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Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries☆

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ABSTRACT

We study the impact of process and product innovations introduced by firms on employment growth with random samples of manufacturing and services from France, Germany, Spain and the UK for 1998–2000, totaling about 20,000 companies. We develop and estimate a model relating firms' and industry's employment to innovation, that leads us to the conclusions that follow. Trend increases in productivity reinforced by process innovation are an important source of reduction of employment requirements for a given output, but the growth of demand for the old products tends to overcompensate these displacement effects. The switch of production towards new products does not reduce employment requirements, and the growth of the demand for the new products is the strongest force behind employment creation. Reallocation due to business stealing is estimated at a maximum of one third of the net employment created by product innovators. The growth of employment originated from the market expansion induced by the new products can be as important as another third.

1. Introduction

This paper studies the impact of process and product innovations introduced by firms on employment growth. We use random samples from manufacturing and services for France, Germany, Spain and the UK which amount to a total of 20,000 firms. Firms report both their sales and employment during the period 1998–2000, as well as information about their innovation activities and, in particular, the introduction of process and product innovations. A key feature that we exploit in this paper is that firms break down their end of period sales between old and new products. We want to answer three main research questions. First, whether innovation stimulates, or not, *firm-level* employment growth. Second, what are the channels through which innovation impacts *firm-level* employment and what is the relative importance of each? Third, what are the likely impacts on *industry-level* employment?

With relative factor prices roughly stable, the output-conditional or Hicksian demand for labor explains how the level of productivity implied by technical change affects labor negatively for a given output, while the level of demand for the firm's output affects it positively for a given level of efficiency. Productivity and demand have some common drivers but also others which differ, and they may, in practice, evolve differently with the result of varying paths of employment growth. For example, economists try to understand the reasons for which the current US economic recovery is "jobless" up to a surprising extent,

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i.e., a strong growth of both firm-level output and productivity is producing scarce job creation (see, for example, Van Zandweghe, 2010).[1] There is even some revival of the ancestral fears on the employment effects of machines (Brynjolfsson and McAfee, 2011).

In our sample, productivity and employment growth tend to be higher for innovators in all countries, but we trace this result back to a complex combination of employment *displacement* and *compensation* forces of innovation. These forces imply continual destruction and creation of jobs, that start at the establishment and firm-level, and shape the flows of job reallocation due to "the development of new products and production processes…" (Davis et al., 1997). Understanding how these effects work at the firm and industry levels may help us to understand how they may combine to produce opposite results as well.

This paper tries to go further than the previous literature on innovation and employment by relying on an explicit model of the firm productive process and demand. It sets a framework for the discussion of the impacts of innovation on employment. The results enlarge some of the previous findings, encompassing and explaining previous evidence. While finding a global effect of similar size than, for example, in Lachenmaier and Rottmann (2011), we get our global effect as the result of an underlying simple structural model. This provides an interpretation for each component. The framework has already been found useful by different authors to study other country-data sets (Peters, 2004, 2008, for Germany; Hall et al., 2008, for Italy; Benavente and Lauterbach, 2008, for Chile; Mairesse et al., 2011, and Mairesse and Wu, 2014, for China; Crespi and Tacsin, 2011; Crespi and Zuniga, 2012, for Latin America; Dachs and Peters, 2014, for Europe).

The main results can be summarized as follows. Innovations create employment at the firm-level. Productivity improvements and process innovations both reduce employment, holding output fixed, but output expansion of the old products overcomes this and raises employment. Price reductions due to process innovation seem to boost this expansion, although the size of the expansion may be period-specific. The big source of employment gains at the firm-level is, in any case, the introduction of the new products. In addition, a maximum of one third of jobs created in this way are stolen from competitors, and a minimum of another third is estimated to come from market expansion induced by the new products. Hence, employment creation by product innovation is also an industry-level fact.

It is worthwhile to briefly comment on a few particular traits of our analysis.

For welfare reasons, economists are rather interested in the industry or even the economy-wide levels of employment. However there are good reasons to build up from the firm-level. Industry employment outcomes are shaped by the relative outcomes of firms that introduce one type or another of innovation and firms that do not.

The focus on the amount of labor demanded by the firm as a whole allows us to be much more detailed in the consideration of the different productivity and demand drivers of the impacts. But, of course, expanding this work to the explicit consideration of the variations in the composition of the labor demand is a desirable target for future research. Unfortunately, the data base we used does not include the composition of the workforce.

The data used come from the Third Community Innovation Survey (CIS3), a kind of data that are available for all European Union countries and many OECD countries. We develop a model based on economic theory but that is tailored to the information contained in this data base. With this way of proceeding, we both provide a framework for research and show the limitations of the information gathered and we suggest ways of improvement.

We use comparable firm-level data sets for France, Germany, Spain and the UK. Applying the same model to the four countries and getting meaningful results is a test for the robustness of the model.[2] The homogeneity of impacts that we find, conditional on the different degrees of technological development and R&D efforts in the four countries, seems also to point out that the effects of innovation override the labor market institutional details.

Finally, it is worthwhile to emphasize that we present evidence separately for manufacturing and the service sectors, and that we conclude that services are not so different. This is important, because much of the employment creation in the four countries in recent years has been in services, as in many other industrialized countries.

The rest of this paper is organized as follows. Section 2 presents the data and some descriptive statistics on employment and innovation outcomes in the four countries. Section 3 presents the model that we take to the data. Section 4 comments on the relationship of this paper to the literature on innovation and employment. Section 5 discusses what effects can be identified using the available information and establishes the estimation strategy. Section 6 presents the main econometric estimates and checks their validity. Section 7 presents the implications for employment, both at the firm and industry level, and briefly comments on the differences between the four countries and the manufacturing and service sectors. Section 8 concludes. A Data Appendix gives details on the construction of the four country samples and on the definition of all the variables used in the empirical analysis. An Online Appendix presents some additional regressions and robustness checks.

2. Innovation and employment across four countries

2.1. Data and variables

The national statistical offices (or delegated institutions) of European countries, under the coordination of Eurostat,[3] carry out the Community Innovation Surveys (CIS) every four years. To a large extent, the questionnaire is "harmonized," including many common core questions as well as some optional ones which can differ among countries. CIS3 was the survey performed in 2001, referring to the period 1998–2000. The target population was all firms with at least 10 employees in manufacturing and services. Answering the questionnaire is compulsory in France and Spain, but voluntary in Germany and the UK. The sizes of the national samples differ, but all samples are representative of industry-size strata. Details on the samples and variable definitions can be found in the Data Appendix.

Core variables include sales and employment in the years 1998 and 2000, and information about whether the firm has introduced process and product innovations during the period. Firms are asked if they introduced "new or significantly improved production processes" or "new or significantly improved products," and the respondents may find explanations about these concepts adapted from the Oslo Manual (OECD and Eurostat, 2005). If the firm has introduced new products it is subsequently asked about the share of sales in 2000 stemming from these products introduced since 1998. We are going to use this variable to decompose total sales in sales of "new" and "old" products.[4]

[1] A recent World Bank study by Pages et al. (2009) finds a negative relationship between firm-level productivity and employment growth during the 90s for the manufacturing firms of Argentina, Chile, Colombia and United States. Also, an industry level decomposition from the early 90s to the early 2000s with data on 13 Latin American countries produces a negative covariance term for all countries.

[2] For a companion study also using the CIS3 firm-level data for France, Germany, Spain and the UK, see Griffith et al. (2006).

[3] INSEE and SESSI for France, ZEW for Germany, INE for Spain and the DTI for the United Kingdom.

[4] Notice that we are not likely to deal with "drastic" product innovations, but more incremental changes in products that the firm considers important enough to report as having introduced a "new product". A "drastic" innovation is likely to completely change the structure of the market: see, for example, Gort and Klepper (1982).

We assume that the new product has a specific demand, and that the old and new products are substitutes whose demands depend on their relative attributes and prices. Notice that firms define the new products with respect to the products existing at the beginning of 1998, whatever they were.[5,6]

We have the *employment growth* 1998–2000. Directly from the questionnaire we can compute an overall (nominal) *sales growth* $\hat{g}$ from 1998 to 2000. Using the reported fraction s of sales in 2000 due to new products introduced in 1998–2000 we compute the *sales growth due to new products* g_2, and the *nominal sales growth due to old products* $\hat{g}_1$. We can express nominal rates $\hat{g}$ and $\hat{g}_1$ approximately in real terms by using an industry price index π, but we cannot adjust g_2 since we do not know the difference in the prices of the new and old products.[7] We will use as notation for the real rates g and g_1 and, given our definitions, $g = g_1 + g_2$.

2.2. Facts in the four countries

Tables 1a and 1b present descriptive statistics for the manufacturing and service sector in the four countries. For each variable, the sample is split into three sub-groups of firms according to whether the firm reports that it has not introduced any innovation, only process innovations, or product innovations, over the whole period 1998–2000. We call these groups of firms *non innovators*, *process innovators only* and *product innovators*.[8]

Our samples are random samples of continuing firms, and our description therefore refers to the process of industry employment reallocation determined by innovation among continuing firms. Due to the absence of data on entry and exit, additional employment creation and destruction that stem from firm entry and exit has to be left for future research with more complete data bases.

Table 1a shows that innovators represent between about 40% (for the UK) and 60% (for Germany) of manufacturing firms in the four countries, and that somewhat more than three fourths of them have introduced product innovations (roughly half of them together with process innovations). Employment growth of innovators is consistently higher than that of non-innovators across the four countries, with the employment growth for product innovators being slightly higher than for process innovators only. Productivity gains also tend to be higher in innovating firms (with the exception of Spain, where there is almost no difference in average productivity growth between innovators and non-innovators). Notice that the increase in employment in innovative firms is higher despite their larger labor productivity gains. This shows that, on average, the effects stemming from the growth of output dominate the displacement effects of innovation. Although not all output effects necessarily come from innovation, this suggests that the compensation effects of innovation are likely to be important.

The average increase in sales over the period 1998–2000 is high in all countries, reflecting both an expansionary phase of the industrial cycle and the fact that we are considering samples of continuing firms.[9] Average sales growth is highest for Spain, even when deflated with the corresponding rate of price increase, which is also highest. At the time, the Spanish economy was experiencing a particularly rapid overall growth. Sales growth is also consistently higher for innovators than for non-innovators, with no systematic difference between firms that only introduce process innovations and those that introduce new products. For product innovators, sales of new or significantly improved products introduced during the period 1998–2000 are a very important component of total sales growth: these sales in 2000 amount to more than one third of sales of old products in 1998 for the German, Spanish and British firms, and to nearly 20% for the French firms. Sales of new products appear to cannibalize sales of old products to a different extent in the four countries.[10]

Table 2b shows that the proportion of innovators is lower in the service sector than in manufacturing for the four countries, though it is relatively high in Germany and particularly low in the UK and Spain. However, in the four countries, the proportion of innovators that only introduce process innovations is slightly higher than in manufacturing. As in manufacturing we observe that, in all four countries, employment growth is somewhat higher for innovators and higher for product innovators than for process innovators only. This suggests that an

Table 1a
Process and product innovators, growth of employment and sales. Manufacturing firms, 1998–2000.[a,b]

	France	Germany	Spain	UK
No. of firms	4631	1319	4548	2533
Non-innovators (%)	47.7	41.5	55.4	60.5
Process innovators only (%)	7.1	10.2	12.2	11.0
Product innovators (%)	45.2	48.4	32.4	28.5
[Of which product & process innovators]	[24.3]	[27.4]	[20.0]	[14.1]
Employment growth (%)				
All firms	8.3	5.9	14.2	6.6
Non-innovators	7.0	2.4	12.6	5.4
Process innovators only	7.5	6.0	16.2	8.0
Product innovators	9.8	8.9	16.2	8.5
Sales growth[c] (%)				
All firms	13.0	15.2	23.2	12.3
Non-innovators	11.0	10.8	21.7	10.8
Process innovators only	13.4	21.7	23.6	16.3
Product innovators	15.0	17.5	25.7	13.9
of which:				
Old products	−2.3	−17.0	−13.7	−21.2
New products	17.3	34.5	39.4	35.1
Productivity growth (%)				
All firms	4.7	9.3	9.0	5.7
Non-innovators	4.0	8.4	9.1	5.3
Process innovators only	5.9	15.7	7.4	8.3
Product innovators	7.5	8.7	9.5	5.4
Prices growth[d] (%)				
All firms	2.5	1.3	3.9	−1.7
Non-innovators	2.5	1.1	4.0	−1.0
Process innovators only	3.1	2.4	4.2	−0.4
Product innovators	2.4	1.3	3.7	−3.3

[a] Rates of growth for the whole period 1998–2000.
[b] Population is firms with 10 or more employees. Entrant firms and firms affected by mergers and scissions not included.
[c] Nominal total sales growth, sales growth for old products and sales growth for new products.
[d] Variation of industry prices assigned to firms according to their activity.

[5] Firms may be selling, in the base-year, mixtures of products of very different vintages, that we group simplifying in what we call the old products. Fixed effects give account of the possible heterogeneity induced by the differences in the product mix.

[6] There may be a problem in the timing of the innovations. A three-year period can be insufficient to adequately pick up all the dynamic effects of product innovations. We are not especially worried about this because of the incremental character of the innovations that we are dealing with (and hence its short run employment effects), and because of the encouraging results of the comparison of our model with the fully dynamic specifications based on data spanned many years (see Section 7.4).

[7] Basically we assume that π is an index of prices for old products, which should be approximately the case if the industry average share of new product sales s remains small. Statistical offices are also likely to produce indices closer to the prices of the old products.

[8] There are firms that report to have introduced product and process innovation at the same time. In fact, we do not know if the innovations are related but, in the rest of the paper, we are going to assume that for these firms both are complementary, i.e., the process innovation of product innovators corresponds to the introduction of new products. Our empirical checks seem to point in this direction (see the Online Appendix).

[9] Rates of growth are likely to be strongly influenced by the moment of the industrial cycle, not only in their level but maybe also in their relative magnitudes. For example, firms may be more prone to introduce new products in booms than in recessions. We definitely think that it is important to apply the model in the future with data belonging to radically different moments of the cycle. A first step in this direction is Peters (2008).

[10] The fact that average growth in sales of old products is negative for product innovators does not necessarily imply cannibalization of old products by new products. For example, it is possible that firms whose traditional markets are declining are more likely to introduce product innovations.

Table 1b
Process and product innovators, growth of employment and sales. Services firms, 1998–2000.[a,b]

	France	Germany	Spain	UK
No. of firms	1653	849	1839	1794
Non-innovators (%)	60.2	51.4	69.1	70.2
Process innovators only (%)	8.5	9.3	9.4	7.0
Product innovators (%)	31.3	39.3	21.5	19.8
[Of which product & process innovators]	[17.2]	[21.7]	[11.9]	[8.1]
Employment growth (%)				
All firms	15.5	10.2	25.9	16.1
Non-innovators	14.2	5.9	24.8	13.8
Process innovators only	9.9	6.1	24.5	18.6
Product innovators	19.4	16.9	30.1	23.7
Sales growth[c] (%)				
All firms	18.4	18.5	32.3	22.7
Non-innovators	16.3	14.4	30.9	21.2
Process innovators only	16.1	11.2	30.9	24.1
Product innovators	23.1	25.6	37.8	28.2
of which:				
Old products	−3.2	−15.9	−8.9	−14.1
New products	26.3	41.5	46.7	42.2
Productivity growth (%)				
All firms	2.9	8.3	6.4	6.7
Non-innovators	2.1	8.5	6.1	7.4
Process innovators only	6.2	5.1	6.4	5.5
Product innovators	3.7	8.7	7.7	4.5
Prices growth[d] (%)				
All firms	1.8	4.2	7.3	2.3
Non-innovators	1.8	5.0	7.3	2.3
Process innovators only	1.8	4.7	7.3	1.0
Product innovators	1.8	3.0	7.3	3.0

[a] Rates of growth for the whole period 1998–2000.
[b] Population is firms with 10 or more employees. Entrant firms and firms affected by mergers and scissions not included.
[c] Nominal total sales growth, sales growth for old products and sales growth for new products.
[d] Variation of industry prices assigned to firms according to their activity.

increase in demand associated with new services plays an important role in employment creation in the service sector as it does in manufacturing. The productivity growth of innovators is, however, sometimes higher (France, Spain) and sometimes lower (Germany, UK) than the productivity growth of non-innovators.

The growth of nominal sales during the three years 1998–2000 is even higher than in manufacturing, but the average price increases are also higher. As with employment growth, sales growth is higher for product innovators but, in this case, less for firms that only introduce process innovations. For product innovators, sales of new products are as large a part of total sales growth as in manufacturing, although it seems that cannibalization of old products by new products may be slightly less.

To summarize, data across the four countries show that employment grows more in innovative firms, and more intensely in firms with product innovations than in firms with process innovations. For firms with product innovations, the demand for old products always decreases, but the increase in sales of new products surpasses this decrease (i.e., new products contribute to an increase in total demand). The descriptive statistics suggest that compensation effects of all kinds are prevalent, but also that there is no hope to assess the relative roles played by process and product innovations without estimating a model.

3. Model

3.1. Two-periods and two-goods production

We observe a firm in two different years, which we denote $t=1$ and $t=2$, possibly introducing some new products in between. A firm can produce in the second period two types of products: old or only marginally modified products (*old products*) and new or significantly improved products (*new products*) which we denote with $j=1$ and $j=2$, respectively. Outputs are denoted by Y_{jt}. In year $t=1$ all products are old products by definition, so there is only Y_{11}. In year $t=2$, the firm may be producing Y_{12} and Y_{22}, but Y_{22} is equal to zero if the firm has not introduced any new products between the two years.

We assume that the production technology for old and new products presents constant returns to scale in capital K, labor L, and intermediate inputs M, and can be written as two separable production functions with different Hicks-neutral technological productivity indexed by θ_{jt} (productivity can change over time for old products). In addition, we assume that firms may deviate from common technology by idiosyncratic advantages modeled by means of a firm fixed effect η_i. Finally, production of old and new products in the second period is subject to unanticipated productivity shocks u_i and v_i. Correlation among these shocks does not create any problem in the theoretical model, but may be an issue in the empirical application (see Section 5.2). That is, production of firm i in the first period takes place according to the production function:

$$Y_{11i}=\theta_{11}F(K_{11i},L_{11i},M_{11i})e^{\eta_i}.$$

Production in the second period, instead, is carried out according to the following production functions:

$$Y_{12i}=\theta_{12}F(K_{12i},L_{12i},M_{12i})e^{\eta_i-u_i}$$

and, if firm i has introduced new products,

$$Y_{22i}=\theta_{22}F(K_{22i},L_{22i},M_{22i})e^{\eta_i-v_i}$$

where the minus sign on u_i and v_i is introduced for convenience.

We assume that the firm invests in R&D to generate product and process innovations and that the predictable efficiency impact of these investments is reflected in the changes of θ. New products can be

Table 2
Firm-level employment effects of innovation.

		Displacement (prod. function)	Compensation (demand)		
	Productivity trend Process innovation	Productivity effect (<0): less labor for a given output (labor saving?)	Price effect (>0): cost reduction, passed on to price, expands demand	⟸	Depends on firm agents' behavior
R&D and innovation expenditures ⟹					
	Product innovation	Productivity differences of the new product (>0 or <0)	Demand-enlargement effect (>0)	⟸	Depends on competition

produced with higher or lower efficiency than old products, and the firm can influence the efficiency of production of both old and new products by investing in process innovation. A key part of our analysis to disentangle employment effects relies in estimating the systematic change in efficiency of producing old products (θ_{12}/θ_{11}) as well as the relative efficiency (θ_{22}/θ_{11}) of producing new and old products.

3.2. An employment equation

We assume that employment and other decisions about inputs are taken according to cost minimization, given the available information on productivity. Applying Shephard's lemma, and given our assumption of constant returns to scale, labor demands corresponding to the production of the old products can be written as:

$$L_{11i} = c_{w_L}(w_{11i})\frac{Y_{11i}}{\theta_{11}e^{\eta_i}}$$

$$L_{12i} = c_{w_L}(w_{12i})\frac{Y_{12i}}{\theta_{12}e^{\eta_i - u_i}}$$

where $c_{w_L}(.)$ represents the derivative of $c(.)$ with respect to the wage. Similarly, labor demand corresponding to production of the new products is:

$$L_{22i} = c_{w_L}(w_{22i})\frac{Y_{22i}}{\theta_{22}e^{\eta_i - v_i}} \quad \text{if } Y_{22i} > 0 \quad \text{and} \quad L_{22i} = 0 \quad \text{otherwise}.$$

In addition, as we have no data on prices and the time period is short, we adopt the simplifying assumptions that $c_{w_L}(w_{11i}) = c_{w_L}(w_{12i}) = c_{w_L}(w_{22i})$. This holds approximately, for example, in the likely case where the relative prices of inputs remain roughly constant over time and equal for old and new products.[11] It should be recognized, however, that shifts in $c_{w_L}(\cdot)$ may be erroneously attributed to technology if the assumption does not hold.

To get an estimating equation we start by decomposing the growth of employment between the two years $t = 1$ and $t = 2$, into the growth of employment due to the production of old products and new products in the following way:

$$\frac{\Delta L_i}{L_i} = \frac{L_{12i} + L_{22i} - L_{11i}}{L_{11i}} = \frac{L_{12i} - L_{11i}}{L_{11i}} + \frac{L_{22i}}{L_{11i}} \simeq ln\frac{L_{12i}}{L_{11i}} + \frac{L_{22i}}{L_{11i}}$$

where by convention the rate of growth of employment induced by new products is defined as L_{22i}/L_{11i}, and where we use a logarithmic rate of growth of the old product to derive a simple linear equation in terms of the relevant variables. Based on this decomposition and the above labor demand equations, we can write the following employment growth equation:

$$\frac{\Delta L_i}{L_i} = -(\ln\theta_{12} - \ln\theta_{11}) + (\ln Y_{12i} - \ln Y_{11i}) + \frac{\theta_{11}}{\theta_{22}}\frac{\overline{Y}_{22i}}{Y_{11i}} + u_i \qquad (1)$$

where $\overline{Y}_{22i} = Y_{22i}e^{v_i}$, that is, the production of the new product excluding the unanticipated shock.[12,13] Notice that the fixed effects η_i are differenced out but the shock u_i, correlated with Y_{12i}, becomes the error of the equation. This does not imply any estimation problem as long as there is no coefficient linked to the term ($\ln Y_{12} - \ln Y_{11}$) and we can move this variable to the left-hand side to carry out regressions.[14] Notice also that $\overline{Y}_{22i}$ implies that both the numerator and the ratio $\frac{\overline{Y}_{22i}}{Y_{11i}}$ are uncorrelated with u_i even in the case that v_i and u_i are correlated.

Eq. (1) accounts for the observed employment growth in terms of four components: i) the change in efficiency in the production process for the old products; ii) the rate of change of demand for these old products over time (assuming that firm's production meets demand); iii) the impact of the expansion in production attributable to the demand for new products; and iv) the impact of old product unanticipated productivity shocks.

Efficiency change ($\ln \theta_{12i} - \ln \theta_{11i}$) is expected to exist anyway because of spillover and other effects (see below) and also is expected to be larger for firms which introduce process innovations. The impact of product innovation on employment growth depends on the ratio (θ_{11}/θ_{22}) or relative efficiency in producing old and new products. If new products are produced more efficiently than old products, this ratio is less than unity, and employment does not grow one-for-one with the growth in output accounted for in new products.

4. Relation to the literature

4.1. Employment effects of innovation

Let us assume that firms operate in differentiated markets, i.e. each firm faces a downward sloping demand for its products. A market consists of a set of products whose demands show significant cross-price elasticities. The potential effects of innovation on firm-level employment are summarized in Table 2.[15,16] Our model distinguishes between the effects of process innovations, which are directed at improving the production process and hence have a direct impact on productivity and unit costs, and the effects of product innovations, which are mainly undertaken to reinforce the firm's demand. As indicated in Table 2, both types of innovations can be interpreted as the (random) result of a firm's investment in R&D and other innovative activities. In addition to the effect of the innovations, there are incremental year-to-year productivity improvements in the production of existing products (productivity trend) that can be thought of as a sort of "innovation-disembodied" technical change (diffusion of past industry innovations, diffusion of general purpose technologies, learning).[17]

Productivity increases arising from both process innovations and productivity trend imply a reduction in unit costs. This cost reduction is likely to be passed along the price. Lower prices lead to an increase in demand, and hence output and employment, to an extent which depends on the competitive conditions that the firm is facing. In particular,

[11] Notice that $c(.)$ is homogeneous of degree one in input prices and hence the derivative $c_{w_L}(.)$ is homogeneous of degree zero. The constancy of relative input prices for old products in the two periods and the equality of input prices for old and new products in the second period thus imply that $c_{w_L}(.)$ is unchanged even if prices change.

[12] One possible way of thinking of this production is as the production expected before knowing the shock (under the simplifying assumption that $E(e^{v_i}) = 1$).

[13] Following the suggestion of a referee, that we acknowledge, we have worked on a more general foundation for this equation. It turns out that it is possible to derive it (up some minor approximation differences) from a multiproduct transformation function with Hicks neutrality in each product but not necessarily in the mix, separable in an additive index of output whose production shows constant returns to scale. This implies that we do not need either input separability or the Cobb–Douglas functional form assumption. While this points to very good nonparametric identification properties of our estimates, we leave the development of more general specifications to future research.

[14] Our stochastic specification is consistent with the production model introduced by Olley and Pakes (1996) and followed, for example, by Levinsohn and Petrin (2003). The difference $(\ln\theta_{12} + \eta_i) - (\ln\theta_{11} + \eta_i) - u_i$ may come from the difference $g(\omega_{1i}) + \xi_{2i} - (g(\omega_{0i}) + \xi_{1i})$ between two realizations of a Markovian process. In fact, we are considering an endogenous process, impacted by R&D, as in Doraszelski and Jaumandreu (2013).

[15] There are scarce theoretical contributions to the analysis of the firm-level impact of innovation on employment (see, among the few, Stoneman, 1983; Katsoulacos, 1984; Hammermesh, 1993).

[16] We summarize the effects that we can expect at the firm level drawing on the papers cited above and the discussions included in Nickell and Kong (1989), Van Reenen (1997) and Garcia et al. (2005).

[17] Production functions account for such ongoing improvements in productivity by including time trends or time dummies when specified and estimated in levels (or, equivalently, constants or time dummies when specified and estimated in first differences). Indicators of innovation, such as knowledge capital stocks, R&D investment or innovation counts, typically account for only a small part of unexplained productivity growth, even when statistically significant. For an illustration of this point, see, for example, the panel data analyses in Hall and Mairesse (1995) and Huergo and Jaumandreu (2004), or the surveys by Mairesse and Sassenou (1991) or Hall et al. (2010).

imperfect competition is associated with a price elasticity of demand greater than one, implying that the demand enlargement is going to be greater than the employment displacement.[18]

Product innovations may also have productivity effects, even if they are not associated with simultaneous process innovations. Theory gives no general indication about the extent and direction of this effect. However the main employment effects of product innovation are expected to result from demand enlargement. Both effects are pinned down by the third term of our equation. The importance of the demand increases will depend again on the nature of competition and the delay with which rivals react to the introduction of new products. Sales of new products may also cannibalize potential sales of the innovating firm's old products (substitution), reducing the size of the effects. Therefore, one should distinguish a gross effect and a net effect, the latter taking into account the induced reduction in sales of old products.

Industry net rates of change in employment are associated with different gross creation and destruction rates of employment determined by the continuing firms that are expanding and shrinking, and to the different rates of entry and exit. In our case, we have three types of firms: *non innovators*, *process innovators only* and *product innovators*. When estimating the employment changes of each one of these types of firms we are hence estimating components of the industry change. In Section 7.2 we pursue the industry-level outcome characterization, including the definition and estimation of the “business stealing” and “market expansion” effects resulting from the interaction of the three types of firms. As remarked before, however, we are not able to include in our analysis the contributions of firm entry and exit.

4.2. Empirical literature

A large number of quite heterogeneous analyses have provided evidence on the relationship between innovation and employment at the firm level. The surveys by Chennells and Van Reenen (2002) and Spiezia and Vivarelli (2002) provide overviews.[19] Existing studies differ widely due to different data sets and sundry measures of innovation. Most of the studies range, however, in a pretty narrow area that goes from the assessment of simple correlations to the estimation of reduced-form relationships. Only a few have tried a more structural modeling approach.

On the whole, product innovation emerges as clearly associated with employment growth, although the intensity of the effect differs across studies (see, for example, Entorf and Pohlmeier, 1990; Garcia et al., 2005; Greenan and Guellec, 2000; König et al., 1995; Smolny, 1998, 2002; Van Reenen, 1997). R&D investment also tends to be positively related to employment growth (see, for example, Regev, 1998, and recently Bogliacino et al., 2012), although not always (see Klette and Forre, 1998). By contrast, the effects of process innovation are found to range from negative to positive (see, for example, Ross and Zimmerman, 1993, for a negative process innovation effect; Doms et al., 1995, or Blanchflower and Burguess, 1998, for positive technology impacts; and Evangelista and Vezzani, 2012, for a result that summarizes the ambiguity in the outcomes; see also the heterogeneous effects of process innovations estimated in many of the above papers).

To situate our paper with respect to the existing literature, it is enlightening to compare it in detail with a few studies closer to our approach. We choose Van Reenen (1997), henceforth VR, and Lachenmaier and Rottmann (2011), henceforth LR. They both have interesting firm-level panel data samples with innovators and non-innovators: almost 600 British firms observed 1976–82, and more than 1000 German firms observed an average of 9 years during the period 1982–2002, respectively. They both aim at specifying a theoretically-based equation: a combination of the first-order conditions for labor and capital for a competitive firm lead to a labor demand which includes capital and relative prices in VR, and a competitive demand for labor conditional on output in LR. Both studies carefully use up-to-date econometric techniques to specify dynamic equations, differencing out potential fixed effects, and dealing with the potential endogeneity of innovation and other variables by means of IV.[20]

Let's put aside the restrictive character of the assumption of perfect competition. An important flaw is that both exercises suffer from lack of observability of variables that should be included in the equations according to theory. VR uses an otherwise interesting database on innovation counts in which it is problematic to separate process and product innovations. Furthermore, he does not observe the cost of capital, and uses a crude measure of capital itself (a deflated sum of historic costs of fixed assets). LR are compelled to use industry-level wage and value added, in an otherwise firm-level equation which uses information on the introduction of process and product innovations. Both papers get quite comparable results that imply a positive and significant impact on employment of process and product innovation.[21]

Our claim is that the misspecification of these equations produces the impossibility of disentangling the theoretical productivity effects of innovation. The negative impact on employment (at least in process innovation), and the compensation effects via demand for output, that should be positive. In particular, if demanded output is not properly controlled for in an output conditional demand for labor, the variable representing process innovation is likely to pick up the mix of productivity and demand effects producing reduced-form coefficients that can go from negative to positive according to the particular sample. Similarly, the inclusion of a product-innovation indicator is likely to pick up a mix of non identified net positive effects.

Our paper contributes to the literature by showing that a simple way to disentangle productivity and demand effects of innovation exists if sales due to the new products are observable at the firm-level. This procedure can get the signs that are expected from theory and estimate magnitudes for each effect.

5. Estimation strategy

Eq. (1) can be written as the following regression:

$$l_i - y_{1i} = \alpha_0 + \alpha_1 d_i + \beta y_{2i} + u_i \tag{2}$$

where l stands for the rate of employment growth over the period (i.e., between the year $t = 1$ and $t = 2$), y_1 and y_2 are the corresponding rates of output growth for old and for new products (i.e., $\ln Y_{12} - \ln Y_{11}$ and $\overline{Y}_{22}/Y_{11}$, respectively), and u is the unobserved random disturbance. 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*).[22] The parameter β

[18] However the size of the effect is also likely to depend on the nature of market competition and the behavior of the agents inside the firm. For example, unions and managers may attempt to transform any gains from innovation into higher wages or compensations, while owners may take advantage of the firm market power to increase profits. These behaviors can dampen or override the compensation effect. See Nickell (1999) for a discussion.

[19] See also Vivarelli (2011), which contains an updated list of studies.

[20] Merikull (2010) develops a recent version of VR that considers some additional dynamics.

[21] The effects of process innovation become negative and non significant in VR, however, when the exercise tries to separate process and product counts.

[22] We can extend Eq. (2) to allow process innovation to affect changes in the efficiency of the production of old and new products. On the coincidence of process and product innovation, see the Online Appendix.

captures the relative efficiency of the production of old and new products (θ_{11}/θ_{22}).[23]

Eq. (2) identifies two effects of major interest. First, thanks to the measurement of the growth of output due to the introduction of new products, it allows us to estimate the *gross effect* of product innovation on employment. Second, the observation of process innovations related to the production of old products allows us to estimate the (displacement) *gross effect* of process innovation.

However, Eq. (2) also has some obvious limitations. Variable y_1 embodies three different employment effects that we cannot separate without additional (demand) data: i) the possible "autonomous" increase in firm demand for the old products (e.g., due to market trend or cyclical effects); ii) the "compensation" effect induced by any old product price decrease following a process innovation; and iii) the reduction of old product demand resulting from the introduction of new products either by the firm or by its competitors.

In what follows, we discuss the problems involved in the identification and estimation of the parameters of Eq. (2): α_0, α_1 and β.

5.1. Identification: economics

Identification and consistent estimation of the three parameters depend on the lack of correlation between the variables representing process and product innovations (d and y_2) and the error term u or, at least, on the availability of instruments correlated with these variables and uncorrelated with u (recall that individual effects have been already differentiated out).

Our model seems quite immune to problems induced by economic correlation between d, y_2 and u, both in theory and practice, and hence, model (2) could be consistently estimated by OLS if there were no other sources of endogeneity such as measurement errors (that we discuss in the next subsection).

First, innovations are the result of the success of "technological investments", mainly R&D, which have to be decided by firms in advance. Correlation of d and y_2 with u depends then on the assumptions which can reasonably be made about the nature of u and the timing of the firm's technological investments. Most of these settings are likely to imply no correlation, because u cannot be forecasted at the time of the investments. However, if firms were, in fact, carrying out these investments within the period affected by the shocks u, the resulting innovations could be correlated with them. In this case, however, lagged values of the included variables or technological investments would be uncorrelated with u and could be used as valid instruments. This is what we use in our sensitivity analysis.

Second, it seems plausible that correlation between d, y_2 and productivity shocks – if any – would be positive. However, if technological investments are positively related to productivity shocks they will be negatively correlated with the random error u which appears in Eq. (2) (remember that we added a minus sign to u for convenience). As a consequence, we should expect a downward bias in the coefficients on d and y_2. In other words, we would estimate employment displacement effects of process innovation that are too large, and an impact of the introduction of new products that is too low. As we will see, our estimates seem free of such biases after controlling for the measurement problems.

5.2. Identification: measurement

To estimate Eq. (2), however, we have to face two observational problems. First, we do not directly observe y_2. What we observe is only the increase in sales, that may include both the effect of the unanticipated shock and the effect of different prices for new and old products. Second, we do not observe the real growth of old product sales y_1 but only its nominal increase. Both problems are related to the unavailability of prices at the firm-level, common to all productivity studies and too often completely neglected. In practice, we are going to use prices observed at the industry level, as detailed as possible, to deflate the growth of sales of the old product and substitute the estimate g_1 for y_1. On the other hand, we are going to use the observed sales growth rate due to new products g_2 as a substitute for y_2. We end up with the equation:

$$l_i - g_{1i} = \alpha_0 + \alpha_1 d_i + \beta g_{2i} + \varepsilon_i. \tag{3}$$

What are the problems? Our imperfect g_2 estimate is likely to create at least a particular version of error-in-variables problem with the consequence of an attenuation bias in the estimation of β. In case the unanticipated shocks are correlated, it would also create a problem of direct endogeneity. To avoid any bias, we will look for instruments correlated with y_2 and that are uncorrelated with all that may be in the error after substituting g_2 for y_2 (u, shock v and difference in prices). We explain our IV strategy in the next subsection. In practice, our instruments seem to work properly and the estimates are sensible, so the consequences of this problem turn out to be quite benign.

However, there is another kind of identification problem. With the imperfect observation implicit in variable g_1, we can underestimate the displacement effect of process innovation if the employed deflators diverge from the relevant firm-level prices. To see how, consider that the error term ε_i includes $-\pi_{1i}$ as a result of no control at all for the change in the prices of the old products (an extreme assumption that we only use to simplify notation). We know that any increase in efficiency decreases marginal cost by the same proportion. Therefore, if firms are pricing their products competitively or pricing them by setting a markup on marginal cost, price variations are likely to be proportional to the efficiency increase (with an opposite sign). If the price change π_{1i} depends on the old-products marginal cost change c_i according to the rule $\pi_{1i} = \pi_0 + \tau c_i$, where π_0 is a constant and τ is the pass-through parameter (with $0 < \tau < 1$), and old-products marginal cost changes themselves are related to process innovation efficiency gains according to $c_i = \alpha_1 d_i$, we get $\pi_{1i} = \pi_0 + \tau\alpha_1 d_i$. Thus, the second term of Eq. (2) will only be able to estimate an attenuated effect $(1-\tau)\alpha_{1i}$. Notice, however, that under our assumptions this is going to be the unique consequence in estimation. In other words, 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 variations.

5.3. Estimation

Summarizing, it is unlikely that our regressors d (*process innovation only* dummy) and g_2 (*sales growth due to new products*) are correlated with the random disturbance of Eq. (3) because of productivity shocks. However, g_2 replaces a term by a counterpart that is likely to include a disturbance (v_i) and does not fully account for possible different prices of new and old products, creating at least a problem of correlation because of errors in variables. A suitable instrumentation of g_2 should avoid any bias. Variable d, in the presence of industry prices which differ from the relevant firm-level prices, is likely to attract a coefficient that understates the gross effect of process innovation. There is no solution for the latter problem without better information.

Firms provide a series of answers about the aims of product innovation. We interpret this information as characterizing the nature of the innovation carried out. In particular, firms answer how important the introduced product innovation has been for getting an *increased range* of products, an *increased market share* or an *improved quality* of products. The variables are coded as zero if innovation is not relevant

[23] Eq. (2) can also be rewritten and reinterpreted in terms of a labor productivity growth equation by simply rearranging it as follows:

$$y_{1i} + y_{2i} - l_i = -\alpha_0 - \alpha_1 d_i + (1-\beta) y_{2i} - u_i,$$

showing that labor productivity growth will depend positively on process innovation if $\alpha_1 < 0$, and on product innovation if β is less than one.

Table 3
The effects of innovation on employment.[a]

Dependent variable: $l - g_1$																
Sector	Manufacturing								Services							
Regression	A (OLS)				B (IV[b])				C (OLS)				D (IV[b])			
	FR	DE	SP	UK	FR	DE	SP	UK	FR	DE	SP	UK	FR	DE	SP	UK
Constant	−1.64	−4.55	−3.62	−4.21	−3.52	−6.95	−6.11	−6.30	−1.62	−1.96	−2.94	−3.72	−5.25	−3.36	−4.04	−5.51
	(0.59)	(1.17)	(0.71)	(0.81)	(0.78)	(1.36)	(0.90)	(0.85)	(2.02)	(2.64)	(2.03)	(1.54)	(2.48)	(3.05)	(2.25)	(1.61)
Process innovation only (d)	−2.88	−8.49	0.30	−5.49	−1.31	−6.19	2.46	−3.51	−4.49	−1.48	−1.05	1.80	−1.45	1.54	−0.38	3.21
	(1.53)	(2.92)	(1.68)	(1.84)	(1.57)	(2.92)	(1.78)	(1.86)	(3.30)	(2.83)	(3.26)	(3.56)	(3.47)	(3.07)	(3.37)	(3.54)
Sales growth d.t. new products (g_2)	0.77	0.87	0.86	0.80	0.98	1.01	1.02	0.99	0.85	0.75	0.91	0.89	1.16	0.92	0.99	1.05
	(0.05)	(0.06)	(0.03)	(0.06)	(0.06)	(0.07)	(0.04)	(0.05)	(0.07)	(0.06)	(0.05)	(0.06)	(0.13)	(0.08)	(0.08)	(0.06)
Standard error	28.01	27.14	35.97	30.07	28.21	27.31	36.25	30.45	44.57	33.44	43.31	37.95	45.11	33.66	43.37	38.02
No. of firms	4631	1319	4548	2533	4631	1319	4548	2533	1653	849	1839	1794	1653	849	1839	1794

[a] Coefficients and standard errors robust to heteroskedasticity. All regressions include industry dummies.
[b] Unique instrument used is *increased range*.

for the considered aim, one if the impact of innovation is low, two if it is medium and three if it is high.[24] Our preferred instrument is the *increased range* (of products) indicator.

On the one hand, the degree by which product innovation is aimed to increase the range of products is likely to be correlated with planning (R&D, design, marketing exploration…) and the expectations of sales. On the other, 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.

We also verify that, in practice, it is not a weak instrument since it appears to be clearly positively and significantly correlated with the possibly endogenous variable in the first-stage reduced-form regressions for the four countries. We settled on that variable after some trials. In addition, we present results using two other possibly appropriate instruments (and also using some inappropriate ones). Finally, while our data base allows us to make only a very limited use of lagged values of innovation or related variables, we have made an effort to present some results for one country.

6. Econometric estimates

6.1. Basic specification

Table 3 presents the results of estimating the basic specification of our model by OLS and by IV using the *increased range* indicator as instrument for the *sales growth due to new products* variable. In all regressions we include a full set of industry dummies, with their coefficients constrained to add up to zero in order to preserve the interpretation of the constant.[25] In the next subsection, we use other possible instruments in addition to our preferred one, we test for their joint validity, and for the endogeneity of the *process innovation only* variable. Other robustness checks are discussed in the Online Appendix. Let us first discuss, in detail, the results for manufacturing and then, more briefly, the corresponding results for services.

Panel A of Table 3 gives the OLS estimates for manufacturing in the four countries. The value of the constant α_0 is an estimate (with negative sign) of the average real productivity growth in the production of old products for the two-year period 1998–2000. The constant shows sensible average productivity growth for each country, which implies constantly decreasing employment for a given old-products output. A negative coefficient α_1 of the *process innovation only* indicator represents an additional increase in productivity in the production of old products (and thus displacement of labor). The coefficient is negative and significant for Germany and the UK. The coefficient is negative but insignificant for France, and positive but insignificant for Spain. These last two estimates could be due to our lack of observability of firm-level prices particularly if they imply a pass-through of productivity improvements larger than what we pick up with our industry price indices.[26] Also recall that the estimated coefficient β of sales growth due to new products is an estimate of the relative efficiency of the production process for new products compared with that for old products. The fact that the coefficient is significantly less than one for all countries suggests that new products are produced more efficiently than old products. However, as discussed above, a problem of endogeneity because of errors in variables is likely to produce a downward bias in this coefficient.

Panel B thus reports our IV estimates, taking the sales growth due to new products variable as endogenous and using as a single instrument the *increased range* of products. We verify that, in practice, it is not a weak instrument, since it turns out to be positively and significantly correlated with the endogenous variable in the first-stage reduced form regressions for the four countries. In France, Germany, Spain and the UK, the R-squared statistics obtained in these first-stage regressions are equal to 0.39, 0.20, 0.35 and 0.28, respectively, and the corresponding coefficients on the increased range equal to 5.3, 10.5, 11.2 and 14.5, with t-statistics of 30.8, 15.8, 26.9 and 16.0.

The IV estimates of the constant and the *process innovation only* dummy change noticeably from the OLS ones. But the most notable result is that the IV estimates of the coefficient β of sales growth due to new products are higher than the OLS estimates, which is consistent with the expected correction of the downward bias related to the error-in-variable problem. Remember that it may be accounting for another type of endogeneity too. In any case, all the IV estimated $\beta's$ are extremely close to one, now showing no evidence that new products are produced with higher efficiency than old products. That is, there is no evidence of productivity gains and employment-displacement effects associated with product innovation.

Turning now to services, we have to take into account the following two differences with respect to what we were able to do for manufacturing. First, in spite of the great heterogeneity of service activities, we are only able to use an overall price deflator in France. In Germany, Spain and the UK, price deflators are only available at a very high level of aggregation. Second, the proportion of innovating firms in services is much lower, particularly so in Spain and the UK, which can affect the precision of the estimates. Despite these caveats, the

[24] We have experimented with a more flexible form of these variables, but this step form appears to fit the data remarkably well, with very little evidence of any non-linear effect in the reduced-form equation.

[25] Firm-size dummies, when included, turned out in general to be insignificant and did not affect our results.

[26] This seems particularly likely for Spain, where prices have been increasing faster than in the rest of the countries during the period.

Table 4a
Testing the specification, Manufacturing firms.[a]

Dependent variable: $l - g_1$									
Regression	A (IV[b])				B (IV[c])				C (IV[d])
	FR	DE	SP	UK	FR	DE	SP	UK	DE
Constant	−3.44	−6.32	−5.99	−6.30	−3.51	−7.49	−5.27	−6.38	−7.03
	(0.77)	(1.30)	(0.88)	(0.85)	(0.76)	(1.25)	(0.86)	(0.84)	(1.36)
Process innovation only (d)	−1.37	−6.80	2.35	−3.51	−1.32	−5.67	1.73	−3.43	−6.11
	(1.55)	(2.90)	(1.76)	(1.85)	(1.56)	(2.93)	(1.76)	(1.85)	(2.92)
Sales growth d.t. new products (g_2)	0.97	0.97	1.01	0.99	0.98	1.04	0.97	1.00	1.02
	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.07)
Standard error	28.19	27.17	36.23	30.45	28.21	27.46	36.09	30.48	27.33
No. of firms	4631	1319	4548	2533	4631	1319	4548	2533	1319
Sargan (m)[e]	2.08 (2)	2.74 (2)	0.54 (2)	1.93 (2)	4.52 (3)	18.47 (3)	8.66 (3)	0.63 (3)	0.03 (1)
Prob. value	(0.36)	(0.25)	(0.76)	(0.38)	(0.21)	(0.00)	(0.03)	(0.89)	(0.86)
Diff. Sargan (m)[e]	1.80 (1)	1.20 (1)	0.27 (1)	0.48 (1)	–	–	–	–	–
Prob. value	(0.18)	(0.27)	(0.60)	(0.49)					

[a] Coefficients and standard errors robust to heteroskedasticity. All regressions include industry dummies.
[b] Instruments used are *increased range*, *clients as a source of information*, and *continuous R&D engagement*.
[c] Instruments used are *increased range*, *improved quality*, *increased market share* and *innovation effort*.
[d] Instruments used are *increased range* and lagged *R&D effort*.
[e] Sargan denotes the test on overidentifying restrictions. Under the null hypothesis the test statistic is $\chi^2(m)$ distributed with the number m of overidentifying restrictions. Diff. Sargan denotes the "difference-in-Sargan" statistic testing the exogeneity of process innovation. The statistic is distributed as a $\chi^2(1)$.

results we obtain, shown in Panels C and D of Table 3, look interesting. Average productivity growth in production of the old product, is higher than in manufacturing for France, lower in Germany and Spain, and about the same in the UK. Not too surprisingly, *process innovation only* is not significant in any country. Here, the problem of the imperfect price information may be more acute. As in manufacturing, the coefficients on sales growth due to new products are less than one in the OLS case (particularly in Germany), but increase to become insignificantly different from one in all four countries when estimated by IV. Thus, we cannot reject the hypothesis that new products are, on average, produced with the same productivity as old products, although there is some slight indication that new products may be produced with lower productivity in France (with an estimated coefficient β of 1.16 statistically different from 1 at the 10% level of confidence).

6.2. Testing endogeneity

The consistency of our IV estimates of Eq. (3) in Table 3 is supported by the a-priori likelihood of the exogeneity assumptions about our preferred instrument. It is important that all coefficient changes, obtained by instrumenting the equation, go in the expected direction. Here we provide some additional statistical evidence for the consistency and robustness of our results.

We look for other potential instruments in addition to the *increased range* variable. We think that the importance of clients or customers as a source of information for innovation (*clients as a source of information*), and the indicator of continuous R&D investment during 1998 to 2000 (*continuous R&D engagement*) are a-priori valid and may be correlated with both the expected sales growth due to new products and process innovations that we want to predict when instrumenting g_2 (and d).[27] Using these three variables as instruments provides two overidentifying restrictions if we maintain the assumption that d is exogenous, and one restriction if we consider d to be endogenous as well. We therefore use them first to test for the two overidentifying restrictions by means of a χ^2 test (Sargan test). This provides us with an indicator of the validity of the employed instruments. Then, we test for the exogeneity assumption maintained up to this point on d by means of a difference in the χ^2 tests ("difference-in-Sargan" test).[28]

Panel A in Tables 4a and 4b for manufacturing and services, respectively, present the IV estimates of Eq. (3) using the three instruments for g_2. The overall Sargan test does not reject the validity of the instruments with high probability value for all four countries in manufacturing and services. The difference-in-Sargan test does not reject the exogeneity of d, again with high probability values. Therefore, the statistical evidence points out the validity of our previous IV estimates in Panels B and D of Table 3.

However, one may argue that such confirmatory evidence is only as good as the discriminatory power of the Sargan tests. To have a feeling of whether such discriminatory power is real, we have also estimated Eq. (3) using a much more doubtful set of instruments, and computed the corresponding overall Sargan tests. To the *increased range* instrument, we add the importance of innovation for the improvement of the quality of the product and the increase of the firms' market share (*improved quality* and *increased market share*), and *innovation effort* (ratio of R&D and other innovation expenditures to sales). As commented above, a product-quality improvement is likely to be associated with a price increase, an increase in firm market share with a price reduction, and a change in the firm innovation effort may be rapidly decided in reaction to productivity shocks. The results, shown in Panel B of Tables 4a and 4b, are clear. The overall Sargan tests clearly reject the validity of this alternative set of instruments at a 1% and 5% level of significance in Germany and Spain for manufacturing, respectively, and at 1% in France and the UK for services and a 5% level of significance for German services. This again, but this time a contrario, supports our choice of the *increased range* variable as an appropriate instrument and the whole instrumenting strategy.

Finally, it is of interest to present one last piece of evidence for the same conclusion, even if only for one country. The instruments that we are able to use pertain to the year 2000 or the period 1998–2000, and are therefore contemporaneous to g_2. A particularly robust choice of instruments, as discussed above, would be lagged firms' innovation or R&D effort. Unfortunately, such information is not available from the standard CIS3 data, and we have only been able to get it in the case of German manufacturing. Column C of Table 4a shows that the

[27] The overall R-square of the first-stage regressions of the *sales growth due to new products* on the set of the three instruments are respectively equal to 0.41, 0.46, 0.39 and 0.37 in manufacturing for France, Germany, Spain and the UK, and, similarly, to 0.36, 0.42, 0.38 and 0.45 in services. The F statistics of the regressions of the *process innovation only* variable on the set of the three instruments are 36.6, 3.5, 61.4 and 23.6 in manufacturing, and 24.7, 5.9, 27.8 and 7.8 in services.

[28] The overall Sargan test evaluates the appropriately scaled value of the objective function at the optimum. The "difference-in-Sargan" test measures the change in the appropriately scaled value of the objective function when the assumption of exogeneity of d is maintained and when it is dropped.

Table 4b
Testing the specification, Services firms.[a]

Dependent variable: $l - g_1$								
Regression	A (IV[b])				B (IV[c])			
	FR	DE	SP	UK	FR	DE	SP	UK
Constant	−5.00	−3.68	−3.78	−5.41	−4.22	−3.96	−3.61	−5.42
	(2.41)	(3.01)	(2.21)	(1.60)	(2.41)	(2.75)	(2.19)	(1.61)
Process innovation only (d)	−1.66	1.84	−0.54	3.14	−2.31	2.41	−0.64	3.15
	(3.46)	(3.00)	(3.34)	(3.53)	(3.46)	(2.93)	(3.34)	(3.55)
Sales growth d.t. new products (g_2)	1.14	0.94	0.97	1.04	1.07	0.97	0.96	1.04
	(0.12)	(0.08)	(0.07)	(0.06)	(0.11)	(0.07)	(0.07)	(0.06)
Standard error	45.04	33.77	43.35	38.00	44.85	34.00	43.34	38.16
No. of firms	1653	849	1839	1794	1653	849	1839	1794
Sargan (m)[d]	0.41 (2)	1.09 (2)	0.28 (2)	3.75 (2)	13.97 (3)	7.71 (3)	5.48 (3)	12.48 (3)
Prob. value	(0.81)	(0.58)	(0.87)	(0.15)	(0.00)	(0.05)	(0.14)	(0.01)
Diff. Sargan (m)[d]	0.01 (1)	0.01 (1)	0.03 (1)	0.59 (1)	–	–	–	–
Prob. value	(0.92)	(0.92)	(0.86)	(0.44)				

[a] Coefficients and standard errors robust to heteroskedasticity. All regressions include industry dummies.
[b] Instruments used are *increased range*, *clients as a source of information*, and *continuous R&D engagement*.
[c] Instruments used are *increased range*, *improved quality*, *increased market share* and *innovation effort*.
[d] Sargan denotes the test on overidentifying restrictions. Under the null hypothesis the test statistic is $\chi^2(m)$ distributed with the number m of overidentifying restrictions. Diff. Sargan denotes the "difference-in-Sargan" statistic testing the exogeneity of process innovation. The statistic is distributed as a $\chi^2(1)$.

results remain unchanged when using lagged R&D effort as another instrument in addition to the increased range variable. The Sargan test does not reject, with a high probability value, the validity of the instruments.

7. Innovation and employment: implications of the estimates

7.1. Contributions to average employment growth

Using ind_j to denote the industry dummies and α_{0j} their coefficients, the estimation Eq. (3) can be written as:

$$l_i - g_{1i} = \alpha_0 + \sum_j \alpha_{0j} ind_{ji} + \alpha_1 d_i + \beta g_{2i} + \varepsilon_i,$$

and the fitted result allows us to write the employment for firm i as:

$$l_i = \sum_j (\hat{\alpha}_0 + \hat{\alpha}_{0j}) ind_{ji} + \hat{\alpha}_1 d_i + [1 - 1(g_{2i} > 0)] g_{1i} + 1(g_{2i} > 0)\left(g_{1i} + \hat{\beta} g_{2i}\right) + \hat{\varepsilon}_i. \tag{4}$$

For a given firm, the first component $(\sum_j (\hat{\alpha}_0 + \hat{\alpha}_{0j}) ind_{ji})$ measures the change of its employment attributable to the (industry specific) *productivity trend* in the production of its old products. The second component $(\hat{\alpha}_1 d_i)$ estimates the change in employment associated with the *gross effect of process innovation* in the production of its old products, if the firm has introduced a process innovation. The third one $([1 - 1(g_{2i} > 0)]g_{1i})$ corresponds to the employment change associated with the *sales growth due to the old product* if the firm is a *non product innovator* (i.e., a *non innovator* or a *process innovator only*). And finally, the fourth one $\left(1(g_{2i} > 0)\left(g_{1i} + \hat{\beta} g_{2i}\right)\right)$ gives the employment growth induced by the *net sales growth of new products* when the firm is producing them (notice that average g_{1i} for product innovators is negative; see Tables 1a and 1b). It depends on the efficiency-weighted sales growth rate for new products.[29] The last term $(\hat{\varepsilon}_i)$ is a zero-mean residual component.

The first three terms tell us how the old products are impacting the evolution of firm-level employment and the fourth term shows how firm-level employment growth is affected by the growth of new products when the firm has developed some new products.

To discuss how these effects contribute to the average employment growth we are going to use this equation averaged across firms. We get

$$l = trend + \hat{\alpha}_1 w_{PO} + w_{NI} g_{NI} + w_I g_I \tag{5}$$

where l is average employment growth; *trend* is a weighted average of the industry specific trends; w_{PO}, w_{NI} and w_I are the sample proportions of *process innovators only*, *non product innovators* and *product innovators*, respectively, and g_{NI} and g_I are defined as the average rates $g_{NI} = \frac{1}{N_{NI}} \sum_{i \in NI} g_{1i}$ for *non product innovators*, and $g_I = \frac{1}{N_I} \sum_{i \in I} \left(g_{1i} + \hat{\beta} g_{2i}\right)$ for *product innovators*. The residuals cancel out in taking the average.

7.2. Demand components

The main limitation of the contributions to average employment growth computed in the previous section is that they are not informative on the sources of the sales growth of the old and new products. In particular, the employment growth based on the sales growth of the *product innovators* includes the losses of employment inflicted to the *non product innovators* of the same market confounded with the likely market enlargement induced by the development of the new products (attraction of new customers and new sales). We are going to show next that our model can also say some useful things about these two industry demand components: *business stealing* and *market expansion*.

However, notice that both business stealing and market expansion are counterfactuals, i.e., sales components that cannot be observed and should be estimated comparing what really happens with what would have happened in the absence of the new products. To fully assess these demand components we would need to estimate a firm-level structural model of demand that lies outside the scope of this paper. Using estimates of the firm-level demand effects commented on in the previous subsection, one can however estimate business stealing and market expansion components if one is willing to make some assumptions.

Current demand for *non innovators* is the demand for the old product. Observed sales of old products are the sales that would have taken place in the absence of new industry products (potential for sales) minus the part stolen by the new products. Notice that this is also valid for *process innovators only*, with the difference that their observed sales for old products may have been boosted by price decreases originated from the introduced process innovations. The current demand for *product innovators* is the demand for old products plus the demand for new products. For *product innovators*, the sales of old

[29] In our case, given the proximity of $\hat{\beta}$ to 1, the employment relevant growth rate of total sales for product innovators virtually coincides with the observed rate of growth of total sales.

Table 5
Impacts of innovation on employment growth[a]: Unweighted averages. Manufacturing and Services firms, 1998–2000.[b]

		Manufacturing				Services			
		France	Germany	Spain	UK	France	Germany	Spain	UK
Firms' employment growth	l	8.3	5.9	14.2	6.6	15.5	10.2	25.9	16.1
Productivity trend in production of old products	$\hat{\alpha}_0$	−3.5	−7.0	−6.1	−6.3	−5.3	−3.5	−4.0	−5.5
Gross effect of process innovation in old products	$\hat{\alpha}_1$	−1.3	−6.2	2.5	−3.5	−1.4	1.5	−0.4	3.2
Sales growth in old products for *non product innovators*	g_1	8.7	11.6	18.0	12.6	14.5	9.0	23.6	19.3
Non innovators	g_1	8.5	9.7	17.7	11.8	14.5	9.4	23.6	18.9
Process innovators only	g_1	10.3	19.3	19.4	16.7	14.3	6.5	23.6	23.1
Net sales growth of *product innovators* (new prods.-subs.)	$g_1+\hat{\beta}g_2$	12.3	16.5	22.8	16.8	25.5	19.3	30.0	27.2
Sales growth due to old products	g_1	−4.7	−18.3	−17.4	−17.9	−5.0	−18.9	−16.2	−17.1
Sales growth due to new products	$\hat{\beta}g_2$	17.0	34.8	40.2	34.7	30.5	38.2	46.2	44.3

[a] Based on descriptives of Table 1a and Table 1b and regressions B and D of Table 3.
[b] Rates of growth for the whole period.

products are the potential for sales (see above) minus the part cannibalized by new products. Observed sales of the new product consist of the sum of three components: the sales substituted for the old product, the sales corresponding to the market expansion induced by the new product (new customers and other non-substitution-based sales) and the sales consisting of business stealing from *non product innovators*.

Provided that the firm samples are random, all stealing effects are going to cancel out industry by industry when aggregating across firms. The only demand components that remain in the industry aggregates are the total potential for sales of old products (plus price decrease effects) and the market expansion due to the launch of the new products.

Let δ_{NIj} and δ_{Ik} be the rates of *potential growth* of sales of the old product for *non product innovator j* and *product innovator k*, respectively (sales that had taken place had the new products not existed). Let s_{NIj} be the growth of sales of the *non product innovator* stolen by the rivals that sell new products and c_k the growth of sales of the old product replaced by sales of the new product or *cannibalization* within firm *k*. Slightly simplifying the demand model (we neglect price decreases) let us write $g_{1j}=\delta_{NIj}-s_{NIj}$ for the sales growth of *non product innovator j*, and $g_{1k}=\delta_{Ik}-c_k$ and $g_{2k}=c_k+e_k+s_{Ik}$ for the sales growth of product innovator *k*. New product gross sales g_{2k} are made of the cannibalization rate plus a rate e_k capturing market *expansion*, and s_{Ik} which is the growth of sales of the new product made of *business stealing* from *non product innovators*.

We can write the average sales growth rates of the previous subsection as:

$$g_{NI}=\delta_{NI}-s_{NI} \qquad (6)$$
$$g_I=(\delta_I-c)+\beta(c+e+s_I)$$

where we denote the mean of each demand component by the absence of any subindex. We do observe the total rates g_{NI} and g_I, and the two parentheses of the second equation (sales growth of the old product, gross sales of the new product). However, we observe none of the demand components: *potential growth* δ_{NI} and δ_I, *business stealing* s_{NI} and s_I, *market expansion e* and *cannibalization c*. With random samples, business stealing and stolen business should cancel market to market. Thus, we know that $s_I=\lambda s_{NI}$ where λ is the ratio of old product sales of *non product innovators* to old product sales of *product innovators* at the beginning of the period.[30]

Our estimates, together with a couple of sensible assumptions, can go quite far in assessing the importance of these demand components. First let us assume that the unobserved average *potential growth* of the old products is the same for all type of firms, so $\delta_I=\delta_{NI}=\delta$. And second, let us assume that the growth of new sales that we have called *expansion* keeps a relation of proportionality with the *potential growth* of old products δ, $e=\gamma\delta$ say. Under these assumptions, and taking for simplicity $\beta=1$, it is easy to see that Eq. (6) can be solved for all the average demand components: $\hat{\delta}=(g_I+\lambda g_{NI})/(1+\gamma+\lambda)$, $\hat{e}=\gamma\hat{\delta}$, $\hat{s}_I=\lambda\left(\hat{\delta}-g_{NI}\right)$ and $\hat{c}=\hat{\delta}-(\delta_I-c)$. We are going to express the results as components of the employment growth for *product innovators* $g_I=\hat{\delta}+\hat{e}+\hat{s}_I$. As we have however no reliable estimate for γ we are going to discuss the results for two alternative possible extreme values, 0 and 0.3.[31]

7.3. Explaining average employment growth

Table 5 reports the values of the statistics which show up in Eq. (4). Let us briefly comment what the numbers show.

First of all the productivity trend, i.e. incremental year to year productivity improvements in the production of existing products, is an important source of reductions in the employment requirements for a given level of output.

The row on *gross effect of process innovation* shows that individual process innovations by *process innovators only* may add a significant reduction in employment, and they especially do so in Germany (on the interpretation of the number for Spain see Section 6).

Except for German manufacturing, these negative employment effects are overcompensated by the employment stimuli due to the growth of the old product sales for *non product innovators*. We know from theory that it should be this way through the demand effect of these productivity increases (see Section 4.1), although we cannot disentangle the compensation effect from the overall growth of the demand for old products.

In fact, Table 5 gives us a nice opportunity to check the practical likelihood of the price-compensation mechanism. One can argue that the sales increase of *process innovators only* should be greater than the sales increase of the *non innovators* by just the average compensation effect which results from price reductions following the additional increases in efficiency induced by process innovations. Relating the two relevant numbers for France, Germany and the UK we get a very reasonable implicit average elasticity of demand of about 1.4–1.5.[32]

Product innovators show a much stronger growth of sales, even after deducing the part of growth that is simply substitution of sales of new products by sales of old products. The average rate of growth of sales for product innovators is between 1.3 and 1.4 times the average rate of growth of the sales of the *non product innovators* (and slightly higher than the sales of the subset of *process innovators only*, except in Germany). Therefore, *product innovators* experience everywhere the strongest employment growth, based on the net growth of the new products.

[30] In practice we will approximate λ by the ratio of the number of *non product innovators* to the number of *product innovators* $\frac{N_{NI}}{N_I}$.

[31] An empirical evaluation of γ could be obtained by looking at the values of g across markets with and without new products.

[32] In practice things are not evident because the data tell us that price growth was also slightly higher for *process innovators only* (see Table 1a), but this can be explained by the different industry composition of the subsamples. For the compensation effect to take place we only need that the prices rise less than the prices of the close rivals.

Table 6
Impacts of innovation on employment growth[a]: Contributions to average growth
Manufacturing and Services firms, 1998–2000.[b]

		Manufacturing				Services			
		France	Germany	Spain	UK	France	Germany	Spain	UK
Firms' employment growth	l	8.3	5.9	14.2	6.6	15.5	10.2	25.9	16.1
Productivity trend in production of old products	*trend*	−1.9	−7.5	−5.7	−6.8	−2.3	−3.0	1.0	−5.0
Gross effect of process innovation in old products	$\hat{\alpha}_1 w_{PO}$	−0.1	−0.6	0.3	−0.4	−0.1	0.1	−0.0	0.2
Sales growth in old products for *non product innovators*	$w_{NI} g_{NI}$	4.8	6.0	12.2	9.0	9.9	5.4	18.5	15.5
Non innovators		4.1	4.0	9.8	7.1	8.7	4.8	16.3	13.8
Process innovators only		0.7	2.0	2.4	1.8	1.2	0.6	2.2	1.6
Net sales growth of *product innovators* (new prods-subs.)	$w_I g_I$	5.5	8.0	7.4	4.8	8.0	7.6	6.5	5.4
Sales growth due to old products		−2.1	−8.9	−5.6	−5.1	−1.6	−7.4	−3.5	−3.4
Sales growth due to new products		7.7	16.9	13.0	9.9	.5	15.0	9.9	8.8

[a] Based on descriptives of Table 1a and Table 1b and regressions B and D of Table 3.
[b] Rates of growth for the whole period.

Table 6 reports the growth components computed by means of Eq. (5). The left-hand side variable may be understood as the average employment growth, and the value corresponding to each concept can be read as contributions to this growth.

The incremental productivity improvements in the production of existing products are, as we have seen before, an important source of reductions in employment requirements for a given level of output. The effect is smallest in France (−1.9% over two years) and largest in Germany (−7.5% over two years).[33] Individual process innovations account however only for small additional displacement effects. This is basically because the proportion of firms that introduce only process innovations is small. The growth in the sales of existing products more than compensates for the trend productivity and process innovation effects in all countries except in German manufacturing.

Finally, the effect of the sales of the new product net of substitution for the old product plays an important role in the determination of employment growth. In Spanish manufacturing, for instance, it surpasses the effect that results from adding up the contributions of all other sources (7.4 against 6.8), in France and in UK it doubles it (5.5 against 2.8 and 4.8 against 1.8), and in Germany it becomes responsible for more than the whole average employment growth during the period (8.0 against −2.1).[34]

7.4. Long-run effects

With our sample being three years long we cannot apply sophisticated dynamic econometrics, contrary to the previous literature. One may then wonder if the results of applying our approach are consistent with previous estimates like VR and LR (see Section 4.2). Somewhat strikingly, the answer is that our results appear to be very consistent with these estimates. If one agrees that the dynamic relationship

$$(1-0.7L)\ ln(employment)_{it} = constant + 0.015(innov_{it} + innov_{it-1} + innov_{it-2})$$

may be taken as roughly representative of the 10 dynamic regressions estimated in VR and in LR, the implication is that the long-run effect of an innovation (process or product, in only one of the three observed years) is the increase in employment by about 5%.[35] If we use Table 5 to compute the average net increases of employment for process and product innovators during 1998–2000 minus the net increases for non innovators (rows 6 and 7, both minus row 5) we find, on average, a very close difference of about 4.8%.

7.5. Estimating business stealing and market expansion

Table 7 shows that we can provide reasonable bounds to these effects. Let's first suppose that the new products do not expand sales at all, i.e., they do not attract new customers or new buys; they only replace old product sales that had taken place in any case, which corresponds to the hypothesis $\gamma = 0$. Then we find that, on average, *business stealing* accounts in manufacturing for between 2 and 3 percentage points of the employment creation by product innovators (5–7 percentage points in services). This approximately amounts to between 20% and 30% of the net employment created by these firms (net sales growth minus productivity trend).

If we now suppose, on the contrary, that *expansion* amounts to 30% of the potential for growth of the sales of the old product ($\gamma = 0.3$), then *stealing business* would have taken place by very small amounts and the employment growth of product innovators with origin in *expansion* is around 3–5 percentage points in manufacturing (4–7 percentage points in services). This employment would not have been created had there been no new products. It approximately amounts to between 30% and 40% of the net employment created by these firms (a little less in services).

Therefore, the maximum stealing that can be in the net employment growth of product innovators is estimated as one third, and the maximum amount that is reasonable to consider as market expansion employment creation is a little higher. How much there is in practice of *business stealing* and how much of *expansion* depend on the demand-creation effect of the new products. We are not aware of previous work trying to separate and quantify these two demand effects in the presence of new products, and we think that it is a topic that deserves attention in future research.

7.6. Summary

Let's summarize the findings. Trend increases of productivity in the production of old products are for all firms the main force in reducing the labor requirements for a given output. Process innovations add some worker displacement but the number of firms that apply process innovations only is small. The growth of the demand for the old products tends to overcompensate these displacements. Part of this growth comes from price reductions. The data confirm that the compensation mechanisms via relative price reductions linked to the increases in productivity work properly. On the other hand, the introduction of new products does not originate worker displacements, because productivity of the new products remains basically the same

[33] Trend diverges from the constant because we are using the weighted average of the constant and the industry dummies.

[34] Peters (2008) estimates the employment effects of innovation in Germany for the recession period 2000–2002. Though the magnitude of the effects she finds are smaller, the overall conclusions remain similar: in particular the net contribution of product innovation accounts for large part of employment growth.

[35] Actually, VR considers only "basic" innovations, which amounts to only 17% of the observations and concerns only 25% of firms, and is based on regressions with 6 and 10 lags. LR is based on regressions with different lag structures for product and process innovations, amounting to about 42% and 34% of the observations, respectively.

Table 7
Estimates of business stealing and market expansion effects[a]. Manufacturing and Services firms, 1998–2000.[b]

			Manufacturing				Services			
			France	Germany	Spain	UK	France	Germany	Spain	UK
Net sales growth of product innovators (new products-substitution)			12.3	16.5	22.8	16.8	25.5	19.3	30.0	27.2
Case $\gamma = 0$	*Potential for growth*	$\hat{\delta}$	10.4	14.3	19.8	13.9	18.2	13.4	25.1	21.0
	Expansion	$\hat{e}$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Stealing business	$\hat{s}_I$	1.8	2.3	3.0	2.9	7.3	5.9	4.9	6.3
Case $\gamma = 0.3$	*Potential for growth*	$\hat{\delta}$	9.1	12.3	17.8	12.7	16.6	11.9	23.5	19.7
	Expansion	$\hat{e}$	2.7	3.7	5.3	3.8	5.0	3.6	7.0	5.9
	Stealing business	$\hat{s}_I$	0.4	0.6	−0.4	0.3	4.0	3.8	−0.5	1.6

[a] Based on descriptives of Table 1a and Table 1b, regressions B and D of Table 3, and Eq. (6).
[b] Rates of growth for the whole period.

as the old products. The growth of demand for the new products generates the main impact on employment, even when the pure replacement of sales of old products is discounted (cannibalization). In the period and samples that we observe, the net creation of jobs by new products tends to be much stronger than the net creation based on old products. The employment-reallocation component associated with this fact, through business stealing by innovators, is estimated as less than one third of the created employment. We also estimate that the creation of employment that had never taken place, had the new products not existed, may be as important as up to a third of the net employment growth induced by the new products.

8. Concluding remarks

This paper derives a single equation model in which the excess of employment growth over the evolution of sales for old products is explained by two variables: the introduction of process innovations affecting the old products and the growth of sales derived from the introduction of product innovations. We have shown that this equation is sufficient to estimate two employment effects of interest: the gross effect of product innovation and process innovation. In the first case we can even disentangle the role of the change in efficiency in the production of the new products with respect to the old. The relative size of the displacement effect is, however, conditional on the quality of our price indices. It could be that the absence of firm-level price information implies some underestimation of its value. Based on these estimates, observed sales outcomes for non innovators and innovators, and with the help of a few assumptions, we have been able to derive bounds for the size of the business stealing and market expansion effects of innovation.

As a whole the results point to the fact that process innovation does not reduce the number of workers. Both the common productivity trend present everywhere and specific process innovations destroy jobs but, during the observed period, the growth of demand for the old products is strong enough to compensate for all this. Part of the demand increases must come from the price reductions following the increases in efficiency, and we even get some indirect evidence that the effect of these price reductions more than compensates for the losses of jobs because of displacement (as expected from theory). On the other hand, product innovations enlarge the number of jobs. First, the efficiency in production of the new products seems to be approximately the same as that in the production of the old products. Second, creation of jobs in the manufacturing of the new products is bigger, firm to firm, than the eliminated jobs because of the substitution of new products' sales for sales of old products. Moreover, the employment destruction because of business stealing to non product innovators is estimated at less than one third of the net jobs created by the new products. The idea that innovation stimulates employment seems then quite well established. Moreover, there does not seem to be any radical difference between the mechanism at work in manufacturing and in the service sector. The doubt that reasonably remains is, to what extent are these employment creation facts idiosyncratic to the analyzed period?

Our simple model shows some advantages on previous estimates. First, it correctly produces the signs predicted by theory, establishing employment evolution as the outcome of different theoretically consistent positive and negative effects at the firm- and industry-levels, going a quite long way in assessing quantitatively their relative importance. Second, the model naturally explains the puzzling mixed-sign results obtained in more correlation-oriented exercises from the relative impact of the expected opposite effects. Third, despite the short period of estimation, the model obtains a whole net effect on employment that is quite close to the effect estimated in sophisticated dynamic large panel-data exercises.

Our sample is drawn from a high growth period, and this undoubtedly influences the relative magnitude of the effects at play. However, the model can be applied to any situation in which employment, innovations, and the demand for the new products are observed. This type of modeling may be particularly useful to gain insights on the forces behind the situations in which the displacement effects of productivity seem to dominate.

Our exercise also sheds light on some limitations that the actual data bases show, and suggests interesting extensions. Having firm-level output prices would be very important to increase the accuracy of the estimates, because many mechanisms depend crucially on how the firm behaves in setting post-innovation prices. Of course, distinguishing groups of workers by skills would be another important improvement. The obvious idea is that innovation may have very different effects in displacement and compensation for the tasks performed by different types of workers, and it would be crucial to have some measures of these effects. Including industry entry and exit would also provide more complete boundaries for the industry effects. These are only a few of a long list of possible extensions.

Appendix A. Data Appendix

A.1. Country samples

The samples used in the present study (corresponding to Tables 1a and 1b in the main text) were defined in a way so as to improve comparability in terms of industry composition and firm-size coverage, as well as to slightly clean these from a priori outliers. Firms with mergers, closures or scissions were excluded to avoid significant reductions or increases in turnover as a result of these facts. Firms which showed incomplete data or changes in sales or employment greater than 300% were dropped. The German sample was restricted to firms with 10 or more employees to match the Spanish and UK samples. However, the French sample refers only to firms with 20 or more employees in manufacturing, and it does not include the transport industry in services. Table A1 gives the list of the eleven manufacturing industries and seven service industries covered in the study samples, as well as the number of firms and the average firm size by country and industry.

Table A1
Number of firms and average firm size, by country and sector.

	Number of firms (%)				Average firm size[a]			
	FR	DE	SP	UK	FR	DE	SP	UK
Manufacturing								
Vehicles	4.3	4.0	5.6	10.5	1164	340	367	222
Chemicals	8.2	7.0	6.5	3.7	483	330	213	337
Machinery	9.2	14.0	6.3	8.0	302	291	150	179
Electrical	9.9	16.2	8.1	15.7	540	482	157	197
Food	19.3	8.6	11.0	7.2	282	149	150	303
Textile	12.3	5.8	14.7	5.7	124	219	78	148
Wood	9.1	8.5	13.8	14.6	234	358	87	144
Plastic/rubber	6.0	8.8	4.4	5.1	396	148	105	132
Non-metallic	3.5	5.9	7.3	2.3	415	247	141	242
Basic metal	13.3	17.2	13.4	14.1	258	153	110	68
NEC	4.9	4.0	8.9	13.2	217	253	66	132
All firms	100	100	100	100	345	276	132	171
Services								
Wholesale	44.9	24.0	22.1	41.4	62	410	146	124
Transport	0.0	24.0	18.5	25.9	–	1272	373	291
Post/telecomm.	1.9	3.1	4.1	3.6	102	220	191	587
Financial int.	15.2	11.4	7.0	13.3	1044	808	527	282
Computers	12.8	9.4	9.8	4.4	81	95	151	238
R&D	3.9	8.8	3.9	1.9	168	91	68	338
Technical serv.	21.4	19.2	34.6	9.6	129	56	301	136
All firms	100	100	100	100	233	531	268	215

[a] Average number of employees in year 2000.

A.2. Variable definitions (in alphabetical order)[36]

Clients as source of information: Variable which takes the value 0 if the firm reports that it does not use clients as a source of information for innovation, and 1/2/3 if they have been of low/medium/high importance.

Continuous R&D engagement: Dummy variable which takes the value 1 if the firms report continuous engagement in intramural R&D activities.

Employment growth: Rate of change in the firm's employment for the whole period.

Increased market share: Variable which takes the value 0 if the firm reports that the effect of innovation has been irrelevant for market share, and 1/2/3 if it has had low/medium/high impact.

Increased range: Variable which takes the value 0 if the firm reports that the effect of innovation has been irrelevant for broadening the range of goods and services, and 1/2/3 if it has had a low/medium/high impact.

Industry dummies: System of industry dummies according to the list of industries given in Table A1.

Improved quality: Variable which takes the value 0 if the firm reports that the effect of innovation has been irrelevant for the quality of goods and services, and 1/2/3 if it has had a low/medium/high impact.

Prices indices at detailed industry levels: For France, they are obtained for manufacturing and services at a 2.5-digit level of classification on the basis of the National Accounts value-added deflators. For Germany, in manufacturing they are constructed at a 3-digit level (and in a few cases at a 2-digit level) on the basis of the producer-price indices published by the German statistical office; in the service sector they have been obtained only at the level of the seven industries on the basis of the producer-price indices or from different components on the consumer price indices (for details, see Peters, 2004). For Spain, for manufacturing they correspond to the 88-industry series of the "Indices de precios industriales" from INE, and for services to different components of the consumer-price indices. For the UK, they are computed at a 4-digit level for manufacturing on the basis of the ONS output deflators, and at a 1.5-digit level for services on the basis of OECD output deflators.

Process and product innovation: Dummy which takes the value 1 if the firm reports having introduced new or significantly improved products and production processes.

Process innovation: Dummy which takes the value 1 if the firm reports having introduced new or significantly improved production processes during the period.

Process innovation only: Dummy which takes the value 1 if the firm reports having introduced new or significantly improved production processes during the period but no new or significantly improved products.

Product innovation: Dummy which takes the value 1 if the firm reports having introduced new or significantly improved products.

R&D effort: Ratio of total R&D expenditure to turnover in year 2000.

Sales growth, sales growth due to new products and sales growth due to old products: Below, the first two rates give our reading of the original survey information, the other four explain how we construct the employed rates from the original information.

$$\text{Nominal sales growth for all products} \equiv \hat{g} = \frac{\text{current sales old} + \text{current sales new} - \text{past sales old}}{\text{past sales old}}$$

$$\text{Proportion of sales of new products} \equiv s = \frac{\text{current sales new}}{\text{current sales new} + \text{current sales old}}$$

$$\text{Sales growth due to new products} \equiv g_2 = \frac{\text{current sales new}}{\text{past sales old}} = s(1+\hat{g})$$

$$\text{Nominal sales growth due to old products} \equiv \hat{g}_1 = \frac{\text{current sales old} - \text{past sales old}}{\text{past sales old}} = \hat{g} - g_2.$$

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

$$\text{Real sales growth due to old products} \equiv g_1 = \hat{g}_1 - \pi$$

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ijindorg.2014.06.001.

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[36] All variables refer to the period 1998–2000 unless stated otherwise.

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