Innovation Effects on Employment in High-Tech and Low-Tech industries: Evidence from Large International Firms within the Triad

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Innovation Effects on Employment in High-Tech and Low-Tech industries: Evidence from Large International Firms within the Triad

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Abstract

In this paper we investigate the role of financial shocks, such as the economic crisis since 2006, in the reallocation process of employment flows in high-tech and low-tech industries. The contributions of the paper to the literature are threefold. First, a general framework of employment growth is estimated by using a dataset made of 879 large international firms observed for the period 2002-2010 and localized in three economic areas: USA, Japan and Europe. Second, we develop a database merging the firms' data with EPO patents data. In particular, the innovation variable is proxied by the R&D capital stock. Third contribution to the literature is to analyse the extent to which the economic crisis may affect the sensitivity of employment with respect to own innovation but also with respect to outside innovation, the R&D spillovers, in high-tech and low-tech industries. The empirical results suggest some important and significant results. This comparative finding could be the source of relevant industrial policy implications.

Keywords: Regional economics; Innovation; R&D spillovers; employment.

JEL Classification: R1; O31; O33; J20.

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Introduction

It is nowadays to deeply investigate all factors recognised statistically significant to foster private sector job creation and firm growth. Employment growth is a relevant indicator of economic performance. For this reason, identifying and exploiting their main drivers has become the objective of researchers and policy makers.

In this paper we investigate the role of financial shocks, such as the economic crisis since 2006, in the reallocation process of employment flows in high-tech and low-tech industries. The main contribution to the literature is to analyse the extent to which the economic crisis may affect the sensitivity of employment with respect to own innovation but also with respect to outside innovation, the R&D spillovers, in high-tech and low-tech industries. The rational behind is that the recession due to world economic crisis determines job losses in every economy of developed country, but crisis should be identified also as an opportunity event for all firms, which increase innovation to be more competitive on the market. Thus, in this paper, we focus our attention to the reallocation process of job flows between low-tech and high-tech industries, employing an international sample based on three economic areas: USA, Japan and Europe[1] and taking into account also eventual R&D spillovers stemming from innovation activities between technological sectors.

The remainder of the paper is organized as follows. The second section reviews the related literature. Section 3 illustrates the theoretical framework. Section 4 introduces the data and offers descriptive statistics, before Section 5 presents regression results. Finally, a concluding section summarizes the most important findings and provides an outlook on future research questions.

Literature review

The empirical debate concerning innovation-employment link can be distinguished into two perspectives: at firm-level and sector-level evidence.

On the basis of first perspective, Vivarelli (2014) emphasizes the role of R&D and product innovation to support a positive relation, especially when high-technology sectors are prevalent. We may find many studies, which suggest a positive correlation between innovation measures and employment (Hall, 1987; Van Reenen, 1997; Greenhalgh et al., 2001; Yasuda, 2005; Yang and Huang, 2005; Stare and Damijan, 2015) and other works with a less clear result (Brouwer et al., 1993; Klette and Førre, 1998; Piva and Vivarelli, 2005).

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[1] European economic area considers the following countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Spain, Sweden, Switzerland, The Netherlands and the UK.

Stam and Wennberg (2009) find no significant relationship between R&D activities and employment growth, unless the attention is restricted to the 10% fastest-growing firms. Moreover, they find a correlation between R&D and the growth of young high-technology firms, but not with low-tech start-ups' employment growth.

Hölzl (2009) analyses how innovation affects employment growth in 16 economies. He identifies innovation success and R&D intensity as two crucial keys for high-growth SMEs in countries closer to the technological frontier.

Bogliacino et al. (2012) apply R&D-employment empirical analysis on 677 European large publicly traded companies between 1990 and 2008. They conclude that there is not a significant impact in low-tech manufacturing sectors but the effect becomes evident in high-tech manufacturing.

There are authors that use also patent data to detect innovation activities. Indeed, Coad and Rao (2011) combine patent and R&D data to explore the relationship between innovation and employment growth in the United States. They confirm that innovation is correlated with employment growth for fast-growing high-tech firms while it has almost no effect on high-tech firms characterized by a negative employment growth.

Van Roy et al. (2015) apply patent data in a sample of European firms for the period 2003-2012, but they include also information about patent quality (forward citations) to investigate the innovation-employment nexus. They show a positive effect of patenting activities on employment, but the result remains significant only in high-tech manufacturing sectors.

According to Balsmeier and Delanote (2015), also firms' age is found to be important for employment growth due to innovation process. Their study examine the employment growth of young, small innovative firms and contrasts it with the employment growth of established mature innovators in 23 European transition economies, where varying degrees intellectual property protection apply. They conclude that innovative youngsters seem to benefit from strong intellectual property protection, while mature innovators exhibit the highest employment growth rates when protection is rather weak.

As far as the sector-level perspective is concerned, we can identify contributions by Vivarelli et al. (1996), Sirilli and Evangelista (1998), Antonucci and Pianta (2002). In particular, there are studies based on the specificities of different technological regimes and sectoral systems of innovation (Malerba, 2002; Malerba and Orsenigo, 1993).

Mastrostefano and Pianta (2009) consider the impact of innovation on employment at industry level in 10 European countries, developing a set of dynamic models in which employment changes are determined by variations in demand (value-added), in wages, in the diffusion of innovation (proxied by the share of innovative firms) and in the economic impact (in terms of turnover share) of new products. Their results suggest a positive contribution of demand growth, a negative role of wage variations, limited effects of the general diffusion of innovation and a positive role of the market impact of product innovation, but only in high-innovation industries.

Buerger et al. (2012) pays attention to the relation between variations in innovativeness (proxied by patents and R&D) and employment in Germany, between 1999 and 2005. They confirm that the relation tends to be sector-specific. Indeed, there is no significant correlation in the transport equipment industry; there is a weak negative relation in the chemicals industry; finally, a positive and significant correlation is found in the electrics and medical instrument industries.

As we may observe from the previous empirical evidence, authors usually consider firms of a particular international economic area, such as United States or Europe. In this paper, we develop an empirical analysis taking into account large firms of three economic areas: USA, Japan and Europe (as in Agovino et al., 2016). Moreover, there are other two contributions. Firstly, we merge our firms' data with EPO patent data to construct R&D spillovers. Hence, we consider both own innovation and external innovation in the empirical framework. Secondly, we explore the extent to which the innovation impact on employment is sensitive to financial shocks, such as economic crisis, since 2006. In manufacturing sectoral field, Lucchese and Pianta (2012) already explore the sensitivity of the impact of innovation on employment to economic booms and recessions. In particular, they exhibit that in upswings job creation is enhanced by product innovation and exports, while during downswings new products and exports become negligible and job displacements are correlated to process innovation and wage dynamics, related to corporate restructuring.

Theoretical framework

In this section, succeeding the model by Garcia, Jaumandreu and Rodriguez (2004), and Aldieri, Garofalo and Vinci (2015) we present a basic background, and the following interactions among sectors on which our empirical model is built. In what follows we assume a two-sector economy with a high technology sector and a low technology one. In each sector, firms are assumed with a technology characterized by constant returns to scale in the traditional input, they minimize costs and invest in R&D for process and product innovation. At the beginning of the next period, innovations are included in production and each firm, keeping in mind new technologies and the expected demand, settles prices and employment.

In each sector innovation effects, on both the technology and the demand function, are assumed to be exemplified by the impact of the accumulated knowledge capital denoted respectively by K^l for the low technology sector, and K^h for the high technology one. Further, defining: $c^l(c^h), w^l(w^h)$, the marginal cost, the vector inputs prices, we can state that $c^l = c^l(w^l, K^l)\left(c^h = c^h(w^h, K^h)\right)$.

Moreover denoting with $p^l(p^h)$ the output prices, $Y^l(Y^h)$ the output, $L^l(L^h)$ employment, $\mu^l(\mu^h)$ the entrepreneurs mark-up on the marginal cost, $d^{e,l}(d^{e,h})$ an index of the market dynamics, and finally with $K_R^l(K_R^h), p_R^l(p_R^h)$, respectively the rival firms' accumulated knowledge capital and output prices, we can state:

$$p^l = (1+\mu^l)c^l(w^l, K^l) \quad (1)$$
$$Y^l = D\left(d^{e,l}, p^l, p_R^l, K^l, K_R^l, K^h, K_R^h\right) \quad (2)$$
$$K_R^l = g\left(K^l, K^h, K_R^h\right) \quad (3)$$
$$p_R^l = \left(1+\mu_R^l\right)c_R^l\left(w_R^l, K_R^l\right) \quad (4)$$
$$L^l = c_L^l(w^l, K^l)Y^l \quad (5)$$

for the low technology sector, and:

$$p^h = (1+\mu^h)c^h(w^h, K^h) \quad (6)$$
$$Y^h = D\left(d^{e,h}, p^h, p_R^h, K^l, K_R^l, K^h, K_R^h\right) \quad (7)$$
$$K_R^h = \tilde{g}\left(K^l, K^h, K_R^h\right) \quad (8)$$
$$p_R^h = \left(1+\mu_R^h\right)c_R^h\left(w_R^h, K_R^h\right) \quad (9)$$
$$L^h = c_L^h(w^h, K^h)Y^h \quad (10)$$

for the high technology one. In eqs. (5) and (10) c_L^l and c_L^h catch the marginal cost derivative with respect to employment[2] (*the Shepard's lemma*) while c_r^l, w_R^l, μ_R^l $\left(c_r^h, w_R^h, \mu_R^h\right)$ stand respectively for the marginal cost, vector inputs prices and mark-up for the rival firms[3] in the low (high) technology sector. From the above we may easily derive:

$$L^l = c_L^l(w^l, K^l)D[d^{e,l}, (1+\mu^l)c^l(w^l, K^l), (1+\mu_R^l)c_R^l(w_R^l, K_R^l), K^l, g(K^l, K^h, K_R^h), K^h, \tilde{g}(K^l, K^h, K_R^l)] \quad (11).$$
$$L^h = c_L^h(w^h, K^h)D[d^{e,h}, (1+\mu^h)c^h(w^h, K^h), (1+\mu_R^h)c_R^h(w_R^h, K_R^h), K^h, \tilde{g}(K^l, K^h, K_R^l), K^l, g(K^l, K^h, K_R^h)] \quad (12).$$

The short run impact of innovation on the employment levels will be:

$$\frac{\partial L^l}{\partial K^l} = \frac{\partial c_L^l}{\partial K^l}Y^l + c_L^l\left\{\frac{\partial Y^l}{\partial K^l} + \frac{\partial Y^l}{\partial p^l}\frac{\partial p^l}{\partial K^l} + \frac{\partial Y^l}{\partial p_R^l}\frac{\partial p_R^l}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^l} + \frac{\partial Y^l}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^l} + \frac{\partial Y^l}{\partial K^h}\frac{\partial K^h}{\partial K^l} + \frac{\partial Y^l}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^l}\right\} \quad (13)$$
$$\frac{\partial L^h}{\partial K^h} = \frac{\partial c_L^h}{\partial K^h}Y^h + c_L^h\left\{\frac{\partial Y^h}{\partial K^h} + \frac{\partial Y^h}{\partial p^h}\frac{\partial p^h}{\partial K^h} + \frac{\partial Y^h}{\partial p_R^h}\frac{\partial p_R^h}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^h} + \frac{\partial Y^h}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^h} + \frac{\partial Y^h}{\partial K^l}\frac{\partial K^l}{\partial K^h} + \frac{\partial Y^h}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^h}\right\} (14).$$

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2 (*the Shepard's lemma)*

3 This model is similar to from the *Garcia, Jaumandreu* and *Rodriguez* one exception made for the introduction of eqs. (3) and (4). In any case we refer to them for further clarifications and details.

From inspection of the right side of the above equations we may observe as the first term captures the displacement effect, the second captures some compensation effects: the effect on demand of product innovation; the effect on demand through the drop of the cost reduction due to price; the effect on demand via the diminution of the rival firms' price for the innovation influence of its rivals; the effect on the demand via the innovations of its rivals, and finally the effects on demand due innovations from the other sector.

Furthermore, assuming a wage bargaining process between firms and unions, taking into account that, at the beginning of the innovations' attainment, changes in prices dynamics (variations in μ^h, μ^l and in μ_R^h, μ_R^l) in line to the new competitive environment, if we denote with z^h, z^l and z_R^h, z_R^h other potential sources of wages and mark-ups' changes, the may introduce the following:

$$w^l = w^l(z^l, K^l) \quad (15)$$

$$w_R^l = w_R^l(z_R^l, K_R^l) \quad (16)$$

$$\mu^l = \mu^l(z^l, K^l) \quad (17)$$

$$\mu_R^l = \mu_R^l(z_R^l, K_R^l) \quad (18)$$

$$w^h = w^h(z^h, K^h) \quad (19)$$

$$w_R^h = w_R^h(z_R^h, K_R^h) \quad (20)$$

$$\mu^h = \mu^h(z^h, K^h) \quad (21)$$

$$\mu_R^h = \mu_R^h(z_R^h, K_R^h) \quad (22)$$

As a consequence the short-run impacts of innovation on the employment levels will change into:

$$\frac{\partial L^l}{\partial K^l} = \left[\frac{\partial c_L^l}{\partial K^l} + \frac{\partial c_L^l}{\partial w^l}\frac{\partial w^l}{\partial K^l}\right] Y^l + c_L^l \left\{\frac{\partial Y^l}{\partial K^l} + \frac{\partial Y^l}{\partial p^l}\left[\frac{\partial p^l}{\partial K^l} c^l + (1+\mu^l)\left[\frac{\partial c^l}{\partial w^l}\frac{\partial w^l}{\partial K^l} + \frac{\partial c^l}{\partial K^l}\right]\right] + \frac{\partial Y^l}{\partial p_R^l}\left[\frac{\partial p_R^l}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^l} c_R^l + (1+\mu_R^l)\left(\frac{\partial c_R^l}{\partial w_R^l}\frac{\partial w_R^l}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^l} + \frac{\partial c_R^l}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^l}\right)\right] + \frac{\partial Y^l}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^l} + \frac{\partial Y^l}{\partial K^h}\frac{\partial K^h}{\partial K^l} + \frac{\partial Y^l}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^l}\right\} \quad (23)$$

$$\frac{\partial L^h}{\partial K^h} = \left[\frac{\partial c_L^h}{\partial K^h} + \frac{\partial c_L^h}{\partial w^h}\frac{\partial w^h}{\partial K^h}\right] Y^h + c_L^h \left\{\frac{\partial Y^h}{\partial K^h} + \frac{\partial Y^h}{\partial p^h}\left[\frac{\partial p^h}{\partial K^h} c^h + (1+\mu^h)\left[\frac{\partial c^h}{\partial w^h}\frac{\partial w^h}{\partial K^h} + \frac{\partial c^h}{\partial K^h}\right]\right] + \frac{\partial Y^h}{\partial p_R^h}\left[\frac{\partial p_R^h}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^h} c_R^h + (1+\mu_R^h)\left(\frac{\partial c_R^h}{\partial w_R^h}\frac{\partial w_R^h}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^h} + \frac{\partial c_R^h}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^h}\right)\right] + \frac{\partial Y^h}{\partial K_R^h}\frac{\partial K_R^h}{\partial K^h} + \frac{\partial Y^h}{\partial K^l}\frac{\partial K^l}{\partial K^h} + \frac{\partial Y^h}{\partial K_R^l}\frac{\partial K_R^l}{\partial K^h}\right\} \quad (24)$$

from inspection of which we detect as introducing eqs.(15-22) modify both the displacement and the compensation effects.

In the following section, a general framework of employment growth is estimated to investigate the innovation effects, before and after the beginning of economic world crisis.

Data and Empirical approach

As in Agovino et al. (2016), the information on company profiles and financial statements stems from all EU R&D investment scoreboard editions issued every year until 2011 by the JRC-IPTS (scoreboards).

For each firm, information is available for net sales (S), the number of employees (L), annual R&D expenditures (RD) and the main industry sectors according to the Industrial Classification Benchmark (ICB) at the two-digit level. Moreover, we use the OECD's REGPAT database from January 2012[4,5] to compute the total stock of knowledge spillovers. This database covers firms' patent applications to the European Patent Office (EPO), including patents published up to December 2011. The dataset covers regional information for most OECD and EU27 countries, plus BRICS countries. The matching procedure is the same as in Agovino et al. (2016). The financial variables are transformed into constant prices by using national GDP price deflators with 2007 as the reference year[6]. The R&D capital stock (K) is constructed by using a perpetual inventory method (Griliches, 1979), considering a depreciation rate of 0.15, which is usually assumed in the literature. The growth rate used for the initial values in this study is the sample average growth rates of R&D expenditures in each two-digit ICB industry.

Also the cleaning procedure of data is the same as in Agovino et al. (2016). Once the firms with missing values for some variables in our sample have been removed, we obtain an unbalanced panel of 879 firms. In this paper, our aim is to understand whether a financial shock, such as the economic crisis since 2006, produces technological unemployment or a reallocation process of employment flows between industrial sectors. Table 1 shows descriptive statistics for the variables used in the regression by geographical area.

[4] See Maraut S., H. Dernis, C. Webb, V. Spieazia and D. Guellec (2008) for the methodology used for the construction of REGPAT.

[5] Please contact Helene.DERNIS@oecd.org to download the REGPAT database.

[6] Eurostat GDP deflators.

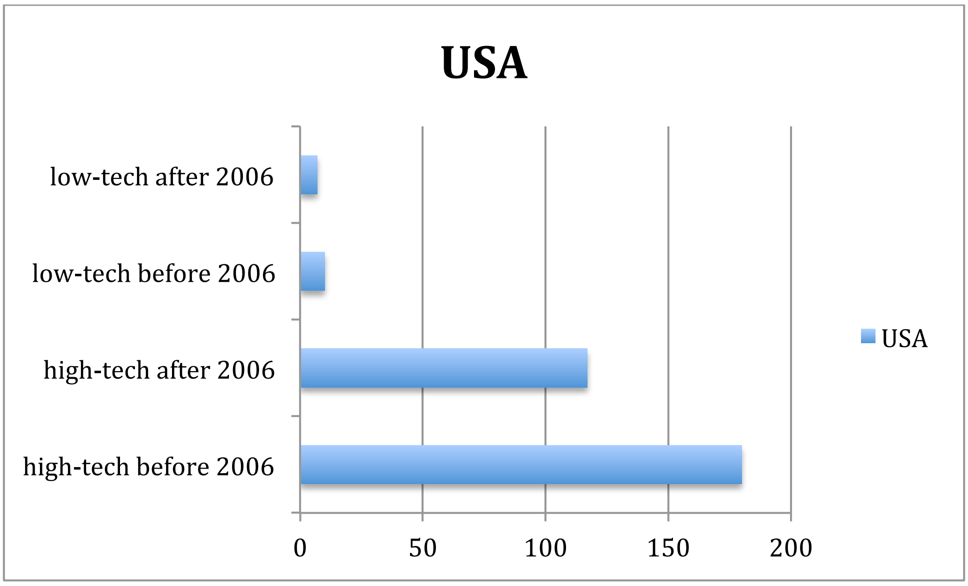
Table 1. Descriptive statistics of main variables by geographical area

Country	LnL*	LnK	LnLS	LnES
Europe				
	9.58 (1.707)	6.44 (1.762)	10.89 (0.469)	12.35 (0.582)
Japan				
	9.57 (1.256)	6.46 (1.218)	11.00 (1.367)	12.72 (0.424)
USA				
	9.28 (1.648)	6.81 (1.357)	11.49 (1.283)	12.46 (0.453)

*L=employment; all variables are expressed in logs; Standard errors are in brackets.

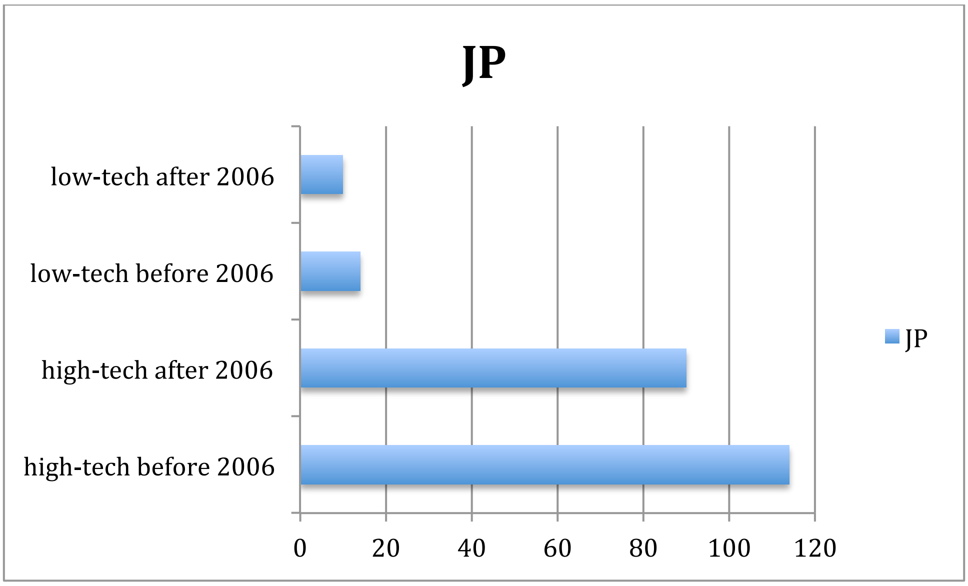
In graphs 1-3 we indicate the number of firms by country and by high-tech/low-tech dichotomy[7] before and after the beginning of economic crisis.

Graph 1.

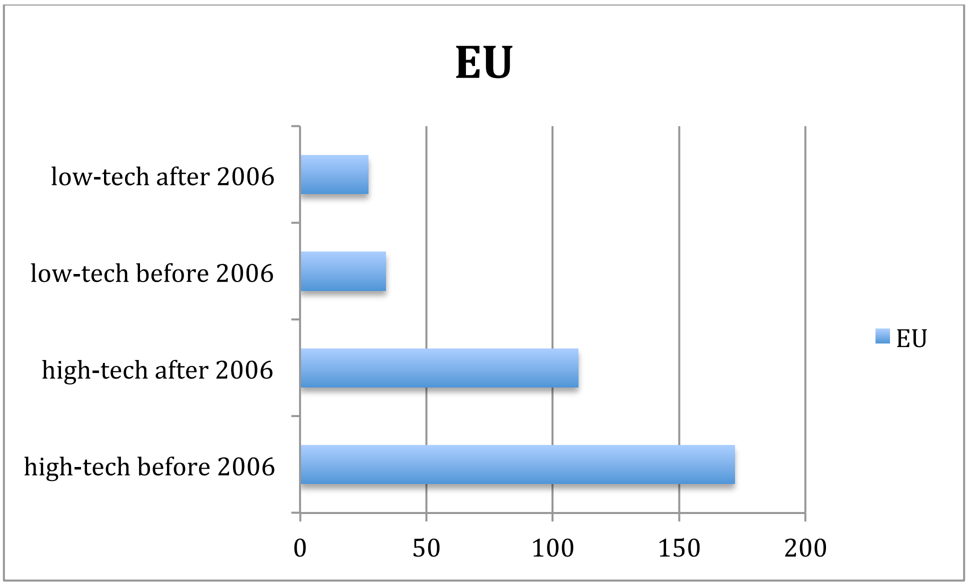


[7] Following the 2015 EU R&D Scoreboard report (Hernandez et al., 2015), we define high-tech firms those belonged to the following sectors: Pharmaceuticals & Biotechnology; Automobiles & Parts; Technology Hardware & Equipment; Software & Computer services with a R&D intensity (R&D/Sales) above 5% and, then, low-tech firms those belonged to other sectors with a R&D intensity below 5%.

Graph 2.



Graph 3.



As we may observe from the previous plots, the beginning of the economic crisis in 2006 determines a reduction of the firms, independently of technology sector. Thus, we expect that there has been also a destruction process of employment. Our research question is whether there is also an employment creation process for surviving firms and whether the distinction between low tech and high tech sectors is relevant in that process.

Following the approach in Stare and Damijan (2015), we explore the effects of innovation using a general framework concerning both for the impact of firm own innovation and innovation based on the knowledge spillovers from other firms. We implement the following model:

$$\Delta l_{ijt} = \alpha + \beta X_{ijt-h} + \gamma Z_{mt-h} + \delta V_{ijt-h} + \phi T + \theta I + u_{it} + \varepsilon_{ijt} \qquad (25)$$

where Δl_{ijt} represents firm's *i* employment growth belonged to sector *j* at time *t*.

The explanatory variables are distinguished into three groups.

- X_{ijt-h} denotes own innovation, proxied by R&D capital stock (K), lagged *h* years to account for long run effects that innovation can exert on employment;

- Z_{mt-h} denotes knowledge spillovers from different sectors *m* to the industry *j*.

In particular, we follow the methodology developed by Jaffe (1986) to compute technological proximity. This procedure is based on the construction of a technological vector for each firm relative the distribution of its patents across technology classes[8] (as in Aldieri and Cincera, 2009). Hence, we use this measure to weight the R&D capital stock between the firms and to construct the total stock of R&D spillovers (TS), which is the weighted sum of R&D capital stock of other firms. In particular, we decompose total stock of spillovers into two components: Local spillovers (LS) relative to externalities derived from firms of the same sector ($j = m$) and External spillovers (ES) relative to those stemming from the firms of different sector ($j \neq m$).

- V_{ijt-h} contains firm-level control variables such as firm size, measured by the net sales, and productivity, measured by total factor productivity (TFP), which is computed from Olley and Pakes (1996) methodology.

Also spillovers and control variables are lagged *h* years to account for long run effects.

Moreover, we include year and industry fixed effects. Finally, also firm fixed effects u_{it} and i. i. d. error terms ε_{ijt} are added in the model.

All variables were considered in logarithmic terms.

The model (25) is estimated using ordinary least squares, because our dependent variable is specified in the first difference (growth rate), which means that the firm specific fixed effects are differenced out. However, we control for the remaining error due to firm fixed effects by adding a set of firm specific control variables, which are firm size and productivity.

[8]118 technological classes make up the International Patent Classification (IPC) at the two-digit level. In order to ease the calculations, these 118 classes are grouped into broader classes. On this basis, a contingency table , i.e. a table reporting the distribution of firms' patents across the 50 IPC classes, was constructed, as in Cincera (1998). This table was used to compute the index of technological closeness and then the stocks of spillovers.

Empirical results

Tables 2-5 present results for the effects of firms' own innovation and knowledge spillovers on overall employment. In particular, Table 2 and 3 show the findings for low-tech firms, while Table 4 and 5 refer to high-tech ones.

Table 2. Employment estimates in low-tech industries *before 2006*

	EU firms: 231 obs.		JP firms: 279 obs.		Sample: US firms: 666 obs.	
	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]
LnK	0.03**	(0.016)	-0.03***	(0.011)	-0.01	(0.009)
LnLS	0.01	(0.018)	0.05	(0.030)	0.01	(0.014)
LnES	-0.08***	(0.028)	0.01	(0.027)	-0.04**	(0.021)
LnS	0.01	(0.027)	0.01	(0.015)	0.01	(0.010)
LnTFP	-0.96***	(0.404)	0.46**	(0.218)	-0.42***	(0.180)
R^2	0.21		0.12		0.10	

a: ***, ** Coefficient significant at 5%, 10%. Industry and time dummies are included.

Table 3. Employment estimates in low-tech industries *after 2006*

	EU firms: 427 obs.		JP firms: 308 obs.		Sample: US firms: 442 obs.	
	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]
LnK	-0.01	(0.009)	-0.01	(0.010)	-0.01	(0.011)
LnLS	-0.02	(0.012)	-0.03	(0.020)	0.01	(0.017)
LnES	0.02**	(0.012)	0.03	(0.023)	-0.01	(0.023)
LnS	0.03***	(0.010)	0.01	(0.011)	0.03***	(0.012)
LnTFP	-0.62***	(0.256)	0.08	(0.141)	-0.56***	(0.233)
R^2	0.16		0.07		0.19	

a: ***, ** Coefficient significant at 5%, 10%. Industry and time dummies are included.

Table 4. Employment estimates in high-tech industries *before 2006*

	EU firms: 429 obs.		JP firms: 167 obs.		Sample: US firms: 506 obs.	
	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]
LnK	-0.04***	(0.012)	-0.02***	(0.010)	-0.03***	(0.011)
LnLS	0.02	(0.015)	0.04	(0.044)	-0.01	(0.015)
LnES	-0.01	(0.015)	0.01	(0.036)	-0.05**	(0.028)
LnS	0.08***	(0.018)	0.01	(0.010)	0.02**	(0.012)
LnTFP	-0.95***	(0.245)	0.38**	(0.221)	-0.30	(0.202)
R^2	0.17		0.11		0.09	

a: ***, ** Coefficient significant at 5%, 10%. Industry and time dummies are included.

Table 5. Employment estimates in high-tech industries *after 2006*

	EU firms: 268 obs.		JP firms: 204 obs.		Sample: US firms: 322 obs.	
	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]
LnK	-0.02***	(0.009)	0.01	(0.011)	-0.05***	(0.015)
LnLS	0.01	(0.015)	-0.04	(0.025)	0.03**	(0.020)
LnES	0.03**	(0.016)	0.04**	(0.024)	-0.02	(0.028)
LnS	0.04***	(0.012)	0.01	(0.014)	0.06***	(0.015)
LnTFP	-0.77***	(0.313)	0.06	(0.167)	-0.48**	(0.252)
R^2	0.24		0.19		0.20	

a: ***, **, Coefficient significant at 5%, 10%. Industry and time dummies are included.

Comparing the results before 2006 and after 2006, we can extrapolate the following considerations. The own innovation effect is always negative, exception made for European low-tech firms before 2006 where a positive correlation is evidenced. The negative impact of own innovation on employment seems to indicate a prevalent destruction rate of innovation process. The creation rate is not important enough or there is a hard reallocation of employment flows between the technology sectors. This aspect of reallocation should be further investigated in the further research taking into account also the human capital level of workforce whose information is not existent in our sample.

As far as the knowledge spillover effects are concerned, we observe that their impact on employment is negative before the beginning of crisis, while it becomes positive where it is significant after 2006. In particular, these results refer to jacobian diversification externalities or external spillovers (ES), stemming from different technology sectors. The unique significant and positive result for marshallian specialization externalities or local spillovers (LS), deriving from the same technology sector, is found for American high-tech firms after 2006. Hence, economic crisis might be viewed as an opportunity event for all firms to improve own competitiveness by investing more in innovation. Our findings reveal that in this way a new stock of external knowledge is developed and all workers may benefit from it.

Policy implications and conclusions

Investing more in innovation to get market success and to create new employment opportunities is becoming a strategic objective for most industrial countries, especially after the economic world crisis since 2006.

The aim of our paper is to investigate the role of the economic crisis in the reallocation process of employment flows in high-tech and low-tech industries. The contributions of the paper to the literature are threefold. First, a general framework of employment growth is estimated by using a dataset made of 879 large international firms observed for the period 2002-2010 and localized in three economic areas: USA, Japan and Europe. Second, we develop a database merging the firms' data with EPO patents data. In particular, the innovation variable is proxied by the R&D capital stock. Third contribution to the literature is to analyse the extent to which the economic crisis may affect the sensitivity of employment with respect to own innovation but also with respect to outside innovation, the R&D spillovers, in high-tech and low-tech industries.

The own innovation effect is always negative. This finding could seem to indicate a prevalent destruction rate of innovation process.

As far as the knowledge spillover effects are concerned, we observe that jacobian diversification externalities or external spillovers (ES) affect negatively employment before the beginning of crisis, and positively after 2006. The unique significant and positive result for marshallian specialization externalities or local spillovers (LS) is found for American high-tech firms after 2006. Hence, economic crisis might be viewed as an opportunity event for all firms to improve own competitiveness by investing more in innovation. Our findings reveal that in this way a new stock of external knowledge is developed and all workers may benefit from it.

The results relative to the correlation between innovation and employment are important from the perspective of public policy. In particular, the innovation policy should more directly pursue the employment target, besides productivity.

However, a word of caution is necessary. In order to handle deeply the reallocation of employment flows between the technology sectors, it should be important to control for also the human capital level of workforce whose information is not existent in our sample. Moreover, the methodology adopted to construct the knowledge spillovers could be viewed as a way to evidence only the potential externalities. In order to test for the robustness of our results, we could compare them to those based on other strategies, such as mobility features in the innovation process (Aldieri and Vinci, 2016).

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