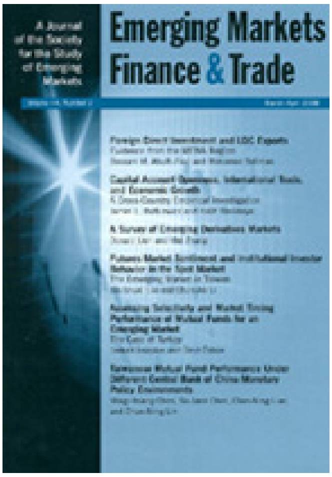
This article was downloaded by: [Diego Aboal]
On: 03 April 2015, At: 17:24
Publisher: Routledge
Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK



Click for updates

Emerging Markets Finance and Trade
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/mree20

Innovation, Firm Size, Technology Intensity, and Employment Generation: Evidence from the Uruguayan Manufacturing Sector

Diego Aboal[abc], Paula Garda[ad], Bibiana Lanzilotta[ab] & Marcelo Perera[abc]

[a] Centro de Investigaciones Económicas (CINVE), Montevideo, Uruguay

[b] Universidad ORT Uruguay, Montevideo, Uruguay

[c] Facultad de Ciencias Económicas y Administración, Universidad de la República, Montevideo, Uruguay

[d] Organisation for Economic Co-operation and Development (OECD), Paris, France

Published online: 02 Apr 2015.

To cite this article: Diego Aboal, Paula Garda, Bibiana Lanzilotta & Marcelo Perera (2015): Innovation, Firm Size, Technology Intensity, and Employment Generation: Evidence from the Uruguayan Manufacturing Sector, Emerging Markets Finance and Trade, DOI: 10.1080/1540496X.2015.998072

To link to this article: http://dx.doi.org/10.1080/1540496X.2015.998072

PLEASE SCROLL DOWN FOR ARTICLE

Taylor & Francis makes every effort to ensure the accuracy of all the information (the “Content”) contained in the publications on our platform. However, Taylor & Francis, our agents, and our licensors make no representations or warranties whatsoever as to the accuracy, completeness, or suitability for any purpose of the Content. Any opinions and views expressed in this publication are the opinions and views of the authors, and are not the views of or endorsed by Taylor & Francis. The accuracy of the Content should not be relied upon and should be independently verified with primary sources of information. Taylor and Francis shall not be liable for any losses, actions, claims, proceedings, demands, costs, expenses, damages, and other liabilities whatsoever or howsoever caused arising directly or indirectly in connection with, in relation to or arising out of the use of the Content.

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan, sub-licensing, systematic supply, or distribution in any form to anyone is expressly forbidden. Terms &

Conditions of access and use can be found at http://www.tandfonline.com/page/terms-and-conditions

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Emerging Markets Finance & Trade, 1–24, 2015
Copyright © Taylor & Francis Group, LLC
ISSN: 1540-496X print/1558-0938 online
DOI: 10.1080/1540496X.2015.998072

Routledge
Taylor & Francis Group

Innovation, Firm Size, Technology Intensity, and Employment Generation: Evidence from the Uruguayan Manufacturing Sector

Diego Aboal[1,2,3], Paula Garda[1,4], Bibiana Lanzilotta[1,2], and Marcelo Perera[1,2,3]

[1]Centro de Investigaciones Económicas (CINVE), Montevideo, Uruguay; [2]Universidad ORT Uruguay, Montevideo, Uruguay; [3]Facultad de Ciencias Económicas y Administración, Universidad de la República, Montevideo, Uruguay; [4]Organisation for Economic Co-operation and Development (OECD), Paris, France

ABSTRACT: In this article, we investigate the effect of product and process innovation on employment growth and on employment composition in terms of skills using data from Uruguayan manufacturing firms' innovation surveys. The results reveal that product innovation is associated with employment growth. There is (weaker) evidence that process innovation displaces labor, especially in high-tech firms. There is evidence that innovation is more complementary to skilled than to unskilled labor. Product innovation seems to have a larger positive effect on skilled labor, especially in high-tech industries. Process innovation in general displaces unskilled labor but is neutral in terms of skilled labor.

KEY WORDS: innovation, employment quantity and quality, firm size, innovation surveys, Uruguay

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Introduction

Innovation, or the introduction of new products and production processes, is increasingly understood as essential for growth (Freeman 1994; Griliches 1986; Grossman and Helpman 1993; Inter-American Development Bank 2010; Organisation for Economic Co-operation and Development 2010). Latin American countries increasingly see innovation as a way to increase competitiveness, diversify their economies, and move to higher value-added activities.

Innovation is an important growth factor for several Organisation for Economic Co-operation and Development (OECD) countries (Organisation for Economic Co-operation and Development 2010). The growth of multifactor productivity that is linked to innovation explains much of the total productivity growth of these countries. The multifactor productivity differences account also for much of the disparity between advanced economies and emerging economies. This indicates that innovation is key to reducing the productivity gap between these two types of economies.

According to this type of evidence, Latin American countries are increasingly supporting innovation policies. However, one aspect that cannot be neglected is that innovation can have effects in terms of employment at the level of the firm. Research on the innovation-employment link can give clues to policy makers in the process of designing innovation policies with the best possible effect on employment.

The Uruguayan economy is characterized by a large presence of small domestic companies and a few large firms with foreign capital. Smaller companies tend to develop less formalized and systematic innovation activities than larger companies, where the probability of carrying out research and development activities is greater (Baldwin 1997). Of course, size is not the only thing that matters: small firms in the most knowledge-intensive sectors (e.g., information and communication technologies) tend to develop more-complex innovation processes and demand more-qualified human resources. However, as is the case in most Latin American countries, the weight of high-tech

Address correspondence to Diego Aboal, Uruguay 1242, Montevideo, Uruguay. E-mail: aboal@cinve.org.uy

or more knowledge-intensive sectors in the Uruguayan economy is significantly lower than in most advanced economies. These characteristics of Uruguayan firms can potentially affect how innovation activities affect the quantity and quality of employment.

This work is the first attempt to understand the relationship between innovation and employment at the firm level, in terms of quantity and quality, in Uruguay. To take into account the particular structure of the Uruguayan economy, we will analyze the effect of firm size and technology intensity of firms on the innovation-employment relationship.

We employ the simple theoretical framework presented in Harrison et al. (2008) to quantify the employment effects of innovation using innovation survey data. We take special care with respect to endogeneity problems. A regression relating firms' employment growth to the introduction of process innovations and the two components of sales growth accounted for by "unchanged" and "newly introduced or substantially improved" products, respectively, is used. We employ data from four waves of the Manufacturing Firms Innovation Surveys (MIS) for the period 1998–2009 and match them with the annual Economic Activity Surveys (EAS).

Our article extends the model by separating skilled and unskilled labor. This is important because innovation might change the demanded skill composition of the labor force and therefore have different effects on skilled and unskilled labor. As an additional innovation, we explore the presence of heterogeneous effects across types of firms. We analyze the differences among high-tech and low-tech subsectors. These subsectors have very different demand profiles for workers and innovate differently, and this could imply differential effects of innovation on employment.[1] We also analyze the possible dissimilar effect of innovation on employment in small firms. This is relevant not only because we know that small firms innovate less (and differently) and have on average less-qualified workers, but also because in Latin America, micro, small, and medium enterprises generate 60 percent of the employment.

The results indicate that product innovation is an important source of firm-level employment growth, while process innovation, which is likely to be associated with price reductions, tends to have negative or no effect on employment depending on the subsample of firms. Results indicate that process innovation displaces labor in high-tech firms, having no effects on small or low-tech firms. Product innovation seems to be more complementary to skilled than to unskilled labor. Results also indicate that the negative effect of process innovation on employment comes from displacing unskilled labor. This is especially true in high-tech industries. No such effect is present in small firms and low-tech industries.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Brief Literature Review

In recent review of the literature, Vivarelli (2011) concludes that in terms of quantitative effects, the literature shows that process innovation tends to have a negative effect on employment, while product innovation tend to exhibit a positive effect.

For Latin American, countries there are only a few empirical studies based on microdata. Crespi and Tacsir (2013) summarize the results of a collective research effort aimed at analyzing the effects of innovation on employment in several countries in the region using innovation surveys and economic activity surveys.[2] This research is based on the analytical model proposed by Harrison et al. (2008), differentiating the effect of process and product innovation on employment. They find that, except for the case of Chile, the introduction of process innovations does not affect employment growth, and there is no evidence of displacement effects due to the introduction of product innovations (they even observe positive employment effects resulting from the compensation effects arising from the introduction of new products). Crespi and Zuñiga (2013) examine the effect of innovation on employment growth, exploring the differences arising from the use of different innovation strategies. The study covers three Latin American countries (Argentina, Chile, and Uruguay) using microdata from innovation surveys and manufacturing activity. They find that, of the three innovation strategies analyzed (make only, buy only, and make and buy), the first (typical of high-tech industries) has the greatest effect on employment followed by the combined strategy (which has a similar effect on employment in low-tech industries).

Prior to this research, there are two articles studying the relationship between employment and innovation in Latin America with microdata: Benavente and Lauterbach (2008) for Chile and Fajnzylber and Fernandes (2004) for Brazil. Benavente and Lauterbach (2008) use innovation surveys from Chile (1998–2001) and find that product innovations positively and significantly affect employment in the manufacturing industry; meanwhile, process innovations have no significant effects. Fajnzylber and Fernandes (2004) indirectly estimate the effect of technology on the demand for skilled labor by studying firms that have important international links; that is, firms that use imported inputs, export, and receive FDI. Their results indicate that companies engaging in these activities have higher demand for skilled labor than companies outside this group. They conclude that such international activities act as a channel for technology diffusion in Brazil and thus that technology diffusion positively affects demand for skilled labor.

Theoretical Framework and Methodological Issues

In general, we expect two predominant effects of innovation on employment at the firm level. The first is a job-loss effect due to reduced input requirements per unit of product. The second is a positive-compensation effect triggered by the expansion of sales and production. This second effect is linked to both the reduction of marginal costs (the reduction of prices generates an increase in demand) and the creation of new products that require additional labor. These effects on employment may be larger or smaller depending on market structure (of both goods and factors) and the sectors in which innovation takes place. The behavior of firms' managers and workers could also exacerbate or reduce the displacement effect and weaken or increase the compensation effects. For example, a firm's market power and workers' wage bargaining power could reduce the size of price reductions linked to cost savings from innovation and therefore weaken the positive employment effects of innovation.

Partial equilibrium effects are present at the sectoral level (reallocation of output and employment between more- and less-innovative companies) in addition to general equilibrium effects linked to interactions between different markets. Finally, it is important to note that innovation affects not only the number of jobs created, but also their quality. Innovation could be associated with lower employment growth among unskilled workers while simultaneously increasing demand for skilled labor. Depending on the skills bias of innovation, its effect may be different for skilled and unskilled workers.

The model presented by Harrison et al. (2008) makes it possible to disentangle some of the theoretical employment effects of innovation and is very useful applicable when analyzing firm-level employment effects of innovation activities using the specific information provided by innovation survey data. The share of sales due to product innovations serves as the key output indicator. One interesting aspect of the approach is that it establishes a theoretical relationship between the employment growth rate and innovation output in terms of sales growth stemming from innovative products. The latter will be directly calculated by means of the available innovation survey data for Uruguayan manufacturing firms.

The model is based on the idea that firms can produce different products. At the beginning of the reference period, a firm *i* produces one or more products, which are aggregated into one product. This aggregate product is called the "old product." In the period under consideration, the firm can decide to launch one or more new (or significantly improved) products: "new products." Firms are observed for two periods, t = 1 and t = 2, and innovation occurs between these two periods (if it occurs at all).

To produce the different outputs, it is assumed that firms use identical separable production technology with constant returns to scale in capital, labor, and intermediate inputs or materials.[3] Each production technology has an associated efficiency parameter that can change between the two periods. New products can be made with higher or lower efficiency with respect to old products, and the firm can affect the efficiency of its production over time through investments in process

Downloaded by [Diego Aboal] at 17:24 03 April 2015

innovation. It is important to note that the model does not allow economies of scale among products, in particular between old and new ones.

Employment growth is going to be determined by: (1) the rate of change in efficiency in the production of old products (negative employment effect), (2) the rate of growth of production of old products (positive effect), (3) the expansion in production from new products (positive effect), and (4) the change in efficiency due to process innovation (negative effect). Equation (1) shows the links between employment and innovation:

$$l = \alpha_0 + \alpha_1 d + g_1 + \beta g_2 + \mu \quad (1)$$

where l: employment growth rate; g_1: nominal growth rate of sales due to old products; g_2: nominal growth in sales due to new products (computed as the sales of new products to total sales of previous period)[4]; d: dummy variable indicating process innovation; α_0: parameter, (negative) average efficiency growth in the production of old products; α_1: parameter, average efficiency growth for process innovations; β: parameter, relative efficiency of the production of old and new products, if $\beta < 1$ then there is gain of productivity in the production of new products with respect to the old ones; μ: unobserved disturbance, which includes productivity shocks, price changes of old products, price changes of new prices relative to old ones, and changes in production of new products.

This equation has already been transformed in order to use nominal sales, which are the usual available variables in innovation surveys.[5] Notice that the variable g_1 has a coefficient equal to one and can thus be subtracted from l on the left-hand side of the equation for estimation, being the new dependant variable l-g_1. This implies that we are estimating a net employment effect.

The three parameters of interest are α_0, α_1, and β. Identification and consistency depend on the lack of correlation of the variables representing innovation ($g2$ and d) and the error term, or alternatively on the availability of instruments uncorrelated with the error term.

Endogeneity could arise because innovation decisions depend on the productivity of the firm and unobservable productivity shocks. Since the equation is in differences, the fixed productivity effects are not present in the equation. However, the unobservable productivity shocks are still in the error term, μ, and could be correlated with the innovation variables. This correlation will depend on the timing of productivity shocks and investment decisions. 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. However, endogeneity is a valid concern if investment decisions and the productivity shocks are contemporaneous or if the productivity shocks are correlated.

Harrison et al. (2008) note that there are good reasons to think that productivity shocks are not predictable by firms at the moment of deciding their technological investments, and therefore consistent estimation of Equation (1) by OLS is not too unlikely. They also show a downward bias would be expected in the coefficients of d and $g2$.

Harrison et al. (2008) transformed the original model in real terms to include nominal sales as in Equation (1). This generates an additional source of endogeneity: the unobserved disturbance includes prices of the old and new products that are correlated with d and $g2$. In other words, d and $g2$ could be correlated with the error term because we do not have firm-level prices, and therefore we are forced to work with nominal variables.

It could also be possible to expect a bias in the coefficient of the variable d if we believe that process innovation could cause a reduction in marginal costs and prices.

Even though we cannot control for firm-level prices, because this information is not available, we can probably do better than estimating Equation (1) without controlling for any prices by at least finding a good proxy for the growth rate of old products, allowing us to avoid problems generated by this variable being included in the error term of (1).

We can control for the change in prices of old products by subtracting the industry price growth index (π) (a proxy for the rate of increase of prices of old products) from the nominal sales growth of old products; the dependent variable will in this case be $l-(g1 - \pi)$.[6] The value of the estimated

Downloaded by [Diego Aboal] at 17:24 03 April 2015

constant will be an estimate of the average real productivity growth in the production of old products between the two periods. To compute price growth rates, we use producer price indexes (IPPN: Producer Price Index of National Products) on a four-digit level of the International Standard Industrial Classification (ISIC).[7]

Hence, the model to be estimated in this case is

$$l - (g_1 - \pi) = \alpha_0 + \alpha_1 d + \beta g_2 + v \tag{1'}$$

Even though we could expect an attenuation of the bias in the coefficient of variable d after the inclusion of π in Equation (1′), $g2$ still could present endogeneity problems because the error term v includes the change in the prices of new products.[8] We should expect a downward bias in β, both because the error term potentially includes productivity shocks and because $g2$ is a nominal variable. Our empirical strategy thus relies on the choice of instrumental variables (IV) for $g2$ that can be considered to be uncorrelated with both prices of new products and the productivity shocks.

The relationship between employment and innovation is very complex. It has the potential to affect not only the quantity of labor, but also its composition. Indeed, innovation might change the composition of skills demanded from the labor force.

To study the effect of (process and product) innovation on the composition of employment, we can estimate Equation (1′) for each type of labor. That is, we can estimate

$$l^{q_j} - (g_1 - \pi) = \alpha_0^{q_j} + \alpha_1^{q_j} d + \beta^{q_j} g_2 + v \qquad j = s, u \tag{2}$$

where l^{q_j} is the employment growth rate of type j labor ($j = s,u$; s = skilled; and u = unskilled), and the rest of the variables are the same as in the previous section. This equation provides us with estimates of the effect of innovations on employment of each labor type.

As before, endogeneity could arise because innovation decisions depend on the productivity of the firm and unobservable productivity shocks. Hence, we are going to control for potential endogeneity using an instrumental variables approach.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Empirical Analysis

Country Context, Data, and Descriptive Statistics

Country Context

Uruguay is a relatively small South American country with a population of 3.3 million. Nearly 70 percent of 2010 gross domestic product (GDP) is accounted for by the production of services, 20 percent by the production of manufacturing goods and construction, and 10 percent by the production of primary goods. Sales of primary goods with low levels of processing together with tourism services account for most of the country's exports.

During 1985–2010, Uruguay's annual GDP growth rate averaged 2.5 percent. However, growth was significantly higher over 2005–10, at an average annual rate of 6.5 percent.

At the beginning of the twenty-first century, the Uruguayan economy went through a severe crisis originating from a macro devaluation of its currency in the year 2002. Despite the depth of the crisis, the economy recovered relatively quickly. In 2004, a period of significant economic growth began, with increases in investment (especially) foreign direct investment (FDI), increases in productivity, reduced unemployment, and diversification of the economic base and of its external markets. In this context, employment rose significantly, and the unemployment rate declined to historically low rates (lower than 7 percent in 2010), from a peak of 20 percent in September 2002.

Data and Descriptive Statistics

We are using the four waves of the Manufacturing Firms Innovation Surveys (MIS) currently available (1998–2000, 2001–3, 2004–6, and 2007–9) and the annual Economic Activity Surveys (EAS) for the period 1998–2007. The MIS data are collected by the National Bureau of Statistics (INE), parallel with the EAS. It is important to note that the database that we are going to use does not have a panel structure.

The same sampling model is used in both surveys. For the MIS, all firms with more than forty-nine workers are mandatorily included. Units with twenty to forty-nine employees and with fewer than nineteen workers are selected using simple random sampling within each economic sector at the two-digit ISIC level up to 2005. After 2005, random strata are defined for those units with fewer than fifty workers within each economic sector at the ISIC four-digit level. The response rate is nearly 90 percent. The number of firms included in the samples for the 1998–2000, 2001–3, 2004–6, and 2007–9 surveys were 761, 814, 839, and 941, respectively.

Matching with the EAS does not come without limitations. The main reason to match the MIS with the EAS is the need to collect sales and employment data at the beginning of each year for the period of reference for each survey of the MIS. Every MIS collects sales and employment data for the year at the end of the reference period, but not for the initial year.

Due to sampling frame changes and registration problems, we lose a significant number of firms. After 2006, the INE modified the sample of the EAS, reducing the number of firms surveyed. Moreover, the 2004–6 MIS was performed with the same sampling frame as 2005. This means that a number of firms in the 2004–6 MIS did not participate in the 2006 EAS. When we merge the MIS 1998–2000, 2001–3, and 2004–6 with the EAS, we lose around 10 percent of the observations. A similar problem arises when matching the 2007–9 MIS (which is a subsample of 2009 EAS) and the 2007 EAS. Approximately half of the firms participating in this survey are not in the 2007 EAS. Finally, some firms were lost because it was impossible to link them between two EAS surveys or between the MIS and the EAS. In any case, the results with and without the 2007–9 MIS are very similar, so we believe the loss of observations is not generating important biases in our estimations.

The final number of observations (firm/period) used in the estimations is 2,532:[9] 722 from the 1998–2000 MIS, 627 from the second MIS, 737 from the third one, and 446 from the most recent survey available.

Table A.1 (Appendix) shows the definition, source, and availability of each variable described in the article.

Table 1 shows descriptive statistics. Mean firm size is ninety-one employees, and 13 percent of these firms are owned by foreign capital. Fifty-one percent of firms in the sample innovated in processes or products. Thirty-two percent are product innovators, of which 87 percent are both product and process (or organizational) innovators. Twenty-percent are process-only or organizational-only innovators (nonproduct innovators).

From now on we refer to process innovators as those that only do process or organizational innovations.

Data on yearly employment growth show that the mean is negative. This figure is being driven by the noninnovating firms.[10] While the noninnovators show negative growth rates, process innovators (nonproduct innovators) and product innovators show moderated positive growth rates. The wage bill per worker grew at a mean rate of almost 5 percent during the first three surveys (information for the most recent one is not available).

The yearly sales growth rate was positive for almost all firms. While noninnovators (no process or product innovators) showed a zero growth rate, process innovators and product innovators showed positive figures. Within the latter, this figure is explained by the sales growth of innovators in new products (30 percent versus −21 percent for innovators in old products).

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table 1. Descriptive statistics: Manufacturing firms pooled surveys, 1998–2009

	All manuf	Small	High Tech	Low Tech
Number of observations	2532	1353	1464	1068
Distribution of firms (%)				
Non-innovators (no process or product innovations)	48.14	62.23	42.6	55.8
Process only or organizational only innovators (non product innovators)	19.39	14.04	21.9	16.0
Product innovators	32.46	23.73	35.6	28.2
of which product AND process innovators (as % of product innovators)	87.96	85.05	89.6	85.1
Number of employees at the beginning of (each) survey	91.20	26.16	102.83	75.24
Foreign Ownsership (10% or more)	0.13	0.06	0.16	0.09
Located in the capital of the country	0.81	0.77	0.77	0.87
Employment growth (%) (yearly rate)				
All firms	–0.7	–3.7	0.3	–2.1
Non-innovators (no process or product innovations)	–3.4	–5.3	–2.2	–4.6
Process only or organizational only innovators (non product innovators)	1.7	–1.5	2.2	0.7
Product innovators	1.8	–1.0	2.1	1.4
Growth wage bill per worker (%) (yearly rate)[3]	5.1	4.0		
Sales growth (%)[1] (nominal growth) (yearly rate)				
All firms	5.5	3.6	6.8	3.7
Non-innovators (no process or product innovations)	1.7	1.2	2.9	0.5
Process only or organizational only innovators (non product innovators)	9.6	9.4	10.5	7.9
Product innovators of which:	8.7	6.4	9.2	7.9
Old products	–21.2	–25.1	–18.9	–25.3
New products	29.9	31.5	28.1	33.2
Labor productivity growth (%)[1] (yearly rate)				
All firms	6.2	7.3	6.5	5.8
Non-innovators (no process or product innovations)	5.1	6.5	5.1	5.1
Process only or organizational only innovators (non product innovators)	7.9	10.9	8.2	7.2
Product innovators	6.9	7.4	7.1	6.6
Prices growth (%)[2,4]				
All firms	6.83	7.69	7.31	6.17
Non-innovators (no process or product innovations)	6.84	7.39	7.38	6.28
Process only or organizational only innovators (non product innovators)	6.79	9.01	7.38	5.70
Product innovators	6.83	7.68	7.17	6.23

[1]Sales growth for each type of firm is the average of variable g; averages for old and new products are the averages of variables g_1 and g_2, respectively.
[2]Period 2001–2009.
[3]Period 1998–2006.
[4]Prices computed for a set of industries and assigned to firms according to their activity.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Nominal labor productivity grew for all types of firms, especially for the process innovators. The same happens to the price growth. In real terms, labor productivity decreases for all type of innovators, with the exception of the organizational change innovators and product innovators.

The second column of Table 1 shows descriptive statistics for the sample of small firms; that is, firms with fewer than 50 employees (1,353 cases). The biggest differences relative to the sample as a whole can be found in the numbers referred to innovation variables. Thirty-seven percent are innovators; 14 percent are process innovators; and 23 percent are product innovators.

According to Crespi and Tacsir (2013), Uruguay is in the lower range in terms of propensity to innovate among the four Latin American economies analyzed in their article. Forty-eight percent of the firms in Argentina innovate in products; 53 percent in Chile; 74 percent in Costa Rica; and 32 percent in Uruguay. It is also worth mentioning that more than half of innovative companies in the region had introduced process innovations (Crespi and Tacsir 2013).

Finally, another sectoral splitting has been made: high- or low-tech sectors. The division is done by calculating the innovation expenditure as a share of turnover. Those sectors below or at the median are classified as low-tech, while the rest are classified as high-tech (see Table A.2 in Appendix).[11]

The last two columns of the table above present some basic descriptive statistics. Fifty-eight percent of the firms in the sample are defined as high-tech firms. Low-tech firms tend to innovate less than the high-tech firms, and among innovators, high-tech tend to be more product-oriented. Another difference between both sectors is that firm size is larger in the high-tech sector.[12] The employment growth figures show that the negative growth rate in the whole sample is driven by the low-tech sector, while the high-tech sector shows slightly positive figures.

Innovation and Employment Quantity

The Basic Model

Table 2 presents the estimation results for three variants of the basic model presented in Equation (1'), where the dependent variable is the employment growth rate minus the real sales growth rate ($l - (g_1 - \pi)$). All of the specifications include the innovation dummy d, sales growth rate of new products g_2, and a constant. The estimations also include fixed industry-specific effects (two-digit level) and fixed time effects (see definition at the bottom of Table 2). Column 1 shows the basic ordinary least squares (OLS) estimation without controls, while in the next columns we add, one at a time, a dummy indicating foreign ownership of the firms and the wage bill growth rate.

The subsequent three columns of Table 2 aim to analyze the sensitivity of results using instrumental variables (IV) for both the entire sample and the subsample of small firms.

The strategy relies on the choice of instrumental variables, which can be considered as uncorrelated with both price differences (new vs. old products) and productivity shocks and must be highly correlated to growth in sales of new products (g_2), the potentially endogenous variable (in the robustness checks section below, the variable d is also instrumented).

Harrison et al.'s (2008) preferred instrument is an increased (broader) range of goods and services indicator, which assesses the effect of innovation on the increase in the range of goods produced by firms. We are going to use the same instrument in our investigation and for the same reasons. The questionnaire also asks whether the innovation helped to improve the quality of the goods along with questions relating to reductions in production costs and changes in the production function. We interpret the increased range of goods as innovation helping to develop new products associated with an increase in demand for reasons other than changes in product prices and quality. Hence, we expect this variable to be uncorrelated with changes in the price of new products compared to old products. As an additional instrument, we are using the variable "*new markets,*" which assesses the effect of innovation on the development of new markets for the firm. In the questionnaire, firms are asked whether the innovation helped maintain or increase market share. The latter variable could be related to a change in prices, while we expect the opening up of new markets to be related to the development of new products and an increase in demand for reasons other than changes in product prices and quality.

Therefore, the instruments used to control for potential endogeneity of the innovation variable (g_2) are: (1) *increased range of goods and services* indicator, which assesses the effect of innovation on the increase in the range of goods produced by firms (scale of 0 to 3: 0 = irrelevant effect, 1 = low, 2 = medium, and 3 = high effect); and (2) *new markets*. This variable assesses the effect of innovation on the development of new markets for the firms (coded between 0 and 3: 0 = irrelevant effect, 1= low, 2 = medium, and 3 = high effect). These indicators were included as a set of dummies due to evidence of a nonlinear effect in the first-stage regressions.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Downloaded by [Diego Aboal] at 17:24 03 April 2015

It should be noted that columns 3 and 6 were estimated using a smaller sample because of the data limitations relating to wage bills.

According to the model, the constant indicates the negative average efficiency growth in the production of old products. The results presented in Table 2 for the whole sample show that the constant (α_0) is significantly different from zero and is positive in all specifications. As indicated in the theoretical section, the value of the estimated constant is expected to be negative (if there is efficiency growth) since it represents the negative average efficiency growth in the production of old products from the first period to the second. Because α_0 is positive, efficiency growth was negative. However, as we can see in Table 1, employment growth (l) is negative for the whole period (1998–2009), but also the growth of sales of old products (g1) is negative, potentially implying that the productivity growth of old products was negative in the period as a whole.

The dummy indicating process-only innovation is negative and significantly different from zero in all regressions, indicating that process innovation is associated with a reduction in the growth rate of labor. This also means that productivity gains in the production of old products (given the interpretation of the parameter α_1 in the model). When the model is estimated by IV, the negative effect of this variable on labor growth is reduced.

In contrast, the coefficient (β) on the growth rate of sales of new products (g_2) is positive, significant, and less than one in all OLS regressions. β measures the relative efficiency of production of old and new products. This result goes in the same direction as theory predicts, and a result of less than one suggests that new products are produced more efficiently than old ones. As noted before, this coefficient could be biased by endogeneity from unobserved price changes or correlation with nontechnological productivity shocks. Any endogeneity is likely to produce a downward bias in this coefficient, overstating the productivity gains associated with the production of new products. This is confirmed by the IV regressions where the parameter β is not significantly different from one, implying that there is no efficiency gain in the production of new products relative to old ones.

The dummy indicating foreign ownership is not significant in all the regressions and does not affect the other coefficients. Columns 3 and 6 show the results of adding the wage bill growth variable for the whole sample. The coefficient of this variable is significantly different from zero, negative, and has an absolute value of less than one. Hence, this shows a positive and lower-than-unity relationship between per-worker wage-bill growth and labor productivity. In addition, the inclusion of this variable increases the value of the constant of the model significantly, showing high correlation between the labor productivity growth of old products and the wage-bill growth.

The Davidson-MacKinnon exogeneity test rejects the null hypothesis of exogeneity for the variable g_2 in all cases, indicating that the effect of the endogenous regressor on the estimates is meaningful and that instrumental variables techniques are in fact required. The results indicate that the validity of the instruments is not rejected in all cases at the 1 percent confidence level. The F-test for g_2 in the first stage of the IV estimation is significant, confirming the validity of these instruments.

The results in the right panel of Table 2, for small firms, are generally very similar to those in the left panel in terms of the magnitude and sign of coefficients. The biggest difference is now the level of significance of the variable d. When the equations are estimated by IV, the variable is significant in just one case and only at the 10 percent confidence level. In addition, when estimated by IV, the constant is not significant in two of three cases. We also arrive at the conclusion, as we did for the sample as a whole, that g_2 is likely to be endogenous and that the instruments are valid.

In Table 3, results are presented for firms in the high- and low-tech sectors. As can be seen there, again, we have similar results to those of Table 2 in terms of the magnitude and sign of coefficients. For firms in the low-tech sector, when Equation (1′) is estimated by IV, in two of three cases the constant and the variable d are not significantly different from zero.

It can be said, summarizing the results found in Tables 2 and 3, that product innovation is complementary to labor, whereas process innovation tends to displace labor. This displacement effect seems to be somehow weaker in the case of small firms and firms in the low-tech sector.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table 2. Effects of innovation on employment quantity dependent variable: *l -(g1-π)*

Sector	Manufacturing						Small firms in manufacturing					
	OLS			IV			OLS			IV		
Regression	1	2	3	1	2	3	1	2	3	1	2	3
Constant	2.854***	2.662***	6.945***	1.544**	1.402**	5.983***	1.563**	1.757**	6.804***	0.064	0.267	5.646***
(se)	(0.54)	(0.56)	(0.65)	(0.65)	(0.66)	(0.77)	(0.78)	(0.78)	(1.02)	(0.89)	(0.91)	(1.25)
Process innovation only (d)	–3.894***	–4.002***	–4.628***	–2.610**	–2.716**	–3.607***	–4.225***	–4.127**	–5.283**	–2.696	–2.595	–3.952*
(se)	(1.06)	(1.06)	(1.06)	(1.10)	(1.10)	(1.23)	(1.68)	(1.69)	(2.07)	(1.77)	(1.77)	(2.03)
Sales growth due to new products (g2)	0.855***	0.853***	0.857***	0.964***	0.961***	0.931***	0.825***	0.826***	0.842***	0.997***	0.998***	0.974***
(se)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)	(0.07)
Foreign owned (10% or more)		1.655	0.833		1.371	0.66		–3.048	–1.999		–3.162	–2.072
(se)		(1.18)	(1.27)		(1.27)	(1.28)		(2.51)	(2.50)		(2.50)	(2.71)
Growth wage bill per worker			–0.547***			–0.554***			–0.535***			–0.548***
(se)			(0.04)			(0.03)			(0.05)			(0.05)
2-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test, g2				171.9	170.8	116.7				89.68	89.62	57.43
p-value				0.0000	0.0000	0.0000				0.0000	0.0000	0.0000
g2 Exogeneity (Davidson-McKinnon)				10.702	10.387	4.625				10.681	10.661	5.793
p-value				0.0011	0.0013	0.0317				0.0011	0.0011	0.0163
Sargan test				2.78	2.643	0.877				4.323	4.21	3.192

Downloaded by [Diego Aboal] at 17:24 03 April 2015

p-value				0.734	0.755	0.972					0.504	0.52	0.67
R squared	0.440	0.441	0.553	0.419	0.420	0.534	0.369	0.369	0.494		0.338	0.338	0.459
Standard error	19.460	19.460	17.310	19.54	19.53	17.34	20.990	20.990	18.730		21.15	21.14	18.82
Observations	2,532	2,532	1,698	2,532	2,532	1,698	1353	1353	857		1,353	1,353	857
Number of ISIC (2 digit)	22	22	22	22	22	22	22	22	22		22	22	22

Notes: Robust standard errors in parentheses. Instruments: g_2 was instrumented by "*increased range of goods*" and "*development of new markets*." These indicators were included as a set of dummies due to evidence of a nonlinear effect in the first-stage regressions. *F*-test is the *F*-test of excluded instruments in the first-stage regressions. Exogeneity is the Davidson-MacKinnon exogeneity test. Sargan test is the overidentifying restrictions test. *Coefficient is statistically significant at the 10 percent level; **coefficient is statistically significant at the 5 percent level; ***coefficient is statistically significant at the 1 percent level.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table 3. Effects of innovation on employment quantity, high- and low-tech sectors dependent variable: *l -(g1-π)*

Sector	Manufacturing - High-Tech						Manufacturing - Low-Tech					
	OLS			IV			OLS			IV		
Regression	1	2	3	1	2	3	1	2	3	1	2	3
Constant	3.345***	3.079***	6.846***	1.870***	1.670*	5.653***	2.208***	2.109**	7.225***	1.178	1.115	6.620***
(se)	(0.71)	(0.73)	(0.84)	(0.92)	(0.93)	(1.06)	(0.84)	(0.86)	(1.04)	(0.93)	(0.94)	(1.13)
Process innovation only (*d*)	–4.169***	–4.336***	–4.457***	–2.721*	–2.897**	–3.178**	–3.474*	–3.504*	–5.301**	–2.498	–2.524	–4.678**
(se)	(1.32)	(1.32)	(1.54)	(1.40)	(1.41)	(1.57)	(1.79)	(1.79)	(2.08)	(1.81)	(1.81)	(2.06)
Sales growth due to new products (*g*2)	0.846***	0.844***	0.838***	0.962***	0.958***	0.927***	0.864***	0.863***	0.877***	0.877***	0.956***	0.927***
(se)	(0.02)	(0.02)	(0.03)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)	(0.06)
Foreign owned (10% or more)		1.889	1.059		1.646	0.865		1.218	0.153		0.844	0.013
(se)		(1.41)	(1.51)		(1.37)	(1.45)		(2.17)	(2.30)		(2.26)	(2.54)
Growth wage bill per worker			–0.530***			–0.539***			–0.566***			–0.570***
(se)			(0.05)			(0.04)			(0.05)			(0.05)
2-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test, g2				82.56	81.97	54.92				95.05	94.37	64.32
p-value				0.0000	0.0000	0.0000				0.0000	0.0000	0.0000
g2 Exogeneity (Davidson-McKinnon)				5.766	5.496	3.017				4.379	4.318	1.176
p-value				0.0165	0.0192	0.0827				0.0366	0.0380	0.2785

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Sargan test				3.724	3.58	1.49				3.388	3.349	2.987
p-value				0.59	0.611	0.914				0.64	0.646	0.702
R squared	0.440	0.441	0.547	0.418	0.419	0.521	0.440	0.441	0.561	0.423	0.423	0.549
Standard error	18.870	18.860	16.610	18.94	18.93	16.63	20.280	20.290	18.310	20.31	20.31	18.25
Observations	1,464	1,464	990	1,464	1,464	990	1,068	1,068	708	1,068	1,068	708
Number of ISIC (2 digit)	10	10	10	10	10	10	12	12	12	12	12	12

Notes: Robust standard errors in parentheses. Instruments: g_2 was instrumented by "*increased range of goods*" and "*development of new markets*." These indicators were included as a set of dummies due to evidence of a nonlinear effect in the first-stage regressions. *F* test is the *F* test of excluded instruments in the first-stage regressions. Exogeneity is the Davidson-MacKinnon test of Exogeneity. Sargan test is the overidentifying restrictions test. *Coefficient is statistically significant at the 10 percent level; **coefficient is statistically significant at the 5 percent level; ***coefficient is statistically significant at the 1 percent level.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table 4a. Contribution of innovation to employment growth, 1998–2009

	All firms		Small firms		High tech		Low tech	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Firms employment growth	*–0.7*	*–0.7*	*–3.7*	*–3.7*	0.3	0.3	–2.1	–2.1
Productivity trend in production of old products[1]	2.2	1.1	1.7	0.3	2.6	1.4	1.7	0.8
Gross effect of process innovation in production of old products.	–0.3	–0.2	–0.2	–0.1	–0.3	–0.2	–0.2	–0.1
Output growth of old products contribution	–1.9	–1.9	–3.8	–3.8	–1.2	–1.2	–2.9	–2.9
Net contribution of product innovation	–0.8	0.3	–1.5	–0.2	–0.8	0.4	–0.7	0.1
Contribution of old products by product innovators	–9.1	–9.1	–7.8	–7.8	–9.3	–9.3	–8.9	–8.9
Contribution of new products by product innovators	8.4	9.4	6.3	7.6	8.5	9.6	8.2	9.0

Decomposition based on (annual) rates of growth over the whole period.
[1]This component is obtained by subtracting the sum of the other components from average employment growth.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Employment Growth Decomposition

Using Equation (1′), the employment growth of each firm can be represented by the following equation (see Harrison et al. 2008):

$$(3) l = \sum_{j} \left(\hat{\alpha}_0 + \hat{\alpha}_{0j}\right) ind_j + \hat{\alpha}_1 d + [1 - 1(g_2 > 0)](g_1 - \pi) + 1(g_2 > 0)(g_1 - \pi + \hat{\beta} g_2) + \hat{\upsilon},$$

where ind_j indicates industry dummies (two-digit level). The first component of the right-hand side, $\sum(\hat{\alpha}_0 + \hat{\alpha}_{oj}) ind_j$, measures the change in employment due to the productivity trend in production of old products (this component is computed as a residual). The term $[1 - 1(g_2 > 0)](g_1 - \pi)$ isthe estimate of the employment change associated with output growth of old products for firms that do not introduce new products, and $1(g_2 > 0)(g_1 - \pi + \hat{\beta} g_2)$ is the net contribution of product innovation after allowing for any substitution of old products for new products. Finally,$\hat{v}$ isa zero-mean residual.

Table 4a presents the decomposition for the whole sample and for the small-firms sample using the proportional averages from Table 1 (all firms and small firms, respectively) and the estimated coefficients of Equation (1’). The decomposition is performed with the parameters of each of these samples estimated by OLS and IV (without any control variables). The OLS and IV estimations yield similar, although not identical, results.

Considering the whole period, the average employment growth was −0.7 percent for the sample as a whole, −3.7 percent among the small firms, 0.3 percent for firms belonging to the high-tech sector, and −2.1 percent for the firms belonging to the low-tech sector.

For the whole sample, productivity improvements in the production of old products are an important source of increased employment (2.2 percent). In all the estimations, process innovations account for only small (negative) employment changes. The sales growth of old products is the most important factor to explain the negative rate of growth of employment in the period for all types of firms (−1.9 percent in the whole sample). The net contribution of product innovation was for the whole sample −0.8 percent in the case of the OLS estimation and 0.3 percent in the IV case. This net contribution is the combined result of a very negative contribution of old products and a very positive contribution of new products (this result is similar across subsamples).

In the decomposition of the employment growth of small firms and firms belonging to the low-tech sector, we observe a more highly negative contribution of old products to output growth, explaining most of the negative performance of these types of firms. In the case of the small firms it is also important that the more

Table 4b. Contribution of innovation to employment growth, 2004–9

	All firms		Small firms		High tech		Low tech	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Firms employment growth	*4.9*	*4.9*	*1.9*	*1.9*	5.6	5.6	3.7	3.7
Productivity trend in production of old products[1]	0.2	−1.2	−2.4	−3.6	1.2	−0.6	−1.0	−1.8
Gross effect of process innovation in production of old products	–0.1	0.1	0.0	0.1	–0.3	0.0	0.1	0.1
Output growth of old products contribution	3.1	3.1	3.5	3.5	3.1	3.1	3.0	3.0
Net contribution of product innovation	1.6	2.9	0.7	1.8	1.6	3.1	1.6	2.4
Contribution of old products by product innovators	–5.7	–5.7	–3.7	–3.7	–6.0	–6.0	–5.2	–5.2
Contribution of new products by product innovators	7.3	8.5	4.4	5.5	7.6	9.1	6.8	7.6

Note: Descomposition based on (yearly) rates of growth for the whole period.
[1]This component is obtained by subtracting the sum of the other components from the average employment growth.

strongly negative net contribution of product innovation and the smaller growth of the productivity trend in the production of old products combine to explain the highly negative annual growth rate.

The above-mean performance of the firms belonging to the high-tech sector is mostly explained by the above-mean productivity trend in the production of old products and the output growth of old products.

Table 4b reports the same exercise for 2004–9 (i.e., the period of recovery and growth following the 1999–2003 crisis in Uruguay). We find that process innovations have a negligible effect and that the productivity trend in the production of old products generates, in almost all cases, a displacement effect on employment (with the exception of the OLS estimation for the whole sample and the high-tech sector). Product innovation appears as the second-most important factor for employment growth over 2004–9, after the output growth of old products.

Innovation and Employment Quality

We analyze the effects of innovation on the composition of labor by estimating Equation (2), controlling for fixed effects at the industry level. Still, nonobservable characteristics may be correlated with innovation variables; hence, we are going to use an instrumental variables approach. The strategy used is the same as in the previous subsection. The instruments we are going to use are also the same. Again, all the indicators (instruments) were included as a set of dummies due to evidence of a nonlinear effect in the first-stage regressions.

Data and Descriptive Statistics

We define the share of skilled labor in a given firm using the percentage of professionals and technicians working for that firm in a certain time period. We use the end-of-period share of skilled labor from each of the last three MIS surveys, covering 1,810 firms in total. Table 5 shows descriptive statistics for the available data on the share of skilled workers, distinguishing by the innovation orientation of firms. We can see that the mean share of skilled labor in the manufacturing sector is 9.5 percent. While noninnovators have the lowest share of skilled labor (7.4 percent), the highest is among product innovators (12.5 percent).

To estimate Equation (2), we need to compute the growth rate for each type of labor. Since we have end-of-period data from three MIS surveys, we compute the growth rate between two consecutive innovation surveys. That is, we calculate the growth rate of employment between 2009 and 2006, and between 2006 and 2003. Hence, we will only have two data points for each firm. We also need to note that the growth rate is only going to be available for firms present in two consecutive surveys. Table 5 shows statistics for the nominal and real growth rates by labor type and by firm type. We do not have available data on firms' capital, which means that we cannot control for complementarities in the use of skilled labor and capital.

The positive annual mean employment growth rate over 2001–9 is explained by positive growth rates in both skilled and unskilled labor. For all types of firms, skilled labor employment grows at a faster rate than unskilled labor employment. The most important growth rates in the use of skilled labor are among firms oriented toward organizational change and product innovation.

Results

Table 6 presents the estimation results for the model in Equation (2), where the dependent variables are the employment growth rate of type q_j labor minus the sales growth rate ($l^{qj} - (g_1 - \pi)$) (for s = skilled and u = unskilled labor). The specifications include the process innovation dummy d, the sales growth rate of new products g_2, a dummy controlling for the foreign ownership of the firm, and a constant. The estimations also include industry fixed effects (two-digit level). The table presents OLS results across the entire sample (columns 1 and 2) and the subsample of small firms (columns 5 and 6).

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table 5. Employment composition: Descriptive statistics, 2001–2009

Share of skilled labor	Mean	Median	Standard Deviation	Minimum	Maximum
All Firms	9.5	5.2	12.4	0.0	100.0
Non-innovators (no process or product innovations)	7.4	3.4	11.9	0.0	100.0
Process only innovators (non product innovators)	10.4	6.0	12.0	0.0	78.0
Product innovators	12.5	8.1	12.7	0.0	95.0
Employment (total) growth (%)					
All Firms	9.5	5.2	12.4	0.0	100.0
Non-innovators (no process or product innovations)	3.3	3.9	12.5	–51.0	53.6
Process only innovators (non product innovators)	6.2	5.7	11.1	–34.1	76.8
Product innovators	7.6	7.4	10.3	–39.5	36.4
Skilled labor growth (%)					
All Firms	10.2	5.8	29.2	–79.7	153.5
Non-innovators (no process or product innovations)	6.3	0.0	28.6	–75.3	153.5
Process only innovators (non product innovators)	13.4	11.2	31.0	–77.8	99.4
Product innovators	14.1	12.0	27.9	–79.7	88.0
Unkilled labor growth (%)					
All Firms	5.1	4.5	16.3	–122.1	154.7
Non-innovators (no process or product innovations)	4.1	3.5	19.6	–122.1	154.7
Process only innovators (non product innovators)	5.2	4.4	12.4	–45.0	73.2
Product innovators	6.8	6.8	12.4	–45.9	66.4

Note: Yearly averages, 2001–9.
Source: Authors' calculations using Innovations Survey, waves 2001–3, 2004–6, and 2007–9.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

The dummy indicating process innovation only is not significantly different from zero in most of the specifications. The exception is for unskilled labor, which has a significant and negative coefficient. This variable controls for the additional increase in the productivity of old products and hence the displacement effect on each type of employment resulting among process-only innovators. Hence, there is evidence of displacement effects in the case of unskilled labor but not for skilled labor.

In contrast, the coefficient on the growth rate of sales of new products (g_2) is significant, positive, and lower than one for both skilled and unskilled labor. As indicated in the previous section, this coefficient measures the relative efficiency of old and new products produced by each type of labor, indicating that new products are produced more efficiently than the old ones.

The dummy indicating foreign ownership is significant and positive for all firms in the sample, indicating positive effects on total employment of skilled and unskilled labor if the firm has foreign ownership.

For the subsample of small firms, the results are very similar. Process innovation is not significantly different from zero in any specification. The growth rate of the production of new products is significantly different from zero and less than unity. The foreign ownership dummy is significantly different from zero and negative for the growth rate of skilled labor, while it is not significantly different from zero for the unskilled labor growth rate. This means that foreign ownership has a differential effect on the growth rate of these two types of labor.

The differences found here with respect to the findings in Table 3, where the *foreign owned* (10 percent or more) variable was not significant, can be associated with the introduction of the *fully foreign owned* variable that generally has negative coefficients in Table 6. What is likely happening in Table 5 is that the positive effect of partly foreign-owned firms is compensated by the negative effect of the fully foreign-owned firms.

The coefficient on the growth rate of new products is similar for skilled and unskilled labor, indicating no significant differential effect for the whole sample when estimated by OLS, although the effect among small firms is somewhat larger for unskilled labor.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table 6. Relationship innovation—labor composition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sector	**Manufacturing**		**Manufacturing**		**Small Manufacturing**		**Small Manufacturing**	
	OLS		**IV**		**OLS**		**IV**	
Regression	**Skilled**	**Unskilled**	**Skilled**	**Unskilled**	**Skilled**	**Unskilled**	**Skilled**	**Unskilled**
Constant	5.302***	0.923	2.934*	0.225	5.354***	–0.420	3.418	–1.132
(se)	(1.414)	(0.965)	(1.748)	(1.100)	(1.915)	(1.376)	(2.282)	(1.500)
Process innovation only *(d)*	–0.151	–4.120***	2.379	–3.373*	3.122	–4.014	5.116	–3.281
(se)	(2.683)	(1.578)	(2.822)	(1.780)	(5.396)	(2.711)	(4.965)	(3.278)
Sales growth due to new products *(g2)*	0.853***	0.860***	1.087***	0.929***	0.687***	0.812***	0.970***	0.916***
(se)	(0.064)	(0.034)	(0.120)	(0.075)	(0.108)	(0.065)	(0.196)	(0.129)
Foreign owned (10% or more)	10.218**	8.406***	8.888*	8.888*	22.204***	2.330	21.396	21.396
(se)	(4.828)	(2.629)	(5.354)	(5.365)	(6.444)	(4.680)	(13.623)	(13.688)
Fully foreign owned	–6.821	–2.809	–5.947	–2.551	–37.843***	6.003	–34.890**	7.089
(se)	(5.527)	(3.192)	(6.128)	(3.856)	(10.184)	(7.536)	(16.121)	(10.593)
2-digit industry dummies	yes	yes	0.468	0.348	0.004	0.004	0.882	0.514
Ho: g2=1 p-value	0.021	0.000	yes	yes	yes	yes	yes	yes
Standard error	33.33	21.09	33.49	21.08	34.63	22.88	34.73	22.82
Number of observations	1037	1037	1037	1037	443	443	443	443
F test, g2			64.87	64.87			32.52	32.52
p-value			0.00	0.00			0.00	0.00
g2 Exogeneity (Davidson-McKinnon)			5.37	1.16			3.17	0.81
P-Value			0.02	0.28			0.08	0.37
Sargan (m)			10.43	6.017			7.666	3.420
Prob. Value			0.0640	0.305			0.176	0.635

Notes: Robust standard errors in parentheses. Dependent variable in columns 1 and 3 is $l^{skilled}$-g_1-π and in 2 and 4 is $l^{unskilled}$-g_1-π. All regressions include two-digit industry dummies. Instruments: g2 instrumented by indicators of "increased range of goods" and "development of new markets." All of these indicators were included as a set of dummies due to evidence of a nonlinear effect in the first-stage regressions. *F*-test in relation to instruments excluded in the first-stage regressions. Exogeneity denotes Davidson-MacKinnon exogeneity test. Sargan test denotes the overidentifying restrictions test. *Coefficient is statistically significant at the 10 percent level; **coefficient is statistically significant at the 5 percent level; ***coefficient is statistically significant at the 1 percent level.

As discussed before, the coefficient on g_2 could be biased because of the presence of endogeneity. As indicated in the previous section, any endogeneity is likely to produce a downward bias in this coefficient, overstating the productivity gains associated with the production of new products.

Table 6 also presents the results when using IV. Columns 3 and 4 show estimates for total manufacturing, and columns 7 and 8 show estimates for small firms, in both cases assuming $g2$ as endogenous. The instrumental variables used are the same as in the previous section. The results show that the coefficient of $g2$ increases when estimated by IV. The coefficient increases for both labor types, and we cannot reject the hypothesis of them being equal to one.

We reject the hypothesis of exogeneity of $g2$ for skilled labor for the sample as a whole, but not when only considering unskilled labor. Similar results apply to the sample of small firms. The F-tests provide evidence that weak instruments are not a problem, while the Sargan test does not reject the hypothesis of valid instruments.

The IV estimations show that product innovation has a slightly larger positive effect in skilled labor, both for the whole sample and for small firms alone. Process innovation has a significant negative effect that is only found for unskilled labor in the whole sample.

To summarize, the results indicate some differential effect of innovation on the composition of the labor force, to the detriment of unskilled labor.[13]

In Table 7, we replicate the above exercise for the high- and low-tech sectors. The results are very similar to the complete sample. When estimating by OLS, the coefficient on $g2$ is smaller than unity. We cannot reject its being equal to one when assuming $g2$ to be an endogenous variable.

When estimated by IV, the coefficient of $g2$ is bigger for skilled labor than for unskilled labor in the high-tech sector. The coefficients of $g2$ in the skilled and unskilled equations are not very different for the low-tech sector.

Process innovation is not significant in most of the cases. However, it is significantly different from zero and negative for unskilled labor in the high-tech sector (in both cases, by OLS and IV). This indicates a displacement effect of process innovation.

Conclusions

Our research provides information on the roles of displacement and compensation effects of product and process innovation on employment, in terms of both its quantity and quality, among Uruguayan manufacturing firms. In the context of the Harrison et al. (2008) model, our article incorporates three novelties: the distinction between low- and high-tech industries, between skilled and unskilled labor, and between small and all industries.

The results suggest that in manufacturing, firm-level product innovation has a positive effect on employment, whereas process innovation tends to displace labor, a finding that contrasts with the findings of Harrison et al. (2008). This effect, however, may vary with firm size and technology intensity. This displacement effect seems to be weaker in the case of small firms and firms belonging to the low-tech sector.

There is some evidence that the positive effect on labor growth of the introduction of new products is weaker when this innovation is introduced together with process innovation (this differential effect does not seem to be present among small firms or firms in the low-tech sector).

Product innovation seems to have a differential effect on labor composition, having larger positive effects on skilled labor (with the exception of the low-tech sector) than on unskilled labor. Process innovation appears to have a displacement effect on unskilled labor, but not on the skilled labor force.

The design of innovation and employment policies and instruments should take into account that the effect of innovation on employment could differ by firm size, sector, and type of workers. The level of coordination among innovation, employment, and training policies in Uruguay is low. Although there are interactions between employers and employees in terms of employment policies and training, there is not sufficient coordination between employment and training policies and the needs of firms that innovate. Given the evidence that process innovation seems to displace unskilled workers and that product innovation has a smaller positive effect on unskilled labor, employment and

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table 7. Relationship innovation—Labor composition, High- and low-tech sectors

	(1)	(2)	(3)	(4)	(7)	(8)	(9)	(10)
Sector	**Manufacturing High Tech**				**Manufacturing Low Tech**			
	OLS		**IV**		**OLS**		**IV**	
Regression	**Skilled**	**Unskilled**	**Skilled**	**Unskilled**	**Skilled**	**Unskilled**	**Skilled**	**Unskilled**
Constant	6.388***	1.448	2.418	0.758	3.633*	0.280	3.181	–0.240
(se)	(1.971)	(1.203)	(2.523)	(1.472)	(1.972)	(1.594)	(2.364)	(1.631)
Process innovation only *(d)*	–0.134	–5.781***	4.118	–5.043**	0.114	–1.587	0.581	–1.050
(se)	(3.425)	(2.031)	(3.820)	(2.237)	(4.324)	(2.514)	(4.235)	(2.936)
Sales growth due to new products (*g2*)	0.873***	0.835***	1.223***	0.896***	0.817***	0.894***	0.872***	0.957***
(se)	(0.072)	(0.042)	(0.165)	(0.096)	(0.122)	(0.059)	(0.170)	(0.118)
Foreign owned (10% or more)	8.490	9.983***	6.427	6.427	13.884*	5.790	13.559	13.559
(se)	(5.988)	(3.304)	(6.696)	(6.718)	(7.958)	(4.216)	(9.126)	(9.171)
Fully foreign owned	–5.531	–5.936	–4.015	–5.673	–9.400	4.083	–9.248	4.258
(se)	(6.848)	(3.885)	(7.529)	(4.394)	(8.955)	(5.537)	(10.837)	(7.477)
2-digit industry dummies	yes	yes	yes	yes	yes	yes	yes	yes
Ho: g2=1 p-value	0.08	0.00	0.181	0.273	0.1343	0.0751	0.480	0.707
Standard error	33.74	19.97	34.15	19.93	32.86	22.66	32.71	22.57
Number of observations	616	616	616	616	421	421	421	421
F test, g2			32.51	32.51			36.42	36.42
p-value			0.00	0.00			0.00	0.00
g2 Exogeneity (Davidson-McKinnon)			6.16	0.43			0.20	0.35
P-Value			0.01	0.51			0.65	0.55
Sargan (m)			6.214	6.799			6.848	1.408
Prob. Value			0.286	0.236			0.232	0.923

Notes: Robust standard errors in parentheses. Dependent variable in "Skilled" columns is $l^{skilled}$-g_1-π and in "Unskilled" columns is $l^{unskilled}$-g_1-π. All regressions include two-digit industry dummies. Instruments: *g2* instrumented by indicators of "increased range of goods" and "development of new markets." All these indicators were included as a set of dummies due to evidence of a nonlinear effect in the first-stage regressions. *F* test denotes the *F* of excluded instruments in the first-stage regressions. Exogeneity denotes Davidson-MacKinnon exogeneity test. Sargan test denotes overidentifying restrictions test. *Coefficient is statistically significant at the 10 percent level; **Coefficient is statistically significant at the 5 percent level; ***Coefficient is statistically significant at the 1 percent level.

training policies have a role in reducing the apparent educational and training gap among unskilled workers in order for them to be valuable after innovations are introduced. This seems to be even more important in high-tech industries and relatively large firms, where the displacement effect of process innovation on unskilled workers seems to be even larger.

Finally, it is interesting to note that the analysis carried out in this article does not give us a sufficient understanding of what is happening at the intersectoral level. In particular, where do new workers for product-innovating firms come from? Do these new workers come from laggard firms, from the same sector or from other sectors? These are topics for further research.

Acknowledgments

Comments and suggestions by Ezequiel Tacsir, Gustavo Crespi, Pierre Mohnen, Jacques Mairesse, David Kaplan, Marco Vivarelli, Alejandro Rasteletti, Belen Baptista, and participants at the first and second discussion workshop of the IADB's Employment Generation, Firm Size and Innovation in Latin America research project in Washington, DC and Costa Rica, at MEIDE 2011, at the 2011 Jornadas de Economía of the Central Bank of Uruguay, and at the 2011 IDB's (Uruguay) economic seminars are gratefully acknowledged.

The views expressed in this article are the author's and are not necessarily shared by the OECD or its member countries.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Notes

1. In addition (as is shown in Uzagalieva et al. 2012, in a study for the new members of the European Union), innovation efforts in high-tech industries may have a significant effect on all other sectors, and therefore on technological progress.
2. The results reported in our article are based on one of the studies of this research project. See, for Chile, de Elejalde et al. (forthcoming).
3. The assumption of constant returns to scale is maintained in this article. This assumption allows us to write the model in Equation (1') below. In the case of nonconstant returns to scale, the model becomes highly nonlinear, with all the implications that this has in terms of estimation methods and problems.
4. By definition, all the sales of the previous period are old in the current period. Therefore, it is not possible to compute the growth rate of new products' nominal sales.
5. Harrison et al. (2008) transformed the original model in real terms to include nominal sales. This generates an additional problem: the unobserved disturbance includes prices of the new products that are correlated with $g2$. In any case, the bias here is an attenuation bias.
6. If this variable is a good proxy for the rate of increase of prices of old products, then the error term v will not include the change in prices of old products.
7. For some sectors for which we did not have information, we used two-digit ISIC prices instead.
8. The unobserved variable is the proportional difference in the prices of new products with respect to the prices of the old products.
9. Firms with missing sales or employment data were also excluded (704 firms); the first and ninety-ninth percentiles of variables l and g were used as bounds to exclude outliers, and three negative values of the variable g_2 were excluded (ninety-seven firms).
10. It is important to note that this figure is a simple average of the annual growth rate across the whole sample (i.e., across years and firms). This implies that all firms are equally weighted, giving small and large firms the same weight. Hence, this percentage is not the real average growth rate of employment in the manufacturing sector. It is also worth noting that this average hides large heterogeneities between surveys, highly correlated to the economic cycle (-6.5 percent in 1998–2000, −6.6 percent in 2001–2, 6.4 percent over 2004–6, and 2.8 percent over 2007–9). At the same time, this simple average underestimates average growth due to observations lost in the most recent survey (2007–9), which covers a period of strong employment growth. Total employment growth between 1998 and 2009 for the total sample is 2.3 percent.
11. This categorization does not exactly match the recognized taxonomy proposed by Pavitt (1984). As is known, Pavitt classifies companies into four categories according to the sources of technological innovation and the degree of appropriability of innovations. We can relate, albeit imperfectly, this taxonomy to the one made in our work. Companies classified as high-tech in our study would be included in categories 2 and 4 of Pavitt (2: Specialist suppliers, especially of equipment and capital goods, which transfer innovations to other companies,

and 4: Companies based on science, performing R&D). Meanwhile, companies classified in Pavitt Class 1 (Companies that acquire their expertise from their suppliers) would be classified mostly as low-tech in our study. Less clear is the location of firms in class 3 of Pavitt (Scale-dominated firms where innovation is associated to scale), but most of them are likely grouped under the low-tech label.

12. High-tech industries also have greater participation of foreign capital (a similar pattern was found in Abedini 2013; Uzagalieva et al. 2012).

13. These results are taken from the OLS estimates since IV estimates indicate that the innovation variable has no endogeneity problem in most of the cases.

References

Abedini, J. 2013. "Heterogeneity of Trade Patterns in High-Tech Goods Across Established and Emerging Exporters: A Panel Data Analysis." *Emerging Markets Finance & Trade* 49, no. 4: 4–21.

Baldwin, J. 1997. "The Importance of Research and Development for Innovation in Small and Large Canadian Manufacturing Firms." WP 107, Statistics Canada.

Benavente, J. M., and R. Lauterbach. 2008. "Technological Innovation and Employment: Complements or Substitutes?" *European Journal of Development Research* 20, no. 2: 318–329.

Crespi, G., and E. Tacsir. 2013. "Effects of Innovation on Employment in Latin America." UNU-MERIT Working Paper Series 2013-001, United Nations University, Maastricht Economic and Social Research and Training Centre on Innovation and Technology.

Crespi, G., and P. Zuñiga. 2013. "Innovation Strategies and Employment in Latin American Firms." *Structural Change and Economic Dynamics* 24(C): 1–17.

de Elejalde, R.; D. Giuliodori; and R. Stucchi. "Employment and Innovation: Firm Level Evidence from Argentina." *Emerging Markets Finance & Trade*. Forthcoming.

Fajnzylber, P., and A.M. Fernandes. 2004. "International Economic Activities and the Demand for Skilled Labor: Evidence from Brazil and China." Policy Research Working Paper no. 3426, World Bank, Washington, DC.

Freeman, C. 1994. "Innovation and Growth." In *Handbook of Industrial Innovation*, ed. M. Dodgson and R. Rothwell, pp. 78–93. Aldershot: Elgar.

Griliches, Z. 1986: "Productivity, R&D and Basic Research at the Firm Level in the 1970s." *American Economic Review* 76, no. 1: 141–154.

Grossman, G., and E. Helpman. 1993. *Innovation and Growth in the Global Economy*. Cambridge: MIT Press.

Harrison, R.; J. Jaumandreu; J. Mairesee; and B. Peters. 2008. "Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data from Four European Countries." Working Paper no. 14216, National Bureau of Economic Research, Cambridge, MA.

Inter-American Development Bank. 2010. *The Age of Productivity: Transforming Economies from the Bottom Up*. Washington, DC: Inter-American Development Bank.

Organisation for Economic Co-operation and Development. 2010. *The OECD Innovation Strategy: Getting a Head Start on Tomorrow*. Paris: Organisation for Economic Co-operation and Development.

Pavitt, K. 1984. "Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory." *Research Policy* 13, no. 6: 343–373.

Uzagalieva, A.; E. Kočenda; and A. Menezes. 2012. "Technological Innovation in New EU Markets." *Emerging Markets Finance & Trade* 48, no. 5: 48–65.

Vivarelli, M. 2011. "Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of the Literature." Technical Notes No. IDB-TN-351, Inter-American Development Bank, Washington, DC.

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Appendix

Table A1: Definition of variables and information available for manufacturing firms

Innovation surveys		**IS**	**1998-2000, 2001–3, 2004–6, 2007–9**
Economic activity surveys		**EAS**	**1998, 2000, 2001, 2003, 2004, 2006, 2007**
Variables	**Description**	**Source**	**Definition**
l	Employment growth rate	IS, EAS	Average annual employment growth
Foreign owned	Foreign ownership	IS	= 1 if percentage of foreign capital is more than 10 percent of total capital
Fully foreign owned	Full foreign ownership	IS	= 1 if 100 percent foreign capital
Small firms	Small firms	IS	Dummy defining firms with up to fifty employees at the end of the survey
Growth wage bill per worker	Wage bill growth rate	EAS	(ln(wagebill_fin)- ln(wagebill_init))/2*100 with wagebill_fin = wage bill, end of period, and wagebill_init = wage bill, beginning of period
d	Process or organizational innovation	IS	Dummy of process innovation only or organizational innovation only: = 1 if the firm introduced new or improved technology or methods that substantially changed the production or if the firm has made innovation in commercialization: methods for the marketing of new products (goods or services), new delivery methods of existing products, and/or changes in packaging
g1	Sales growth rate of old products	IS, EAS	g1 = g-g2. g is the average annual sales growth, calculated by (ln(turn_fin)–ln(turn_init))/2*100, with turn_fin = sales, end of period, and turn_init = sales, beginning of period
g2	Sales growth rate of new products	IS, EAS	g2 = innovation*(1+g/100). g is the average annual sales growth, calculated by (ln(turn_fin)–ln(turn_init))/2*100
$l^{skilled}$	Growth rate of skilled labor	IS, EAS	ls = (ln(skill_fin)-ln(skill_fin(-3)))/3*100
$l^{unskilled}$	Growth rate of unskilled labor	IS, EAS	lu = (ln(unskill_fin)-ln(unskill_fin(-3)))/3*100
π	Prices growth rate	National Institute of Statistics	Average annual prices growth rate, calculated as (ln (pindex_fin)–ln(pindex_init))/2*100. Index of prices is computed on the basis of the producer price index of national products (IPPN) for the industry at a four-digit level (ISIC-Rev. 3). For some activities where no information was available, the two-digit level IPPN was used.
range	Increased range of goods and services.	IS	Assesses the effect of innovation on the increase in the range of goods produced by firms. The variable indicates the effect on a scale of 0 to 3 (0 = irrelevant effect, 1 = low, 2 = medium, and 3 = high effect)
newmkt	Effect of innovation on development of new markets	IS	Coded between 0 and 3 (0 = irrelevant effect, 1= low, 2= medium, and 3 = high effect)

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Downloaded by [Diego Aboal] at 17:24 03 April 2015

Table A2: Sectors (two-digit ISIC) classified as high-tech and low-tech

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

n.e.c. = not elsewhere classfied.

Table A3: Correlation among dependent variables, instruments, and instrumented variable

	l-(g1-π)	*-(g1-π) skilled*	*l–(g1–π) unskilled*	*g2*	*range*
All manufacturing					
g2	0.65	0.42	0.58		
Range	0.37	0.28	0.34	0.51	
Newmarkt	0.30	0.21	0.24	0.41	0.59
Small					
g2	0.58	0.31	0.48		
Range	0.34	0.25	0.31	0.50	
Newmarkt	0.28	0.21	0.19	0.42	0.59
High-tech					
g2	0.65	0.42	0.60		
Range	0.40	0.28	0.34	0.56	
Newmarkt	0.34	0.23	0.23	0.48	0.65
Low-tech					
g2	0.65	0.40	0.55		
range	0.35	0.26	0.34	0.47	
Newmarkt	0.27	0.19	0.25	0.37	0.55