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PERSISTENCE OF INNOVATION AND JOB CREATION: Evidence from a panel of Spanish manufacturing firms

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Abstract

This paper estimates the effect of innovation on employment in Spanish manufacturing firms during the period 1990-2008. In particular, we analyze the employment effects of innovation strategies taken into account the persistence of innovation. Using a GMM-system estimation, we study the importance of persistence of product and process innovation on employment´s growth controlling by potential endogeneity and unobserved firm heterogeneity. The results support that process innovation measures show a positive effect on employment while the effect of product innovation is positive but not significant. The study also distinguishes that this effect appear in the same year, but it increases with the number of lags confirming that compensation effects of process innovation may appear with a certain delay justifying the advisability to get persistent innovators to compatibilize innovation with employment growth.

Key words: innovation, persistence, firm growth, employment growth manufacturing.

1. Introduction.

Since the beginnig of the crisis, job creation is one of the biggest concerns all over the world. With unemployment stubbornly stuck at around 10 percent in the European countries, and with the global economic panorama threatening more difficult times ahead, the question is what firms can do to spur job creation. High unemployment rates justify moving fast on changes in labor policy with more flexible rules on hiring and firing. However, job destruction cannot be solved only with major labor reforms, the European economies will need to create jobs.

In this context, it is claimed that innovation has a crucial role to play. Although there is a vast amount of literature about the relationship between innovation and employment, the impact of different types of innovation affecting the employment change at the firm level still remains unclear (Lachenmaier and Rottmann, 2011).

There exists a recent growing empirical literature that strengthens the positive effect of innovation (or technological change) on employment in manufacturing (Bogliacino, Piva and Vivarelli, 2012). However, the empirical evidence about the stimulating effect of process innovation on labor demand in manufacturing firms cannot be always confirmed even though the magnitude of displacement and compensation effects of process innovations can operate in the manufacturing sector (Entorf and Pohlmeier, 1990; Peters, 2004; Harrison, Jaumandreu, Mairesee and Peters, 2008; Hall, Lotti and Mairesse, 2008). In contrast, other authors found a higher positive impact of process than of product innovation (Greenan and Guellec, 2000; Lachenmaier and Rottmann, 2007 and 2011).

Substantial research effort has also been made to examine the persistence in innovation activities at the firm-level. Nevertheless, studies focused on innovation persistence considering the technological level are still very limited. Among the most recent researches we find Roper and Hewitt-Dundas (2008), Peters (2009), Raymond *et al.* (2010), Antonelli *et al.* (2010) and Triguero and Córcoles (2010). Nevertheless, there are very few studies that focus on the effect of innovation persistence on firms´ performance (Cefis, 2003; Cefis and Ciccarelli, 2005).

This paper contributes to this discussion. We investigate the linkage between employment growth and innovation at firm-level taken into account the persistence of innovation, the potential endogeneity between the dependent and explanatory variables and the importance of unobserved firm heterogeneity. Our paper distinguishes in three important points from other contributions: First, we employ an econometric model that links innovation and employment growth at the firm level, which allows us to observe the effect of innovation strategies (product and process innovation) in net employment effect (not job flows of creation/destruction). Second, in contrast to other studies on this topic, we investigate effects at the firm level with a large panel data set of observations covering 19 yeas from Spanish manufacturing instead of CIS data[1]. Third, we provide an additional analysis for the potential effect of persistence in innovative activities on firm´s growth because we hope that persistent-innovator firms contribute more to employment growth than non-innovators firms or discontinous innovators.

The paper is organized as follows: Section 2 revises the empirical studies on the effects of innovation on employment onsidering product and process innovation. Section 3 describes data and presents some figure and descriptive statistics on employment growth and innovation. Section 4 introduces the model used and the econometric methodology of this study. Section 5 explains the main results and finally, section 6 draws conclusions from the analysis.

2. Literature Review

The existing theoretical literature states that product innovations have a large positive impact on employment since they often create new goods and/or services which are not simply substitutes for existing ones, new markets and jobs. Process innovations, on the other hand, are often thought to be labor saving. In this sense, product innovation contributes to employment growth by the sales growth of new products or services. Product innovations lead to new markets. Additionally, if consumers like these differentiated products, the overall demand increase and innovative firms will employ more workers. Thus, we could expect a positive relationship from the direct effect of product innovations on employment at least in the short run (compensation effect). However, product innovation could have a contrary effect if: i) old workers could be laid off if product innovation require the use of different labor inputs (workers with high or different skills) and the net employment effect is negative ii/ the new product substitute old products of the firm decreasing the existing

[1] García et al. (2004) is the only study that assesses the employment effects of the product and process innovation of Spanish manufacturing firms using this dataset. They estimate firm level displacement and compensation effects in a model in which the stock of knowledge capital raises firm relative efficiency through process innovations and firm demand through product innovations. They remark that the availability of information on a number of key market idiosyncratic variables provided by the firm is an advantage of this data set.

sales (cannibalization) or iii) the production of the new products requires fewer employees than the production of the old products.

On the other side, if process innovation contributes to substantial productivity gains (it could even affect the production of old products) the firm will need hire less workers. Thus, we could hope a negative relationship from the direct effect of process innovations on employment (displacement effect/ short run effect). However, process innovation displacement effect could be compensated[2]. The productivity increase leads to employment growth if achieved cost reduction passed on to price and this price reductions expand demand. Thus, process innovation means less labor input for a given output but more workers if sales grow. Displacement effect will depend on the extent to which the process improvement is labor or capital-augmenting. Elasticity of demand for the firm's products is going to determine the size of compensation effect, "but is also likely to depend on the behavior of the agents inside the firm and the nature of market competition. For example, unions may attempt to transform any gains from innovation into higher wages, while managers may take advantage of their firm market power to increase profits"(Harrison et al., 2008).

Regarding to the empirical evidence, there also exist a considerable amount of studies contrasting the employment effects of innovation at macroeconomic, sectoral and firm level. From the available evidence, the results differ according to different level of analysis (Spiezia and Vivarelli, 2002). We focus exclusively on the relationship between employment and innovation at microeconomic level.

In the 1990s, only few studies investigated the impact of innovation on employment at the firm´s level. Among these studies, some authors strength the positive effect of product innovations on employment and insignificant effect of process innovation (Entorf and Pohlmeier (1995) for German firms; Leo and Steiner (1994) for Austrian firms) or significative larger effects of product innovations on employment effects (Van Reenen (1997) for British firms). However, the empirical evidence about the stimulating effect of process innovation on labor demand in manufacturing firms cannot be confirmed. For example, Blanchflower and Burgess (1999) estimate the employment effect of the introduction of a new technology (process innovation) for 831 UK and 888 Australian firms and found a positive effect in both countries (weakly in Australia). Using a panel data of french firms, Greenan and Guellec (2000) also find

[2] There exist six different market compensation mechanisms that are triggered by technical change itself and which can counterbalance the initial labor saving impact of process innovation (for an extensive analysis, see Petit, 1995; Pianta, 2005; or Bogliaciano et al., 2012).

that process innovation has a strong positive effect at the firm level but not for product innovation using a sample of 15,186 firms, over the period 1986–90. This paper describes the dynamics of employment at firm and sector level in French industry and concludes that process innovation is more about job creation than product innovation at the firm level (but the opposite is true at the sector level probably due to substitution effects in the industry)[3].

Although the earlier studies are cross-section (i.e., Entrof and Pohlmeier, 1990), the availability of more comprehensive data and the advances in econometrical techniques have allowed to obtain new empirical evidence on the effect of innovation on employment at the firm-level. Among these empirical studies at the firm-level, we distinguish between the studies using innovation surveys (i.e. Community Innovation Surveys (CIS)) and empirical evidence obtained by using other surveys not based on the Oslo Manual (such as the Spanish annual “Encuesta Sobre Estrategias Empresariales” (ESEE))[4].

Most of the first group of studies use modified versions of the model proposed firstly by Jaumandreu (2003). This model relates employment growth to process innovations and to the sales growth due to old and innovated products using Spanish data of CIS3 (1998-2000) referred to 4,548 firms of the manufacturing and service sectors. Thus, this author finds that process innovation does not displace employment and that product innovation expands employment with a gross unit elasticity with respect to innovative sales. Peters (2004) also contributes to this strand of literature by analysing the effect of different types of both product and process innovations using specific information provided by CIS data of 4,611 firms (1998-2000) in Germany. The econometric analysis confirms that product innovations have more positive impact on employment than process innovation in the German manufacturing and services firms. However, the net decomposition of employment growth provides evidence that the net effect of process innovation is small in both manufacturing and service sectors. After these first studies, this model was adapted by Harrison, Jaumandreu, Mairesse and Peters (known as HJMP model) to evaluate employment effects of innovation in a cross-country comparison (Harrison et al., 2008). Furthermore, it has been used to

[3] See table A.1 in the appendix.

[4] The CIS surveys are conducted in all EU member states, but also in emerging economies, transition countries and developing countries. Although there are some differences across countries – the innovation surveys usually have the same structure and the same questions regarding innovation.

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contrast the evidence in Chile (Benavente and Lauterbach, 2007) and Italy (Hall et al., 2008) among others.

In particular, Harrison et al. (2005, 2008) relate innovation output to productivity growth and then decompose the employment growth into the fraction due to the growth in old products, the sales due to new products and the effects due to process innovation in Germany, France, Spain and the UK. They report that process innovation displaces employment in manufacturing but less in services, but that in any case the compensation effect dominates. Product innovations are also job creating.

Benavente and Lauterbach (2007) found that product innovations affect positively and significantly employment levels in Chile using data from 558 firms in the period 1998-2001. On the other hand there is no evidence to suggest that process innovation significantly affects employment after controlling for investment and sectorial patterns.

Hall et al. (2008) apply the HJMP model to Italian firms and find similar results. Using firm-level data for three CIS covering the period 1995–2003, they find lower contribution of product innovation to employment growth comparing these results with the ones of HJMP 2008 for France, Germany, Spain and the U.K. Furthermore, they find no evidence of significant employment displacement effects stemming from process innovation They suggest that this result could indicate that Italian firms may not be able to obtain productivity benefits from process innovation.

While last studies have focused on CIS questionnaire data having a short time dimension, longer panel studies of the impact of innovation on employment are scarce. Hence, Van Reenen (1997) uses a panel of 598 firms over the period 1976–1982 resulted of matching the London Stock Exchange database of manufacturing firms with the SPRU innovation database. Running GMM-differences estimates, the author found a positive impact of innovation on employment, and this result turned out to be robust even after controlling for fixed effects, dynamics and endogeneity. Piva and Vivarelli (2004, 2005) using a unique longitudinal dataset of 575 Italian manufacturing firms over the period 1992–1997 estimate a model rather similar to Van Reenen (1997) applying GMM-system equations. Thus, they find a significant – although small – positive relationship between a firm’s gross innovative investment (their innovative proxy) and employment.

García et al. (2004) estimate four GMM-sys (production function, labor demand, product demand and wage and margin equations as endogenous) using a panel of 1,286 Spanish firms during the period 1990-98. They show that the potential compensation effect is greater than the displacement effect of employment generated by product innovation in the short and in the long term horizon. Their results find that product innovation duplicates the effects of employment expansion by the cost unit reduction through process innovation due to the behavior of the rivals in the industry.

Mairesse et al. (2009) analyze the impact of product innovations on employment growth at the firm level in China for the four major industries. Using the model proposed by HJMP, they study the effect on overall employment of the output growth (2-year growth rate in 2006 respect to 2004) of innovating firms in new products and in “old” (unchanged) products, the output growth of non-innovating firms, and the average productivity growth in the production of old products. The results are not too different from those found for manufacturing as a whole in France, Germany, Spain and the United Kingdom in HJMP (2008), and for Italy in Hall et al. (2008). They find that the effects related to product innovations are strong enough in general to over-compensate these displacement effects. Nonetheless the main contribution of this paper is related to the different results obtained for the four major industries (Textile, Wearing Apparel, Transport Equipment and Electronic Equipment) and across the four city districts (Beijing Tianjin Zhejiang Shandong Guangdong) and the impact of new product output on employment growth by separated categories of ownership (State owned, Limited Liability, Share Holding, Private, Hong Kong Macao and Taiwan (HMT) Funded firms and Foreign[5].

Meriküll (2008) also investigates the effect of innovation on firm- and industry-level merging the data from Estonian Commercial Register with two CIS, (1998–2000 and 2002–2004). He confirms that considering 830 firms there exists a positive and statistically significant effect of both types of innovation on employment. As often, product innovation tends to have a stronger positive effect on employment than process innovation-although only moderately significant. One of the main conclusion is that the level of analysis in terms of firms or industries is robust confirming that the business stealing effect from one firm to the rest of the industry could be very small.

Bogliacino et al. (2011) analyze the employment effect of business R&D expenditures, using a unique longitudinal database covering 677 European manufacturing and service firms over the period 1990-2008. Main results from the whole sample dynamic LSDVC (Least Squared Dummy Variable Corrected) show positive and significant job creation effect of R&D expenditures in services and high-

[5] Unfortunately, process innovation is not available and is not included as explanatory variable.

tech manufacturing but not present in the more traditional manufacturing sectors. In this paper GMM cannot be applied efficiently because the panel is characterised by a relative low number of firms.

Coad and Rao (2008) limit their focus on US high-tech manufacturing industries over the period 1963-2002 and investigate the impact of a composite innovativeness index (comprising information on both R&D and patents) on employment. The main outcome of their quantile regressions is that innovation and employment are positively linked and that innovation has a stronger impact for those firms that reveal the fastest growth in employment. They also use a Principal Components Analysis to generate a firm- and year-specific ‘innovativeness’ index and estimate semi-parametric quantile regressions.

Finally, Lachenmaier and Rottmann (2011) estimate a dynamic employment equation including wages, gross value added, year and industry dummies, and alternative proxies (dummies) of current and lagged product and process innovation. Their GMM-system especifications based on a dataset of 1,073 German manufacturing firms over the period 1982-2002 – show a significantly positive impact of different innovation measures on employment. In particular, there exists a higher positive impact of process than of product innovation. However, the most significant contribution for our research interest is that they find significant and different effects mostly for first or second lag (except for product innovations with patent applications which have also have a contemporaneous effect on employment). Results suggest that the significance of product and process innovation has different effects on employment depending on the considered lag (one or two lags). Hence, we believe that the firms could show different response in terms of employment growth depending on the degree of persistence in innovative activities. Since lagged innovation enables to measure persistence in the most of studies, the introduction of lagged innovation explanatory variables enable us to test this hypothesis. Although some studies based in patent concluded that there is no persistence (Geroski, van Reenen and Walters, 1997; Malerba and Orsenigo, 1999) others find that persistence in innovation is characteristic of major innovators (Cefis, 2003) or find persistence for product innovation but not for process innovation (Parisi et al. (2006)). Substantial research effort has also been made to examine the persistence in innovation activities at the firm-level controlling for individual heterogeneity and the initial conditions to try to identify a true and not just a spurious persistence (Roper and Hewitt-Dundas, 2008; Peters, 2009; Raymond et al., 2010; and Triguero and Córcoles, 2010). Nevertheless, there are very few studies that focus on the effect of innovation persistence on firms´ performance (Cefis, 2003; Cefis and Ciccarelli, 2005). This is one of the attempts of this paper using employment´s growth as measure of firm´s performance.

In particular, little work has been done more generally on the dynamics of innovation in the sense of capturing the time lags of the effects of innovation on economic performance. One example is Huergo and Jaumandreu (2004), who have estimated that process innovation has a positive impact on productivity that persists for about three years, using semi-parametric methods and data on Spanish firms. Another study that investigates the role played that R&D in driving firm growth is Demirel and Mazzucato (2012). These authors explore the differences in how innovation affects firm growth in US pharmaceutical firms between 1950 and 2008. They observe that the positive impact of R&D on firm growth is highly conditional upon a combination of firm characteristics such as firm size, patenting and *persistence* in patenting. For large pharmaceutical firms, R&D affects firm growth positively with the exception of those that do not patent. On the other hand, for small firms, it is crucial that patent persistently for at least five years to result in firm growth.

Taking into account these insights, a full assessment of long–term employment effects is on the agenda of future research and is potentially possible using long-panel data at the firm-level and more sophisticated econometrical techniques. Even Peters (2004) admited that one might ask whether this is enough to assess the entire employment consequences considering a three–year period (CIS surveys) of one or more countries. "*While it is sensible to assume that displacement effects of process or product innovations won't be lagging much to the time of their introduction, compensation effects especially of process innovations may appear with a certain delay. Given that this assumption is true, this would imply that I may even overestimate the negative, respectively underestimate the presumably positive employment impact of process innovations. Estimating the time period in which compensation effects of product innovations arise is further complicated by the fact that the amount and sustainability of such compensation effects resulting from demand increases depend on the competition and the way and delay with which competitors react*." (p. 37)".

3. Data and methodology

3. 1. Data and descriptive analysis

The analysis is carried out at firm-level, covering the Spanish manufacturing industry over a period of 19 years, from 1990 to 2008. The data come from the Survey of Business Strategies (ESEE, *Encuesta sobre Estrategias Empresariales*) compiled by the Spanish Ministry of Science and Technology. The panel data is an unbalanced panel that includes all the industrial sectors. The coverage of the data set is mixed. A random sample is drawn for small companies (with less than 200 employees), keeping the sample representative of the industrial distribution, whereas the sample is complete for large firms (with more than 200 employees). Furthermore, new companies enter the Survey each year to maintain the representativeness of the industry over the whole population.

We have chosen as dependent variable the employment growth measured by the log of number of employees. The ESEE Survey deals with both types of innovations: product and process innovations. Our measure of the innovation is the question of whether any product innovation has been introduced in the market by the firm or whether any process innovation has been implemented in the contemporaneous year.

The rest of variables we have used in the analysis refer to the average wage in the firm, the level of sales per employees, as a proxy for the labour productivity, the size of the firm, the R&D intensity and the market dynamism in which the firm operates. The definition of the variables is shown in Table 1.

Table 1. Definition of the dependent and explanatory variables

Variable	Definition
Employment (L)	Total employees in the firm
Log(employment) (l)	Log of total employees in the firm
Product innovation (pi)	pi =1 if firm has achieved product innovations pi=0 if not
Process innovation (pri)	pri =1 if firm has achieved process innovations pri=0 if not
Average wage (w)	Total labour cost over total employees (in euros)
Sales over employees (sales)	Total sales over total employees (in euros)
Size	Size=1 if the firm sales are equal or above 10.000.000 euros Size= 0 1 if the firm sales are below 10.000.000 euros
R&D/sales	% R&D expenditures over total sales
Market dynamism	Dynamism of the main market covered by the company: - Mdynamism = 1 expansive market - Mdynamism =0 recessive o stable market

Our estimation sample contains 4,627 manufacturing firms (Table 2). We have divided the sample into product, process and product and/or process innovators. At the same time, we can distinguish among persistent, occasional and non-innovators. A firm is considered a persistent innovator if it has introduced an innovation for three or more consecutive years. Firms that reported an innovation at least for one year are classified as occasional innovator. Finally, firms that have never reported an innovation during the sample period are considered non-innovators.

Most firms are process innovators (2,900 firms) although the percentage of persistent innovators (24.25%) is lower than the occasional innovators (38.43%). Nevertheless, more than 37% of the firms recognize to be a non-innovator in process.

In the case of product innovators, more than 50% have never reported an innovation of this type during the period of study. The rest of the firms innovate in product, but only 18.67% of firms introduce new products persistently.

If we consider firms that report at least one type of innovation, the percentage of non-innovators reduces up to less than 30% whereas the percentage of persistent firms is above 32%.

Table 2. Number of firms according frequency and type of innovation

	Product innovation	Process innovation	Product and/or process innovation
Persistent innovators	864 (18.67%)	1,122 (24.25%)	1,493 (32.27%)
Occasional innovators	1,356 (29.31%)	1,778 (38.43%)	1,759 (38.02%)
Non-innovators	2,407 (52.02%)	1,727 (37.32%)	1,375 (29.72%)
TOTAL EMPRESAS	4,627 (100.0%)	4,627 (100.0%)	4,627 (100.0%)

Source: Survey of Business Strategies (ESEE)

Looking at the model variables in Table 3, we can observe the characteristics of the sample. Distinguishing between product and process innovation we see that more firms have introduced process innovations (32.46% of the observations) than product innovations (24.27%). Therefore, product innovation is less frequent than process innovation in Spanish manufacturing sector. Other important characteristic is that 47.98% of the firms have innovated in product at least once during the observation period; meanwhile this percentage is 62.68% for the process innovation.

In addition, most firms report to operate in stable or recessive markets (more than 72% of observations). This could be related to the low degree of innovation.

Table 3. Descriptive statistics

Variable	Num. of Obs. (# firms)	Average	Min.	Max.	Standard Error
Employment	34,848 (4,629)	262.737	1	25,363	817.27
Log(employment)	34,848 (4,629)	4.254	0.000	10.141	1.546
Average wage	34,747 (4,617)	25,401.42	281.150	5,193,989	37433.870
Sales over employess	34,744 (4,617)	142,807.50	1509,375	213,000,000	1,158,679
R&D/sales	34,493 (4,612)	0.865	0,000	32.664	0.190
	Overall		**Between**		**Num. of Obs. (# firms)**
	Num. of obs if Var=1	**Num. of obs if Var=0**	**Num. of firms if Var=1**	**Num. of firms if Var=0**	
Product innov.	8,423 (24.27%)	26,378 (75.73%)	2,220 (47.98%)	4.323 (93.43%)	34,831 (4,627)
Process inov.	11,305 (32.46%)	23,527 (67,54%)	2,900 (62.68%)	4,225 (91.31%)	34,832 (4,627)
Dynamism.market	9,542 (27.43%)	25,240 (72.57%)	2,783 (60.23%)	4,276 (92.53%)	34,782 (4,621)
Size	14,471 (41,65%)	20,274 (58.355)	1,883 (40,78%)	3,141 (68.03%)	34,745 (4,617)

Source:ESEE

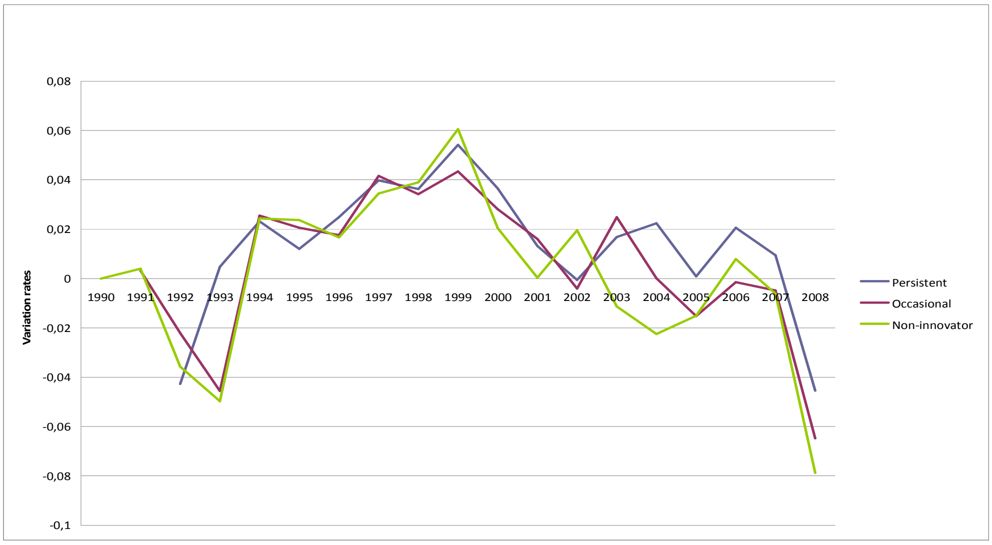
In broad terms, differences in the employment growth by innovation frequency are more pronounced in crisis or economic recession periods. Crisis at the beginning of the 1990s and specially economic recession from 2007 are charecterised by higher (lower) growth (decrease) rates for the persistent innovators. In other words, innovation provides a more stable status, in terms of employment, in uncertainty periods . On the contrary, the occasional and non-innovators firms are more prone to do adjustments via employment losses.

If we distinguish among types of innovation, the differences of employment growth by innovation frequency are higher in the process (Figure 1) than in the product innovation (Figure 2). These graphs suggest that productivity growth due to persistence of process innovation could give certain advantage to these kind of innovators during the crisis periods or economic recession. Persistence in process innovation decrease the probability of job destruction in unfavourable business cycles. In the case of product innovators, the three curves are closer but, similarly, the persistent innovative firms are better possitioned in terms of destruction jobs.

Figure 1. Employment grothw by innovation frecuency. Product innovation

Figure 2. Employment grothw by innovation frecuency. Process innovation

Figure 3. Employment grothw by innovation frecuency. Product and/or process innovation



Source:ESEE

4. Methodology

4. 1.The model

We start from a static model of panel data, where the dependent variable, *l*, is the logarithm of the employment level of firm i (i= 1, 2, …,N) at time t (t= 1, 2,…, T).

$$l_{i,t} = \alpha + \beta_1 X_{i,t} + \lambda_i + \varepsilon_{i,t} \tag{1}$$

X denotes a set of explanatory variables, including innovation variables; λ_i is an unobserved firm- specific time-invariant effect; and $\varepsilon_{i,t}$ is a disturbance term (with zero mean and constant variance, which is distributed independently of the explanatory variables).

Nevertheless, an estimation of this type could create problems. Following Lachenmaier and Rottmann (2011), employment adjustments are costly because of the high cost of hiring and firing. In this sense, the decision about employment are not automatically and depends on the adjustments cost, expectation formation and decision processes. Therefore, it is necessary to take into account a lagged structure. That implies to estimate an autoregressive model where the firm employment in the current period depends on its lag levels (employment persistence) and on a series of firm current and past characteristics. The dynamic model to estimate is the following:

$$l_{i,t} = \alpha + \sum_{k=1}^{n} \beta_k l_{i,t-k} + \sum_{k=0}^{n} \delta_k X_{i,t-k} + \lambda_i + \varepsilon_{i,t} \tag{2}$$

Among X we also include lagged values of our innovation variable to capture the impact of the time lag between the implementation of the innovation (persistence) and its effects on employment. We distinguish between the effects of persistence of product (pi) and process (pri) innovations and control for another variables. On the one hand we introduce the average wage of the firm (w) and on the other hand we consider sales per employee (sales) as a proxy for the productivity of the firm. Finally, we include industry dummies to capture technological opportunities in each industry and year dummies to consider the effect of business economic cycles. The final specification is:

$$l_{i,t} = \alpha + \beta_1 l_{i,t-1} + \beta_2 l_{i,t-2} + \beta_3 pi_{i,t} + \beta_4 pi_{i,t-1} + \beta_5 pi_{i,t-2} + \beta_6 pri_{i,t} + \beta_7 pri_{i,t-1} + \beta_8 pri_{i,t-2} + \beta_9 w_{i,t} + \beta_{10} sales_{i,t} + \lambda_i + \varepsilon_{i,t} \quad (3)$$

In alternative specifications for the robustness analysis we have added more control variables like the size of the firm trough the levels of sales, the R&D intensity and the market dynamism.

4.2. Econometric strategy

The estimation of dynamic panel data models presents some econometric problems. The most important refers to the unobserved heterogeneity of the sample, in this case, the λ_i firm specific effects whose incorrect treatment would lead to inconsistent estimators. The presence of individual fixed effects in dynamic panel data models may cause that the within estimator (LSDV estimator) shows upward bias in the estimation of the parameters. Although this bias tends to cero as the number of year increases, it not can be ignored in small samples.

Other problem is the presence of the lagged dependent variable as a regressor which implies correlation between this variable and the error term, so that LSDV estimations are inconsistent. In other words, $l_{i,t-1}$ and $l_{i,t-2}$ are endogenous variable. Moreover, $l_{i,t-1}$ and $l_{i,t-2}$ will be correlated with the unobserved firm fixed effects. In this sense:

$$E[\lambda_i \; l_{i,t-1}] \neq 0 \quad \text{and} \quad E[\lambda_i \; l_{i,t-2}] \neq 0 \quad (4)$$

With the aim of solving these problems, Arellano and Bond (1991) propose to use the GMM estimator (Generalised Method of Moments) which is more efficient. GMM estimation allows to control for the endogeneity and correlated firm specific effects problems. The first step consists in rewriting equation (3) in first-differences. So that, an error term in first differences is generated without being correlated with any level of the lagged variable $l_{i,t-s}$ (s ≥ 2). The first differenced model eliminates the firm specific fixed effects, so they can not be observed directly like in the LSDV estimation. The expression of the model would be:

$$\begin{aligned} l_{i,t} - l_{i,t-1} &= \beta_1(l_{i,t-1} - l_{i,t-2}) + \beta_2(l_{i,t-2} - l_{i,t-3}) + \beta_3(pi_{i,t} - pi_{i,t-1}) + \beta_4(pi_{i,t-1} - pi_{i,t-2}) \\ &+ \beta_5(pi_{i,t-2} - pi_{i,t-3}) + \beta_6(pri_{i,t} - pri_{i,t-1}) + \beta_7(pri_{i,t-1} - pri_{i,t-2}) + \beta_8(pri_{i,t-2} - pri_{i,t-3}) \\ &+ \beta_9(w_{i,t} - w_{i,t-1}) + \beta_{10}(sales_{i,t} - sales_{i,t-1}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}) \qquad (5) \end{aligned}$$

or what is the same:

$$\Delta l_{i,t} = \sum_{j=1}^{2} \beta_j \Delta l_{i,t-j} + \sum_{j=0}^{2} \beta_{3+j} \Delta pi_{i,t-j} + \sum_{j=0}^{2} \beta_{6+j} pri_{i,t-j} + \beta_9 \Delta w_{i,t} + \beta_{10} \Delta sales_{i,t} + \Delta\varepsilon_{i,t} \qquad (6)$$

where $\Delta l_{i,t} = l_{i,t} - l_{i,t-1}$ and $\Delta l_{i,t-j} = l_{i,t-j} - l_{i,t-j-1}$ and in the same way for the rest of the variables.

With the differentiation, for example, $\Delta l_{i,t-1}$ is correlated with the error term $\Delta\varepsilon_{i,t}$ causing a biased estimated parameter. GMM method tries to find variables or instruments which may replace $\Delta l_{i,t-1}$ but without being correlated with $\Delta\varepsilon_{i,t-1}$. For instance, $l_{i,t-2}$ is not correlated with the error term $\Delta\varepsilon_{i,t}$, but it is correlated with the variable it has to replace ($\Delta l_{i,t-1}$), then $l_{i,t-2}$ could be chosen as instrument to estimate equation (6).

Therefore, the lagged levels of the dependent variable are instruments to estimate the parameter attached to the lagged differenced dependent variable, starting from the second lag and going back until the beginning of the sample.

The GMM estimator consistence depends on the validity of two model's assumptions: the error term has not to present second order autocorrelation and instruments have to be valid. Arellano and Bond (1991) propose two tests to contrast it.

The serial correlation test assumes no second order autocorrelation in the model in differences errors. The model could present first order autocorrelation ($\Delta\varepsilon_{i,t}$ is correlated with $\Delta\varepsilon_{i,t-1}$ and with $\Delta\varepsilon_{i,t+1}$), but if it is well specified there will not be second order autocorrelation between the error terms (test p-value > 0.1) This is:

$$Ho: E[\Delta\varepsilon_{i,t}\ \Delta\varepsilon_{i,t-2}] = 0 \tag{7}$$

Sargan test of overidentifying restrictions is used to contrast global validity of instruments in the regression. The test follows a chi-square distribution with (J-K) degrees of freedom, where J is the number of instruments and K is the number of regressors. The null hypothesis is that the chosen instruments are valid. If the model is well specified may not be rejected (test p-value > 0.1).

Nevertheless, when there is a high degree of persistence in the series and the number of observations is short, the GMM difference estimator could be biased. That means that lagged levels of explanatory variables are weak instruments to estimate the parameters of the first-difference variables. In this conditions, Arellano and Bover (1995) and Blundell and Bond (1998) have shown using Monte Carlo studies that GMM system estimation works better. This estimator solves this problem because it serves to estimate a system of equations that include first-differenced equations and the equations in levels. The equations differ in their instruments. In the first-differenced equations, the lagged level values of the explanatory variables are used as instruments (like en the GMM difference estimator). In the levels equations, the instruments are the lagged first-differences. Since the set of instruments used in the GMM difference approach are a strict subset of the instruments used in the GMM system estimation, a specific contrast of the additional instruments is the Sargan/Hansen difference test.

Both the difference GMM and system GMM estimators have one-step and two-step variants. The two-step estimates of the GMM standard errors have been shown to have a severe downward bias. Therefore, to improve the precision of the two-step estimators we have applied the Windmeijer finite-sample correction to these standard errors (Windmeijer, 2005)

5. Main Results

Table 4 shows the results of the model defined in equation 3 using the GMM system estimator. Specifications (1) to (3) differ in the introduction of the innovation variable. In specification (1) we only consider the process innovation. Specification (2) includes only the variable referred to product innovation. And specification (3) considers both types of innovation. All the estimations include dummy variables for industry (NACE 2-digit level) and year. The GMM system estimator will be consistent provided that the Sargan/Hansen test of overidentifying restrictions and the no second order autocorrelation were accepted. In the three specifications the Hansen/Sargan test does not reject our instruments used, and the AR(2) test does not reject the null hypothesis of no second order autocorrelation. Therefore, our model is valid[6]. In addition, we have tested for the validity of the additional instruments in the GMM system estimator compared to the GMM difference estimator with the difference-in-Sargan/Hansen test. The p-value higher than 0.1 indicates the validity of the additional instruments in the GMM system compared to the GMM difference estimation.

The coefficients of the lagged dependent variable are very similar in the three specifications (between 0.056-0.068) and are only positive and significant in the first lag. The impact of this variable is not significant with a lag of two periods. The coefficients of the control variables are very stable in all regressions and show significant effects. The average wage has a significant negative effect on employment, as expected, whereas the proxy of labour productivity has a significant positive effect, although this variable losses significance when the product innovation is included in the second specification. Year and sector dummies are jointly significant.

The innovation variables show a different behaviour according to the type of innovation. We can see that in specification (1) and (3), the coefficients attached to process innovation are positive and significant for the current period and for the first and the second lag. The coefficients are also very stable across the different specifications. In addition we can observe that the effect increases with the number of lags. Therefore, the effect of the process innovation on employment increases across the years. Lachenmaier and Rottmann (2011) also find a positive significant effect of process innovation on employment, but in their study for German firms, the process innovations take al least one year to show their effects and these effects decrease with the number of lags.

Our study supports the hypothesis of the indirect effects of process innovation on employment. The introduction of a process innovation leads to productivity gains,

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[6] In our model we use the first two lags as instruments in the differenced equation. That means, that for the endogenous explanatory variable $l_{i,t}$ in the first- differenced equation we use $l_{i,t-1}$ and $l_{i,t-2}$ as instruments, for the variable $l_{i,t-1}$ we use $l_{i,t-2}$ and $l_{i,t-3}$ and for $l_{i,t-2}$ we use $l_{i,t-3}$ and $l_{i,t-4}$. To test the robustness of our model we also estimate specifications with one to four lags and with all the lags available as instruments. The positive significant effect of process innovation remains and the rest of coefficients hardly change.

and these gains allow the firm to reduce prices with the corresponding positive effect on demand and employment. Harrison et al. (2008) find no evidence for a displacement effect of process innovation in Spanish manufacturing, possibly due to greater pass-through of productivity improvements in lower prices. In this study, product innovation appears to play a larger role in employment growth in Germany than in the other countries, and possibly a smaller role in the UK, while higher levels of firm-level employment growth over this period in Spain are largely explained by faster growth in output of existing products.

As for product innovation, although in both specification (2) and (3) the correlation between employment and product innovation is positive, in the specification (2) only the second lag of product innovation shows a weakly significant effect. In this sense, our results are similar to those ones reached in Lachenmaier and Rottmann (2011). Like these authors point out, this result is surprising because most studies find a positive and significant effect for product innovation on employment(Jaumandreu (2003); Peters (2004);Harrison et al. (2008); Hall et al. (2008); Benavente and Lauterbach (2007)).

In Table 5, we test the robustness of our model including some other control variables which could affect the relation between employment and innovation. In specification (4) we control for the size of the firms to take into account the differences between large and small firms in terms of sales. This variable is not significant, that means that there are not significant differences in the effect of innovation on employment according to the size of the firm. The coefficients are very similar to specification (3), although the first lag of employment and the proxy of productivity decrease their significance.

In specification (5) we still control for the size and we add the R&D intensity. Size now is rather significant. But surprisingly, R&D intensity is significant but it is negatively correlated with the employment. Therefore, we have included a lag of this variable, and in this case, R&D intensity loses some significance but is positively correlated with employment. In this sense, we can conclude that R&D takes some time to show their effect on employment.

Table 4. GMM system estimation results

	(1)	(2)	(3)
Lag log(employment)	0.056** (0.016)	0.068*** (0.005)	0.056** (0.016)
2nd lag log(employment)	0.024 (0.267)	0.025 (0.260)	0.023 (0.282)
Process innovation	0.033*** (0.001)		0.033*** (0.000)
Lag process innovation	0.062*** (0.000)		0.060*** (0.000)
2nd lag process innovation	0.103*** (0.000)		0.099*** (0.000)
Product innovation		0.014 (0.258)	0.004 (0.757)
Lag product innovation		0.021 (0.183)	0.007 (0.649)
2nd lag product innovation		0.045* (0.081)	0.022 (0.377)
Avarage wage	-0.278E-05*** (0.002)	-0.278E-05 *** (0.002)	- 0.278-05*** (0.002)
Sales over employees	0.432E-07** (0.048)	0.434E-07* (0.053)	0.433E-07** (0.048)
Constant	3.636* (0.062)	3.584* (0.064)	3.653* (0.059)
Observations	25,678	25,677	25,677
Number of firms	3,582	3,582	3,582
Wald test chi2 p-value	(0.000)	(0.000)	(0.000)
Wald test Industry dummies p-value	(0.000)	(0.000)	(0.000)
Wald test time dummies p-value	(0.000)	(0.000)	(0.000)
AR1 p-value	(0.041)	(0.040)	(0.041)
AR2 p-value	(0.147)	(0.159)	(0.150)
Sargan/Hansen p-value	(0.390)	(0.364)	(0.368)

Note:*** p<0.01, ** p<0.05, * p<0.1
Windmeijer corrected standard error in bracket.
Additional control variables (omitted in the table): twenty industry dummies and eighteen time (years) dummies.

Finally, we include into the model a variable according to the market dynamism (specification 6). Results show that the fact of operating in expansive markets has a significantly positive effect on employment. Again, we find a significantly positive effect of the process innovation variables on employment.

Table 5. Further GMM system estimation results

	(4)	(5)	(6)
Lag log(employment)	0.044* (0.078)	0.068** (0.044)	0.066* (0.051)
2nd lag log(employment)	0.004 (0.867)	-0.001 (0.975)	0.002 (0.915)
Process innovation	0.031*** (0.002)	0.029*** (0.003)	0.029*** (0.003)
Lag process innovation	0.060*** (0.000)	0.054*** (0.000)	0.053*** (0.000)
2nd lag process innovation	0.100*** (0.000)	0.098*** (0.000)	0.099*** (0.000)
Product innovation	0.004 (0.719)	0.006 (0.625)	0.006 (0.593)
Lag product innovation	0.007 (0.612)	0.01 (0.441)	0.009 (0.508)
2nd lag product innovation	0.022 (0.368)	0.034 (0.14)	0.034 (0.139)
Avarage wage	-0.352E-05*** (0.003)	-0.842E-05* (0.053)	-0.830E-05** (0.048)
Sales over employees	0.705E-07* (0.051)	0.190E-06* (0.072)	0.187E-06* (0.066)
Size	0.170 (0.101)	0.184* (0.064)	0.178* (0.071)
R&D/sales intensity		-0.216E-03*** (0.000)	-0.215E-03*** (0.000)
Lag R&D/intensity		0.004* (0.054)	0.004* (0.085)
Market dynamism			0.043*** (0.000)
Constant	3.970** (0.038)	3.530* (0.092)	3.415 (0.103)
Observations	25,642	25,364	25,351
Number of firms	3,580	3,568	3,568
Wald test chi2 p-value	(0.000)	(0.000)	(0.000)
Wald test Industry dummies p-value	(0.000)	(0.000)	(0.000)
Wald test time dummies p-value	(0.000)	(0.000)	(0.000)
AR1 p-value	(0.022)	(0.025)	(0.023)
AR2 p-value	(0.144)	(0.150)	(0.145)
Sargan/Hansen p-value	(0.450)	(0.710)	(0.751)

Note:*** p<0.01, ** p<0.05, * p<0.1
Windmeijer corrected standard error in brackets.
Additional control variables (omitted in the table): twenty industry dummies and eighteen time (years) dummies.

To sum up, in all specifications the process innovation measures show a positive and significant effect on employment, and this effect appear in the same year, but it increases with the number of lags. On the contrary, the product innovation variables do not have a significant effect on employment, although the correlation is positive but lower than for the process innovations.

6. Conclusions

In this paper we investigate the potential differences in the impact of product and process innovations in terms of employment generation (to find an answer to classical question “Does technology creates or destroys jobs?”). “*Technological progress is not translated into economic benefits and jobs by governments, countries, or sectors, but by innovative firms…The most important finding of recent economic research might be that new evidence from longitudinal microeconomic data reveals that firms that innovate more consistently and rapidly employ more workers*,..”[7]. Since this classical question remains rather unclear in the empirical evidence, we implement dynamic panel techniques which allow us to control for problems of unobserved heterogeneity and endogeneity of the explanatory variables. Furthermore, we use an unbalanced panel data of 3,582 firms covering the period 1990-2008 from Spanish manufacturing instead of CIS data. Finally, we provide an additional analysis for the potential effect of persistence in innovative activities on firm´s growth.

The results confirm the significant and positive effect of process innovation on employment similar to Greenan and Guellec, 2000; Lachenmaier and Rottmann, 2007; Lachenmaier and Rottmann, 2011 that also found a higher positive impact of process than of product innovation. This effect tends to be higher for the first and the second lag of process innovation in comparison to the contemporaneous value. In contrast with some of studies based in CIS data, product innovation does not have effect on employment. Although the relation between both variables is positive, we only find certain degree of significance for the second lag of product innovation, but excluding of the analysis the process innovation. The robustness of our result is confirmed by several additional specifications. Controlling for the size, the R&D intensity and the market dynamism do not alter the effect of process innovation on employment.

Our study supports the hypothesis of the indirect effects of process innovation on employment. However, one of the main contributions of the paper are the effects of persistent innovation on employment. This point of view is particularly important for policy makers . The impact of persistence of product and process innovation for the

[7] OECD (1996), Technology, Productivity and Job Creation, Paris, p.45.

growth of employment has important implications for government policies. The establishment of EC's Lisbon Agenda (2005) which sets an R&D target of 3% of GDP is not enough to achieve employment growth from this spending because we need a more detailed and sophisticated understanding of the conditions under which R&D is most likely to lead to economic growth—and how such conditions differ between industries (e.g. high-tech, medium tech, low tech, manufacturing, services etc.), between periods in the industry life-cycle or in the macroeconomic context, and between different types of firms (e.g. young, old, etc). Studies, such as ours, providing evidence of what types of combinations are necessary to affect employment growth in a high unemployment period, and a major knowledge of how these innovation strategies can have different effects, will allow policy makers to better target innovation-led growth policies. In this sense, two of five targets of which define where the EU should be by 2020 and against which progress can be tracked are that 75 % of the population aged 20-64 should be employed.

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Appendix

Table A.1. Summary of more recent empirical studies on effects of innovation on employment growth.

Study	**Proxy for technology**	**Controls**	**Used Method**	**Data**	**Country or countries**	**Main result**
Greenan and Guellec (2000)	Indicators of intensity of process and product innovations in 1991	Labor costs, capital costs, size, industry	3 GMM-sys(value-added, labor and capital)	Panel of 5,919 firms during the period 1985-1991	France	Product innovation (+) Process innovation(+) (zero at sector level)
García et al. (2004)	dummy for process innovations and product innovation	User cost of capital, Wage, Price int. Consumption, Knowledge capital, size, industry and time dummies (in the labor demand)	4 GMM-sys (production function, labor demand, product demand and wage and margin equations)	Panel of 1,286 firms, period 1990-98	Spain	Process innovation (+) (reduced in long run) Product innovation (+) (persist in the long run).
Jaumandreu (2003)	Sales growth due to new product Dummy for process innovations	Investment growth , Expected employment and industry dummies	OLS and Instrumental Estimations	4,548 firms In one CIS (1998-2000)	Spain	Product innovation (+) Process innovation(-)process innovation is not responsible for employment decreases, while product innovation is at least responsible for the increase in employment due to the net sales increase effect of innovative sales
Peters (2004)	Sales growth due to old/new product Dummy for process innovations	R&D intensity, innovation intensity, i range, market share, continuous R&D, source of innovation (clients, universities), range, impact on market share, impact on improved	OLS and Instrumental Estimations	4,611 firms in one CIS (1998-2000)	Germany	Product innovation (+) Process innovation(-)

		quality, turnover due to market novelties, export intensity and industry dummies				
Harrison et al. (2005, 2008)	Sales growth due to old/new product Dummy for process innovations	increased range, clients as a source of information, continuous R&D engagement, improved quality, market share and innovation/R&D effort	HJMP 2005 specification(OLS and instrumental estimations)	1,653 firms in France, 849 in Germany, 1,839 in Spain and 1,794 in UK) CIS (1998-2000)	France, Germany, Spain and the UK.	Product innovation (+) Process innovation (compensation>displacement weak) (small) inconclusive fragile
Hall et al. (2008)	Sales growth due to new products and Process innovation	R&D intensity , dummies for doing R&D or relevant investments to new product creation, industry and time dummies	HJMP 2005 specification(OLS and instrumental estimations)	4,290, 4618 and 4040 firms in three CIS (1995–2003) (1995-1997 1998-2000 and 2001-2003)	Italy	Product innovation (+) Process innovation (+) (weak but little displacement effect)
Benavente and Lauterbach (2007)	Sales growth due to old/new product Dummy for process innovations	increased range, clients as source of information, permanent R&D engagement, novel inputs utilization as an origin of the innovation idea, investment and economic sector	HJMP 2005 specification(OLS and instrumental estimations)	558 firms one CIS (1998-2001)	Chile	Product innovation (+) Process innovation (+) (weak but little displacement effect
Bogliacino et al. (2011)	R&D expenditures			677 European manufacturing and service firms over the period 1990-2008.	18 European Countries	R&D expenditures (+) in services and high-tech manufacturing, but absent for the more traditional manufacturing
Piva and Vivarelli (2004, 2005)	Innovative investments			575 manufacturing firms Mediocredito Centrale in the period	Italy	Innovativeness (+))

				1992–97,		
Mairesse et al. (XX)	Output growth due to old/new products	R&D expenditures per employee, Long-term Investments per employee, dummies to identify firms without R&D or Investments.		Firms in four major industries: Textile, Wearing Apparel, Transport Equipment and Electronic Equipment (2004-2006)	China	Product innovation (+)
Meriküll (XXX)	Dummy variables for process innovators and product innovators	Real wages, real capital stock and time dummies	OLS and GMM estimation	830 firms Estonian Commercial Register with two (CIS), (1998–2000 and 2002–2004)	Estonia	Product innovation(+) Process innovation(+) at firm and industry levels.
Coad and Rao (2011)	R&D expenditure and patents	lagged growth, lagged size, industry dummies and time dummies	OLS ,FE ,LSDVC, WLS and semi-parametric quantile using a firm- and year-specific 'innovativeness' index	1,920 manufacturing firms belong to 'complex technology' sectors (SIC 35 to SIC 38)NBER patent database +Compustat (1963–1998)	USA	Innovation expenditures (+) Patents (+)
Lachenmaier and Rottmann (2011)	Dummy variables for process innovators and product innovators	Sectoral gross value added, sectoral real hourly wage, industry and time dummies	GMM-dif and GMM-system estimations	1073 manufacturing firms IFO Survey from 1983 to 2003	Germany	Process innovation(+) Product innovation (+)