R&D, spatial proximity and productivity at firm level: evidence from Italy

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Abstract. The aim of this paper is to evaluate the effect of research and development (R&D) on productivity by taking into account productivity spillovers. To this end, by using a sample of Italian manufacturing firms provided by the Xth UniCredit-Capitalia survey (2008), which covers the period 2004-2006, we have analyzed the role of R&D in firm productivity by using a spatial autoregressive model. In so doing, we have allowed the total factor productivity (TFP) of each firm to be affected by the TFP of nearby firms. Results show that R&D play an important role in Italian firm productivity. Moreover, we find evidence in favor of productivity spillovers across firms due to spatial proximity. In addition, intrasectoral R&D spillovers seem to have a relevant effect on firm productivity, while intersectoral R&D spillovers do not have a significant effect.

Keywords.R&D, TFP, spillovers, spatial econometrics, Italian manufacturing firms

Jel-codes. O33, D24, C21

1. Introduction

An often cited remark by Paul R. Krugman states that “Productivity isn’t everything, but in the long run it is almost everything. A country’s ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker”. Productivity is considered a crucial source of economic growth and competitiveness and understanding how to improve productivity is a key issue for economists and policy makers. It has been largely recognized that one of the most important determinants of productivity is technological progress. Indeed, there is a large consensus among economists regarding the relevance of research and development (R&D) in improving firm productivity and, in recent years, policy efforts have been increased to enhance research and innovation. For example, the EU's Structural Funds for 2007-2013 have given increased attention to research and innovation activities with respect to previous years (European Commission, 2011). In Italy, research and innovation are a relevant issue since it is largely acknowledged that the lack of a bullish economic growth is due to, among other things, the fact that Italian innovative activities lag significantly behind those of the other main European countries, and are still far from achieving the objectives of the Lisbon strategy (Bugamelli et al, 2012).[1]

Several empirical contributions have provided evidence about the positive role of R&D activities at the firm level (e.g., Hall and Mairesse, 1995; Harhoff, 1998; Aiello et al, 2005).[2] However, in order to adequately evaluate the effect of R&D on productivity, productivity spillovers should also be taken into account. Indeed, productivity spillovers could arise because of such factors as face-to-face contacts, intra-firm worker mobility and R&D cooperation between firms (Baltagi et al, 2012).

At the regional level, a number of studies have employed spatial econometric tools in order to take productivity spillovers into account when evaluating the effect of innovative efforts (e.g., Antonelli et al, 2011, Dettori et al, 2012; LeSage and Fischer, 2009). As regards firm-level analyses, Baltagi et al (2012) recently assessed the effect of intangible assets on the productivity of Chinese chemical firms by considering the spatial correlation of the error term across firms. Moreover, Lamieri and Sangalli (2013) evaluated the impact of patents on the total factor productivity (TFP) of Italian manufacturing firms by allowing for spatial dependence in both TFP and error terms across firms. In both contributions, results show that productivity spillovers matter.[3]

The aim of this paper is to contribute to the literature on the R&D-productivity relationship by controlling for the existence of productivity spillovers at the firm level. To be more precise, using a sample of Italian manufacturing firms observed over the period 2004-2006, the aim is to investigate the effect of R&D on TFP by employing a spatial econometric model.

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[1] A number of studies suggest that most of the decline in Italian productivity since 1995, one of the lowest in Europe (Daveri and Jona-Lasinio, 2005), is due to the decline in total factor productivity (e.g., Bassanetti et al., 2004; Daveri and Jona-Lasinio, 2005; Saltari and Travaglino, 2008).

[2] A survey on this topic is provided by Hall et al (2009).

[3] Carboni (2013a and 2013b) recently used spatial econometric techniques to investigate related issues: the importance of geographical and sectoral proximity in promoting R&D investment and R&D collaboration among Italian manufacturing firms.

To this end, and unlike related contributions, we have evaluated whether a spatial Durbin model (SDM)[4] might be more appropriate in analyzing the effect of R&D on productivity. Indeed, SDM is an appropriate point of departure for the choice of the spatial specification to be used (LeSage and Pace, 2009; Elhorst, 2010). In the SDM, both the spatially lagged dependent variable and the spatially lagged independent variables are included in the specification. Following suggestions by Elhorst (2010), tests are carried out to compare the SDM with the spatial autoregressive model (SAR), which only includes the spatially lagged dependent variable, and the spatial error model (SEM), which only considers the spatial correlation in the error term. In addition, we have taken into account the fact that R&D undertaken by a firm could also benefit other firms. Since the effect of the flow of knowledge between firms in the same sector may differ from that between firms of different sectors, we have distinguished between the impact of intrasectoral and intersectoral R&D spillovers. This allows to evaluate whether the Marshall (1890)-Arrow (1962)-Romer (1986) (MAR) and Jacobs (1969) externalities are relevant for Italian manufacturing firms. Indeed, according to the MAR model, knowledge spillovers between firms are mainly due to sector concentration in a given region. On the other hand, according to the Jacobs model, the variety of geographically proximate industries primarily stimulates knowledge externalities.

Results show that the SAR specification, in which the productivity of each firm is affected by the productivity of nearby firms, should be the preferred model. Moreover, R&D seem to play an important role in Italian firm productivity. We also find evidence in support of productivity spillovers across firms due to spatial proximity. This, in turn, determines an indirect effect of R&D on firm productivity because of the effect of a firm's R&D on productivity of all nearby firms. Results also show that firm TFP is positively affected by R&D spillovers due to knowledge flows across firms within the same sector, i.e. intrasectoral spillovers, while there is no significant effect of intersectoral spillovers, i.e. due to knowledge flows across firms in different sectors.

The paper is organized as follows. In the second section, the model specification and a brief description of data used in the empirical analysis are presented. In the third section, the estimation method is illustrated. Results are discussed in the fourth section. In the fifth section, the analysis is extended to take into account intrasectoral and intersectoral spillovers. Finally, the sixth section concludes.

[4] Autant-Bernard and LeSage (2011), who estimated a knowledge production function for French industries and regions over the period from 1992 to 2000, started with a non-spatial model and showed that the presence of unmeasurable or unobserved regional inputs to the knowledge production process leads to a specification that includes a spatial lag of both the dependent and the independent variables, that is an SDM.

2. Model specification and data description

In order to address the effect of R&D on productivity, we first compute the total factor productivity by considering a log-linear specification of a Cobb-Douglas production function with constant returns to scale,[5] that is:

$$\ln\frac{Y_i}{L_i} = \alpha_0 + \alpha_1 \ln\frac{K_i}{L_i} + \varepsilon_i \qquad [1]$$

where i=1,..,N indicates the firm, Y is the 2006 value added, K is the physical capital proxied by 2006 tangible fixed assets, L represents the number of employees in 2006. The likely endogeneity[6] of physical capital per employee is taken into account by considering its lagged value as instrumental variable (Marrocu et al, 2013).[7]

Once we obtain an estimate of α_1, we then compute TFP as:

$$TFP_i = exp(lnY_i - (1-\hat{\alpha}_1)lnl_i - \hat{\alpha}_1 lnk_i) \qquad [2]$$

TFP is then related to R&D intensity and firm specific control variables. To be more precise, we consider the following specification:

$$\begin{aligned}\ln TFP_i = {} & \beta_0 + \beta_1 RD_i + \beta_2 \ln LC_i + \beta_3 group_i + \beta_4 exp_i + \beta_5 small_i + \beta_6 pav2_i + \\ & \beta_7 pav3_i + \beta_8 pav4_i + u_i\end{aligned} \qquad [3]$$

where *RD* is the average 2004-2006 R&D investment per employee, *LC* indicates the 2005 cost of labor per employee as a proxy of labor quality,[8] *group* is equal to one if the firm belongs to a group of enterprises and zero otherwise; *exp* and *small* are dummy variables equal to one if the firm exported in 2006 and has fewer than 50 employees, respectively;

[5]A production function was estimated without any assumption regarding returns to scale and the hypothesis of constant returns to scale was tested. Results indicated that we cannot reject this hypothesis.
[6]Endogeneity was tested by using both Wu-Hausman F test and Durbin-Wu-Hausman chi-squared test. Results indicated that we cannot reject this hypothesis.
[7]The value added has been deflated by using the Italian National Institute of Statistics (Istat) production price index which is available for each sector according to the Ateco (Italian edition of Nace) classification of economic activities. For the tangible fixed assets, values have been deflated by using the average production price indices of the following sectors: machines and mechanical appliances, electrical machines and electrical equipment, electronics and optics and means of transport. The source of the sectoral indices is Istat.
[8]Cost of labor per employee should be correlated with skill intensity if more skilled workers receive higher wages. R&D investments and labour costs are deflated by considering the producer price index for industrial products and consumer price index for families of workers and office workers from Istat, respectively.

pav2, *pav3* and *pav4* are dummies which are equal to one if the firm is in the scale intensive, specialized suppliers or science based sectors, respectively, according to the Pavitt (1984) taxonomy, and zero otherwise; finally, *u* indicates the error term.

Our firm-level data come from the Xth UniCredit-Capitalia survey (2008), which covers the 2004-2006 period and is compiled on the basis of information collected by means of a questionnaire sent to a sample of Italian manufacturing firms.[9] The survey is complemented with balance sheet data. Information about the sample used in this paper is reported in Table 1. On average, small firms have a higher TFP and R&D investment per employee than the medium-large firms in the sample. Moreover, firms in the science based and specialized suppliers sectors register higher values of both R&D and TFP. As regards the other sub-samples, R&D and TFP do not have the same pattern. To be more precise, TFP is higher for exporting firms and firms in a group while R&D investment per employee is greater for non-exporting firms and firms which are not part of a group.

The main descriptive statistics of the variables in eq. [3] are provided in table A.2 of the Appendix.

[9]The survey design includes all firms with a minimum of 500 employees. A sample of firms with between 11 to 500 employees is selected according to a three-dimension stratification: geographical area, Pavitt sector and firm size. Although the survey covers the 2004-2006 period, some parts of the questionnaire refer to 2006 only. The original sample was cleaned of potential outliers by eliminating the firms for which values below the first percentile and over the 99th percentile of valued added, employees and gross fixed assets were observed in 2006.

Table 1 – R&D and TFP in Italian manufacturing firms (data in value expressed in constant thousands of Euro).

	Number of Observations	R&D investment per employee (average 2004-2006)	TFP (2006)
ALL	3538	2.622	3.681
Medium-large (more than 50 employees)	1107	2.071	3.469
Small (less than 50 employees)	2431	2.873	3.778
Non-exporters	1303	2.655	3.423
Exporters	2235	2.603	3.831
Non belonging to a group	2884	2.639	3.549
Belonging to a group	654	2.550	4.262
Supplier dominated sector	1751	2.554	3.22
Scale intensive sector	683	2.441	3.959
Specialized suppliers sector	949	2.762	4.051
Science based sector	155	3.342	5.401

Source: author elaborations on data from UniCredit-Capitalia (2008)

3. Estimation method

Several studies have evaluated the contribution of R&D to firm productivity (see, among others, Hall and Mairesse, 1995, Harhoff, 1998, Aiello et al, 2005; a survey is provided by Hall et al, 2009). However, in order to analyze the effect of innovative efforts on productivity properly, spillovers enhanced by spatial proximity should be taken into account (Baltagi et al, 2012; Lamieri and Sangalli, 2013). To this end, a spatial approach may be considered. Indeed, since the outcome for a firm in location *l* could be affected by those of other firms located nearby, we may include a spatial lag of the dependent variable in eq.[3], hence estimating the following spatial autoregressive (SAR) or spatial lag model:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad [4]$$

where **y** indicates the vector of the dependent variable, which is the log of firm TFP in our case, **X** is a matrix standing for all the regressors included in eq. [3] (it also includes the intercept for simplicity), **β** is the vector of the coefficients and **u** is the vector of the error term. **W** is a spatial weighting matrix based on the distances between the home municipalities of each firm-pair; the coefficient ρ is referred to as the spatial autoregressive coefficient.

Moreover, a random shock to a firm in a specific location *l*, i.e. a shock in the error *u* of a firm at a location *l*, could be transmitted to other firms located nearby. In this case, a spatial error model (SEM) could be used in order to control for the likely spatial interaction among units:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{u},\ \mathbf{u}=\lambda\mathbf{Wu}+\boldsymbol{\varepsilon} \qquad [5]$$

where $\boldsymbol{\varepsilon}$ is the error term with the usual properties and λ is the spatial autocorrelation coefficient.

We also verify whether the spatial Durbin model (SDM), which includes spatial lags of both the dependent and independent variables, is more adequate. Indeed, SDM is an appropriate point of departure for the choice of the spatial specification (LeSage and Pace, 2009; Elhorst, 2010). This is because the cost of ignoring spatial dependence in the dependent and independent variables is relatively high with respect to ignoring spatial dependence in the disturbances. Moreover, SDM also produces unbiased estimates if the true-generated process is a SEM, a SDM, a SAR or a spatial autoregressive model with autoregressive disturbances (SAC).

A number of papers point out the nexus between spatial agglomeration and knowledge spillovers (Aldieri and Cincera, 2009; Arrow,1962; Audretsch and Feldman, 2004; Bottazzi and Peri, 2003; Koo, 2005; Orlando, 2000; Romer, 1986). For this reason, the computation of **W** is based on a distance matrix. To this end, the latitude and longitude coordinates of the town where each firm is located, provided by the Italian National Agency for New Technology, Energy and the Environment-ENEA, are used.[10] In more detail, by using h_{qs} to denote the haversine distance[11] between the municipalities *q* and *s*, in which firms *i* and *j* are located, respectively, we have computed the distance matrix **D** in which each element is given by:

$$d_{qs} = \frac{1}{1+h_{qs}} \qquad [6]$$

[10] http://clisun.casaccia.enea.it/Pagine/Comuni.htm (last accessed: January 2014). Data regarding the two towns "Due Carrare" and "Mosso Santa Maria", which were not available in the ENEA dataset, are taken from http://www.tuttitalia.it/veneto/87-due-carrare/ and http://www.tuttitalia.it/piemonte/24-mosso/ , respectively (last accessed: January 2014).

[11] We used the *spmat* (version 1.0.1) command provided by Drukker *et al* (2011) for the STATA software to compute the haversine distance matrix, and the *spatdiag* command provided by Pisati (2001) for LM and robust LM tests on spatial dependence. For the estimations, we employed the R *spdep* (version 0.5-34) package.

W is obtained by row-standardizing the matrix **D**.[12]

In models which include a spatial lag of the dependent variable, the interpretation of parameters needs some caution. Indeed, we cannot interpret parameter estimates as we would in non-spatial linear regressions, but rather impacts should be calculated. To be more precise, we may compute the average direct, indirect and total effects. The direct effect measures the impact of changes in the i-th observation of the r-th regressor, that is X_{ir}, on y_i, while the effect of X_{jr}, on y_i gives the indirect effect (LeSage and Pace, 2009). In fact, since in the model we take into account the spatial dependence among units in the dependent variable, a change in an explanatory variable may affect the dependent variable in other observations. Consider the spatial autoregressive model of eq.[4], which can be written as follows:

$$(\mathbf{I}-\rho\mathbf{W})\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad [7]$$

that is:

$$\mathbf{y} = \sum_{r=1}^{k} S_r(\boldsymbol{W})\boldsymbol{X}_r + (\mathbf{I}-\rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \qquad [8]$$

with $S_r(\boldsymbol{W}) = (\mathbf{I}-\rho\mathbf{W})^{-1}\mathbf{I}\beta_r$ [9]

The derivatives of y_i with respect to X_{ir} and X_{jr} are given, respectively, by:

$$\frac{\partial y_i}{\partial X_{ir}} = S_r(\boldsymbol{W})_{ii} \text{ and } \frac{\partial y_i}{\partial X_{jr}} = S_r(\boldsymbol{W})_{ij} \qquad [10]$$

The average direct impact of the r-th regressor could be summarized by the average of all $S_r(\boldsymbol{W})_{ii}$. The average total impact is the average of all derivatives of y_i with respect to X_{jr}, for any *i,j* (LeSage and Pace, 2009). It is worth mentioning that LeSage and Pace (2009) distinguish between "the average total impact to an observation" and "the average total impact from an observation". "The average total impact to an observation" is the average of the *n* sums across each row of $S_r(\boldsymbol{W})$, and each sum measures how changes in all firms affect a single firm *i*. "The average total impact from an observation" is the average of the *n* sums down each column of $S_r(\boldsymbol{W})$, and each sum measures how changes in a single firm *j* affect all firms. Even though the interpretative viewpoints are different, the values of the two average measures are numerical equal (LeSage and Pace, 2009).[13] The average indirect effect is the difference between the average total impact and the average direct impact (LeSage and Pace, 2009).

[12]With row-standardization, the rows sum to one. This transformation is used in the related firm-level literature, Baltagi et al (2012), Carboni (2013a and 2013b) and Lamieri and Sangalli (2013), and allows the spatial variable to be the weighted average of neighboring values.
[13] The average total impact for a spatial lag model with a row-standardized weighting matrix takes the simple form of $(1-\rho)^{-1}\beta_r$ (LeSage and Pace, 2009).

4. Results

Equation [3] is firstly estimated through OLS. In line with previous contributions, results, reported in table 2, show that labor quality, proxied by the cost of labor per employee, fosters TFP (Aiello et al, 2014; Ciccone, 2004). In addition, exporting firms have, *ceteris paribus*, higher TFP (see, among many others, ISGEP, 2008; Serti and Tomasi, 2008; Aiello et al, 2014).

In line with the descriptive results presented in table 1, we find that small firms and those in more intensive technology sectors, i.e. the specialized and science based ones, have higher TFP. In addition, firms which are part of a group seem to be more efficient, probably because these firms are likely to share financial, technological and marketing resources.

It is worth mentioning that we included in the specification [3] also a dummy which is equal to one if a firm is family-owned, since it is likely that family firms are less efficient (Cucculelli et al, 2014). However, in our case the coefficient was not significant.

Moreover, from table 2 it emerges that R&D investment has a positive and strongly significant effect on TFP. This is in line with other studies evaluating the effect of R&D on Italian firm productivity (e.g., Aiello and Pupo, 2004; Matteucci and Sterlacchini, 2009; Medda et al, 2005). On the contrary, the spatial lag of R&D, included as additional regressor in specification [3], does not have a significant coefficient (column 2 of table 2). This seems to suggest absence of geographical spillovers contrary to many previous works (among the others, Orlando, 2000; Adams and Jaffe, 1996; Aiello and Cardamone, 2012). However, it would seem more appropriate to evaluate the role of R&D on the basis of spatial econometric techniques (Autant-Bernard and LeSage, 2011; Autant-Bernard 2012). To this end, we have carried out a Lagrange multiplier (LM) test and a robust Lagrange multiplier (RLM) test for both the spatial error model (eq. [5]) and the spatial autoregressive model (eq. [4]). The LM-error and RLM-error test for the presence of spatial error dependence, while LM-lag and RLM-lag verify spatial lag dependence in TFP.[14] LM tests on specification [3], reported in table 3, show that we cannot reject both the hypotheses of the spatial autoregressive and spatial error models, but, if we consider the RLM tests, we find that the test p-value is lower in the case of the spatial lag model, which therefore appears to be more

[14]The RLM-error and RLM-lag are indicated as robust because they take into account the potential presence of a spatial lag when testing for the presence of spatially correlated errors or, vice versa, spatially correlated errors when testing for a spatial lag (Anselin et al, 1996).

appropriate. This result is also in line with the theoretical claim that productivity in a region depends on productivity in nearby regions and this dependence does not simply relate to unmeasured variables, but to an underlying spatial correlation of all variables (Caragliu and Nijkamp, 2012).

Table 2. The effect of R&D on TFP in Italian manufacturing firms, OLS estimates.

	(1)	(2)
RD	0.0049***	0.0049***
	(0.0015)	(0.0015)
lnLC	0.5827***	0.5827***
	(0.0282)	(0.0282)
small	0.0778***	0.0778***
	(0.0178)	(0.0178)
exp	0.0748***	0.0748***
	(0.0174)	(0.0175)
group	0.0703***	0.0703***
	(0.0241)	(0.0241)
pav2	0.0202	0.0202
	(0.0227)	(0.0226)
pav3	0.1500***	0.1500***
	(0.0190)	(0.0190)
pav4	0.2549***	0.2548***
	(0.0417)	(0.0417)
W*RD		0.0001
		(0.0085)
Constant	4.5045***	4.5041***
	(0.1555)	(0.1562)
Observations	3,538	3,538
R-squared	0.459	0.459
Adj. R-squared	0.458	0.457
F-statistics	111.1	98.80

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3 – Spatial dependence tests

Lagrange multiplier-SEM	45.058 (.)
Robust Lagrange multiplier-SEM	3.241 (.072)
Lagrange multiplier-SAR	72.509 (.)
Robust Lagrange multiplier-SAR	30.693 (.)

Note: p-value in parentheses.

As suggested by Elhorst (2010), we carry out likelihood ratio (LR) tests to compare the spatial Durbin model with the spatial autoregressive model and the spatial error model. Test results, reported in the bottom of table 4, show that we cannot reject the hypothesis that the SAR describes the data better than the SDM, while, on the contrary, we can reject the hypothesis that the SEM describes the data better than the SDM. Hence, we focus on the SAR as the model to be preferred.[15] Lamieri and Sangalli (2013) adopted both the SAR and the SAC model, but , they indicated the SAC as the model to be preferred. The spatial model adopted here is also different from that adopted by Baltagi et al (2012), who considered a panel model with spatially correlated disturbances.

Results for the *rho* coefficient, reported in table 4, show a positive spatial dependence in TFP among firms.[16] As discussed in section 3, we need to compute impacts in order to interpret results. Table 5 reports the direct, indirect and total impacts of the explanatory variables of main interest.

Direct effects vary only slightly from those obtained in OLS estimates. However, it is now possible to identify a spillover effect due to the fact that each variable impacts on a firm's productivity and this affects the productivity of nearby firms because of spatial TFP dependence among observations. Indeed, results show that an increase of one percent in the other firms' labor cost determines an increase of a firm's TFP of about 0.6 percent; this indirect effect should be added to the direct effect due to the increase of the firm's indicator of its own labor quality. As regards the specific aim of this paper, we find that the indirect effect of R&D is significant and slightly higher than the direct effect. While a unitary increase in a firm's own R&D expenditure per employee will determine an average increase in its TFP of about 0.5 percent, the average total effect of a unitary increase in firm R&D per employee, given by the sum of direct and indirect effects, will determine an increase in TFP of about 1 percent. Hence, if productivity spillovers are not considered, the effect of R&D is likely to be largely underestimated because their indirect effects are disregarded.

[15] We have also tested whether a specification of [3] with the inclusion of the spatial lag of the R&D indicator is appropriate, but the LR test rejects this hypothesis.

[16] We have estimated the model by using the maximum likelihood estimator. The spatial two stage least squares (STSLS) do not yield substantially different results (see table A.3 of the appendix).

Table 4. The effect of R&D on TFP in Italian manufacturing firms, spatial lag model, LM estimates.

RD	0.0050	(.0007)	***
lnLC	0.5739	(.0118)	***
small	0.0747	(.0186)	***
exp	0.0655	(.0174)	***
group	0.0737	(.0218)	***
pav2	0.0098	(.0217)	
pav3	0.1354	(.0195)	***
pav4	0.2338	(.0401)	***
Constant	0.4613	(.6361)	
Rho:	0.5128	(.0804)	***
Log likelihood:	-2388.24		
Obs.	3538		
LM test for residual autocorrelation			
test value:	0.40595		
p-value	0.52403		
LR test SLM vs SDM			
Test value:	12.3662		
p-value:	0.1356		
LR test SEM vs SDM			
Test value:	24.6869		
p-value:	0.001756		

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5. The effect of R&D and labor cost on TFP in Italian manufacturing firms, spatial lag model, average impacts.

	Direct			Indirect			Total		
RD	0.0050	[6.982]	***	0.0053	[2.626]	***	0.0103	[4.255]	***
lnLC	0.5748	[48.561]	***	0.6032	[2.916]	***	1.1780	[5.561]	***

Note: simulated z-values in brackets; *** p<0.01, ** p<0.05, * p<0.1

5. Intrasectoral and intersectoral R&D spillovers

Certain studies have highlighted the importance of spillovers among firms, both in the same industry and in different industries (Scherer, 1982; Bernstein, 1988; Wolff and Nadiri, 1993; Aiello et al, 2005, Aiello and Cardamone, 2005; Carboni, 2013a; Medda and Piga, 2013). According to the relevant literature, these spillovers may be related to the trade in intermediate goods among sectors. Following these authors, we estimate model [3] with the addition of intrasectoral (*intraRD*) and intersectoral (*extraRD*) spillovers, computed as a weighted sum of the R&D of other firms in the same sector and of firms in other sectors, respectively; weights are determined by the share of intermediate goods and services used in each manufacturing industry. To this end, the 2003 use-table at NACE-2 digit level provided by ISTAT is used. Moreover, just as for geographical weights, these weights are also row-standardized. In more detail, intrasectoral and intersectoral spillovers for firm *i* in sector *k* are computed as follows:

$$intraRD_i^k = \sum_{i \neq j} \left(\upsilon_{jkk} RD_{jk} \right) \qquad [11]$$

$$extraRD_i^k = \sum_{\substack{i \neq j \\ k \neq l}} \left(\upsilon_{jkl} RD_{jl} \right) \qquad [12]$$

where RD is the R&D indicator defined in the previous section and υ is the weight based on the share of intermediate goods and services in the same sector *k* in the case of [11], and between sector *k* and *l* for [12].

Hence, model [3] becomes:

$$\begin{aligned} \ln TFP_i = \beta_0 + \beta_1 RD_i + \beta_2 \ln LC_i + \beta_3 group_i + \beta_4 exp_i + \beta_5 small_i + \beta_6 pav2_i + \\ \beta_7 pav3_i + \beta_8 pav4_i + \beta_9 intraRD_i^k + \beta_{10} extraRD_i^k + u_i \end{aligned} \qquad [13]$$

Table 6 reports OLS and spatial lag model estimation results of equation [13], while direct, indirect and total effects for the spatial lag model are reported in table 7. Estimates regarding variables which are included in both equations [3] and [13] do not substantially differ. In addition, the *rho* coefficient in the spatial lag model estimation is similar to that obtained when intrasectoral and intersectoral R&D spillovers are not taken into account. As a result, the direct and indirect effects are not substantially different from those obtained in the model without intrasectoral and intersectoral spillovers. This means that the inclusion of intrasectoral and intersectoral knowledge flow indicators does not affect the TFP spillover effect due to spatial proximity. Moreover, results show that only knowledge flows among firms in the same sector is relevant for firm productivity, as intersectoral R&D spillovers do not have a significant effect. This result suggests evidence in support of MAR externalities, that is that firms located nearby benefit from R&D produced in the same sector, while there is no evidence in favor of Jacobs externalities, due to knowledge flows between firms in different sectors. Results in the literature are not univocal. As regards Italian manufacturing firms, Aiello and Cardamone (2005) found that both intrasectoral and intersectoral R&D spillovers significantly affect the rate of growth of labor productivity, Medda and Piga (2014) obtained that firms seem to benefit from both the knowledge spillovers generated in their own industries and the knowledge embodied in the products purchased from suppliers, while Aiello and Pupo (2004) and Aiello et al (2005) found an outcome similar to that obtained here, i.e. only intrasectoral R&D spillovers exhibit a significant impact on firm productivity. Our results are in line with those obtained by de Lucio et al (2002) and Wixe (2014), who found evidence in favor of MAR externalities and did not find evidence about the presence of Jacobs externalities for Spanish industries and Swedish manufacturing plants, respectively.

Hence, our outcome suggests that Italian firms seem to be able to benefit from sectoral knowledge flows while they are not capable of taking advantage of knowledge from other sectors. This result could be explained by the fact that firms in the same industry are also technologically similar and this may facilitate the flow and absorption of knowledge among them. Therefore, both spatial agglomeration and sectoral specialization seem to be beneficial for Italian firm productivity.

Table 6. The effect of R&D and R&D spillovers on TFP in Italian manufacturing firms, spatial lag model.

	OLS§			LM		
RD	0.0049	(0.0015)	***	0.0050	(.0007)	***
lnLC	0.5840	(0.0280)	***	0.5752	(.0118)	***
small	0.0805	(0.0178)	***	0.0774	(.0185)	***
exp	0.0695	(0.0174)	***	0.0600	(.0174)	***
group	0.0663	(0.0239)	***	0.0697	(.0217)	***
pav2	0.0231	(0.0230)		0.0119	(.0223)	
pav3	0.1575	(0.0197)	***	0.1420	(.0203)	***
pav4	0.2218	(0.0438)	***	0.1989	(.0411)	***
IntraRD	0.0362	(0.0101)	***	0.0371	(.0082)	***
ExtraRD	0.0093	(0.0144)		0.0072	(.0148)	
Constant	4.3782	(0.1648)	***	0.2937	(.632)	
Rho				0.51847	0.07973	***
R-squared	0.462					
Adj. R-squared	0.460					
Observations	3,538			3,538		
F	90.23					
Log likelihood:				-2377.812		
LM test for residual autocorrelation						
test value:				0.4795		
p-value				0.48865		

Note: standard errors (§ robust standard errors) in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7. The effect of R&D, labor cost and R&D spillovers on TFP in Italian manufacturing firms, spatial lag model, average impacts.

	Direct			Indirect			Total		
RD	0.0050	[6.889]	***	0.0054	[2.682]	***	0.0104	[4.301]	***
lnLC	0.5761	[48.669]	***	0.6185	[2.94]	***	1.1946	[5.546]	***
IntraRD	0.0372	[4.514]	***	0.0399	[2.407]	**	0.0771	[3.444]	***
ExtraRD	0.0072	[.497]		0.0077	[.46]		0.0149	[.484]	

Note: simulated z-values in brackets; *** p<0.01, ** p<0.05, * p<0.1

6. Concluding remarks

The aim of this paper is to evaluate the effect of R&D on the productivity of Italian manufacturing firms by employing a spatial econometric model in which TFP spillovers across firms are taken into account. To this end, by using a sample of firms from the Xth UniCredit-Capitalia survey (2008), which covers the 2004-2006 period, we have first estimated TFP and then assessed the role of R&D and R&D spillovers in firm TFP. Results show that R&D play an important role in Italian firm productivity. Moreover, we find evidence of productivity spillovers across firms due to spatial proximity. This, in turn, also determines an indirect effect of R&D to firm productivity, because the R&D effect on each firm productivity then spills over to other nearby firms.

Results also show that firm TFP is positively affected by the R&D spillovers due to knowledge flows across firms in the same sector, while there is no significant effect of intersectoral spillovers due to knowledge flows across firms in different sectors. What is more, the indirect effect of intrasectoral R&D spillovers, which is due to productivity spillovers, is positive and significant. Hence, results seem to provide support for MAR externalities while there is no evidence of Jacobs externalities. This result could be explained by the fact that firms in the same sector are also technologically similar and, hence, firms may have a greater capacity for absorbing knowledge from the same industry.

To sum up, our results show that R&D investment has a threefold effect. First, there is a significant direct effect of a firm's own R&D investments on its productivity. A second effect is due to the intrasectoral spillovers: knowledge generated by a firm's R&D efforts spills over to firms in the same sector, hence determining a further improvement in firms' productivity. A third effect, which has so far been disregarded in the analysis assessing the effect of R&D on productivity at micro-level, is brought about by the productivity spillovers: R&D increase firm productivity and this, in turn, brings benefits to nearby firms increasing their productivity. In addition, the analysis also shows that sector specialization in a spatial context has a positive effect on firm productivity because it facilitates both R&D and productivity spillovers. Hence, policy measures addressing both increasing firm innovative activities and sectoral specialization and agglomeration seem to be helpful in promoting economic growth.

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Appendix

Table A.1: Cobb-Douglas production function, instrumental variable estimates. Dependent variable: 2006 valued added per employee.

ln(K/L)	0.2706***
	(0.0137)
Constant	7.9677***
	(0.1643)
Observations	3,538
R-squared	0.193
Wu-Hausman F test	60.80
P-value	*0.000*
Durbin-Wu-Hausman chi-sq test	59.83
P-value	*0.000*

Note: Clustered standard errors at regional level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnTFP	3538	7.967702	0.6497425	2.4273	12.05945
RD	3538	2.622471	11.16087	0	427.3504
lnLC	3538	5.631583	0.7000281	-1.6508	11.03293
small	3538	0.687111	0.463735	0	1
exp	3538	0.631713	0.482408	0	1
group	3538	0.18485	0.3882309	0	1
pav2	3538	0.193047	0.3947453	0	1
pav3	3538	0.268231	0.443101	0	1
pav4	3538	0.04381	0.2047012	0	1

Source: author elaborations on data from Uncredit-Capitalia (2008)

Table A.3: The effect of R&D on TFP in Italian manufacturing firms, spatial lag model, STSLS estimates.

RD	0.0051	(.0015)	***
lnLC	0.5724	(.0281)	***
small	0.0742	(.0176)	***
exp	0.0638	(.0174)	***
group	0.0743	(.0239)	***
pav2	0.0080	(.0222)	
pav3	0.1329	(.0191)	***
pav4	0.2302	(.0415)	***
Constant	-0.2337	(.8271)	
rho	0.6009	(.1106)	***

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1