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The Relationship between Innovation and Employment in the Peruvian Manufacturing Industry, 2012-2014[1]

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Abstract. This paper explores the relationship between innovation and employment in the Peruvian manufacturing industry based on the model developed by Jaumandreu (2003) and Harrison et al. (2008) and distinguishes between two types of innovation: product and process. The results show that process innovation reduces the level of employment by an average of 0.45% by replacing employment with more efficient physical capital. However, product innovation is found to increase the level of employment by an average of 0.67%, mainly because a new product is brought to market. The results obtained are robust according to size of firm, labor quality, and technological capacity.

Keywords: process innovation; product innovation; employment; instrumental variables.

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Introduction

Recent economic development across countries has been enabled by production processes rendered more efficient by technologies that allow new ideas to be transformed into new products, representing competitive advantage for companies (Crépon, Duguet, & Mairesse, 1998; Griffith et al., 2006; Álvarez et al., 2011; Crespi & Zúñiga, 2012; Baumann & Kritikos, 2016; Baum et al., 2016). The literature focusing on this evidence is abundant. But it centers on transmission mechanisms between product and productivity[2] research and development (R+D) activities, and less so on the changes in employment that innovation processes can induce (Hall & Rosenberg, 2010; Bravo-Ortega, Benavente, & González, 2014; Cirera, Martin, & Markwald, 2015; among others). In Peru, in fact, no papers on this topic have been published as yet. Therefore, this study provides evidence on the effects that innovation processes in the Peruvian manufacturing industry have had on employment. Empirical analyses of the relationship between R+D and employment present ambiguous results, partly because of factors that vary according to the economic actors involved. Most notably, results may differ depending on the type of innovation[3] that a company undertakes (Harrison et al., 2008; Hall, Lotti, & Mairesse, 2008; Lachenmaier & Rottmann, 2011); the economic sector in which the innovation is concentrated[4] (Greenhalgh, Longland, & Bosworth, 2001; Coad & Rao, 2011; Bogliacino, Piva, & Vivarelli, 2011); and the institutional factors to which an economy is subject (Pianta, 2006; Vivarelli, 2011). Inconsistent results are also related to the fact that changes in employment depend on the state of technology, which determines the extent to which innovation improves productivity and the demand conditions that give rise to different compensatory effects.

The aim of this study is to contribute to a better understanding of the relationship between innovation and employment in Latin America based on the Peruvian experience. The focus is on Peru for several reasons. First, Peru presents structural characteristics that differ from the major Latin

2 From an empirical perspective, the international literature has shown that R+D is one of the main factors behind the differences in total factor productivity (TFP) and economic growth between countries (Griliches, 1995; Hall & Jones, 1999; Álvarez et al., 2011).

3 International evidence reveals that the impact on employment of product and process innovation is ambiguous. Thus, while it is often found that product innovation has a positive impact on employment growth (Hall et al., 2008; Lachenmaier & Rottmann, 2011; Dachs & Peters, 2014), process innovation is associated with low recruitment (Dachs & Peters, 2014) and job stability (Hall et al., 2008), as well as employment growth (Lachenmaier & Rottmann, 2011).

4 At the sectoral level, innovation can also trigger indirect effects, including competitive redistribution of products and jobs from low-technology to high-technology companies, job losses due to the exit of non-innovative companies, and job creation for those companies that do innovate.

American countries already evaluated by Benavente and Lauterbach (2008)[5] and Crespi and Tacsir (2012).[6] Second, the business structure in Peru is strongly dominated by small companies, most of them informal,[7] and it is of interest to determine whether this particularly Peruvian characteristic has any bearing on the effects of innovation on employment. Third, no studies have drawn on Peruvian data to identify the impact that innovation in the Peruvian manufacturing sector has in terms of changes in employment. Consequently this study constitutes the first contribution to the literature.

The effects of innovation on employment are calculated using the model developed by Jaumandreu (2003) and Harrison et al. (2008). This conceptual model captures various mechanisms that result in changes in emnpployment in a context of business innovation. The theoretical model allows innovation to be broken down into two forms: product and process. Product innovation refers to a company successfully introducing a new or significantly improved product (good or service) to the market, and the scope of the innovation. In turn, process innovation refers to the introduction to the market of a new or significantly improved production method, distribution method, or production support activities, as well as the scope of the innovation. This study highlights two effects identified in the model developed by Jaumandreu (2003) and Harrison et al. (2008): displacement and compensation. Both effects have been explored in empirical studies focusing on certain countries in Latin America. The displacement or substitution effect occurs when a company, after introducing a process innovation, decreases its marginal costs by replacing part of its workforce with physical capital. In the case of product innovation, a new good introduced may be substituting an old one, causing the level of employment to fall. The compensation or complementarity effect is what happens when, as a result of a process innovation, marginal costs and prices are reduced, generating greater demand for products and increasing employment. With regard to product innovation, the introduction to the market of a new product complements an old one, pushing up demand for products and increasing the workforce.

The empirical approach in the present study entails the use of a reduced-form regression model associated with the above-mentioned model. In our model, the level of employment is related to a policy variable that identifies the innovation processes pursued by the companies during a year year. The

5 Benavente and Lauterbach (2008) study the case of Chile.
6 Crespi and Tacsir (2012) centers on the cases of Argentina, Chile, Costa Rica, and Uruguay.
7 According to data from Peru's National Institute of Statistics and Informatics (Instituto Nacional de Estadística e Informática, INEI), 72.4% of the country's active workforce is estimated to be in informal employment.

data used are taken from the National Manufacturing Innovation Survey (Encuesta Nacional de Innovación Manufacturera), which collected information for the period 2012-2014. The estimation method employs ordinary least squares (OLS) and instrumental variables (IV).

As will be explored, notable among the results is that product innovation has a positive effect on employment: employment at companies that innovate in products is 0.67% greater than for companies that do not innovate. Thus, in this case, the complimentary effect appears to predominate over the substitution effect. As mentioned above, this impact is a result of the rise in demand for labor prompted by the introduction to the market of an innovative product. This effect is similar to that observed by Benavente and Lauterbach (2008) for Chile (0.56%), but less than that recorded by Crespi and Tacsir (2012) for certain Latin American countries (by an average of 1.22%).

Moreover, it is notable that process innovation, understood as the means by which internal production processes are improved, leads to a reduction in the workforce; on average, companies that engage in process innovation have a level of employment 0.45% lower than those that do not innovate. In the case of this form of innovation, the substitution effect is found to predominate over the complementarity effect. For instance, Peruvian manufacturing companies replace labor, usually unskilled, with physical capital.

These two results are robust to company size (micro, small, and medium/large enterprises), labor quality (skilled and unskilled), and technological capacity (high technology and low technology).

The rest of this article is organized as follows: Section 1 presents the literature review. Sections 2 and 3 describe the data and empirical strategy used, respectively. Finally, sections 4 and 5 set out the results and conclusions, respectively.

1. Literature review

Much of the literature on innovation focuses on studying its impact on productivity or export activity. The seminal work within this approach is Crépon et al. (1998), whose authors develop the CDM model that connects R+D investment decisions, R+D spending intensity, the probability of introducing an innovation as a result of this effort, and the impact of the innovation on productivity.

The CDM model serves as the basis for subsequent studies, such as those of Griffith et al. (2006), Crespi and Zúñiga (2012), Bravo-Ortega et al. (2014), Aboal and Garda (2015), Crowley and McCann (2015), De Fuentes et al. (2015), Gallego et al. (2015), and Lööf, Mairesse and Mohnen (2016).

Other authors expand the model to evaluate the direct and indirect impacts of exports in relation to innovation and productivity. On the one hand, a company that only operates in the domestic market and which constantly invests in innovation will see its productivity evolve continuously, and this will prepare it indirectly to compete on the international market. On the other hand, a company that already exports needs to invest directly in innovation in order not to lag behind other companies that compete in the global market (Yasar, Nelson, & Rejesus, 2006; Baum et al., 2016; Cintio, Ghosh, & Grassi, 2017; Nolazco, 2018; among others).

The empirical studies that seek to identify and relate the effect of technological innovation on the level of employment tend to employ one of two models: (i) a model aiming to quantify the impact of technological innovation on the aggregate employment level; or (ii) a model focusing on structural labor change as a consequence of technological innovation.

The former model was initially developed by Jaumandreu (2003)[8] and extended by Harrison et al. (2008). Subsequently, Benavente and Lauterbach (2008), Álvarez et al.(2011), Crespi and Tacsir (2012), and De Elejalde, Giuliodori and Stucchi (2015) carried out applications for some countries in Latin America. The latter model[9] entails empirical approaches and is applied by Chennels and Van Reenen (1999), and later Kaiser (2000, 2001), and Falk and Seim (2001a, 2001b).

Jaumandreu (2003) evaluates the impacts of product and process innovation on the level of employment in Spain by way of OLS and IV regressions.[10] The results of the estimations show that product innovation has a positive and significant effect of 0.84% and 1.3%, respectively, on employment. However, the impact of process innovation is not significant due to the complementarity effect between both variables.

Peters (2004) extends the model of Jaumandreu (2003) by applying the approach to a multiproduct company in Germany, using OLS and IV.[11] The results of the estimations confirm that product innovation has a

8 Peters (2004) empirically extends the proposal of Jaumandreu (2003) by incorporating the multiproduct company approach.

9 The latter model is not considered a case study, because it considers innovation as an aggregate variable, which hampers estimation of effects on employment according to the type of innovation achieved. Moreover, other studies add variables that are beyond the scope of this study, such as transport quality, taxes, financial restrictions, and others (Kaiser, 2001; Falk & Seim, 2001a).

10 The instrumental variables used are: the fraction of sales considered innovative, spending on sales innovation, and a dichotomy that takes the value of one if a company considers innovation to have had a medium-high effect on the production increase.

11 The instrumental variables used are: ratio of R+D spending level to total sales, expansion of total production as a cause of product innovation, degree of product innovation in the industry, and appropriability conditions, among others. These instruments fulfill the conditions of exogeneity

positive and significant effect of between 0.89% and 1% on employment. However, unlike the findings of Jaumandreu (2003), in this instance process innovation presents a negative and significant effect, of between 1.7% and 4.3%, on employment, which provides evidence of the displacement effect.

Harrison et al. (2008) develop a theoretical model that demonstrates the relationship between sales due to product innovation and companies that innovate in both products and processes, and the impact of this relationship on the level of employment. Determining this relationship makes it possible to identify whether process innovation entailed a production improvement in old products or new products. To this end, they apply the model to a group of European countries (Spain, France, Germany, and the United Kingdom) using OLS and IV. The authors find a positive and significant effect of 0.83% and 1.27%, respectively, of product innovation on employment. On the other hand, they find a negative effect of 4% (OLS) and 3.4% (IV), showing that the compensation effect prevails.

Benavente and Lauterbach (2008) add investment in physical capital as a percentage of total sales to the model of Harrison et al. (2008), as they consider capital intensity in relation to the level of production to be of relevance to the model. Using the OLS and IV methodologies,[12] they find that product innovation has a significant effect of 0.4% and 0.6%, respectively, on employment in the Chilean economy. Moreover, while process innovation presents a negative impact of 0.13% on employment, the effect is not significant. As such, it is concluded that the complementary effect prevails. These results are consistent with those obtained by Álvarez et al. (2011), who, on the one hand, record that product innovation has a positive and significant impact on employment at a significance level of 0.8% and 1.7%; and, on the other hand, that process innovation has an insignificant impact on employment at a significance level of -2.7%.

Crespi and Tacsir (2012) apply the model of Harrison et al. (2008) to a group of Latin American and Caribbean countries (Argentina, Chile, Costa Rica, and Uruguay) using OLS and 2SLS with VI.[13] They detect that the impact of product innovation on employment is between 0.85%

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and relevance. It should be noted that fulfillment of these conditions is not taken into account in the present study.

12 The instrumental variables used are: increase in the product range due to innovation, and novel inputs as the origin of an innovative idea. These instruments fulfill the conditions of relevance, but the condition of exogeneity is assumed. It should be noted that fulfillment of these conditions is not taken into account in the present study.

13 The instrumental variables used are: public support of innovation, obstacles to innovation, and additional product range due to innovation. These instruments fulfill the conditions of relevance, but the condition of exogeneity is assumed.

and 1.2%, with both impacts significant at the 1% level. Moreover, process innovation presents a coefficient of 0.8% and 1.5% depending on the econometric methodology used; however, these effects are not significant, which indicates that the complementarity effect prevails over the substitution effect.

De Elejalde et al. (2015) implement the model of Harrison et al. (2008) with the aim of estimating the effects of innovation (product/process) on the employment level for the case of Argentina between 1998 and 2001. Based on OLS and two-stage least squares (2SLS) estimations using IV,[14] the authors find that product innovation has an impact of 0.96% and 1.51% on employment (both significant at 1%). Conversely, process innovation has an insignificant coefficient of -0.56% and -1.25%. This indicates the prevalence of the complementarity effect of process innovation on employment. Notably, the international evidence points to a marked heterogeneity in the effect of innovation on employment, in which the preponderance of the complementary effect over that of substitution stands out in some cases. For the Peruvian case, there have been no national-level studies on this topic—the vast majority of the literature evaluates the relationship between innovation and productivity (Hall & Rosenberg, 2010; Bravo-Ortega et al., 2014; Cirera et al., 2015; among others). Thus, the objective of the present study is to identify the scope of the impact of product and process innovation on employment.

2. Data

The database employed in this study is that of the 2015 National Survey of Innovation in the Manufacturing Industry (Encuesta Nacional de Innovación de la Industria Manufacturera, ENIIM), collected by the INEI. The 2015 ENIIM is representative at the national level, given that it collects information on 8,844[15] formal sector companies[16] engaged in manufacturing activities throughout Peru's 24 departments as well as the Constitutional Province of Callao. Moreover, the survey has the advantage of measuring changes, progress, and evolution of innovation processes in each of the business initiatives aimed at improving production processes, developing new products, and so on.

14 The instrumental variable used is: public innovation support programs. This instrumental variable fulfills the conditions of exogeneity and relevance.

15 The number is determined by way of simply random sampling with a 12% margin of error, an expected non-response rate of 12%, and a confidence level of 95%.

16 According to the INEI, during the period 2012-2018, participation of the formal manufacturing sector in terms of GDP was around 88%.

The period of study of the 2015 ENIIM is 2012-2014 for the qualitative variables, while information on the amount invested in innovation and on the company's economic performance (sales, exports, fixed capital) is provided for each year during which the survey was ongoing (2012, 2013, and 2014). A limitation of the 2015 ENIIM is that it cannot be combined with the 2012 ENIIM (2009-2011) in order to create panel data, because less than 20% of the companies are included in both surveys. Thus, combining these surveys would give rise to biased results since the sample would not be representative at the national level.

An important aspect to take into account is heterogeneity in the innovation spending by manufacturing companies and the results of innovation. Indeed, according to the 2015 ENIIM, 61.2% of companies invested in some type of technological[17] and non-technological[18] innovation activity. Of all companies in the manufacturing industry, 56.2% are innovative. Of these, 50.2% have engaged in some form of technological innovation, whether product or process, and 43.8% undertook organizational or marketing innovation.

As noted earlier, product innovation is defined as that related to the introduction of new products and services, and significant improvements in functional characteristics or utilization of existing goods and services. Process innovation is the introduction of a new or significantly improved production or distribution process. In turn, marketing innovation entails the application of significant changes in product design or packaging. Organizational innovation is related to a new organizational method put into practice. The present study opts for the analysis of product and process innovation, which are more central to a company's hiring decisions (Crespi & Tacsir, 2012; Harrison et al., 2008).

Based on the above description, the results of innovation in Peru are similar to those reported by Harrison et al. (2008) for France, Germany, Spain, and the United Kingdom. However, there are notable differences in comparison to the results of Benavente and Lauterbach (2008), who report that only 17% of Chilean companies do not innovate, in comparison with half of all Peruvian companies (Table 1).

With respect to employment growth, non-innovative Peruvian companies experience less growth in employment (2.3%) than those that invest in

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17 Spending on technological innovation goes toward internal and external R+D activities, acquisition of capital goods, hardware, software, technology transfer, industrial design and engineering, training for innovation activities, and market research for introducing innovation.

18 Spending on non-technological innovation denotes activities related to the new form of organizational implementation, as well as improvements in product packaging design.

processes alone (4.3%), and less still than those that invest in products alone or in products and processes (10%). In Harrison et al. (2008), Germany, Spain, and the United Kingdom present similar results. Only France appears to show differences between companies that do not innovate in processes and those that do. Interestingly, Benavente and Lauterbach (2008) show that non-innovative Chilean companies present a decrease in employment (3.3%); moreover, the growth in employment is markedly greater among companies that only innovate in processes (25.4%), in comparison with those that innovate in products, or in both (6.7%). With regard to the total increase in nominal sales for Peruvian companies, the reduction of 0.4% is caused by the 16.8% drop in sales among non-innovative companies, which account for 50% of all companies, despite the nominal sales of innovative companies rising by 16.4%. This result contrasts starkly with those of Harrison et al. (2008), who find that nominal sales of European companies grew by an average of 13.3% and total sales by 16%; and those of Benavente and Lauterbach (2008), in which the nominal sales of non-innovative Chilean companies rose by 9.6% and total nominal sales by 30%.

Finally, productivity across the industry fell by 0.6%, as a result of the 18.9% reduction in productivity among non-innovative companies; while those that innovated in processes alone increased their productivity by 13.5%, and those that engaged in product innovation did so by 5.9%. Again, the database structure differs from the results of Harrison et al. (2008), and Benavente and Lauterbach (2008)[19]: non-innovative companies managed to increase their productivity by 6.7% and 12.9% on average, respectively. What is more, European companies pushed up industry productivity by 7.2%, while their Chilean counterparts achieved collective growth of 24.4%.

19 The difference in productivity among non-innovative Peruvian companies is reflected in the constant with a positive sign estimated econometrically from Table 3 to Table 8, which differs from the findings of Harrison et al. (2008), and Benavente and Lauterbach (2008). This sign is justified, because as the productivity of Peruvian companies fell, that of European and Chilean companies rose.

Table 1
Basic characteristics

Characteristics/studies	**A**[2]	**B**[3]		**C**[4]		
	Peru	**Peru**	**France**	**Germany**	**Spain**	**UK**
No. of companies	8,844	514	4,631	1,319	4,548	2,533
Not innovators (%)	49.8	17.0	47.7	41.5	55.4	60.5
Only process (%)	5.3	50	7.1	10.2	12.2	11.0
Innovators in products[1](%)	44.7	77.0	45.2	48.4	32.4	28.5
Innovators in product and process (%)	50.2	76.0	24.3	27.4	20.0	14.1
Growth in employment (%)						
All companies	5.8	5.6	8.3	5.9	14.2	6.6
Not innovators	2.3	-3.3	7.0	2.4	12.6	5.4
Only process	4.3	25.4	7.5	6.0	16.2	8.0
Innovators in products[1]	10.0	6.7	9.8	8.9	16.2	8.5
Growth in nominal sales (%)						
All companies	-0.4	30.0	13.0	15.2	23.2	12.3
Not innovators	-16.8	9.6	11.0	10.8	21.7	10.8
Only process	17.8	29.0	13.4	21.7	23.6	16.3
Innovators in products[1]	15.9	35.2	15.0	17.5	25.7	13.9
Growth in productivity (%)						
All companies	-0.6	24.4	4.7	9.3	9.0	5.7
Not innovators	-18.9	12.9	4.0	8.4	9.1	5.3
Only process	13.5	3.6	5.9	15.7	7.4	8.3
Innovators in products[1]	5.9	28.9	7.5	8.7	9.5	5.4

Notes
[1] Innovators in product only + innovators in product and process
[2] Encuesta Nacional de la Innovación Manufacturera 2015. Period: 2012-2014.
[3] Benavente and Lauterbach (2008), using the Tercera Encuesta Nacional de la Industria Manufacturera. Period: 1998-2001.
[4/]Harrison et al. (2008), using the Tercera Encuesta de Innovación en la Comunidad (CIS3). Period: 1998-2000.
Sources: Harrison et al. (2008); Benavente and Lauterbach (2008).

Table 2 presents column A of Table 1 disaggregated by company size[20] for the Peruvian case. It can be seen that as companies grow, the number

20 The business strata (size) defined in this study are based on annual sales levels. These are, as noted earlier: (i) micro-enterprises: those with annual sales up to a maximum of 150 tax units; (ii) small enterprises: annual sales income between 150 and 1,700 tax units; (iii) medium-sized enterprises: annual sales between 1,700 and 2,300 tax units; and (iv) large companies: annual sales above 2,300 UIT (tax unit). The tax unit set for 2014 is equivalent to 3,800 soles.

of non-innovative companies decreases. In other words, companies increase in both size and investment in R+D activities, and, thus, the number of innovations achieved also rises. This can be seen clearly in the increase in investments in processes or products alone as companies develop.

Table 2
Basic characteristics by size of Peruvian manufacturing companies

Company size/characteristics	Micro-enterprise[2]	Small enterprise[3]	Medium-sized and large enterprise[4]
No. of companies	1,820	5,717	1,307
Not innovators	66.9	46.7	41.1
Only process	2.1	5.1	10.4
Innovators in products[1]	30.9	48.2	48.5
Growth in employment (%)			
All companies	10.2	3.9	8.3
Not innovators	3.7	1.3	4.1
Only process	0	4.3	5.4
Innovators in products[1]	25.0	6.4	12.6
Growth in nominal sales (%)			
All companies	-46.9	11.2	13.9
Not innovators	-68.7	0	17.6
Only process	0	24.1	9.3
Innovators in products[1]	-2.9	20.6	11.9
Growth in productivity (%)			
All companies	-57.1	7.3	5.6
Not innovators	-72.5	-1.4	13.5
Only process	0	19.8	3.9
Innovators in products[1]	-27.9	14.3	-0.01

Notes
[1] Innovators in product only + innovators in product and process
[2] Micro-enterprises are those with sales income below 150 tax units.
[3] Small enterprises are those with sales income between 150 and 1,700 tax units.
[4] Medium-sized and large enterprises are those with sales income of at least 1,700 tax units. A tax unit is equivalent to 3,800 soles.
Source: compiled by authors based on the 2015 ENIMM.

The fall in employment (from 10.24% to 3.9%) among micro-enterprises is notable. However, once companies come to be medium-sized or large, demand for labor is restored (8.33%).

The explanation for this behavior lies in companies' need to be productive.

Presumably, a micro-enterprise will be incentivized to innovate in process (for example, introducing new machinery), since this type of innovation is the easiest to realize (it is not necessary for a company to possess a research and development department to acquire new machinery, but it is necessary if a company wishes to innovate in products) as part of the goal to become more productive, which causes labor displacement (Jaumandreu, 2003; Harrison et al., 2008; Benavente & Lauterbach, 2008). As a company prospers, growth in marginal productivity is reduced; once it establishes itself as a small or medium-sized enterprise, the only way to stay productive is by innovating in product, for which skilled labor is needed as the company develops (Álvarez et al., 2011; Crespi & Tacsir, 2012).

A final conclusion that can be drawn the data is that micro-enterprises make a sizeable contribution to the aggregate averages, which reflects a structural characteristic of the Peruvian manufacturing industry. It is micro-enterprises that are behind the sector's negative figures in both fields; nominal sales exhibit a decrease of 46.9%, while productivity falls by 57.1%. Moreover, in the case of large enterprises, nominal sales and productivity respond similarly.

3. Empirical strategy

To estimate the impact of innovation on employment, an initial econometric specification associated with the theoretical model[21] developed by Jaumandreu (2003) and Harrison et al. (2008) is proposed:

$$l_i = \propto_0 + \propto_1 d_i + y_1 + \beta_i y_2 + u_i \tag{1}$$

where l is the employment growth rate throughout the period (between t=1 and t=2), y_1 and y_2 correspond to production growth rates for new and old products, respectively, and u is the error term ($E(u|d; y_1, y_2)=0$). The parameter $\propto_0$ represents average production efficiency for old products, and the dichotomous variable d_i is equal to 1 if the company has implemented a specific process innovation not related to product innovation, that is, "only process innovation."

Finally, the parameter β_i captures relative production efficiency among old and new products. Given that what is produced is sold, it is assumed that company production of old products (goods or services) occurred in 2012. On the other hand, production of new products (goods or services)

21 The annex explains the theoretical model developed by Jaumandreu (2003) and Harrison et al. (2008).

corresponds to the company's sales recorded in 2014, but the level of innovation indicates that the products are new or significantly improved for the company and the market (domestic and/or international). The 2015 ENIIM allows this distinction to be made.

Given the above, the conditions for proper estimation of the model described, as Harrison et al. (2008) and Benavente and Lauterbach (2008) propose, are as follows:

First, the variable contains three different effects that cannot be separated due to data restrictions: (i) the "independent" increase in the demand for old products; (ii) the "complementarity or compensation" effect from variation in the price of these old products due to incorporation of a process innovation; and (iii) the "substitution or displacement" effect due to incorporation of a product innovation.

Second, the proportion between production of new and old products or growth in sales due to the production of new products (y_2) is an unobserved variable, and for its construction it is necessary to separate nominal growth of total sales (g) into growth in nominal sales due to old products (g_1) and growth in nominal sales due to new products (g_2). Both growth rates ($g1$ y g_2) are constructed using the ratio of sales due to new products to total sales (s), the data for which is available for the final period of analysis. Thus, $g_2 = s(1+g)$ and $g1 = g–s(1+g)$ is obtained.

If g_1 is the growth in nominal sales due to old products and π is the growth rate in the price of the products, the following can be described: $g_1 = y_1 + \pi$, where y_1 is the real unobservable growth in sales due to old products. Now, if g_2 is the growth in nominal sales due to old products and π is the growth rate in the product price, then it can be said that: $g_2 = y_2\ (1+\pi) = y_2 + \pi\ y_2$, where y_2 is the unobservable real growth in sales due to new products. It is important to note that the growth rate in new and old product prices are assumed to be similar since there is no detailed information available about the products sold.

Because it is not possible to observe product prices at the company level, the equations are replaced by g_1 and g_2, demonstrated in (A5[22]) and reordered (1), obtaining:

$$l - g_1 = \propto_0 + \propto_1 d + \beta g_2 + v \qquad (2)$$

where the new error term is: $v = - \pi - \beta\pi y_2 + u$. It is important that $\propto_1$ does not depend on the company's level of productivity (Harrison et al., 2018).

22 See the annex for more details.

Continuing with (2), it can be appreciated that in this expression g_2 is an endogenous variable with respect to inflation (π) and real production of new products (y_2), since it has been corroborated that the residual v contains information related to these two variables. On this point, it should be stressed that it is extremely difficult to find an instrumental variable that is exogenous both for the level of inflation and for the company's decision to innovate; therefore, and in accordance with the instrumental variables used in the empirical literature, it is assumed that d is not correlated with $v = - \pi - \beta\pi y_2 + u$.

The problem of endogeneity is tackled using the instrumental variables method for g_2. Two instruments are taken into account. The first is public support for innovation, which is a dichotomous variable that takes the value of 1 if the company innovates due to public innovation support programs, such as: (i) support for innovation through Innóvate Perú or FIDECOM[23]-FINCyT[24]; (ii) technological services for CITES[25]; (iii) support for entrepreneurship and science, technology, and technological innovation; (iv) technical assistance programs for the adoption of technology and business management; and (v) incentives for R+D and export promotion programs.This instrument is used in a similar way by Crespi and Tacsir (2012), and de Elejalde et al. (2015). The second is a dichotomous variable that is equal to 1 if the company is based in Lima or Callao. The logic behind the aggregation of this instrumental variable is based on the idea that industrial competition in Lima is of greater intensity than in Peru's other departments, and thus for companies in the capital, innovation represents a fundamental tool for improving their levels of productivity and competitiveness. The two instruments fulfill the conditions of exogeneity (that is, they are not correlated to v) and relevance (that is, they are not related to g_2), as Wooldridge (2006) suggests.

4. Results

First, in Table 3, and in accordance with the proposal of Benavente and Lauterbach (2008), expression (2) is estimated taking into account only the variable of sales growth due to having innovated in products (product innovation). This is a reference estimation, as it allows evaluation of the

23 Research and Development Fund for Competitiveness (Fondo de investigación y Desarrollo para la Competitividad)

24 Fund for Innovation, Science and Technology (Fondo para La inovación, Ciencia y Tecnología).

25 Center of Production Innovation and Technology Transfer (Centro de Innovación Productiva y Transferencia Tecnológica)

coefficient estimated with a single regressor variable, and subsequent analysis of how it gradually changes or whether it is robust to the inclusion of more exogenous variables. Second, in Table 4, the variable of innovation in processes only (process innovation) is added, thus completing the specification of expression (2). The purpose of this strategy is to incorporate variables progressively in order to discern the evolution of the results as the model converges on its final form. Third, in keeping with Harrison et al. (2008), Table 5 shows the interaction between the variables of product innovation and process innovation. This is to determine whether process innovation is intended to improve the manufacturing process for old or new products. Finally, in tables 6, 7, and 8, regressions of expression (2) are performed but in proportion to company size, labor skill, and technological capacity. This is to verify the robustness of the results.

Effects of product innovation on employment

In line with the theoretical framework, expression (2) is estimated, which results from replacing y_1 with g_1 and then reordering the expression. This expression captures the effect of real production of old and new products not previously considered in expression (1). Expression (2) presents, as a dependent variable, recruitment not aimed at the real production of old products. However, only the increase in sales due to having innovated in products (product innovation) is included as an independent variable. The purpose of this strategy is to evaluate the effects of innovation separately as the specification of the model proposed is completed in expression (2). To this end, regressions are estimated using both OLS and IV, as shown in Table 3. The regressions are controlled for using the fixed effect variable of number of CITEs per region, the variable of investment in physical capital as a proportion of sales, and dummies by industry.

Column A presents the results of the OLS regression. The coefficient that accompanies the variable of growth in sales due to innovation in new products represents the relative efficiency between the production of new and old products. Since the value is 0.61%, less than the unit, and is significant at the 1% level, it can be said that new products are produced more efficiently than old ones. This means that the number of factors used to produce new products is less than is the case for old products, and recruitment is in lesser proportion than the unit. Moreover, it can be affirmed that when a product innovation is incorporated, the growth in sales due to that innovation increases the level of employment by 0.61%. In turn, when binomial variables by industry are included, the impact changes by just 1%, which proves the robustness of the result.

Column B presents an estimation by instrumental variables (IV). The variable of growth in sales due to product innovation is taken as an endogenous variable and requires the use of instrumental variables. The most appropriate instrument for this case is that related to the growth in sales due to product innovation, but which is not related to the change in prices. The instrument used is the dichotomous variable of the public innovation support program as an originator of new innovative ideas. This variable takes the value of 1 if the company received public innovation support and developed an innovation as a result.

Curiously, the impact of growth in sales due to product innovation is less in this regression (0.57%) in comparison with OLS (0.61%), so, in the first instance, it can be stated that the instrumental variable does not fulfill the function of eliminating the inflation effect. But this is explained by the fact that in the regression in Table 3, only the variable of product innovation is used, and so a conclusion cannot be reached based on this result. As has been mentioned, the strategy is to evaluate the individual effect of innovation and complete the final model to examine the evolution of the results. As with column A, the result in column B does not point to a drastic change when binomial variables by industry (2.5%) are incorporated, which confirms the robustness of this impact. Moreover, the instrument satisfactorily passes the tests of endogeneity and weak instruments.

In column C, another instrument is added in order to overidentify the regression. The instrument is a dichotomous variable that captures those companies that operate in Lima and Callao. The results are consistent due to the non-drastic variation in the coefficient of this new regression by IV in comparison with that of column B (0.57%). Moreover, the different tests for the instrumental variables are added. For the case of the endogeneity test, the null hypothesis is rejected; as such, the use of instrumental variables is justified. Finally, the null hypothesis in the weak instruments test is rejected, and it is concluded that the instruments are not weak. Moreover, the overidentification test shows that the instruments selected comply with the condition of orthogonality.

Table 3
Effect of product innovation on employment

Variables	A: OLS		B: IV[1]		C: IV[2]	
Sales growth new product innov.	0.612***	0.619***	0.566***	0.591***	0.565***	0.585**
	(0.0125)	(0.012)	(0.0206)	(0.021)	(0.0201)	(0.021)
Constant	0.140**	-0.078**	0.152**	-0.068**	0.152**	-0.067**
	(0.0167)	(0.023)	(0.0182)	(0.025)	(0.0181	(0.025
Observations	8,844	8,844	8,844	8,844	8,844	8,844
R-squared	0.278	0.328	0.277	0.328	0.277	0.328
Dummies by industry	No	Yes	No	Yes	No	Yes
Endogeneity test (p-value)[3]			0.0156	0.1252	0.0119	0.0627
Weak instruments test[4]			3,715>16	3,990>16	2,090>19	1,565>13
Overidentification test (p-value)[5]					0.8551	0.185

Notes
Dependent variable: $l - g_1$. The standard errors are robust to heteroskedasticity. All regressions include control variables for the number of CITEs per region and the "investment/sales" ratio.
***p<0.01, **p<0.05, *p<0.1.
[1] The only instrument used is (0/1) "public support for innovation."
[2] The instruments used are "public support for innovation" and (0/1) "if based in Lima or Callao."
[3] Null hypothesis: the independent variable is exogenous (the use of instrumental variables is not justified).
[4] Null hypothesis: the instruments are weak.
[5] Null hypothesis: the instruments are valid (comply with orthogonality).

The results in Table 3 reveal a greater impact in comparison with those of Benavente and Lauterbach (2008): 0.4% for OLS and 0.5% for IV. Moreover, it is important to consider the positive value of the constant when dichotomous variables by industry are not taken into account, given that this sign differs from that which emerges in studies such as Harrison et al. (2008) and Benavente and Lauterbach (1998). As noted in Table 1, labor productivity among non-innovative companies fell by 18.9%. As a result, the positive value of the constant is justified, because it represents the change in production efficiency (in negative value) of non-innovative products; and when the negative sign appears due to a decrease in productivity, the negative values produce a positive effect. It should be noted that once the dichotomous variables by industry are included, the effect of the constant recovers the desired sign; this demonstrates the importance of adding control variables to correct for the heterogeneous effects of each sector of the sample on the results.

Effects of product and process innovation on employment

Now, the independent variable of process only (process innovation) is incorporated into the regression in Table 3, such that the econometric variable of expression (2) is completed. The results are shown in Table 4. As with the previous model, this model makes it possible to evaluate the effect of product innovation on employment growth not related to increased production of old products. However, unlike the estimation in Table 3, it also allows for identification of the impact of process innovation on a company's labor demand.

Column A presents the OLS results. The value of the coefficient of growth in sales due to new products represents an estimation of the relative efficiency of production among new and old products. This value, of +0.59%, is significant at the 1% level and is less than the unit, which indicates that new products are produced more efficiently than old ones and employment is created, albeit to a lesser degree than the unit. Moreover, the effect of the variable "process only" is -0.4% and is statistically significant at the 1% level. This shows that incorporation of a process innovation negatively impacts a company's labor growth not derived from changes in sales growth due to old products. Both results are robust since the coefficients of product and process innovation do not change abruptly when dichotomous variables by industry are incorporated.

Table 4
Effect of product and process innovation on employment

Variables	A: OLS		B: IV[1]		C: IV[2]	
Sales growth new product innov.	0.585**	0.586**	0.631**	0.668**	0.634**	0.665**
	(0.0128)	(0.012)	(0.0183)	(0.019)	(0.0176)	(0.018)
Only process	-0.402**	-0.488**	-0.382**	-0.452**	-0.381**	-0.454**
	(0.0233)	(0.027)	(0.0240)	(0.027)	(0.0238)	(0.027)
Constant	0.155**	-0.068**	0.142**	-0.095**	0.142**	-0.094**
	(0.0168)	(0.023)	(0.0180)	(0.025)	(0.0178)	(0.025)
Observations	8,844	8,844	8,844	8,844	8,844	8,844
R-squared	0.293	0.349	0.292	0.345	0.292	0.346
Dummies by industry	No	Yes	No	Yes	No	Yes
Endogeneity test (p-value)[3]			0.0043	0.000	0.0019	0.000
Weak instruments test[4]			4,619>16	5,130>16	3,016>19	2,275>13
Overidentification test (p-value)[5]					0.5066	0.5439

Notes
Dependent variable: $l - g_1$. The standard errors are robust to heteroskedasticity. All regressions include control variables for the number of "CITEs" per region and the "investment/sales" ratio.
***p<0.01, **p<0.05, *p<0.1.
[1] The only instrument used is (0/1) "public support for innovation."
[2] The instruments used are "public support for innovation" and (0/1) "if based in Lima or Callao."
[3] Null hypothesis: the independent variable is exogenous (the use of instrumental variables is not justified).
[4] Null hypothesis: the instruments are weak.
[5] Null hypothesis: the instruments are valid (comply with orthogonality).

Column B presents the estimation using instrumental variables to recover the assumption of homogeneity due to the correlation between growth in sales due to having innovated in products and inflation; the latter is present in the error term. The instrument used is the discrete variable that represents whether or not the company obtained public support for the development of its innovation idea.

The coefficient that accompanies the variable of increase in sales due to new products presents an impact of 0.63%, greater than for the OLS regression (0.59%). This indicates that the regression using IV does now recover the assumption of heterogeneity, because it eliminates the effect of inflation on the variable of growth in sales due to product innovation. Thus, the creation of employment is not greater than in column A. In addition, the evidence persists that efficiency in the production of new products is greater than is the case for old products, because the coefficient that accompanies the variable of product innovation (0.63%) is still less than the unit. Finally, the result is robust because it does not present a change in the coefficients estimated when dichotomous variables by industry are incorporated.

When it comes to the variable of innovation in process only, the coefficient obtained is -0.38%, significant at the 1% level, and greater than that presented in the OLS estimation (-0.40%). This result reveals, as with the case of product innovation, the improvement in the assumption of heterogeneity in the results due to the exclusion of the inflation effect. Thus, the effect of job loss is now less than is the case of column A (0.70%). Both results are robust because they do not exhibit a sudden change when dichotomous variables by industry are introduced (0.70%). In addition, the instrument used in column B fulfills the conditions of exogeneity and relevance.

In column C, another instrumental variable is added in order to over-identify the regression. This variable is dichotomous and represents whether the company is operating in Metropolitan Lima or Callao. On the one hand, the impact of product innovation on growth in employment in column C is similar to that in column B (0.631% and 0.634%, respectively). On the other hand, the impact of process innovation on growth in employment in column C also closely resembles that in column B (-0.381% and -0.382%, respectively). Thus, there is evidence of consistence in the coefficients of both product innovation and process innovation, in relation to the level of employment. It is notable that the instruments used satisfactorily meet the conditions of exogeneity, relevance, and orthogonality.

As mentioned previously, the positive value of the constant is justified by the loss in productivity or efficiency in the production of non-innovative companies, as shown in Table 1. The sign of the model is negative and is presented in expression (A5), because it is assumed that there was an increase in the productivity of non-innovative products and that this increase in production efficiency has a negative impact on employment. The structure of the Peruvian database reveals an opposite effect, and thus the opposite sign (positive) is presented. However, the desired sign is recovered when the binomial variables per industry are included, which verifies the importance of including them in the results.

In comparison with the results of Harrison et al. (2008)between 0.77% and 0.86% for OLS and 0.89% and 1.02% for IV--the impact of growth in sales due to innovation in new products is relatively limited.In the case of, Benavente and Lauterbach (2008), the result is less: 0.4% for OLS and 0.6% for IV. Then, in comparison with process innovation only, the impact in the study of Harrison et al. (2008) is substantially greater, presenting an impact that is insignificant at the 10% level and between -8,49% and 0.30% for OLS and between -6.19% and 2.46% for IV.For their part, Benavente and Lauterbach (2008) present a coefficient insignificant at the 10% level of +0.133% for OLS and +0.132% for IV.

Interaction between product and process innovation in employment

Product and process innovations form part of a single production process; as such, it is reasonable to infer the existence of mutual synergies between them. In specific terms, it is of interest to ascertain whether process innovation is aimed primarily at the production of old or new products (Harrison et al., 2008). The expression estimated earlier is extended to incorporate interaction effects between two types of innovation.

First, the estimates are presented taking into account the two types of innovation. It is notable that the coefficient of the variable of companies that innovated in both products and processes is insignificant (-0.02%), which implies that process innovation is not related to the production of old products and is probably oriented mainly toward new ones. However, when the discrete variables by industry are incorporated, the level of significance is 1%. Because of the lack of consistency, these results do not clearly answer the question of whether companies innovate in processes to continue making old products more efficiently.

Column B shows the interaction between innovation (in products and processes) and the growth in sales of new products. This specification allows productivity in the production of new products to differ for companies that also introduce innovation. The fact that the coefficient of the interaction variable is significant (-0.135% in column B) proves that greater productivity among companies that introduce new products and innovate leads to higher levels of employment in comparison with companies that do not innovate. This result is robust even when fixed effect by industry are incorporated.

In both columns A and B, the separate effects of growth in sales due to product innovation alone and process innovation alone are robust regardless of whether fixed effects by industry are controlled for. In column A, the coefficients of product innovation are 0.66% and 0.71%, both less than the unit, and thus the superior productivity for new products in comparison with old products remains. As to process innovation, the effects are -0.38% and -0.45%, which reveals the consistency of employment displacement by physical capital. In column B, the impacts of product innovation are 0.74% and 0.81%; again, the impacts are less than the unit, and thus there proves to be greater efficiency in the production of new products over that of old ones. With respect to process innovation, the coefficients are -0.37% and -0.44%, which corroborates its negative effect on the level of employment.

By way of comparison, in Harrison et al. (2008) the coefficient of the variable of product and process innovation presented in column A is 2.03% on average, greater than that in the present study and insignificant at the 10% level. With regard to Benavente and Lauterbach (2008), the coefficient is even less, -0.002%, and likewise insignificant at the 10% level. This shows, for both studies, that process innovation might not have an impact on productivity improvements for old products.

As to the impact of sales due to product innovation, shown in column B, Harrison et al. (2008) find an impact of -5.7%, indicating that, for their study, new products are produced more efficiently than old ones. Benavente and Lauterbach (2008) also present a coefficient greater than the unit, and conclude in like manner.

Table 5
Interaction between product and process innovation

Variable	A: VI[1]		B: VI[2]	
Sales growth new product innov.	0.658***	0.706***	0.744***	0.809***
	(0.0203)	(0.021)	(0.051)	(0.049)
Only process	-0.379***	-0.450***	-0.373***	-0.441***
	(0.0237)	(0.027)	(0.0243)	(0.028)
Process and product	-0.0237	-0.042***		
	(0.0144)	(0.015)		
Sales growth new product innov. * X product and process innovation			-0.135***	-0.187***
			(0.0484)	(0.045)
Constant	0.142***	-0.091***	0.141***	-0.092***
	(0.0179)	(0.025)	(0.0177)	(0.025)
Observations	8,844	8,844	8,844	8,844
R-squared	0.290	0.342	0.287	0.338
Dummies by industry	No	Yes	No	Yes
Endogeneity test (p-value)[4]	0.0001	0.000	0.0015	0.000
Weak instrument test[5]	1,542>19	1,092>13	408>19	369>13
Over-identification test (p-value)[6]	0.682	0.2712	0.7739	0.0515

Notes
Dependent variable: $l - (g_1 - \pi_1)$. The standard errors are robust to heteroskedasticity. All regressions include control variables for the number of CITEs per region and the "investment/sales" ratio.
***p<0.01, **p<0.05, *p<0.1.
[1] The instruments used are "public support for innovation" and (0/1) "if based in Lima or Callao."
[2] The instruments used are "public support for innovation" and (0/1) "if based in Lima or Callao," and both interact with "product and process innovation."
[3] The covariance between the parameters "growth in sales due to innovation in new products" and "growth in sales due to innovation in new products * product and process innovation" is 0.23.
[4] Null hypothesis: the independent variable is exogenous (the use of instrumental variables is not justified).
[5] Null hypothesis: the instruments are weak.
[6] Null hypothesis: the instruments are valid (comply with orthogonality).

Analysis of robustness

The results referred to above represent average effects. Next, a robustness analysis is performed, taking into account the observable heterogeneity of the companies. The levels of heterogeneity employed in this study are company size, technological capacity, and labor skill composition. These levels of disaggregation are incorporated by way of artificial variables in the regression presented in column B of Table 5. It should be recalled that this is the most complete specification; in addition, it contains instrumental variables and controls for fixed effects at the industry level, which allows for better identification of expression (2).

- **Role of company size**

Innovation has effects on employment that differ according to company size, and the greatest effect is on large enterprises (0.32% for micro-enterprises, 0.947% for small enterprises, and 1.172% for medium-sized and large enterprises). This is because as a company develops and its size increases, so too does its capacity to implement R+D policies. This boosts the prospects of achieving product innovation through significant improvement or creation of products for the market. R+D policy stimulates recruitment, and this stimulus will be greater the more a company grows due to the economies of scale created. Moreover, it should be noted that new labor demand will be for a more skilled workforce, and so it can be argued that the more a company grows, the more its labor skill composition will change, with skilled workers replacing the unskilled (Álvarez et al., 2011; Crespi & Tacsir, 2012).

Table 6
Process and product innovation by company size

Column	IV[1]			
Variables	All	Micro	Small	Medium-large
Sales growth new product innov.	0.668***	0.327***	0.947***	1.172***
	(0.019)	(0.057)	(0.018)	(0.041)
Only process	-0.452***	-0.346***	-0.286***	0.051
	(0.027)	(0.054)	(0.026)	(0.050)
Constant	-0.095***	0.824***	-0.208***	-0.013
	(0.025)	(0.058)	(0.028)	(0.048)
Observations	8,844	8,844	8,844	8,844
R-squared	0.345	0.296	0.500	0.554
Dummies by industry	Yes	Yes	Yes	Yes
Endogeneity test (p-value)[2]	0.000	0.001	0.000	0.000
Weak instruments test[3]	5,130.6>16.38	233.54>16.38	5,023.94>16.38	979.81>16.38

Notes
Dependent variable: $l - (g_1 - \pi_1)$. The standard errors are robust to heteroskedasticity. All regressions include control variables for the number of CITEs per region and the "investment/sales" ratio.
***p<0.01, **p<0.05, *p<0.1.
[1] The only instrument used is (0/1) "public support for innovation."
[2] Null hypothesis: the independent variable is exogenous (the use of instrumental variables is not justified).
[3] Null hypothesis: the instruments are weak.

As to the impact of process innovation, the substitution effect fades away as the company grows (-0.346% for micro-enterprises, -0.286% for small enterprises, and +0.051% for medium-sized and large companies; the latter is insignificant at the 10% level, while the former two are significant at the 1% level). This is consistent with the theory that a smaller company has more of an interest in innovating in processes with the aim of achieving immediate efficiency improvements in its production. As the company grows, its impact on the marginal product gradually falls due to convergence on the saturation of its installed capacity. Given a certain point of growth, the only way to keep on growing is to innovate using an alternative source of improved productivity: product innovation (Álvarez et al., 2011; Crespi & Tacsir, 2012).

- **Role of technological capacity and labor skill**

The database allows identification of a company's technological capacity and labor skill. These data make it possible to determine whether the effects of innovation on employment differ in these observable company-level characteristics.

The effects of innovation on employment in the case of high-technology companies are robust in all cases (0.617% and -0.484%, respectively, for product and process innovation in low-technology companies, in contrast with +0,959% and -0,234% for high-technology companies). A company with limited technology creates less employment if it decides to innovate in products, and eliminates more employment if it decides to innovate in processes. A company with high technological capacity, taking into account that it probably has a R+D department, will have a greater probability of innovating in products and doing so more frequently. This serves to create jobs. If a company decides to innovate in processes, this will probably not have a major impact on its productivity, because, as must be recalled, the company is already technologically competitive. It should be noted that among companies in emerging countries such as Peru, process innovation tends only to mean the importation of technology already implemented internationally; these countries do not usually create new technology that can give them comparative advantages over the global market (Cirera et al., 2015).

Table 7
Product and process innovation by technological capacity and labor skill

Column	VI[1]				
Variables	All	Low technology	High technology	Unskilled	Skilled
Sales growth new product innov.	0.668***	0.617***	0.959***	0.677***	0.673***
	(0.019)	(0.019)	(0.062)	(0.018)	(0.020)
Only process	-0.452***	-0.484***	-0.234***	-0.446***	-0.186***
	(0.027)	(0.030)	(0.047)	(0.027)	(0.031)
Constant	-0.095***	-0.069***	-0.087***	-0.099***	0.150***
	(0.025)	(0.026)	(0.073)	(0.025)	(0.018)
Observations	8,844	7,484	1,360	8,782	6,537
R-squared	0.345	0.375	0.156	0.347	0.343
Dummies by industry	Yes	Yes	Yes	Yes	Yes
Endogeneity test (p-value)[2]	0.000	0.0579	0.000	0.000	0.000
Weak instruments test[3]	5,130.6>16.4	4,753.6>16.4	537.1>16.4	5,234.7>16.4	4,069.9>16.4

Notes
Dependent variable: $l - (g_1 - \pi_1)$. The standard errors are robust to heteroskedasticity. All regressions include control variables for the number of CITEs per region and the "investment/sales" ratio.
***p<0.01, **p<0.05, *p<0.1.
[1] The only instrument used is (0/1) "public support for innovation."
[2] Null hypothesis: the independent variable is exogenous (the use of instrumental variables is not justified).
[3] Null hypothesis: the instruments are weak.

With respect to the labor skill composition, the results verify the conclusions of Table 6 and the second and third columns of Table 7. Product innovation creates jobs, regardless of a company's labor quality structure. If a small company (with a high level of unskilled labor) innovates in products, the demand for labor will be boosted; this applies to both unskilled workers (0.677%), for the manufacture of the innovative product, and skilled workers (0.673%), for ongoing product improvements or creation. As far as process innovation is concerned, the impact of process innovation displaces unskilled labor (-0.446%) to a much greater degree than skilled labor (-0.186%). This is consistent with the results of Table 7 and with the second and third columns of Table 8.

Finally, Table 8 provides an overview of the results. The conclusions are consistent: as the company grows and develops, the impact of product innovation increases, and in all cases, new jobs are always created. In turn, process innovation loses its effect as companies grow and converge on a state of saturation of physical capital.

Table 8
Technological capacity and labor skill by company size

Column	VI[1]												
Variables	All	Low technology			High technology			Unskilled			Skilled		
		Micro	Small	Medium-large	Micro	Small	Medium-large	Micro	Small	Medium-large	Micro	Small	Medium-large
(1)	0.67	0.24	0.85	1.12	-0.50	0.89	1.33	0.30	0.86	1.17		0.74	1.17
	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
(2)	-0.45	-0.34	-0.31					-0.38	-0.28				
	Yes	Yes	Yes	No	No	No	No	Yes	Yes	No	No	No	No

Notes
Dependent variable: $l - (g_1 - \pi_1)$. The standard errors are robust to heteroskedasticity. All regressions include control variables for the number of CITEs per region and the “investment/sales” ratio.
[1] Growth in sales by new product.
[2] Process innovation only.
“Yes” or “no” indicate whether the coefficient obtained is significant at the 1% level or not.

5. Conclusions and recommendations

The present study evaluates the impact of product and process innovation on employment growth in the Peruvian manufacturing industry during 2012-2014. To this end, the database compiled by INEA and published in ENIMM (2015) is used.

Product innovation was found to have a positive impact of 0.67% on employment growth, statistically significant at the 1% level and robust to the inclusion of discrete variables by industry. This result attests to the predominance of the compensation (or complementarity) effect over the displacement (or substitution) effect in relation to product innovation. Moreover, the impact is less than the unit, which entails high growth in labor productivity associated with the incorporation of new products by Peruvian companies. This is similar to the findings of Benavente and Lauterbach (2008) for the Chilean case.

As to the inclusion of process innovation, the impact is -0.45%, significant at the 1% level and robust to the inclusion of dichotomous variables in the regression. This result signals the predominance of the displacement (or substitution) effect over the compensation (or complementarity) effect of process innovation on the level of employment. The above-mentioned substitution effect can be exemplified in the classic situation of incorporation of machinery or physical capital to replace labor, usually unskilled.

Through the interaction effect, it can be shown that the increase in productivity of companies that innovated in processes is due primarily to the incorporation of new products. This is because the interaction with the growth in sales due to having innovated in products and processes (co-innovation) is significant at the 1% level, and has an impact of -0.14% or -0.18% depending on the inclusion or exclusion, respectively, of discrete variables by industry.

When the effects of product and process innovation are evaluated on different levels, such as company size, technological capacity, or labor skills, the results corroborate the consistency. As a company grows and develops, it has a lower probability and interest in engaging in product innovation due to its greater investment in R+D, which contributes to job creation. The positive effect of employment demand when product innovation is engaged in is indifferent to size, technological capacity, or labor structure. However, the effect is amplified the more the company prospers. As to process innovation, as a company increases its competitive capacity, the effect of incorporating new machinery gradually diminishes. However, it is necessary to reduce the brutal effect of job displacement when a micro- or small enterprise decides to innovate in processes.

It is important that future research evaluate the consistency of the results obtained in this study using additional historical information (for example, through panel data) and other possible instruments to control for the endogeneity of the model, enabling identification of the coefficients of interest in the best possible way.Should the evidence found continue to hold (that is, that product innovation has a positive effect on the level of employment, regardless of company size), then public policies should seek to encourage companies (especially micro- and small enterprises) to innovate more and take advantage of the positive effects in terms of fulfilling growth potential and ensuring the labor market is not affected by technological development. For instance, expanding access to credit for R+D and improving tax and labor regulations are vital means of increasing innovation in other Latin American countries. Such policies should be implemented in a collective and sustained manner over the medium and long term in order to assure their effectiveness.

Finally, the negative effect of process innovation on employment requires greater analysis to corroborate this evidence. However, the results obtained in this initial study of the Peruvian case indicate that this type of innovation displaces high levels of unskilled human capital, so public policies ought to focus on improving the quality of working capital through training in order to curb this disproportionate impact (Álvarez et al., 2011). In this regard, a useful instrument is on-the-job training (OJT), which consists of companies themselves training their workers through government incentives such as tax breaks (González-Velosa, Rosas, & Flores, 2016).

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Annex

Models of the relationship between innovation and employment

The conceptual framework used in this study corresponds to that developed initially by Jaumandreu (2003) and extended by Harrison et al. (2008). This model enables formalization of the relationship between technological innovation (product and/or process) and employment, demonstrating the existence of the substitution (or displacement) effect or the complementarity (compensation) in both variables. This is a two-period model and assumes that the product (Y) is manufactured by means of a production function with constant returns to scale, and uses production factors such as labor (L), capital (K), and intermediate inputs (M).

$$Y_{it} = \theta_{it} F(L_{it}, K_{it}, M_{it}) \quad \text{(A1)}$$

It is assumed that a company, in periods t = 1.2, takes the decision to produce old or not significantly improved products (i = 1), or new and significantly improved products (i = 2). Although a company can produce different types of products in each period (Y_{11}, Y_{12}, Y_{21} and Y_{22}), in the initial period (t = 1) all the company's products are considered to be old because no innovative product has been introduced to the market (Harrison et al., 2008; Benavente & Lauterbach, 2008). Therefore, the total products produced by the company in the initial period will be equivalent to Y_{11} since Y_{21} = 0. For t = 2, the company's production is composed of old products (Y_{12}) and new products (Y_{22}).

The variable θ_{it} represents efficiency or knowledge capital or the increase in the marginal productivity of the conventional production factors due to the incorporation of knowledge (Jaumandreu, 2003; Peters, 2004). As a result, this variable enables more efficient development of production processes, and increases proportionally according to the marginal productivity of each production factor, which provides each one with a particular efficiency (Benavente & Lauterbach, 2008).

It is important to mention that the decision to innovate is determined before the decision period for hiring or dismissing employees. This is because if the product innovation incorporated is a substitute for a previous product, these new products can only replace the old products; and if they are complementary, they can increase the demand for employment at the company level (Benavente & Lauterbach, 2008). The company's cost function (C) is determined by (A2):

$$C(w_{1t}, w_{2t}, Y_{1t}, Y_{2t}, \theta_{1t}, \theta_{2t}) = c(w_{1t})\frac{Y_{1t}}{\theta_{1t}} + c(w_{2t})\frac{Y_{2t}}{\theta_{2t}} + C_0 \quad \text{(A2)}$$

where $c(w_{it})$ represents the marginal costs of each product i in period t, and C_0 represents the fixed costs. Using Sheppard's lemma in (A2), the following is obtained:

$$L_{it} = c_{L(W_{it})}\frac{Y_{it}}{\theta_{it}} \qquad \text{(A3)}$$

Moreover, $c_{L(W_{it})}$ corresponds to the derivative of the marginal cost function in relation to salary (w_{it}), which does not change over time, or is equal for both old and new products. $c_{L(W_{11})} = c_{L(W_{12})} = c_{L(\widehat{W}_1)} = c_{L(\widehat{W}_2)}$. This scenario can occur when the relative prices of both production factors are equal (in this case, the cost of labor is equal to the opportunity cost of capital) for both products and for both periods (Benavente & Lauterbach, 2008). The growth in employment between the two periods is broken down into the change in employment both in the production of old products ($(L_{12} - L_{11}) / L_{11}$) and in that of new products (L_{22} / L_{21}):

$$\frac{\Delta L}{L_{11}} = \frac{L_{12} + L_{22} - L_{11}}{L_{11}} = \frac{L_{12} - L_{11}}{L_{11}} + \frac{L_{22}}{L_{11}} \simeq \ln\frac{L_{12}}{L_{11}} + \frac{L_{22}}{L_{11}} \qquad \text{(A4)}$$

Incorporating the expression (A3) in (A4) gives rise to the decomposition of employment:

$$\frac{\Delta L}{L} \cong -(\ln\theta_{12} - \ln\theta_{11}) + (\ln Y_{12} - \ln Y_{11}) + \frac{\theta_{11}Y_{22}}{\theta_{22}Y_{11}} \qquad \text{(A5)}$$

The expression (A5) indicates that employment growth is explained by:

(i) the change in the efficiency of the production process of the old products ($-ln\theta_{12} + ln\theta_{11}$), (ii) the production growth rate for old products [26]($lnY_{12} - lnY_{11}$) and (iii) the expansion of production attributable to the demand for new products (Y_{22}/Y_{11}).

The increase in the production efficiency of old products from one period to another ($ln\theta_{12} - ln\theta_{11}$) is expected to be greater for those companies that introduce process innovation (for example, high-technology physical capital) to produce these products, even if the company's efficiency is expected to increase through other important factors, such as the effects of learning and training (Harrison et al., 2008).

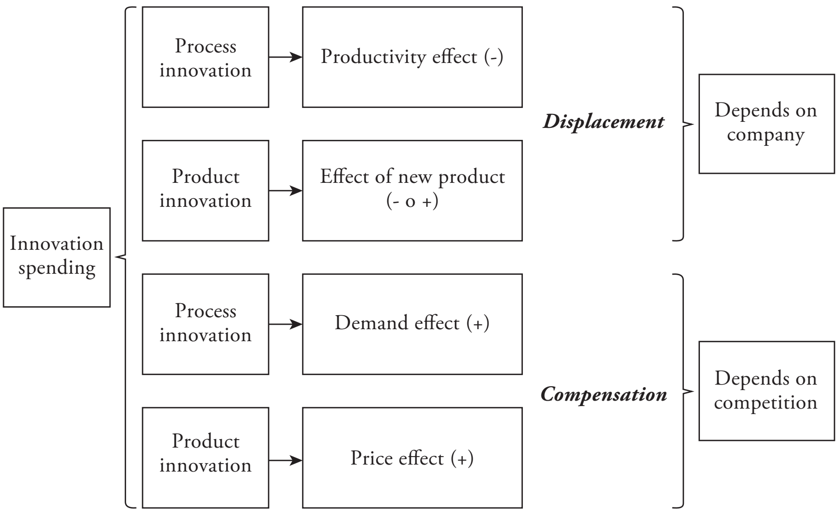
The relationship between employment growth and product innovation is reflected in the ratio (θ_{11}/θ_{22}) of relative efficiency between the production

26 Partially determined by the incorporation of a new product. The sign would be negative if the old and new products are substitutes, and positive if they are complementary.

of old and new products. Thus, if new products are being produced more efficiently than old products, this ratio should be less than the unit and employment would not grow in the ratio of one to one to production of the new product (Harrison et al., 2008; Benavente & Lauterbach, 2008). The effect on employment of product and process innovation is captured in (A5) and, to distinguish between the different impacts that are generated, the following diagram is used (Figure 1).

According to Crespi and Tacsir (2012), process innovation occurs when there are high production costs, which creates the need to incorporate new machinery and reduce labor in order to improve the company's productive efficiency (negative displacement effect). However, after the reduction in marginal costs, a decrease in the prices of the products and/or services placed on the market may result from the increase in production efficiency, causing an increase in demand and, consequently, a greater requirement for new labor (positive compensation effect). On product innovation, the authors suggest that it can displace labor so long as the new product is a replacement for the previous one (substitute goods). Otherwise, when both goods (new and old) complement each other, this causes an increase in employment. As to the positive compensation effect on employment, this is because of the increase in demand due to having introduced a new product, regardless of its relationship with the old product.

Figure 1
Effects of innovation on employment



Sources: Harrison et al. (2008); Crespi and Tacsir (2012).