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Abstract

This paper analyses the effects of product innovations introduced by firms in upstream and downstream sectors and firms in the same sector on firm employment. To this aim, we extend the Harrison et al. (2014) model to analyse the relationship between firm innovation and employment to account for innovation in the same and related sectors. We employ panel data for the innovation activities of Spanish firms together with input–output data. The results show that product innovation by firms in the same sector harms the firm's employment, which is consistent with a business-stealing mechanism. A negative effect on employment is found for the introduction of new products in upstream sectors, which results in the reduction of labour in the focal firm. The type of labour that is displaced by innovations introduced by both same-sector and upstream firms is predominantly low-skilled. No significant effects are found for innovations introduced in downstream industries.

Keywords: same sector, downstream and upstream sectors, product innovation, employment growth

JEL: J23, O31, O33, L6

1. Introduction and background

The relation between innovation and employment has historically been a point of focus for economists and has attracted the attention of classical economists such as Ricardo and Marx (Hecht, 2001). Ricardo argued that the beneficial effects attributable to the introduction of efficient machinery could compensate for the potential negative impact on employment. However, he later contended that the "employment of machinery is frequently detrimental" to the interests of workers (Ricardo, 1821: 392). Marx put forward a strong critical stance, noting that the unemployment created by technical change could not be counterbalanced by the demand for new workers associated with the accumulation of capital (Pianta, 2005).

More recently, neo-Schumpeterian economists have focused on the impact of emerging techno-economic paradigms on employment. Their attention follows from the debate on the effect of industrial revolutions and waves of investment. In particular, the rise of new industries and technologies generates direct effects on the jobs required to produce and deliver new products and services and also has indirect effects on supplying and adopting economic sectors (Freeman & Louca, 2001; Freeman & Soete, 1994).

Disentangling the impact of innovation on employment is not an easy task when the focus is on both the quantity of the employment and the nature of the jobs created and destroyed. The effect of innovation varies according to the type of innovation —product or process— that is undertaken. Product innovation has a positive effect on the employment of the focal firm via higher demand, while process innovation is generally considered to be detrimental to employment because of its labour-saving nature. However, a number of compensation mechanisms (e.g. via induced demand for capital and intermediate goods, reduced prices or wages dynamics) may counterbalance this baseline relation (Vivarelli, 2014).

In recent decades, there has been a spate of empirical studies that, from a micro-level perspective, analyse the effect of firm innovation on firm employment (Pianta, 2005; Vivarelli, 2014; Calvino & Virgillito, 2018). At the micro-level, the approach proposed by Harrison et al. (2014) allows us to disentangle the differentiated employment effects of product and process innovation. In particular, it leads to assessing the effects that sales growth induced by the introduction of new products and process innovations has on employment. Most of the empirical studies that have applied this methodology have found a positive effect of product innovation on employment in the focal firms. However, they do not always confirm the negative effect of process innovation foreseen by theoretical arguments (Dachs et al., 2016; Díaz et al., 2020; Hall et al., 2008; Peters et al., 2017).[1]

In this paper, we argue that the effect of innovation on employment is caused not only by firms' own innovation activities but also by innovations carried out by firms in the same and related industries. The impact of innovation from other firms in the same sector has already been discussed in the literature, which has found a negative impact related to a business-stealing effect (Vivarelli, 2014). The main contribution of our paper is to

[1] A second main empirical framework can be traced in studies like Bogliacino et al. (2012, 2014). Their approach is based on innovation inputs, such as R&D expenditure, and detected positive effects of innovation inputs on employment (Calvino & Virgillito, 2018).

explore the influence of innovations introduced by other companies located upstream or downstream with respect to the focal firm.

A first set of relevant studies focuses on how input–output networks allow for a propagation of firm and sector shocks using sectoral data. Acemoglu et al. (2017) postulate that supply-side shocks propagate downstream more powerfully than upstream; i.e. customers are hit more strongly than suppliers. On the contrary, for demand shocks, the propagation is expected to be stronger for upstream suppliers than for downstream customers. Their industry-level empirical analysis, focused on the US, considers innovation-related shocks like those associated with total factor productivity and the variation in foreign patenting, which may capture technological improvements and fiercer international competition. They find that improved productivity and foreign technologies lead to employment creation in downstream sectors. Autor & Salomons (2018) provide a complementary industry-level analysis, focusing on 18 OECD countries. They find that labour-displacing productivity growth in upstream sectors has a beneficial offsetting impact on customers' industries, which are benefiting from a price decline.

Another recent study that connects with our analysis is the contribution of Dosi et al. (2021). Their empirical analysis does not directly account for input–output linkages and is carried out on two separate sets of industries: upstream sectors, which pursue R&D activities, and downstream sectors, which are not considered to be introducing product innovations or investing in R&D, but invest only to replace or expand fixed capital. Their results indicate a negative effect of capital replacement and a weaker positive effect of expansionary capital investments as well as R&D. Overall, their results question the labour-friendly nature of technological change.

We advance in different ways from these contributions. First, while directly considering inter-sectoral input-output relations, we do not disregard the micro-level heterogeneity within sectors. Second, our micro-level analysis provides a characterisation of the actual innovation output and performance of firms rather than focusing on productivity, inventions, or investments in R&D or fixed capital. As we will discuss below, we also consider the types of jobs that are created or destroyed by other firms' innovation, distinguishing between low- and high- skilled employment.

In this paper, we place particular emphasis on the effect of product innovations introduced by other companies on employment at the focal firm. We have already mentioned the potential relevance of product innovation by firms in the same sectors (Vivarelli, 2014).

Let us now focus on the potential effect that upstream innovation may have on employment in the focal firm. A useful starting point, which connects with the description of inter-industry relations through an input-output lens, is Hirschman's (1967) idea that forward linkages are related to output utilisation. The evidence of Scherer (1982) on the differences between industry of origin and use of new products points to the relevance of purchasing innovation in addition to a firm's own innovation efforts. In a similar vein, Pavitt (1984), Dosi (1984) and Dosi et al. (2021) argue that and discuss how new products developed in an upstream sector may result in improved processes for downstream firms. These processes can have detrimental effects on labour. The attention given to the effect of established and recent forms of automation on employment (e.g. Acemoglu

& Restrepo, 2020; Hecht, 2001) can be seen as an example of the adoption of improved processes, which are developed upstream and could be aimed at cutting costs via reduced labour demand. However, we cannot exclude that upstream product innovation may engender a positive effect on firm employment. Product innovations of upstream sectors can be seen as new or improved investment and intermediate goods that embed all the R&D endeavours that go into their development and benefit downstream firms through knowledge circulation (Meyer-Krahmer, 1992; Hauknes & Knell, 2009). In turn, this could result in better inputs, which positively affect the demand of the focal firm itself (via higher quality or cheaper products) and thereby its employment.

Employment in the focal firm can be affected by innovation in downstream sectors, too. Users can request or demand improvements of their supplier firms and enhance beneficial mutual learning opportunities for upstream producers (Lundvall, 1992; Montresor & Marzetti, 2008; von Hippel, 1976). Product innovation may also be an element of dynamism in downstream (user) sectors that may induce a higher demand of supplies for downstream industries (Malerba, 2007), thus translating to higher employment for the focal firm located upstream. Nevertheless, we cannot exclude negative effects on employment in the focal firm arising from downstream innovation if this innovation contracts the demand of external supplies. For instance, downstream innovation may outpace the capacity of upstream firms to supply adequate inputs for the new requirements of the purchasing companies, resulting in reduced reliance on national suppliers in favour of foreign suppliers or in-house development of technology- and human capital-intensive components (Belderbos et al., 2001; Javorcik, 2004). Moreover, it is possible that downstream innovation results in increased efficiency and a reduced demand for inputs from upstream suppliers. A notable and increasingly relevant example are the environmental innovation strategies aimed at reducing the use of (and cost associated with) materials (Ambec & Lanoie, 2008; Dangelico & Pujari, 2010).

In addition to analysing the effect of innovations on employment in the same sector and in upstream and downstream industries, we provide another contribution. We consider the types of jobs that are created or destroyed by other firms' innovations, distinguishing between workers with and without a university degree. In so doing, we connect with studies that have considered the extent to which skill levels influence the relation between innovation and employment. Although recent forms of technological change (e.g. artificial intelligence) may potentially substitute high-skilled jobs, these jobs have been shielded from prior waves of automation given the complexity of the tasks that involve human judgment, problem solving and analytical skills (Acemoglu & Restrepo, 2018b, 2018a). The substitutability–complementarity relation between labour and machines is at the core of the well-known polarisation dynamics that have merged in many developed economies, including Spain, which is the focus of our analysis (Sebastian, 2018). Extant contributions document that among manufacturing jobs, production and operative labourers and even specialised blue collars have seen a reduction of employment shares in recent decades (Autor, 2015; Katz & Margo, 2014). Arguably, these workers are characterised by lower educational attainments than those in the manufacturing jobs which are winning from these dynamics. Indeed, as documented by Mokyr et al. (2015), workers without tertiary education experience a lower work effort (i.e. higher unemployment) compared with workers with a bachelor's degree.

Based on the above, we address two related research questions: (i) How is the employment of the focal firm affected by product innovations introduced by the same sector and by firms operating in downstream and upstream sectors? (ii) Does the skill level play a role in the effect of product innovation from outside the firm's boundaries on employment in the focal firm?

In order to answer these questions, we follow the empirical methodology proposed by Harrison et al. (2014), and we extend it drawing on the Javorcik (2004) methodology to build variables that capture the effect of innovation in upstream and downstream sectors. The data used in this article comes from the Panel of Technological Innovation (PITEC) along with information on input–output flows that characterise the Spanish economy and are provided by the Spanish National Statistics Institute.

The results show that product innovation in the same industry affects the focal firm's employment negatively, which is consistent with the idea that this type of innovation triggers a business-stealing effect. A negative effect on employment is also found for the introduction of new products in upstream sectors. These innovations result in labour-saving processes within the focal firm. The bulk of the effects on employment that we observe seem to be associated with low-skilled workers, even though the evidence regarding the impact of upstream innovation for workers without a university degree is less statistically significant. Arguably, these low-skilled workers, engaged in production phases, suffer from the consequence of shrinking demand, which arises from the business-stealing effect and the cost-cutting processes adopted by the focal firm, which results from the upstream innovation.

The remainder of the paper is structured as follows. In the next section, we present the main characteristics of the empirical approach. In Section 3, we describe the data. In Section 4, we present the results. Section 5 concludes and discusses implications.

2. Empirical model

In order to measure the effects of product innovation from firms in upstream, downstream and the same sectors, an extended Harrison, Jaumandreu, Mairesse and Peter (2014) model is proposed. The basic Harrison et al. (2014) model estimates the effects of innovation on employment in a threefold manner. The first element captures the impact of product innovation introduced by the focal firm, measured by the variable 'sales growth due to new products.' The coefficient for this variable shows two types of effects. It reveals the direct effects of product innovation on employment and simultaneously analyses the possible loss of employment in the case that new products are produced more efficiently than old ones. Another type of effect on employment is generated by the process innovations of the focal firm. Therefore, the model includes an indicator that reflects whether firms carried out 'only process innovation' not associated with product innovation. Moreover, in this specific model, the constant term expresses the average efficiency growth in the production of old products

(Harrison et al., 2014). Here below we offer a synthetic description of the components of the model.[2] The model can be depicted with the following equation (1).

$$l_t - g_{1t} - \pi_t = \alpha_0 + \alpha_1 d_t + \beta g_{2t} + \varepsilon_{it} \quad (1)$$

l_t is the employment growth rate, g_{1t} is the sales growth rate due to old products, g_{2t} is the sales growth rate due to new products and π_t is the prices growth rate at the industrial level as a proxy of firm prices. Every growth rate is between year *t* and year *t-2*. d_t is a binary variable that picks up the additional effect of process innovations related to old products by means of the efficiency parameter α_1. The variable d_t is equal to one if the firm has implemented a process innovation not associated with product innovation (process innovation only) in year *t*. If a firm introduces a new process, the production efficiency for old products improves, and, subsequently, employment drops. On the other side, the parameter α_0 represents (minus) the average efficiency growth in production of the old product (in other words, the growth of employment in the absence of innovation). The parameter β captures the relative efficiency of the production of old and new products (Harrison et al., 2014). If the coefficient is less than unity, it means that the new products are produced more efficiently than old products. In other words, the new products require less labour input than the old ones. ε_i is an error term.

From equation (1), it is possible to extend the original Harrison et al. model by adding the new variables that capture the innovation through the value chain (new product) of upstream (up), downstream ($down$) and same sectors ($intra$) as in equation 2. ε_{it} is the uncorrelated zero mean error term. We build these variables following the literature that has analysed spillovers from foreign direct investment (FDI) (Javorcik, 2004) and uses a one-year lag to allow the new products to diffuse across sectors and produce an effect on employment.

$$l_t - g_{1t} - \pi_t = \alpha_0 + \alpha_1 d_t + \beta g_{2t} + \gamma_1 intra_{t-1} + \gamma_2 down_{t-1} + \gamma_3 up_{t-1} + \varepsilon_{it} \quad (2)$$

The intensity of product innovation of firms that belong to the same industry of a focal firm (*intra*) is defined as the ratio between total innovative sales (*innosales*[3]) in the industry (without the focal firm) and total sales (*sales*) in the industry (without the focal firm) in each year. Accordingly, this new variable reflects industry innovativeness and varies by firm (*i*), industry (*j*) and time (*t*).

$$Intra_{ijt} = \frac{[\sum_{i \forall i \in j} innosales_{it}] - [innosales_{it}]}{[\sum_{i \forall i \in j} sales_{it}] - [sales_{it}]} \quad (3)$$

To build the indicator for product innovation by downstream industries (*down*), we use $\propto_{jk}$,which is the share of industry *j*'s production that is sold to industry *k*, taken from the 2010 input-output tables. *Down*$_{jt}$ reflects, for each industry, the level of innovativeness of the industries located downstream, that is, their 'customers', and varies by industry (*j*) and time(*t*).

$$down_{jt} = \sum_{k \; if \; k \neq j} \propto_{jk} * \; Intra_{\;kt} \quad (4)$$

[2] See Harrison et al. (2014); Peters et al. (2017) and Dachs & Peters (2014) for more details.

[3] *Innosales* is sales in *t* from new-to-the-market products introduced between *t* and *t-2*.

To build the indicator for product innovation by upstream industries (*up*), we use σ_{jm},which is the share of industry *j*'s inputs that is purchased from national industry m, taken from the 2010 input-output tables. up_{jt} reflects, for each industry, the level of innovativeness of the industries located upstream, that is, their 'providers', and varies by industry (*j*) and time (*t*).[4]

$$up_{jt} = \sum_{m\ if\ m\neq j} \sigma_{jm} * Intra_{\ mt} \quad (5)$$

3. Data

We employ data from the Spanish Panel of Technological Innovation (PITEC), which is managed by the Spanish Foundation of Science and Technology and the National Statistics Institute. The data includes information about sales, employment, investment and variables related to input and output of innovation. This database has been widely employed for the analysis of different aspects of firm innovation, such as the importance of demand-pull factors (García-Quevedo et al., 2017), university technology transfers (García-Vega & Vicente-Chirivella, 2020), green innovation (Kunapatarawong & Martínez-Ros, 2016) and innovation failures (D'Este et al., 2018), among many others. We employ data from the PITEC waves from 2005 to 2015. Given that our dependent variable captures the two-year growth rate of the firm's employment, our estimations cover the period 2007-2015.

In the baseline analysis, we use the balanced version of PITEC so that the number of firms in each industry is kept stable and the measures of same-industry, downstream and upstream innovation reflect the dynamics of innovation in each industry rather than the appearance or disappearance of some firms from the sample for a variety of reasons, such as mergers, acquisitions and closures.[5]

A feature of this study is that we deal with growth rates between *t* and *t-2* for employment and for sales due to new and old products. Sometimes these growth rates are very extreme, which might reflect extraordinary circumstances or just measurement errors (e.g. different firm respondents using different criteria in two waves). To alleviate this problem, we winsorize the upper and lower 1% of the employment growth and the sales growth due to new products (that is, we set these values equal to the 99th percentile and the 1st percentile of the original distribution for the growth rates).[6]

Table 1 shows the descriptive statistics for the firms in the balanced sample. First, we observe a decreasing trend in the share of innovative firms from 2010 onwards. Second, the average employment growth rate for the whole sample is 0.5%. Employment growth is negative in 2009, 2010, 2012 and 2013 and positive in the other years, reflecting the fact that most of our period is one of economic crisis. For non-innovators, the average employment growth rate is -1.1%, while for innovators it is 1.0%. Third, the average sales growth rate for the

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[4] Following the standard approach in the literature (Javorcik, 2004), to build the upstream indicator, we subtract exports when calculating *sales* and *Innosales.* For example, if a firm sells 100% of its new products to the foreign market, this does not contribute to defining the upstream innovation that is relevant for the focal firm.

[5] We are aware that this choice leads to survivorship bias. To explore the magnitude of this problem, we replicated the analysis using the unbalanced panel. The results are similar. We show them in Appendix A (Table A1, A2, and A3).

[6] The results are robust to the elimination of these extreme observations. They are available upon request.

whole sample is 7.1%, with negative growth rates only in 2009 and 2010. As in the case of employment, the growth rate is remarkably lower for non-innovators (4.4%) than for innovators (7.9%). It is important to highlight that the sales growth due to old products has a negative growth in the whole period (-19.9%). However, this negative behaviour is compensated by the positive growth rate of the sales of new products (26.1%).

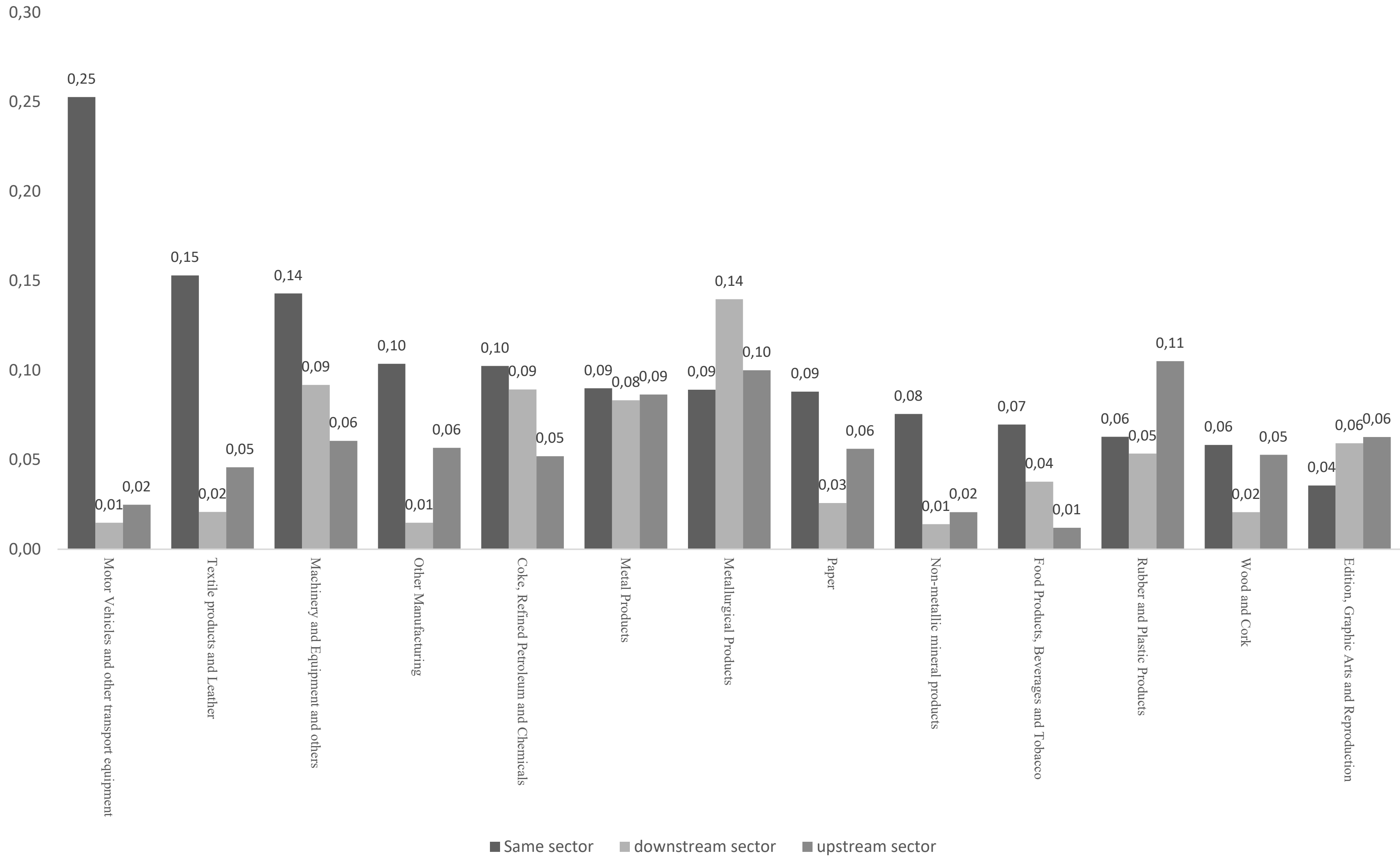
Figure 2 shows the average share of product innovation by upstream, downstream and same sectors. The industries with higher levels of product innovation are motor vehicles and other transport equipment, textiles and leather, and machinery and equipment and others.

The industries that show more innovation from downstream industries are rubber and plastic products, metallurgical products, and metal products, while the industries that show more innovation from upstream industries are metallurgical products, machinery and equipment and others, and coke, refined petroleum and chemicals.

Table 1. Descriptive statistics in percentages. Manufacturing firms (2007-2015)

Years	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Total**
No. of firms	3201	3201	3201	3201	3201	3201	3201	3201	3201	28809
Non-innovators (%)	16.1	14.2	12.9	11.7	21.7	26.5	27.8	29.7	31.3	21.3
Innovators (%)	83.9	85.8	87.1	88.3	78.3	73.5	72.2	70.3	68.7	78.7
Process innovators only (%)	17.3	16.2	15.1	15.1	17.2	16.9	16.6	15.1	14.5	16.0
Product innovators (%)	66.7	69.7	72.0	73.3	61.0	56.6	55.6	55.2	54.2	62.7
Product innovators only (%)	17.8	16.6	14.7	14.4	18.8	19.6	21.1	21.9	21.0	18.4
[% of which are product & process innovators]	48.9	53.1	57.4	58.9	42.2	37.0	34.4	33.3	33.2	44.3
Employment growth (%)										
All firms	6.5	4.2	-4.6	-5.5	0.1	-0.4	-1.6	0.7	4.7	0.5
Non-innovators (%)	5.1	2.3	-5.7	-6.6	-0.5	-1.2	-3.8	-1.8	2.0	-1.1
Innovators (%)	6.7	4.6	-4.4	-5.4	0.3	-0.1	-0.8	1.8	5.9	1.0
Process innovators only (%)	5.3	3.5	-4.5	-5.9	0.7	-0.2	-0.5	3.0	6.3	0.9
Product innovators (%)	7.1	4.8	-4.4	-5.3	0.2	0.0	-0.9	1.5	5.8	1.0
Product innovators only (%)	7.6	5.2	-4.8	-6.1	-0.8	-1.6	-2.3	-0.3	4.8	0.2
[% of which are product & process innovators]	6.9	4.7	-4.3	-5.1	0.6	0.8	0.0	2.6	6.4	1.4
Sales growth (%)										
All firms	26.1	14.5	-12.0	-7.9	16.0	5.8	0.3	7.7	13.3	7.1
Non-innovators (%)	22.7	9.3	-13.0	-8.5	14.5	3.6	-2.1	4.3	9.2	4.4
Innovators (%)	26.8	15.4	-11.9	-7.8	16.5	6.6	1.2	9.2	15.1	7.9
Process innovators only (%)	24.8	17.3	-11.9	-9.6	17.6	8.3	3.3	8.3	16.7	8.3
Product innovators (%)	27.3	15.0	-11.9	-7.4	16.1	6.1	0.6	9.4	14.7	7.8
Old products	-6.5	-17.8	-36.8	-34.8	-13.3	-18.2	-22.2	-17.7	-11.8	-19.9
New products	31.1	31.2	24.1	26.3	28.3	23.2	21.8	24.7	24.3	26.1
Prices growth (%)										
All firms	7.8	7.8	2.8	1.2	5.9	5.0	1.8	0.1	-0.2	3.6
Non-innovators (%)	8.0	8.0	3.2	1.5	5.8	5.2	2.2	0.4	0.1	3.8
Innovators (%)	7.8	7.8	2.8	1.2	6.0	4.9	1.6	-0.1	-0.3	3.5
Process innovators only (%)	8.5	8.5	3.0	1.4	6.3	4.7	1.8	0.1	0.0	3.8
Product innovators (%)	7.6	7.7	2.7	1.2	5.9	4.9	1.6	-0.1	-0.3	3.5
Product innovators only (%)	7.2	7.4	2.9	1.1	5.1	4.4	1.4	-0.2	-0.4	3.2
[% of which are product & process innovators]	7.8	7.8	2.7	1.2	6.2	5.3	1.7	-0.1	-0.3	3.6
Same sector (%)										
All firms	11.7	12.0	14.0	13.0	11.0	10.0	10.2	10.3	12.1	11.6
Non-innovators (%)	11.2	11.7	13.9	12.3	10.5	9.7	10.2	10.1	10.9	11.2
Innovators (%)	11.8	12.0	14.0	13.1	11.2	10.1	10.1	10.4	12.6	11.7
Process innovators only (%)	10.5	11.1	12.5	11.4	10.5	9.7	9.9	10.0	11.4	10.8
Product innovators (%)	12.1	12.2	14.3	13.5	11.3	10.2	10.2	10.5	13.0	11.9
Product innovators only (%)	12.5	12.5	15.5	15.0	11.9	10.8	10.0	10.6	12.9	12.4
[% of which are product & process innovators]	11.9	12.2	14.0	13.1	11.1	9.9	10.3	10.5	13.0	11.8
Downstream Sector (%)										
All firms	5.1	5.3	6.6	6.2	5.8	4.8	5.2	4.5	5.9	5.5
Non-innovators (%)	5.0	5.3	6.6	6.2	5.7	4.6	4.9	4.3	5.9	5.4
Innovators (%)	5.1	5.3	6.6	6.2	5.9	4.9	5.3	4.6	5.9	5.5
Process innovators only (%)	5.0	5.1	6.3	5.8	5.7	4.8	5.2	4.7	6.3	5.4
Product innovators (%)	5.2	5.3	6.7	6.3	5.9	4.9	5.3	4.6	5.8	5.6
Product innovators only (%)	5.5	5.4	6.8	6.6	6.2	5.0	5.5	4.8	6.1	5.8
[% of which are product & process innovators]	5.0	5.3	6.6	6.3	5.8	4.9	5.2	4.4	5.6	5.5
Upstream Sector (%)										
All firms	6.3	6.3	7.6	7.3	6.8	5.6	5.3	5.3	7.5	6.4
Non-innovators (%)	5.6	5.7	6.7	6.6	6.2	5.2	4.8	4.9	7.1	5.9
Innovators (%)	6.4	6.4	7.7	7.4	7.0	5.8	5.5	5.4	7.7	6.6
Process innovators only (%)	5.7	5.8	7.0	6.3	6.3	5.3	5.1	5.1	7.6	6.0
Product innovators (%)	6.6	6.5	7.9	7.6	7.2	5.9	5.7	5.5	7.7	6.7
Product innovators only (%)	7.2	6.8	8.4	8.3	7.5	6.2	6.0	5.7	8.1	7.1
[% of which are product & process innovators]	6.4	6.4	7.7	7.5	7.0	5.8	5.5	5.4	7.5	6.6

Figure 2. Average share of product innovation in upstream, downstream and same sector



Source: Own elaboration with data of PITEC and input-output matrix (2010).

4. Results

4.1. Baseline results

Table 2 shows the baseline results concerning the effect of innovations introduced by other companies on employment (countries operating in the same sectors as well as in upstream and downstream industries), holding the focal firm innovation constant. Column 1 provides the results from the OLS estimation, column 2 provides the results from the random effects estimation and column 3 provides the results from the IV specification, where g2 is instrumented following Harrison et al (2014).[7]

The results are in line with the findings of previous studies for Spain (Díaz et al., 2020; Harrison et al., 2014) using this model: the effect of product innovation (g_2) is close to 1 (especially when instrumented), which suggests that the production of new products is as efficient as the production of old ones. The coefficient for 'only' process innovation (d) is negative, turning out non-significant in the IV specification. Finally, the constant term is not significant in the IV specification.[8]

The different models show a negative and significant effect of the same-sector variable, which indicates that, holding focal firms' innovation constant, being located in a more product-innovative industry has a negative influence on firm employment. This result follows the logic of the business-stealing effect (Vivarelli, 2014), whereby new products introduced by competitors contract demand and, consequently, employment in the focal firm.

The results for product innovation in downstream industries show a negative but non-significant effect on focal firms' employment. That is, there is not enough evidence to reject the null hypothesis of a null effect. On the one hand, downstream innovation might induce higher demand of inputs, thus increasing employment in the focal firm (Malerba, 2007). On the other hand, downstream innovation may require fewer inputs (e.g. Ambec & Lanoie, 2008; Dangelico & Pujari, 2010) or different inputs that may be bought abroad or developed in-house (Belderbos et al., 2001; Javorcik, 2004).

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[7] Following Harrison et al. (2014), we instrument g_2 using information from the increased range of products as an objective of innovation and the importance of clients as a source of information.

[8] Studies that use periods of economic growth usually find a negative value for the constant term in the Harrison et al. (2014) model, while studies that focus only on periods of economic recession usually find a positive value. Our period of analysis includes both types of periods, so the average value is not significant (Díaz et al., 2020; Peters et al., 2017)).

Table 2. Baseline results

	1	2	3
VARIABLES	OLS	RE	REIV
Only process innovation	-0.0568***	-0.0569***	-0.0193
	[0.006]	[0.006]	[0.013]
Sales growth due to new products	0.8290***	0.8265***	0.9519***
	[0.007]	[0.009]	[0.037]
Lag same sector	-0.1142***	-0.1106***	-0.1659***
	[0.032]	[0.034]	[0.036]
Lag downstream sector	-0.0517	-0.0495	-0.0775
	[0.076]	[0.083]	[0.083]
Lag upstream sector	-0.1237*	-0.1215*	-0.1965***
	[0.065]	[0.070]	[0.071]
Constant	0.0314***	0.0321***	-0.0067
	[0.003]	[0.003]	[0.012]
Observations	28,800	28,800	28,800

Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise.

The results for product innovation in upstream industries are negative, significant and of similar magnitude compared with the effects of innovations developed by same-sector firms. Linking this result with the insights available from the literature (Dosi, 1984; Dosi et al., 2021), we argue that new products developed in upstream sectors may result in improved processes for downstream firms, which show a detrimental effect on labour. This finding appears consistent with the insights in Dosi et al. (2021) on the negative effect of investments in fixed capital aimed at replacing vintage capital.

One feature of our data is that they include some erratic evolution patterns with very large (sometimes implausibly large) growth rates.[9] To make sure that our results are robust, we explore this element further. First, we detect the 'noisiest' firms as follows. We calculate the *dfbeta*, which is the change in the coefficient when an observation is removed from the analysis, for each observation (firm–year) in each of the same, downstream and upstream sector innovation variables. In this way, we have three *dfbeta*s per observation. We then compute the standard deviation of the *dfbeta* for each firm and each of the three aforementioned innovation variables over the whole estimation period. Finally, we calculate a summary indicator by adding up the squares of these standard deviations. By doing this, we end up with a measure of the firms that generate noise in the results.[10] We explore whether our results are robust to the elimination of the noisiest firms.

Table 3 shows the results for the first robustness check when the percentiles 95 and beyond (columns 1-3) and 90 and beyond (columns 4-6) of noisiest firms are eliminated from the analysis and Figure 3 shows the evolution of coefficients and confidence intervals when different percentiles are removed (up to 10% of the original sample). All in all, the results are very stable, which suggests that the noisiest firms were not driving the baseline results. First, for same-sector innovation, the coefficients are always significant from a statistical point of view. Their confidence intervals largely overlap, and their point estimates vary between -0.1093 and -0.1622 depending on the method and sample used. Second, for downstream sector innovation, the coefficient is always negative but not significant. Third, for upstream sector innovation, the coefficient is always negative and significant, ranging from -0.1690 to -0.228.

[9] For instance, there is one firm in 2007 showed a huge decrease in sales from old products (-82%) with a 7% increase in employment. In 2008, there was a huge increase in sales from old products (+839%) with just a 4% increase in employment. Then, in 2010, there was another huge decrease in sales from old products (-88%) with just a 2% reduction in employment, followed in 2011 by another huge increase (+1216%) in sales from old products with just a 4% increase in employment. In 2013, there was a decrease in sales from old products (-515) with an important increase in employment of 10.8%. Finally, in 2015, sales from old products decreased by 100% (all sales came from new products) with an employment decrease of 2%. The consequence of the evolution described above is that in 2008 and 2011, this firm shows a large contribution (around 20 standard deviations) which is positive for the upstream coefficient and negative for the downstream coefficient. However, in 2007, 2010, 2013 and 2015, it shows a large contribution (between 7 and 12 standard deviations) which is negative for the upstream coefficient and positive for the downstream coefficient. To sum up, this firm is an outlier because of the extremely large jumps in sales from old products with employment remaining quite stable.

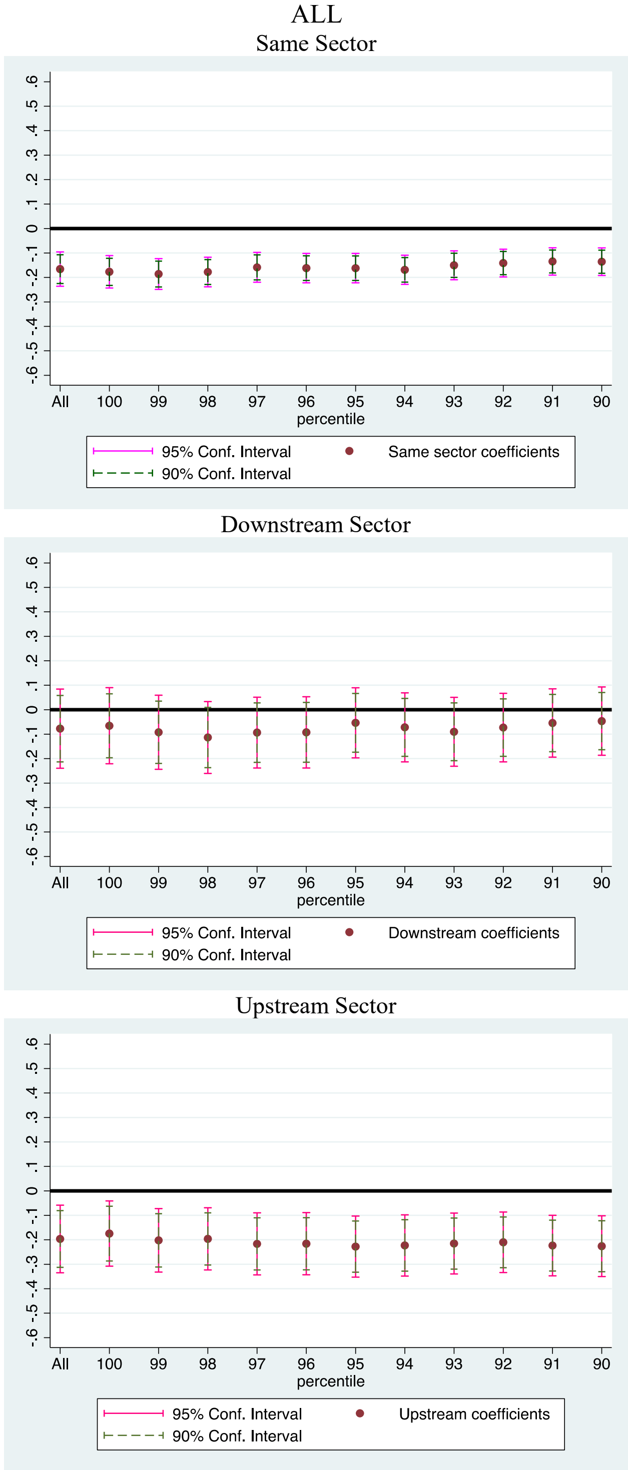
[10] Firms with large and positive contributions to the effect of the innovation variables in some years and negative effects in other years.

Table 3. Results without the noisiest firms

	Without percentiles 95-100			Without percentiles 90-100		
	1	2	3	4	5	6
VARIABLES	OLS	RE	REIV	OLS	RE	REIV
Only process innovation	-0.0507***	-0.0504***	-0.0205*	-0.0471***	-0.0470***	-0.0235**
	[0.005]	[0.005]	[0.011]	[0.005]	[0.005]	[0.011]
Sales growth due to new products	0.8428***	0.8393***	0.9402***	0.8465***	0.8421***	0.9202***
	[0.006]	[0.008]	[0.034]	[0.006]	[0.008]	[0.034]
Lag same sector	-0.1214***	-0.1165***	-0.1622***	-0.1093***	-0.1013***	-0.1357***
	[0.026]	[0.028]	[0.031]	[0.023]	[0.025]	[0.029]
Lag downstream sector	-0.0377	-0.0318	-0.0538	-0.0473	-0.0379	-0.0467
	[0.065]	[0.074]	[0.073]	[0.062]	[0.073]	[0.071]
Lag upstream sector	-0.1690***	-0.1680***	-0.2279***	-0.1800***	-0.1818***	-0.2263***
	[0.056]	[0.062]	[0.064]	[0.055]	[0.062]	[0.063]
Constant	0.0298***	0.0307***	-0.0004	0.0313***	0.0325***	0.0083
	[0.002]	[0.003]	[0.011]	[0.002]	[0.003]	[0.011]
Observations	27,072	27,072	27,072	25,632	25,632	25,632

Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.10, ** p<0.05, *** p<0.01. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise.

Figure 3. Results without the noisiest firms



Notes: These results come from the REIV estimation. The point estimates, the 95% and the 90% confidence intervals are shown. The percentile in the x-axis denotes the lowest percentile from which noisy firms are removed.

4.2. Effect on High- and Low-Skilled employment

To delve into the effects on employment depicted above, we also analyse the effects of product innovation of upstream, downstream and the same sectors for high-and low-skilled employment. This also sheds light on the mechanisms that lead to the creation or destruction of employment due to other companies' innovation. We use two equations based on Harrison et al. (2014), one for low-skilled employees (equation 6) and one for high-skilled employees (equation 7):

$$l^{ls} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \gamma_1 intra_{\,prod_{jt}} + \gamma_2 down_{prod_{jt}} + \gamma_3 up_{prod_{jt}} + \varepsilon_i^{ls} \quad (6)$$

$$l^{hs} - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \gamma_1 intra_{prod_{jt}} + \gamma_2 down_{prod_{jt}} + \gamma_3 up_{prod_{jt}} + \varepsilon_i^{hs} \quad (7)$$

where $l^{ls}(l^{hs})$ is the employment growth rate of the workers without (with) a university degree. The rest of the variables are the same as the general model (see equation 2). Table 4 shows the results using the same structure as Table 2. We also conducted the robustness check on 'noisy firms', which are shown in Tables 5 and 6 and Figure 4.

All in all, the results for low-skilled workers are similar to the general results presented above in Table 2: the effect of innovations introduced by firms in the same sector is negative, the effect of innovations introduced in downstream sectors is negative but non-significant and the effect of innovations introduced in upstream sectors is also negative, although it becomes significant only after the 'noisy firms' are removed from the analysis (see Tables 4 and 5 and Figure 4).

On the other hand, we find no significant relationship between any of the industry variables and the high-skilled employment in firms. Actually, sometimes the coefficients are positive, albeit lacking significance, in the different specifications (see Tables 4 and 6 and Figure 4). To sum up, these results suggest that the effect of innovation that comes from outside the firm boundaries on firms' employment impacts low-skilled workers almost exclusively, while we do not find evidence that the employment of high-skilled workers is affected by innovation outside the firm.

This set of results helps us to understand the mechanisms by which innovation by external companies induces employment changes in the focal firm. The business-stealing effect engendered by same-sector companies seems to reduce the focal firm's demand and scale of production. This may be at the heart of the reduced number of low-skilled workers rather than high-skilled jobs, which may involve innovative and creative rather than routine tasks associated mainly with production phases.

The type of employment destroyed by innovation in upstream sectors is also low-skilled. Notably, as argued above, upstream innovation seems to translate to more efficient inputs and processes for the focal firm, which can save on labour. Consistently, this labour displacement occurs mainly with low-skilled workers engaged in production. In addition, this effect is not counterbalanced by the compensation mechanism that might emerge because of the expanded demand resulting from higher efficiency and lower prices.

Table 4. Results for low- and high-skilled employment

	Low-skilled			High-skilled		
	1	2	3	4	5	6
VARIABLES	OLS	RE	REIV	OLS	RE	REIV
Only process innovation	-0.0604***	-0.0608***	-0.0288*	-0.0447***	-0.0445***	-0.0179
	[0.007]	[0.007]	[0.016]	[0.015]	[0.015]	[0.037]
Sales growth due to new products	0.8442***	0.8424***	0.9511***	0.8430***	0.8425***	0.9311***
	[0.008]	[0.009]	[0.049]	[0.015]	[0.016]	[0.112]
Lag same sector	-0.0763*	-0.0745*	-0.1193***	0.0755	0.0766	0.0413
	[0.040]	[0.041]	[0.046]	[0.085]	[0.087]	[0.097]
Lag downstream sector	-0.1308	-0.1289	-0.1479	-0.0014	-0.0017	-0.0116
	[0.096]	[0.098]	[0.098]	[0.207]	[0.214]	[0.214]
Lag upstream sector	-0.0520	-0.0513	-0.1112	0.0385	0.0403	-0.0053
	[0.083]	[0.085]	[0.088]	[0.174]	[0.183]	[0.191]
Constant	0.0397***	0.0402***	0.0076	0.1105***	0.1102***	0.0827**
	[0.003]	[0.004]	[0.015]	[0.007]	[0.007]	[0.036]
Observations	25,441	25,441	25,441	22,085	22,085	22,085

Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.1, ** p<0.05, *** p<0.01. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise. The number of observations is different because firms without low-skilled employees in t-2 do not enter the specifications in columns (1)-(3), and firms without high-skilled employees in t-2 do not enter the specifications in columns (4)-(6).

Table 5. Results for low-skilled employment without the noisiest firms

	Without percentiles 95-100			Without percentiles 90-100		
	1	2	3	4	5	6
VARIABLES	OLS	RE	REIV	OLS	RE	REIV
Only process innovation	-0.0547***	-0.0550***	-0.0308**	-0.0534***	-0.0537***	-0.0316**
	[0.006]	[0.007]	[0.015]	[0.006]	[0.007]	[0.015]
Sales growth due to new products	0.8585***	0.8565***	0.9396***	0.8613***	0.8584***	0.9343***
	[0.007]	[0.008]	[0.045]	[0.007]	[0.008]	[0.046]
Lag same sector	-0.1033***	-0.1006***	-0.1371***	-0.0709**	-0.0666**	-0.0995***
	[0.032]	[0.034]	[0.039]	[0.030]	[0.032]	[0.038]
Lag downstream sector	-0.1086	-0.1046	-0.1185	-0.0526	-0.0458	-0.0552
	[0.084]	[0.090]	[0.090]	[0.082]	[0.091]	[0.091]
Lag upstream sector	-0.0967	-0.0981	-0.1429*	-0.1303*	-0.1348*	-0.1713**
	[0.073]	[0.077]	[0.081]	[0.072]	[0.077]	[0.080]
Constant	0.0343***	0.0348***	0.0099	0.0359***	0.0366***	0.0139
	[0.003]	[0.003]	[0.014]	[0.003]	[0.003]	[0.014]
Observations	23,933	23,933	23,933	22,662	22,662	22,662

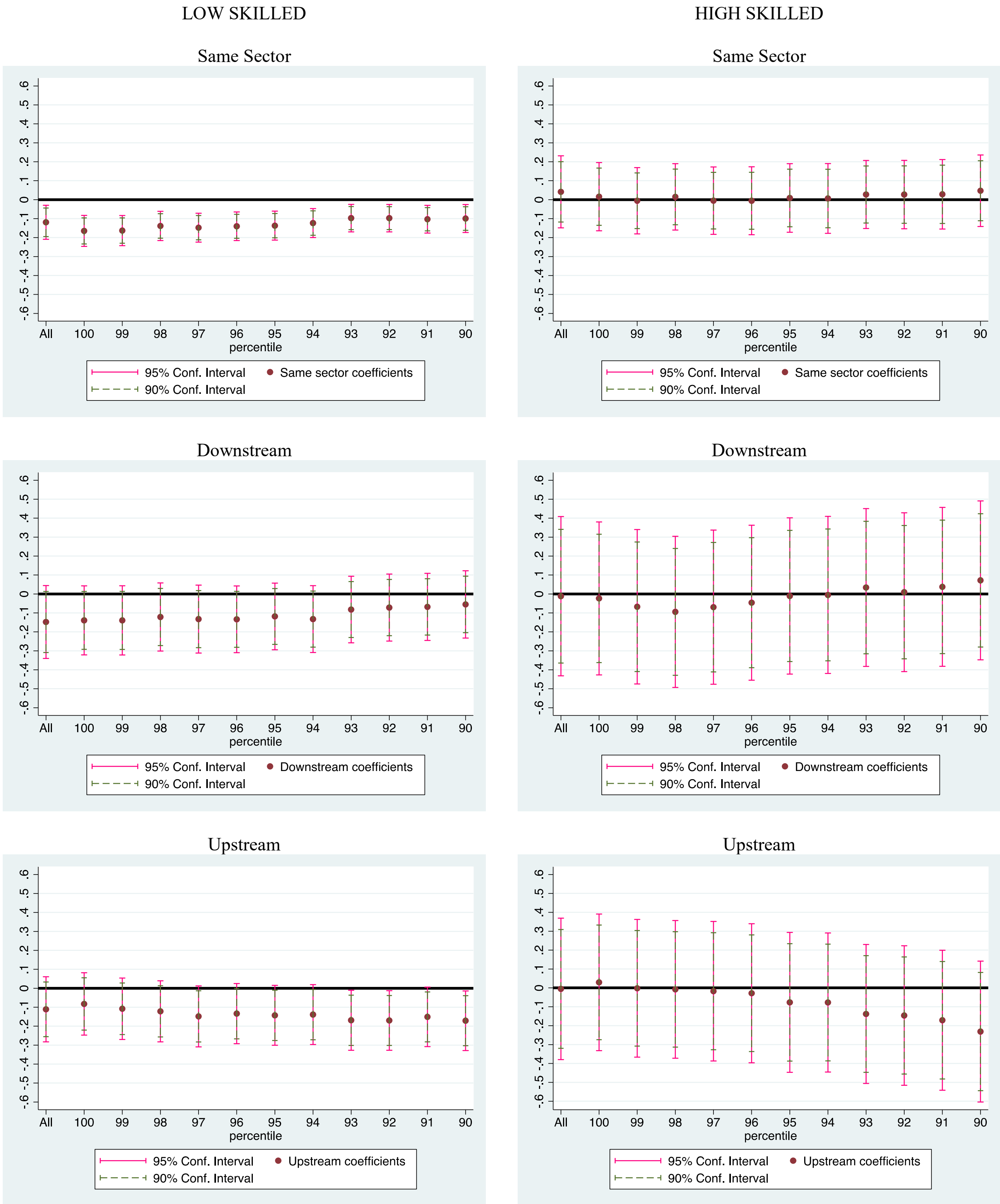
Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.10, ** p<0.05, *** p<0.01. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise.

Table 6. Results for high-skilled employment without the noisiest firms

	Without percentiles 95-100			Without percentiles 90-100		
	1	2	3	4	5	6
VARIABLES	OLS	RE	REIV	OLS	RE	REIV
Only process innovation	-0.0372***	-0.0366**	-0.0170	-0.0362**	-0.0360**	-0.0270
	[0.014]	[0.015]	[0.035]	[0.015]	[0.015]	[0.037]
Sales growth due to new products	0.8658***	0.8651***	0.9327***	0.8646***	0.8644***	0.8950***
	[0.015]	[0.016]	[0.107]	[0.014]	[0.016]	[0.113]
Lag same sector	0.0362	0.0380	0.0089	0.0597	0.0601	0.0470
	[0.080]	[0.080]	[0.092]	[0.082]	[0.082]	[0.096]
Lag downstream sector	-0.0066	-0.0077	-0.0106	0.0726	0.0719	0.0718
	[0.201]	[0.211]	[0.210]	[0.207]	[0.214]	[0.214]
Lag upstream sector	-0.0416	-0.0383	-0.0767	-0.2164	-0.2154	-0.2313
	[0.169]	[0.180]	[0.189]	[0.172]	[0.181]	[0.190]
Constant	0.1081***	0.1073***	0.0870**	0.1124***	0.1122***	0.1028***
	[0.007]	[0.007]	[0.034]	[0.007]	[0.007]	[0.036]
Observations	20,755	20,755	20,755	19,730	19,730	19,730

Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.10, ** p<0.05, *** p<0.01. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise.

Figure 4. Results for low- and high-skilled workers without the noisiest firms



Notes: These results come from the REIV estimation. The point estimates, the 95% and the 90% confidence intervals are shown. The percentile in the x-axis denotes the lowest percentile from which noisy firms are removed.

5. Conclusions

In this article, we focused on the relation between employment and innovation, looking at the impact of innovation introduced by other companies on firm employment. Specifically, we investigated the extent to which innovations by firms operating in the same sector and in upstream and downstream industries influence the employment of the focal firms and whether this impact depends on the skill level of the workers. We extended the model by Harrison et al. (2014) to capture product innovations introduced by firms in the same and related sectors. We exploited an original dataset that combines micro data from the Spanish Panel of Technological Innovation (PITEC) for the period 2005-2015 and input-output matrixes produced by the Spanish National Statistics Institute.

The results show that product innovation in the same industry affects the focal firm's employment negatively. This is consistent with the business-stealing mechanism (Vivarelli, 2014), which contracts the demand faced by the focal firm. While we find no effect for downstream innovation, a negative effect on employment is also found for the introduction of new products in upstream sectors. Arguably, new products developed in upstream sectors may result in changes in downstream companies' production processes (Dosi, 1984; Dosi et al., 2021; Meyer-Krahmer, 1992). The evidence we find can thus be interpreted as the presence of labour-saving processes which are made possible by upstream innovation. The effects on employment we observe are associated with low-skilled jobs. The emerging picture is consistent with the mechanisms described above. Innovations introduced by other companies in the same or upstream sectors either contract the demand of the focal firm or lead to the introduction of cost-efficient processes (i.e. labour). In turn, this reduces the employment of people without a university degree, workers who are more likely to be engaged in production phases. High-skilled workers, who are likely to nurture the distinctive capabilities upon which the competitive advantage of the firm is based (Teece et al., 1997), are shielded from these dynamics.

These results provide insights into the possible effects of innovation on employment, an area of research that has recently flourished, paying special attention to the effect of automation and robotisation (e.g. Acemoglu & Restrepo, 2020; Bessen, 2019). In light of the differential effects of innovation for the different skill levels, our results seem to support the idea that technological change can be biased in favour of specific classes of workers, triggering processes of inequality (Acemoglu & Autor, 2011). From a policy perspective, this last element is particularly important. Rising inequality might justify interventions in favour of people who are losing from the introduction of innovations. This could take the form of basic income provision or reskilling and training schemes that would allow low-skilled workers to transfer to stabler occupations.

Our study limitation opens other avenues of research. First, because of data limitations, we could not analyse heterogeneous effects using interaction terms. The reason is that our estimates rely on sectoral variation, and this is limited by the number of sectors considered in the PITEC. It would be of great interest to analyse the moderation effect of different firm-level variables (e.g. innovative or exporting behaviour). In addition, because of a lack of granular data, we could not reconstruct the networks of the actual competitors, suppliers and customers of the surveyed firms. This element would have allowed us to directly capture the actual relations with external firms without relying on sector-level information. Finally, in the absence of detailed information, we could not disentangle the specific task profile of the workers that are affected by innovations introduced in the same, upstream and downstream sectors. We hope that future research can focus on these aspects.

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Appendix A

Table A1. Results of total employment and without the noisiest firms (Unbalanced Panel)

	Whole sample			Without percentiles 95-100			Without percentiles 90-100		
	1	2	3	4	5	6	7	8	9
VARIABLES	OLS	RE	REIV	OLS	RE	REIV	OLS	RE	REIV
Only process innovation	-0.0598***	-0.0591***	-0.0289***	-0.0498***	-0.0467***	-0.0232***	-0.0471***	-0.0446***	-0.0243***
	[0.005]	[0.006]	[0.008]	[0.004]	[0.005]	[0.007]	[0.004]	[0.005]	[0.007]
Sales growth due to new products	0.8175***	0.8021***	0.9269***	0.8366***	0.8213***	0.9252***	0.8402***	0.8238***	0.9141***
	[0.006]	[0.008]	[0.023]	[0.005]	[0.007]	[0.021]	[0.005]	[0.007]	[0.021]
Lag same sector	-0.1538***	-0.1344***	-0.1955***	-0.1602***	-0.1531***	-0.1982***	-0.1515***	-0.1421***	-0.1812***
	[0.031]	[0.033]	[0.033]	[0.025]	[0.029]	[0.029]	[0.022]	[0.027]	[0.027]
Lag downstream sector	0.0177	0.0600	0.0301	-0.0276	0.0362	-0.0011	0.0107	0.0716	0.0471
	[0.071]	[0.081]	[0.078]	[0.059]	[0.072]	[0.069]	[0.055]	[0.068]	[0.064]
Lag upstream sector	-0.1931***	-0.2019***	-0.2890***	-0.2372***	-0.2621***	-0.3246***	-0.2289***	-0.2426***	-0.3026***
	[0.059]	[0.065]	[0.065]	[0.050]	[0.059]	[0.058]	[0.046]	[0.056]	[0.056]
Constant	0.0420***	0.0461***	0.0124*	0.0409***	0.0449***	0.0170***	0.0422***	0.0466***	0.0224***
	[0.002]	[0.003]	[0.006]	[0.002]	[0.002]	[0.006]	[0.002]	[0.002]	[0.006]
Observations	41,432	41,432	41,432	38,963	38,963	38,963	36,910	36,910	36,910

Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.05, ** p<0.01, *** p<0.001. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise.

Table A2. Results of low-skilled employment and without the noisiest firms (Unbalanced Panel)

	Whole sample			Without percentiles 95-100			Without percentiles 90-100		
	1	2	3	4	5	6	7	8	9
VARIABLES	OLS	RE	REIV	OLS	RE	REIV	OLS	RE	REIV
Only process innovation	-0.0597***	-0.0607***	-0.0364***	-0.0516***	-0.0512***	-0.0326***	-0.0520***	-0.0519***	-0.0347***
	[0.006]	[0.007]	[0.010]	[0.005]	[0.006]	[0.009]	[0.005]	[0.006]	[0.009]
Sales growth due to new products	0.8388***	0.8282***	0.9275***	0.8512***	0.8397***	0.9201***	0.8537***	0.8406***	0.9154***
	[0.007]	[0.009]	[0.029]	[0.007]	[0.008]	[0.027]	[0.006]	[0.008]	[0.027]
Lag same sector	-0.1323***	-0.1245***	-0.1676***	-0.1337***	-0.1211***	-0.1613***	-0.1227***	-0.1051***	-0.1468***
	[0.038]	[0.040]	[0.041]	[0.031]	[0.034]	[0.036]	[0.030]	[0.035]	[0.036]
Lag downstream sector	-0.1528*	-0.1353	-0.1452	-0.0912	-0.0623	-0.0740	-0.0613	-0.0213	-0.0342
	[0.089]	[0.093]	[0.091]	[0.076]	[0.085]	[0.083]	[0.074]	[0.085]	[0.083]
Lag upstream sector	-0.0504	-0.0512	-0.1216	-0.1448**	-0.1589**	-0.2085***	-0.1480**	-0.1682**	-0.2079***
	[0.074]	[0.078]	[0.078]	[0.064]	[0.070]	[0.072]	[0.062]	[0.070]	[0.071]
Constant	0.0545***	0.0573***	0.0315***	0.0509***	0.0539***	0.0331***	0.0519***	0.0554***	0.0361***
	[0.003]	[0.003]	[0.008]	[0.003]	[0.003]	[0.007]	[0.002]	[0.003]	[0.007]
Observations	35,601	35,601	35,601	33,524	33,524	33,524	31,802	31,802	31,802

Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.05, ** p<0.01, *** p<0.001. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise.

Table A3. Results of high-skilled employment and without the noisiest firms (Unbalanced Panel)

	Whole sample			Without percentiles 95-100			Without percentiles 90-100		
	1	2	3	4	5	6	7	8	9
VARIABLES	OLS	RE	REIV	OLS	RE	REIV	OLS	RE	REIV
Only process innovation	-0.0443***	-0.0399***	0.0107	-0.0363***	-0.0296**	0.0141	-0.0391***	-0.0319**	0.0073
	[0.013]	[0.014]	[0.022]	[0.012]	[0.014]	[0.022]	[0.013]	[0.014]	[0.022]
Sales growth due to new products	0.8417***	0.8296***	1.0307***	0.8624***	0.8525***	1.0305***	0.8607***	0.8520***	1.0134***
	[0.013]	[0.015]	[0.067]	[0.013]	[0.015]	[0.067]	[0.013]	[0.015]	[0.068]
Lag same sector	0.0534	0.0755	-0.0117	0.0138	0.0234	-0.0570	0.0027	-0.0008	-0.0712
	[0.079]	[0.082]	[0.084]	[0.076]	[0.080]	[0.084]	[0.079]	[0.083]	[0.087]
Lag downstream sector	0.1081	0.1323	0.1345	0.1613	0.1970	0.2000	0.1039	0.1240	0.1401
	[0.185]	[0.204]	[0.199]	[0.180]	[0.202]	[0.197]	[0.181]	[0.203]	[0.199]
Lag upstream sector	-0.0232	0.0054	-0.1404	-0.1031	-0.0781	-0.2085	-0.1565	-0.1208	-0.2376
	[0.149]	[0.164]	[0.166]	[0.143]	[0.161]	[0.163]	[0.144]	[0.161]	[0.163]
Constant	0.1089***	0.1010***	0.0499**	0.1079***	0.0983***	0.0538***	0.1117***	0.1015***	0.0617***
	[0.006]	[0.007]	[0.020]	[0.006]	[0.006]	[0.020]	[0.006]	[0.007]	[0.020]
Observations	29,923	29,923	29,923	28,150	28,150	28,150	26,779	26,779	26,779

Notes: Every specification includes year dummies. All industry variables are demeaned so that the constant term keeps its original interpretation. Clustered standard errors are shown between brackets. * p<0.05, ** p<0.01, *** p<0.001. The instrumenting strategy is based upon the "increased range" of products as an innovation objective and "clients as a source of information". In our dataset, the values of variables are recorded using four-point Likert scales (i.e. high, medium, low importance and no importance). We define dummy variables for the extremes categories (high importance and no importance, respectively), with the reference categories capturing medium and no importance. Accordingly, we employ *range_high* and *range_no,* to capture whether an increased range of products is a very important (not important) innovation objective, and zero otherwise. Similarly, and c*lients_high* and *clients_no* capture whether clients are considered a very important (not important) source of information, and zero otherwise.

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