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The effect of innovation on skilled and unskilled workers during bad times

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ABSTRACT

The recent economic crises generated a dramatic reduction of employment, but the role of innovation has barely been analyzed. This study contributes to the literature by analyzing the differentiated effect of product and process innovation on high- and low- skilled employment during bad times. We focus on the case of Spain, a country with one of the largest reductions in employment during the crisis. The main results suggest a positive effect of innovation on employment during bad times, although this effect is remarkably larger for high-skilled than for low-skilled workers. These results hold across industries and are exacerbated in high-tech industries. It is estimated that product and process innovations account for around 13% of the different evolution between high-skilled and low-skilled employment during the crisis. These results implicitly reflect that innovation – especially product innovation – favors a bias towards the demand of high-skilled employment in detriment of low-skilled workers.

1. Introduction

Recent employment dynamics have clearly been influenced by the economic crisis, which destroyed more than 30 million jobs globally, while in Spain around 4.5 million jobs were lost between 2007 and 2013 (ILO, 2015). It seems that the crisis more intensely affected unskilled employment, taking into account that, at least in Spain, the total number of employees with a university degree remained more or less stable during this period. The main goal of this paper is to analyze the effect of product and process innovation on high-skilled and low-skilled workers during bad times in order to explain the differentiated effect of product and process innovation on this relationship.

The paper is embedded in three main approaches reflected in the theoretical and empirical literature. On the one hand, the general relationship between innovation and employment has already been discussed by classical authors like Ricardo and Marx, because the various labor-saving and labor-creating effects of product and process innovation have always been problematic from a social or economic point of view. The best-known early example of social turmoil related to this aspect is the Luddite movement of the early 19th century, when English textile well-skilled artisans protested against the mechanization of textile production by destroying some machines (Autor, 2015). On the other hand, another important aspect is the effect of innovation on labor composition, which has been discussed since the 1960s, leading to the formulation of the skill-biased technological change (SBTC) and routine-biased technological change (RTBC) hypotheses that expect a shift of the demand of total employment toward more highly skilled workers and less routine tasks. Finally, we focus on a period of economic turmoil, because the relationship between innovation and the economic cycle has been controversial. While Schumpeter (1939) considered innovation activities to be countercyclical because of the lower opportunity cost of investments, recent empirical evidence usually shows a procyclical pattern (van Ophem et al., 2019).

The main contributions of our manuscript are the following. First, we analyze the specific effect of each type of innovation (product and process) on different types of workers (high-skilled

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and low-skilled). While product innovation has usually been found to have a positive effect on employment and the results for process innovation are mixed, no stylized knowledge has been built regarding their specific effect on different type of workers. Second, we focus on a period of economic turmoil where employment is being destroyed, while previous studies usually cover expansion periods characterized by employment creation. Third, we analyze whether the effects of product and process innovation on high- and low-skilled workers are pervasive across industries or whether there are some features specific to high- or low- tech industries.

To accomplish these goals, we use Spanish data from the “Panel de Innovación Tecnológica” (PITEC) on over 27,800 observations for manufacturing firms from 2006 to 2014 and make use of the structural model of Harrison et al. (2014), who analyze the differentiated effects of product and process innovation on employment.

The structure of this paper is as follows. In Section 2, we offer a very short overview of some of the compensation mechanisms that reduce the loss of employment because of the introduction of innovations and also discuss the causes of the growing demand of the different types of employment. In Section 3, we show contextual evidence of the Spanish situation during this period and review previous empirical evidence on the relationship between innovation and employment in this context. In Section 4, we present the theoretical model of Harrison et al. (2008, 2014), its limitations and the specification of this empirical model. In Section 5 we review the main empirical works using this model. In Section 6 we offer details of the specification of the model and the database and present the basic statistics of the variables used. In Section 7 we show the estimations for the Spanish case, offering the results for total employment, high-skilled employment and low-skilled employment. In the last section, we present some conclusions, the limitations of our work and some final remarks.

2. Some basic notions of the effect of innovation on employment and the skill composition

One of the main theoretical debates of the effect of innovation on employment in quantitative terms is related to compensation mechanisms. Although process innovation has a direct negative effect on employment, there are some specific direct and indirect mechanisms that compensate the initial loss of employment. We offer only some short discussion about these mechanisms, highlighting relevant aspects for this paper.[1] The discussion of the compensation mechanisms clearly distinguishes between product innovation and process innovation. Table 1 relates the employment effects of each compensation mechanism with the two types of innovation. Theoretically, the direct effect of process innovations is an increase in innovators’ production efficiency (*productivity effect of process innovation*) (Peters et al., 2017). It means that production requires less input to produce an item and, hence, process innovation is likely to reduce labor demand. However, the increased efficiency of production reduces costs and, consequently, a *price effect* that could stimulate overall demand of goods. The corresponding higher level of production could compensate the loss of employment with the creation of new jobs (Say’s law)[2] (Vivarelli, 2014).

For their part, product innovations may affect employment via three channels (Peters et al., 2017). The first is introducing new products in the market, which generates a new demand and therefore increases labor demand (*direct demand effect of product in-*

Table 1
Effects of product and process innovation on employment at the firm level.

	Product innovation	Process innovation
Employment-reducing effects (displacement effects)	Indirect demand effect: Decrease in demand if the firm substitutes old products by new ones (cannibalization of old products) (−)	Productivity effect of process innovation: Less labor input for a given output (−)
Employment-ambiguous effects	Productivity effect of product innovation: New products require less (or more) labor input (−,+)	
Employment-creating effects (compensation effects)	Direct demand effect: New products increase overall demand (+) Indirect demand effect: Increase in demand of existing complementary products (+)	Price effect: Cost reduction passed on to the price expands demand (+)

Source: Own elaboration based on Dachs and Peters (2014) and Harrison et al. (2014).

[1] For a broader discussion, see Vivarelli, 1995, 2014; Peters et al. 2017; Calvino and Virgillito, 2018.

[2] There are more compensation mechanisms related to process innovations, like the potential effects of increased benefits and wages, the reduction of general salary level versus labor intensive investments, and the employment effects in the machine and tools sector.

novation). Second, if new products are produced more (less) efficiently than old products, they will require less (more) input for a given output. This dampens (strengthens) the positive demand effect, thus also employment growth (*productivity effect of product innovation*). Third, there is an *indirect demand effect of product innovation*: if products are substitutive, new product demand may replace the demand for the innovators' old products to some degree (product cannibalization[3]). However, if new products are complementary to the old ones, the new product demand stimulates the old product demand.

Besides the overall effect of innovation on employment, this paper tries to assess the quantitative and qualitative impact of innovation on skilled versus unskilled jobs. Therefore, it is important to discuss the reasons that could explain the increasing demand of skilled (or higher educated) labor in absolute terms. Welch (1970) mentions three basic causes, firstly, the structural change in the composition of the production sector towards high-tech industries observed in the most advanced countries. These industries – which are the most skill intensive – grow faster than low-tech manufacturing sectors. The products of these high-tech sectors have higher income-demand elasticities, changing the composition of the consumption (because of the rising income), because richer citizens demand more innovative products (Porter, 1993). Also, process innovation increases productivity and therefore average income per capita with a similar stimulating effect on the demand of high-tech products.

Secondly, the increasing use of non-labor input factors can generate –*ceteris paribus*– a positive bias towards the demand of skilled labor. In particular, capital investments substitute unskilled labor activities more frequently. In this case, it is not the technology that causes the lower demand of unskilled workers. Nevertheless, the real cause would be the increase of capital intensity. Thirdly, technical change is not neutral between skill classes.[4] *"It may be that increments in technology result in increments in the relative productivity of labor that is positively related to skill level"* (Welch, 1970, P.38).

In the case of analyzing the effect of innovation on employment in qualitative terms, an important notion is the skill-biased technological change (SBTC) hypothesis. This idea –already mentioned by Nelson and Phelps (1966), Griliches (1969) and Welch (1970) – implies that the introduction of new technologies requires workers with new suitable capabilities and skills. The SBTC hypothesis suggests that new technologies and the required skills are intrinsically complementary, so it favors the hiring of skilled over unskilled workers by increasing their relative productivity (Violante, 2008). This theory has been complemented with routine-based technological change (RBTC) (Autor et al., 2008; Goos et al., 2014; Jaimovich and Siu, 2018), which places the emphasis on the routine versus cognitive contents of the tasks and argues that most of the new technologies would replace workers that perform routine tasks. The presence of a labor-saving and skill-biased process innovation can generate unemployment among unskilled workers. The recent consensus of empirical studies is that technical change favors more skilled workers, replacing tasks previously performed by the unskilled, and exacerbates inequality (Acemoglu, 2002).

The introduction of new products –not standardized and with a low demand– often implies the need for labor-intensive production process and skilled workers. Once a product has success in the market and its design gets to be standardized, firms are prone to introduce labor-saving process innovation in order to simplify the production process, which would imply that firms substitute skilled for unskilled workers. For example, the rise of the ICT sector initially implied an increase of skilled employment because of changes in the nature and requirements of jobs (Berman et al., 1998; Falk and Biagi, 2017). However, the standardization of those technologies and user-friendly software programs implies a lower demand of skilled workers (Tether, 2005).

It can be highlighted that the SBTC/RBTC studies analyze the impact of a specific technology – ICT– while in this paper only two global indicators are used to represent technical change: product and process innovation activities. Vivarelli (2014) states in his literature review that the main member countries of the Organization for Economic Cooperation and Development (OECD) showed a significant change in the composition of the labor force in favor of the skilled component of the labor force. However, there is no robust evidence yet on the differential effect of product and process innovation on the different types of workers. The following work aims to contribute in this regard.

Finally, this paper deals with a period of economic turmoil. There is some consensus that innovation efforts are procyclical (Archibugi et al., 2013; van Ophem et al., 2019) mainly because of low demand expectations during turmoil (Cohen, 2010) and internal and external financial constraints (Himmelberg and Petersen, 1994; Aghion et al., 2012). Regarding the type of innovation output, Lucchese and Pianta (2012) show that, during downswing periods, firms introduce more process innovation and less product innovation. Also, Peters et al. (2014) argue that the positive effect of product innovation on employment would be higher in upswing periods because of higher potential for demand expansion and extra-normal profits, while process innovation would destroy more employment during downswings, because in shrinking markets, firms would fully use the potential of new process technologies to cut labor costs. Regarding the relationship between skills and the economic cycle, Jaimovich and Siu (2018) highlight that in the last 30 years in the US labor market, almost all the contraction in aggregate employment during recessions can be attributed to job losses in middle-skilled, routine occupations followed by jobless recoveries (Groshen and Potter, 2003). In this same line, Foote & Ryan (2015) highlight the relationship between labor market polarization and non-participation, as middle-skilled workers find it hard to increase education to become high-skilled and would face large salary cuts if competing against low-skilled workers.

3. The Spanish case

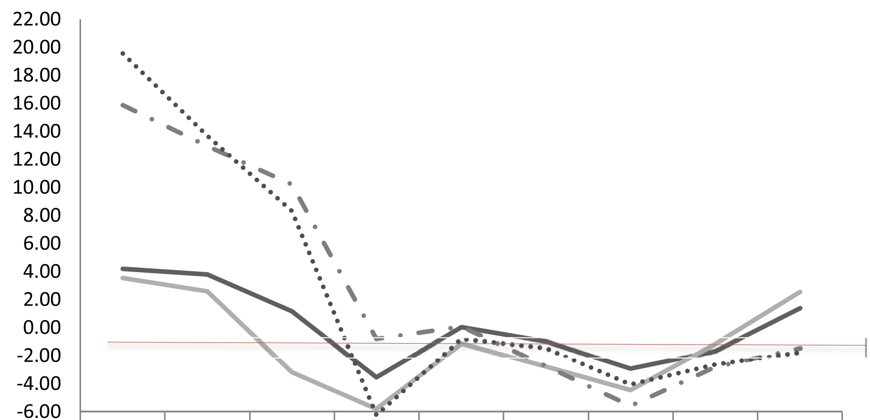
Fig. 1 shows the evolution of GDP, employment, GERD and BERD in Spain from 2006 to 2014. While in 2006 and 2007 all indicators grew considerably, employment started to decline in 2008 and did not recover positive rates of growth until 2014. The rest of the indicators started their negative growth in 2009, and GERD and BERD still showed negative growth rates in 2014.[5] The period covered by our analysis is characterized by a hard economic crisis.

The analysis of the relationship between innovation and employment in Spain has received some attention in recent years. Trigueros et al. (2014) analyze data from the Spanish Survey of Business Strategies (ESEE) for the period 1990–2008 and conclude that process innovation shows a larger positive employment effect than product innovation, especially for SMEs. Bianchini and Pellegrino (2019) use the same database for a longer period (1991–2012) and find a positive effect of product innovation on employment but no evidence of an effect of process innovation. Harrison et al. (2014) use data from four European countries. Data for Spain come from the Community Innovation Survey for the period 1998–2000. The results show a positive effect of product in-

[3] The reduction of the labor demand related to the old products.

[4] However, even a strict neutral technological change would increase skilled labor demand more (Welch, 1970; Vivarelli, 2014).

[5] In 2010, there was practically zero growth rate in GDP and GERD.



	2006	2007	2008	2009	2010	2011	2012	2013	2014
GDP	4.17	3.77	1.13	-3.57	0.02	-1.00	-2.93	-1.70	1.38
EMPLOYMENT	3.52	2.59	-3.20	-5.81	-1.14	-2.79	-4.48	-1.18	2.53
GERD	15.87	12.93	10.19	-0.81	0.05	-2.77	-5.59	-2.84	-1.47
BERD	19.55	13.67	8.31	-6.27	-0.81	-1.47	-4.08	-2.65	-1.77

Fig. 1. Growth rates of some selected indicators of the Spanish economic and innovative evolution.
Source: Source: Own elaboration based on data from INE and EUROSTAT.

novation and no effect of process innovation. Pizarro (2013) uses data from the Spanish Panel of Technological Innovation for the period 2004–2010. He finds a positive and similar effect of both new-to-the- market and new-to-the-firm products and a negative effect of process innovation. Finally, Calvino (2019) uses data from the Spanish Panel of Technological Innovation (PITEC) for the period 2004–2012. He focuses not only on the average but on the entire distribution of employment growth. He concludes that product innovation shows a positive effect on employment, especially for fast-growing and shrinking firms. The results for process innovation are, however, mixed. None of the previous studies distinguish the effect of innovation on bad times, nor do they distinguish between types of workers. Shedding light on these issues would be the main goal of this work.

4. The dynamic output oriented model of innovation and employment

The adopted framework is based on the model by Harrison et al. (2014). In their magisterial article, the authors proposed a new vision for analyzing the relationship between innovation and employment using innovation surveys. In the model, it is assumed that a firm can produce old and new products. We identify those firms with $i=1$ (old) and $i=2$ (new). Two periods of time, $t=1$ and $t=2$, are established (a firm can introduce new products between). In the first period, all the products are old (Y_{11}). However, in the second period, firms can produce either new (Y_{22}) or old (Y_{12}) products if the firm has not introduced any new products between the two years (Harrison et al., 2014).

It is assumed that capital (K), labor (L) and intermediate inputs (M) present constant return to scale in the production of technology. Also, the production function can be divided into two separable equations with different technological productivity (Hicks-neutral parameter (Θ) .

$$Y_{it} = \theta_{it} F(K_{it}, L_{it}, M_{it}) e^{\eta+\omega_{it}} \tag{1}$$

Furthermore, η is a fixed effect that captures the idiosyncrasy of the firm. The last parameter represents all the factors –non-observables– that make a firm more productive than the average firms using the same technology (in this case Θ). ω represents unanticipated productivity shocks[6] ($E(\omega_{it})=0$).

According to Harrison et al. (2008), firms invest in research and development in order to generate product and process innovation. This is the reason why a firm can influence the efficiency of production of both old and new products. The main interest of the model is to compute the change in the efficiency of producing old products θ_{12}/θ_{11}, and also the relative efficiency of producing old and new products θ_{22}/θ_{11}.

In order to calculate the employment equation, it is assumed that the decisions of inputs (employment, capital and intermediate inputs) are made to minimize cost, taking into account individual productivity effects η and productivity shocks ω. Given the technology, the cost function takes the form:

$$C(w_{it}, Y_{it}, \theta_{it}) = c(w_{it}) \frac{Y_{it}}{\theta_{it} e^{\eta+\omega_{it}}} + F_i \tag{2}$$

where $\frac{c(w)}{\theta_{it} e^{\eta+\omega_{it}}}$ is the marginal cost which is in function of the price w, and F is the fixed cost. Applying Shephard's lemma, the labor demand equation can be expressed for old products as

$$L_{1t} = c_{wL}(w_{1t}) \frac{Y_{1t}}{\theta_{1t} e^{\eta+\omega_{1t}}} \tag{3}$$

In the same way, the labor equation of new products is:

$$L_{22} = c_{wL}(w_{22}) \frac{Y_{22}}{\theta_{22} e^{\eta+\omega_{22}}} \tag{4}$$

The expression $c_{wL}(.)$ represents the derivative of $c(.)$ with respect to the wage. It is supposed that the price of inputs is constant in all the years $c_{wL}(w_{11}) = c_{wL}(w_{12}) = c_{wL}(w_{22})$. Decomposing employment growth into two years $t=1$ and $t=2$:

$$\frac{\Delta L}{L} = \frac{L_{12}+L_{22}-L_{11}}{L_{11}} = \frac{L_{12}-L_{11}}{L_{11}} + \frac{L_{22}}{L_{11}} \simeq ln\frac{L_{12}}{L_{11}} + \frac{L_{22}}{L_{11}} \tag{5}$$

In theory, the growth rate of new products is defined as L_{22}/L_{11}. Replacing Eqs. (3) and (4) in (5), and applying logarithms:

$$\frac{\Delta L}{L} \cong -(\ln\theta_{12} - \ln\theta_{11}) + (lnY_{12} - \ln Y_{11}) + \frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}} - (\omega_{12} - \omega_{11})$$

[6] The parameter captures all the non-observable changes of the productivity function that are not related to technological change, for example, industrial organization, work problems and so on.

Table 2
Empirical evidence related to micro level studies: the effect of innovation on manufacturing employment (European countries).

Study	Sample	Period	Country	Process Innovation Only	Sales growth due to new products	Const
Harrison et al. (2014)	Complete sample	1998–2000	France	−1.31	0.98*	−3.52*
		1998–2000	Germany	−6.19*	1.01*	−6.95*
		1998–2000	Spain	2.46	1.02*	−6.11*
		1998–2000	United Kingdom	−3.51*	0.99*	−6.30*
Pizarro (2013)		2004–2010	Spain	−3.73*	0.90*	−5.44*
Hall et al. (2008)		1995–2003	Italy	−1.22*	0.95*	−2.80*
Dachs et al. (2016)	High-tech	1998–2010	EU	−1.026	0.99*	−22.33*
Dachs et al. (2016)	Low-tech	1998–2010	EU	−1.179*	0.98*	−21.03*

* p-value < 0.05.

$$(6)$$

According to Harrison et al. (2008), Eq. (4) describes the growth of employment in four terms: firstly, the change on efficiency of old products in the production process $-(\ln\theta_{12} - \ln\theta_{11}$; secondly, the rate of change of the demand of old products $(lnY_{12} - \ln Y_{11})$; thirdly, the increase of production related to new products $\frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}}$; and finally, the impacts of non-technological perturbation of productivity $-(\omega_{12} - \omega_{11})$. Eq. (6) can be represented in the following form:

$$l = \alpha_0 + \alpha_1 d + y_1 + \beta y_2 + u \tag{7}$$

where l stands for the employment growth rate over the period (between the year $t=1$ and $t=2$), y_1 and y_2 are the rates of output growth for old and for new products, and u is the unobserved random disturbance $(u = -(\omega_{12} - \omega_{11}) + \xi)$. The parameter α_0 represents (minus) the average efficiency growth in production of the old product. The binary variable d picks up the additional effect of process innovations related to old products by means of the efficiency parameter α_1. Variable d is equal to one if the firm has implemented a process innovation not associated with a product innovation (process innovation only). Finally, the parameter β captures the relative efficiency of the production of old and new products (Harrison et al., 2014). As can be seen in Eq. (7), the coefficient of y_1 is equal to one. Therefore, this equation can be written as the following regression:

$$l - y_1 = \alpha_0 + \alpha_1 d + \beta y_2 + u \tag{8}$$

Eq. (8) is the function to estimate. It is expected that the efficiency of new processes increases more for innovative firms because of spillovers and other factors. In other words, according to Harrison et al. (2008, 2014) the ratio $(\Theta_{21}/\Theta_{22})$ determines the impact of product innovation on employment growth or relative efficiency in producing old and new products. The ratio is less than the unity if the new products are produced more efficiently than old products.

5. Previous results based on this model

This section offers a short synthesis of the results obtained by studies that follow the model of Harrison et al. (2008, 2014). The results of the studies on developed and developing countries differ in a certain way and therefore they are presented in two different tables (Tables 2 and 3) .[8]

The studies for European countries (Table 2) usually show a negative effect of process innovation on employment,[9] a positive effect of product innovation with the coefficient around one (meaning that the production of new products is as efficient as the production of old products) and a negative constant, which means that the efficiency in the production of old products increases, thus leading to employment destruction without innovation. The studies for Latin American countries (Table 3) show very heterogeneous results. For example, the coefficients of process innovation vary broadly with values from −2.7 in Uruguay to 18.4 in Costa Rica (Crespi and Tacsir, 2012). Regarding product innovation, the effect is always positive, but the coefficient varies from 0.549 in Benavente and Lauterbach (2008) to 1.75 in Crespi and Tacsir (2012) .[10] This huge heterogeneity might be due to the fact that there are other crucial forces behind employment dynamics in these countries, such as trade, or the location of multinationals.[11]

In the case of Europe, only one study (Dachs et al., 2016) offers additional analysis based on two subsamples of firms: those belonging to either low- or high-tech sectors. This study showed that process innovation has only a significant and negative impact on employment for low-tech sectors. The sales growth due to new products is significant and close to one and the constant is negative (significant) for both sectors. Four studies offer some estimation of the differences of the effect of innovation on skilled and unskilled workers in Latin America. However, no clear picture emerges. In the case of process innovation, the estimations are rather imprecise.[12] In the case of sales growth due to new products, the coefficients, except for one, are positive and statistically significant. The results might somehow reflect a bias to high-skilled workers because the values of the coefficients are greater for high-skilled workers. All in all, these few studies do not allow us to establish stylized facts regarding the differential effect of technological change in different industries or in labor composition. Again, other crucial forces might be behind high- and low-skilled employment dynamics, such as specialization trends within the globalizing economy, where a large number of low-skilled, routinized jobs are relocated to low-income countries like those in Latin America.

6. Methodological framework of the application of the model for Spain

6.1. Data base and specification of the model

In this section, we present the model of Harrison et al. (2008, 2014). The firm-level panel data set is based on the Spanish Inno-

[8] It is important to mention that the results which are captured in Tables 2 and 3 include for each study only one model, selecting the "best model" for the estimations with instrumental variables. For more detail about the rest of the studies, see Appendix Table 1a.

[9] The coefficient was negative for five of the eight models: in the other three models, the coefficient was not significant.

[10] We eliminate the "constant" column because the majority of the studies on Latin America countries applied dummy variables to control for time and/or sectors. If a control dummy is introduced in the model, the interpretation of the constant changes completely. To assure the same interpretation of the constant, the dummy variables should have been introduced in a specific way so that their sum is zero.

[11] We thank one referee for highlighting this point.

[12] Despite having positive and large coefficients for high-skilled workers, these coefficients are non-significant. On the other hand, the coefficient for unskilled workers is positive and very significant for Argentina, but negative and significant for Uruguay

Table 3
Empirical evidence related to micro level studies: the effect of innovation on manufacturing employment (Latin American countries).

Study	Sample	Period	Country	Process Innovation Only	Sales growth due to new products
Crespi and Tacsir (2012)	All sample	1998–2001	Argentina	1.398	1.17*
Crespi and Tacsir (2012)		1995–2007	Chile	0.333	1.751*
Crespi and Tacsir (2012)		2006–2007	Costa Rica	18.413*	1.015*
Crespi and Tacsir (2012)		1998–2009	Uruguay	−2.716*	0.961*
de Elejalde et al. (2015)		1998–2001	Argentina	1.252	1.151*
Aboal et al., 2015;		1998–2009	Uruguay	-2.610*	0.964*
Alvarez et al. (2011)		1995–2007	Chile	0.297	1.74*
Benavente and Lauterbach (2008)		1998–2001	Chile	0.132	0.549*
Fioravante and Maldonado (2008)		2001–2003	Brazil	0.0012	0.933*
de Elejalde et al. (2015)	High-tech	1998–2001	Argentina	3.767	1.143*
Aboal et al. (2015)		1998–2009	Uruguay	-2.721*	0.962*
Alvarez et al. (2011)		1995–2007	Chile	0.028	1.734*
de Elejalde et al. (2015)	Low-tech	1998–2001	Argentina	0.323	1.145*
Aboal et al. (2015)		1998–2009	Uruguay	-2.498	0.877*
Alvarez et al. (2011)		1995–2007	Chile	−0.551	1.356*
Crespi and Tacsir (2012)	All sample_skilled	1998–2001	Argentina	3.048	1.308*
Crespi and Tacsir (2012)		2006–2007	Costa Rica	2.448	1.126*
Crespi and Tacsir (2012)		1998–2009	Uruguay	10.465	1.01*
de Elejalde et al. (2015)		1998–2001	Argentina	−1.125	0.963*
Aboal et al. (2015)		1998–2009	Uruguay	2.379	1.087*
Alvarez et al. (2011)		1995–2007	Chile	2.296	1.81*
Crespi and Tacsir (2012)	All sample_unskilled	1998–2001	Argentina	26.26*	1.02*
Crespi and Tacsir (2012)		2006–2007	Costa Rica	2.379	1.087*
Crespi and Tacsir (2012)		1998–2009	Uruguay	−3.373*	0.929*
de Elejalde et al. (2015)		1998–2001	Argentina	0.755	0.952*
Aboal et al. (2015)		1998–2009	Uruguay	-3.373*	0.929*
Alvarez et al. (2011)		1995–2007	Chile	−1.792	1.299
de Elejalde et al. (2015)	High-tech_skilled	1998–2001	Argentina	7.88	1.327*
Aboal et al. (2015)		1998–2009	Uruguay	13.813	1.245*
Alvarez et al. (2011)		1995–2007	Chile	3.983	1.906
de Elejalde et al. (2015)	High-tech_unskilled	1998–2001	Argentina	8.171	1.246*
Aboal et al. (2015)		1998–2009	Uruguay	−4.271	0.898*
Alvarez et al. (2011)		1995–2007	Chile	−5.288	0.696
de Elejalde et al. (2015)	Low-tech_skilled	1998–2001	Argentina	1.564	1.266*
Aboal et al. (2015)		1998–2009	Uruguay	-8.642	0.892*
Alvarez et al. (2011)		1995–2007	Chile	−1.776	1.581
de Elejalde et al. (2015)	Low-tech_unskilled	1998–2001	Argentina	0.523	1.143*
Aboal et al. (2015)		1998–2009	Uruguay	-6.127	0.968*
Alvarez et al. (2011)		1995–2007	Chile	2.635	1.686

* Means significant.

vation Survey –available on line[13] conducted by the Spanish Foundation of Science and Technology and the National Statistics Institute. We use the data of the so-called "Panel of Technological Innovation" (PITEC) for the time span of 2006–2014. Similar to the model of Harrison et al. (2008), we classify the firms into five categories: non-innovators, only process innovators, product innovators, only product innovators, and a category that includes both (product and process innovators). Additionally, the PITEC data allows us to obtain the sales growth related to new and old products. Finally, the PITEC provides information on the percentage of workers with a university degree, which allows us to analyze the differential effect of innovation on workers with and without a degree (high-skilled vs low-skilled).

In order to interpret the results correctly, it should be highlighted that PITEC takes account of product and process innovations developed during the three previous years. For this reason, growth rates are estimated for a three-year period (*t*–3). Another important aspect is that, in order to have a more homogeneous data set, the analysis is only applied to manufacturing firms. We exclude service sector firms because the characteristics of innovation[14] are very different in this sector (Cainelli et al., 2005). The original model of Harrison et al. uses cross-section data, while in our case, we work with panel data as other authors[15] did with other countries.

Table 2a (in the appendix) describes the information of the sample (all the statistics come from the PITEC). The number of innovative firms represents more than 50% in the whole sample. It is clear from the data that we are dealing with a period characterized by an economic crisis: employment growth has been negative through all the three-year windows. This decrease is more remarkable in non-innovators than in innovating firms. In terms of sales, the average growth taking into account the whole sample is −2.85%. In the first three periods (2006–2009, 2007–2010 and 2008–2011), sales have a negative growth rate. Afterwards, the sales growth rate becomes positive. The sales growth rate due to old products (on average) has decreased 19.64% while the sales growth rate due to new products (on average) has increased 24.62%. An important aspect is that the sales growth rates due to old products are always negative and they are smaller than sales growth rates due to new products. To summarize, Table 2a shows that employment growth is negative, but it is higher for innovative firms than for non-innovative firms. Even so, this effect is more intense in firms with product innovations than in firms with process innovations. Another important aspect is related to the sales of innovative firms. In the case of the demand for old products, they always decrease. However, the demand for new products increases.

[13] https://icono.fecyt.es/pitec.

[14] For example, in such sectors, it is often difficult to distinguish clearly between process and product innovation.

[15] Hall et al. (2008), Crespi and Tacsir (2012), de Elejalde et al. (2015), Aboal et al. (2015), Alvarez et al. (2011).

6.2. Specification of the model: instrumental variables

As we stated before, this article is based on the Harrison et al. model. It is important to mention that the original work uses cross section data. In our case, we are going to work with panel data (because of the PITEC) as other authors did with other countries (Hall et al., 2008; Crespi and Tacsir, 2012; de Elejalde et al., 2015; Aboal et al., 2015; Alvarez et al., 2011). However, our model has to face specification problems, as does Harrison's.

Firstly, we do not directly have either y_1 or y_2. In the latter, we observe only the increase of sales. This variable may include the effect of different prices for both new and old products. In the former, we only have the nominal growth of old products. As we can see, both problems are related to unavailability of firm prices. To solve this problem, we will use the prices at the industrial level (π) to deflate the growth of sales due to old products (substitute g_1 for y_1). Furthermore, we will substitute g_2 for y_2 because we observe sales growth due to new products (Harrison et al., 2014). Taking into account these changes, we obtain Eq. (9):

$$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i \tag{9}$$

Eq. (9) still has several issues to be addressed. In the first place, β is biased because there is a problem of measure (error in variables) in g_2. This variable also included unanticipated shocks. Both problems mentioned earlier would create an endogeneity problem. To avoid this, we will seek instruments correlated with y_2, but not correlated with ε_i when we substitute g_2 for y_2.

Moreover, there is another problem related to g_1. If there is a divergence between the prices of the firm and the industry, it would cause an identification problem. In other words, we would underestimate the displacement effect of process innovation. We follow Harrison et al. (2014) assuming that in the absence of firm-level price information, we can only identify an effect of process innovation on employment net of (direct) compensating firm-level price variation.[16]

The solution to the problem is to apply the methodology of instrumental variables. Harrison et al. (2014) recommend some variables to be used as instruments. Their preferred instrument is increased range of products, although they check robustness by trying other instruments, such as an increased market share, improved quality of products, clients as a source of information and others.[17]

There are two main theoretical reasons to support the use of increased range of products as an instrument. First, the degree by which product innovation is aimed to increase the range of products is likely to be correlated with planning (R&D, design, and marketing exploration) and the expectations of sales. Second, enlarging the range of products does not imply any particular direction of the changes in prices (increased market share is likely to be correlated with lower prices and improved quality with possibly higher prices). It also seems unlikely that the range of products is correlated with unanticipated productivity shocks (Harrison et al., 2014).

Also, the instruments must satisfy the inclusion and exclusion restrictions. The first refers to the relation between the endogenous variable and the instrument, which has to be significant ($cov(z_{i,} g_2) \neq 0$). The second postulate is associated with the relation of the instrument and the residual of the structural equation, which has to be zero ($cov(z_{i,} \varepsilon_i) = 0$). This means that there is no information in the instrument that would explain the structural equation.

[16] For more information about these problems, see Harrison et al. (2008; 2014).

[17] To see more details, see the table of instrumental variables in the empirical studies.

7. The empirical results for Spain

In this section, we present the results for the Spanish case, applying the following different methodologies in order to obtain robust estimations: ordinary least squares with panel data (OLS), OLS with instrumental variables (OLSIV), panel data models of fixed effects (FE) and random effects (RE) ,[18] and RE with instrumental variables (REIV). The instruments that are applied in our model are the importance of the increased range of goods and services as an objective and the importance of clients as a source of information. The first of these instruments was used by all the studies that applied the model of Harrison et al. (2008, 2014), while the second one was used less frequently.[19]

We will carry out three different analyses. First, we are going to replicate the original work of Harrison et al. (2014) but using panel data for Spain in a period affected by the crisis (2006 to 2014). Second, we will estimate the effect of innovation on different types of workers (separating high- and low-skilled employment). Using the variable that reflects the "percentage of paid staff with higher education," we calculate the number of high- and low-skilled workers for each firm. They are used as dependent variables to estimate the effect of innovation on the employment dynamics of each type of worker. Third, we estimate the models earlier mentioned by sectors based on the R&D intensity of their firms.[20] We estimated additional models for four subsamples: high-tech, medium high-tech, medium low-tech, and low-tech, following the classification of the OECD.

7.1. Global effect of innovation on employment

The results of the estimations of Eq. (9) are presented in Table 4. The endogenous variable is the employment growth rate (l) minus the sales growth rate due to old products (g_1) and inflation (π) ($l - g_1 - \pi$). The independent variables are only process innovation (d) and sales growth rate due to new products (g_2). All the estimations include time and industry dummies. As in Harrison et al. (2014), the coefficients of time and sector dummies were restricted to add up to zero to maintain the interpretation of the constant term.

We present the estimations of OLS, FE and RE, although they suffer from measurement errors and include unanticipated shocks which might likely result in biased results. For this reason, we focus our discussion on the results of the estimations that include instrumental variables.[21] The results of the IV estimations[22] (iv^a and $reiv^a$) are in columns 2 and 6.

A first result is that the parameter of "only process innovation" (d) for both models (iv^a and $reiv^a$) has a negative sign (−0.0540

[18] The regression with fixed effects with instrumental variables looks too demanding for the data at hand, especially when estimating the effect of only process innovation (standard errors more than doubled compared with fixed effects estimation or IV estimation). This situation happens in all the estimations when fixed effects are used. For this reason, we are going to omit the results of fixed effects with instrumental variables for the next estimations.

[19] Like Dachs and Peters (2014), Harrison et al. (2008, 2014), Peters et al. (2017). Moreover, for this paper, some other instruments were tested, like quality of goods and services as an objective and innovation effort (research and development expenditure over sales), but they did not satisfy the assumptions (exclusion and inclusion restrictions), especially the Sargan Test.

[20] As did Dachs et al. (2016), Elejalde et al. (2015), Aboal et al. (2015), Alvarez et al. (2011).

[21] There is a difference between their instrument and ours. We took only the extreme values of the variable. To do it more clearly, we constructed a variable which takes only two values (1 or 4). If the value of the variable is 1, it is put in the new variable 1, but if the instrument is 4, the new variable is 0.

[22] In the case of IV estimations, the test of endogeneity is shown for all of them whose null hypothesis is exogeneity of the variable. In the case of our models, the null hypothesis is rejected, so it is possible to say that sales growth due to new products is an endogenous variable, as we assumed theoretically.

Table 4
The effects of innovation on employment of manufacturing (t–3)[c].

Dependent variable: l-g1-π Variables	ols(1)	iv[a] (2)	iv[b](3)	fe(4)	re(5)	reiv[a](6)	reiv[a](7)
d	−0.0742***	−0.0540***	−0.0556***	−0.0552***	−0.0668***	−0.0440***	−0.0441***
	[0.00662]	[0.00956]	[0.00900]	[0.0105]	[0.00836]	[0.0124]	[0.0115]
g2	0.803***	0.888***	0.881***	0.780***	0.793***	0.895***	0.895***
	[0.00817]	[0.0285]	[0.0255]	[0.0139]	[0.0109]	[0.0391]	[0.0335]
cons	0.0847***	0.0686***	0.0673***	0.0824***	0.0872***	0.0639***	0.0599***
	[0.00295]	[0.00723]	[0.00655]	[0.00365]	[0.00396]	[0.00961]	[0.00849]
Tests of endogeneity		9.20	10.18			−3.090	−3.47
p-value		0.002	0.001			0.002	0.001
Test of Sargan		0.020	0.999			0.276	0.641
p-value		0.888	0.802			0.599	0.887
First-Stage		615.0	418.2			402.84	589.87
p-value		0.000	0.000			0.000	0.000
H0: g2=1	580.7	15.50	21.86	251.2	360.1	7.263	9.919
p-value	0.0000	0.0001	0.0000	0.0000	0.0000	0.00704	0.00164
N	27,805	27,805	27,805	27,805	27,805	27,805	27,805
R-sq	0.412	0.409	0.409	0.341			

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.
[c] We have performed a robustness check, analyzing only firms that stay in the panel for the whole period. The results of the estimations are very similar for all the models (general employment, high- and low-skilled employment).

and −0.0440 respectively). This means an additional increase in productivity of old products, which generates an additional reduction on employment, in line with the results of previous studies. In our estimation (iv[a] and reiv[a]), the sign of g_2 –which measures the employment effect of product innovation– is positive in both models and offers very similar significant values smaller than one. As in Harrison et al. (2014), the magnitude of this coefficient is higher with IV estimations than with OLS or RE estimations. This is consistent with the expected correction of the downward bias related to the error-in-variable problem and includes an adjustment for unanticipated shocks.

In the structural model, the coefficient of g_2 reflects the ratio between the efficiency of the production of old and new products. If this coefficient –the sales growth rate due to new products– is less than one, it means that the efficiency of the production of new products is greater than the old ones. Our general model shows values below one (for iv[a] 0.888, and for reiv[a] 0.895). In fact, when we apply an F-test for both models, the null hypothesis is rejected.[23] Therefore, there is evidence to state that new products are produced more efficiently than old ones.

Third, the constant term for both models (iv[a] and reiv[a]) is positive and has similar statistically significant values. This implies, within the theoretical and conceptual framework of the model, that the model detects a loss of efficiency of the production of old products. This decrease of productivity means that –*ceteris paribus*– the production process is more labor-intensive, requiring more employees. Most studies obtained, as expected by the theory, a negative coefficient for the constant term, indicating continuous productivity growth. The results obtained in this study seem to be specific to recession periods (Peters et al., 2017). Those authors explained this unexpected result by the existence of so-called 'labor hoarding'. This concept means that in recession periods firms might reduce their staff by less than the number required by the reduction of demand (Bhaumik, 2011) with the aim of retaining workers for the following expansion period, because this may be a better choice than firing, hiring and training new workers after the recession has subsided (Biddle, 2014). In other words, labor hoarding is understood as the holding of workers that are not necessary for production during the recession period (Horning, 1994).

In order to provide some additional statistical evidence for the consistency and robustness of our results, we add a second instrument to our estimations: importance of clients as a source of information.[24] The estimations are in Table 4, in columns 3 and 7 (iv[b] and reiv[b]). The results are practically the same as those described previously with only one instrument (increased range). Regarding the exclusion restriction, the Sargan test reflects the validity of the instruments, and the inclusion restriction satisfies the requirements of the specifications.

To summarize, the effect of process innovation on employment is negative and the effect of sales growth due to new products is positive, with the magnitude of these two effects much in line with previous studies for Europe. The constant terms suggest the existence of labor hoarding during the period analyzed.

7.2. Effect of innovation on employment by skill level

In the previous section, we show that the results of the Harrison et al. model using Spanish data agree with those obtained by previous literature. In what follows, we will address the main goal of this work: to analyze the effect of innovation on low-skilled and high-skilled workforces. As we mentioned before, we have at our disposal a variable that allows us to divide the total employment into two categories, high-skilled and low-skilled. We modify Harrison et al. model to obtain Eqs. (10) and (11).

$$l^{hs} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i^{hs} \quad (10)$$

$$l^{ls} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i^{ls} \quad (11)$$

where l^{hs} is the high-skilled employment growth rate and l^{ls} is the low-skilled employment growth. That is, we do not analyze the evolution of the ratio of workers that pertain to a specific skill level (which is dependent on the evolution of the specific type of employment but also on the general evolution of employment), but rather the growth rates of the absolute number of high-skilled and

[23] The coefficient is less than one because the null hypothesis of the F-test is rejected, saying that g2 is equal to one.

[24] The way to calculate this instrument is the same as increased range (taking only extreme values).

Table 5
The effects of innovation on high-skilled employment of manufacturing (t–3).

Dependent variable: l-g1-π Variables	ols(1)	iv[a] (2)	iv[b](3)	fe(4)	re(5)	reiv[a](6)	reiv[a](7)
d	−0.0658***	−0.00373	−0.0207	−0.0561*	−0.0617**	0.016	−0.00704
	[0.0172]	[0.0269]	[0.0250]	[0.0256]	[0.0195]	[0.0318]	[0.0291]
g2	0.846***	1.092***	1.024***	0.801***	0.831***	1.151***	1.056***
	[0.0187]	[0.0841]	[0.0740]	[0.0273]	[0.0217]	[0.106]	[0.0909]
cons	0.207***	0.150***	0.164***	0.207***	0.190***	0.117***	0.135***
	[0.00744]	[0.0215]	[0.0192]	[0.00784]	[0.00897]	[0.0268]	[0.0234]
Tests of endogeneity		8.834	6.044			−3.120	3.630
p-value		0.003	0.014			0.002	0.000
Test of Sargan		0.120	3.719			0.141	3.676
p-value		0.728	0.293			0.708	0.299
First-Stage		409.491	276.208			296.730	441.150
p-value		0.000	0.000			0.000	0.000
H0: g2=1	67.79	1.190	0.108	53.12	60.94	2.031	0.384
p-value	0.0000	0.275	0.742	0.0000	0.0000	0.154	0.535
N	23,093	23,093	23,093	23,093	23,093	23,093	23,093
R-sq	0.122	0.113	0.117	0.096			

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

Table 6
The effects of innovation on low-skilled employment of manufacturing (t–3).

Dependent variable: l-g1-π Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
d	−0.0729***	−0.0658***	−0.0619***	−0.0597***	−0.0682***	−0.0613***	−0.0532***
	[0.00798]	[0.0116]	[0.0110]	[0.0123]	[0.00981]	[0.0148]	[0.0122]
g2	0.828***	0.858***	0.874***	0.791***	0.813***	0.847***	0.882***
	[0.00998]	[0.0360]	[0.0321]	[0.0165]	[0.0128]	[0.0480]	[0.0386]
cons	0.0815***	0.0759***	0.0683***	0.0819***	0.0850***	0.0741***	0.0614***
	[0.00362]	[0.00897]	[0.00808]	[0.00430]	[0.00471]	[0.0117]	[0.00954]
Tests of endogeneity		0.727	0.929			−3.170	−3.630
p-value		0.394	0.818			0.002	0.000
Test of Sargan		0.009	0.929			0.027	2.310
p-value		0.923	0.818			0.870	0.511
First-Stage		602.473	409.129			396.570	581.560
p-value		0.000	0.000			0.000	0.000
H0: g2=1	296	15.46	15.31	161.4	211.5	10.14	9.293
p-value	0.000	0.000	0.000	0.000	0.000	0.001	0.002
N	27,603	27,603	27,603	27,603	27,603	27,603	27,603
R-sq	0.331	0.331	0.33	0.265			

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

low-skilled workers. As with the previous results for general employment, these estimations contain variables that control the difference between sectors and time (using dummy variables for each of these). Also, we estimate the model for high- and low-skilled with diverse methodologies (OLS, OLSIV, FE, RE, REIV).

Tables 5 and 6 show the results of the effect of innovation on labor composition (high- and low- skilled workers). We focus the discussion on our preferred specifications from columns 6 and 7, where both random effects and instrumental variables are used. In the case of process innovation, a negative effect is found for low-skilled employment, which means a labor-saving effect for this kind of worker. By contrast, no effect of process innovation on high-skilled employment is found. That is, the displacement effect of process innovation exists for low-skilled workers only.

The effect of sales growth due to new products is positive and significant for the employment growth for high- and low-skilled workers. It is important to mention that new products are less efficient in high-skilled than in low-skilled workers because the estimated coefficients are lower for low-skilled than for high-skilled employment. It means that there is no evidence found of labor displacement of product innovation for high-skilled workers. In the case of low-skilled workers, this coefficient is less than one, so the efficiency production of new products is higher than old ones, resulting in less labor demand for low-skilled workers (see the F-test for all the estimations). In other words, new products are relatively more demanding of high-skilled workers and less demanding of low-skilled workers.

The constant is significant and positive for both high- and low-skilled workers. However, the effect is greater for high-skilled workers than for low-skilled workers. It means that there is a stronger labor hoarding effect for high-skilled employment than for low-skilled employment during the period analyzed. In fact, Rinne and Zimmermann (2012) highlight that in German labor hoarding, it is especially important for high-skilled workers, as

Table 7
The effects of innovation on general, high-, and low-skilled employment of manufacturing (Yt–3) by sectors.

Dependent variable: l-g1-π Sector	Total employment Variables	High-skilled workers reiv[b](1)	Low-skilled workers reiv[b](2)	reiv[b](3)
High-tech	d	−0.0201	0.18	−0.0795
		[0.0708]	[0.134]	[0.0977]
	g2	0.931***	1.396***	0.786**
		[0.191]	[0.364]	[0.270]
	cons	−0.0222	−0.0971	0.0789
		[0.0654]	[0.128]	[0.0950]
	H0: g2=1	0.130	1.187	0.631
	P-value	0.718	0.276	0.427
HighM-tech	d	−0.038	0.029	−0.0698*
		[0.0224]	[0.0535]	[0.0278]
	g2	0.907***	1.092***	0.870***
		[0.0540]	[0.139]	[0.0691]
	cons	0.0599***	0.140***	0.0698***
		[0.0160]	[0.0411]	[0.0200]
	H0: g2=1	2.979	0.437	3.532
	P-value	0.0843	0.509	0.0602
LowM-tech	d	−0.0527**	−0.0181	−0.0409
		[0.0197]	[0.0544]	[0.0224]
	g2	0.881***	1.149***	0.929***
		[0.0597]	[0.197]	[0.0700]
	cons	0.0701***	0.149***	0.0564***
		[0.0143]	[0.0435]	[0.0162]
	H0: g2=1	3.940	0.572	1.023
	P-value	0.0471	0.450	0.312
Low-tech	d	−0.0448*	−0.0523	−0.0452*
		[0.0184]	[0.0485]	[0.0214]
	g2	0.892***	0.906***	0.878***
		[0.0584]	[0.160]	[0.0701]
	cons	0.0594***	0.144***	0.0589***
		[0.0136]	[0.0394]	[0.0161]
	H0: g2=1	3.447	0.341	3.033
	P-value	0.0633	0.559	0.0816

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[b] Instruments used are increased range and clients as a source of information.

firms are afraid of a future shortage of skilled workers in the industries and regions most affected by the crisis.[25]

To sum up, we find that process innovation destroys low-skilled employment but has no effect on high-skilled employment, while product innovation increases both types of employment, but it is relatively more demanding of high-skilled workers. Finally, a labor hoarding effect is found for both types of workers, but this effect is larger for high-skilled workers.

7.3. Analysis by subsamples based on the R&D intensity of the sectors

Once we have assessed the impact of innovation (product and process innovation) on employment (general, high-skilled and low-skilled employment), it is important to know whether there is a differential effect at the sector level, the same as Dachs et al. (2016) (although the classification is different). As we mentioned earlier, the sample was divided into four categories, high-tech, medium high-tech, medium low-tech, and low-tech sectors (it is made based on the OCDE classification) .[26] To save space in Table 7, the results are reported only for instrumental variable estimations with random effects (increased range and clients as a source of information as instrumental variables[27]).

For process innovation, no effect is found for high-skilled workers in any sector. It suggests that there is no evidence of labor displacement due to process innovation for high-skilled employment even in low-tech sectors. On the other hand, for low-skilled employment, a displacement effect of process innovation is found in all sectors, except in the high-tech sector. Similar results are achieved for the general model with the exception that for medium low-tech a non-significant effect is found.

A positive and significant effect is found for sales growth due to new products for all sectors. The coefficient is bigger for high-skilled than for low-skilled in every industry, with the difference being much higher in high-tech industries. Also, its value is more than one for high-skilled employment, meaning that new products do increase demand for high-skilled workers. In the general case, the value of sales growth due to new products is one (see F-test). There is no evidence that new products are produced more efficiently than the old ones at the sector level.

In the case of the constant, a positive (significant sign) is usually found, with values higher for high-skilled than for low-skilled workers. The only exception is for the high-tech industry, where both coefficients are not statistically different from zero. To sum up, these results show that the general relationships between innovation and different types of workers hold across industries. The differential effect of product innovation between high- and low-skilled workers is remarkably larger in high-tech industries.

7.4. Employment growth decomposition

Estimating Eq. (9), it is possible to decompose employment growth into several components (Harrison et al., 2014) using

[25] In addition, high-skilled workers are usually costlier to fire and require larger investments in specific training.

[26] In this section, we estimated interaction models in order to evaluate the heterogeneity among sectors (see appendix Tables 3a, 4a, and 5a). The results suggest no differences among sectors. Then, we estimated sector by sector to analyze the effect of innovation on employment growth for general, high- and low-skilled workers.

[27] In the appendix, the rest of the estimations are presented (Tables 6a, 7a, and 8a).

Table 8
Unweighted averages.

	All sample	High-skilled	Low-skilled
Firm's employment growth	−6.03	8.09	−6.28
Productivity trend in production of old products	0.06	0.14	0.06
Gross effect of process innovation on old products	−0.04	−0.01	−0.05
Sales growth in old products for non- product innovators	−12.62	−12.62	−12.62
Non-innovators	−16.07	−16.07	−16.07
Process innovators only	−4.86	−4.86	−4.86
Net sales growth of product innovators (new prods.-subs.)	−10.75	−7.39	−11.02
Sales growth due to old products	−29.42	−29.42	−29.42
Sales growth due to new products	18.67	22.03	18.40

Based on descriptives of Table 7 and regression IV (only with increased range as instrument).
The period of all-sample is from 2007 to 2014. For high- and low-skilled, it is from 2009 to 2014.

Table 9
Contribution to average growth of employment.

	All-sample	High-skilled	Low-skilled
Firms' employment growth	−6.03	8.09	−6.28
Due to productivity trend in production of old products trend	5.59	17.93	5.48
Due to gross effect of process innovation on old products	−0.0065	−0.0010	−0.0078
Due to sales growth in old products for non-product innovators	−5.95	−5.95	−5.95
Due to non-innovators	−5.23	−5.23	−5.23
Due to process innovators only	−0.72	−0.72	−0.72
Due to net sales growth of product innovators (new prods-subs.)	−5.67	−3.90	−5.81
Due to sales growth due to old products	−15.51	−15.51	−15.51
Due to sales growth due to new products	9.84	11.61	9.70

Based on descriptive of Table 7 and regression IV (only with increased range as instrument).
The period of all=sample is from 2007 to 2014. For high- and low-skilled, it is from 2009 to 2014.

Eq. (10):

$$l = \sum_j (\hat{\alpha}_0 + \hat{\alpha}_{0j}) ind_{ji} + \hat{\alpha}_1 d + [1 - 1(g_2 > 0)](g_1 - \pi) + 1(g_2 > 0)\left(g_1 - \pi + \hat{\beta} g_2\right) + \hat{\varepsilon}_i \qquad (10)$$

The first element computes the change of employment due to (industry specific) productivity trends in the production of old products $\sum_j (\hat{\alpha}_0 + \hat{\alpha}_{0j}) ind_{ji}$. The second element $\hat{\alpha}_1 d$ estimates the gross effect of process innovation on the growth of employment in the production of old products for firms innovating only in process). The third element $[1 - 1(g_2 > 0)](g_1 - \pi)$ captures the employment changes related to sales growth due to old products if a firm has not introduced any product innovation (non-innovator or process innovator only). The fourth element $1(g_2 > 0)(g_1 - \pi + \hat{\beta} g_2) + \hat{\varepsilon}_i$ gives information about the employment growth associated with the net sales of new products (if a firm has introduced a new one). $\hat{\varepsilon}_i$ is a zero-mean residual. Taking into account Eq. (10), it is possible to discuss how the different effects contribute to the average employment growth in Eq. (11):

$$l = t + \hat{\alpha}_1 P_{PO} + P_{NI} g_{NI} + P_I g_I \qquad (11)$$

The average employment growth is l. The weight average of the indsustrial specific trends is t. The sample proportions are P_{PO} of process innovator only, P_{NI} of non-product innovator and P_I of product innovator. g_{NI} is the average of rate of non-product innovator[29] and g_I is the average of rate of product innovator.[30]

In Table 8, the statistics related to Eq. (10) are presented. In this case, it is calculated for general, high- and low-skilled samples. Firstly, it is possible to see that the productivity trend has improved a little for all the samples (the impact is small; it is not bigger than 0.15). These results mean that during the period=analyzed, there has not been a big improvement in efficiency because productivity growth has been low in Spain. The gross effect of process innovation in old products has an additional negative impact on employment (−0.04), mainly for low-skilled workers (−0.05) and almost null for high-skilled workers. Negative sales growth of old products for non-product innovators due to less demand during the crises results in additional employment losses.

Another important aspect that can be checked is the price=compensation effect. The condition is that the sales growth of non-innovators is smaller than the sales growth of process innovation only. In this case, although the sales growth is negative for non-product innovators (for all the samples), there is a price compensation mechanism because the sales increase of process innovators only (still negative in high- and low-skilled) is higher than the sales increase of non-innovators. Finally, product innovators also suffered from negative sales growth but to a lesser extent because of the increase of sales due to new products.

Table 9 shows the components in terms of contribution to average growth of employment. The productivity trend in the production of old products has a positive effect, especially for high-skilled workers. As we commented in the interpretation of the constant, labor hoarding is detected when a recession period is presented, and this labor hoarding is especially important for high-skilled workers. These results differ from Harrison et al. (2014), but they are similar to the findings of Dachs et al. (2016) when the authors analyzed the recession. Individual process innovations account for only a small displacement effect (because there are few process-only innovators), in line with previous studies. The (negative) sales growth of old products contributes to employment destruction while the effect of the sales growth of new products is quite similar to those found in expansion periods by previous studies, although it is not able to compensate the employment losses caused by the decrease of old product sales.

[29] $g_{NI} = \frac{1}{N_{NI}} \sum_{i \in NI} g_{1i}$.

[30] $g_I = \frac{1}{N_I} \sum_{i \in I} (g_{1i} + \hat{\beta} g_{2i})$.

All in all, there is a difference of 14.37 points in employment growth between high- and low-skilled workers. 12.45 points are explained by the different productivity trend, which is greater in high-skilled than in low-skilled workers, and 1.91 points are explained by the different effect of new product sales on employment. These results suggest that innovation explains approximately 13.3% of the different evolution between high- and low-skilled employment for manufacturing firms in Spain during the period of economic turmoil. We do not know whether this result could be different in an expansion period as we do not have data to analyze it.[31]

8. Conclusions

Our research sheds light on the effect of innovation on the Spanish manufacturing case from 2006 to 2014. Our models fit in the empirical literature based on the model of Harrison et al. (2008, 2014), but our study introduces some novelties in relation to other studies for developed counties. First, our analysis covers a period with huge employment losses. Second, the existing studies for developed countries do not distinguish between different types of workers. We address this limitation by calculating individual models for the labor demand for high- and low-skilled workers.

The descriptive data of our sample shows that the negative growth of employment during the crisis seemed to be less accentuated in innovative firms than in non-innovative ones, and that this positive effect of innovation is remarkably larger for high-skilled than for low-skilled workers. It seems that the crisis affected unskilled employment more intensely, taking into account that, at least in Spain, the total number of employees with a university degree remained more or less stable during this period.[32] The main results of the estimations confirm the conclusions of earlier studies, suggesting a positive general effect of innovation on the total employment of firms, even in a period of economic crisis. In addition, a labor hoarding effect is found for both types of workers, but this effect is larger for high-skilled workers, an atypical effect that seems to appear at the time of the crisis, as mentioned by Peters et al. (2017). Moreover, the models for the sector-based subsamples reflect that this result holds across different industries and the impact of product and process innovation is exacerbated in high-tech industries.

Process innovation seems to have a small effect on overall and high- and low-skilled employment. For the correct interpretation of the results, it should be stated, as discussed in section two, that introduction of process innovation can have different contradictory effects on mechanisms of compensation. On the one hand, it can generate a loss of employment due to higher productivity but, at the same time, if such lower costs result in lower prices, total demand might increase, implying that the loss of employment would be eased.

Regarding the relationship between innovation and type of employment, our empirical data show that the product innovation is largely responsible of the skill-biased effect of innovation. Although product innovation positively affected both types of employment, the effect is much larger for high-skilled workers. It is estimated that product innovations account for around 13% of the different evolution between high-skilled and low-skilled employment during the crisis, while the role of process innovation was very limited. We do not know whether this result is specific to a period of economic turmoil.

Observing the additional models for subsamples by sectors, it can be stated that the effect of product innovation on high-skilled employment is larger in high-tech industries and lower in low-tech industries (see also Peters et al., 2017). This would confirm the role of structural change in explaining the skill bias in labor demand, as mentioned by Welch (1970).

One limitation of our study is that it is firm-level in scope. However, the overall effect of product and process innovations at the industry level may be different because of the different competitive and selection dynamics. In addition, the estimated effects cover a three-year period. That is, they are short-term effects. It could be that long-term effects are different. A third limitation of our study is that the indicator used for high- and low-skilled workers in the Spanish innovation survey can distinguish only two groups of employees based on their educational level, not on the kind of job that they carry out. That is, no information is available for the group with studies of an intermediate level, so it is impossible to analyze the important potential issue of labor polarization in very high- and very low-skilled workers accompanied by a reduction of medium-skilled workers (Autor et al., 2006). A fourth limitation is that we observe only a turmoil period, so we cannot compare the effect of product and process innovation on high- and low-skilled workers against an expansion period. Another limitation is the lack of data on wages, so we cannot analyze the effect of innovation on relative wages of high- and low- skilled workers. These are important topics for future research.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.strueco.2019.09.012.

Annexes

Table 1a, Table 2a, Table 3a, Table 4a, Table 5a, Table 6a, Table 7a, Table 8a.

Box 1. Definitions and creations of the variables

Nominal increased rates for all the products:

$$\hat{g} \equiv \frac{(current\ \ sales\ \ old + current\ \ sales\ \ new) - past\ \ sales\ \ old}{past\ \ sales\ \ old}$$

Proportion of sales of new products:

$$s \equiv \frac{current\ \ sales\ \ new}{current\ \ sales\ \ old + current\ \ sales\ \ new}$$

Sales growth due to new products:

$$g_2 \equiv \frac{current\ \ sales\ \ new}{past\ \ sales\ \ old} = s\left(1+\hat{g}\right)$$

Nominal sales growth due to old products:

$$\widehat{g_1} \equiv \frac{current\ \ sales\ \ old - past\ \ sales\ \ old}{past\ \ sales\ \ old} = \hat{g} - g_2$$

Real sales growth for all products: $g \equiv \hat{g} - \pi$

Real sales growth due to old products: $g_1 \equiv \widehat{g_1} - \pi$

[31] Unfortunately, we are not able to perform such an analysis for 2004–2006. The reason is that the data for high- and low-skilled workers start in 2006.

[32] Anyhow, the debate on this subject that could limit the generalization of our study is the increasing percentage of people –and therefore workers– that have university studies. This fact might imply an increase of the percentage of workers with a university degree independent of the kind of job they carry out. In fact, some firms require a bachelor's degree for jobs that in earlier times were done by workers with less education, especially if one compares the cohort of persons that are at the age of retirement with young people entering the labor market.

Table 1a
Empirical evidence related to level studies: The Effect of Innovation on Employment (European countries).

Study	Sample	Country	Const	Process Innovation Only	Sales growth due to new products
Harrison et al. (2014)	MSa	France	−3.520	−1.310	0.980
	MSb	Germany	−6.950	−6.190	1.010
	MSc	Spain	−6.110	2.460	1.020
	MSd	United Kingdom	−6.300	−3.510	0.990
Peters et al. (2017)	Ta	EU	−64.522	−2.283	0.966
	Tb	EU	3.931	−0.698	0.96
	Tc	EU	−21.702	−2.08	0.98
	Td	EU	2.973	−0.359	0.98
Dachs et al. (2016)	MSa	EU	−22.334	−1.026	0.999
	MSb	EU	−21.032	−1.179	0.977
	MSaa	EU	−53.55	−2.813	0.995
	MSab	EU	−9.65	1.522	0.964
	MSac	EU	−20.328	−1.408	1.021
	MSad	EU	−0.632	0.568	0.993
	MSba	EU	−69.29	−1.613	0.972
	MSbb	EU	−39.935	−0.573	0.97
	MSbc	EU	−14.044	−1.921	0.997
	MSbd	EU	3.554	−0.634	0.955
Dachs et al. (2016)	MSa	EU	−14.062	−1.970	1.011
	MSb	EU	−14.020	−1.970	1.011
	MSc	EU	−14.015	−1.973	1.011
Pizarro (2013)	MSa	Spain	−0.660	−3,57	0.900
	MSb	Spain	−4.280	−6.570	0.920
	MSc	Spain	9.210	−2.610	0.950
	MSd	Spain	11.610	−0.640	0.900
	MSe	Spain	−5.440	−3.730	0.900
Leitner et al. (2011)	MS	EU		2.397	0.621
Hall et al. (2008)	MSa	Italy	−2.8	−1.22	0.95
	MSb	Italy	−2.98	−1.84	0.96
	MSc	Italy	−5.84	0.18	0.94
	Msd	Italy	1.91	−1.15	1.07

Notes: MS=Manufacturing Sector, SS=Services Sector.
Harrison et al. (2014), *a*= France, *b*=Germany, *c*=Spain, and *d*= United Kingdom; Peters et al. (2017), *a*=Upturn, *b*= Boom, *c*=Downturn, and *d*= Recession; Dachs et al. (2016), *a*=high-tech manufacturing, *b*= low-tech manufacturing. The second letter means *a*=Upturn, *b*=Boom, *c*= Downturn, and *c*=Recession; Dachs and Peters (2014), *a*= Domestically owned group firms (DGF) and Foreign-owned firms (FOF), *b*= Foreign-owned EU firm (FOFEU) and Foreign-owned NON-EU firm (FOFNONEU), and *c*= Foreign-owned US firm (FOFUS) and Foreign-owned Rest of the World firm (FOFROW); Pizarro (2013), *a* = 2004–2007, *b* = 2005–2008 *c* = 2006–2009, *d* = 2007–2010, *e*=Total; Hall et al. (2008); *a*=All years, *b* = 1995–1997, *c* = 1998–2000, *d* = 2001–2003.
*Means significant.

Table 2a
Descriptive statistics in percentage (triennial): product and process innovators, growth of employment and sales. Manufacturing firms (2004–2014).

	2006–2009	2007–2010	2008–2011	2009–2012	2010–2013	2011–2014	Total
No. of firms	5427	5189	5000	4777	4569	3559	28,521
Non-innovators (%)	21.60	20.99	36.18	41.80	43.34	31.33	32.12
Process innovators only (%)	15.79	15.42	14.94	14.19	13.35	14.84	14.80
Product innovators (%)	62.61	63.60	48.88	44.00	43.31	53.84	53.08
Product innovators only (%)	14.94	14.47	16.00	15.64	16.57	21.33	16.22
[Of which are product & process innovators]	47.67	49.12	32.88	28.37	26.75	32.51	36.86
Employment growth (%)							
All firms	−5.92	−9.69	−9.27	−5.30	−4.82	−1.14	−6.03
Non-innovators (%)	−11.90	−14.59	−14.45	−10.85	−10.69	−6.64	−11.52
Process innovators only (%)	−7.46	−11.16	−8.13	−2.26	−0.40	2.20	−4.54
Product innovators (%)	−3.49	−7.75	−5.81	−1.03	−0.36	1.07	−2.89
Product innovators only (%)	−8.19	−11.50	−8.42	−3.82	−2.80	−1.78	−6.09
[Of which are product & process innovators]	−2.01	−6.64	−4.54	0.52	1.15	2.94	−1.43
Sales growth (%)							
All firms	−7.85	−13.23	−8.72	7.16	1.66	3.90	−2.85
Non-innovators (%)	−14.27	−20.70	−15.33	−1.77	−6.33	−1.93	−10.06
Process innovators only (%)	−6.63	−13.18	−6.79	13.96	9.61	9.51	1.08
Product innovators (%)	−5.95	−10.81	−4.46	13.41	7.16	5.69	0.84
Old products	−31.89	−36.45	−28.61	−13.27	−17.30	−20.21	−24.62
New products	22.85	22.44	19.10	19.25	18.17	23.36	20.86
Prices growth (%)							
All firms	6.8	4.8	4.2	6.7	4.9	1.4	4.8
Non-innovators (%)	7.4	5.2	4.3	6.8	5.3	2.0	5.2
Process innovators only (%)	7.3	5.2	4.5	6.8	5.2	1.4	5.1
Product innovators (%)	6.6	4.8	4.4	7.3	5.1	1.3	4.9
Product innovators only (%)	6.7	4.5	4.1	6.2	4.6	1.1	4.5
[Of which are product & process innovators]	6.6	4.9	4.6	7.9	5.4	1.5	5.1

Table 3a
The total effect of innovation on employment of manufacturing by sectors.

Dependent variable: l-g1-π Variables	ols	iv[a]	iv[b]	fe	re	reiv[a]	reiv[b]
d	−0.135***	−0.0352	−0.00684	−0.137**	−0.142***	−0.0497	−0.00505
	[0.0273]	[0.0615]	[0.0494]	[0.0432]	[0.0347]	[0.0810]	[0.0652]
g2	0.587***	0.844***	0.917***	0.459***	0.521***	0.790***	0.912***
	[0.0333]	[0.142]	[0.107]	[0.0554]	[0.0470]	[0.213]	[0.162]
islowtech	0.0223	0.111	0.138**		−0.00243	0.0856	0.129*
	[0.0138]	[0.0574]	[0.0433]		[0.0210]	[0.0836]	[0.0639]
ismlowtech	0.0412**	0.094	0.127**		0.0236	0.0613	0.116
	[0.0140]	[0.0582]	[0.0439]		[0.0211]	[0.0847]	[0.0649]
ismhightech	0.0406**	0.0853	0.118**		0.0238	0.0624	0.113
	[0.0138]	[0.0580]	[0.0443]		[0.0210]	[0.0842]	[0.0650]
d*islowtech	0.0515	−0.0366	−0.0634	0.0823	0.0718	−0.00885	−0.05
	[0.0292]	[0.0633]	[0.0512]	[0.0461]	[0.0373]	[0.0834]	[0.0674]
d*ismlowtech	0.0617*	0.00948	−0.0236	0.0688	0.0714	0.0428	−0.0101
	[0.0295]	[0.0641]	[0.0520]	[0.0468]	[0.0376]	[0.0847]	[0.0688]
d*ismhightech	0.0257	−0.019	−0.0522	0.0397	0.0373	0.00486	−0.0437
	[0.0302]	[0.0643]	[0.0526]	[0.0482]	[0.0389]	[0.0847]	[0.0693]
g2*islowtech	0.226***	0.0135	−0.0533	0.361***	0.294***	0.084	−0.0238
	[0.0367]	[0.149]	[0.114]	[0.0605]	[0.0512]	[0.221]	[0.169]
g2*ismlowtech	0.159***	0.0939	0.00151	0.269***	0.214***	0.208	0.0508
	[0.0378]	[0.153]	[0.117]	[0.0613]	[0.0528]	[0.228]	[0.174]
g*2ismhightech	0.152***	0.0713	−0.0172	0.226***	0.186***	0.126	−0.00924
	[0.0360]	[0.149]	[0.115]	[0.0593]	[0.0503]	[0.221]	[0.170]
cons	0.0424**	−0.0654	−0.0890*	0.0827***	0.0656***	−0.054	−0.0912
	[0.0130]	[0.0571]	[0.0427]	[0.00396]	[0.0199]	[0.0804]	[0.0620]
Tests of endogeneity		8.620	11.043				
p-value		0.000	0.000				
Test of Sargan		6.904	18.405			6.735	14.357
p-value		0.141	0.104			0.151	0.278
First-Stage		0.020	0.035			430.95	612.33
p-value		0.019	0.034			0.000	0.000
N	37,871	37,871	37,871	37,871	37,871	37,871	37,871
R-sq	0.368	0.35	0.349	0.291			

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

Table 4a
The effects of innovation on high-skilled employment of manufacturing by sectors.

Dependent variable: l-g1-π Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
D	−0.0325	0.197	0.194	0.0198	−0.0292	0.222	0.197
	[0.0659]	[0.156]	[0.116]	[0.0980]	[0.0705]	[0.185]	[0.141]
g2	0.762***	1.424***	1.415***	0.603***	0.715***	1.482**	1.399***
	[0.0557]	[0.400]	[0.292]	[0.0914]	[0.0686]	[0.512]	[0.380]
islowtech	0.0517	0.273	0.279**		0.0298	0.281	0.265
	[0.0274]	[0.145]	[0.107]		[0.0336]	[0.183]	[0.137]
ismlowtech	0.115***	0.246	0.279**		0.103**	0.247	0.26
	[0.0283]	[0.146]	[0.108]		[0.0347]	[0.184]	[0.138]
ismhightech	0.0973***	0.262	0.270*		0.0879**	0.268	0.247
	[0.0267]	[0.144]	[0.107]		[0.0329]	[0.183]	[0.138]
d*islowtech	−0.0335	−0.254	−0.260*	−0.0698	−0.0311	−0.269	−0.257
	[0.0712]	[0.162]	[0.122]	[0.105]	[0.0768]	[0.192]	[0.148]
d*ismlowtech	−0.0585	−0.189	−0.222	−0.107	−0.059	−0.192	−0.207
	[0.0731]	[0.163]	[0.124]	[0.110]	[0.0793]	[0.194]	[0.150]
d*ismhightech	−0.0112	−0.177	−0.184	−0.0559	−0.00851	−0.182	−0.163
	[0.0745]	[0.163]	[0.125]	[0.111]	[0.0811]	[0.194]	[0.151]
g2*islowtech	0.116	−0.512	−0.541	0.320**	0.169*	−0.541	−0.515
	[0.0655]	[0.425]	[0.317]	[0.103]	[0.0791]	[0.541]	[0.408]
g2*ismlowtech	0.0634	−0.139	−0.299	0.175	0.0906	−0.115	−0.227
	[0.0690]	[0.439]	[0.331]	[0.106]	[0.0811]	[0.557]	[0.425]
g*2ismhightech	0.101	−0.333	−0.362	0.191	0.128	−0.344	−0.29
	[0.0633]	[0.418]	[0.313]	[0.102]	[0.0776]	[0.533]	[0.404]
cons	0.125***	−0.0918	−0.0917	0.207***	0.122***	−0.119	−0.0972
	[0.0237]	[0.139]	[0.101]	[0.00783]	[0.0295]	[0.177]	[0.131]
Tests of endogeneity		3.249	2.976				
p-value		0.011	0.018				
Test of Sargan		6.326	14.632			4.048	10.232
p-value		0.176	0.262			0.400	0.596
First-Stage		0.013	0.022			305.260	453.430
p-value		0.012	0.020			0.000	0.000
N	23,093	23,093	23,093	23,093	23,093	23,093	23,093
R-sq	0.122	0.105	0.11	0.097			

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

Table 5a
The effects of innovation on low-skilled employment of manufacturing by sectors.

Dependent variable: l-g1-π Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
D	−0.0807*	−0.0754	−0.0435	−0.111	−0.0945*	−0.119	−0.0862
	[0.0388]	[0.0940]	[0.0775]	[0.0604]	[0.0481]	[0.115]	[0.0970]
g2	0.795***	0.811**	0.906***	0.681***	0.751***	0.678*	0.778**
	[0.0373]	[0.256]	[0.207]	[0.0589]	[0.0452]	[0.330]	[0.266]
islowtech	0.0219	0.0415	0.0662		0.0042	−0.000676	0.0185
	[0.0185]	[0.0884]	[0.0713]		[0.0235]	[0.112]	[0.0905]
ismlowtech	0.0400*	0.0296	0.0601		0.0259	−0.024	0.00479
	[0.0186]	[0.0886]	[0.0714]		[0.0236]	[0.112]	[0.0906]
ismhightech	0.0484**	0.032	0.0632		0.0423	−0.00145	0.0283
	[0.0186]	[0.0889]	[0.0721]		[0.0237]	[0.112]	[0.0914]
d*islowtech	0.0198	0.0000932	−0.0245	0.0829	0.0453	0.0481	0.03
	[0.0408]	[0.0956]	[0.0791]	[0.0633]	[0.0505]	[0.117]	[0.0991]
d*ismlowtech	0.0107	0.021	−0.00948	0.0643	0.0335	0.0819	0.0543
	[0.0413]	[0.0959]	[0.0795]	[0.0639]	[0.0509]	[0.117]	[0.0995]
d*ismhightech	−0.00804	0.00833	−0.0228	0.0158	0.00359	0.0459	0.0168
	[0.0419]	[0.0965]	[0.0803]	[0.0662]	[0.0525]	[0.119]	[0.101]
g2*islowtech	0.0776	−0.00443	−0.0661	0.215***	0.129**	0.112	0.0771
	[0.0409]	[0.262]	[0.213]	[0.0648]	[0.0498]	[0.339]	[0.274]
g2*ismlowtech	0.0134	0.0733	−0.0149	0.123	0.0542	0.254	0.175
	[0.0418]	[0.264]	[0.214]	[0.0667]	[0.0516]	[0.341]	[0.275]
g*2ismhightech	0.02	0.0832	−0.00894	0.0561	0.034	0.179	0.0916
	[0.0410]	[0.262]	[0.214]	[0.0657]	[0.0505]	[0.338]	[0.275]
cons	0.0459**	0.0697	0.0286	0.0820***	0.0610**	0.118	0.0661
	[0.0177]	[0.0883]	[0.0711]	[0.00429]	[0.0222]	[0.111]	[0.0898]
Tests of endogeneity		1.199	1.396				
p-value		0.309	0.232				
Test of Sargan		5.040	9.074			2.971	6.491
p-value		0.283	0.697			0.563	0.889
Partial R-sq.		0.015	0.024			403.610	591.220
Adj. Partial R-sq.		0.014	0.023			0.000	0.000
N	27,603	27,603	27,603	27,603	27,603	27,603	27,603
R-sq	0.332	0.33	0.329	0.267			

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

Table 6a
The effects of innovation on employment of manufacturing by sectors (Yt–3).

Dependent variable: l-g1-π Sector	Variables	ols	vi[a]	vi[b]	Fe	re	reiv[a]	reiv[b]
High-tech	d	−0.135***	−0.0507	−0.0189	−0.140**	−0.143***	−0.0697	−0.0207
		[0.0271]	[0.0585]	[0.0483]	[0.0432]	[0.0344]	[0.0777]	[0.0638]
	g2	0.593***	0.813***	0.895***	0.469***	0.531***	0.744***	0.883***
		[0.0326]	[0.134]	[0.104]	[0.0550]	[0.0461]	[0.208]	[0.160]
	cons	0.0424**	−0.0654	−0.0890*	0.0884***	0.0654**	−0.052	−0.091
		[0.0130]	[0.0571]	[0.0427]	[0.0214]	[0.0199]	[0.0849]	[0.0617]
HighM-tech	d	−0.108***	−0.0539**	−0.0583**	−0.0960***	−0.103***	−0.0449	−0.0489*
		[0.0130]	[0.0186]	[0.0181]	[0.0212]	[0.0177]	[0.0244]	[0.0234]
	g2	0.742***	0.915***	0.901***	0.688***	0.710***	0.916***	0.904***
		[0.0137]	[0.0436]	[0.0412]	[0.0212]	[0.0179]	[0.0578]	[0.0528]
	cons	0.0841***	0.022	0.0262	0.0996***	0.0914***	0.0176	0.0214
		[0.00500]	[0.0144]	[0.0137]	[0.00678]	[0.00667]	[0.0186]	[0.0171]
LowM-tech	d	−0.0771***	−0.0289	−0.0356*	−0.0750***	−0.0759***	−0.0163	−0.0244
		[0.0111]	[0.0181]	[0.0164]	[0.0178]	[0.0142]	[0.0243]	[0.0223]
	g2	0.742***	0.936***	0.909***	0.722***	0.732***	0.976***	0.942***
		[0.0177]	[0.0561]	[0.0461]	[0.0261]	[0.0234]	[0.0758]	[0.0636]
	cons	0.0853***	0.0306*	0.0360**	0.0893***	0.0902***	0.0211	0.0276
		[0.00549]	[0.0153]	[0.0127]	[0.00686]	[0.00694]	[0.0200]	[0.0170]
Low-tech	d	−0.0825***	−0.0708***	−0.0693***	−0.0518**	−0.0672***	−0.0536*	−0.0498**
		[0.0104]	[0.0153]	[0.0139]	[0.0160]	[0.0138]	[0.0213]	[0.0188]
	g2	0.813***	0.859***	0.865***	0.822***	0.817***	0.883***	0.899***
		[0.0155]	[0.0442]	[0.0382]	[0.0244]	[0.0204]	[0.0660]	[0.0537]
	cons	0.0638***	0.0491***	0.0484***	0.0575***	0.0621***	0.0406*	0.0388**
		[0.00492]	[0.0117]	[0.0102]	[0.00625]	[0.00667]	[0.0167]	[0.0137]

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

Table 7a
The effects of innovation on high-skilled employment of manufacturing by sectors.

Dependent variable: l-g1-π Sector	Variables	ols	vi[a]	vi[b]	Fe	re	reiv[a]	reiv[b]
High-tech	d	−0.0392	0.176	0.177	0.00531	−0.0392	0.176	0.18
		[0.0655]	[0.152]	[0.114]	[0.0979]	[0.0675]	[0.162]	[0.134]
	g2	0.769***	1.395***	1.398***	0.625***	0.747***	1.395**	1.396***
		[0.0555]	[0.391]	[0.291]	[0.0900]	[0.0648]	[0.430]	[0.364]
	cons	0.125***	−0.0918	−0.0917	0.159***	0.124***	−0.0918	−0.0971
		[0.0238]	[0.139]	[0.101]	[0.0329]	[0.0283]	[0.154]	[0.128]
HighM-tech	d	−0.0426	0.0209	0.0104	−0.0352	−0.0377	0.0402	0.029
		[0.0347]	[0.0483]	[0.0464]	[0.0529]	[0.0393]	[0.0567]	[0.0535]
	g2	0.863***	1.087***	1.050***	0.792***	0.847***	1.133***	1.092***
		[0.0302]	[0.126]	[0.116]	[0.0449]	[0.0358]	[0.156]	[0.139]
	cons	0.225***	0.159***	0.168***	0.238***	0.215***	0.130**	0.140***
		[0.0122]	[0.0368]	[0.0342]	[0.0137]	[0.0145]	[0.0456]	[0.0411]
LowM-tech	d	−0.0937**	0.00297	−0.0342	−0.0934	−0.0918*	0.0236	−0.0181
		[0.0320]	[0.0501]	[0.0467]	[0.0493]	[0.0371]	[0.0587]	[0.0544]
	g2	0.823***	1.270***	1.098***	0.772***	0.799***	1.349***	1.149***
		[0.0409]	[0.185]	[0.160]	[0.0539]	[0.0436]	[0.229]	[0.197]
	cons	0.254***	0.143***	0.178***	0.243***	0.226***	0.117*	0.149***
		[0.0161]	[0.0415]	[0.0362]	[0.0144]	[0.0186]	[0.0497]	[0.0435]
Low-tech	d	−0.0623*	−0.0528	−0.0608	−0.0436	−0.0546	−0.0363	−0.0523
		[0.0271]	[0.0452]	[0.0408]	[0.0376]	[0.0305]	[0.0551]	[0.0485]
	g2	0.884***	0.923***	0.890***	0.934***	0.895***	0.974***	0.906***
		[0.0345]	[0.149]	[0.127]	[0.0489]	[0.0396]	[0.194]	[0.160]
	cons	0.177***	0.169***	0.176***	0.154***	0.145***	0.129**	0.144***
		[0.0136]	[0.0370]	[0.0319]	[0.0129]	[0.0163]	[0.0472]	[0.0394]

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

Table 8a
The effects of innovation on low-skilled employment of manufacturing by sectors.

Dependent variable: l-g1-π Sector	Variables	ols	vi[a]	vi[b]	fe	re	reiv[a]	reiv[b]
High-tech	d	−0.0781*	−0.0645	−0.0345	−0.106	−0.0945	−0.106	−0.0795
		[0.0392]	[0.0929]	[0.0772]	[0.0610]	[0.0499]	[0.113]	[0.0977]
	g2	0.795***	0.836***	0.925***	0.671***	0.735***	0.704*	0.786**
		[0.0371]	[0.252]	[0.206]	[0.0584]	[0.0460]	[0.326]	[0.270]
	cons	0.0459**	0.0697	0.0286	0.0784***	0.0654**	0.109	0.0789
		[0.0177]	[0.0883]	[0.0711]	[0.0212]	[0.0229]	[0.108]	[0.0950]
HighM-tech	d	−0.0890***	−0.0677**	−0.0671**	−0.0953***	−0.0909***	−0.0731*	−0.0698*
		[0.0157]	[0.0222]	[0.0216]	[0.0270]	[0.0208]	[0.0288]	[0.0278]
	g2	0.815***	0.892***	0.895***	0.736***	0.790***	0.858***	0.870***
		[0.0171]	[0.0588]	[0.0560]	[0.0289]	[0.0221]	[0.0748]	[0.0691]
	cons	0.0965***	0.0718***	0.0680***	0.113***	0.104***	0.0774***	0.0698***
		[0.00642]	[0.0171]	[0.0164]	[0.00818]	[0.00835]	[0.0215]	[0.0200]
LowM-tech	d	−0.0725***	−0.0572**	−0.0568**	−0.0517*	−0.0657***	−0.0431	−0.0409
		[0.0142]	[0.0198]	[0.0184]	[0.0206]	[0.0161]	[0.0239]	[0.0224]
	g2	0.808***	0.881***	0.884***	0.799***	0.804***	0.919***	0.929***
		[0.0191]	[0.0660]	[0.0547]	[0.0311]	[0.0247]	[0.0846]	[0.0700]
	cons	0.0992***	0.0718***	0.0669***	0.0804***	0.0893***	0.0633***	0.0564***
		[0.00670]	[0.0153]	[0.0131]	[0.00704]	[0.00817]	[0.0189]	[0.0162]
Low-tech	d	−0.0573***	−0.0720***	−0.0638***	−0.0179	−0.0416**	−0.0633**	−0.0452*
		[0.0125]	[0.0180]	[0.0167]	[0.0184]	[0.0150]	[0.0238]	[0.0214]
	g2	0.877***	0.810***	0.848***	0.910***	0.889***	0.796***	0.878***
		[0.0168]	[0.0575]	[0.0504]	[0.0269]	[0.0210]	[0.0852]	[0.0701]
	cons	0.0678***	0.0814***	0.0708***	0.0506***	0.0642***	0.0790***	0.0589***
		[0.00598]	[0.0136]	[0.0120]	[0.00652]	[0.00788]	[0.0192]	[0.0161]

Standard errors in brackets * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
d Process innovation only.
g2 Sales growth due to new products.
[a] Instrument used is increased range.
[b] Instruments used are increased range and clients as a source of information.

References

Aboal, D., Garda, P., Lanzilotta, B., Perera, M., 2015. Innovation, firm size, technology intensity, and employment generation: evidence from the Uruguayan manufacturing sector. Emerg. Markets Finance .Trade 51 (1), 3–26.

Acemoglu, D., 2002. Technical change, inequality, and the labor market. J. Econ. Lit. 40 (1), 7–72.

Aghion, P., Askenazy, P., Berman, N., Cette, G., Eymard, L., 2012. Credit constraints and the cyclicality of R&D investment: evidence from France. J. Eur. Econ. Assoc. 10 (5), 1001–1024.

Alvarez, R., Benavente, J.M., Campusano, R., Cuevas, C., 2011. Employment Generation, Firm Size, and Innovation In Chile. IDB.

Archibugi, D., Filippetti, A., Frenz, M., 2013. Economic crisis and innovation: is destruction prevailing over accumulation? Res. Policy 42 (2), 303–314.

Autor, D.H., 2015. Why are there still so many jobs? the history and future of workplace automation. J. Econ. Perspect. 29 (3), 3–30.

Autor, D.H., Katz, L.F., Kearney, M.S., 2008. Trends in US wage inequality: revising the revisionists. Rev. Econ. Stat. 90 (2), 300–323.

Autor, D.H., Katz, L.F., Kearney, M.S., 2006. The polarization of the US labor market. Am. Econ. Rev. 96 (2), 189–194.

Benavente, J.M., Lauterbach, R., 2008. Technological innovation and employment: complements or substitutes? Eur. J. Develop. Res. 20 (2), 318–329.

Berman, E., Bound, J., Machin, S., 1998. Implications of skill-biased technological change: international evidence. Q. J. Econ. 113 (4), 1245–1279.

Bhaumik, S.K., (2011). Productivity and the economic cycle. BIS Economics Paper No. 12, London.

Bianchini, S., Pellegrino, G., 2019. Innovation persistence and employment dynamics. Res. Policy 48 (5), 1171–1186.

Biddle, J., 2014. The cyclical behavior of labor productivity and the emergence of the labor hoarding concept. J. Econ. Perspect. 28 (2), 197–212.

Calvino, F., Virgillito, M.E., 2018. The innovation-employment nexus: a critical survey of theory and empirics. J. Econ. Surv. 32 (1), 83–117.

Calvino, F., 2019. Technological innovation and the distribution of employment growth: a firm-level analysis. Ind. Corporate Change 28 (1), 177–202.

Cainelli, G., Evangelista, R., Savona, M., 2005. Innovation and economic performance in services: a firm-level analysis. Cambridge J. Econ. 30 (3), 435–458.

Cohen, W.M., 2010. Fifty years of empirical studies of innovative activity and performance. In: Handbook of Economics of Innovation, 1, pp. 129–213.

Crespi, G., Tacsir, E., 2012. Effects of innovation on employment in Latin America. In: Paper presented at the *2011 Atlanta Conference on Science and Innovation Policy*, pp. 1–11.

Dachs, B., Hud, M., Koehler, C., Peters, B., 2016. Innovation, creative destruction and structural change: firm-Level evidence from European countries. Ind. Innov. 24 (4), 346–381. doi:10.1080/13662716.2016.1261695.

Dachs, B., Peters, B., 2014. Innovation, employment growth, and foreign ownership of firms: a European perspective. Res. Policy 43 (1), 214–232.

De Elejalde, R., Giuliodori, D., Stucchi, R., 2015. Employment and innovation: firm-level evidence from Argentina. Emerg. Markets Finance .Trade 51 (1), 27–47.

Falk, M., Biagi, F., 2017. Relative demand for highly skilled workers and use of different ICT technologies. Appl. Econ. 49 (9), 903–914.

Fioravante, D.G., Maldonado, W.F.L., 2008. Impacts of technological innovation on employment: the Brazilian manufacturing case. Georgia Inst. Technol..

Foote, C.L., Ryan, R.W., 2015. Labor-market polarization over the business cycle. In: NBER Macroeconomics Annual, 29. University of Chicago Press, pp. 371–413.

Groshen, E.L., Potter, S., 2003. Has structural change contributed to a jobless recovery? Curr. Issues Econ. Finance 9-8.

Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. 104 (8), 2509–2526.

Griliches, Z., 1969. Capital-skill complementarity. Rev. Econ. Stat. 465–468.

Hall, B.H., Lotti, F., Mairesse, J., 2008. Employment, innovation, and productivity: evidence from Italian microdata. Ind. Corp. Change 17 (4), 813–839.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2008. Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data from Four European Countries *Working Paper*.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2014. Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. Int. J. Ind Organiz. 35, 29–43.

Himmelberg, C.P., Petersen, B.C., 1994. R&D and internal finance: a panel study of small firms in high-tech industries. Rev. Econ. Stat. 76 (1), 38–51.

Horning, B.C., 1994. Labor hoarding and the business cycle. Int. Econ. Rev. 87–100.

International Labour Office, 2015. World Employment and Social outlook: Trends 2015. International Labour Organization, Geneva.

Jaimovich, N., Siu, H.E., 2018. Revision of the paper: the trend is the cycle: job polarization and jobless recoveries (No. w18334). Nat. Bureau .Econ. Res..

Lucchese, M., Pianta, M., 2012. Innovation and employment in economic cycles. Comp. Econ. Stud. 54, 341–359.

Nelson, R.R., Phelps, E.S., 1966. Investment in humans, technological diffusion, and economic growth. Am. Econ. Rev. 56, 69–75.

Porter, M.E., 1993. The Competitive Advantage of Nations. Harvard Business School Management Programs, Cambridge, pp. 73–93.

Peters, B., Dachs, B., Dünser, M., Hud, M., Köhler, C., Rammer, C., 2014. Firm Growth, Innovation and the Business cycle: Background Report for the 2014 Competitiveness Report. ZEW Gutachten/Forschungsberichte.

Peters, B., Hud, M., Dachs, B. & Köhler, C. (2017): Employment Effects of Innovations over the Business Cycle: Firm-Level Evidence from European Countries, *Beiträge zur Jahrestagung des Vereins für Socialpolitik 2017*: Alternative Geld- und Finanzarchitekturen - Session: Organization and Firms I, No. A12-V3, ZBW -Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg.

Pizarro, F.B.R. (2013). Innovación y empleo en las empresas manufactureras españolas. Documentos De Trabajo De La Facultad De Ciencias Económicas y Empresariales, N°.7, 201341 Pags, (7).

Rinne, U., Zimmermann, K.F., 2012. Another economic miracle? The German labor market and the Great Recession. IZA J. Labor Policy 1 (1), 3.

Schumpeter, J., 1939. Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process. McGraw-Hill.

Tether, B.S., 2005. Do services innovate (differently)? Insights from the European innobarometer survey. Ind. Innov. 12 (2), 153–184.

Triguero, A., Córcoles, D., Cuerva, M.C., 2014. Persistence of innovation and firm's growth: evidence from a panel of SME and large Spanish manufacturing firms. Small Bus. Econ. 43 (4), 787–804.

van Ophem, H., van Giersbergen, N., van Garderen, K.J., Bun, M., 2019. The cyclicality of R&D investment revisited. J. Appl. Econ. 34 (2), 315–324.

Violante, G.L., 2008. Skill-biased technical change. New Palgrave Dictionary of Economics, 2.

Vivarelli, M., 2014. Innovation, employment and skills in advanced and developing countries: a survey of economic literature. J. Econ. Issues 48 (1), 123–154.

Vivarelli, M., 1995. The economics of technology and employment: theory and empirical evidence. Aldershot: Elgar.

Welch, Finis, 1970. Education in production. J. Polit. Econ. 78, 312–327.