Do intangible investments affect companies' 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 intangibles 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, obtained using cluster analysis. These are included in the econometric specification in the form of shift and interactive dummies. The results provide evidence of higher productivity in R&D 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 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 company accounts 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 employing 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). There is plentiful empirical support for the notion that labour force skills impact positively on productivity. These range from case studies, e.g. a series of plant level international comparisons carried out at NIESR and summarised in Prais (1995) to sophisticated econometric analyses which deal with aspects of the underlying technology such as evidence for skill biased technical change (e.g. Autor et al., 1998, Machin and van Reenan, 1998)[1].

[1] On the other hand, cross country studies based on conventional growth accounting calculations, which treat skills as an increase in the quality of labour, generally do not show very large impacts from skilled labour (Crafts and O'Mahony 2001). Hence the question of the existence of spillovers from human capital formation, complementarities between skilled labour and physical capital and the form of technological change are seen as crucial.

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 based on factor intensities using a taxonomy of industries developed for manufacturing by Peneder (2000), extended to cover industries in non-manufacturing. The second is a division of industries according to skill intensities based on data from labour force surveys. The 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, while, at the same time, 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).In fact, investing in R&D not only generates innovations but also enhances the firm's ability to absorb existing information (Cohen and Levinthal 1989).What happens if the firm's internal research effort is equal to zero? Is it possible for a firm that does not invest in R&D to gain from other firms' R&D effort? This is another question addressed in this paper. Because of the nature of R&D activities, we expect that even those firms that do not invest in intangible assets may enjoy the benefit of the general stock of knowledge within a particular industrial sector. For example, exchanges of ideas between two companies can result in a more efficient way of using the existing equipment, without direct investments in R&D[2].

Sections 2 and 3 discuss the relationship between R&D and productivity and the impact of R&D spillovers on productivity, presenting a brief summary of the recent econometric evidence. Section 4 describes the methodology used in order to integrate industry information in the analysis of R&D and productivity at the firm level, and how these data can be used to evaluate the presence of technological spillovers. Section 5 presents the empirical framework which is the basis of the econometric analysis. Section 6 summarises the main features of the data set and section 7 discusses the methodology used in the empirical investigation. Section 8 presents the results and section 9 concludes the paper.

[2] This assumption follows the traditional view of technological knowledge as a public good, whose effects are realised by all firms operating within an R&D intensive environment (Arrow 1962a, Nelson 1959).

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, 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 the economic growth literature (Griliches 1979, Griliches 1988, Grossman and Helpman 1991, Coe and Helpman 1995).

The literature on R&D and productivity is very rich and it covers both macro and micro evidence[3]. In this section we mainly refer to the evidence on the output elasticity of R&D at the firm-level as it provides a base for comparison for our own empirical analysis. In all studies, R&D is invariably found to have a significant and positive effect on output growth, after taking account of the influence of other inputs. But the range of estimates of the elasticity of output with respect to R&D does vary by study. For example, Griliches, in two successive papers, finds that, in United States manufacturing, the elasticity of output to R&D is 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). Shenkerman (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 difference which can partly be explained by the availability of better data for France[4].These results mainly refer to the 1970s. A more recent study by Mairesse and Hall (1996), based on a panel of US and French firms, reveals that the contribution of R&D to productivity during the 1980s has slowed down in both countries.

The evidence for other countries is not as rich as for the US and France but it still provides some interesting results. 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

[3] 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.

[4] 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 (Shankerman 1981).

between 0.072 and 0.155, in a sample of 443 manufacturing firms (Harhoff 1998)[5]. Finally previous research tends to concentrate on manufacturing with little evidence available for service activities some of which have high R&D intensities (see below).

3. *The search for R&D spillovers.*

A large part of the theoretical literature on endogenous growth has stressed the cumulative nature of knowledge and the ability to generate spillovers in the rest of the economy. As stated in Romer (1986): "*The creation of new knowledge by one firm is assumed to have a positive external effect on the production possibilities of other firms because knowledge cannot be perfectly patented or kept secret.*"

The presence of spillovers provides an explanation of aggregate increasing returns to scale without abandoning the assumption of perfect competition and constant returns to scale at the firm level. There are various interpretations of how externalities originate. New knowledge can be generated from growth in activity, e.g. with increasing investment and production (Arrow 1962b), with the accumulation of human capital (Uzawa 1965) or via the acquisition of quality-improved inputs (Goto and Suzuki 1989)[6]. Exchange of ideas within research teams of different firms and within industries that operate in similar fields is another way of diffusing knowledge and generating externalities. According to Griliches (1992) these are genuine spillovers and they particularly affect companies working in the same 4-digit or 3-digit SIC[7].

The different ways of accounting for externalities has produced a wide range of empirical results. 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 Terlekyi (1980) 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[8]. Similarly, in Goto and Suzuki (1989)

[5] See also Klette (1996) for evidence on a set of Norwegian companies.

[6] 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).

[7] As an example of this type of spillovers, Griliches (1992) mentions the exchange of ideas between the photographic industry and the scientific instruments industries.

[8] Part of the difference is explained by the source of R&D financing. Specifically, privately financed R&D is much more productive than Government financed R&D programmes (Terleckyj 1974, 1980).

coefficient on the embodied R&D is 0.80 while the coefficient on own industry R&D is 0.25[9]. Equally large coefficients are estimated by Berntein and Nadiri (1989), using a cost function framework.

Following Griliches' (1992) suggestion of considering the technical similarities across firms as a source of spillovers, Jaffe (1986) includes a distance measure in the computation of a spillover variable based on data for technology-based patent classes for the US[10]. Goto and Suzuki (1989) construct a similar measure based on R&D data for the electronic industry and they evaluate the spillovers from this industry to the rest of the manufacturing sector[11] 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. In Jaffe's (1986) model the direct impact of the R&D spillover variable is to decrease profits and market value[12].

4. Industry and skill taxonomies as a measure of technological proximity.

In this paper we evaluate spillovers using a new methodology which, like Jaffe (1986) and Goto and Suzuki (1989), accounts for the similarities across companies. One of the advantages of our method is that it can directly be extended to countries that share similar industry structures in terms of factor inputs utilisation and skill intensity. The method employed to account for spillovers is based on two newly developed taxonomies, an industry and a skill taxonomy, that classify industries according to their factor and skill intensity.

The industry taxonomy for the manufacturing sector is derived from Peneder (2000). This uses cluster analysis to group industries into five groups: 1. Mainstream; 2. labour intensive; 3. capital intensive; 4. advertising intensive and 5. R&D intensive. The analysis was carried out for 3-digit groups of the NACE industrial classification

[9] Mansfield et al. (1977) obtain very high social returns using a different methodology. The authors collect data directly from firms asking questions about recent innovations and basing their inference on information for 17 industries on the type of innovation (product or process). In 13 industries the social returns are much higher than the private ones. While the median private rate is about 25%, the median social rate is about 56%.

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

[11] 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.

[12] Further results regarding estimates of the social returns to R&D can be found in Cameron (1996) and Jones and Williams (1998).

and was based on US data for the early 1990s[13]. Peneder's (2000) manufacturing taxonomies were extended to non manufacturing in order to match all the companies in our data set . The skill taxonomy was constructed following a clustering technique similar to Peneder (2000). This was mainly based on information drawn from the 1998 British Labour Force Survey . The inclusion of information on skills for other countries proved impractical, either because the level of industry detail was insufficient or there were problems in matching qualifications across countries. Nevertheless data for the US and Germany were used to check the plausibility of the clusters. Qualifications were divided into three groups, Higher (graduates and above), Intermediate (all vocational qualifications plus A-levels) and No Vocational Qualifications. Further details on both taxonomies and on the clustering techniques are given in the Appendix.

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. Grouping companies according to their factor and skill intensity takes into account the likely exchange of ideas and products that can be an important source of spillovers. Thus this paper is concerned with identifying intra sector spillovers with sectors defined according to the taxonomies.

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 group is in the R&D intensive and in the High skill intensive. However, the situation is a bit 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 studies (see, for example, Haroff 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. We believe that

[13] Specifically, (i) *labour intensity* (average ratio of gross wages and salaries to value added from 1990 to 1995); (ii) *capital intensity* (average ratio of total investments to value added from 1990 to 1994); (iii) *advertising sales ratio* (average ratio of advertising outlays to total sales from 1993 to 1995); (iv) *R&D sales ratio* (average ratio of expenditures on research and development to total sales from 1993 to 1995).

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)[14]. 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. 2000).

Table 1

Mapping of the companies in the Industry and skill taxonomies

Total number of companies						
Industry	Total	USA	France	Germany	Japan	UK
Mainstream (F1)	1204	381	77	101	469	175
Labour intensive (F2)	2039	641	146	128	718	406
Capital intensive (F3)	830	355	53	56	272	94
Advertising intensive (F4)	1066	400	58	77	333	198
R&D intensive (F5)	1598	1010	69	73	298	148
Low skill intensive (S1)	1873	658	72	159	608	376
Intermediate skill intensive (S2)	2445	768	220	187	967	303
High skill intensive (S3)	2418	1361	111	89	515	342
R&D performing companies						
Mainstream (F1)	549	24	32	215	76	202
Labour intensive (F2)	505	15	30	237	81	142
Capital intensive (F3)	365	16	20	168	40	121
Advertising intensive (F4)	245	14	5	88	43	95
R&D intensive (F5)	1324	33	51	221	113	906
Low skill intensive (S1)	516	16	21	213	92	174
Intermediate skill intensive (S2)	1069	58	72	424	108	407
High skill intensive (S3)	1403	28	45	291	153	885

See section 6 below for details of data sources.

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 (Griliches 1980, O'Mahony and Vecchi 2000, for example). However the taxonomies used in this

[14] Basic accounting principles are similar in the OECD countries analysed and the remaining differences are unlikely to be of a first-order effect (Bhagat and Welch 1995). Also, there is evidence of increased cross country harmonisation in the tax treatment of physical capital (Bloom et al. 2000).

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 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 whether it can be interpreted as a spillover effect.

5. 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:

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

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 (Griliches 1980), as well as some exogenous forces:

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

In equation (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 a Cobb-Douglas function[15]. The model then becomes:

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

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

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

[15] 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).

where $\Delta\varepsilon_{it}$ is the rate of growth of Total Factor Productivity (TFP). In our data set, y is net sales[16], 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 expenses converted to a stock measure. Tangible capital at historic cost was converted into capital at replacement costs (Arellano and Bond 1991), while R&D expenditure was 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. This spillover effect is modelled 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:

(5)
$$\Delta\varepsilon_{it} = \sum_i \phi_i D_i \ ,$$
$$\Delta\varepsilon_{it} = \sum_j \phi_j D_j$$
$$i = 1,...,5$$
$$j = 1,...,3$$
$$D_i = F1,...,F5$$
$$D_j = S1,...,S3$$

As in table (1), F1,..,F5 are the dummies derived from the factor intensity taxonomies, while S1,…S3 are the dummies derived from the skill intensity groups. Spillover effects are expected to originate from the R&D intensive and the intermediate/high skill intensive groups of companies. These are the companies that are more likely to carry on research projects and develop and exchange new ideas, while the rest of the companies are more likely to be users of existing technologies. A simplified version of equation (4) can also be estimated using the sample of companies that do not undertake any R&D investments, i.e.:

(6)
$$\Delta y_{it} = a_i + \alpha\Delta k_{it} + \beta\Delta l_{it} + \Delta\eta_{it} \ .$$

16 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).

Using equation (6) we will investigate whether companies that do not undertake any R&D investments experience some spillover effects from operating in a knowledge intensive environment[17]. Therefore:

(7)
$$\Delta\eta_{it} = \sum_i \rho_i D_i \ ,$$
$$\Delta\eta_{it} = \sum_j \rho_h D_j$$
$$i = 1,...,5$$
$$j = 1,...,3$$
$$T_i = F1,...,F5$$
$$T_j = S1,...,S3$$

where the dummies are defined as in equation (5).

In equation (5) and (7) a significant and positive coefficient on the R&D intensive dummy, F5, suggests that firms in this industry group gain productivity improvements from being located in this group, above those that they gain from their own individual investment in R&D. This can *per se* be interpreted as a spillover effect. However, in equation (5) a significant and positive coefficient on F5 can be the result of a the simple form of equation (4), since it imposes an equal R&D coefficient across all industry groups. Therefore, we will relax this assumption by allowing a different coefficient in the R&D intensive companies and testing again for the presence of spillovers, as follows:

(8)
$$\Delta y_{it} = a_i + \alpha\Delta k_{it} + \beta\Delta l_{it} + \gamma_1\Delta r_{it} + \gamma_2\Delta r_{it} * F5 + \Delta\varepsilon_{it}$$

The spillover effect will be modelled as in equations (5) and (7).

Interaction between the industries 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.

[17] We are also assuming that companies that do not report any R&D expenditure do not perform any investments in R&D.

6. 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 were net sales, employment, net physical capital defined as equipment and structures, (PPE) and R&D expenditures. Companies that did not disclose any data for employment, net physical capital or net sales were dropped as were a few UK companies whose financial year changes of more than a month throughout the 10 years of observations.

The Worldscope database classified 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 were included. For non-manufacturing we excluded 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 included 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 differed from other firms so these were 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 were considerably more data available for the UK than the other three 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 and Italian sample and a slightly lower share of the US sample.

Table 2.

Composition of the sample: manufacturing and non-manufacturing

Country	10-17	20-39	40-47	484	50-57 & 59	58 & 70	72,76,78, 79	73,75,78	Total
France	20	276	16	1	65	9	15	42	444
Germany	26	327	14	0	42	2	1	14	426
Japan	216	1272	107	0	375	0	25	63	2058
UK	88	583	40	3	235	0	37	154	1140
USA	182	1511	101	26	391	98	60	556	2925
Total	532	3,696	278	30	1108	109	138	829	6,720

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.

7. *Econometric methodology*

The empirical analysis of the relationship between intangible assets and companies' productivity performance will be 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), (6) and (8). 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 effect. Estimating equations (4), (6) and (8) using Ordinary Least Squares (OLS) usually provides estimates that are generally consistent with a-priory knowledge of factor shares and constant returns to scale (Griliches and Mairesse 1997, Blundell and Bond 1999). However, the OLS estimates are likely to be affected by endogeneity and simultaneity bias . In this case an instrumental variable estimator can, produce consistent estimates. In this study we will consider two versions of the Generalised Method of Moments (GMM) estimator, the First Difference GMM (FD GMM) and the System GMM (SYS GMM). 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, Hall and Mulkay 1999). However, the results from this type of estimation have not always been very satisfactory. The problem is related to the weak correlation between the growth rates of the independent variables and their lagged levels, especially in the case of highly persistent variables. Weak instruments can cause large finite sample biases when using the first difference GMM (Blundell and Bond 1999).

The SYS GMM is an extended version of the FD GMM and it 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 (Blundell and Bond 1998). The SYS GMM has proved to give more reasonable results in the context of production function estimation (Blundell and Bond 1999).

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 groups (F5 and S3). An interaction term is introduced to control for the contemporaneous presence of highly skilled labour within R&D intensive companies. We expect productivity to be higher among companies operating in an extremely technology intensive sector.

In a standard estimation in first difference, the dummy variables could be included directly into 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 system GMM, which compounds a specification in first difference and in levels, they pick up levels effects which are comparing across industries within and between countries. Hence for example it is comparing productivity levels in computing services 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, i.e. in a commonly used terminology we are attempting to compare apples and oranges (Baumol and Wolff, 1981, 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. Furthermore, as a robustness check, we compared the results of the two-step procedure with the single step alternative, based on a production function including the taxonomy dummies on the right hand side. This was estimated using FD OLS and

FD GMM. The coefficients on the taxonomy dummies were substantially the same as the ones presented in this paper. Also the coefficient on labour, fixed capital and R&D capital were not affected by the introduction of the dummies in the production function estimation.

8. Results

8.1. Pooled specification

The empirical analysis begins with a presentation of the results based on the three estimators discussed above, for comparison purposes. Therefore, we estimate equation (4) using FD OLS, FD GMM and SYS GMM. Results are presented in the 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. Table 3 also shows first order (AR(1)) and second order (AR(2)) serial correlation tests of the first differenced residuals. In order to obtain consistent GMM estimates the assumption of no serial correlation in the residual 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). Additionally, Table 3 also presents the Sargan test of overidentifying restrictions.

The three estimators produce quite different coefficient values reinforcing the finding that the estimation method matters (Blundell and Bond 1999). The coefficient estimates using SYS GMM turn out to be more consistent with a-priori information on input shares using growth accounting. They overall 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 level, while it was rejected when including R&D. In the FD OLS the labour coefficient is quite low compared to growth accounting coefficients while the impact of R&D is a bit higher than existing empirical evidence based on firm-level data. Overall the OLS estimates suggest decreasing returns to scale (the assumption of constant returns was rejected at 1% level of significance). 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. 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.

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

Standard errors in parentheses. (*)=coefficient significant at 95% level.

Table 3 also presents estimates of the production function allowing for the interaction between the R&D variable and the R&D intensive dummy (Column 4). The introduction of the R&D interaction term lowers the overall estimate of the R&D coefficient from 0.153 to 0.096 The results also show that companies operating in the R&D intensive industry enjoy significantly higher returns to their R&D investments of approximately 4%. These results are consistent with existing estimates of the R&D elasticity (Griliches 1984, Griliches and Mairesse 1984, Mairesse and Cuneo 1985).

The serial correlation tests presented in table 3 are consistent with our assumption of no serial correlation in the residuals in levels. The Sargan test, on the other hand, rejects the null hypothesis of valid instruments. However, there is evidence that the Sargan test tends to over-reject the null hypothesis in equations specified in first difference (Blundell and Bond 1998).

Table 4 presents the estimates of the spillover effect, derived from the second step of our analysis. The results show that the dummies for the R&D/Skill intensive sectors, included separately, are positive and significant. Also these two taxonomies are significant when interacted. Hence 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 suggest companies enjoy a 3.7% productivity gain from operating in sectors which are both R&D and human capital intensive (column 3). When interacting the R&D variable with the R&D intensive dummy (columns 4-6), the size of the spillover effect goes to about 2% in all three specifications, and remains statistically significant. 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.

Table 4
Second step: Evaluation of the spillover effect.
Dependent variable: rate of growth of Total Factor Productivity
(Ordinary Least Squares regression)

Factor intensity dummies	First step SYS GMM			First step: SYS GMM with interaction		
	(1)	(2)	(3)	(4)	(5)	(6)
Mainstream	0.014		-0.014	-0.014		-0.014
	(.007)		(.007)	(.007)		(.007)
Capital	0.006		-0.008	-0.008		-0.008
	(.007)		(.007)	(.007)		(.007)
Advertising	-0.000		-0.014	-0.014		-0.014
	(.008)		(.008)	(.008)		(.008)
R&D	0.036*			0.017*		
	(.006)			(.005)		
Skill (med.)		0.002			0.001	
		(.006)			(.006)	
Skill (high)		0.022*			0.019*	
		(.005)			(.006)	
R&D & High Skill			0.037*			0.018*
			(.006)			(.006)
Other R&D			0.030			0.011
			(.008)			(.008)

Standard errors in parentheses, (*) = coefficient significant at 95% level, (**) = coefficient significant at 90% level. The rate of growth of TFP is derived from the residuals of the production function specification (3) and (4) in table 3.

We next 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, presented in table 5, appear to support this intuition, even though 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[18]. Companies operating in the intermediate and highly skilled sectors appear to enjoy

[18] The coefficients on the other industry dummies were not significantly different from zero and therefore they are not presented in table 5.

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 environment.

Table 5

Non R&D reporting companies

First and second step estimation

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

Standard errors in parentheses,
(*) = coefficient significant at 95% level

Next we investigate whether there are differences in the returns to own R&D and in the spillover effects between manufacturing and non manufacturing. Results are presented in table 6. These show that there are high and positive returns to R&D in the non-manufacturing sector but, contrary to our expectations these are higher than in manufacturing. This probably 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 coefficients estimates for labour and capital on the other hand are consistent with growth accounting estimates, with non-manufacturing companies being characterised by higher labour elasticity and lower capital elasticity.

Table 6

R&D in manufacturing and non-manufacturing

First and second step estimatio.

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

Standard errors in parentheses, (*) = coefficient significant at 95% level

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 were substantially unchanged when the two sets of industry and skill dummies were individually estimated. We found 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.

8.2 Country results.

In this section we discuss the econometric evidence for the US, Japan and the three European countries pooled together, presented in table[19]7. As anticipated in section (4), the country samples do not fully represent the different industrial sectors and this is reflected, in the first instance, in the coefficient estimates for the R&D reporting companies. In the US, where the population of R&D intensive companies is fairly large, we do obtain a positive and significant 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 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 do not reject the hypothesis of no serial correlation in the levels of the residuals.

The results for Japan are quite puzzling, as the R&D coefficients 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 Mariesse 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

[19] The number of observations for each European country was not large enough to allow consistent coefficient estimates.

financial statements vastly under-report R&D expenditure in Japan (Goto and Suzuki 1989).

Table7.

Country Estimates

First and second step estimation

(Standard errors in brackets)

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

Standard errors in parentheses, (*) = coefficient significant at 95% level

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 is often considered as an important source 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.

9. *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 have shown 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.

Our next task was to 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 t, depending on the specification used and the country of reference. 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 industry 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. It is 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 only refer to the spillovers originating among companies operating in an R&D intensive industry. This can be considered as one 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, our results do not consider such issues as the international transfer of technology which can have important effects (see the discussion in Griffith et. al 2000). Further research is needed in order to fully assess the impact of knowledge generating activities on companies' performance.

Appendix A. Statistical Clustering Techniques.

The k-means algorithm is a commonly used method for partitioning *n* data points with *m* variables into *k* clusters or families such that the resulting matrix of cluster centres, *J(k,m),* minimises the Euclidean sums of squares, given by the following objective function:

$$J(k,m) = \sum_{l=1}^{k} \sum_{i=1}^{n} \left\| x_i - v_l \right\|^2$$

where x_i is the vector of variables associated with observation *i* and v_l is the cluster centre for cluster *l*.

There are a number of well known problems with clustering techniques. Depending on the number of dimensions available and the number of groups chosen the technique can give rise to groups which are difficult to describe. Frequently data points can appear to be in the 'wrong group' so that researchers often resort to manual reclassification. This arises for data points which are in the middle between two or more cluster centres. Against this the technique can be a powerful tool in summarising a large number of dimensions.

These problems have largely been overcome in the present paper. First the cluster are carried out for clearly defined groups. Secondly, in the case of the industry structure types, Peneder (2000) defined a group, mainstream, to take account of the fact that some industries do not fit neatly into the cluster. Finally although some manual reallocation across clusters was carried out in the case of the skill taxonomies, this was based on extraneous information for additional countries rather than a purely ad hoc procedure.

Statistical clustering was employed by Peneder (2000) to create an industry taxonomy for manufacturing and the skill taxonomy used in this paper. Although initially we had hoped to use a similar technique on non-manufacturing industry groups, it proved to be impossible 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 are 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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