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# **Knowledge Spillovers and Productivity in Italian manufacturing firms.**

by

**Luigi Aldieri**<sup>♦</sup>

## **Abstract**

In this paper we analyze the relationship between R&D spillovers and productivity. To this aim, we use data from 9<sup>th</sup> and 10<sup>th</sup> “Indagine sulle imprese manifatturiere” (IMM) surveys carried out by Capitalia. These two surveys, which cover the period 2001-2006, contain both quantitative and qualitative information on a large sample of Italian firms. The main contribution of this paper is to stress the importance of replacing the traditional high-tech/low-tech industries with a classification more suitable to capture the nature of new technologies. Indeed, the industry data are summarised in a particular taxonomy, according to Pavitt methodology: Supplier dominated, Scale intensive, Specialized suppliers and Science based. This taxonomy accounts for differences in the knowledge intensity and innovative activities within sectors. The estimation method takes into account the endogeneity of regressors and simultaneity issue regarding firms’ decision to invest in R&D. The results provide evidence of higher productivity in R&D intensive industries and this can be interpreted as the signal of the relevance of spillover effects.

**Keywords:** Industry taxonomies, R&D, Productivity, Spillovers.

**JEL Classification:** C23, D24, D62, O3.

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## 1.Introduction.

This paper investigates the impact of Research and Development (R&D) spillovers on firms' productivity performance using a large sample of manufacturing companies in Italy. Indeed, it is widely recognised that R&D capital stock affects both the productivity performance of the company that undertakes such activities and also the performance of other firms, through the spillover effect. According to Jaffe (1986), the idea is that the research effort of other firms may allow a given firm to achieve productivity with less research effort. The literature on R&D and productivity is very rich and collects both macro and micro evidence (Aldieri, 2011a). Empirical research confirms the presence of R&D spillovers, but the sign of the effect is not unique. Even though many studies find the impact of R&D spillovers to be positive and significant (Bernstein, 1988; Brandstetter, 1996; Raut, 1995), other studies find that spillover effects are not relevant or even negative (Antonelli, 1994; Gerosky, 1991; Wakelin, 2001). In particular, R&D externalities may be associated with competitive pressures which will translate into negative effects on firms' performance (Kafouros and Buckley, 2008). As far as the way how the spillover stock can be constructed is concerned, there are different methodologies in the literature. Technological proximity as form of spillover has been introduced by Jaffe (1986), who considers a technological distance based on data for technology-based patent classes for the US. Goto and Suzuki (1989) use a similar measure based on R&D data for the electronics industry and explore the spillovers from this industry to the rest of the manufacturing sector. Geographical proximity is applied to show that UK firms locating their R&D activity in the US have higher spillover effects compared to firms that perform R&D in the UK (Griffith, Harrison and Van Reenen, 2006). Orlando (2004) investigates the two types of technology and geography R&D externalities in a unified framework. Also Aldieri and Cincera (2009) implement an empirical investigation to gauge the extent to which R&D spillover effects are intensified by both geographic and technological proximities between spillover generating and receiving firms, but they also control for the firm's ability to identify, assimilate and absorb the external knowledge stock (absorptive capacity) in a unified framework. Following this line of research, Lychagin, Pinkse, Slade and Van Reenen (2010) assess the contributions to productivity of three sources of research and development spillovers: geographic, technology and product-market proximity. To do this, they construct a new measure of geographic proximity that is based on the distribution of a firm's inventor locations rather than its headquarters, and they report both parametric and semiparametric estimates of their geographic-distance functions. They find that geographic and technological proximities matter, while the product-market one is less relevant. In order to construct the pool of spillover stock, it is possible to use the input-output weighting. Indeed, Kafouros and Buckley (2008) use input-output data on the use of intermediate goods to construct a technological proximity matrix. Finally, recent works show the usefulness of patent citations for exploring knowledge flows across regions, countries and technologies (Peri, 2005; Aldieri, 2011b). In this paper we investigate the spillover effects on productivity of

Italian manufacturing firms, by following a new procedure. As in O'Mahoni and Vecchi (2009), the industry data are summarised in a particular taxonomy, according to Pavitt methodology (1984): Supplier dominated, Scale intensive, Specialized suppliers and Science based (10<sup>th</sup> “Indagine sulle imprese manifatturiere italiane”, 2008). This taxonomy accounts for differences in the knowledge intensity and innovative activities within sectors. In this way we replace the traditional high-tech/low-tech industry split with a classification more suitable to gauge the nature of new technologies (von Tunzelmann and Acha, 2005). Furthermore, the literature considers the relevance of investing in R&D to improve own absorptive capacity. Another contribution of this paper is to evaluate also possible spillover effects among firms that do not report any R&D expenditure in their balance sheet. The idea is that the technological knowledge as a public good produces effects to all firms operating within a R&D-intensive group (Arrow, 1962; Nelson, 1959).

The paper is organised as follows. Section 2 describes the features of the dataset and the industry taxonomy used for the analysis. Section 3 presents the empirical framework, which is the basis of the econometric analysis. Section 4 summarises the results and Section 5 points out suggestions for further research.

## 2.Data

We use data from the 9<sup>th</sup> and the 10<sup>th</sup> IMM surveys carried out by Capitalia. These two surveys cover the period 2001-2006 and consider both qualitative and quantitative information on a large sample of Italian manufacturing firms. After a cleaning procedure, based on deleting firms whose target variables are missing, we obtain a balanced sample of 3563 firms over 6 years (21378 observations). For each firm we consider value added, number of employees, the physical capital stock and the R&D expenditures. The monetary variables are transformed into constant prices by using national GDP price deflators<sup>1</sup> with 2006 as the reference year.

The R&D stock is constructed by using a perpetual inventory method (Griliches, 1979). For each firm, the R&D stock at time  $t$  is defined by:

$$Krd_t = (1 - \partial)Krd_{t-1} + R_t \quad [1]$$

where  $\partial$  represents the depreciation rate of R&D capital and  $R$  is the deflated amount of R&D expenditures. The initial value of  $Krd$  can be computed by using the following formula:

$$Krd_0 = \frac{R_0}{(g + \partial)} \quad [2]$$

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<sup>1</sup>International Monetary Fund (IMF) GDP deflators.

where  $g$  is the growth rate of  $R$  and it is assumed to be constant. In this study, we assume a depreciation rate of 15% and a growth rate of 5%, which are usually assumed in the literature (Hall and Mairesse, 1995; Aldieri, 2011a).

According to the number of employees, the firms are distinguished into five classes: small firms (11-20 employees), small-medium firms (21-50), medium firms (51-250), medium-large firms (251-500) and large firms (more than 500 employees). According to Pavitt methodology (1984), we identify four patterns of firms: i) Supplier dominated, characterized by a low number of employees, belong to traditional technological sectors, such as food and textile. In this type of pattern, the source of innovative activity is external, relative to specialised suppliers; the customers are sensitive to the price variations, the instruments to protect innovations are relative to marketing. The main objective of the firms in this case is the reduction of production costs. ii) Scale intensive, characterised by highly specialised production processes, based on scale economy. They are mainly medium-large firms, where the source of innovative activity may be internal and external, the customers are sensitive to price variations and the innovations are protected by patents. Their main objective is the introduction of new production processes to get more efficiency. iii) Specialised suppliers, small-medium firms characterised by production of machinery for the firms of other sectors. The source of innovative activity comes from interactions with users sensitive to product features. The innovations are protected by patents and know-how on planning stage. Their main objective is the improvement of product quality. iv) Science based, medium-large firms characterised by high R&D-intensive sectors. The source of innovative activity is the relation with Public Scientific Institutions and internal, relative to high investments in R&D. The customers are sensitive to price variations and product quality. The innovations are protected by more instruments and activities. Their main objective is the reduction of production costs and the improvement of product quality. Table 1 summaries the main features of firms patterns and Table 2 shows the distribution of firms, based on the two-digit ATECO industry level and Pavitt methodology (1984).

**Table 1. Patterns of firms**

Pattern	Sector	Size	Source technology
Supplier dominated	Traditional	Small	External
Scale intensive	Large-scale production	Medium-Large	Internal/External
Specialized suppliers	Machinery and instruments	Small-Medium	Planning stage and development
Science based	High R&D-intensive	Medium-Large	R&D and Public Scientific Institutions

“10<sup>th</sup> Indagine sulle imprese manifatturiere italiane” Corporate Report, December 2008, Unicredit Corporate Banking

**Table 2. Classification of firms by ATECO and Pavitt methodology**

Two-digit ATECO	Pavitt	N. firms
10 Food	Supplier dominated	1
11 Beverages	Supplier dominated	1
14 Textiles	Supplier dominated	36
15 Leather	Supplier dominated	292
17 Paper and Paper production	Supplier dominated	253
18 Printing	Supplier dominated	105
19 Petroleum Refineries & Product	Supplier dominated	132
20 Chemicals	Supplier dominated	97
21 Pharmaceuticals	Scale intensive	103
22 Rubber and plastic products	Scale intensive	105
23 Non-metallic Mineral Product	Scale intensive	14
24 Basic Metal	Scale intensive	175
25 Metal production	Specialized suppliers	197
26 Computers and electronics	Scale intensive	245
27 Non-electrical Machinery	Scale intensive	146
28 Electrical Machinery	Supplier dominated	513
29 Motor vehicles	Specialized suppliers	574
30 Other transport	Science based	17
31 Furniture	Specialized suppliers	137
32 Other Manufacturing industries	Science based	58
33 Machinery upkeep	Science based	95
35 Gas and electricity	Supplier dominated	38
36 Water supply	Supplier dominated	229

We split the sample into R&D performing firms and non-R&D performing firms. The first group collects the firms with positive R&D expenditures. There are 953 R&D performing firms and 2610 non-R&D performing firms. As we may observe from Table 2, the sample is dominated by firms in Supplier dominated pattern (50%), characterized by traditional activity.

Table 3 displays the distribution of R&D-performing and non-R&D performing firms by Pavitt methodology (1984) and the R&D intensity, computed as the ratio between R&D expenditures and the value added, for R&D-performing firms.

**Table 3. Sample distribution of R&D-performing and non-R&D performing firms**

	Pavitt	N. firms	R&D intensity
R&D performing firms			
	Supplier dominated	460	0.03
	Scale intensive	147	0.03
	Specialized suppliers	292	0.04
	Science based	54	0.09
Non-R&D performing firms			
	Supplier dominated	1313	
	Scale intensive	536	
	Specialized suppliers	653	
	Science based	108	

### 3. Empirical Framework

As in O'Mahoni and Vecchi (2009), in order to investigate the relation between R&D capital stock and productivity for firm  $i$  at time  $t$ , we consider the following production function:

$$Y_{it} = TF(K_{it}, L_{it}) \quad [3]$$

where  $Y$  is the output, measured by the value added,  $K$  is the physical capital stock,  $L$  is labour and  $T$  is total factor productivity. Now we assume that  $T$  is a function of the knowledge stock accumulated within the firm (R&D capital stock) and other exogenous components:

$$T_{it} = Z(Krd_{it}, E_{it}) \quad [4]$$

where  $Krd$  represents R&D capital stock, as defined also in [1], and  $E$  presents all other exogenous components that affect productivity.

The previous equations can be combined and expressed as a Cobb-Douglas production function:

$$Y_{it} = E_{it}^{\lambda} K_{it}^{\alpha} L_{it}^{\beta} Krd_{it}^{\gamma} \quad [5]$$

We can rewrite [5] in rates of growth by taking logs and first differencing to get:

$$\Delta y_{it} = a_i + \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta krd_{it} + \Delta \varepsilon_{it} \quad [6]$$

where  $\Delta \varepsilon_{it}$  is the rate of growth of total factor productivity. A simpler version of [6] is also estimated using the sample of firms that do not report any R&D expenditures, to pick out the effects of R&D spillovers on their productivity.

As in O'Mahoni and Vecchi (2009), we use a two-step procedure. In the first step we estimate the production function [6]. In the second step, we use the residuals from the above estimation to investigate the presence of spillover effects.

In the first step, equation [6] is estimated by means of three econometric models for panel data: Ordinary Least Squares in first-differences (OLS-FD), first difference (FD) and system (SYS) IV-GMM. OLS-FD estimates the model specified in (log) first-differences to remove the unobserved time-invariant firms fixed effects. However, OLS estimates produce biased and inconsistent results in the presence of endogeneity and simultaneity (Griliches, 1979). GMM-FD and GMM-SYS models allow controlling for firms' permanent unobserved specific effects, and taking into account the possible endogeneity or simultaneity issue of the explanatory variables with the error term<sup>2</sup>. The system GMM (GMM-SYS) estimator combines the standard set of equations in first difference (GMM FD) with suitably lagged levels as instruments, with an additional set of equations in levels with suitably lagged first differences as instruments<sup>3</sup>. The validity of these additional instruments, which consist of first difference lagged values of the regressors, can be tested through difference Sargan over-identification tests. The GMM-SYS estimator can lead to considerable improvements in terms of efficiency as compared to the GMM-FD one<sup>4</sup>. Since the model is overidentified in the sense that there are more instruments than parameters to be estimated, the validity of the instruments can be tested by means of the Sargan test for overidentified restrictions. Considering the set of instruments used and the need to satisfy the orthogonality conditions, it helps to verify the null hypothesis of joint validity of the instruments. The Sargan test is  $\chi^2$  distributed under the null with  $(p - k)$  degrees of freedom (where  $p$  is the number of instruments and  $k$  is the number of variables in the regression).

The second step of our analysis tries to verify the presence of spillover effects across firms operating in similar technological areas. For this aim, we regress (by OLS) the residuals from the production function estimation on each industry taxonomy

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<sup>2</sup>See Griliches and Mairesse (1995) for a discussion.

<sup>3</sup>See Blundell and Bond (1998) for a discussion about the instruments available for the first-differenced equations.

<sup>4</sup>This occurs when the lagged levels of the series are only weakly correlated with subsequent first differences, so that the instruments available for the first difference equations are weak. See Arellano and Bover (1995), Blundell and Bond (1998).



dummy variables (Supplier dominated, Scale intensive, Specialized suppliers and Science based).

## 4. Results

### 4.1 Estimation of the production function

We begin the empirical investigation with the estimation of production function [6] using the three estimators discussed in the previous section (OLS-FD, GMM-FD and GMM-SYS). The dependent variable is the rate of growth of output. Results are shown in the Table 4. All model specifications include time dummies, which capture the impact of factors that change over time but not over the cross-sectional dimension of the sample. The three estimators produce quite different coefficients values and this seems to display that the estimation method matters (Blundell and Bond, 2000). From GMM-SYS results, which are more consistent, we may observe that the effect of R&D capital stock is significant and positive. Table 4 presents also the Sargan test of overidentifying restrictions as well as tests for first order (AR(1)) and second order (AR(2)) serial correlation tests of first-differenced residuals. Results of AR(1) and AR(2) tests are consistent with the assumption of no serial correlation in the residuals in levels and Sargan tests does not reject the null hypothesis of valid instruments, indicating that the instruments are not correlated with the error term.

**Table 4. First step: production function estimation**

	OLS-FD	GMM-FD	GMM-SYS
Labour	0.36 (0.070)***	0.34 (0.173)**	0.63 (0.119)***
Capital	0.30 (0.069)***	0.41 (0.186)**	0.16 (0.078)**
R&D	0.03 (0.026)*	0.05 (0.060)	0.07 (0.035)**
R <sup>2</sup>	0.33		
Sargan		23.12 (0.283)	14.27 (0.284)
AR(1)		-3.78 (0.000)	-3.82 (0.000)
AR(2)		-0.34 (0.731)	-0.47 (0.636)

Note: Standard errors are reported in brackets next to the coefficient estimates. Sargan is the Sargan (1958) test of overidentifying restrictions. AR(1) and AR(2) are tests for first and second order serial correlation. *P-values* are reported in brackets next to the Sargan and serial correlation tests.

\*\*\*, \*\*, \* Coefficient significant at 1%, 5%, 10% significance level.

#### 4.2 Estimation of the spillover effect

In the Table 5 we estimate the spillover effect, which is derived from the regression of the rate of growth of total factor productivity on the industry taxonomy dummies. In particular, the rate of growth of total factor productivity is computed using the residuals from the production function estimation using the GMM-SYS.

The results suggest a spillover effect of 17% among firms operating in the R&D intensive industry (Science based pattern).

**Table 5. Second step: evaluation of the spillover effect**

Industry taxonomy dummies	OLS
Scale intensive	0.13 (0.024)***
Specialized suppliers	0.16 (0.018)***
Science based	0.17 (0.036)***

Note: Standard errors are reported in brackets next to the coefficient estimates.

\*\*\* Coefficient significant at 1%

#### 4.3 Spillover effects in non-performing R&D firms

Now we explore whether also firms that do not report R&D expenditures may benefit from operating in a R&D intensive environment. The results from the estimation of the production function and the spillover effect are shown in the Table 6. As we may observe, the evidence of spillovers is not as strong as among R&D-performing firms. However, also in this case the spillover effects are significant and positive. In particular, the results suggest a spillover effect of 14% among firms operating in the R&D intensive industry (Science based pattern).

**Table 6. Non-performing R&D firms. First and second step estimation**

	First step: GMM-SYS	Second step: OLS
Labour	0.90 (0.055)***	
Capital	0.16 (0.037)***	
Scale intensive		0.04 (0.010)***
Specialized suppliers		0.08 (0.010)***
Science based		0.14 (0.020)***
Sargan	18.98 (0.041)	
AR(1)	4.18 (0.000)	
AR(2)	1.75 (0.080)	

Note: Standard errors are reported in brackets next to the coefficient estimates. Sargan is the Sargan (1958) test of overidentifying restrictions. AR(1) and AR(2) are tests for first and second order serial correlation. *P-values* are reported in brackets next to the Sargan and serial correlation tests.

\*\*\* Coefficient significant at 1% significance level.

## 5. Discussion and concluding remarks

In this paper we analyze the relationship between R&D spillovers and productivity. To this aim, we use data from 9<sup>th</sup> and 10<sup>th</sup> “Indagine sulle imprese manifatturiere” (IMM) surveys carried out by Capitalia. These two surveys, which cover the period 2001-2006, contain both quantitative and qualitative information on a large sample of Italian firms. The main contribution of this paper is to stress the importance of replacing the traditional high-tech/low-tech industries with a classification more suitable to capture the nature of new technologies. Indeed, the industry data are summarised in a particular taxonomy, according to Pavitt methodology: Supplier dominated, Scale intensive, Specialized suppliers and Science based. This taxonomy accounts for differences in the knowledge intensity and innovative activities within sectors. Furthermore, the literature considers the relevance of investing in R&D to improve own absorptive capacity. Another contribution of this paper is to evaluate also possible spillover effects among firms that do not report any R&D expenditure in their balance sheet. The idea is that the technological knowledge as a public good produces effects to all firms operating within a R&D-intensive group (Arrow, 1962; Nelson, 1959). As in O’Mahoni and Vecchi (2009), we use a two-step procedure. In the first step we estimate the production function. In the second step, we use the residuals from the above estimation to investigate the presence of spillover effects.

In the first step, the production function is estimated by means of three econometric models for panel data: Ordinary Least Squares in first-differences (OLS-FD), first difference (FD) and system (SYS) IV-GMM. OLS-FD estimates the model specified in (log) first-differences to remove the unobserved time-invariant firms fixed effects. However, OLS estimates produce biased and inconsistent results in the presence of endogeneity and simultaneity (Griliches, 1979). GMM-FD and GMM-SYS models allow controlling for firms’ permanent unobserved specific effects, and taking into account the possible endogeneity or simultaneity issue of the explanatory variables with the error term. The three estimators produce quite different coefficients values and this seems to display that the estimation method matters (Blundell and Bond, 2000). The second step of our analysis tries to verify the presence of spillover effects across firms operating in similar technological areas. We derive the spillover effect from the regression of the rate of growth of total factor productivity on the industry taxonomy dummies. In particular, the rate of growth of total factor productivity is computed using the residuals from the production function estimation using the GMM-SYS. The results suggest a spillover effect of 17% among firms operating in the R&D intensive industry (Science based pattern). Finally, we explore whether also firms that do not report R&D expenditures may benefit from operating in a R&D intensive environment. As we may observe from the results, the evidence of spillovers is not as strong as among R&D-performing firms. However, also in this case the spillover effects are significant and positive. In particular, the results suggest a spillover effect of 14% among firms operating in the R&D intensive industry (Science based pattern).

The work could be extended to investigate the presence of other channels through which knowledge can spread across firms and industries, such as the mobility of skilled and unskilled workers.

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