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Similarity and Geographical Issues in Evaluating the Impact of R&D Spillovers at firm level. Evidence from Italy.

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Abstract

This paper assesses the impact of R&D spillovers on production for a balanced panel of 1203 Italian manufacturing firms over the period 1998-2003. Estimations are based on a translog production function augmented by a measure of R&D spillovers that combines the geographical distance and the technological similarity within each pair of firms. We find three key results. Firstly, we show that the translog production function is more suitable than the Cobb-Douglas to model firm behaviour. Secondly, we argue that the external stock of technology exerts a significant impact on production output. This impact is high, whatever way we choose to weight the innovation flows, and is very sensitive to the geographical diffusion of technology. Lastly, it emerges that R&D spillovers are Morishima complements to physical and R&D own-capital and Morishima substitute for labour.

Key words: R&D spillovers, panel data, translog, Italian firms, Morishima elasticity.
JEL codes: O33, L29, C23.

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1. Introduction

Starting from theoretical predictions of the role of R&D as a source of growth (Romer, 1990), many researchers have looked at how to measure and model R&D spillovers. The common approach has been to consider the stock of indirect R&D capital as an augmenting variable of a production function, whatever the level of analysis (firm, industry, country). However, at firm level there are few papers which explicitly deal with this issue[1]. These studies have two main common denominators, although their comparison is not very informative (they differ in the span periods and the sample of firms they analyze and in the methodologies they use). The first common denominator regards the use of the Cobb-Douglas as the preferred functional form to include the R&D spillovers in a production function. Secondly, in all papers, R&D spillovers are measured through other firms' stock of R&D capital. If on one hand, there is no application which uses a more flexible production function than the Cobb-Douglas, on the other hand several methodological improvements have been made in order to properly measure R&D spillovers.

Because the relationship between internal and external factors is one of the most interesting issues relating to technological transfers across firms, in this paper we use a translog production function rather than a Cobb Douglas. This is mainly due to the fact that the translog does not constrain the elasticity of substitution among the factors to any particular value. Hence, and differently from the dominant literature using the Cobb-Douglas specification, this paper allows us to understand whether external technology is complementary to or a substitute for standard inputs (i.e., labour, physical, human and technological capital).

With regards the measurement of R&D spillovers, there are two issues to deal with . The first refers to the identification of the variable to be transferred. Following Griliches

[1] Aiello and Pupo (2004), Aiello, Cardamone and Pupo (2005) Aiello and Cardamone (2005), Cincera (2005), Jaffe (1986, 1988), Los and Verspagen (2000), Medda and Piga (2004), Raut (1995), Wakelin (2001).

(1979), many authors agree that spillovers can be measured by the indirect stock of technological capital, which is determined by the current and past investments in R&D made by other firms. We follow this literature and measure the technological spillovers by the indirect stock of R&D capital. The second issue is related to the modelling of how and to what extent R&D spillovers flows from one firm to another. Again, many researchers agree with the hypothesis that firms are not able to absorb all the technology produced by others, and that absorptive capacity differs from one firm to another. This means that the R&D spillovers of a given firm must be the weighted sum of the R&D stock of other firms. However, scholars disagree about how to weight the innovation flows. The most used weighting schemes are based on either patents (Jaffe, 1986, 1988; Los and Verspagen, 2000, Cincera, 2005) or input-output matrices (Wakelin, 2001; Medda and Piga, 2004; Aiello and Pupo, 2004, Aiello, Pupo and Cardamone, 2005, Aiello and Cardamone, 2005). We will argue that these approaches are not proper to measure the flows of knowledge across firms. Finally, all these papers disregard the issues relating to the geographical diffusion of technology.

In this paper the weighting system of the external stock of R&D capital is based on the use of an index of similarity for each pair of firms. The hypothesis is that the more similar two firms are, the greater the flow of innovation between them (Jaffe, 1986 and 1988; Cincera, 2005). As an index of similarity we use the uncentered correlation metric calculated by considering a set of firm-specific variables (value added, investments in ICT, skilled employees, internal and external R&D investments) which defines the technological space of the sample of firms to be analysed.

Unlike most previous studies based on input-output matrices or sectoral patent data, our approach allows the capacity to absorb external technology to differ from firm to firm. From a purely econometric perspective, this property yields desirable results because the variance of technological spillovers is high.

Furthermore, we introduce two elements of originality with regards the micro-econometric applications of the concept of similarity. The first focuses on the asymmetry of the index of similarity. For any given level of similarity, it is likely that direction matters in determining technological transfers from one firm to another. In other words, this is assuming that for any pair of firms, A and B, innovation flows from A to B at a different degree from that occurring from B to A. Thus, we propose an asymmetric transformation of similarity measure based on differences in firms' sizes.

The second original element refers to the inclusion of a geographical dimension in the set of variables that are used to measure the flows of innovation. In theory, it is widely agreed

that spatial agglomeration is positively correlated to diffusion of technology (Marshall, 1920; Jacobs, 1969; Romer, 1986; Arrow, 1962; Koo, 2005; Audretsch and Feldman, 2003). However, it is worth noticing that in Italy the spatial dimension of the flow of knowledge has been disregarded by all the existing papers analysing the impact of R&D spillovers on firms' productivity. On the other hand, it was partially taken into account in Adams and Jaffe (1996) for the USA, Orlando (2000) for the USA and Lu, Cheng and Wang (2005) for Taiwan. Therefore, we test the hypothesis that the closer two firms are, the more they will mutually benefit from each other' R&D. This is done through a spatial weighting scheme based on the great circle distance. The distance we consider is between the capital of the province where each firm is located.

Using a panel of 1203 manufacturing firms for the period 1998-2003, obtained from the 8th and 9th "Indagine sulle imprese manifatturiere" surveys by Capitalia (formerly Mediocredito Centrale), we use a system of equations derived from the translog production function (Christensen, Jorgenson and Lau, 1973), whose set of inputs includes the internal and the external stock of R&D capital. In the econometric setting we address the issue of non-random selection that zero values in R&D investments pose in all log- linearization of a production function. This is done by modelling the decision to invest or not in R&D and then by estimating the production function with the 3SLS estimator. Empirical results show that output elasticity with respect to R&D spillovers is always positive and significant. Moreover, we find that the geographical dimension of technology spillovers matters in determining the final result: indeed, our regressions which disregard geography in the process of technology diffusion seem to overestimate the role of R&D spillovers.

The remainder of the paper is organized as follows. The second section describes the data used. In section III the procedures to determine the different R&D spillover indicators are presented. Section IV presents the production function specification and the estimation method adopted. Section V reports the econometric results, while Section VI concludes.

2. Data source

Data used in the empirical analysis come from the 8th and 9th "Indagine sulle imprese manifatturiere" (IMM) surveys made by Capitalia (formerly Mediocredito Centrale). These two surveys cover the period 1998-2003, contain standard balance sheets and collect a great deal of qualitative information from a large sample of Italian firms. Each survey considers more than 4500 firms, including all Italian manufacturing firms with more than 500 workers and a representative sub-sample of firms with more than 10 workers (stratification used by

Capitalia considers location, size and sector of the firm). Firms in both surveys are 1650, but after data cleaning we obtain a panel of 7213 observations, with large N (1203 cross sections) and small T (6 years).

Table 1 shows a breakdown of the sample of firms. We split the sample into R&D performing firms and non-R&D performing firms. The group of R&D performing firms comprises those with positive R&D investments for at least one year over the period 1998-2003: for each year there are 557 R&D performing firms and 646 non-R&D performing firms. With regards the geographical location of firms, it emerges that about two-thirds are located in the North of Italy (445 in the North West and 382 in the North East of Italy). Moreover, the sub-sample of non-R&D performing firms is always larger than the R&D performing one, except for the firms operating in the North-East. In the Southern regions of Italy, the proportion of the innovative firms is barely 33 per cent of the entire sample for that area. At industry level, the sample is dominated by firms in textiles, base metals and non electrical machinery industries, while the petroleum refinery industry is represented by 6 firms only. In the case of R&D performing firms, most firms are located in North of Italy and are active in the non-electrical and electrical machinery industries. Finally, the non-R&D performing firms are more numerous in the food and beverage, the textile and the basic metal industries (Table 1).

Table 2 reports firm's productivity and physical and technological capital intensity. Labour productivity is expressed as value added to employees, whereas both capital intensities are computed with respect to value added. Physical capital is given by book value of the total assets and technological capital is determined by applying the perpetual inventory method to the R&D investments (depreciation rate is assumed to be 15 per cent). Data are expressed at real prices 2000 and are six-year weighted average[2].

It is significant to point out that the average value of labour productivity is 67000 euros for the entire sample of firms and 63000 euros for the R&D performing ones. Furthermore, output per worker differs by geographic area: it ranges from 90000 euros, that is the value observed for the firms operating in the Centre of Italy, to 62000 euros observed in the Northern regions. With regards size, the highest value of labour productivity refers to the large firms, while, as far as sectors are concerned, the most productive firms belong to the paper and petroleum industries. Finally, the leather industry is the sector with the lowest value

[2] Weights are given by $f_i = F_{it} \Big/ \sum_{t=1998}^{2003} \sum_{i=1}^{N} F_{it}$ where F_{it} are the sales of the *i*th firm at time *t* (*t*=1998,…,2003) belonging to a group sized *N* (*i*=1,…,*N*).

of labour productivity. Moreover, table 2 shows that physical capital is 1.31 for the total sample of firms and 1.26 for the R&D performing entities. What emerges is that physical capital is high for firms located in the North-East and in the South and low in other areas. With regards size, we notice that the large R&D performing firms register high values of physical capital intensity, while, for the entire sample, firms with 11-50 employees have a higher physical capital intensity than firms with 51-250 employees. At an industry level, physical capital intensity is high for food and rubber and plastic industries whatever the group of firms we consider (full sample or the R&D performing one). Limiting the comment to the full sample, physical intensity is also high in the petroleum sector.

Bearing in mind the specific aim of this paper, the analysis of R&D capital intensity is of great interest. At a national level, it is 0.3 for all the R&D performing firms; moreover the firms operating in the North of Italy register a value (0.37 for North West and 0.28 for North East) higher than the national average, while in the Centre-South of Italy the R&D intensity is low (0.2 in the Centre and 0.09 in the South). The R&D intensity strongly differs when one considers firm size: it is 0.36 in the case of the firms with more than 250 employees, 0.24 for small firms (11-50 workers) and 0.2 for medium ones (51-250 employees). Finally, intensity is high in the chemical (0.78), electrical (0.48) and in non-electrical (0.37) sectors and low in the wood (0.03) and paper (0.03) industries.

Table 3 reports the distribution of R&D investments and of R&D capital among the innovative firms. What clearly emerges is that R&D investments and R&D capital are highly concentrated: 5 per cent of the sample, that is 28 firms, absorbs about 71 per cent of the total R&D investments and 74 per cent of the total R&D. This 5 per cent of firms invests, on average, more than five million euro per year. Furthermore, 20 per cent of the sample is composed of 11 firms and accounts for 89 per cent of R&D investments and about 91 per cent of R&D capital. The distribution has a positive skewness: 50 per cent of the sample absorbs less than 3 per cent of total investments in R&D.

Table 1. Italian Manufacturing Firms by area and industry.

	Full sample					R&D performing firms					Non-R&D performing firms				
	Area					Area					Area				
Industries	North West	North East	Centre	South	Total	North West	North East	Centre	South	Total	North West	North East	Centre	South	Total
Food, Beverages & Tobacco	23	26	15	39	**103**	6	13	5	11	**35**	17	13	10	28	**68**
Textiles & Apparel	61	28	43	16	**148**	27	15	22	7	**71**	34	13	21	9	**77**
Leather	4	13	27	6	**50**	3	8	10	1	**22**	1	5	17	5	**28**
Wood Products & Furniture	11	23	9	4	**47**	1	8	5	1	**15**	10	15	4	3	**32**
Paper, Paper Prod. & Printing	28	25	11	4	**68**	7	8	2	2	**19**	21	17	9	2	**49**
Petroleum Refineries & Product	1	1	2	2	**6**	0	1	1	0	**2**	1	0	1	2	**4**
Chemicals	27	12	9	7	**55**	18	9	7	2	**36**	9	3	2	5	**19**
Rubber & Plastic Products	34	20	7	4	**65**	20	7	3	2	**32**	14	13	4	2	**33**
Non-Metallic Mineral Products	20	22	22	17	**81**	7	8	7	4	**26**	13	14	15	13	**55**
Basic Metal & Fab. Met. Prod.	73	67	28	25	**193**	19	23	8	8	**58**	54	44	20	17	**135**
Non-Electrical Machinery	81	71	16	6	**174**	53	55	11	3	**122**	28	16	5	3	**52**
Electrical Machinery and Electronics	51	28	17	4	**100**	41	20	8	2	**71**	10	8	9	2	**29**
Motor vehicles & Other Transport Equipment	10	6	5	6	**27**	6	2	2	2	**12**	4	4	3	4	**15**
Other Manufacturing Industries	21	40	16	9	**86**	7	18	7	4	**36**	14	22	9	5	**50**
Total	**445**	**382**	**227**	**149**	**1203**	**215**	**195**	**98**	**49**	**557**	**230**	**187**	**129**	**100**	**646**

Source: Our calculation from data by Capitalia (2002; 2005).

Note: The sample of firms is balanced over the period 1998-2003. Data in the table refer to a single year.

Table 2. Labour Productivity and factor intensity for Italian manufacturing firms by industry, area and size. Weighted average*, 1998-2003

	Total sample										R&D performing firms														
	Y/L**					K/Y**					Y/L**					K/Y**					CT/Y**				
Sectors	11-20 E***	21-50 E	51-250 E	>250 E	Total	11-20 E	21-50 E	51-250 E	>250 E	Total	11-20 E	21-50 E	51-250 E	>250 E	Total	11-20 E	21-50 E	51-250 E	>250 E	Total	11-20 E	21-50 E	51-250 E	>250 E	Total
Food, Beverages & Tobacco	43	54	43	61	53	3.37	2.50	1.19	4.45	3.12	50	63	44	57	54	1.89	2.29	0.98	4.68	3.33	0.10	0.05	0.09	0.10	0.09
Textiles & Apparel	52	49	41	61	55	0.69	0.97	1.33	1.28	1.19	53	51	41	67	60	0.78	1.02	1.21	1.15	1.11	0.32	0.20	0.20	0.06	0.12
Leather	40	38	43		41	0.68	0.58	1.36		1.09	41	37	45		44	0.54	0.56	1.44		1.28	0.22	0.16	0.06		0.08
Wood Products & Furniture	34	43	37	72	44	0.86	1.76	1.26	1.46	1.43	31	46	40	72	49	0.90	1.03	1.28	1.46	1.28	0.11	0.06	0.02	0.01	0.03
Paper, Paper Prod. & Printing	40	56	50	183	147	0.90	0.89	1.25	0.73	0.82	47	64	62	169	128	0.89	0.65	1.56	1.18	1.16	0.13	0.04	0.08	0.01	0.03
Petroleum Refineries & Product	74	260			229	1.32	1.92			1.82	54	98			80	0.74	0.51			0.61	0.07	0.18			0.13
Chemicals	69	78	67	74	73	1.09	1.40	1.30	0.59	0.83	59	99	67	74	73	1.06	1.11	1.28	0.59	0.77	0.51	0.67	0.26	0.94	0.78
Rubber & Plastic Products	49	45	60	81	67	0.95	1.19	2.79	1.62	1.79	65	49	59	81	72	1.17	1.31	1.79	1.62	1.60	0.34	0.13	0.32	0.41	0.35
Non-Metallic Mineral Products	60	53	51	85	72	1.67	1.99	2.10	1.56	1.72	43	57	51	76	68	1.14	1.80	1.44	1.36	1.40	0.09	0.13	0.13	0.08	0.09
Basic Metal & Fab. Met. Prod.	63	46	73	60	62	1.23	1.34	1.21	1.74	1.36	48	39	48	62	53	1.06	1.40	1.52	1.42	1.41	0.11	0.06	0.16	0.50	0.30
Non-Electrical Machinery	49	56	64	65	63	0.57	0.55	0.76	0.90	0.80	55	57	65	63	63	0.51	0.52	0.75	0.88	0.80	0.30	0.27	0.21	0.49	0.37
Electrical Machinery and Electronics	40	44	59	51	51	0.63	0.56	0.67	1.02	0.85	43	45	60	51	52	0.67	0.54	0.65	1.01	0.85	0.15	0.22	0.42	0.58	0.48
Motor vehicles & Other Transport Equipment	39	42	35	58	55	0.71	0.87	0.99	1.56	1.48	43	34	38	61	59	0.82	2.22	1.15	1.30	1.30	0.04	0.03	0.23	0.23	0.22
Other Manufacturing Industries	47	36	40	38	40	0.79	0.85	1.05	0.78	0.91	63	38	41	38	42	0.62	0.87	1.15	0.78	0.97	0.11	0.15	0.12	0.28	0.16
Area																									
North West	54	50	57	66	61	0.95	1.31	1.07	1.18	1.14	53	51	59	64	62	0.84	1.14	1.05	1.12	1.09	0.18	0.32	0.25	0.45	0.37
North East	48	53	54	72	62	1.02	1.08	0.92	1.82	1.40	51	59	46	72	64	0.91	0.60	0.94	1.82	1.45	0.22	0.19	0.14	0.36	0.28
Centre	58	50	60	120	90	1.03	0.87	1.30	1.05	1.06	55	54	66	64	62	0.80	0.97	1.35	1.12	1.13	0.45	0.14	0.17	0.21	0.20
South	40	88	50	69	68	3.28	1.96	2.82	1.47	2.12	42	46	53	75	64	1.71	2.34	1.58	1.02	1.41	0.14	0.05	0.22	0.05	0.09
Total	52	58	55	79	67	1.27	1.27	1.18	1.38	1.31	52	54	55	68	63	0.94	1.04	1.07	1.40	1.26	0.24	0.19	0.20	0.36	0.30

Source: See Table 1

Notes: * Weights are expressed as the sales of the i-th firm to the aggregate sales of the group. ** Y/L= Value added/employee (in .000 of Euro); K/Y=Physical capital/Value added; CT/Y=Technological capital/Value added. *** **E=Employees**

Table 3. R&D investments and the stock of R&D capital of the Italian manufacturing R&D-performing firms.
Distribution and descriptive statistics. Average values, 1998-2003.

		R&D investments		Stock of R&D capital	
Cumulative percentage of firms	(N. of firms)	Cumulative percentage	Average value	Cumulative percentage	Average value
5%	(28)	70.5%	5052	74.2%	24918
10%	(56)	80.4%	2881	82.9%	13928
15%	(84)	85.8%	2049	87.6%	9808
20%	(111)	89.3%	1614	90.8%	7690
25%	(139)	92.0%	1327	93.1%	6298
40%	(223)	96.1%	865	96.9%	4089
50%	(279)	97.7%	702	98.2%	3311
100%	(557)	100%	360.1	100%	1688.7
Mean		360.1		1688.7	
Min		0		0	
Max		42099.9		170212.8	
1st quartile		0		33.9	
Median		29.4		162.0	
3rd quartile		146.8		645.7	
Coefficient of variation		5.2		5.7	
Observations		3342		3342	

Source: see Table 1.

3. On Measuring the stock of R&D Spillovers

Following Griliches (1979), we argue that the external technology available to a firm is related to the R&D investments of other firms. At first glance, if one assumes that all external technology is relevant for a firm and that the capacity to absorb technology does not differ across firms and sectors then the simplest proxy of R&D spillovers will be the unweighted sum of the R&D stocks of the other n-1 firms. However, there is reason to question whether all the investment efforts made by others are relevant for a firm (Griliches, 1991). In line with this argument, many papers agree that the measure of technological spillovers must be a weighted sum of R&D capital stock of other firms, but no consensus is achieved on the weighting system to be used. The most commonly used weights are based on either patents data (Jaffe, 1986 and 1988; Los and Verspagen, 2000; Cincera, 2005) or input-output matrices (Wakelin, 2001; Medda and Piga, 2004; Aiello and Pupo, 2004; Aiello, Cardamone and Pupo, 2005; Aiello and Cardamone, 2005).

Using patent data, it is possible to determine *k*-dimensional patent distribution vectors, whose elements are the fraction of firm *j*'s research efforts devoted to *k* fields of patent activity (Jaffe, 1986 and 1988; Cincera, 2005). The weighting scheme is then calculated using a similarity metric. With regards the I/O approach, the weighting scheme of the flows of innovation is based on the hypothesis that the more one industry buys from another, the more

it will absorb the technology produced by others. These methods are subject to criticisms. Indeed, the use of patents to measure the flows of knowledge runs into the same problem encountered when patents are used as an indicator of a firm's innovative activities, that is "not all inventions are patentable, not all inventions are patented" (Griliches, 1990, p. 1669). With regards the input-output approach, it tends to underestimate the real magnitude of pure knowledge spillovers, as it is related to the flows of goods and services rather than to purely technological flows. Moreover, both I/O and patent matrices are generally available at industry level only and, consequently, their use at firm level (see, i.e., Los and Verspagen 2000, Aiello and Pupo, 2004, Aiello, Cardamone and Pupo, 2005, Medda and Piga, 2004) requires the absorption of technology not to vary within a sector and extra-industry technology to be the same for all firms belonging to the same industry.

3.1. Technological similarity as a weighting scheme

The understanding of the firm's position in a technological space helps to determine its technological opportunities, that is the amount of technological resources available for each entity (Cohen and Levinthal, 1990). Furthermore, technological opportunities affect the absorptive capability, which consists of the capacity to use new technology and to be innovative (Cohen and Levinthal, 1989). Many authors (Jaffe, 1986 and 1988; Griliches, 1979 and 1991; Cincera, 2005; Harhoff, 2000; Inkmann and Pohlmeier 1995; Kaiser, 2002) agree that absorptive capability depends on technological proximity: the closer two firms are in technological space, the more they benefit from each other's research efforts.

From an empirical perspective, there are two questions to deal with before measuring the similarity between firms. The first question regards the choice of variables which define technological space, whereas the second issue refers to the index of similarity to be used. Several authors (Jaffe, 1986 and 1988, Los and Verspagen, 2000, Cincera, 2005) argue that patent data allow the proper definition of an innovative space, others use investments in R&D (Harhoff, 2000, Jaffe and Adams, 1996), while Inkmann and Pohlmeier (1995) consider a set of firm specific characteristics (size, demand expectations, industry affiliation). As for the mere calculation of firms' similarity, all the authors use the uncentered correlation metric (Jaffe, 1986 and 1988; Cincera 2005; Kaisern 2002; Los and Verspagen, 2000) or the Euclidean distance (Inkmann and Pohlmeier, 1995).

In what follows we consider the uncentered correlation metric as a proper index of similarity[3]. This index is defined as follows:

$$\omega_{ij} = \frac{\mathbf{X}_i \mathbf{X}'_j}{\left((\mathbf{X}_i \mathbf{X}'_i)(\mathbf{X}_j \mathbf{X}'_j)\right)^{1/2}} \qquad [1]$$

where X_i is a set of variables that define the technological dimension of our selected sample of firms[4]. The index ω_{ij} ranges from zero to one. It is zero when firm i and firm j are not related at all, while it is unity if the k-variables in X_i and X_j are identical. The variables used to construct the index of similarity are the value added, the skilled (with at least high schooling) and unskilled (with only primary schooling) employees, investments in ICT and internal and external R&D investments. The index is calculated for each and every year over the span period analysed (1998-2003). We normalize all variables with respect to their average.

The uncentered correlation (as specified in the equation [1]) yields a symmetric matrix of weights. This means that the intensity of the technological flows from firm *i* to firm *j* is equal to that observed from firm *j* to firm *i*. This property of the index ω_{ij} contrasts with the evidence that direction matters in determining how technology circulates from one firm to another. Therefore, and differently from all the applications of the uncentered correlation, we consider the following asymmetric transformation of the index of similarity:

$$\begin{aligned} \hat{\omega}_{ij} &= \frac{\mathbf{X}_i \mathbf{X}'_j}{\left((\mathbf{X}_i \mathbf{X}'_i)(\mathbf{X}_j \mathbf{X}'_j)\right)^{1/2}} \left[\frac{V_i}{\max(V_i, V_j)}\right] \\ \hat{\omega}_{ji} &= \frac{\mathbf{X}_i \mathbf{X}'_j}{\left((\mathbf{X}_i \mathbf{X}'_i)(\mathbf{X}_j \mathbf{X}'_j)\right)^{1/2}} \left[\frac{V_j}{\max(V_i, V_j)}\right] \end{aligned} \qquad [2]$$

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3 It is possible to show that the Euclidean measure is sensitive to the length of the vector which comprises the variables of each firm. Indeed, the "length depends on the level of concentration of the firm's research activities among the technological classes. With this measure, the more two firms are diversified, the lesser the length of their technological vectors. As a result, these firms will be located in the central region of the technological space. Hence, they will be close each other even if their technological vectors are orthogonal" (Cincera, 2005, p.12).

4 In the prevailing literature, the index of similarity is determined using only one variable (the investments in R&D or the sectoral patent data) and this choice appears to be a strong constraint, because it is a very partial way to gauge the firm's capacity to absorb external technology (two firms may be similar in terms of R&D investments, but their "absorptive capacity" may be limited because of other factors, one of which might be, i.e., the availability of human capital). Moreover, our index of similarity differs at firm-pair level and this allows us to overcome the strict assumption that the firms operating in a given sector have the same absorptive capacity. Such an assumption is commonplace in all the papers that use I/O models and sectoral patent data.

where the variable V is the value added. In equation [2], the value added is excluded from the calculation of the index ω_{ij}. The index $\hat{\omega}_{ij}$ is asymmetric, that is $\hat{\omega}_{ij} \neq \hat{\omega}_{ji}$ and, for one firm of each pair, is equal to the index obtained when the symmetry is imposed.

3.2. Geography matters

The previous section emphasizes that the spread of knowledge is hindered only by the technological distance between firms. However, it is worldwide argued that the flow of innovation is related to the geographical proximity of firms: face-to-face contacts enhance knowledge spillovers whatever the technological similarity between firms. Although a huge number of papers deals with the theoretical issues of the nexus between spatial agglomeration and knowledge spillovers (Marshall, 1920; Jacobs, 1969; Romer, 1986; Arrow, 1962; Koo, 2005; Audretsch and Feldman, 2003), it emerges that, at firm level, the empirical analyses addressed at estimating to what extent geography affects the diffusion of technology are very limited. The few exceptions are the studies by Adams and Jaffe (1996), Orlando (2000) [5] and Lu, Cheng and Wang (2005)[6]. To the best of our knowledge there is no paper focusing on Italian manufacturing firms.

A very simple way to weight the diffusion of innovation among firms located in different areas is to take into account the geographical distance between them. In this paper we measure the distance using the great circle system, which is the shortest distance between any two points on the surface of a sphere. It is given by the length of the arc joining the two points[7]. In our case, the two points needed to calculate the great circle distance are the capitals of the provinces where the firms are located.

Given the spatial distance between a pair of firm (d_{ij}), a weight of geographical proximity is:

$$g_{ij} = 1 - \frac{d_{ij}}{\max(d_{ij})} \qquad [3]$$

[5] In these papers a firm may absorb technology from two sources, which are the group of firms located within or beyond a certain distance (less or more than 500 miles) This method, in some ways, tests whether geographical distance affects the flow of technology, but it does not say anything about the magnitude of this impact.

[6] Lu *et al.* (2005) consider a geographic weighting system based on the great circle distance between each firm and the centre of gravity of the industry where the firm operates. The centre of gravity is determined averaging the latitude and longitude of the firms belonging to a given industry.

[7] The distance is given by $dist_{xi}$=69.1*(180/π)*ARCOS(SIN(LAT1)*SIN(LAT2)+COS(LAT1)*COS(LAT2) *COS(LONG2-LONG1)) where LAT1 and LONG1 are the latitude and the longitude for point 1, respectively, and LAT2 and LONG2 are the latitude and the longitude for point 2, respectively.

which is unity when the pair (i,j) is in the same place and is zero when the two firms are located at the points with the maximum distance between them.

Finally, we attempt to merge the basic ideas beyond the equations [2] and [3]. In equation [2], we simply state that technological similarity is the only factor that explains the flow of innovation, while equation [3] attributes this uniqueness to geographical proximity. Since it is likely that the closer and more similar firms are, the more they benefit from each other's technology, we average the indexes $\hat{\omega}_{ij}$ and g_{ij}:

$$v_{ij} = \frac{\hat{\omega}_{ij} + g_{ij}}{2} \qquad [4]$$

The index v_{ij} is asymmetric and ranges from zero to one. It is zero when firm i and firm j are both technologically and geographically "dissimilar", while it is unity if the closeness of the pair (i,j) is unity in both dimensions (technology and geography).

All the weighting systems can be used to determine technological spillovers. For the *i-th* firm, the stock of R&D spillovers ($Spill_i$) is the weighted sum of R&D capital of other N-1 firms, that is:

$$Spill_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} \upsilon_{ij} CT_j \qquad \text{with } i=1,2,.........N \qquad [5]$$

where υ_{ij} indicates a generic weighting system. Bearing in mind all previous considerations, we construct several stocks of R&D spillovers. First of all, we use the unweighted sum of the other firms' R&D stock, where $\upsilon_{ij}=1$ for every *i* and *j*. Secondly, we compute the spillover stock considering the symmetric and the asymmetric similarity approach, that is $\upsilon_{ij}=\omega_{ij}$ and $\upsilon_{ij}=\hat{\omega}_{ij}$, respectively. Thirdly, we weight the flows of innovation considering the geographic proximity ($\upsilon_{ij}=g_{ij}$). Finally, we refer to the average of the geographical and technological proximity ($\upsilon_{ij}=v_{ij}$).

4. Production function specification and the estimation method

This paragraph describes the production function used to estimate the impact of technological spillovers on output. As already said, the Cobb Douglas production function is the most used functional form, although no paper tests whether this choice finds confirmation in the data. Differently from much of the evidence in this field of research, the empirical strategy we follow is to consider a translog production function which is more flexible than the Cobb-Douglas. If some specific restrictions on some estimated parameters in the translog estimates

are not rejected then we will switch to the Cobb-Douglas, otherwise we will proceed using the translog.

Following Christensen, Jorgenson and Lau (1973), we use the following trascendental logarithmic production function:

$$\begin{aligned}\ln Y_{it} &= \alpha_i + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_{Ct} \ln CT_{it} + \alpha_{Sp} \ln Spill_{it} + \\ &+ \frac{1}{2}\beta_{LL}(\ln L_{it})^2 + \frac{1}{2}\beta_{KK}(\ln K_{it})^2 + \frac{1}{2}\beta_{CtCt}(\ln CT_{it})^2 + \frac{1}{2}\beta_{SpSp}(\ln Spill_{it})^2 + \\ &+ \beta_{LK} \ln L_{it} \ln K_{it} + \beta_{LCt} \ln L_{it} \ln CT_{it} + \beta_{LSp} \ln L_{it} \ln Spill_{it} + \beta_{KCt} \ln K_{it} \ln CT_{it} + \\ &+ \beta_{KSp} \ln K_{it} \ln Spill_{it} + \beta_{CtSp} \ln CT_{it} \ln Spill_{it} + \varepsilon_{it}\end{aligned} \quad [6]$$

where Y denotes the output, L is labour, K is physical capital, CT is technological capital and $Spill$ is the stock of R&D spillovers; ε is a white noise. The condition to move from the equation [6] to a Cobb-Douglas specification is that all the β parameters must be non significant.

Following Berndt and Christensen (1973) and May and Danny (1979) we estimate the equation [6] jointly with a the cost-share equations. This is because the system of equations allows us to use additional information without increasing the number of parameters to be estimated (Antonioli *et al.*, 2000). Furthermore, it improves the efficiency of estimations and reduces the multicollinearity suspected to be present in the equation [6] (Feser, 2004; Lall *et al.*, 2001; Goel, 2002).

The cost share equations are specified as follows. Denoting with S_L, S_K, S_{CT}, S_{SP} the cost shares of labour, physical capital, technological capital and R&D spillovers stock, respectively, under the assumption of constant returns to scale[8], we obtain:

$$S_{L,it} = \alpha_L + \beta_{LL} \ln L_{it} + \beta_{LK} \ln K_{it} + \beta_{LCt} \ln CT_{it} + \beta_{LSp} \ln Spill_{it} + u_{L,it} \quad [7]$$

$$S_{K,it} = \alpha_K + \beta_{LK} \ln L_{it} + \beta_{KK} \ln K_{it} + \beta_{KCt} \ln CT_{it} + \beta_{KSp} \ln Spill_{it} + u_{K,it} \quad [8]$$

$$S_{CT,it} = \alpha_{Ct} + \beta_{LCt} \ln L_{it} + \beta_{KCt} \ln K_{it} + \beta_{CtCt} \ln CT_{it} + \beta_{CtSp} \ln Spill_{it} + u_{CT,it} \quad [9]$$

$$S_{SP,it} = \alpha_{Sp} + \beta_{LSp} \ln L_{it} + \beta_{KSp} \ln K_{it} + \beta_{CtSp} \ln CT_{it} + \beta_{SpSp} \ln Spill_{it} + u_{Sp,it} \quad [10]$$

[8] Constant returns to scale imply that $\sum_i \alpha_i = 1$ and $\sum_j \beta_{ij} = 0$.

Since constant returns to scale are imposed and the sum of input cost shares is assumed to be equal to one, estimation of the system of equations [6], [7], [8] and [9] would yield estimates of all the parameters.

Standard production variables have been derived from the dataset published by Capitalia (see section 2). Output is measured by the value added of firms. Physical capital is measured by the book value of total assets. Labour is the number of employees. Furthermore, for each firm the stock of internal technological capital is determined by current and past investments in R&D. This stock of capital is used to determine the stock of R&D spillovers that every firm faces (see equation [5])[9].

We estimate the system of equations [6-9] using the 3SLS estimator and, in order to take into account endogeneity, we consider as instruments the one-year lagged value of each endogenous regressor[10]. Furthermore, we also control for sample selection because the stock of R&D capital is constructed using R&D investments and, in many cases, firms do not invest in R&D (zero-investment-values). As a consequence, we have a sub-sample of R&D performing firms (with positive values for R&D capital) and a sub-sample of non-R&D performing firms (with zero values for R&D capital). The log-linearization of equation [5] restricts the sample of firms to the R&D performing firms, and in so doing, it forces one to work with a sample which is no longer random, because it ignores the underlying process that leads each firm to invest, or not, in R&D. Consequently, there might be a selection problem due to likely correlation between the decision process to invest in R&D and the production function we intend to estimate (equation [6]). The selection process can be modelled using a treatment effect model because the selection occurs for the stock of R&D capital, which is a regressor. Following (Wooldridge, 2002), we address this issue through the two-step IV method[11]: in the first step we consider a probit model to explain the decision to invest in R&D, and in the second step we estimate the translog production function using as instruments the fitted probabilities derived from the first step.

[9] The labour cost share S_L is the total labour cost to the value added. According to Verspagen (1995), we compute S_K and S_{CT} as $[P_I(\delta+r)]Z/V$ where P_I is the investment price deflator, δ is the rate of depreciation assumed to be equal to 5% for physical capital and 15% for technological capital, r is the interest rate, which is assumed to be 5%, Z is the stock of capital (physical or technological) and V is the Value Added.

[10] We consider as endogenous variables all the regressors of eq. [5], but lnsp and lnsp^2. The Hausman test supports this choice.

[11] The underlying assumption is that we have homogeneous treatment. In other words, the impact of treatment (to invest or not in R&D) on output does not vary across firms.

The dependent variable of the probit model is unity if the i-th firm invests in R&D and is zero if it does not. The regressors of the probit model are the explanatory variables of the production function (equation 6), plus the key determinants of the decision to invest in R&D, which we select following the literature on this subject (Leo, 2003; Becker and Pain, 2003; Gustavsson and Poldhal, 2003; Bhattacharya and Bloch, 2004). Our determinants of the decision to invest in R&D are human capital, cash flow, investments in ICT, a dummy equal to unity if firm *i* exports and a set of dummies measuring the geographical location and the economic sector of each firm[12]. From the probit model we get the fitted probabilities ($\hat{G}_{it}$) that enter in equation [6] as instruments. This procedure allows us to run the equation [6] for the R&D-performing firms only and is suitable for two main reasons. First of all, the usual standard errors and test statistics are asymptotically valid and, secondly, no particular specification of the probit model has to be set up (this depends on the use of variable $\hat{G}_{it}$ as an instrument)[13] (Wooldridge, 2002).

5. Results

In estimating the translog production function, we consider several proxies of R&D spillovers which have been calculated using the weighting systems presented above (equations 1-4). We expect that the manner of weighting the flow of innovation matters in determining the impact of R&D spillovers on the firm's output. The estimated parameters of a translog are not interpretable from a theoretical point of view[14] and, hence, we will only report the implied output elasticities with respect to each input.

[12] Because IMM surveys report the number of employees' by years of schooling (primary school, high school and university) for the last year of each survey (that is 2000 and 2003) only, we assume that the proportion of employees' by years of schooling is constant over the periods 1998-2000 and 2001-2003. Human capital is computed by $\exp(\varphi_R Sh)$ where Sh is the average number of years of schooling (8 for primary and middle school, 13 for high school and 18 for bachelor degree) and φ_R is the regional rate of returns on education drawn from Ciccone (2004). The cash flow variable is computed as gross profits minus taxes plus depreciation. The ICT variable is the sum of hardware, software and telecommunication investments. Finally, the IMM surveys report information on exports only for the last year of each survey, that is 2000 and 2003. Thus, we assume that this dummy is constant over each three-year period.

[13] Indicating with w the treatment indicator, which is equal to 1 if there is treatment and 0 otherwise, and with $G(x, z, \gamma^*)$ the probit specification, "what we need is that the linear projection of w onto $[x, G(x, z, \gamma^*)]$ actually depends on $G(x, z, \gamma^*)$, where we use γ^* to denote the plim of the maximum likelihood estimator when the model is misspecified […] These requirements are fairly weak when z is partially correlated with w" (Wooldridge 2002, p. 624).

[14] It is necessary to note that the majority of the interactive terms and the squared variables of the translog are significant. Hence, if we used a Cobb-Douglas production function we would introduce

The econometric results for the full sample of firms are summarized in table 4. In column 1, we present the findings obtained when a firm's R&D spillovers are measured by the unweighted sum of the external technological capital. Column 2 refers to the outcomes that we obtain using the symmetric index of technological similarity (see equation 1). The successive columns of output elasticities (3, 4 and 5) are those that are obtained using the other weighing systems (the asymmetric index of technological similarity, the index of geographical proximity and their average, respectively).

The first interesting outcome is that all the output elasticities are positive and highly significant. As for the conventional inputs (physical capital and labour), it emerges that the output elasticities ranges from 0,23 to 0,37 in the case of the labour, while the coefficient associated with physical capital is always about 0,19, except when we use the asymmetric index of technological proximity (0,8). Similar results are obtained for the internal stock of R&D capital: output elasticity is 0,11, except for column 3 (0,029). The magnitude of the impact of R&D spillovers on the level of firm production is high: elasticity is roughly 0,34, but it is as high as 0,65 when the flow of innovation is weighted through the pure asymmetric index of technological similarity (column 3, table 4)[15]. To sum up, these outcomes confirm our hypothesis that elasticities vary according to the procedure used to weight technology flows.

Table 3 reports the estimated elasticities which one obtains sub-aggregating the firms according to their location. Although the results are analogous to those obtained for the entire sample of firms, some peculiarities emerge. To weight the diffusion of knowledge through the asymmetric index of technological similarity gives the lowest output elasticities with respect to the labour, physical and technological capital inputs, while the elasticity of spillovers is very high (about 0,65).

The outcomes change when we consider geographical proximity. For example, we observe that in every sub-area we consider, the choice to weight the flow of technology by combining technological and geographical proximity (table 5, columns 7-9) yields results which are substantially different from those obtained using the other weighting schemes. Furthermore, the input elasticity vary from one area to another.

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a bias in the estimations due to the omission of relevant variables. Estimated coefficients are not reported but are available from the authors on request.

[15] A high spillover elasticity, about 0,60, is also obtained by Cincera (2005) and Los and Verspagen (2000). The sample analyzed by Cincera (2005) is composed of large firms and the period he considers is 1987-1994. Los and Verspagen (2000) use a panel of USA manufacturing firms from 1977 to 1991. In both papers the weighting system is the uncentered correlation calculated considering patent data and the production function is the Cobb-Douglas.

In fact, with regards the sample of firms operating in the Centre and in the South of Italy we note that the elasticities of labour (0.32) and technological capital (0.08) are lower that those obtained in the other areas of the country, while the elasticity of physical capital (0.19) is slightly higher. Moreover, our findings clearly show that the level of firm output is strongly dependent on the technology that firms absorb from other firms (the elasticity of spillovers is always high). This is found to be particularly true in the Centre-South of Italy, where the elasticity of technological spillovers is 0.40 and, thus, seems to compensate for the low level of internal innovative efforts, whose elasticity is 0.08 (table 5, column 9).

Table 4. Output elasticities for the R&D performing firms.
3SLS estimations (1998-2003).

ITALY										
Output Elasticities	Unweighted Spill. (1)		Symmetric Technol. Spill. (2)		Asymmetric Technol. Spill. (3)		Geograph. Spill. (4)		Asymmetric Technol. & Geograph. Spill. (5)	
L	0.3689	***	0.3751	***	0.2374	***	0.3710	***	0.3535	***
	(.00452)		(.00438)		(.00321)		(.00435)		(.00431)	
K	0.1908	***	0.1930	***	0.0800	***	0.1951	***	0.1846	***
	(.00384)		(.00376)		(.00303)		(.00379)		(.00386)	
CT	0.1168	***	0.1141	***	0.0289	***	0.1162	***	0.1072	***
	(.00263)		(.0025)		(.00141)		(.00253)		(.00253)	
SPILL	0.3235	***	0.3177	***	0.6537	***	0.3177	***	0.3546	***
	(.01025)		(.00989)		(.00692)		(.00988)		(.00988)	
Number of obs.	1537		1537		1537		1537		1537	
F-test	33845.85		73349.39		157521.6		29783.58		70756.98	
Prob > F	0		0		0		0		0	
R-squared	0.84		0.83		0.89		0.84		0.84	

Note: Standard errors reported in brackets. (***) denote statistical significance at the 1% level. The instrumental variables are the one-year lagged values of the endogenous regressors.

Table 5. Output elasticities for Italian manufacturing firms by area. 3SLS estimations (1998-2003).

	Asymmetric Technol. Spill.						Geograph. Spill.						Asymmetric Technol. & Geograph. Spill.					
Output Elasticities	NORTH WEST (1)		NORTH EAST (2)		CENTRE-SOUTH (3)		NORTH WEST (4)		NORTH EAST (5)		CENTRE-SOUTH (6)		NORTH WEST (7)		NORTH EAST 8)		CENTRE-SOUTH (9)	
L	0.2527	***	0.2226	***	0.2112	***	0.4021	***	0.3603	***	0.3396	***	0.3822	***	0.3439	***	0.3214	***
	(.0049)		(.00542)		(.00652)		(.00726)		(.00722)		(.00951)		(.00715)		(.00713)		(.00944)	
K	0.0639	***	0.0771	***	0.0745	***	0.1773	***	0.1845	***	0.2069	***	0.1670	***	0.1784	***	0.1922	***
	(.00355)		(.0054)		(.00701)		(.00504)		(.00614)		(.00927)		(.00513)		(.00628)		(.00941)	
CT	0.0338	***	0.0222	***	0.0156	***	0.1291	***	0.1218	***	0.0917	***	0.1201	***	0.1129	***	0.0819	***
	(.00255)		(.00225)		(.00169)		(.00406)		(.00448)		(.00484)		(.00411)		(.00444)		(.00475)	
SPILL	0.6496	***	0.6781	***	0.6987	***	0.2915	***	0.3334	***	0.3619	***	0.3308	***	0.3648	***	0.4045	***
	(.0101)		(.01142)		(.01392)		(.01566)		(.01636)		(.02265)		(.01563)		(.01634)		(.02267)	
Number of obs.	587		496		366		587		496		366		587		496		366	
F-test	130933.70		38408.84		9719.34		46746.18		11189.94		9048.85		36302.80		10504.68		9503.91	
Prob > F	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	
R-squared	0.89		0.90		0.86		0.84		0.84		0.81		0.83		0.84		0.81	

Note: Standard errors reported in brackets. (***) denote statistical significance at the 1% level. The instrumental variables are the one-year lagged values of the endogenous regressors.

5.1. Elasticities of substitution

The use of the translog production function allows us to evaluate the degree of substitution or complementarity among inputs. This is done considering the technical and the Morishima (1967) elasticities of substitution. Given two inputs (*i* and *j*), the first index (TES) indicates the percentage change in the use of a production factor in response to an exogenous shock from the supply of another input, $TES_{ij} = -\frac{x_j}{x_i} \Big/ \frac{\partial x_j}{\partial x_i} = -\frac{x_j}{x_i}\frac{\partial x_i}{\partial x_j}$. The underlying assumption is that all other inputs are fixed in the short term. In other words, it quantifies how the reduction of 1 per cent of *j* forces a rise in factor *i* in order to maintain the level of production constant in the short term. In the case of the translog production function, it can be shown (Frondel, 2003) that the technical elasticity of substitution can be expressed as follows:

$$TES_{ij} = \frac{\alpha_j + \beta_{jj} \ln x_j + \sum_{k \neq j} \beta_{kj} \ln x_k}{\alpha_i + \beta_{ii} \ln x_i + \sum_{k \neq i} \beta_{ki} \ln x_k} \qquad [11]$$

Eq. [11] indicates that the technical elasticity of substitution between inputs i and j is inversely related to their output elasticities. Thus, the index TES_{ij} is the inverse of TES_{ji}. Both are always positive. The Morishima elasticity of substitution is defined as the percentage change in the ratio of input *i* and input *j* due to the percentage change of the price of input *j*, all other prices being constant:

$$MES_{ij} = \frac{\partial \ln\left(\frac{x_i}{x_j}\right)}{\partial \ln p_j} \qquad [12]$$

If $MES_{ij}>0$ then factors *i* and *j* will be substitutes, whereas if $MES_{ij}<0$ they will be complementary. It should be noted that Morishima elasticity of substitution is not symmetric: two factors, i and j, can be complementary when the changes of p_j are considered, and substitutes when one considers the changes of p_i $\left(MES_{ij} \neq MES_{ji}\right)$. Frondel (2003) show that the Morishima elasticity of substitution derived from a translog is given by:

$$MES_{ij} = \frac{\beta_{ij}}{S_i} - \frac{\beta_{jj}}{S_j} + 1 \qquad [13]$$

where S_i and S_j denote the cost shares of input i and input j, respectively. In table 6, we report the results of the estimated elasticities of substitution obtained by weighting the flow of

technology through the equation [4]. A first outcome to be emphasized is that none of the elasticity of substitution is unity, which is, on the contrary, the value that one assumes when using a Cobb-Douglas production function.

In more detail, if we consider technical elasticities of substitution, it is to be noted that, in the short run, a decrease of 1 per cent in labour implies an increase of 1.9 per cent for physical capital and of 3.3 per cent for R&D capital while technical elasticity of substitution between R&D and physical capital is equal to 1.7. Moreover, with regards the R&D spillover, a 1 per cent decrease in spillover stock implies an increase of about 1 per cent in labour, 1.9 per cent for physical capital and 3.3 per cent for technological capital. If we consider results obtained for sub-samples, there are no relevant differences, except for the Centre and the South of Italy: in these areas a decrease of 1 per cent for spillover stock implies an increase about of 1.3 per cent for labour and of 4.9 per cent for technological capital (Table 6).

Morishima elasticity of substitution indicates that labour and R&D capital and spillovers and R&D capital are complementary. In particular, an increase of 1 per cent in the price of R&D capital implies a decrease of about 2.5 per cent in the labour/R&D capital and R&D spillovers/R&D capital ratios, respectively. A similar outcome emerges for physical and technological capital (-2.3) and R&D capital and spillovers stock (-6.6). Indeed, an increase of 1 per cent in the price of labour and physical capital implies an increase of 2.8 per cent and 1.9 per cent in the ratios of R&D capital to labour and R&D capital to physical capital, respectively. Furthermore, the Morishima elasticities are positive, but less than one for physical capital and labour and for labour and spillover stock. If we split the sample according to geographical areas, we observe that Morishima elasticities in the Centre-Southern are different than those of other areas. Indeed, in the Centre-South of Italy some inputs are more complementary (labour and technological capital, physical and R&D capital, physical capital and spillover stock) or more substitutes (technological capital and labour, R&D and physical capital). Moreover, in this area the R&D capital and the stock of R&D spillovers are strongly complementary (see tab 6).

6. Conclusions

Compared to the existing empirical literature on the role of technological spillovers at firm level, this paper provides two original contributions. The first deals with the functional form to be used in modelling the impact of R&D, whereas the second concerns the use of different measurements of R&D spillovers.

As far as functional form is concerned, we use the translog production function functional form, which is more flexible than the Cobb-Douglas. The results support our choice, because we reject the assumption of a Cobb-Douglas technology. It is worth noticing the literature to which this paper refers never uses the flexible production function and generally omits to test the suitability of the Cobb-Douglas specification.

With regards R&D spillovers, we consider and compare different measures of external technology. This procedure helps us to understand whether the role of R&D spillovers is sensitive to the method used to weight the flows of innovation. To be precise, in order to determine the R&D spillovers stock we use a measure of similarity between firms. It is assumed that the greater the similarity between two firms in terms of size and R&D efforts, the more they will absorb each other's technology. To overcome the problem that the similarity index gives a symmetric weighting scheme, we consider an asymmetric transformation of the uncentered correlation. We also test the hypothesis that the closer two firms are, the more they will mutually benefit from each other's R&D. This is done through a spatial weighting scheme based on the great circle distance between firms. The distance we consider is that between the capital of the province where each firm is located.

In the econometric section we control for selection bias by using the 2-steps IV estimator, where in the first step we model the selection model that leads the firms to invest or not in R&D. In the second step, we estimate the translog production function with the 3SLS method. Data are from Capitalia and refer to a balanced panel data of 1203 manufacturing firms. The period is 1998-2003.

The key result is that the output elasticity with respect to R&D spillovers is always positive and significant. Moreover, we find that different measures of spillovers bring about different effects of inputs on firm output. In fact, we show that the geographical dimension of the technology spillovers is relevant in determining the final result: our regressions that disregard geography in the process of technology diffusion seem to overestimate the role of the external stock of technological capital. In such cases, all the external innovation is weighted through an index of technological similarity, but this approach broadly gauges the firms capacity to absorb technology. Therefore, this paper confirms the hypothesis that absorptive capacity is strongly related to the geographical distance between firms. Finally, from a regional point of view, it emerges that the role of external technology is higher in the Centre and South of Italy than in the North of the country.

Table 6. Technical and Morishima elasticities of substitution by geographic areas.
Asymmetric technological and geographic spillovers (1998-2003).

Technical Elasticities of Substitution

	ITALY		NORTH WEST		NORTH EAST		CENTRE-SOUTH	
L & K	0.522	***	0.437	***	0.519	***	0.598	***
	(.0071)		(.0079)		(.0119)		(.0164)	
K & L	1.915	***	2.286	***	1.925	***	1.674	***
	(.0262)		(.041)		(.0441)		(.04581)	
L & CT	0.303	***	0.314	***	0.328	***	0.255	***
	(.0047)		(.0066)		(.0089)		(.00914)	
CT & L	3.297	***	3.181	***	3.047	***	3.924	***
	(.0515)		(.0669)		(.0831)		(.14077)	
L & Sp	1.003	***	0.865	***	1.061	***	1.262	***
	(.0397)		(.0566)		(.0687)		(.10679)	
Sp & L	0.997	***	1.156	***	0.943	***	0.792	***
	(.0395)		(.0756)		(.0611)		(.06701)	
K & Sp	1.921	***	1.978	***	2.041	***	2.113	***
	(.0918)		(.1526)		(.16)		(.22014)	
Sp & K	0.521	***	0.506	***	0.490	***	0.473	***
	(.0249)		(.039)		(.0384)		(.04932)	
K & CT	0.581	***	0.719	***	0.632	***	0.426	***
	(.0095)		(.0104)		(.0185)		(.01073)	
CT & K	1.722	***	1.391	***	1.583	***	2.345	***
	(.0282)		(.0201)		(.0463)		(.05897)	
CT & Sp	3.307	***	2.752	***	3.232	***	4.954	***
	(.1655)		(.2212)		(.263)		(.55733)	
Sp & CT	0.302	***	0.363	***	0.309	***	0.202	***
	(.0151)		(.0292)		(.0252)		(.02271)	

Morishima Elasticities of Substitution

	ITALY		NORTH WEST		NORTH EAST		CENTRE-SOUTH	
L & K	-0.008		0.365	***	-0.089		-0.513	***
	(.0602)		(.061)		(.1132)		(.1222)	
K & L	0.615	***	0.544	***	0.595	***	0.604	***
	(.07)		(.0856)		(.133)		(.1458)	
L & CT	-2.480	***	-1.857	***	-1.778	**	-6.240	***
	(.3374)		(.3251)		(.71)		(.8735)	
CT & L	2.801	***	0.327		2.960	***	6.698	***
	(.472)		(.5325)		(.9031)		(1.45)	
L & Sp	0.569	***	0.723	***	0.573	***	0.257	***
	(.0315)		(.0489)		(.0547)		(.0809)	
Sp & L	0.655	***	0.712	***	0.654	***	0.468	***
	(.0202)		(.0295)		(.0359)		(.0449)	
K & Sp	-0.186		0.502		-0.293		-1.198	***
	(.1135)		(.152)		(.2149)		(.2898)	
Sp & K	-0.035		0.382	***	-0.113		-0.613	***
	(.0617)		(.065)		(.1158)		(.1374)	
K & CT	-2.349	***	-1.816	***	-1.597	**	-5.903	***
	(.3379)		(.308)		(.7146)		(.8477)	
CT & K	1.905	***	0.692	**	2.219	***	7.735	***
	(.3838)		(.33)		(.7346)		(1.2072)	
CT & Sp	-6.625	***	-1.788	*	-6.473	***	-20.930	***
	(.7916)		(.9463)		(1.5064)		(2.7045)	
Sp & CT	-2.539	***	-1.864	***	-1.836	***	-6.351	***
	(.3403)		(.3307)		(.7142)		(.8803)	

Note: Standard errors reported in brackets. (***), (**) and (*) denote statistical significance at 1%, 5% and 10% level, respectively.

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