important productivity gains; hence, there is no displacement effect on employment. Second, a process innovation may generate productivity gains (displacement effect) which induce an increase in demand through market competition (creation effect). The creation effect on employment compensates for the displacement effect on employment.

The results for small firms are almost identical to those for the full sample, suggesting similar effects of the different types of innovations on employment. The results for low-tech and high-tech firms suggest that new products are produced relatively more efficiently than old products in high-tech firms. Hence, the job creation effect of product innovation is lower in the High-tech sector because of the displacement effect due to improvements in efficiency.

Specification tests support using an IV approach and the validity of the chosen instruments. In addition, the empirical results are robust for a stricter definition for new products, additional instruments, dealing with the endogeneity of process innovation, and allowing differential effect for product and process innovators.

The analysis of the effect of innovation on the skill composition offers some non-conclusive evidence that product innovations are more skilled intensive. Similar results are found for small firms and low-tech and high-tech firms.

The results of the effect of innovation strategies on employment suggest that *a mixed strategy of make and buy* (in-house developed innovation and externally acquired innovation) has a larger impact on employment growth than *a buy only strategy* (only externally acquired innovation). An important finding is that firms following a mixed strategy of make and buy create employment through the introduction of new products, while firms following a buy only strategy create employment through the sale of old products. Similar results are found for small firms and low-tech firms. Interestingly, the results for high-tech firms do show differences between the make and buy strategy and the buy only strategy in terms of employment.

## 11. References


Autor, D., L. Katz, and A. Krueguer. 1998. “Computing inequality: Have computers changed the labor market?” *The Quarterly Journal of Economics* 113: 1169-1214.

Barlevy, G. 2007. “On the Cyclicality of Research and Development”. *American Economic Review* 94: 1131-1164.

Basu, S. and J. Fernald. 2001. “Why is Productivity Procyclical? Why do we Care?” in *New Developments in Productivity Analysis*, Hulten, Dean, and Harper, editors. Chicago, IL, United States: The University of Chicago Press.

Benavente, J. M. and R. Lauterbach. 2008. “Technological innovation and employment: complements or substitutes,” *The European Journal of Development Research*, 20(2), 318–329.

Berman, E., K. Bound, and Z. Griliches. 1994. "Changes in the Demand for Skilled Labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufacturers". *The Quarterly Journal of Economics* 109: 367-397.

Binelli, C. and A. Maffioli. 2007. "A Micro-econometric Analysis of Public Support to Private R&D in Argentina". *International Review of Applied Economics* 21(3): 339-359.

Bresnahan, T., E. Brynjolfsson, and L. Hitt. 2002. "Information Technology, Workplace Organization and the Demand for Skilled Labor: Firm-Level Evidence". *The Quarterly Journal of Economics* 117: 339-376.

Caroli, E. and J. Van Reenen. 2001. "Skill-biased Organizational Change? Evidence from a Panel of British and French Establishments". *The Quarterly Journal of Economics* 116(4): 1449-1492.

Castillo, V., A. Maffioli, A. Monsalvo, S. Rojo, and R. Stucchi. 2010. "Can SME Policy Improve Firm Performance? Evidence from an Impact Evaluation in Argentina," OVE Working Papers 0710. Washington, DC, United States: Inter-American Development Bank, Office of Evaluation and Oversight.

Cerdán-Infantes, P., A. Maffioli, and D. Ubfal. 2008. "The Impact of Agricultural Extension Services: The Case of Grape Production in Argentina," OVE Working Papers 0508. Washington, DC, United States: Inter-American Development Bank, Office of Evaluation and Oversight.

Giuliodori, D and R. Stucchi. 2010. "Innovation and Job Creation in a Dual Labor Market: Evidence from Spain". MPRA Paper No. 23006.

Greenan, N. 2003. "Organizational Change, Technology, Employment and Skills: An empirical study of French Manufacturing". *Cambridge Journal of Economics* 27: 287-316.

Guner, N., G. Ventura, and X. Yi. 2007. "Macroeconomic Implications of Size-dependent Policies". *Review of Economic Dynamics* 11(4): 721-744.

Hall, B., F. Lotti, and J. Mairesse. 2006. “Employment, Innovation, and Productivity: Evidence from Italian Microdata,” Discussion paper, United Nations University, Working Paper Series 2006-43.

Harrison, R., J. Jaumandreu, J. Mairesse, and B. Peters. 2008. “Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data from Four European Countries,” NBER Working Papers 14216. Cambridge, MA, United States: National Bureau of Economic Research, Inc.

INDEC. 2003. *Segunda encuesta nacional de innovación y conducta tecnológica de las empresas argentinas 1998-2001*, INDEC, SECYT, CEPAL, Estudios 38. Buenos Aires, Argentina.

López, A., A. M. Reynoso, and M. Rossi. 2010. “Impact Evaluation of a Program of Public Funding of Private Innovation Activities. An Econometric Study of FONTAR in Argentina,” OVE Working Papers 0310. Washington, DC, United States: Inter-American Development Bank, Office of Evaluation and Oversight.

MINCYT. 2010. *Indicadores de Ciencia y Tecnología: Argentina 2008* Ministerio de Ciencia, Tecnología, e Innovación Productiva (MINCYT), Buenos Aires, Argentina.

OECD. 2005. *OSLO Manual, Guidelines for Collecting and Interpreting Innovation Data*, Paris, France: OECD Publishing.

Pages, C., editor. 2010. *The Age of Productivity: Transforming Economies from the Bottom Up*. Palgrave Macmillan Ltd.

Pianta, M. 2006. “Innovation and Employment,” in Fagerberg, J., D. Mowerey and R. Nelson Eds. *Oxford Handbook of Innovation*.Oxford University Press.

Stock, J., J. Wright, and M. Yogo. 2002. “A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments,” *Journal of Business and Economic Statistics* 20: 518-29.

USAID. 1996. “Conducting Key Informant Interviews”. *Performance Monitoring and Evaluation Tips*, Number 2. Washington, DC, United States: USAID.

Veugelers, R. and B. Cassiman. 1999. “Make and Buy in Innovation Strategies: Evidence from Belgian Manufacturing Firms,” *Research Policy* 28: 63-80.

## Appendix

## A. The Innovation-Employment Model with Non-Constant Returns to Scale

The innovation-employment model introduced in HJMP assumes constant returns to scale in the production of old and new products. In this section we present an extension of the innovation-employment model that allows for non-constant returns to scale in the production of old and new products. We use this model to evaluate the sensitivity of the results to the constant returns to scale assumption.

Assume that the production function for old (new) products is:

$$Y_{it} = \theta_{it}^{\sigma_i} F_i(L_{it}, K_{it}, M_{it}) e^{\sigma_i(\eta_i + \omega_{it})},$$

where $Y_{it}$ is production of product i (1 for old products, 2 for new products) in period t, $L_{it}$ denotes labor, $K_{it}$ denotes physical capital, $M_{it}$ denotes materials, $\theta_{it}$ it is a Hicks neutral parameter of technological change (that could vary by product or period), and $\sigma_i$ is the scale parameter. The firm's time invariant productivity is $\eta_i$ and the productivity shock is $\omega_{it}$. Notice that the scale parameters appear in the Hicks neutral technological change. We make this assumption because we will be able to identify the ratio $\theta_{11}/\theta_{22}$.

Let us assume that $F_i(.)$ is homogenous of degree $\sigma_i$ where $\sigma_i < 1$ or $\sigma_i > 1$. Thus we maintain the homogeneity assumption of HJMP but we allow for decreasing returns to scale ($\sigma_i < 1$) or increasing returns to scale ($\sigma_i > 1$). [15]Notice that we allow *economies of scale to be product-specific*.

If $F_i(.)$ is homogenous of degree $\sigma_i$ then the cost function is of the form:

$$C_i(w, Y_{it}) = c_i(w) \frac{Y_{it}^{\frac{1}{\sigma_i}}}{\theta_{it} e^{\eta_i + \omega_{it}}},$$

where $w$ is the vector of input prices. Using the enveloped theorem, the labor demand function is:

$$L_{it} = L_i(w, Y_{it}) = c_{w_l,i}(w) \frac{Y_{it}^{\frac{1}{\sigma_i}}}{\theta_{it} e^{\eta_i + \omega_{it}}},$$

[15] We maintain the following assumptions used in HJMP: (i) Perfect competition in input markets, (ii) Separable and identical production functions (up to the scale parameter), and (iii) $\omega_{11} = \omega_{12}$.

Assume that $c_{w_l,i}(.)$ does not depend on $\sigma_i$, otherwise wages and interest rates would appear in the employment growth equation.[16]

Using the expression derived in HJMP for the growth in employment and plugging in the labor demand we get:

$$\frac{\Delta L}{L} \approx \log\left(\frac{L_{12}}{L_{11}}\right) + \frac{L_{22}}{L_{11}}$$

$$= -(\log\theta_{12} - \log\theta_{11}) + \frac{1}{\sigma_1}(\log Y_{12} - \log Y_{11}) + \left(\frac{\theta_{11}}{\theta_{22}}\right)\frac{{Y_{22}}^{1/\sigma_2}}{{Y_{11}}^{1/\sigma_1}} - (\omega_{12} - \omega_{11})$$

The estimating equation is:

$$l = \alpha_0 + \alpha_1 d + \beta_1 g_1 + \beta_2 \frac{{y_{22}}^{\beta_3}}{{y_{11}}^{\beta_1}} + \vartheta.$$

which is a non-linear equation in the coefficients. The relationship between the structural parameters and the estimated coefficients is $\sigma_1 = 1/\beta_1$, $\sigma_2 = 1/\beta_3$, and $\theta_{11}/\theta_{22} = \beta_2$.

Table 35 shows the different models depending on the restrictions imposed on the scale parameters. For example, HJMP impose CRS in the production of old and new products. Model 2, 3, 4, and 5 are non-lineal models and they must be estimated by non-lineal least squares (NLS) or non-lineal GMM.

Tables 36 and 37 show estimates of scale parameters for old and new products $\sigma_1$ and $\sigma_2$) and the relative efficiency in the production of old products in 1998 vs. the production of new products in 2001 ($\theta_{11}/\theta_{22}$) with its corresponding standard errors.

[16]These conditions are verified, for example, by the Cobb-Douglas and the CES production functions.

## Table 35: Non-CRS Models under Different Assumptions

| Model | Old products | New products | $\beta_1$ | $\beta_2$ | Estimating equation |
|---|---|---|---|---|---|
| Model 1: HJMP | CRS | CRS | 1 | 1 | $l - g_1 = \alpha_0 + \alpha_1 d + \beta_2 g_2 + \vartheta$ |
| Model 2 | NonCRS | CRS | $\beta_1$ | 1 | $l = \alpha_0 + \alpha_1 d + \beta_1 g_1 + \beta_2 \frac{y_{22}}{y_{11}^{\beta_1}} + \vartheta$ |
| Model 3 | CRS | NonCRS | 1 | $\beta_3$ | $l - g_1 = \alpha_0 + \alpha_1 d + \beta_2 \frac{y_{22}^{\beta_3}}{y_{11}} + \vartheta$ |
| Model 4 | Same for both old and new | | $\beta$ | $\beta$ | $l = \alpha_0 + \alpha_1 d + \beta g_1 + \beta_2 g_2^{\beta} + \vartheta$ |
| Model 5 | NonCRS | NonCRS | $\beta_1$ | $\beta_3$ | $l = \alpha_0 + \alpha_1 d + \beta_1 g_1 + \beta_2 \frac{y_{22}^{\beta_3}}{y_{11}^{\beta_1}} + \vartheta$ |

## Table 36: Scale and Efficiency Parameters - NLS Estimation

| **Method** | **NLS** | **NLS** | **NLS** | **NLS** | **NLS** |
|---|---|---|---|---|---|
| **Regression** | **Model 1: HJMP** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
| Scale parameter for old products ($\sigma_1$) | 1.000 | 1.040 | 1.000 | 4.465 | 4.224 |
| (se) | (0.000) | (0.009) | (0.000) | (0.550) | (0.511) |
| Scale parameter for new products ($\sigma_2$) | 1.000 | 1.000 | 1.002 | 4.465 | 3.496 |
| (se) | (0.000) | (0.000) | (0.007) | (0.550) | (0.396) |
| Relative efficiency old in 1998-new in 2001 | 0.959 | 0.489 | 0.998 | 6.885 | 2.537 |
| (se) | (0.013) | (0.070) | (0.145) | (0.296) | (0.866) |
| Test: $H_0: \sigma_1 = \sigma_2 = 1$ | - | Reject $H_0$ | Do not reject $H_0$ | Reject $H_0$ | Reject $H_0$ |

*Notes:* (i) Standard errors computed by delta method in parenthesis.

## Table 37: Scale and Efficiency Parameters - GMM Estimation

| **Method** | **GMM** | **GMM** | **GMM** | **GMM** | **GMM** |
|---|---|---|---|---|---|
| **Regression** | **Model 1: HJMP** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
| Scale parameter for old products ($\sigma_1$) | 1.000 | 0.943 | 1.000 | 1.380 | 1.242 |
| (se) | (0.000) | (0.074) | (0.000) | (0.386) | (0.339) |
| Scale parameter for new products ($\sigma_2$) | 1.000 | 1.000 | 1.126 | 1.380 | 1.517 |
| (se) | (0.000) | (0.000) | (0.127) | (0.386) | (0.614) |
| Relative efficiency old in 1998-new in 2001 | 1.170 | 2.897 | 10.172 | 2.319 | 36.271 |
| (se) | (0.124) | (4.190) | (20.761) | (1.309) | (92.553) |
| Test: $H_0: \sigma_1 = \sigma_2 = 1$ | - | Do not reject $H_0$ | Do not reject $H_0$ | Do not reject $H_0$ | Do not reject $H_0$ |

*Notes:* (i) Standard errors computed by delta method in parenthesis, (ii) Instruments: *knowledge of public support for innovation activities* for model 1, and *knowledge of public support for innovation activities*, *continuous R&D dummy, and product life cycle dummies* for all other models.

Some observations of these results are in order. First, if we compare the HJMP and the Non-CRS, it seems that Non-CRS assumption may affect the estimation of the efficiency parameter. Second, identification of the efficiency parameter in the non-linear GMM is complicated. Third, the estimates of the scale parameters are quite stable and they suggest increasing returns. We reject CRS in both the production of old and new products in most of the NLS estimations while it is not possible to reject CRS in the GMM estimation due the loss in precision. Fourth, in general the IV estimations provide more reasonable but less precise estimates than the LS estimations.

## B. Case Studies: The Views of an Innovation and Employment Firm

Firm: Multinational firm which manufactures mobile, fixed, and other telecommunication devices.

Sector: Telecommunications and Technology

Size: 360 employees in Argentina

Interviewed: Arquitecto de Soluciones y Desarrollo de Nuevos Negocios

About the labor market: The main obstacle the firm faces is finding skilled workers. After hiring a new employee the firm needs to provide training to that worker for at least one year. Regulations are not considered to be a barrier for hiring. However, the firm subcontracts workers because it is less expensive. The firm's hiring strategy is to hire a relatively small number of employees and subcontract the rest.

He identified a trend in the sector in terms of hiring, which is a reduced number of permanent employees, subcontracting everything they need. He calls these types of firms "empresas integradoras" (EI). He points out that this characteristic differentiates this sector from the manufacturing sector.

About the innovativeness of the sector: This is a very competitive and innovative sector. Product innovation is more frequent than process innovation. Process and organizational innovation are marginal. EI are more innovative because they are more flexible.

In the past, firms developed three new products and then decided which product to produce depending on the market reception. Nowadays, to reduce costs firms develop only one.

Innovation and employment: Process innovation destroys employment. However, there is a transformation in terms of the quality of employment. He is not sure about the relationship between product innovation and employment. But in any case, he claims that product innovation is not very important for employment.

In general, process innovation destroys non-skilled jobs. There is also an age pattern; younger workers and employees over 45 have a higher probability of being fired. This pattern is more evident in small firms because large firms do not have these considerations when they need to fire workers. Temporary workers are fired first. However, process innovation also destroys permanent jobs. When there is a technological change, those permanent workers that are not able to learn the new technique are replaced. Not every fired worker is replaced; therefore, the final impact is a contraction in employment.

In general, the sector follows a "buy" innovation strategy because they subcontract everything they need.

Size considerations: Size is important; small firms are more innovative than large firms because they are more flexible.

Sector of activity considerations: In the manufacturing sector there is no EI trend. Services are more innovative in terms of process and organization. He mentioned that workers in the service sector are more prepared to innovate than workers in the manufacturing sector.

Firm: Multinational consulting company

Sector: Services (Strategic Consulting)

Size: 750 employees in Argentina, 9000 in LAC

Interviewed: Vice-President of Business Development for Latin America

About the labor market: In the last five years, the firm grew in Latin America from 300 employees to 9000 (2900 percent). In Argentina this growth was smaller but still large; it grew from 100 to 750 employees (650 percent). In spite of this impressive growth, he observes important obstacles for hiring new workers. These obstacles are related to regulatory instability, high inflation, and conflict. He also mentions as a second obstacle labor costs and labor-market rigidities. In this large expansion, the availability of skilled workers was not a constraint.

About the innovativeness of the sector: The sector is innovative in terms of products.

Innovation and employment: Product innovation creates jobs. The creation of jobs in Argentina was large but below the creation of jobs in other LAC countries due to uncertainty about future regulations and possible conflict with employees.

Process innovation is not important in the sector, but he mentions that in other sector it destroy some jobs and generate more qualified ones.

Firm: Provides services (customs services, accounting, tax administration, etc.) to other firms in the same group.

Sector: Service, Business Administration

Size: 280 employees in Argentina

Interviewed: Country Manager and Systems Manager.

About the labor market: Labor-market regulation is not an obstacle for hiring or firing workers, nor are regulatory instability, inflation, or labor conflicts. At the moment there is no labor union for administrative workers. Most of the workers are in Córdoba where the firm is highly competitive and able to attract and retain highly skilled workers.

About the innovativeness of the sector: The firm introduced a large organizational change. It centralized the management of twelve firms of the firm group. In the past, each firm had its own administration. The objective of the innovation was to improve efficiency by eliminating duplication and automating some processes. This innovation is not new to the market, as several groups are moving in this direction.

The firm also introduced an important organizational innovation related to international trade. The administration of imports and exports is managed internally. This innovation allowed the firm to increase efficiency in several areas, including the number of days that goods spend in customs.

Innovation and employment: The organizational innovation discussed above and other process innovations both destroy jobs and generate new jobs. When analyzing the impact of innovation on employment, is important to consider long-run effects. Employment is not very sensitive to innovation. After the innovation, the number of worker is approximately the same but the volume of sales is considerably larger. This growth in productivity would allow the firm to become larger.

With respect to the quality of employment destroyed and generated, in general, workers fired are those non-skilled or over 40 years old. Innovation makes no difference in terms of permanent vs. temporary employees.

Firm: Local pasta maker

Sector: Manufacturing, Food (Pasta Producer)

Size: 50-60 employees

Interviewed: Vice-president

About the labor market: In terms of regulatory obstacles, he was of the view that the probationary period is too short. In three months, it is not possible to screen workers. To avoid this problem, the company hires temporary workers (with a fixed-term contract). Another issue related to the cost of hiring employees is that labor suits are becoming increasingly common. Because of this problem, the firm's strategy is to reduce the number of workers hired.

About the innovativeness of the sector: He considers lack of credit as the main obstacle for innovation.  He also points out that corruption is a problem that the firm faces when applying for credit.

Innovation and employment: The firm is very innovative in terms of products. The firm has two regional strategies. In Cordoba, where they are the leader, they are trend makers. In Buenos Aires, they are followers, producing products similar to those produced by the industry leader.

The effect of product innovation on employment is positive. In the last ten years, demand has increased by 1000 percent and employment grew from 13 workers to 50-60 (360 percent). He considers that product innovation has a multiplier effect, generating jobs in other firms, such as publicity and marketing firms.

Process innovation in the food industry is not as frequent as in technological sectors and is often the result of product innovation. When innovation destroys jobs, non-skilled and temporary workers are fired. The firm is changing its location and its production process. They are planning to maintain the level of employment even when the new process is labor-saving because they expect higher demand. The firm's marketing strategy is also innovative. Its growth is based on the expansion of its market to Buenos Aires and Chile more than expansion of local demand. In fact, after 2008 local demand was observed to be lower.

## A. List of Persons Interviewed

Arquitecto de Soluciones y Desarrollo de Nuevos Negocios, Multinational firm which manufactures mobile, fixed, and other telecommunication devices.

Vice-President for Business Development for Latin America, Multinational consulting company

Gerente de Sistemas y Métodos, Firm which provides different services (customs services, accounting, tax administration, etc.) to other firms in the same group.

Country Manager, Firm which provides different services (customs services, accounting, tax administration, etc.) to other firms in the same group.

Vice-President, Local pasta maker.

Diaz Cafferata, Alberto (Professor of Economics, Universidad Nacional de Córdoba)

Gertel, Héctor (Professor of Economics, Universidad Nacional de Córdoba)

Novick, Marta (Subsecretaria de Programación Técnica y Estudios Laborales, Ministerio de Trabajo, Empleo, y Seguridad Social)

Robbio, Jorge (Subsecretario de Estudios y Prospectivas, Ministerio de Ciencia, Tecnología, e Innovación productiva)

Sibilla, Fernando (Director Ejecutivo, Unión Industrial Córdoba)

Trupia, Gabriela (Subsecretaria de Políticas en Ciencia, Tecnología e Innovación Productiva, Ministerio de Ciencia, Tecnología e Innovación Productiva)

## C. Tables

**Table 38: Definitions of Variables**

| **Variable** | **Definition** | **Question ENIT01** |
|---|---|---|
| Total employment growth ($l$) | Rate of employment growth between 2001 and 1998. Difference between the log of employment in 2001 and the log of employment in 1998. | 301d |
| Only process innovation ($d$) | Dummy variable that takes value one if the firm introduced a process innovation in the production of old products or an organizational innovation between 2008 and 1998. (without introducing a new product) | 901 |
| Nominal growth in sales of old products ($g_1$) | ln($Y_{12}$)-ln($Y_{11}$)<br>where $Y_{12}$ is the real value of sales of old products in 2001 and $Y_{11}$ is the real value of sales of old products in 1998.<br>The nominal value of $Y_{11}$ is provided in ENIT01 as question number 201c.<br>$Y_{12}$ is obtained as<br>$Y_{12} = Domestic\ Sales\ 01\ \frac{100 - pnd}{100} + Exports\ 01\frac{100 - pnx}{100}$<br>where $pnd$ and $pnx$ are the percentage of sales to the domestic market and exports corresponding to new products (variable 902). Exports are provided in variable 202 and, therefore, domestic sales can be obtained as the difference between total sales and exports. Nominal variables are deflated using the producer price index (at the industry level). | 201c, 202, and 902. |
| Nominal growth in sales of new products ($g_2$) | $Y_{22}/Y_{11}$ where $Y_{22}$ is the real value of sales of new products in 2001 and $Y_{11}$ is the real value of sales of old products in 1998.<br>$Y_{22}$ is obtained as $Y_{22}$ replacing (100-pnd) by pnd. | 201c, 202, and 902. |

| | | |
|---|---|---|
| Firm knows about the existence of public support programs | Dummy variable that takes value one if the firm reports that knows (independently of use) about the existence of public support programs. | 103 a to d |
| Continuous R&D | Dummy variable that takes the value one if the firm reports positive expenditure in R&D for every year. | 401 and 402 |

## Table 39: Descriptive Statistics by Industry (2 digits ISIC)

| | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
|---|---|---|---|---|---|---|---|---|
| Number of observations | 282 | 6 | 129 | 46 | 41 | 36 | 46 | 76 |
| Number of employees in 1998 | 107,467 | 4,166 | 20,666 | 4,876 | 15,353 | 5,967 | 8,629 | 12,158 |
| Foreign Ownership (*10% or more*) | 16.3 | 33.3 | 9.3 | 4.4 | 9.8 | 8.3 | 23.9 | 11.8 |
| Located in the capital of the country | 41.3 | 66.7 | 79.7 | 63.6 | 72.5 | 37.1 | 77.8 | 73.7 |
| Employment growth (*%*) (*yearly rate*) | -1.9 | 0.2 | -7.4 | -1.6 | -1.5 | -5.7 | -0.9 | -2.5 |
| Sales growth (*%*)[1] (*nominal growth*) (*yearly rate*) | -3.9 | 5.6 | -15.7 | -11.9 | -10.1 | -8.2 | -3.5 | -9.1 |
| Knowledge/innovation | | | | | | | | |
| Continuous R&D engagement (0/1) | 17.4 | 16.7 | 8.5 | 8.7 | 14.6 | 13.9 | 19.6 | 11.8 |
| R&D/sales | 0.2 | 0.1 | 0.3 | 0.3 | 0.3 | 0.2 | 0.5 | 0.5 |
| Innovation expenditures /sales | 1.1 | 0.3 | 1.7 | 1.3 | 1.6 | 1.0 | 2.4 | 2.2 |
| Innovator (product and/or process innovation) (0/1) | 56.4 | 50.0 | 43.4 | 30.4 | 61.0 | 44.4 | 65.2 | 50.0 |
| Innovator (product and/or process innovation and/or organizational innovator) (0/1) | 62.1 | 50.0 | 47.3 | 32.6 | 63.4 | 47.2 | 65.2 | 56.6 |
| Process innovation only (non product innovator) | 14.5 | 0.0 | 6.2 | 2.2 | 9.8 | 13.9 | 8.7 | 15.8 |
| Organizational change innovator (non product innovators) (0/1) | 12.8 | 0.0 | 7.0 | 2.2 | 9.8 | 13.9 | 8.7 | 14.5 |
| Product innovation | 41.8 | 50.0 | 37.2 | 28.3 | 51.2 | 30.6 | 56.5 | 34.2 |
| *[of which product & process innovators]* | 35.8 | 50.0 | 26.4 | 17.4 | 34.2 | 22.2 | 45.7 | 30.3 |
| Organizational change | 37.2 | 50.0 | 22.5 | 8.7 | 36.6 | 33.3 | 47.8 | 32.9 |
| Share of sales with new products (for the whole estimation sample) | 20.3 | 14.2 | 18.4 | 16.2 | 24.7 | 11.5 | 33.5 | 15.9 |
| Share of sales with new products (for firms with product innovation) | 37.3 | 28.5 | 42.3 | 41.8 | 29.0 | 34.3 | 50.7 | 33.5 |
| Labor productivity | 171,260 | 206,572 | 70,754 | 52,542 | 67,564 | 56,151 | 182,664 | 100,458 |

## Descriptive statistics by Industry (2 digits ISIC)

| | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 |
|---|---|---|---|---|---|---|---|---|
| Number of observations | 12 | 144 | 84 | 77 | 40 | 76 | 128 | 2 |
| Number of employees in 1998 | 8,923 | 35,740 | 10,353 | 14,944 | 17,251 | 12,903 | 16,755 | 70 |
| Foreign Ownership (*10% or more*) | 50.0 | 38.9 | 16.7 | 24.7 | 15.0 | 22.4 | 21.9 | 0.0 |
| Located in the capital of the country | 66.7 | 81.1 | 71.1 | 59.5 | 66.7 | 63.2 | 53.5 | 100.0 |
| Employment growth (%) (*yearly rate*) | 2.5 | -2.0 | -2.1 | -5.4 | -6.9 | -4.1 | -4.7 | 10.0 |
| Sales growth (%)[1] (*nominal growth*) (*yearly rate*) | 5.4 | -4.9 | -8.3 | -9.7 | -11.8 | -11.1 | -9.9 | 0.0 |
| Knowledge/innovation | | | | | | | | |
| Continuous R&D engagement (0/1) | 25.0 | 36.8 | 20.2 | 22.1 | 35.0 | 11.8 | 29.7 | 50.0 |
| R&D/sales | 29.3 | 1.2 | 0.7 | 0.6 | 0.3 | 0.3 | 0.6 | 1.0 |
| Innovation expenditures /sales | 146.3 | 5.9 | 3.3 | 3.0 | 1.4 | 1.7 | 3.2 | 4.8 |
| Innovator (product and/or process innovation) (0/1) | 91.7 | 70.1 | 75.0 | 58.4 | 67.5 | 56.6 | 75.8 | 50.0 |
| Innovator (product and/or process innovation and/or organizational innovator) (0/1) | 91.7 | 72.9 | 76.2 | 62.3 | 70.0 | 61.8 | 78.9 | 50.0 |
| Process innovation only (non product innovator) | 25.0 | 9.7 | 15.5 | 14.3 | 10.0 | 13.2 | 7.8 | 0.0 |
| Organizational change innovator (non product innovators) (0/1) | 16.7 | 9.7 | 13.1 | 10.4 | 5.0 | 15.8 | 7.8 | 0.0 |
| Product innovation | 66.7 | 60.4 | 59.5 | 44.2 | 57.5 | 43.4 | 68.0 | 50.0 |
| *[of which product & process innovators]* | 50.0 | 50.0 | 39.3 | 41.6 | 50.0 | 36.8 | 56.3 | 50.0 |
| Organizational change | 50.0 | 48.6 | 45.2 | 31.2 | 42.5 | 46.1 | 43.0 | 50.0 |
| Share of sales with new products (for the whole estimation sample) | 36.8 | 25.3 | 26.9 | 25.0 | 25.1 | 17.7 | 32.3 | 0.0 |
| Share of sales with new products (for firms with product innovation) | 48.9 | 37.5 | 40.4 | 45.5 | 43.7 | 32.0 | 42.8 | 0.0 |
| Labor productivity | 1,448,769 | 182,525 | 103,580 | 100,677 | 126,625 | 93,658 | 99,241 | 249,328 |

## Descriptive Statistics by Industry (2 digits ISIC)

| | **31** | **32** | **33** | **34** | **35** | **36** |
|---|---|---|---|---|---|---|
| Number of observations | 54 | 17 | 18 | 63 | 28 | 45 |
| Number of employees in 1998 | 5,821 | 6,202 | 1,255 | 19,625 | 5,389 | 3,724 |
| Foreign Ownership (*10% or more*) | 16.7 | 47.1 | 11.1 | 39.7 | 7.1 | 6.7 |
| Located in the capital of the country | 83.0 | 88.2 | 72.2 | 54.8 | 71.4 | 75.0 |
| Employment growth (*%*) (*yearly rate*) | -7.3 | -9.3 | -3.3 | -9.7 | -6.5 | -6.9 |
| Sales growth (*%*)[1] (*nominal growth*) (*yearly rate*) | -12.7 | -9.9 | -5.6 | -19.3 | -19.3 | -15.3 |
| Knowledge/innovation | | | | | | |
| Continuous R&D engagement (0/1) | 29.6 | 23.5 | 27.8 | 30.2 | 10.7 | 15.6 |
| R&D/sales | 0.8 | 0.1 | 1.1 | 0.7 | 0.7 | 0.2 |
| Innovation expenditures /sales | 4.2 | 0.7 | 5.3 | 3.5 | 3.3 | 1.0 |
| Innovator (product and/or process innovation) (0/1) | 70.4 | 64.7 | 61.1 | 69.8 | 35.7 | 48.9 |
| Innovator (product and/or process innovation and/or organizational innovator) (0/1) | 70.4 | 64.7 | 66.7 | 74.6 | 39.3 | 57.8 |
| Process innovation only (non product innovator) | 9.3 | 0.0 | 11.1 | 15.9 | 14.3 | 4.4 |
| Organizational change innovator (non product innovators) (0/1) | 5.6 | 0.0 | 11.1 | 12.7 | 14.3 | 8.9 |
| Product innovation | 61.1 | 64.7 | 50.0 | 54.0 | 21.4 | 44.4 |
| *[of which product & process innovators]* | 48.2 | 52.9 | 44.4 | 42.9 | 14.3 | 31.1 |
| Organizational change | 44.4 | 29.4 | 38.9 | 47.6 | 21.4 | 31.1 |
| Share of sales with new products (for the whole estimation sample) | 28.0 | 27.1 | 40.3 | 31.4 | 7.3 | 35.7 |
| Share of sales with new products (for firms with product innovation) | 41.5 | 38.2 | 73.9 | 47.8 | 33.2 | 69.2 |
| Labor productivity | 78,955 | 201,665 | 82,306 | 107,565 | 63,035 | 48,256 |

## Table 40: Dependent Variable: g2 – First-stage Estimation –All Firms

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-g2** | **Manufacturing**<br>**2-g2** |
|---|---|---|
| Process only innovator *(d)* | -9.023*** | -9.710*** |
| | (2.478) | (2.485) |
| Knowledge of public support for innovation | 7.647*** | 7.590*** |
| | (1.951) | (1.969) |
| 2-digit industry dummies | Yes | Yes |
| Additional controls | | Yes |
| F test for excluded instruments | 15.370 | 14.858 |
| Pvalue | 0.000 | 0.000 |
| R-squared | 0.020 | 0.027 |
| Number of firms | 1,415 | 1,415 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 41: Dependent Variable: g2 – First-stage Estimation - Small Firms

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-g2** | **Manufacturing**<br>**2-g2** |
|---|---|---|
| Process only innovator *(d)* | 0.020 | -0.246 |
| | (5.208) | (5.211) |
| Knowledge of public support for innovation | 11.700** | 11.191** |
| | (3.926) | (3.998) |
| 2-digit industry dummies | Yes | Yes |
| Additional controls | | Yes |
| F test for excluded instruments | 8.883 | 7.835 |
| Pvalue | 0.003 | 0.005 |
| R-squared | 0.022 | 0.029 |
| Number of firms | 417 | 417 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 42: Dependent Variable: g2 – First-stage Estimation - Low-tech Firms

| **Sector**<br>**Regression** | **Manufacturing**<br>**1-g2** | **Manufacturing**<br>**2-g2** |
|---|---|---|
| Process only innovator *(d)* | -5.258 | -5.595 |
| | -3.566 | -3.58 |
| Knowledge of public support for innovation | 7.986** | 7.865** |
| | -2.827 | -2.908 |
| Continuous R&D | 20.362*** | 20.196*** |
| | -3.273 | -3.274 |
| Product Life Cycle Dummy 1 | 0.711 | 0.619 |
| | -3.74 | -3.742 |
| Product Life Cycle Dummy 2 | -0.935 | -0.758 |
| | -4.096 | -4.101 |
| Product Life Cycle Dummy 3 | 6.391 | 6.374 |
| | -3.956 | -3.958 |
| Product Life Cycle Dummy 4 | -4.701 | -4.465 |
| | -5.471 | -5.485 |
| 2-digit industry dummies | Yes | Yes |
| Additional controls | | Yes |
| F test for excluded instruments | 9.010 | 8.650 |
| Pvalue | 0.000 | 0.000 |
| R-squared | 0.093 | 0.096 |
| Number of firms | 672 | 672 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 43: Dependent Variable: g2 – First-stage Estimation - High-tech Firms

| Sector<br>Regression | Manufacturing<br>1-g2 | Manufacturing<br>2-g2 |
|---|---|---|
| Process only innovator *(d)* | -7.952* | -8.873** |
| | -3.352 | -3.365 |
| Knowledge of public support for innovation | 1.754 | 1.822 |
| | -2.663 | -2.663 |
| Continuous R&D | 17.625*** | 17.132*** |
| | -3.04 | -3.04 |
| Product Life Cycle Dummy 1 | 0.066 | -0.405 |
| | -3.177 | -3.173 |
| Product Life Cycle Dummy 2 | -3.014 | -3.006 |
| | -4.319 | -4.318 |
| Product Life Cycle Dummy 3 | 2.105 | 1.47 |
| | -3.757 | -3.754 |
| Product Life Cycle Dummy 4 | -2.914 | -4.063 |
| | -4.791 | -4.797 |
| 2-digit industry dummies | Yes | Yes |
| Additional controls | | Yes |
| F test for excluded instruments | 5.380 | 5.170 |
| Pvalue | 0.000 | 0.000 |
| R-squared | 0.061 | 0.069 |
| Number of firms | 743 | 743 |

*Notes:* (i) Robust standard errors, (ii) Significance level: *** 1%, ** 5%, and * 10%.

## Table 44: Low- and High-tech Sectors

| ISIC | Low Technology Sectors | ISIC | High Technology Sectors |
|---|---|---|---|
| 15 | Food and beverages | 17 | Textile |
| 16 | Tobacco | 21 | Pulp, paper and paper products |
| 18 | Wearing apparel | 22 | Publishing, printing and reproduction of recorded media |
| 19 | Leather | 24 | Chemicals and chemical products |
| 20 | Wood and wood products | 25 | Rubber and plastic products |
| 23 | Coke, refined petroleum and nuclear fuel | 26 | Other non-metalic mineral products |
| 27 | Basic metals | 28 | Fabricated metals |
| 29 | Machinery and equipment nec | 30 | Office machinery and computers |
| 31 | Electrical machinery and apparatus nec | 32 | Radio, television and communication equipment and apparatus |
| 33 | Medical, precision and optical instruments, watches & clocks | 34 | Motor vehicles, trailers and semi-trailers |
| 35 | Other transport equipment | 36 | Furniture, manufacturing nec |