



## R&D, knowledge spillovers and company productivity performance

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### ABSTRACT

Using company accounts data for 5 countries (US, UK, Japan, France and Germany) we analyse the relationship between intangible assets and productivity. We integrate the company data with industry information on tangible and intangible investments and skill composition of the labour force. The industry data are summarised in two different taxonomies, factor and skill intensive groups, which account for differences in the knowledge intensity and innovative activities within sectors. The results provide evidence of higher productivity in R&D and skill intensive industries. This can be interpreted as evidence in favour of the presence of spillover effects.

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### 1. Introduction

This paper investigates the impact of intangible assets on companies' productivity performance using a large sample of manufacturing and non-manufacturing companies in five OECD countries (the US, the UK, France, Germany and Japan). Although commentators frequently take it as given that intangible assets are an important contributor to economic well-being, academic research has still a long way to go to quantify their impact (Griliches, 1998). One problem is that intangible investments such as R&D outlays, advertising, marketing and human capital, are quite difficult to measure. Academic research has generally employed either firm-level or industry data sets. Previous work using the former has tended to concentrate on research activities alone, due to the lack of data on other forms of intangible investment. Research employ-

ing industry data benefits from the availability of more universal information on forms of intangible capital but at a level that is often considered to be too aggregated. Thus intangible investments such as R&D tend to be concentrated in a few industries and disentangling this variable from other sources of industry variation in productivity is difficult.

The main contribution of this paper is to integrate the standard analysis using company accounts data with industry measures of investment in knowledge-generating activities, specifically R&D and human capital, to add to our understanding of the impact of intangibles on company performance. Like R&D, the accumulation of human capital has long been considered an important engine of economic growth in theoretical models (e.g. Lucas, 1988) and the empirical evidence on balance supports the proposition that countries which invest in human capital have stronger economic performance (e.g. Judson, 2002; Mason et al., 2007).

In order to introduce industry-level information on R&D and human capital we utilise two newly developed industry and skill taxonomies. The former is a factor intensity taxonomy constructed by Peneder (1999, 2001). The second is a skill taxonomy based on data from labour force surveys. The choice of these taxonomies mirrors recent developments in innovation studies. These stress the importance of replacing the traditional high-tech/low-tech industry split with a classification more suitable to capture the pervasive

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nature of new technologies (von Tunzelmann and Acha, 2005). Our results show that introducing these taxonomies adds to our understanding of the relationship between intangibles and productivity. More importantly these results can be interpreted as evidence of the presence of R&D spillovers, even when controlling for the impact of the skill level that typically characterises the industry in which the company operates.

The essence of the spillover effect is that the research effort of other firms may allow a given firm to achieve results with less research effort (Jaffe, 1986). However, the literature has also stressed the importance of investing in R&D to enhance the possibility to absorb existing information (Cohen and Levinthal, 1989; Griffith et al., 2004). Following these considerations it is not surprising that little effort has been devoted to assessing the absorptive capacity of those firms that do not engage in R&D activities. However the traditional view of technological knowledge as a public good implies that its effects are realised by all firms operating within an R&D-intensive environment (Arrow, 1962; Nelson, 1959). Our analysis will try to evaluate possible spillover effects among companies that do not report any R&D expenditure in their balance sheet.

The paper is organised as follows. Section 2 discusses the relationship between R&D and productivity and the impact of R&D spillovers on productivity, summarising the recent econometric evidence on firm-level studies. Section 3 describes the use of industry taxonomies in the analysis of R&D and productivity at the firm level, and specifically in the evaluation of spillovers originating from technological proximity. Section 4 presents the empirical framework, which is the basis of the econometric analysis. Section 5 summarises the main features of the data set and Section 6 discusses the methodology used in the empirical investigation. Section 7 presents the results and Section 8 concludes the paper.

## 2. The relationship between knowledge-based capital and productivity

Since Solow's (1957) decomposition of economic growth much research by economists has focused on the factors which underlie the productivity residual, i.e. that part of output growth not explained by changes in factor inputs. Investments in R&D have been one of these factors, and the analysis of the relationship between R&D and productivity has played a major role in economic growth studies (Griliches, 1979, 1988; Grossman and Helpman, 1991; Coe and Helpman, 1995).

The literature on R&D and productivity is very rich and covers both macro and micro evidence.<sup>2</sup> In all studies considered by the authors, R&D is invariably found to have a significant and positive effect on output growth. However, the range of estimates of the elasticity of output with respect to R&D does vary by study. Looking for example at firm-level evidence, Griliches, in two successive papers, found that the elasticity of output to R&D in US manufacturing was around 0.07 on average, ranging between 0.1 for the research-intensive sector and 0.04 for the remaining manufacturing industries (Griliches, 1979, 1984). Schankerman (1981) and Griliches and Mairesse (1984) present estimates of the output elasticity to R&D for the US which rise to about 0.18. In France the elasticities are higher than in the USA, ranging between 0.09 and 0.33 (Cuneo and Mairesse, 1984; Mairesse and Cuneo, 1985), a dif-

ference which can partly be explained by the availability of better data for France.<sup>3</sup>

Griffith et al. (2006) provide evidence for a sample of UK manufacturing firms listed on the London Stock Exchange. Their estimated output elasticity to R&D ranges between 0.012 and 0.029, depending on the estimation technique and model specification. Similar results for the UK (approximately 0.03) are presented in Bloom and Van Reenen (2002), using the stock of patents as a measure of innovation instead of R&D capital.<sup>4</sup> Sassenou (1988), in a cross-section analysis of Japanese firms, reports coefficients of 0.10 for the whole sample and 0.16 for those firms belonging to the scientific sector. However, the same estimates drop to insignificant coefficients in the panel dimension. In Germany returns to R&D range between 0.072 and 0.155 for a sample of 443 manufacturing firms (Harhoff, 1998).<sup>5</sup>

A large part of the theoretical literature on endogenous growth has focused not only on the impact of the firm's own R&D but also on its ability to generate spillovers in the rest of the economy (Romer, 1986). There are various interpretations of how externalities originate, including growth in activity, e.g. with increasing investment and production (Arrow, 1962), accumulation of human capital (Uzawa, 1965), or the acquisition of quality-improved inputs (Goto and Suzuki, 1989).<sup>6</sup> Knowledge diffusion also benefits from the technological proximity of firms, i.e. via exchange of ideas among firms that operate in similar fields. According to Griliches (1992) these are *genuine spillovers* and they particularly affect companies working in the same 4-digit or 3-digit SIC.<sup>7</sup> Finally, the literature also stresses the importance of being geographically close to innovators, either research centres (Adams and Jaffe, 1996; Fischer and Varga, 2003), or the country leader in the production of innovation (Griffith et al., 2006).

Similarly to the estimation of the own-firm R&D investment on productivity, analyses of R&D spillovers have produced a wide range of empirical results (Sena, 2004). In some cases the estimates of the 'social returns' are found to be extremely high and to exceed the internal returns by a wide margin. This happens particularly when the level of R&D undertaken in other industries, or the R&D flows embodied in the purchases of intermediate inputs, are included in the production function specification. For example, in Terleckyi (1975) the returns to R&D embodied in purchased goods range from 0.45 to 0.78, while the returns to R&D conducted in the industry range from 0.12 to 0.37. Similarly, in Goto and Suzuki (1989) the coefficient on the embodied R&D is 0.80 while the coefficient on own-industry R&D is 0.25. Equally large coefficients are estimated by Bernstein and Nadiri (1989), using a cost function framework.

Technological proximity as a form of spillover first found empirical application in Jaffe (1986, 1989), who includes a technological distance measure in the computation of a spillover variable based on data for technology-based patent classes for the US.<sup>8</sup> Goto and

<sup>3</sup> In fact, the French data allow a distinction between capital and employment used in research departments from their use in other productive activities. This allows the research to deal with the problem of double counting, which imparts a downward bias to the estimates of the output elasticities of R&D (Schankerman, 1981).

<sup>4</sup> See Table 5 in Bloom and Van Reenen (2002).

<sup>5</sup> See also Klette (1996) for evidence on a set of Norwegian companies.

<sup>6</sup> For example, the growth of the airline industry was made possible by the introduction of excellent aircraft by the aircraft manufacturing industry (Goto and Suzuki, 1989).

<sup>7</sup> As an example of this type of spillover, Griliches (1992) mentions the exchange of ideas between the photographic industry and the scientific instruments industries.

<sup>8</sup> Specifically Jaffe constructs a technological position vector for each firm which is then used to construct the distance measure. He assumes that the total relevant activity of other firms can be summarised by a potential 'spillover pool' that is simply a weighted sum of the firm's R&D, with weights proportional to the proximity of the firm in technology space. The vector is also used to cluster all firms into

<sup>2</sup> See, for example, Cameron and Muellbauer (1995) for an analysis of the manufacturing sector, Patel and Soete (1988) for the total economy and Lichtenberg (1992) for an international investigation of R&D investments and productivity.

**Table 1**  
Mapping of the companies in the industry and skill taxonomies.

Industry	Total	USA	France	Germany	Japan	UK
<i>Total number of companies</i>						
Mainstream (F1)	1210	381	77	101	469	182
Labour intensive (F2)	2062	645	146	128	724	419
Capital intensive (F3)	835	357	54	56	272	96
Advertising intensive (F4)	1078	400	59	78	333	208
R&D intensive (F5)	1618	1017	69	75	298	159
Low skill intensive (S1)	1884	658	73	159	608	386
Intermediate skill intensive (S2)	2459	772	220	189	967	311
High skill intensive (S3)	2460	1370	112	90	521	367
<i>R&amp;D performing companies</i>						
Mainstream (F1)	556	202	25	32	216	81
Labour intensive (F2)	506	143	15	30	237	81
Capital intensive (F3)	367	122	16	20	169	40
Advertising intensive (F4)	249	95	14	6	88	46
R&D intensive (F5)	1331	908	33	51	221	118
Low skill intensive (S1)	522	174	17	21	213	97
Intermediate skill intensive (S2)	1075	408	58	75	426	111
High skill intensive (S3)	1412	888	28	46	292	158

See Section 5 for details of data sources.

Suzuki (1989) construct a similar measure based on R&D data for the electronics industry and evaluate the spillovers from this industry to the rest of the manufacturing sector.<sup>9</sup> Estimates based on distance measures produce a smaller impact of R&D externalities than those based on expenditure levels. For example, Goto and Suzuki (1989) obtain a spillover effect of 0.043. Geographical proximity has found an interesting application in Griffith et al. (2006) where the authors show that UK firms locating their R&D activity in the US enjoy substantially higher spillover effects compared to firms that perform R&D in the UK. Their estimated spillover effect ranges between 0.068 and 0.174, depending on the estimation technique and alternative measures of geographical distance.<sup>10</sup> They conclude that (foreign) firms must invest in innovative activities in the US to reap the full benefit from their investment.

### 3. Industry and skill taxonomies as a measure of technological proximity

In this paper we account for spillovers originating from technological proximity using industry taxonomies. These provide a way of classifying industries according to their knowledge intensity and therefore recognise the similarities in terms of production of innovative activities, consistently with the notion of sectoral systems of innovation (Malerba, 2004).<sup>11</sup> Companies that are technologically closer because they operate within an R&D-intensive sector are more likely to be involved in exchanges of new ideas and therefore to enjoy *genuine spillovers* in the spirit of Griliches (1992). Our approach to the analysis of spillovers has also the advantage of merging the structuralist approach with regression analysis, pro-

technological groups and use this information to introduce dummy variables in the final specification.

<sup>9</sup> The same methodology is employed in Branstetter and Sakakibara (2002), to evaluate the impact of spillovers, measured by a technological proximity variable on the patenting outcome of research consortia.

<sup>10</sup> See Table 3 in Griffith et al. (2006).

<sup>11</sup> Traditional industrial classifications based, for example, on the type of technology used (high- and low-tech industries) or the type of product produced (Hatzichronoglou, 1997) have been criticised in recent years. For example, von Tunzelmann and Acha (2005) observe that these classifications tend to become obsolete because technologies spill over across sectors and make the boundaries unclear. Malerba (2004) also emphasises that this approach does not account for the knowledge and learning processes within firms.

viding one of the few examples of the application of taxonomies within a neoclassical economic framework.

The two taxonomies used in this paper draw on the work of Peneder (2001) who recognises the importance of accounting for the technology and product dimension of industries, as well as the changes in firms' strategic behaviour and technology evolution (von Tunzelmann and Acha, 2005). The first is a factor intensity taxonomy (Taxonomy I in Peneder, 2001) that uses cluster analysis to group industries into five groups: mainstream,<sup>12</sup> labour intensive, capital intensive, advertising intensive, and R&D intensive. The analysis in Peneder (2001) was carried out for 3-digit groups of the NACE industrial classification and was based on US data for the early 1990s.

One of the shortcomings of this taxonomy is the exclusive focus on the manufacturing sector (Peneder, 2003). In our study we expand this taxonomy to non-manufacturing, in order to match all companies in our data set. The extension of this taxonomy was carried out using an ad-hoc methodology as the application of cluster technique proved impossible given the paucity of information available for non-manufacturing (further details are presented in Appendix A).<sup>13</sup>

Next to the factor intensity taxonomy, we construct our own skill taxonomy following a clustering technique similar to Peneder (2001) using K-means clustering (see Appendix A). This was based on information drawn from the 1998 British Labour Force Survey and covers both the manufacturing and the non-manufacturing sectors. Qualifications were divided into three groups: Higher (graduates and above), Intermediate (all vocational qualifications plus A-levels), and No Vocational Qualifications.

All companies in our data set are mapped into the taxonomy groups, using each company's 4-digit SIC code and matching this with the NACE code. As emphasised by Griliches (1992), the SIC code can be a useful tool to identify companies with similar characteristics. Table 1 shows the number of companies in each group by country. Considering the total sample, the various groups are adequately represented (see column 1). Among the R&D-performing companies the largest groups are in the R&D intensive and in the

<sup>12</sup> The group defined as *mainstream* includes those industries that are characterised by their lack of a pronounced reliance on any of the four factor inputs. They represent the input combination of a 'typical' 3-digit manufacturing industry (Peneder, 1999).

<sup>13</sup> For a new taxonomy of manufacturing and service industries see Castellacci (2008).

High skill intensive categories. However, the situation is somewhat different at the country level. For example, the R&D intensive sector is particularly under-represented among the R&D-performing companies in Japan. This contrasts with the general perception of Japan as an R&D intensive user. Finding a sample of companies at the country level that adequately represents all industrial sectors is a common problem in this type of study (see, for example, Harhoff, 1998). For this reason, most of the empirical investigation will be based on the pooled sample, and only some marginal considerations will be based on the country-specific results. The shortcoming of putting together companies operating under different accounting regimes and institutional frameworks can be counter-balanced by the higher degree of heterogeneity of our sample (Baghat and Welch, 1995).<sup>14</sup> Moreover, the introduction of country-specific intercepts in the empirical analysis will control for all the various country-specific factors, such as intellectual property rights or geographical location, as long as these factors do not change or change slowly over time (Bloom et al., 2002).

The classification of firms into fairly homogeneous groups such as R&D and non-R&D intensive is not new in studies of R&D and productivity (for example, Griliches, 1984; O'Mahony and Vecchi, 2000). However the taxonomies used in this paper, based on data at a low level of aggregation, allow a much more refined classification of our companies. For example within the chemical sector, usually considered as a whole as R&D intensive, we distinguish between sector 2820 (plastic materials and synthetics) which is capital intensive, sector 2840 (soap, cleaners and toilet goods) which is advertising intensive, sector 2851 (paints and allied products) which is mainstream, and sector 2830 (drugs) which is R&D intensive. This will allow us to define with more precision how much a company gains in terms of productivity by belonging to a very narrowly identified industry group. In what follows we show how such information is included in our analysis and how it can be interpreted as a spillover effect.

#### 4. Model specification

The approach we use for the analysis of the relationship between tangible/intangible capital and productivity for firm  $i$  at time  $t$  is based on the following production function:

$$Y_{it} = TF(K_{it}, L_{it}) \quad (1)$$

where  $Y$  is output,  $K$  is physical (tangible) capital,  $L$  is labour and  $T$  is total factor productivity. Rather than treating  $T$  as completely exogenous, we assume that it is a function of the stock of knowledge accumulated within the firm (stock of R&D capital) and other components that may affect productivity, as well as some exogenous forces:

$$T_{it} = Z(R_{it}, E_{it}) \quad (2)$$

In Eq. (2),  $R$  represents R&D capital, and  $E$  represents all the other external factors that affect productivity.

Both (1) and (2) are usually expressed as Cobb–Douglas functions.<sup>15</sup> The combined model then becomes:

$$Y_{it} = E_{it}^{\lambda} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} \quad (3)$$

<sup>14</sup> Basic accounting principles are similar in the OECD countries analysed and the remaining differences are unlikely to be of a first-order effect (Baghat and Welch, 1995). Also, there is evidence of increased cross-country harmonisation in the tax treatment of physical capital (Bloom et al., 2002).

<sup>15</sup> Although frequently criticised for its restrictive assumptions, the Cobb–Douglas production function remains the primary specification employed in firm-level studies of R&D. The additional complications introduced by alternative specifications such as the CES or the translog function do not appear to be matched by substantial improvements to the estimates (Griliches and Mairesse, 1984).

We can re-write Eq. (3) in rates of growth by taking logs and first differencing to obtain:

$$\Delta y_{it} = a_i + \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta r_{it} + \Delta \varepsilon_{it} \quad (4)$$

where  $\Delta \varepsilon_{it}$  is the rate of growth of Total Factor Productivity (TFP). In our data set,  $y$  is net sales,<sup>16</sup> deflated by industry-specific price indices for each country and then converted to \$US using the market exchange rate,  $k$  is tangible capital (net property, plant and equipment),  $l$  is labour (number of employees),  $r$  is R&D expenditure converted to a stock measure. A simplified version of equation (4) is also estimated using the sample of companies that do not undertake any R&D investments. Tangible capital at historic cost is converted into capital at replacement cost (Arellano and Bond, 1991), while R&D expenditure is converted into a stock measure using a perpetual inventory method, together with the assumption of a pre-sample growth rate of 5% and a depreciation rate of 15% (see Hall, 1990, for details).

Among the external factors that can affect productivity growth, exchanges of ideas and products across companies operating in similar technological areas can play an important role. We account for this effect by using dummy variables derived from the taxonomies described in the previous section. If these dummies capture some genuine spillovers they should provide an explanation for the rate of growth of TFP:

$$\Delta \varepsilon_{it} = \sum_i \phi_i D_i, \quad \Delta \varepsilon_{it} = \sum_j \phi_j D_j \quad (5)$$

$i = 1, \dots, 5 \quad j = 1, \dots, 3 \quad D_i = F1, \dots, F5 \quad D_j = S1, \dots, S3$

As in Table 1,  $F1, \dots, F5$  are the dummies derived from the factor intensity taxonomies, while  $S1, \dots, S3$  are the dummies derived from the skill intensity groups. While all dummies are included to account for different industry characteristics, spillover effects are expected to originate from the R&D intensive and the intermediate/high skill intensive groups of companies. A significant and positive coefficient on the R&D intensive dummy,  $F5$ , suggests that firms in this industry group are more productive than firms operating in the rest of the economy. This can *per se* be interpreted as a spillover effect. However, since we have so far imposed equal coefficients on all factor inputs across all sectors, the R&D intensive dummy might pick up differences in the returns to R&D across the economy. To correct for this potential miss-specification we rewrite the production function equation (Eq. (4)) to include the interaction of the company's own R&D with the R&D intensive dummy and then test again for the presence of spillovers, as follows:

$$\Delta y_{it} = a_i + \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma_1 \Delta r_{it} + \gamma_2 \Delta r_{it} * F5 + \Delta \varepsilon_{it} \quad (6)$$

The spillover effect will be modelled as in Eq. (5).

Interaction between own company's R&D and the skill dummies will also be analysed. As emphasised by Hall (2002), approximately 50% of the R&D expenditure within a company goes towards the wages and salaries of highly educated workers. Therefore, analysing R&D spillovers and, at the same time, controlling for the impact of human capital within a particular industry can provide a more precise evaluation of whether externalities can emerge from knowledge-generating activities.

<sup>16</sup> Ideally we should either use sales and include intermediate materials on the right-hand side or use value added as the dependent variable. However, excluding intermediate materials does not seem to affect the estimates of the R&D coefficient, while it might slightly lower the labour coefficient. (Mairesse and Hall, 1996).

**Table 2**  
Composition of the sample: manufacturing and non-manufacturing.

Country	10–17	20–39	40–47	50–57, 59	58 & 70	72,76,78,79	73,75,78	Total
France	22	238	16	64	9	15	41	405
Germany	26	323	13	60	2	3	11	438
Japan	216	1,272	107	375	39	27	60	2096
UK	88	535	40	213	32	71	85	1064
USA	182	1,511	109	369	86	141	402	2800
Total	534	3879	285	1081	168	257	599	6803

Notes: 10–17: mining and construction; 20–39: manufacturing; 40–47: transport; 50–57 & 59: wholesale and retail trade, excluding eating and drinking places; 58 & 70: eating and drinking places and hotels; 72, 76, 78, 79: personal and amusement services; 73, 75, 78: business and professional services.

## 5. Data

The company accounts database employed in the analysis, *Worldscope*, includes consolidated company accounts information for approximately 16,000 companies worldwide for 10 years from 1988 to 1997. From this we have extracted information for the United States, Japan and three European economies, Germany, France and the United Kingdom. The primary data series extracted from the company accounts are net sales, employment, net physical capital defined as equipment and structures (PPE) and R&D expenditures. Companies that do not disclose any data for employment, net physical capital or net sales are dropped, as are a few UK companies whose financial year changes by more than a month throughout the 10 years of observations.

The *Worldscope* database classifies companies to industries according to the 1987 US Standard Industrial Classification. Companies are sampled from a wide range of industrial sectors, both manufacturing and service sectors. All manufacturing companies are included. For non-manufacturing we exclude agriculture and companies operating within the regulated industry (public utilities, and most of transport and communications) because of the heavy government influence in these sectors. Nevertheless, we include transport by air (US SIC 45) and cable TV (US SIC 484), as these industries are now mostly deregulated. Finally the accounting methods employed by firms in the financial and insurance sectors differ from other firms so these are also excluded from the analysis.

Table 2 shows the composition of the sample. Companies in the US and Japan dominate the sample, whereas within Europe there are considerably more data available for the UK than for the other two major economies. Just under 60% of the sample is in manufacturing but there is some variation across countries, with manufacturing accounting for a much greater share of the German sample and a slightly lower share of the US sample.

## 6. Econometric methodology

The empirical analysis of the relationship between intangible assets and companies' productivity performance is undertaken using a two-step procedure, similar to that used by Black and Lynch (2001). In the first step we estimate the production functions (4) and (6). In the second step we use the residuals from the above estimation to investigate the presence of spillover effects.

There are alternative ways of dealing with the estimation of production functions using panel data models. The specification of our model in (log) first differences allows us to deal with the problem of unobserved time-invariant firms fixed effects. Estimating equations (4) and (6) using Ordinary Least Squares (OLS) usually provides estimates that are generally consistent with *a priori* knowledge of factor shares and constant returns to scale (Griliches and Mairesse, 1995; Blundell and Bond, 2000). However, OLS produces biased and inconsistent estimates in the presence of endogeneity. Measurement errors and simultaneity are frequently

cited as possible causes of endogeneity in the estimation of production functions (Griliches, 1979). To address the endogeneity problem we will compare the performance of two instrumental variable estimators: the First Difference Generalised Method of Moments (FD-GMM) and the System GMM (SYS-GMM) (Arellano and Bond, 1998).

An instrumental variable must satisfy two requirements: it must be correlated with the included endogenous variables and orthogonal to the error process. The FD-GMM is based on equations in first differences and on lagged levels of the endogenous variables as instruments (Mairesse and Hall, 1996; Mairesse et al., 1999). Unfortunately, given the high persistence of the variables used in our analysis, the correlation between the growth rates of the independent variables and their lagged levels is likely to be very small, hence presenting a weak instrument problem (Blundell and Bond, 2000). This can produce highly biased estimates, with the bias increasing with the decreasing degree of correlation between endogenous variable and instrument.

To reduce the weak correlation problem, Blundell and Bond (2000) recommend the use of the SYS-GMM. This is an extended version of FD-GMM and is a system composed of equations in first differences and equations in levels. Lagged levels are used as instruments for the equations in first differences and lagged first differences are used as instruments for the equations in levels. The SYS-GMM has proved to give more reasonable results in the context of production function estimation (Blundell and Bond, 2000).

The second requirement for a valid instrument set, the orthogonality between the instrument and the error term, is tested by means of a Sargan test of overidentifying restrictions. This test can be applied in the case where more than one instrumental variable is available for each endogenous variable. Under the null hypothesis that the instrumental variables are valid, the Sargan test is distributed as a chi-square with degrees of freedom equal to the number of overidentifying restrictions.

The second step of our investigation attempts to evaluate the presence of spillover effects across companies working in similar technological areas. This is done by regressing the residuals from the production function estimation (i.e. the growth in total factor productivity) on each group of dummy variables, as well as on the interaction between the R&D and the high skill intensive dummies (F5 and S3). The latter is intended to control for the contemporaneous presence of highly skilled labour within R&D intensive companies.

In a standard estimation in first differences, the dummy variables could be included directly in the estimation of the production function with the signs and magnitudes of the taxonomy dummies interpreted as the impact of spillovers on output growth. However, when these dummies are included in the SYS-GMM, which compounds a specification in first difference and in levels, they result in implausibly large coefficient values. The reason is that the set of dummies in SYS-GMM pick up levels effects which are comparing across industries within and between countries. Hence for example it is comparing productivity levels in computing services

**Table 3**

First step: production function estimation. Dependent variable: rate of growth of output.

Factor inputs	(1) FD-OLS	(2) FD-GMM	(3) SYS-GMM	(4) SYS-GMM
Employment	0.332* (.028)	0.681* (.085)	0.726* (.059)	0.788* (.063)
Capital	0.284* (.023)	0.558* (.068)	0.268* (.042)	0.274* (.044)
R&D	0.241* (.029)	−0.304* (.089)	0.153* (.039)	0.096* (.044)
R&D interaction				0.039* (.013)
Sargan		498.1 (.000)	327.3 (.000)	239.0 (.000)
AR(1)	−2.335 (.020)	−3.352 (.001)	−3.237 (.001)	−3.406 (.001)
AR(2)	−0.359 (.720)	−1.077 (.281)	−0.608 (.543)	−0.654 (.515)

R&D interaction is the interaction between R&D capital and the R&D intensive dummy. Standard errors (in brackets) are reported 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 (in brackets) are reported next to the Sargan and the serial correlation tests.

\* Coefficient significant at the 5% significance level.

**Table 4**

Second step: evaluation of the spillover effect. Dependent variable: rate of growth of Total Factor Productivity (Ordinary Least Squares regression).

Factor intensity	(1)	(2)	(3)	(4)	(5)	(6)
Mainstream	0.014* (.007)		−0.014* (.007)	−0.014* (.007)		−0.014* (.007)
Capital	0.006 (.007)		−0.008 (.007)	−0.008 (.007)		−0.008 (.007)
Advertising	−0.000 (.008)		−0.014 (.008)	−0.014 (.008)		−0.014 (.008)
R&D	0.036* (.006)			0.017* (.005)		
Skill (med.)		0.002 (.006)			0.001 (.006)	
Skill (high)		0.022* (.005)			0.019* (.006)	
R&D and high skill			0.037* (.006)			0.018* (.006)
Other R&D			0.030 (.008)			0.011 (.008)

Standard errors in parentheses. The rate of growth of TFP is derived from the residuals of the production function. Columns 1–3 use the residuals obtained from the estimation of the production function without interactions term, while columns 4–6 use the residuals from the estimation of the production function with interaction term.

\* Coefficient significant at the 5% significance level.

in the US with the production of textiles in France. These levels comparisons are never valid since real values are not defined in a comparable sense (Bernard and Jones, 1996). The two-step procedure adopted in the paper overcomes this problem and should provide an unbiased estimate of the impact of spillovers on TFP growth.

## 7. Results

### 7.1. Estimation of the production function

The empirical analysis begins with the estimation of the production function (Eq. (4)) using the three estimators discussed above, FD-OLS, FD-GMM and SYS-GMM. Results are presented in Table 3. All specifications include time and country dummies, with the US as the base case. The country dummies account for time-invariant, country-specific effects, such as differences in the tax and accounting system. The time dummies capture the impact of factors that change over time but not over the cross-sectional dimension of our data set.

The three estimators produce quite different coefficient values, reinforcing the finding that the estimation method matters (Blundell and Bond, 2000). In the FD-OLS estimation, the labour coefficient is quite low compared to *a priori* information on input shares based on growth accounting coefficients, while the impact of R&D is higher than existing empirical evidence based on firm-level data. This is likely to be the result of the endogeneity problem discussed in the previous section. The FD-GMM gives a very high estimate of the capital elasticity (0.558) and produces a negative coefficient on R&D capital, which is inconsistent with the existing empirical evidence. The coefficient estimates using SYS-GMM turn out to be more consistent with expectations based on factor returns and existing evidence. The size of the R&D coefficient (0.153) is well within the range of 0.04–0.33 which has emerged in related studies (see Section 2).

Overall, our results suggest the presence of increasing returns to scale, due to the presence of R&D capital. In fact, the null of constant returns to capital and labour together could not be rejected at standard significance levels, while it was rejected when including R&D. Since SYS-GMM has attractive theoretical properties in the face of endogeneity issues, the reminder of the analysis will be based on the SYS-GMM estimation.

Table 3 also presents estimates of the production function including an interaction between the R&D variable and the R&D intensive dummy (Column 4). This allows us to gauge the productivity advantage of companies operating in the R&D intensive sectors compared to all other companies. The introduction of the R&D interaction term lowers the overall estimate of the R&D coefficient from 0.153 to 0.096, as one would expect. The interaction term is positive and statistically significant at standard significance levels and indicates that companies operating in the R&D intensive industry enjoy significantly higher returns to their R&D investments of approximately 4%. Consistent with this result, the returns to R&D for the other companies (0.096) are now lower compared to those in column 3 (0.153), although this difference is not statistically significant.

The last section of Table 3 presents the Sargan test of overidentifying restrictions as well as tests for first order (AR(1)) and second order (AR(2)) serial correlation tests of the first-differenced residuals. While the latter are consistent with the assumption of no serial correlation in the residuals in levels,<sup>17</sup> the Sargan test rejects the null hypothesis of valid instruments, indicating that some of the instruments in our set are correlated with the error term. However, given the plausibility of the results, we rely on existing evidence on

<sup>17</sup> In order to obtain consistent GMM estimates the assumption of no serial correlation in the residuals in levels is essential. This assumption holds if there is evidence of significant and negative first-order serial correlation and no evidence of second-order serial correlation in the first-differenced residual (Arellano and Bond, 1998).

the tendency of the Sargan test to over-reject the null hypothesis in equations specified in first differences (Blundell and Bond, 1998).

7.2. Estimation of the spillover effect

Table 4 presents the estimates of the spillover effect, derived from the second step of our analysis, i.e. from the regression of the rate of growth of total factor productivity on the factor intensity and skill dummies. The rate of growth of total factor productivity is measured using the residual from the production function estimation using the SYS-GMM, with and without the R&D interaction term.

The results show that the dummies for the R&D/skill intensive sectors, included separately, are positive and significant. These two taxonomies are also significant when interacted (columns 3 and 6). When an equal coefficient is imposed on the R&D variable in the first step of the analysis (columns 1–2), they suggest a spillover effect of 3.6% among companies operating in the R&D intensive industry, and 2.2% in the high skill intensive industry. Interacting these two dummies suggests companies enjoy a 3.7% productivity gain from operating in sectors which are both R&D and human capital intensive (column 3).

When we allow for different R&D impacts on productivity by interacting the R&D variable with the R&D intensive dummy in the first step of the analysis, the size of the spillover effect goes to about 2% in all three specifications, and remains statistically significant (columns 4–6, Table 4). This shows that the dummy variables derived from the two new factor intensity and skill taxonomies are indeed capturing some extra forces at work outside the control of the firm.

7.3. Spillover effects in non-R&D reporting companies and in the manufacturing and non-manufacturing sectors

We next expand our analysis of the spillover effect to consider the question of whether firms that do not undertake any R&D investments benefit from operating in a technology intensive environment. Because knowledge does not have boundaries and can easily spread across companies and industries there may be some spillovers at work also among non-R&D performers. The results from the estimation of the production function and the spillover effect are presented in Table 5. Production function coefficients are slightly different from the ones presented in Table 4, although with the exception of labour elasticity such differences are not statistically significant. The evidence of spillovers is not as strong as among the R&D-performing companies. Companies that do not invest in R&D are only affected by spillovers originating through the presence of human resources, i.e. highly skilled workers. The results

**Table 5**  
Non-R&D reporting companies. First and second step estimation.

Factor inputs	First step Dependent variable: output growth	Second step Dependent variable: TFP growth
Employment	0.513* (.052)	
Capital	0.340* (.042)	
Sargan	85.02 (.224)	
AR(1)	-9.054 (.000)	
AR(2)	-3.519 (.000)	
Skill (medium)		0.019* (.006)
Skill (High)		0.026* (.007)

Standard errors (in brackets) are reported 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 (in brackets) are reported next to the Sargan and the serial correlation tests.

\* Coefficient significant at the 5% significance level.

**Table 6**  
R&D in manufacturing and non-manufacturing. First and second step estimation.

Factor inputs	Manufacturing	Non-manufacturing
First step. Dependent variable: output growth		
Employment	0.631* (.064)	0.721* (.017)
Capital	0.342* (.043)	0.171* (.099)
R&D	0.170* (.042)	0.251* (.077)
Sargan	299.6 (.000)	105.1 (.059)
AR(1)	-2.610 (.009)	-2.934 (.003)
AR(2)	-0.563 (.574)	-0.598 (.550)
Factor intensity dummies	Manufacturing	Non-manufacturing
Second step. Dependent variable: TFP growth		
Mainstream	0.011 (.008)	-0.019 (.050)
Capital	0.002 (.009)	0.003 (.022)
Advertising	-0.006 (.009)	0.037 (.037)
R&D and skill (high)	0.043* (.008)	0.005 (.011)
Other R&D	0.027* (.009)	-0.104 (.106)

Standard errors (in brackets) are reported 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 (in brackets) are reported next to the Sargan and the serial correlation tests.

\* Coefficient significant at the 5% significance level.

for the other industry taxonomies are not significantly different from zero and therefore they are not presented in Table 5. Companies operating in the intermediate and highly skilled sectors appear to enjoy higher returns than companies operating in the rest of the economy, with a stronger effect in the highly skilled industry, as one would expect. Therefore even though non-R&D performers enjoy some benefit from operating in a knowledge intensive environment, companies that do invest in R&D are more likely to capture the benefit of such an environment.

Finally, we investigate whether there are differences in the returns to own R&D and in the spillover effects between manufacturing and non-manufacturing companies. As above, the first step of our analysis involves the estimation of the production function separately for the two sectors. Results are presented in the top half of Table 6. The results regarding the capital and labour elasticities display the expected pattern of higher labour and lower capital elasticity in non-manufacturing compared to manufacturing. We also observe higher R&D elasticity in non-manufacturing which, at first, may seem surprising. However, it partly reflects the composition of our non-manufacturing sample that includes a large number of companies operating in the R&D intensive sectors, for example business and professional services (see Table 2).

The second part of Table 6 presents the estimates of the spillover effect. To simplify the exposition we only report estimates for the impact of the industry dummies on TFP, including the interaction between the R&D and the high skill intensive dummy. The results do not change substantially when the two sets of industry and skill dummies are individually estimated. We find a major difference between manufacturing and non-manufacturing in the evaluation of spillovers. Specifically, while the spillover effect is strong and significant in manufacturing, we do not find any evidence of it in non-manufacturing.

7.4. Country results

In this section we discuss the econometric evidence for the US, Japan and the three European countries pooled together, presented in Table 7.<sup>18</sup> In the US we obtain a positive and significant

<sup>18</sup> The number of observations for each European country was not large enough to allow consistent coefficient estimates.

**Table 7**  
Country estimates. First and second step estimation.

Factor inputs	USA		Europe		Japan	
	R&D > 0	R&D = 0	R&D > 0	R&D = 0	R&D > 0	R&D = 0
First step. Dependent variable: output growth						
Employment	0.884* (.076)	0.695* (.081)	0.464* (.118)	0.481* (.065)	0.578* (.105)	0.594* (.122)
Capital	0.188* (.052)	0.227* (.064)	0.441* (.077)	0.304* (.057)	0.555* (.082)	0.499* (.123)
R&D	0.113* (.049)		0.124** (.075)		−0.099 (.068)	
Sargan	140.00 (.000)	36.340 (.988)	165.8 (.001)	53.500 (.643)	157.6 (.002)	21.020 (1.000)
AR(1)	−3.413 (.001)	−6.520 (.000)	−1.524 (.128)	−5.986 (.000)	−.028 (.977)	−4.009 (.000)
AR(2)	−0.189 (.850)	−2.430 (.015)	−1.533 (.125)	−1.778 (.075)	−0.497 (.619)	−3.592 (.000)
Factor intensity dummies						
	USA		Europe		Japan	
	R&D > 0	R&D = 0	R&D > 0	R&D = 0	R&D > 0	R&D = 0
Second step. Dependent variable: TFP growth						
Mainstream	0.009 (.014)		−0.015 (.016)		0.027* (.006)	
Capital	0.003 (.016)		−0.010 (.018)		0.017 (.017)	
Advertising	−0.009 (.017)		−0.000 (.019)		0.014 (.008)	
Skill (medium)		0.024* (.013)		0.019** (.011)		0.008 (.009)
Skill (high)		0.028* (.013)		0.010 (.012)		−0.062* (.013)
R&D & Skill (high)	0.029* (.014)		0.024 (.016)		0.049* (.006)	
Other R&D	0.021 (.017)		0.002 (.022)		0.053* (.010)	

Standard errors (in brackets) are reported 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 (in brackets) are reported next to the Sargan and the serial correlation tests.

\* Coefficient significant at the 5% significance level.

\*\* Coefficient significant at the 10% significance level.

coefficient on the R&D variable. Moreover, this result is consistent with previous estimates by Griliches (1979, 1984), suggesting that a 1% increase in R&D increases output growth by 0.11%. The average R&D coefficient in the three European countries is slightly higher than in the US, as one would expect from existing studies that suggest, for example, higher elasticities in France (Mairesse and Cuneo, 1985) and in Germany (Harhoff, 1998). However, this coefficient is only marginally significant and the serial correlation test does not reject the hypothesis of no serial correlation in the levels of the residuals.

The results for Japan are at first glance quite puzzling, as the R&D coefficient is not significantly different from zero. This is, however, not totally surprising as similar results for the R&D elasticity in Japan were found in Sassenou (1988) and also discussed in Mairesse and Sassenou (1991). Among the reasons provided for the bias in the R&D coefficient estimate is the omission of variables reflecting short-term adjustments to business cycle fluctuations by the firms, such as hours of work and capacity utilisation. This misspecification is likely to affect the Japanese results more than the other countries because changes in factor utilisation rates, rather than changes in the factors employed, are particularly common in the Japanese industrial structure (Odagiri, 1994; Hart and Malley, 1996; Vecchi, 2000). Moreover there is evidence that financial statements vastly under-report R&D expenditure in Japan (Goto and Suzuki, 1989).

Table 7 also presents the estimates of the impact of the industry and skill dummies on the rate of growth of TFP, our measure of the spillover effect. We do not find any evidence of spillovers among the European countries while spillover effects are positive and significant in the USA, in both the R&D and non-R&D performing companies. As in Table 4, only human capital spillovers affect productivity growth in those companies that do not invest in R&D.

In Japan the evidence of spillovers is particularly strong, suggesting a 5% additional productivity growth in those companies operating in the R&D and high skill intensive sectors (similar results are obtained when using the S1–S3 dummies). The spillover effect is quite high also among companies that do not undertake R&D investments. Although we are aware of the fact that the country results can be biased because of the relatively poor performance of the first-step estimation, they nevertheless

confirm the conclusions from previous studies evaluating the presence of externalities in the Japanese economy (Vecchi, 2000). The presence of business groups and the importance of research consortia in Japan are often considered as important sources of spillovers (Odagiri, 1994; Branstetter and Sakakibara, 2002). It is possible that if R&D is a team effort phenomenon in Japan, it is relatively more difficult to find positive and significant returns to R&D at the firm level than to capture spillover effects.

## 8. Conclusions

This paper has considered the impact of knowledge-generating activities on output growth in a large panel of companies across five OECD countries. First we show the importance of R&D capital in affecting productivity, in accordance with the existing literature. Extending the investigation to companies operating in the retail and the service sector has provided new evidence of the relationship between R&D and productivity in non-manufacturing. Our results show that, in this sector, internal R&D activities play a very important role.

Second, we merge firm-level data with industry information on factor and skill intensity. This has proved to be a useful exercise as it has shown the importance of operating in a technology-intensive environment. Companies operating in an R&D/skill intensive sector enjoy between 2% and 5% higher productivity growth, approximately 40% of the direct impact of R&D. This result can be interpreted as evidence of spillovers originating among companies characterised by a similar technological base. Companies in the capital intensive or advertising intensive industries do not seem to be affected by such productivity gains. On the other hand, even companies that do not undertake investments in R&D do enjoy higher productivity if they operate in a high skill intensive sector. However, the productivity gain for the non-R&D performing companies is, on average, smaller than for the R&D performers. This implies that such gains mainly affect companies that actively engage in R&D activities, confirming Cohen and Levinthal's (1989) argument that R&D performers are better able to absorb and exploit existing information.



Many studies of external effects based on industry data suggest very large coefficients (e.g. as surveyed in Griliches, 1992), often considerably greater than the direct effect of engaging in innovative activity. These studies often assume that the spillover effect is proportional to the actual amount spent on R&D. Whether the latter is a reasonable assumption or not depends, among other things, on the extent to which R&D expenditures are rivalrous, producing overlapping ideas, and on the nature of the expenditure. For example, much of R&D expenditure in the aerospace industry is on fuel for testing, so that the amount spent may not be a good proxy for number of ideas generated.

The results from our study suggest that this 'manna from heaven' impact is significant but quite small. They are more in the spirit of the growth accounting results of Jorgenson and collaborators who argue that there is 'no silver bullet' or magic solution to raising productivity and that economies need to invest in order to grow. Against this, the figures resulting from the analysis in this paper refer only to the spillovers originating among companies operating in an R&D intensive industry. This is just one potential source of spillovers and it does not exclude the presence of other channels through which knowledge can spread across companies, industries and countries. For example, we do not consider such issues as the international transfer of technology which can have important effects (see the discussion in Griffith et al., 2004). Further research is needed in order to fully assess the impact of knowledge generating activities on company performance.

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### Appendix A. Statistical clustering techniques

The clustering technique adopted for the derivation of the skill taxonomy is based on the K-means algorithm. The construction of the skill taxonomy uses data on the proportion of workers in each industry with High, Intermediate and no Vocational Qualification, as described in Section 3.

A similar clustering technique was used by Peneder (1999, 2001) to derive the factor intensive taxonomy for manufacturing industries. The advantage of the cluster technique is "...to reveal patterns hidden within the data simultaneously across a multidimensional set of variables" (Peneder, 1999). The set of variables used by Peneder are: wages and salaries as a ratio to value added, total investment to value added ratio, average ratio of advertising outlays to total sales and R&D expenditure in total sales. These reflect both industry endowments of capital and labour, as well as strategic investments in intangible assets.

Our initial aim was to use a similar cluster technique to extend the factor intensive taxonomy to non-manufacturing. However, it was not possible to derive data at a suitable level of disaggregation – the statistical techniques underlying clustering require a reasonably large sample. Instead we used a more ad-hoc method. After checking the patterns of capital/output ratios across countries for broad sectors, we derived 24 two-digit non-manufacturing groups of companies. We then divided the sample into three equal-sized groups according to investment intensity.

We next looked for information on R&D expenditures and advertising. Neither is available in published sources for the required

industry disaggregation. In the case of advertising, Euromonitor marketing yearbooks show the top ten advertising sectors for the European countries considered in this paper. Again the main advertising sectors are similar across the four countries – all show that outside manufacturing the main advertising sectors are retail trade and entertainment (US SIC group 78). Hence all retail sectors except the miscellaneous industry (SIC group 59) were deemed to be advertising intensive.

In terms of R&D we considered the R&D to sales ratios in the company accounts database. Outside manufacturing only two 2-digit groups show significant R&D to sales ratios (SIC 73 – business services and SIC 87 – engineering, accounting, research management, etc.). We then considered these groups in more detail. R&D to sales ratios were only significant in the groups 733 (commercial art, mailing etc.), 737 (computing services), 872 (accounting, auditing etc) and 873 (R&D testing and engineering services). These were deemed to be R&D intensive. Otherwise the non-manufacturing sectors were allocated according to their capital intensity division with the middle group termed mainstream services.

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