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16 October 2015

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Abstract
In this paper we analyze the relationship between R&D activity, spillovers and employment at the firm level. A reduced form labour demand equation is estimated. R&D expenditures can account for both product and process innovation. The analysis is based upon a new dataset composed of 879 worldwide R&D-intensive manufacturing firms whose information has been collected for the period 2002-2010. We use data from all EU R&D investment scoreboards editions issued every year until 2011 by the JRC-IPTS (scoreboards). The main contribution to the existing literature is to investigate also the impact of outside R&D activity on own employment level. In particular, the paper investigates the role of R&D spillovers within the pillars of the Triad: United States, Japan and European economic area, but it goes beyond the previous studies by considering more opportune spillover components. Indeed, the potential stock of spillovers is dissociated into four components: the national stock, the international stock, the intra-industry stock and finally the inter-industry one. In this way, we will be able to appreciate to what extent geographical and cultural contiguity matters, by using an updated sample relative to large worldwide firms. The empirical results suggest a significant impact of R&D spillover effects on firms' employment but the results are quite differentiated according to the spillover stock type and this may represent a relevant source of policy implications.

Keywords: Panel Data Models, R&D Spillovers, Employment

JEL codes: O33, J20

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1. Introduction

Starting from theoretical models in Harrison, Jaumandreu, Mairesse, Peters (2008), Peters (2005), Garcia, Jaumandreu, Rodriguez (2004), Hall, Lotti, Mairesse (2008), we identify two main effects of innovation process: the *displacement effect*, which reduces the number of employees to obtain a given amount of output and the *compensation effect*, for which the number of employees goes up because of higher efficiency of productive process, lower marginal costs transferred into lower prices lead to a higher market demand of product. The final effect of innovation on occupation depends also on other characteristics: type of innovation (process or product), market power of firms, wage bargaining, elasticity of market demand of product with respect to its price. Much theoretical and empirical work has been realized to analyze the effects of innovation on employment at both the industry and firm level. Literature analyzing the effect of innovation on employment has stressed both positive and negative relationship between them.

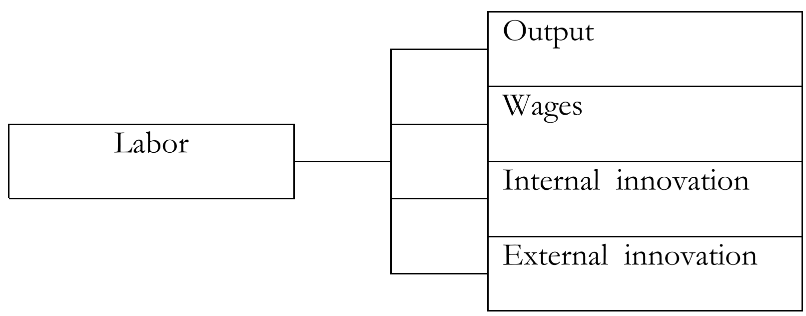
Empirical analyses based on these different results are identified at firm, industry and macro level (Chennells and Van Reenen, 2002).

Many authors discuss the job creating effects of innovation. Freeman (1990) investigates how full employment can be restored alongside the introduction of innovations. Spiezia and Vivarelli (2000) provide a theoretical overview, while Simonetti, Taylor and Vivarelli (2000) provide an empirical test of some of the most interesting aspects of innovation-employment relationship.

Many single country studies look at the different impact of innovation on employment in the developed countries (Bogliacino et al., 2012). Zimmerman (1995) and Brouwer et al. (1993) estimate the negative effects of innovation on employment growth rate. Blanchflower and Burgess (1998) find a positive relation between innovation and employment growth. Other single country studies uses Spanish data (Jaumandreu 2003), German data (Peters, 2004 Zimmerman 1995), US data (Askenazy 2001) French data (Greenan and Guellec 2000). Other comparative studies evidence positive effects of innovation on employment growth in France, Germany, Spain and the UK and many others developed countries (Harrison et al., 2005; Smolny, 1998; Lachenmaier and Rottmann, 2007; Reenen, 1997; Piva and Vivarelli, 2004, 2005; Piva and Vivarelli, 2004, 2005).

Despite of studies on innovation have reported various rates of average employment creation, some key aspects appear to emerge (Westhead and Cowling, 1995; Tether and Massini, 1998). In most of cases innovative firms are likely to create employment. The average rate of employment creation within an innovative firm tends to be influenced by several factors. The main factors that affect employment are firms' output, labor wages, firms' innovation, and outside innovation (Storey and Tether, 1998a). Summarizing these factors in the following framework our study evidences the role of R&D spillovers within the pillars of the Triad: United States, Japan and European economic area.

Figure 1 Factors affecting firms' labor demand



The paper is structured as follows: Section 2 presents the theoretical framework. In Section 3 we describe the database. The results are presented in Section 4. Section 5 discusses policy implications and suggests ideas for further research.

2. Theoretical Framework

In this section, in order to better expound a theoretic basic background, and the following interactions on which our empirical model is built, succeeding the model by Garcia, Jaumandreu and Rodriguez (2004), we assume that a firm minimizes costs with a technology characterized by constant returns to scale in the traditional input, which competes in a differentiated product market. The firm currently invests in R & D for process and product innovation. The innovations, once made, are included in production at the beginning of the next period, when the firm adjusts the product price, employment, taking into account the new technology and the expected demand. We assume that the innovation effects on both the technology and the demand function may be exemplified by the impact of the accumulated Knowledge capital denoted by K. If we define respectively with: $c, w,$ the marginal cost, the vector inputs prices, we can state that $c = c(w, K)$. Furthermore denoting with p the output price, Y the output, L the employment level, μ the entrepreneur mark-up on the marginal cost, d^e an index of the market dynamics, and finally with $K_R, p_R,$ respectively the rival firms' accumulated Knowledge capital and output prices, we can state:

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

where c_L captures the derivative of the marginal cost with respect to labor input (*the Shepard's lemma*) and c_R, w_R, μ_R denote marginal cost, vector inputs prices and mark-up for the rival firms[1]. After simple substitution eq. (4) may be rewritten as follows:

$$L = c_L(w,K)D\left[d^e, (1+\mu)c(w,K), (1+\mu_R)c_R\left(w_R, g(K)\right), K, g(K)\right] \quad (6).$$

As a consequence the short run impact of innovation on the employment level may be given by the following:

$$\frac{\partial L}{\partial K} = \frac{\partial c_L}{\partial K}Y + c_L\left\{\frac{\partial Y}{\partial K} + \frac{\partial Y}{\partial p}\frac{\partial p}{\partial K} + \frac{\partial Y}{\partial p_R}\frac{\partial p_R}{\partial K_R}\frac{\partial K_R}{\partial K} + \frac{\partial Y}{\partial K_R}\frac{\partial K_R}{\partial K}\right\} \quad (7).$$

The first term on the right side of this expression (eq.(7)) is the displacement effect, the second one is the sum of more compensation effects: the first is the effect on demand of product innovation; the second is the effect on demand via the drop of the cost reduction due to price; the third is the effect on demand through the reduction of the price of rival firms via the effect on innovation of its rivals; finally, the fourth captures the effect on demand via the innovations of its rivals.

Moreover if we assume that, at the beginning of the innovations' achievement, each firm has to bargain wages w with unions, and take into account changes in prices dynamics (variations in μ and in μ_R) according to the new competitive environment due to innovation, by denoting with z and z_R other possible causes of changes on wages and mark-ups we can add the following equations:

$$w = w(z,K) \quad (8)$$
$$w_R = w_R(z_R, K_R) \quad (9)$$
$$\mu = \mu(z,K) \quad (10)$$
$$\mu_R = \mu_R(z_R, K_R) \quad (11).$$

[1] 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.

As a consequence eq.(6) may be rewritten as follows:

$$L = c_L(w(z,K),K)D\left[d^e,(1+\mu(z,K))c(w(z,K),K),\left(1+\mu_R(z_R,g(K))\right)c_R\left(w_R(z_R,g(K)),g(K)\right),K,g(K)\right] \quad (12).$$

The short-run impact of innovation on the employment level will be converted in the following condition:

$$\frac{\partial L}{\partial K} = \left[\frac{\partial c_L}{\partial K} + \frac{\partial c_L}{\partial w}\frac{\partial w}{\partial K}\right]Y + c_L \left\{\frac{\partial Y}{\partial K} + \frac{\partial Y}{\partial p}\left\{\frac{\partial \mu}{\partial K}c + (1+\mu)\left[\frac{\partial c}{\partial w}\frac{\partial w}{\partial K} + \frac{\partial c}{\partial K}\right]\right\} + \frac{\partial Y}{\partial p_R}\left[c_R\left\{\frac{\partial \mu_R}{\partial K_R}\frac{\partial K_R}{\partial K}\right\} + (1+\mu_R)\left\{\frac{\partial c_R}{\partial w_R}\frac{\partial w_R}{\partial K_R}\frac{\partial K_R}{\partial K} + \frac{\partial c_R}{\partial K_R}\frac{\partial K_R}{\partial K}\right\}\right] + \frac{\partial Y}{\partial K_R}\frac{\partial K_R}{\partial K}\right\} \quad (13).$$

From inspection of eq. (13) we may observe as the addition of the four conditions (eqs. 8-11) may alter both the displacement and the compensation effects.
In the following section, we estimate a reduced labor demand equation to capture the final effect derived from the realization of both displacement effect and compensation one. In this case, we focus our attention about R&D spillovers impact on the labor market structure of firms.

3. Data and Model

The dataset is constructed with the view of setting up a representative sample of the largest firms at the international level that reported R&D expenditures. The information on company profiles and financial statements comes from all EU R&D investment scoreboards editions issued every year until 2011 by the JRC-IPTS (scoreboards). R&D data from the scoreboards represent all R&D financed by the companies, regardless of the geographical localization of R&D activities. Scoreboard data are collected from audited financial accounts and reports[2]. Combining the most recent scoreboard to avoid multiple counting of the same observation, we obtain an unbalanced panel of 22697observations for 3430 firms, for the period 2000-2010.
For each firm, information is available for net sales (S), the number of employees (L), the annual capital expenditures (C), annual R&D expenditures (RD), annual operating surplus (OP) and main industry sectors according to the Industrial Classification Benchmark (ICB) at the two digits level. OECD, REGPAT database, January 2012[3,4] is the second source of information used in this study. 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 consists of two steps. In a first step, patents are assigned to firms on the basis of their generic name; in a second one, this procedure is repeated for each firm of the sample. For about 22% of the sample, there is only one first name in the retrieved documents. For the rest, firm names that could be identified without any doubts as subsidiaries are matched with generic names. Each monetary observation is converted into constant currency (in EUR) and prices[5]. It should be noted that data in the R&D scoreboards are already expressed in Euros and that a single scoreboard uses a fixed exchange rate for each currency to convert data into Euros for

[2] See Moncada Paternò Castello et al. (2009) for more details.
[3] See Maraut S., H. Dernis, C. Webb, V. Spieazia and D. Guellec (2008) for the methodology used for the construction of REGPAT.
[4] Please contact Helene.DERNIS@oecd.org to download REGPAT database.
[5] Reference year is 2007. Sources for exchange rates and deflators are EUROSTAT.

every periods that it covers. Thus, first we convert the data into original currencies by using the exchange rates specific to each scoreboard. Second, data in original currencies are converted into Euros using a fixed exchange rate[6]. Transforming data into constant prices are performed by using national GDP price deflators with 2007 as the reference year[7]. The R&D capital stocks (K) is constructed by using a perpetual inventory method (Griliches, 1979), by considering a depreciation rate of 0.15, which is usually assumed in the literature. The growth rate that is used for the initial values in this study is the sample average growth rates of R&D expenditures in each two-digit Industry Classification Benchmark (ICB) industry.

Once the firms with missing values for some variable of our sample are removed, we get 909 firms over the period 2002-2010. Furthermore, in order to trim the dataset from outliers, the following procedure is implemented. All observations for which the R&D intensity (defined as the R&D investments divided by the firm's net sales) is below 0.1% or above 100% are deleted. This removes 5 firms for the first threshold (mainly firms from the retail and travel and leisure industry sectors) and 25 firms for the second criteria (firms mainly in the pharmaceuticals sector[8]). This leads to an unbalanced panel of 879 firms. Appendix A gives a view of the geographical and sectorial composition of the sample.

In this paper, we follow the methodology developed by Jaffe (1986) to compute the technological proximity. This procedure rests in the construction of a technological vector for each firm based on the distribution of its patents across technology classes[9]. Hence, we use this measure to weight the R&D capital stock between the firms and to construct the R&D spillovers: National stock of spillovers (NS), International stock of spillovers (IS), Intra-industry stock of spillovers (IntraS) and Inter-industry stock of spillovers (InterS).

Since Scoreboard data do not provide information on wages, we use capital expenditures and operating surplus as proxies, as in Bogliacino (2010). Indeed, capital expenditures are correlated with the bargaining power, while the operating surplus indicates the health status by the firm. All variables are considered in logarithmic terms.

The model to be estimated is a reduced labour demand equation, where employment is the dependent variable and the regressors are net sales (proxy of output), operating surplus and capital expenditures (proxies of wages), R&D expenditures (proxy of own innovation), R&D spillovers (proxy of outside innovation):

$$L = (S, OP, C, RD, NS, IS, IntraS, InterS) \qquad (14)$$

Since the number of employees is a count data, we estimate the previous model by conditional fixed-effect poisson estimator.

4. Empirical results

Table 1 shows estimates of (14) by geographical area and table 2 indicates estimates of (14) by intra-/inter-industry spillovers. As expected, output with a significant positive effect represents the most relevant determinant of employment. Also our proxies for wages are significant. In particular, the impact of operating surplus is negative, because when it increases this means that the firm is succeeding, and this leads to higher wages and thus to lower employment. The impact of capital expenditures is positive, because it has labour saving effects, this leads to lower wages and thus to higher employment. These results are in line with the empirical literature (Bogliacino, 2010).

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6 We use the exchange rates in Eurostat for year 2007.

7 Eurostat GDP deflators.

8 These firms are research specialized laboratories whose unique activity is R&D. Sales are very limited and this explains a very high R&D intensity, i. e. above 100%.

9 118 technological classes compose 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 table of contingency, i. e. a table reporting the distribution of the firms' patents across the 50 IPC classes, is constructed, as in Cincera (1998). This table is used to compute the index of technological closeness and then the stocks of spillovers.

Table 1. Employment Estimates by Geographical Area

	316 EU firms x 9 years		232 JP firms x 9 years		Sample: 290 US firms x 9 years	
	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]
LnS	0.61***	(0.001)	0.42***	(0.005)	0.65***	(0.002)
LnC	0.01***	(0.001)	0.00	(0.002)	0.10***	(0.001)
LnOP	-0.04***	(0.001)	-0.03***	(0.001)	-0.02***	(0.001)
LnRD	0.05***	(0.001)	0.28***	(0.004)	0.06***	(0.001)
LnNS	0.01	(0.002)	0.35***	(0.006)	-0.10***	(0.003)
LnIS	0.24***	(0.004)	0.03**	(0.016)	-0.45***	(0.006)
Wald X^2	308153.93	P = 0.0000	87062.5	P = 0.0000	716098.15	P = 0.0000

a: ***, ** Coefficient significant at the 1%, 10%. Time dummies are included.

Table 2. Employment Estimates by Intra- /Inter- industry spillovers

	316 EU firms x 9 years		232 JP firms x 9 years		Sample: 290 US firms x 9 years	
	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]
LnS	0.61***	(0.002)	0.40***	(0.005)	0.63***	(0.002)
LnC	0.01***	(0.001)	0.00	(0.002)	0.00	(0.001)
LnOP	-0.04***	(0.001)	-0.03***	(0.001)	-0.03***	(0.001)
LnRD	0.05***	(0.001)	0.23***	(0.004)	0.01***	(0.001)
LnIntraS	0.02***	(0.002)	0.18***	(0.007)	0.05***	(0.003)
LnInterS	0.20***	(0.005)	0.23***	(0.015)	-0.71***	(0.007)
Wald X^2	307110.04	P = 0.0000	84126.90	P = 0.0000	383986.17	P = 0.0000

a: *** Coefficient significant at the 1%. Time dummies are included.

As far as the innovation effects are concerned, we distinguish own innovation effect, proxied by R&D expenditures and outside innovation effecs, proxied by R&D spillovers, disaggregated into four components: National stock of spillovers, International stock of spillovers, Intra-industry spillovers and Inter-industry spillovers. From the empirical results, we see that the own innovation effect on employment is always positive; this seems to indicate that the compensation effect of innovation overcomes the destruction one. By analysing outside innovation effects, National and International spillovers have a positive effect on employment in European economic area and Japan and a negative effect in USA. These results might be explained by role of countries in innovation system. USA, leader country, is characterized by negative effects of outside innovation on employment, because American firms are able to assimilate and exploit outside knowledge and this leads to higher productivity, higher wages and thus to lower employment. In European area and Japan, the previous effect can be positive, because outside innovation might lead also to lower productivity.

Furthermore, intra-inter-industry spillovers have a positive impact on employment, exception made for inter-industry spillovers in USA. Also in this case, the positive effects of outside innovation on employment could be explained through the competition activity between firms, while the negative effect derives from a high R&D capital stock, which leads to a good absorptive capacity.

5. Conclusions and policy implications

This paper analyzes the relationship between R&D activity, spillovers and employment at the firm level. The analysis is based upon a new dataset composed of 879 worldwide R&D-intensive manufacturing firms whose information has been collected for the period 2002-2010. The main contribution to the existing literature is to investigate also the impact of outside R&D activity on own employment level. In particular, the paper investigates the role of R&D spillovers within United States, Japan and European economic area. The empirical results suggest a significant impact of R&D spillover effects on firms' employment and this represents a relevant source of policy implications.

The investigation of relationship innovation-employment is usually relevant to capture further evidence to the debate over the factor bias of technological change. In this paper, we extend the analysis of R&D

spillovers effects on productivity also to job creation effects. In this way, we confirm that innovation for employment assumes a strategical role of a firm, but it produces statistical effects also to other firms, through technological spillovers. Thus, Government policy to promote occupation has to focus attention also on these industrial mechanisms to be fully effective.
However, we estimate a reduced form of labour demand equation. In order to handle all factors able to produce a relevant effect on employment, it would be interesting to structure the empirical analysis into four steps: analysis of relationship innovation-productivity; analysis of market demand of product; analysis of bargaining of wages and profits; analysis of total effects of innovation on occupation.

References

Askenazy, P. (2001). Innovative workplace practices and occupational injuries and illnesses in the United States. Economic and Industrial Democracy, 22(4), 485-516.

Blanchflower, D. G., & Burgess, S. M. (1998). New Technology And Jobs: Comparative Evidence From A Two Country Study‡. Economics of Innovation and New Technology, 5(2-4), 109-138.

Bogliacino F. (2010). Innovation and Employment: A firm level analysis with European R&D Scoreboard data. IPTS Working paper on Corporate R&D and Innovation N. 08/2010.

Bogliacino, F., Piva, M., & Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European microdata. Economics Letters, 116(1), 56-59.

Brouwer, E., Kleinknecht, A., & Reijnen, J. O. (1993). Employment growth and innovation at the firm level. Journal of Evolutionary Economics, 3(2), 153-159.

Chennells, L., & Van Reenen, J. (2002). Technical change and the structure of employment and wages: A survey of the microeconometric evidence. Productivity, Inequality and the Digital Economy, MIT Press, Cambridge, MA, 175-223.

Cincera M. (1998). Economic and technological performances of international firms. PhD thesis, Université Libre de Bruxelles.

European Commission (2011) "The 2000-2010 EU Industrial R&D Investment Scoreboard" JRC Scientific and Technical Research series

Freeman, R. B. (1990). Employment and earnings of disadvantaged young men in a labor shortage economy (No. w3444). National Bureau of Economic Research.

Garcia A, Jaumandreu J. and Rodriguez C. (2004). Innovation and Jobs: evidence from Manufacturing firms. MPRA Working Paper N. 1204.

Greenan, N., & Guellec, D. (2000). Technological innovation and employment reallocation. Labour, 14(4), 547-590.

Griliches Z. (1979). Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics*, 10, 92–116.

Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: evidence from Italian microdata. Industrial and Corporate Change, 17(4), 813-839.

Harrison R., Jaumandreu J., Mairesse J., Peters B. (2008). Does innovations stimulate employment? A firm-level analysis using comparable microdata from four European countries. NBER Working paper 14216

Jaffe A.B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. *American Economic Review*, 76, 984–1001.

Jaumandreu, J. (2003). Does innovation spur employment? A firm-level analysis using Spanish CIS data. Universidad Carlos III de Madrid.

Karaömerlioglu, D., & Ansal, H. (2000). Innovation and employment in developing countries. The employment impact of innovation: Evidence and policy, 165-181.

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. International Journal of Industrial Organization, 29(2), 210-220.
Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. International Journal of Industrial Organization, 29(2), 210-220.

Maraut, S., H. Dernis, C. Webb, V. Spiezia, and D. Guellec. 2008. "The OECD REGPAT Database: A Presentation." STI Working Paper 2008/2, OECD, Paris.

Moncada Paterno Castello P., Ciupagea C., Smith K., Tübke A. and Tubbs M. (2009). *Does Europe perform too little corporate R&D?,* IPTS Working Paper on Corporate R&D and Innovation, No. 11/2009, European Commission, JRC 51955 – Joint Research Center – Institute for Perspective Technological Studies, Luxembourg: Office for Official Publications of the European Communities.

OECD, REGPAT database, January. (2013).

Peters, B. (2005). Employment effects of different innovation activities: Microeconometric evidence (No. 04-73). ZEW Discussion Papers.

Piva, M., & Vivarelli, M. (2004). Technological change and employment: some micro evidence from Italy. Applied Economics Letters, 11(6), 373-376.

Piva, M., & Vivarelli, M. (2005). Innovation and employment: evidence from Italian microdata. Journal of Economics, 86(1), 65-83.

Simonetti, R., Taylor, K., & Vivarelli, M. (2000). 3 Modelling the employment impact of innovation. The employment impact of innovation: Evidence and policy, 26-43.

Smolny, W. (1998). Innovations, prices and employment: A theoretical model and an empirical application for West German manufacturing firms. The Journal of Industrial Economics, 46(3), 359-381.

Spiezia, V., & Vivarelli, M. (2000). The analysis of technological change and employment. The Employment Impact of Innovation. Evidence and policy. London, New York, 12-25.

Storey, D. J., & Tether, B. S. (1998). New technology-based firms in the European Union: an introduction. Research Policy, 26(9), 933-946.

Tether, B. S., & Massini, S. (1998). Employment creation in small technological and design innovators in the UK during the 1980s. Small Business Economics, 11(4), 353-370.

Van Reenen, J. (1997). Employment and technological innovation: evidence from UK manufacturing firms. Journal of labor economics, 255-284.

Westhead, P., & Cowling, M. (1995). Employment change in independent owner-managed high-technology firms in Great Britain. Small Business Economics, 7(2), 111-140.

Zimmerman, M. A. (1995). Psychological empowerment: Issues and illustrations. American journal of community psychology, 23(5), 581-599.

Appendix A.
Sectorial and Geographical characteristics of Variables (average over the period 2002-2010)

Sectors	Number of firms RW[a]	EU[b]	JP	US	S[c]	L	C	K	RD	TS	R&D intensity
Low-tech											
Oil & Gas	5	7	4	8	5273	8908	1607	110	24	54157	0.9
Basic Resources	3	11	10	3	1939	7577	655	82	14	44189	0.8
Construction & materials	0	12	9	4	975	4486	265	62	11	50797	1.4
Food & Beverage	0	11	12	6	2087	8788	721	151	30	76492	1.7
Telecommunications	2	9	2	1	3146	10410	5269	257	46	57913	1.9
Utilities	1	6	9	1	1994	5292	3209	204	20	85770	1.1
Banks	0	4	0	0	6777	41823	2874	210	72	110734	0.9
Medium-tech											
Automobiles & parts	0	27	22	13	2818	10191	1515	668	116	72162	4.1
Industrial goods & services	5	93	53	44	766	4360	247	146	27	62671	4.7
Chemicals	1	26	34	20	766	2725	318	180	30	65250	3.6
Personal & household goods	0	21	24	18	1313	6923	428	331	62	79193	4.4
Media	0	4	2	3	1081	3973	554	132	22	70621	4.1
Retail	0	2	1	4	1199	3137	238	55	13	53202	4.6
Travel & leisure	1	0	1	1	108	405	23	19	5	31517	4.3
High-tech											
Health care	8	42	29	59	749	2904	404	407	103	84864	16.8
Technology	15	41	20	105	638	3289	234	360	68	78181	15.5
Average					1744	7765	1164	227	45	69955	4.4
Rest of the World	41				1705	8464	881	254	56	90807	3.3
Europe		316			1452	5880	777	297	55	64834	3.8
Japan			232		993	4079	497	199	40	89654	4
United-States of America				290	1090	4244	436	333	69	60746	6.3

a: Australia, Canada, China, Croatia, Hong Kong, India, Israel, Norway, Russia, South Africa, South Korea, Taiwan
b: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Spain, Sweden, Switzerland, The Netherlands and the United Kingdom
c: S=net sales, L=number of employees, C=physical capital stock, K=R&D capital stock, RD=R&D expenditures, TS=Total stock of spillovers, R&D intensity=R&D expenditures/net sales (in %)

Appendix B.
Correlation between technological spillover components

	(1)	(2)	(3)	(4)
NS (1)	1			
IS (2)	0.17	1		
Intra (3)	0.38	0.36	1	
Inter (4)	0.39	0.71	-0.24	1