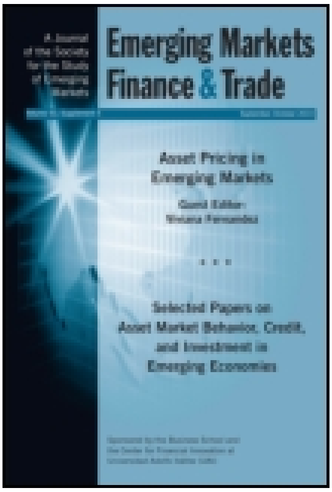

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Employment and Innovation: Firm-Level Evidence from Argentina

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Employment and Innovation: Firm-Level Evidence from Argentina

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ABSTRACT: This article provides evidence about the effect of innovation on employment in Argentina in the period 1998–2001. In particular, we quantify the effect of process and product innovations on employment growth and the skill composition. Our results show that: (1) Product innovations have a positive effect on employment growth biased toward skill labor; (2) Process innovations do not affect employment growth or composition; (3) There are no heterogeneous effects in technology intensity and size; (4) Most of the contraction in employment in this period was explained by noninnovators.

KEY WORDS: Argentina, employment growth, process innovation, product innovation

Introduction

The effect of innovation on employment has been attracting the attention of economists and policy makers for a long time. This fact is not surprising. On the one hand, it has been argued that technical change could destroy jobs and, on the other hand, economic theory does not provide a clear answer about the employment effect of innovation. The relationship between innovation and employment is not straightforward. The literature has documented several compensation mechanisms that can counterbalance the initial effect of innovation and render the final effect undetermined (see Petit 1995; Pianta 2005; Piva and Vivarelli 2005; Vivarelli 1995, 2012). Innovation can create or destroy jobs depending on the institutional setting, market structure, and the type of innovation the firm introduces. The development—or the adoption—of a new production process usually leads to greater efficiency in production, with savings in labor and/or capital and with a potential for price reduction. The first expected outcome is higher productivity with loss of employment. However, demand could grow after the innovation due to increased quality or lower price, and this increase in demand could lead to higher employment.

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. Therefore, the net effect of a product innovation could be a contraction in employment. A new product can also destroy jobs if it is designed to reduce costs. It is also possible that product innovations do not change employment; this would be the case if new products replace old products without changes in demand.

Despite the fact that the theoretical effect of innovation on employment is ambiguous, several firm-level studies have found that the fear that innovation could destroy jobs has little empirical support. In fact, the evidence shows a positive relationship between innovation and employment (Blanchflower and Burgess 1998; Entorf and Pohlmeir 1990; Giuliodori and Stucchi 2012; Piva and Vivarelli 2005; Smolny 1998; Van Reenen 1997).

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Firm-level evidence also suggests that while product innovation creates jobs, process innovation might in fact destroy jobs. To capture this idea, Harrison et al. (2014) pose a simple model to study the differential effect of product and process innovation on employment growth. They estimate their model for the manufacturing and service sectors in France, Germany, Spain, and the United Kingdom. They find that the increase in employment due to product innovations is large enough to compensate the negative effect of process innovations. The results are similar across countries, although there emerge some interesting differences. In fact, they find no evidence for a displacement effect of process innovation in Spanish manufacturing firms. They argue that this result can be explained by a greater pass-through of productivity improvements in lower prices. Hall et al. (2008) estimate Harrison et al.'s (2014) model using Italian data and find similar results.

Innovation affects not only the number of employees but also the composition of employment within each firm. The basic intuition is that innovations are skill biased because they replace tasks traditionally carried out by unskilled workers, with new jobs demanding qualified workers. Acemoglu (1998) argues that new technologies are not complementary to skills by nature, but innovators decide the direction of technological change. Acemoglu shows that an increase in the supply of skills can explain skill-biased technical change in the United States. More relevant to our article, Acemoglu (2003) extends the basic model of directed technical change to study the interaction between technology and international trade. In his model, technical change in developing countries is skill biased due to the transfer of technology from developed countries.

There is a vast empirical literature on the skill bias of technological change for developed countries. After the seminal work by Griliches (1969), the effect of innovation on the skills composition has been largely studied (Autor et al. 1998; Bresnahan et al. 2002; Caroli and Van Reenen 2001; Doms et al. 1997; Greenan 2003). Giuliodori and Stucchi (2012) analyze a related question about the effect of innovation on the composition of employment in terms of labor contract. They present evidence for Spain, where the labor market is segmented in temporary and permanent contracts, and find that innovations can affect both types of contracts depending on the institutional environment.

Firm-level studies discussed above focus on the direct effect of innovation on employment—that is, the effect of innovation on the level of employment of the innovating firm. Innovation also has indirect effects—that is, on noninnovating firms. The indirect effects are intuitive for product innovations; it is not difficult to imagine a scenario in which a product innovation increases the demand of the innovating firm and its employment but reduces the demand of its competitors and their employment level. Process innovation also has indirect effects. The innovating firm can increase its productivity and by reducing price can gain market share, increase its demand for labor, and reduce the demand of labor of competitors. Pianta (2005) reviews several industry-level studies addressing these issues. The empirical evidence reviewed by Pianta (2005) shows that the effect of product innovation on employment is positive in industries characterized by high demand growth and an orientation toward product (or service) innovation, while process innovation leads to job losses. The evidence about overall effect is mixed; it depends on the country and period considered.

The evidence on the relationship between innovation and employment in Latin America is scarce, and because of the idiosyncratic nature of innovation in Latin America—mainly acquisition of technological knowledge from abroad—the evidence from developed countries cannot be simply extrapolated to this region. In addition, in Latin America there are important structural features that might lead to different outcomes of innovation on employment. First, the current production structure is strongly dominated by small- and medium-sized enterprises (SMEs). Second, Latin America's production structure is heavily dominated by the manufacturing of commodities and low technologically intensive goods. The available evidence comes from Benavente and Lauterbach (2008), who estimate the Harrison et al. (2014) model for Chile. Contemporaneous to our article, Aboal et al. (2011), Álvarez et al. (2011), and Monge-Gonzalez et al. (2011) estimate Harrison et al.'s (2014) model for Chile, Costa Rica, and Uruguay, and Crespi and Tacsir (2013) present a comparative analysis for the four countries. They find that while product innovations increase employment, process innovations do not affect it. Additional evidence on the relation between innovation and employment comes from the evaluation of innovation public policies. Álvarez et al. (2012), who evaluate the effect of two innovation programs (FONTEC and FONDEF) in Chile, find that these programs increased employment and productivity. Castillo et al. (2014) evaluate the effect of the Support Program for the Organizational Change in Argentina. They find that while support for both process and product innovation lead to increased employment, the support for product innovation has a higher effect on wages, survival rate, and exporting probability.

This article aims at providing evidence about the relationship between innovation and employment in the manufacturing sector in Argentina. More precisely, we aim at answering two important questions: (1) How do different types of innovation—product and process innovations—affect employment? (2) How do the different types of innovation affect the skill composition? In addition, given the Argentinean production structure, we are interested in knowing whether the results vary between low- and high-tech industries or small and large firms.

To answer those questions, we use data from Innovation Surveys for Argentina for the period 1998-2001. This period coincides with one of the deepest recessions of Argentina's history. As a consequence, it provides an interesting opportunity to estimate the effects of innovation on employment growth in a highly recessive scenario. A few statistics help to describe the rough economic environment in Argentina in 1998–2001. The gross domestic product 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. Interestingly, the reduction in employment was different between innovators and noninnovators. The reduction in employment was 7 percent in those firms that reported process or product innovations and 13 percent in firms that did not introduce any innovation.

We find that while product innovation creates jobs, process innovation does not affect the level of employment. Another important finding is that product innovation is skilled biased. In fact, we find that while product innovation creates both skilled and unskilled jobs, it creates a higher proportion of skilled jobs. In the case of process innovation, we find that there is no effect on skilled or unskilled jobs. These findings provide evidence not only against the fear that innovation could destroy jobs but also against the hypothesis that innovation could destroy unskilled jobs. From a policy perspective, our results shed light on two important issues. First, Argentina—like the rest of Latin American economies—faces a productivity problem that calls for attention. Our results point out that innovation programs—whose main objective is to increase productivity—could be attractive also from an employment point of view. Some warnings on SME policies that distort the size distribution of firms have been raised because they could affect the aggregate level of productivity (Guner et al. 2008; Pagés 2010). Interestingly, this is not the case of innovation policies because innovation is one of the main drivers of productivity growth. Second, the complementarity of innovation and skilled workers justify the need for training programs in addition to innovation programs.

The rest of the article is organized as follows. Section 2 presents the analytical framework. Section 3 presents the data and some descriptive statistics. Section 4 presents the main results of innovation on employment. Section 5 discusses the robustness of our results. Finally, Section 6 concludes.

Analytical Framework

The analytical framework follows the model in Harrison et al. (2014). In this framework, a firm produces two types of products in period t: old or only marginally modified products ("old products" denoted by Y_{1t}) and new or significantly improved products ("new products" denoted by Y_{2t}). Assuming separability in the production of old and new products, the production function for product of type i in period t can be written as

$$Y_{it} = \theta_{it} F(L_{it}, K_{it}, M_{it}) e^{\eta + \omega_{it}},$$

where $F(.)$ is homogeneous of degree one in labor (L_{it}), capital (K_{it}), and intermediate goods (M_{it}); θ_{it} is a Hicks neutral technical change parameter (which can depend on process innovation); and $e^{\eta+\omega_{it}}$ is unobserved firm's productivity that can be decomposed in firm's attributes that are mainly time invariant (η) and productivity shocks (ω_{it}).

Under perfect competition in input markets, the cost function of a firm in period t is

$$C_t(w_t, Y_{1t}, Y_{2t}) = c(w_t)\left(\frac{Y_{1t}}{\theta_{1t}e^{\eta+\omega_{1t}}} + \frac{Y_{2t}}{\theta_{2t}e^{\eta+\omega_{2t}}}\right),$$

where w_t are input prices, and the conditional labor demand function is

$$L_{it} = c_{w_L}(w_t)\frac{Y_{it}}{\theta_{it}e^{\eta+\omega_{it}}},$$

where w_L is the price of labor, and $c_{w_L} = \partial c/\partial w_L$.

Using the labor demand function, we can approximate employment growth at the firm level as

$$\frac{\Delta L}{L} \approx log\left(\frac{L_{12}}{L_{11}}\right) + \frac{L_{22}}{L_{11}} = -(\log\theta_{12} - \log\theta_{11}) + (\log Y_{12} - \log Y_{11}) + \frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}} - (\omega_{12} - \omega_{11}).$$

Employment growth is then decomposed into the part due to the increased efficiency in production of old products (which could be related to process innovations), the part due to sales of old products, and the part due to the introduction of new products. The estimating equation is given by

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

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.

The parameter β 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 noninnovators.

We observe employment and total sales in 1998 and 2001, and firms report whether 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 effect of innovations on employment composition is estimated with a version of Equation (1) for employment growth of skilled and unskilled workers. For the two types of workers, skilled (s) and unskilled (u), we estimate

$$l^q = \alpha_0^q + \alpha_1^q d + g_1 + \beta^q g_2 + v^q \quad q = s, u, \tag{2}$$

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

A concern about the identification[1] of the coefficients in Equation (1) is the fact that innovation can be correlated with the error term, then ordinary least squares (OLS) can produce inconsistent estimates. The 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. Then, if productivity is in the error term because it is an omitted variable, the error term will be correlated with innovation leading to an endogeneity problem.

In order to better understand the endogeneity problem, it is useful to decompose productivity in two unobserved components: firm's attributes that are mainly time invariant (such as managerial skills or organizational capital) and 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.

The remaining source of correlation between innovation outputs and productivity are productivity shocks.

Part of the 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.

Once we control for time-invariant unobservables and industry-specific temporal shocks, there are good reasons to think that process innovation can be exogenous.[2] First, innovations expenditures are usually made well before they result in applicable innovations. Second, it seems realistic to assume that firms cannot predict future labor problems, supply chain disruptions, or demand shocks when deciding their innovations expenditures. For these reasons, we treat process innovation as exogenous, but we run a robustness exercise instrumenting the process innovation variable.

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 sales. Then the growth in the price of old and new products is in the error term, and the correlation between the growth in prices and g_2 can create an attenuation bias in the estimation of β. To deal with this measurement error problem, we follow Harrison et al. (2014). First, we use industry price indexes π 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 main advantage of Harrison et al.'s (2014) approach is the use of economic theory to model the possible mechanisms linking innovation and employment. In particular, under the assumption of perfect competition in input markets and general assumptions about the firm's technology, Harrison et al. derive an estimating equation linking process and product innovation with optimal hiring decisions. This, in turn, leads to parameters with a clear and meaningful economic interpretation. In comparison, a reduced form approach that regresses employment growth on innovative variables is difficult to interpret, and the mechanisms are difficult to disentangle. We illustrate this point by running a reduced form approach in Table 2 and remark how difficult it is to interpret the coefficients in that model.

Another advantage is that Harrison et al. (2014) estimate their model for several European countries that can serve as a benchmark for the effects of innovation on employment in developing countries. In that sense, we can not only interpret the evidence for Argentina, but also compare it with the evidence for developed countries.

An important point concerns the identification strategy and how it compares with alternative approaches. An alternative identification strategy used in the literature is a generalized method of moments (GMM) system estimator proposed in Blundell and Bond (1998). For a recent application, see Lachenmaier and Rottmann (2011). The basic approach is to specify a labor demand equation that depends on lags of the dependent variable, contemporaneous and lags of the innovation variables, industry controls, and a firm level fixed effect. Such a model is estimated using lagged level variables to instrument the difference equation and lagged differences to instrument the level equation. In this article, identification relies on contemporaneous level variables to instrument the difference equation controlling for industry and location dummies. Unfortunately, the data available consist of two periods, and this prevents us from including lagged variables as instruments. For that reason, we run several exercises to show that the results in the article are robust to departures from the basic assumptions such as instrument validity, alternative controls, and exogeneity of the process innovation.

Data and Descriptive Statistics

We use data from the Second National Innovation Survey (ENIT01).[3] 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 ten or more employees. The sample is representative of the manufacturing sector in the sense that the percentage of aggregate sales by industries in the sample is close to the percentage of sales by industry using the Annual Industrial Survey (Instituto Nacional de Estadísticas y Censos 2003).

The survey contains detailed information on firms' characteristics, innovative activity, and employment. Importantly, it also has detailed information on the composition of sales, which allows us to compute the percentage of sales corresponding to new products. A firm in the survey reports the share of domestic sales (*pnd*) and the share of exports (*pxd*) that correspond to new or significantly improved products in 2001. Using that information, we construct sales of new products in 2001 as $Y_{22} = Domestic\ Sales\ 01 \frac{pnd}{100} + Exports\ 01 \frac{pxd}{100}$ and sales of old products in 2001 as $Y_{12} = Domestic\,Sales\,01\,\frac{100-pnd}{100} + Exports\,01\,\frac{100-pxd}{100}$. Using the above definitions, we can decompose the nominal growth in sales as $g = \left(\frac{Y_{12}+Y_{22}}{Y_{11}} - 1\right)100 = \left[\left(\frac{Y_{12}}{Y_{11}} - 1\right) + \frac{Y_{22}}{Y_{11}}\right] = g_1 + g_2$, where g_1 is the nominal growth in sales of old products, and g_2 is the nominal growth in sales of new products.

ENIT01 has also detailed information about the composition of employment by educational level, which allows us to study the effect of innovation on skill composition. We define skilled workers as employees with a university degree or tertiary education (one- to three-year degree related to technical professions), and unskilled workers are employees with primary or secondary education.

As usual with firm-level data, prices are not reported at the firm level, and we use industry price indexes at the two-digit level to deflate nominal variables. Given that product prices can differ between firms or even within the firm for multiproduct firms, the use of price indexes introduces a measurement error problem in the estimation. In the empirical implementation, we use instrumental variables to correct this measurement error bias.

We classify firms in mutually exclusive categories according to their innovative activity: product innovators, process-only innovators, and noninnovators. Product innovators are firms that introduce product innovations; process-only innovators are firms that introduce process innovations or organizational change innovations, excluding product innovators; and noninnovators are firms not classified as product or process innovators.[4]

Table 1 shows the descriptive statistics for the share of innovative firms, employment growth, sales growth, and labor productivity, where labor productivity is defined as real sales per worker. A large share of firms (63 percent) introduced at least one innovation in 1998–2001. Most of the innovators are product innovators (48 percent) rather than process-only innovators (15 percent). Harrison et al. (2014) 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 innovative activities undertaken by firms in Argentina are different from those 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 research and development.

Table 1. Descriptive statistics

	All firms		Low-technology[a]		High-technology[b]		Small firms[c]		Large firms[d]	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Number of observations	1,415		953		462		417		998	
Distribution of firms (percent)										
Noninnovators (no process or product innovations)	36	48	40	49	28	45	56	50	28	45
Process only innovators (nonproduct innovators)	15	36	16	37	13	34	12	32	17	37
Product innovators	48	50	43	50	59	49	32	47	55	50
Number of employees at the beginning of 1998	233	556	242	608	215	427	28	12	319	642
Foreign ownership (1 if 10 percent or more)	20	40	15	36	29	45	6	24	25	44
Located in Buenos Aires	65	48	62	49	70	46	65	48	65	48
Share of skilled labor										
All firms	34	28	30	26	44	30	28	28	37	28
Noninnovators (no process or product innovations)	28	27	25	26	37	30	24	27	31	27
Process-only innovators (nonproduct innovators)	34	27	29	24	48	29	41	33	32	25
Product innovators	39	28	34	27	46	29	29	27	41	28
Employment growth (percent)										
All firms	–4.0	12.3	–3.5	12.2	–4.9	12.4	–3.5	13.4	–4.2	11.7
Noninnovators (no process or product innovations)	–6.0	12.8	–5.6	11.3	–7.2	16.4	–5.8	12.9	–6.2	12.7
Process-only innovators (nonproduct innovators)	–3.9	12.3	–3.5	13.2	–4.8	9.7	1.5	11.6	–5.4	12.1
Product innovators	–2.5	11.6	–1.6	12.3	–3.8	10.5	–1.2	14.0	–2.8	11.0
Skilled labor growth (percent)										
All firms	–1.6	14.5	–1.0	14.4	–3.0	14.7	–2.7	17.6	–1.3	13.3
Noninnovators (no process or product innovations)	–4.1	15.8	–3.7	14.6	–4.9	18.9	–4.8	18.6	–3.6	13.7
Process-only innovators (nonproduct innovators)	–1.6	14.6	–0.9	15.4	–3.5	12.3	0.4	12.7	–2.2	15.0
Product innovators	–0.1	13.3	1.3	13.4	–2.0	12.9	–0.8	17.4	0.1	12.3
Unskilled labor growth (percent)										
All firms	–5.3	14.0	–5.0	13.7	–5.9	14.7	–4.5	16.0	–5.7	13.1
Noninnovators (no process or product innovations)	–7.0	13.9	–6.6	12.7	–8.3	17.0	–6.9	15.2	–7.1	12.7
Process-only innovators (nonproduct innovators)	–4.3	14.5	–4.4	13.7	–4.1	16.6	2.6	14.0	–6.2	14.1
Product innovators	–4.4	13.8	–3.8	14.4	–5.2	12.9	–2.8	17.2	–4.8	12.9
Sales growth (percent) (nominal)[e]										
All firms	–9.0	16.0	–8.5	16.1	–10.0	15.8	–9.7	17.4	–8.7	15.4
Noninnovators (no process or product innovations)	–12.5	17.5	–12.2	17.0	–13.4	19.1	–12.8	17.8	–12.3	17.3
Process-only innovators (nonproduct innovators)	–8.1	15.3	–7.4	15.4	–10.1	15.0	–3.0	16.5	–9.6	14.7

(*Continued*)

Table 1. Descriptive statistics (Continued)

	All firms		Low-technology[a]		High-technology[b]		Small firms[c]		Large firms[d]	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Product innovators	–6.6	14.5	–5.5	14.7	–8.4	14.0	–6.6	15.7	–6.7	14.2
Labor productivity growth (percent)[f]										
All firms	–5.0	15.2	–5.0	15.5	–5.1	14.6	–6.2	18.7	–4.5	13.5
Noninnovators (no process or product innovations)	–6.5	17.4	–6.6	16.7	–6.2	19.5	–7.0	19.6	–6.0	15.4
Process-only innovators (nonproduct innovators)	–4.3	13.4	–3.8	13.4	–5.4	13.5	–4.5	15.9	–4.2	12.6
Product innovators	–4.2	13.9	–3.9	15.0	–4.5	12.0	–5.4	18.1	–3.9	12.7
Prices growth (percent)[g]										
All firms	–2.0	2.3	–2.5	1.5	–1.2	3.2	–2.0	2.0	–2.0	2.4
Noninnovators (no process or product innovations)	–2.3	2.2	–2.6	1.6	–1.5	3.2	–2.2	2.0	–2.4	2.3
Process-only innovators (nonproduct innovators)	–1.9	2.0	–2.4	1.2	–0.5	2.6	–1.4	1.9	–2.0	2.0
Product innovators	–1.9	2.5	–2.3	1.5	–1.2	3.4	–1.9	1.9	–1.9	2.6

Notes: s.d. = standard deviation. Product innovators are firms that have introduced product innovations between 1998 and 2001. Process-only innovators are firms that have introduced process innovations or organizational change innovations excluding product innovators between 1998 and 2001. Noninnovators are firms not classified as product or process innovators. Skilled workers are employees with a university degree or tertiary education (one- to three-year degree related to technical professions). Unskilled workers are employees with primary or secondary education. Growth rates are annual rates. Sample: Firms with information in all the relevant variables for the empirical analysis.

[a]Includes firms in the sectors of food, beverages, and tobacco; textiles, wearing apparel, and leather products; wood, wood products, and furniture; pulp, paper, and paper products; publishing, printing, and reproduction of recorded media; rubber and plastic products; basic metals, fabricated metals, and nonmetallic mineral products.

[b]Includes firms in the sectors of chemicals and chemical products, coke, refined petroleum and nuclear fuel, machinery, equipment, office machinery, computers, communication equipment, electrical machinery, and medical, precision and optical instruments, motor vehicles and transport equipment.

[c]Firms with fewer than fifty employees.

[d]Firms with more than fifty employees.

[e]Sales growth for each type of firm is the unweighted mean in growth rates across firms conditional on type.

[f]Labor productivity is real sales per worker.

[g]Prices computed at the two-digit level of the ISIC and assigned to firms according to their activity.

Interestingly, the reduction in employment was different between innovators and noninnovators. The annual reduction in employment was 2.5 percent for product innovators and 3.9 percent for process-only innovators while it was 6 percent for noninnovators. A similar pattern is observed in sales growth with a smaller reduction in sales for innovators than for noninnovators. The annual reduction in sales was 6.6 percent for product innovators, 8.1 percent for process-only innovators, and 12.5 percent for noninnovators.

For product innovators we decompose growth in sales in the part corresponding to old products (g_1) and the part corresponding to new products (g_2), as explained above. It is remarkable the rapid pace at which product innovators substituted old products with new products during the analyzed period in Argentina: 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 that for France, Germany, Spain, and the United Kingdom reported in Harrison et al. (2014). This 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 4.2 percent for product innovators, 4.3 for process-only innovators, and 6.5 percent for noninnovators. This evidence suggests that innovators might be able to compensate a negative aggregate shock through the introduction of new products or processes.

Table 1 shows the descriptive statistics for skilled and unskilled labor. In our sample, employment contracted at an annual rate of 4 percent. However, skilled employment decreased 1.6 percent while unskilled employment decreased 5.3 percent. Differences in skilled-unskilled labor growth rates were greater for innovators than for noninnovators suggesting complementarity between innovation and skilled labor.

We study the presence of heterogeneous effects for sectors with different technological intensity. The nature of innovations can be very different for low-tech and high-tech, and this can be reflected in the employment effects of innovations. Sectors are classified as low-tech or high-tech sectors following Czarnitzki and Thorwarth (2012), who study the productivity effects of basic research in low-tech and high-tech industries in Belgium. The low-tech sectors are food, beverages, and tobacco (ISIC 15 and 16); textiles, wearing apparel, and leather products (ISIC 17, 18, and 19); wood, wood products, and furniture (ISIC 20 and 36); pulp, paper, and paper products (ISIC 21); publishing, printing, and reproduction of recorded media (ISIC 22); rubber and plastic products (ISIC 25); and basic metals, fabricated metals, and nonmetallic mineral products (ISIC 26, 27, and 28). The high-tech sectors are chemicals and chemical products, coke, refined petroleum, and nuclear fuel (ISIC 23 and 24); machinery, equipment, office machinery, computers, communication equipment, electrical machinery, and medical, precision, and optical instruments (ISIC 29, 30, 31, 32, and 33); and motor vehicles and transport equipment (ISIC 34 and 35). Low-tech sectors have a lower share of skilled labor but greater growth in employment than high-tech sectors. However, the difference in employment growth for innovators and noninnovators is similar for low-tech and high-tech sectors.

We also study the presence of heterogeneous effects for firms with different sizes. In developing countries, and Latin America in particular, the share of small firms in manufacturing is important. Thus, it is relevant to study whether the effects of innovation on employment vary by firm size. Small firms are firms with fewer than fifty employees, and large firms are firms with more than fifty employees. The share of innovators is 44 percent for small firms and 72 percent for large firms (Table 1). However, the difference in employment growth for innovators and noninnovators is greater for small firms than for large firms. This suggests that heterogeneous effects may exist between small and large firms.

Empirical Results

Exploratory Regressions

Table 2 shows OLS exploratory regressions of employment growth on innovation variables, real growth in sales, industry and location dummies, and a foreign ownership dummy. We run these

Table 2. Exploratory regressions, OLS estimation

Dependent Variable: l (Employment growth)	All firms [1]	All firms [2]	Low-technology [1]	Low-technology [2]	High-technology [1]	High-technology [2]
Constant	–2.219*	–2.214*	–2.122	–2.117	–2.462	–2.459
	(1.049)	(1.047)	(1.241)	(1.239)	(1.891)	(1.887)
Process-only innovator (nonproduct innovator)	0.944	0.942	0.711	0.708	1.992	1.990
	(0.893)	(0.893)	(1.053)	(1.052)	(1.754)	(1.753)
Product-only innovator (nonprocess innovator)	1.804		1.838		1.648	
	(1.125)		(1.519)		(1.819)	
Product and process innovator	2.035**		2.075*		1.780	
	(0.735)		(0.850)		(1.538)	
Product innovator		2.002**		2.040*		1.763
		(0.714)		(0.817)		(1.516)
Real sales growth (g-Π)	0.325***	0.326***	0.311***	0.312***	0.357***	0.357***
	(0.031)	(0.031)	(0.033)	(0.033)	(0.070)	(0.070)
Test: *Process&Product=Product only* (p-value)	0.825		0.875		0.918	
Test: *Process&Product=Process only* (p-value)	0.196		0.207		0.872	
R-squared	0.24	0.24	0.23	0.23	0.27	0.27
Number of firms	1,415	1,415	953	953	462	462

Notes: Robust standard errors. All regressions include as additional controls a dummy variable taking value one for those firms with more than 20 percent of foreign capital, dummy variables for the province where the firm's headquarters are located, and two-digit industry dummies. A product innovator is a firm that has introduced at least one product innovation. A process innovator is a firm that has introduced at least one process innovation or organizational change innovation. *Significance level 10 percent; **significance level 5 percent; ***significance level 1 percent.

regressions for two reasons: first, and more important, to illustrate how challenging it is to understand the mechanisms linking innovation and employment without imposing additional structure; second, to justify grouping product-only innovators and product and process innovators.

Columns (1), (2), and (3) differ in the allocation of those firms that introduce both product and process innovations. In column (1), product and process innovators are included in separate categories; in column (2), product and process innovators are included with product innovators; and in column (3), product and process innovators are included with process innovators.

The estimate of the constant is approximately -2.2 percent, and it captures the mean employment growth for noninnovators. Innovators are associated with a 2 percent higher employment growth than noninnovators. There are not statistically significant differences between product and process-only innovators, product-only innovators, and product and process innovators. It will be difficult to estimate separate effects on employment for process-only innovators, product-only innovators, and product and process innovators. Thus, we decide to group all product innovators (product and process innovators and product-only innovators). This decision is supported by the point estimates shown in the table.

The estimated coefficient on real growth in sales suggests that sales are associated with a less-than-proportional increase in employment: a 10 percent increase in sales growth of old products implies a

3.2 percent increase in employment growth. As a comparison, Harrison et al. (2014) found elasticities between 0.35 and 0.45 for European countries.

Innovation and Employment

Column (1) in Table 3 shows the estimates of the effect of innovations on employment using the Harrison et al. (2014) model. In all the specifications, we control for two-digit industry dummies, location dummies,[5] and foreign ownership.

Panel A in Table 3 shows the OLS estimates. These results show that while product innovation has a positive and significant effect on employment, process innovation does not have a significant effect. The estimated coefficient on g_2 is close to one, which indicates no differences in efficiency in the production of old and new products.

Panel B in Table 3 shows the instrumental variable (IV) estimates. As we discussed in the Analytical Framework section, 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 prices at firm level. These endogeneity issues tend to generate a downward bias in the OLS estimate of the coefficient on g_2.

The instrument used in the IV estimation is an indicator of the firm knowledge of public support for innovation activities. The identification strategy relies on knowledge of public programs being exogenous once we control for industry, location, size, and time-invariant productivity. We believe

Table 3. The effect of innovation on employment and skill composition: OLS and IV Estimation of the Harrison et al. (2014) model

Dependent variable: l -(g1-Π)	Labor	Skilled labor	Unskilled labor
A) OLS			
Process-only innovator (*d*)	–0.560	–0.125	0.755
	(1.025)	(1.176)	(1.187)
Sales growth due to new products *(g2)*	0.958***	0.963***	0.952***
	(0.013)	(0.015)	(0.015)
R-squared	0.84	0.81	0.80
B) IV			
Process-only innovator (*d*)	1.252	2.998	2.265
	(1.612)	(2.094)	(1.818)
Sales growth due to new products *(g2)*	1.151***	1.307***	1.102***
	(0.122)	(0.165)	(0.143)
R-squared	0.796	0.703	0.773
First stage (*F*-test)	13.94	12.13	
p-value	0.000	0.001	
Endogeneity test (Davidson-MacKinnon)	2.79	6.51	1.17
p-value	0.095	0.011	0.279
H0: β = 1 (*p*-value)	0.215	0.062	0.475
H0: βskilled = βunskilled (*p*-value)	0.106		
Number of firms	1,415	1,209	1,209

Notes: Robust standard errors. All regressions include as additional controls a dummy variable taking value one for those firms with more than 20 percent of foreign capital, dummy variables for the province where the firm's headquarters are located, and two-digit industry dummies. Skilled workers are employees with a university degree or tertiary education (one- to three-year degree related to technical professions). Unskilled workers are employees with primary or secondary education. Endogenous variables: g2. Instruments: knowledge of public support for innovation activities. *Significance level 10 percent; **significance level 5 percent; ***significance level 1 percent.

this is a valid assumption for several reasons. First, if information acquisition is costly, only more-productive and larger firms will be willing to make such an investment. Given that we control for invariant productivity and size, these effects are taken into account. In addition, it seems less likely that firms decide to invest in information acquisition because of productivity shocks that could be temporary. Second, public innovation policies can be targeted to specific regions, industries, or sizes. In those cases, the information cost would vary at that level, and we control for that. Third, in 1998–2001 in Argentina, there were policy changes that can provide some exogenous shocks that we exploit in the estimation. In particular, the main innovation program in Argentina is FONTAR. In 1998, this program introduced a new source of financing in the form of fiscal subsidies applied to income taxes (Binelli and Maffioli 2008). Another important innovation program in this period was PRE, which was created at the end of 1997. These programs targeted SMEs, and conditional on size, there were no additional requirements to bias the provision of information about the public programs (Castillo et al. 2014).

A valid instrument must also satisfy a relevance condition that requires significant correlation between the instrument and the endogenous variable. This condition can be tested with a joint significance test on the excluded exogenous variables in the first-stage regression. Stock et al. (2002) 2002) recommend an F statistic greater than ten to avoid weak instruments problem that can create small sample bias in IV estimates. The first column shows that this F statistic is approximately fourteen, showing no evidence of weak instruments problem. In addition, given that just-identified models are better behaved in small samples, we are confident that the instrument satisfies the relevance condition and the estimates have good small-sample properties.

Table 3 shows that the IV estimates of the coefficient on g_2 move upward, which is consistent with a downward bias in the OLS estimate. The estimate increases from 0.96 in the OLS estimation in panel A to 1.15 in the IV estimation in panel B. A coefficient greater than one offers evidence that new products are produced less efficiently than old products. However, this evidence is tenuous because the estimate is not statistically different from one. These results show that there is evidence that product innovations create employment (creation effect) due to demand enlargement.

Table 3 also shows that the IV estimate of the coefficient on process innovation is also corrected upward. 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 induce a demand enlargement through market competition (creation effect). In the end, the creation effect on employment compensates the displacement effect on employment.

We run a Davidson-MacKinnon test to assess the endogeneity of g_2. We reject exogeneity of g_2 at 10 percent. Thus our preferred specification for the innovation-employment model is the IV estimation where g_2 is endogenous.

Skill-Biased Innovations

The effect of innovation activity on skilled and unskilled labor is 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 can justify the implementation of labor-training programs simultaneously with proinnovation policies.

Columns (2) and (3) in Table 3 show the OLS and IV results for skilled and unskilled labor. Consistent with the expected downward bias in the OLS estimation, the IV estimates of the coefficients in g_2 and d are greater than the OLS estimates.

Interestingly, the IV results suggest that product innovations are more skilled intensive. The p-value of the test $H_0 : \beta^u = \beta^s vs. H_1 : \beta^u \neq \beta^s$ is equal to 0.106. If the alternative hypothesis is that innovation is skilled biased—that is, $H_1 : \beta^u < \beta^s$—it is possible to reject the null hypothesis at 10 percent (p-value 0.053). There is no evidence that process innovations affect the skill composition.

It should be noted that we cannot reject exogeneity of g_2 in the case of unskilled labor. Given the difference in point estimates between OLS and IV, the test fails to reject exogeneity of g_2 because of the lack of precision in IV estimates. For this reason, we follow the more conservative approach of treating g_2 as endogenous in all the specifications.

Heterogeneous Effects by Technology Intensity and Size

In Tables 4 and 5, we study heterogeneous effects by technology intensity (low-tech and high-tech sectors) and size (small and large firms).

Table 4. The effect of innovation on employment and skill composition: Heterogeneous effects by technology intensity

	Low-technology[a]			High-technology[b]		
Dependent variable: l-(g1-Π)	**Labor**	**Skilled labor**	**Unskilled labor**	**Labor**	**Skilled labor**	**Unskilled labor**
A) OLS						
Process-only innovator (*d*)	–0.754	–0.181	0.261	–0.397	0.550	2.296
	(1.219)	(1.367)	(1.340)	(1.959)	(2.534)	(2.668)
Sales growth due to new products *(g2)*	0.967***	0.961***	0.947***	0.935***	0.964***	0.957***
	(0.016)	(0.019)	(0.019)	(0.022)	(0.026)	(0.025)
R-squared	0.83	0.81	0.80	0.84	0.82	0.80
B) IV						
Process-only innovator (*d*)	0.323	1.564	0.523	3.767	7.788	8.171
	(1.665)	(2.234)	(1.820)	(3.743)	(4.677)	(4.719)
Sales growth due to new products *(g2)*	1.145***	1.266***	0.978***	1.143***	1.327***	1.246***
	(0.171)	(0.253)	(0.205)	(0.162)	(0.199)	(0.201)
R-squared	0.80	0.72	0.79	0.80	0.70	0.72
First stage (*F*-test)	6.56	4.77		8.25	8.47	
p-value	0.011	0.029		0.004	0.004	
Endogeneity test (Davidson-MacKinnon)	1.17	2.09	0.02	1.78	4.62	2.73
p-value	0.280	0.148	0.888	0.183	0.032	0.099
H0: β = 1 (*p*-value)	0.397	0.293	0.916	0.376	0.100	0.222
H0: βskilled = βunskilled (*p*-value)	0.179			0.590		
H0: β high–tech = β low–tech (*p*-value)	0.994					
Number of firms	953	808	808	462	401	401

Notes: Robust standard errors. All regressions include as additional controls a dummy variable taking value one for those firms with more than 20 percent of foreign capital, dummy variables for the province where the firm's headquarters are located, and two-digit industry dummies. Skilled workers are employees with a university degree or tertiary education (one- to three-year degree related to technical professions). Unskilled workers are employees with primary or secondary education. Endogenous variables: g2. Instruments: knowledge of public support for innovation activities. *Significance level 10 percent; **significance level 5 percent; ***significance level 1 percent.

[a]Includes firms in the sectors of food, beverages, and tobacco; textiles, wearing apparel, and leather products; wood, wood products, and furniture; pulp, paper, and paper products; publishing, printing, and reproduction of recorded media; rubber and plastic products; basic metals, fabricated metals, and nonmetallic mineral products.

[b]Includes firms in the sectors of chemicals and chemical products, coke, refined petroleum and nuclear fuel, machinery, equipment, office machinery, computers, communication equipment, electrical machinery, and medical, precision and optical instruments, motor vehicles and transport equipment.

Table 4 shows the results for low-tech and high-tech firms. There is no evidence of heterogeneous effects by technology intensity in the effect of innovation on employment. There is evidence of heterogeneous effects in the effect of innovation on employment composition: product innovations are skill biased for low-tech firms but not for high-tech firms. The evidence comes from a one-sided test against the alternative that product innovations are skill biased, and we reject the null at 10 percent. This result is even more surprising given that the power of the test is lower when we split the sample into low-tech and high-tech firms.

Table 5 shows the results for small and large firms. On the effect of innovation on employment and skill composition, there is no evidence of heterogeneous effects by firm size. We cannot reject the null hypothesis that product innovations are not skill biased, but this may be due to the small sample and the lack of power in the test.

Table 5. The effect of innovation on employment and skill composition: Heterogeneous effects by size

	Small firms[a]			Large firms[b]		
Dependent variable: l -(g1-Π)	**Labor**	**Skilled labor**	**Unskilled labor**	**Labor**	**Skilled labor**	**Unskilled labor**
A) OLS						
Process-only innovator (*d*)	–3.300	–4.172	–0.598	–0.706	0.185	0.488
	(2.522)	(3.236)	(3.112)	(1.118)	(1.243)	(1.268)
Sales growth due to new products *(g2)*	0.962***	0.985***	0.959***	0.952***	0.950***	0.941***
	(0.032)	(0.043)	(0.039)	(0.013)	(0.015)	(0.016)
R-squared	0.78	0.73	0.75	0.87	0.85	0.83
B) IV						
Process-only innovator (*d*)	–3.045	–4.183	–0.210	2.158	3.714	2.378
	(2.656)	(3.816)	(3.021)	(2.481)	(2.705)	(2.638)
Sales growth due to new products *(g2)*	1.150***	1.357***	1.075***	1.170***	1.239***	1.085***
	(0.208)	(0.388)	(0.308)	(0.174)	(0.194)	(0.184)
R-squared	0.73	0.61	0.71	0.82	0.77	0.80
First stage (*F*-test)	6.43	3.29		6.20	6.43	
p-value	0.012	0.071		0.013	0.011	
Endogeneity test for *g2* (Davidson-MacKinnon)	0.96	1.40	0.14	1.90	3.08	0.64
p-value	0.329	0.237	0.706	0.169	0.080	0.424
HO: β = 1 (*p*-value)	0.471	0.358	0.806	0.329	0.218	0.643
HO: βskilled = βunskilled (*p*-value)	0.312			0.328		
HO: β large = β small (*p*-value)	0.994					
Number of firms	414	304	304	997	902	902

Notes: Robust standard errors. Significance level: ***1%, **5%, and *10%. All regressions include as additional controls a dummy variable taking value one for those firms with more than 20 percent of foreign capital, dummy variables for the province where the firm's headquarters are located, and two-digit industry dummies. Skilled workers are employees with a university degree or tertiary education (one- to three-year degree related to technical professions). Unskilled workers are employees with primary or secondary education. Endogenous variables: g2. Instruments: knowledge of public support for innovation activities.

[a]Firms with fewer than 50 employees.

[b]Firms with more than 50 employees.

Robustness Checks

Innovation and Employment

In this section, we run some robustness checks to evaluate the sensitivity of the results about the effect of innovation on employment to alternative modeling assumptions. First, we include additional instruments to test for exogeneity of the instruments using a Sargan-Hansen overidentification test. The additional instrument is an indicator of positive R&D investment in each year (continuous R&D dummy). If continuous R&D is correlated with time-invariant firm attributes—something we control for—rather than productivity shocks, continuous R&D satisfies the exogeneity assumption. Given the definition of continuous R&D, exogeneity of continuous R&D seems like a sensible assumption. Column (1) in Table 6 shows the estimates for the overidentified model. The Sargan-Hansen test does not reject exogeneity of the instruments. These results provide additional evidence of the validity of the chosen instrument.

Second, we estimate the Harrison et al. (2014) model under the assumptions that both g_2 and process-only innovation are endogenous. Column (2) in Table 6 shows the results. The estimate on the coefficient on process-only innovation experiences an important loss in precision. However, 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-only innovation variable.

Third, we evaluate whether product-only innovators are different from product and process innovators. To do that, we add an interaction between g_2 and a product and process innovator dummy as an additional covariate. This new variable is endogenous, so we use the interaction between knowledge of support for innovation activity and the product and process innovator dummy as an additional instrument. Column (3) in Table 6 shows the results. Although 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-only innovators.

Fourth, we control for industry-location shocks including the average employment growth at the industry-regional level as an additional regressor. In the basic specification, we control for industry-specific shocks using two-digit industry dummies, and we control for location-specific shocks using location dummies. To control for industry-location shocks, we define five regions: Buenos Aires, Center, Cuyo, South, and North.[6] Then we construct the mean employment growth at the industry-regional level. We expect that this variable is able to capture industry-location-specific shocks. Column (4) in Table 6 shows that the variable is not significant and the results are similar to the basic model.

Fifth, given that part of the endogeneity comes from unobserved productivity, we include labor productivity as a proxy for unobserved productivity. The proxy for unobserved productivity is labor productivity in 1998 defined as real sales over workers. Column (5) in Table 6 shows that the variable is not significant and the results are similar to the basic model.

Sixth, measurement error in sales of new products can potentially bias our results. To ease concerns about the presence of measurement error in sales of new products, we use a more restricted definition for g_2. We consider new products not already sold in local or international markets by other firms. Column (6) in Table 6 shows that the results are similar to the basic model.[7]

Skill-Biased Innovations

In this section, we run some robustness checks to evaluate the sensitivity of the results on the effect of innovation about employment composition. Table 7 shows the results of the different robustness exercises.

As in the previous case, we first include continuous R&D as an additional instrument. In this case, the effect of process innovation is again nonsignificant and therefore robust to different instruments. The effect of product innovation, however, is equal for skilled and unskilled labor. This contradicts the skill bias found using our preferred specification using only knowledge of public support. The fact that different instruments yield different results is shown in the fact that we reject overidentification for skilled labor. We interpret these results in two ways. First, if we have to choose between the two instruments, we are inclined to believe in the exogeneity of knowledge of public support. The arguments behind this statement are

Table 6. Robustness exercises on the effect of innovation on employment

Dependent variable: l -(g1-Π)	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Process-only innovator (*d*)	0.000	23.066	–3.590	1.218	1.215	1.182
	(1.117)	(20.216)	(3.407)	(1.667)	(1.593)	(1.611)
Sales growth due to new products *(g2)*	1.018***	1.099***	1.632**	1.148***	1.137***	1.282***
	(0.045)	(0.091)	(0.557)	(0.130)	(0.122)	(0.237)
*g2**Product and process innovator (*g2* prod&proc*)			–0.467			
			(0.403)			
Mean employment growth				0.040		
				(0.116)		
Labor productivity in 1998					0.002	
					(0.002)	
R-squared	0.83	0.76	0.68	0.80	0.80	0.59
First stage for *g2* (*F*-test)	38.18	40.19	25.37	12.40	13.34	8.81
p-value	0.000	0.000	0.000	0.000	0.000	0.003
First stage for *d*		8.56				
p-value		0.000				
First stage for *g2*prod&proc*			149.12			
p-value			0.000			
Overidentification test (Sargan-Hansen)	1.88					
p-value	0.170					
Endogeneity test for *g2* (Davidson-MacKinnon)	1.52	2.37	2.51	2.53	2.32	2.45
p-value	0.217	0.123	0.113	0.112	0.128	0.118
Endogeneity test for *d*		1.47				
p-value		0.225				
Endogeneity test for *g2*prod&proc*			1.64			
p-value			0.200			
H0: β = 1 (p-value)	0.691	0.277	0.257	0.255	0.264	0.233
H0: β prod&proc = β product only (*p*-value)			0.247			
Number of firms	1,415	1,415	1,415	1,415	1,415	1,415

Notes: Robust standard errors. All regressions include as additional controls a dummy variable taking value one for those firms with more than 20 percent of foreign capital, dummy variables for the province where the firm's headquarters are located, and two-digit industry dummies. [1] Endogenous variables: g2. Instruments: knowledge of public support for innovation activities and a continuous R&D dummy. [2] Endogenous variables: g2 and d. Instruments: knowledge of public support for innovation activities and a continuous R&D dummy. [3] Endogenous variables: g2 and g2 × product and process innovator. Instruments: knowledge of public support for innovation activities and knowledge of public support for innovation activities × product and process innovator. [4] Endogenous variables: g2. Instruments: knowledge of public support for innovation activities. Additional control: Mean employment growth at the industry and regional level. [5] Endogenous variables: g2. Instruments: knowledge of public support for innovation activities. Additional control: Firm's labor productivity in 1998. [6] Endogenous variables: g2, sales of new products not already sold in the market by other firms. Instruments: knowledge of public support for innovation activities. *Significance level 10 percent; **significance level 5 percent; ***significance level 1 percent.

Table 7. Robustness exercises on the effects of innovation on skill composition

	[1]		[2]	
Dependent variable: l-(g1-Π)	**Skilled labor**	**Unskilled labor**	**Skilled labor**	**Unskilled labor**
Process-only innovator (*d*)	0.774	1.730	3.479	2.335
	(1.285)	(1.291)	(2.585)	(2.077)
Sales growth due to new products *(g2)*	1.050***	1.040***	1.394***	1.118***
	(0.052)	(0.053)	(0.242)	(0.193)
Exports in 1998 (in logs)			0.031	0.061
			(0.108)	(0.094)
Imports in 1998 (in logs)			–0.294	–0.102
			(0.201)	(0.158)
Technology transfer in 1998 (in logs)			–0.592	–0.126
			(0.382)	(0.307)
R-squared	0.80	0.79	0.65	0.77
First stage (*F*-test)	35.87		6.71	
p-value	0.000		0.010	
Overidentification test (Sargan-Hansen)	4.82	0.26		
p-value	0.028	0.612		
Endogeneity test for *g2* (Davidson-MacKinnon)	2.51	2.46	5.63	0.81
p-value	0.113	0.117	0.018	0.368
H0: β = 1 (*p*-value)	0.335	0.449	0.103	0.542
H0: βskilled = βunskilled (*p*-value)	0.813		0.126	
Number of firms	1,209	1,209	1,209	1,209

Notes: Robust standard errors. All regressions include as additional controls a dummy variable taking value one for those firms with more than 20 percent of foreign capital, dummy variables for the province where the firm's headquarters are located, and two-digit industry dummies. Skilled workers are employees with a university degree or tertiary education (one- to three-year degree related to technical professions). Unskilled workers are employees with primary or secondary education. [1] Endogenous variables: g2. Instruments: knowledge of public support for innovation activities and a continuous R&D dummy. [2] Endogenous variables: g2. Instruments: knowledge of public support for innovation activities. Additional controls: Exports in 1998 (in logs), Imports in 1998 (in logs), and Technology transfer in 1998 (in logs). *Significance level 10 percent; **significance level 5 percent; ***significance level 1 percent.

written in detail in the Empirical Results section. Second, if the effect of innovation is heterogeneous across firms, even if the two instruments are equally valid, the difference between two IV instruments is related to the fact that the IV estimate measures a local effect on compliers.

Next, we include several regressors used in the literature of skilled technical change for developing countries (see, for example, Meschi et al. 2011). We include log of exports; log of imports of physical capital, equipment, and inputs; and log of technology transfer. Exports capture skill-enhancing effects of exporting activity (learning-by-exporting); imports capture technological transfers embedded in physical capital; and technology transfers capture explicit transfer of technology through licenses and patents. The results in [2] in Table 7 show that these variables are not significant and the results do not change.[8]

Quantifying the Effect of Innovation on Employment and Productivity

The effect of each type of innovation on employment growth can be decomposed in a productivity trend, the contribution of noninnovators, the contribution of process-only innovators, and the contribution of product innovators. This decomposition is similar to the employment growth decomposition proposed in Harrison et al. (2014), but we modify the original decomposition to present separately the contribution of noninnovators. Firm's employment growth can be written as

$$l_i = \left(\sum\nolimits_j \alpha_j \, industry_{ji} + \sum\nolimits_k \alpha_k \, location_{ki}\right) + 1(g_{2i} = 0)(1 - d_i)(g_{1i} - \pi_i) \\ + d_i 1(g_{2i} = 0)(\alpha_1 + g_{1i} - \pi_i) + 1(g_{2i} > 0)(d_i\alpha_1 + g_{1i} - \pi_i + \beta g_{2i}) + v_i, \tag{3}$$

where $industry_{ji}$'s are industry dummy variables; $location_{ki}$'s are location (province) dummy variables; and $1(.)$ is an indicator function. Thus employment growth can be decomposed into four main components. The first component ($\sum_j \alpha_j \, industry_{ji} + \sum_k \alpha_k \, location_{ki}$) measures the contribution of the (industry-location specific) productivity trend; the second component $(1(g_{2i} = 0)(1 - d_i)(g_{1i} - \pi_i))$ measures the contribution of noninnovators; the third component $(d_i 1(g_{2i} = 0)(\alpha_1 + g_{1i} - \pi_i))$ measures the contribution of process-only innovators; and the fourth component $(1(g_{2i} > 0)(d_i\alpha_1 + g_{1i} - \pi_i + \beta g_{2i}))$ measures the contribution of product innovators.

Column (1) in Table 8 shows the contribution of the different components to employment growth using the IV estimates. The contribution of the productivity trend is −0.6 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 translate the full extent of the adjustment to the labor force. This can be an optimal decision for the firms under the presence of labor adjustment costs or if firms have more optimistic expectations for the future (Basu and Fernald 2001).

The contribution of noninnovators is −4.1 percent. This is the largest contribution and shows that the destruction of jobs during this period was concentrated in noninnovators. The contribution of process-only innovators is −0.6 percent. Two factors affect this contribution. First, there are few firms that introduce only process innovations (15 percent of the sample). Second, process innovations seem to have rather small effects on employment. The contribution of product innovators is 1.4 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).

Columns (2) and (3) in Table 8 show the decomposition for low- and high-tech sectors. Employment growth for low-tech firms is −3.5 percent, and employment growth for high-tech firms is −4.9 percent. The decomposition shows that the difference in employment growth can be fully explained by the contribution of product innovators. Given that the relative efficiency of new products is similar for low- and high-tech firms, the differential contribution of product innovators is associated with the larger real sales for product innovators in low-tech sectors.

Table 8. Contributions of innovation to employment growth (annual rates of growth 1998–2001 in percentage)

	All firms	Low-technology[a]	High-technology[b]	Small firms[c]	Large firms[d]
Firms' employment growth	−4.0	−3.5	−4.9	−3.5	−4.2
Productivity trend	−0.6	−0.5	−0.3	1.9	−2.0
Contribution noninnovators	−4.1	−4.2	−3.9	−5.9	−3.4
Contribution process-only innovators	−0.6	−0.6	−0.6	−0.4	−0.7
Contribution product innovators	1.4	1.8	0.0	0.9	2.0

[a]Includes firms in the sectors of food, beverages, and tobacco; textiles, wearing apparel, and leather products; wood, wood products, and furniture; pulp, paper, and paper products; publishing, printing, and reproduction of recorded media; rubber and plastic products; basic metals, fabricated metals, and nonmetallic mineral products.
[b]Includes firms in the sectors of chemicals and chemical products, coke, refined petroleum, and nuclear fuel; machinery, equipment, office machinery, computers, communication equipment, electrical machinery, and medical, precision, and optical instruments; motor vehicles and transport equipment.
[c]Firms with fewer than 50 employees.
[d]Firms with more than 50 employees.

Columns (4) and (5) in Table 8 show the decomposition for small and large firms. Employment growth for small firms is −3.5 percent, and employment growth for large firms is −4.2 percent. The decomposition shows that both innovators and noninnovators in small firms destroy more employment than innovators and noninnovators in large firms. Thus, the larger employment growth for small firms is explained by the lower productivity trend.

Conclusions

This article presents evidence about the relationship between innovation and employment in the manufacturing sector in Argentina. We aim at understanding whether different types of innovation create or destroy employment and the type of employment that is created or destroyed. To accomplish this, we estimated the model proposed in Harrison et al. (2014) using an IV approach with data from the Argentinean Innovation Surveys for the period 1998–2001.

The estimation of the effect of the different types of innovation on employment shows that product innovation generates employment, but 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. Thus, the displacement effect of product innovation on employment has no empirical support in our data.

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 a demand enlargement through market competition (creation effect). In the end, the creation effect on employment compensates the displacement effect on employment. Unfortunately, with the available data, we cannot distinguish one explanation from the other. Specification tests support use of an IV approach and the validity of the chosen instruments. These results are robust to using additional instruments, allowing different effects for product and process innovators, adding additional controls, endogeneity of process innovation, and using a different definition of new products.

Our results also show that product innovation is skilled biased. Although the innovation created both skilled and unskilled jobs, the proportion of skilled jobs was higher than the proportion of unskilled jobs. Therefore even if the innovation replaces tasks traditionally carried out by unskilled workers with new jobs demanding qualified workers, the increase in demand also leads to an increase in the demand of unskilled workers.

During the period we analyzed, there was an important contraction in employment due to the recession. We found that most of the contraction in employment was due to noninnovators. Process-only innovators contributed—although marginally—to the reduction in employment while product innovators more than compensated for the effect of process innovators. These results were valid both for low- and high-tech industries and for small and large firms. Interestingly, low-tech firms destroyed fewer jobs than high-tech firms because sales decreased less for low-tech product innovators than for high-tech product innovators. Small firms destroyed fewer jobs than large firms because small firms had a lower productivity trend than large firms.

Notes

1. The identification discussion focuses on Equation (1), but similar arguments apply to the identification of Equation (2).
2. 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.
3. Segunda Encuesta Nacional de Innovación y Conducta Tecnológica de las Empresas Argentinas 1998-2001.
4. Following Harrison et al. (2014), 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.

5. "Location dummies" means a dummy variable for each province in Argentina. We consider that a firm is located in a province if its headquarters are located in that province. There are twenty-three provinces in Argentina, and around 64 percent of the firms are located in the city of Buenos Aires.

6. Buenos Aires includes the city of Buenos Aires; Center includes the provinces of Buenos Aires, Cordoba, and Santa Fe; Cuyo includes Mendoza, San Luis, and San Juan; South includes Chubut, Neuquén, La Pampa, Santa Cruz, Rio Negro, and Tierra del Fuego; and North includes the rest of the provinces.

7. We also extended the model to consider non-CRS. However, we could not reject the CRS hypothesis. See de Elejalde et al. (2013) for further details.

8. We also included in the regression the mean employment growth at the industry-regional level to capture industry-location-specific shocks. The coefficient of this variable is not significant, and the results do not change. The same occurs when we include labor productivity in 1998 as an additional regressor. These estimates can be found in de Elejalde et al. (2013).

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