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R&D spillovers and productivity: Evidence from U.S. manufacturing microdata*

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Abstract. This paper deals with the estimation of the impact of technology spillovers on productivity at the firm level. Panel data for American manufacturing firms on sales, physical capital inputs, employment and R&D investments are linked to R&D data by industry. The latter data are used to construct four different sets of 'indirect' R&D stocks, representing technology obtained through spillovers. The differences between two distinct kinds of spillovers are stressed. Cointegration analysis is introduced into production function estimation. Spillovers are found to have significant positive effects on productivity, although their magnitudes differ between high-tech, medium-tech and low-tech firms.

Key words: R&D spillovers, productivity, production functions, enterprise data

JEL classifications: D24, O30, O31, O34

1. Introduction

In many of the recent so-called 'endogenous growth models' (e.g. Romer, 1986, 1990 and Grossman and Helpman, 1991a), as well as the 'non-mainstream' literature on growth and technology (e.g., Nelson and Winter, 1982), the generation of technology is the main driving force of economic growth. The (steady state) growth rates of countries devoting relatively much

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of their resources to Research and Development (R&D) are assumed to reach higher values, other things equal. In this literature, the non-rival character of knowledge is often stressed: its use by one firm does not preclude other firms from using it simultaneously. As an immediate consequence, the technology producer is not the only one that benefits from its R&D-efforts: technology spillovers occur.

The empirical literature on the productivity effects of R&D also stresses these technology spillovers. Recently, following the seminal contributions by Griliches (1979) and Scherer (1982), many authors have investigated the productivity effects of technology spillovers, either at the industry or at the country level.[1] Although the estimated magnitudes of the effects appear to vary largely with the industries and countries under consideration (and with estimation methods), the importance of technology spillovers is beyond dispute.[2] However, measuring technology spillovers and their impacts at the micro level remains a less explored area.[3] The principal aim of this paper is to estimate the impacts of technology spillovers at the firm level, thereby trying to shed light on the empirical plausibility of some assumptions and results of (important parts of) the endogenous growth theory, like increasing returns to scale and significant technology spillovers. We estimate Cobb-Douglas production functions, with two factors representing technology: R&D undertaken by the firm itself, as well as R&D undertaken by other firms.

As is well known (see e.g. Griliches, 1990), technology is hard to measure. Faced with the basic choice between input- and output-indicators of technology, we decided to use inputs rather than outputs, for reasons of data availability. This is an approach chosen by most authors who have investigated the relationships between (own) technology and productivity (see e.g. Griliches and Mairesse, 1984, Cuneo and Mairesse, 1984, Lichtenberg and Siegel, 1991, and Hall and Mairesse, 1995). It has the disadvantage that we cannot measure the 'efficiency' of research and development, but it also has the advantage that we do not have to worry about how to evaluate rather simple indicators such as patent counts.

Our empirical study focuses on U.S. manufacturing firms between 1977 and 1991. The estimations are based on three data sources. First, we use an extensive panel data set constructed by Bronwyn Hall and available from the NBER ftp-server, containing data on sales, plant and equipment, employment and R&D expenditures for thousands of U.S. firms. Second, R&D expenditures by industry are taken from the OECD STAN/ANBERD database. Finally, the spillover measures we utilize (introduced in Verspagen, 1997) are based on patent documents of the European Patent Office.

The plan of the paper is as follows: Section 2 is devoted to a brief review of the theory on technology spillovers. The two basic questions that will be answered are which different types of technology spillovers can be distinguished, and what their impact on economic growth and productivity is. In

[1] For studies on the industry level, see e.g. Terleckyj (1974), Griliches and Lichtenberg (1984), Goto and Suzuki (1989), Mohnen and Lépine (1991), Wolff and Nadiri (1993) and Verspagen (1997). Very recent examples of studies considering international technology spillovers are Coe and Helpman (1995), Park (1995) and Bernstein and Mohnen (1998).

[2] Nadiri (1993) offers an extensive survey of estimation results.

[3] Jaffe (1986), Bernstein (1988), Sassenou (1988), Bernstein and Nadiri (1989) and Fecher (1990) are notable exceptions.

Section 3 we elucidate the construction of most of our variables. We devote an entire section to the discussion of the construction of our 'indirect' R&D stocks, because we think this variable is the most important element in our study and because in our opinion even after Griliches' (1979) seminal contribution two basically different kinds of spillovers (so-called rent spillovers and knowledge spillovers) are often confused. Section 5 presents the models we estimate, trying to explore various aspects of the panel-nature of our database. Section 5 also presents the first estimation results. In Section 6, using co-integration tests and error-correction models, we will investigate whether the results in Section 5 can be considered as long-term relationships. Finally, Section 7 provides a summary of the results and a discussion of the empirical relevance of the assumptions on technology made in the endogenous growth models.

2. Technology, spillovers and endogenous growth theories

During the late 1980s, with the contribution of Romer (1986), the idea of 'endogenous technological change' entered the mainstream of economic theory. Romer (1986) and Lucas (1988) provided models (partly similar to Arrow, 1962) that endogenize technological change.[4] An important innovation over the traditional neoclassical growth model was the introduction of knowledge spillovers. The use of a 'unit of knowledge' (R&D) by one firm (say the firm that generated the knowledge) does not prevent other firms from using the same unit (knowledge is non-rival), and no firm can be excluded from such use (knowledge is non-excludable). Consequently, a positive difference between the social returns and private returns to R&D occurs and the economy as a whole faces increasing returns to scale.

In the models by Romer (1990), Grossman and Helpman (1990, 1991b) and Aghion and Howitt (1992) the R&D sector is assumed to have two kinds of output. First, general knowledge, which is non-appropriable and is spilled over to other firms (like in Romer, 1986) and second, blueprints for new products or new varieties of an existing product. The rents of these blueprints can be appropriated (by patenting or secrecy), so firms have an incentive to engage in R&D. But this introduces differentiated products into the analysis, and hence the market structure must be characterized as monopolistic competition rather than perfect competition. This leaves open the possibility of increasing returns to scale at the firm level, rather than only at the aggregate level.

In the empirical literature, technology spillovers had attracted attention long before the developments in growth theory described above took place. The most common approach found in the literature (suggested by Griliches, 1979) is to estimate an extended Cobb-Douglas production function (assuming homogeneous output and inputs), similar to the one assumed by Romer (1986):

$$Q_{it} = AF\left(\sum_{j} R_{jt}\right) K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma}, \tag{1}$$

[4] Surveys are offered by Helpman (1992) and Verspagen (1992).

in which Q, K, L and R denote output, physical capital input, labour input and technological capital, respectively. Subindices i, j and t indicate the firm and time period under consideration. A is a constant and $F(\cdot)$ a function that is necessarily monotonically increasing in the 'economy wide technology-capital', according to Romer (1986, 1990).

Generally, although a setting of homogeneous output and inputs is not compatible with an assumption of increasing returns to scale at the firm level, one does not wish to impose a restriction of constant returns to scale *a priori* (e.g., Griliches and Mairesse, 1984). Thus, unlike Romer (1986), the typical approach is to let the estimation results indicate whether constant returns with respect to either all factors ($\alpha + \beta + \gamma = 1$) or only the traditional, non-rival factors ($\alpha + \beta = 1$) applies or not.

It is clear that such an approach is highly pragmatic as compared to the theoretical models in the new growth literature. However, given the rather crude nature of available empirical data, more sophisticated theoretical devices such as product differentiation, are hard to implement in empirical analyses. Thus, we will not set ourselves the aim of testing new growth theory. But we do feel that the above discussed empirical models can provide some insight into one crucial assumption underlying new growth theory, namely the existence of knowledge spillovers. The importance of knowledge spillovers for productivity at the firm level is therefore what we want to test in this paper.

With regard to the measurement of technology spillovers, we will proceed from the distinction made by Griliches (1979) between rent spillovers and pure knowledge spillovers. Rent spillovers are solely caused by product innovations. Due to competitive pressures, the producer of the innovation is often unable to capture the 'full price increase' that results from efficiency gains for customers, due to the higher quality of the innovation relative to the 'old' product. For example, a new personal computer that can perform certain calculations twice as fast as the existing ones, will often be sold at a price between once and twice the price of the existing machines. As an immediate consequence, the price per efficiency unit has fallen, and the productivity of the firms using the new computer will rise.

Part of the effect of rent spillovers is in fact due to 'mis-measurement'. Even if all innovation producers would have sufficient market power to set prices according to efficiency for buyers, conventional price index systems (not taking into account quality changes) would interpret the price increases as inflation. In this case, the rent spillover would again spill from producer to user. As pointed out by Griliches (1992), rent spillovers are not true spillovers, because they are often caused by measurement errors connected to crude assumptions like homogeneous products.[5] Moreover, one can not speak of a true externality even in the case of rent spillovers not caused by mis-measurement, because of the transaction-nature of the phenomenon.

Although the 'later' new growth models, as well as some of the empirical implementations of these (such as Coe and Helpman, 1995), seem to be implicitly taking into account rent spillovers by the imperfect competition as-

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[5] In reality, a firm's output in current prices will be determined not only by its quality itself, but also by the number and quality of close substitutes available to buyers. The same applies to a firm's (capital) inputs. Even the use of hedonic price deflators can not always guarantee perfect deflation (see Trajtenberg, 1990), so our aggregate measures of output and inputs (see the next section) and crude deflators are bound to cause rent spillovers.

sumption, Griliches' concept of pure knowledge spillovers is more central to the debate on endogenous growth, technology and increasing returns. In contrast to rent spillovers, knowledge spillovers are not embodied in traded goods, and thus do not occur in relation to market transactions. Pure knowledge spillovers are related to the partly public character of knowledge, and may occur when information is exchanged at conferences, when an R&D engineer moves from one firm to another, when a patent is disclosed, etc. Many more examples of sources for knowledge spillovers could be mentioned, but the most important common property is that relevant knowledge is transferred from one firm to another, without the receiver having to pay for it directly to the producer of the knowledge, as in the case of the 'general knowledge' connected to the production of blueprints in the new growth models.[6]

Due to the variety of ways in which knowledge spillovers and rent spillovers may occur, and given the generally poor quality of technology indicators, measuring spillover flows is not an easy task. Our aim in this paper is to test a number of ways of measuring spillovers that have been proposed in the literature, by estimating elasticities of output with respect to different types of knowledge (spillovers). Before we discuss the various ways in which we attempt to measure knowledge spillovers, we will discuss the construction of the other variables that are more commonly found in firm-level productivity studies.

3. Data and construction of variables

In the preceding section, we already presented the extended Cobb-Douglas production function (Eq. 1), on which we base most of our analysis. This section explains the construction of the variables Q, K, L and R. We took our observations for these variables from a data set constructed by Bronwyn Hall (made available through the NBER ftp server, under the name BLONG.ZIP). This database contains data on production related quantities for approximately 7000 U.S. firms, for the period 1974–1993. For many firms in the database, however, data are not available for the full twenty years. In order to avoid disturbing short-run effects we decided to include into our study only those firms for which data for at least ten consecutive years are available. We also decided to concentrate our analysis on manufacturing firms only, mainly because we feel that the concepts of technology and technology spillovers as we use them are most relevant to manufacturing. In addition, conceptual problems associated with the measurement of output (sales) in many services industries also provide an argument to focus on the manufacturing sector only. Finally, it must be noted that the data are for firms rather than establishments, which may often imply that we are dealing with heterogeneous units. The database provides a sector variable, which classifies the firms according to their main output.

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[6] Although the spillover-receiving firm does not pay directly to the knowledge-producing firm, the debate on knowledge spillovers has pointed out that spillovers cannot be assimilated without costs. E.g., Cohen and Levinthal (1989) argue that a firm has to do some R&D itself to benefit from spillovers, thus arguing that knowledge spillovers and the development of 'own' knowledge are complements rather than substitutes. In our simple Cobb-Douglas framework, knowledge spillovers and knowledge developed by the firm itself appear as substitutes.

An immediate implication of these decisions is that our database cannot be seen as a random sample. We think, however, that our remaining sample (even after eliminating all non-manufacturing firms) is large enough to generate results that offer some insight into the relations we want to investigate. A final note on the Hall database concerns the dating of the variables. Like in the case of Griliches and Mairesse (1984), the data for some of the firms concern fiscal rather than calendar years. Following Hall, we chose to include these data, taking the year that overlaps most with the fiscal year as the calendar year.

Concerning firm output Q, our preference was either to use value added instead of sales as our measure of output, or to include intermediate inputs as an additional input (see e.g. Cuneo and Mairesse, 1984 for a comparison), but the database forced us to use sales. We deflated sales by US industrial output price indices taken from OECD's STAN database, which are given for 3-digit ISIC (rev. 2) industries (OECD takes its data from national U.S. sources). As a measure for physical capital K, we chose 'net plant, property and equipment' (nppe) from Hall's database. Alternative measures for the physical capital stock were 'total assets', or 'gross plant, property and equipment' (gppe). Although a measure of the gross capital stock would be more appropriate if one would be interested in estimating rates of return to invested capital, we considered a net measure more useful for the present purposes because it is closer to the concept of 'productive' capital.[7] As a deflator for the capital stock variable, we used the price index for the total U.S. manufacturing capital stock, which is available from OECD's database on Stocks and Flows of Fixed Capital. For labour input L, the database provided us only with annual numbers of persons employed. This does not correct for a decrease in the average number of hours worked between 1974 and 1993, or the increased education and training of employees during the same time interval. Both effects are likely to cause biases in our estimations, but the biases might partly offset each other.

In the literature on this subject, two different approaches with respect to the modelling of R&D can be distinguished. In the first approach, R&D expenditures are accumulated into a knowledge stock, with gross investment in the form of R&D expenditures and depreciation because knowledge gets obsolete. Assuming a fixed rate of depreciation, the perpetual inventory method can be applied and firm i's R&D stock at time t may be expressed as $R_i(t) = \Sigma_\tau w_\tau RE_i(t-\tau)$, where the weights w_τ are exogenously fixed according to a geometrical lag: $w_\tau = (1-\delta)^\tau$, in which δ is the assumed rate of obsolescence. $RE_i(t)$ denotes the R&D expenditures of firm i in year t. This approach can be found in, among others, Griliches and Mairesse (1984), Cuneo and Mairesse (1984) and Coe and Helpman (1995).

In the alternative approach (originating with Terleckyj, 1974) technology is treated as a flow, measured by R&D expenditures over output or value added. This is equivalent to setting the depreciation rate of R&D equal to zero.[8] This approach yields a direct estimate of the rate of return to R&D instead of the output elasticities (these must be calculated from the estimated

[7] Griliches and Mairesse (1984, p. 342) report that the use of various measures of physical capital stocks and deflators did not yield important differences on their estimation results. We have no reason to believe this is different in our case.

[8] For a short mathematical proof, see e.g. Griliches and Mairesse (1984, p. 342–344).

rates of return and the data on stocks). Since Eq. 1, our point of departure, includes output elasticities as the parameters to be estimated, the use of R&D stocks seems more natural.

Our data contain annual company R&D expenditures, which we use to implement the perpetual inventory model. Before constructing the R&D stock, we deflated all R&D expenditures by the U.S. GDP deflator (taken from OECD's Main Science and Technology Indicators database). We used a depreciation rate of 15% for the construction of the R&D stocks. This percentage is quite common in firm level studies (see Griliches, 1990).[9] The initial R&D stocks (for the year prior to the first observation for R&D expenditures) were approximated by multiplying the first observation on the R&D expenditure variable by five. This implies a 15% depreciation rate and an initial 5% growth rate of the R&D stock. Although these seem reasonable approximations, we decided to exclude the first two values for each firm's R&D capital stock from our analysis. Moreover, we included R with a one-year lag (for econometric reasons that will be discussed in Section 5), which caused a further loss of one observation per firm. Constructing our variables in this way, we obtained 11238 observations from 859 firms.

As Griliches and Mairesse (1984) point out, estimations based on samples like the one described might be disturbed by the presence of firms that have merged. We partly copied their approach, creating a 'restricted' sample of 9223 observations from 680 firms by deleting those firms from the unrestricted sample that have at least once shown a year-to-year increase of sales of more than 80%. Probably, this has led to the deletion of some non-merged rapidly growing firms, but Griliches and Mairesse found most of these jumps in output to be the result of mergers indeed. We will only report estimation results for this restricted sample, which is unbalanced.[10] For some of our purposes, we preferred a balanced sample with the longest possible series length (15 years). Hence, we selected those firms in the restricted sample for which data for the complete time span were available. This balanced sample contains 7275 observations from 485 firms.

Table 1 presents some summary statistics for the two samples. Furthermore, statistics for three subsamples are included, because we also present regression results for these subsamples in sections below. The labels 'high-tech', 'medium-tech' and 'low-tech' are assigned to industries in line with the OECD classification.[11] Two points with regard to this classification need to be kept in mind. First, as explained above, firms are classified according to their main output, which means that minor activities may be misclassified. Second, the division into the three types of industries is done solely on the basis of the

[9] In a recent paper, Nadiri and Prucha (1996) apply a dynamic factor demand model to estimate R&D's depreciation rate. Their result is rather close to the 15%-rule of thumb: 12%.

[10] Estimation results using the unrestricted sample are available upon request.

[11] High-tech industries (ISIC rev 2 codes in brackets): pharmaceuticals (3522), computers and office machines (3825), electronics (3832), aerospace (3845), instruments (385). Medium-tech: electricals (383-3832), chemicals (351+352-3522), automotive (3843), other transport equipment (384-3845-3843), machinery (382-3825), rubber and plastic products (355+356). All other manufacturing industries assigned to low-tech. The sector 'other transport equipment', which is a very heterogeneous sector, is often assigned to low-tech. It includes high-speed trains and the like, as well as bicycles. Thus, the R&D intensity of this sector depends quite a lot on the product mix found in a particular country. We assigned it to medium tech industries, given the nature of the industry in the U.S.

Table 1. Summary statistics, two samples (means, standard deviations between brackets)

Sample	NI		NOB		log Q		log Q/L		log K/L		log R/L	
	unbal.	bal.	unbal.	bal.	unbal.	bal.	unbal.	bal.	unbal.	bal.	unbal.	bal.
Total	680	485	9223	7275	5.59	5.86	4.52	4.53	2.95	2.99	1.62	1.69
					(2.26)	(2.15)	(0.52)	(0.51)	(0.91)	(0.89)	(2.44)	(2.32)
High-tech	245	166	3203	2475	4.92	5.24	4.35	4.33	2.70	2.72	2.67	2.62
					(2.42)	(2.41)	(0.39)	(0.38)	(0.78)	(0.78)	(1.38)	(1.34)
Med-tech	224	168	3110	2520	5.93	6.26	4.61	4.63	3.04	3.12	1.92	2.14
					(2.09)	(1.86)	(0.48)	(0.46)	(0.71)	(0.67)	(1.99)	(1.61)
Low-tech	211	151	2910	2265	5.95	6.10	4.61	4.63	3.14	3.15	0.14	0.17
					(2.07)	(1.99)	(0.62)	(0.62)	(1.13)	(1.13)	(3.00)	(3.00)

NI: Number of firms in sample; NOB: Number of observations in sample.
Q, K and R in millions of 1985 US\$, L in thousands of employees.

mean R&D-value added ratio, and is known to be problematic because of the simplicity of the method (see, e.g., Grupp and Münt, 1998, for a critique). Thus, the split into the three types of industries should only be taken as indicative.

The table shows that the differences between the unbalanced and balanced (sub)samples are rather small. In general, the average turnovers are higher in the balanced sample, indicating that the relatively large firms were the 'stable' ones (on average), being present in the database for the full time span.

As might be expected, the average value for $\log(R/L)$ is highest in high-tech firms, followed by medium-tech and low-tech, respectively. More surprising is the quite large dispersion of R&D intensities, especially within the low-tech subsamples. We studied this phenomenon at a lower degree of aggregation and found that even within many of 22 STAN industries the dispersion is of the same order of magnitude. The apparent heterogeneity is roughly equal for the two samples, so we do not think that the summary statistics presented in Table 1 give rise to a clear preference for either sample.

In order to shed some more light on the development over time of key variables in our sample, Table 2 gives a limited number of summary statistics for four years. The means and standard deviations are calculated from the firm data in the unbalanced samples. Turnover does not appear to have changed very rapidly and labour productivities have been rising rather steadily, in all three sectors. The same applies to capital intensities. R&D intensities have increased drastically in the period under consideration, because of both a changing mix of high-tech, medium-tech and low-tech firms in the sample and increased R&D efforts within these three sectors.

Although we do not want to consider our samples as random samples, we think our data broadly reflect developments often noted by other authors and may serve as a starting point for a study aiming at an assessment of the importance of R&D for firms in American manufacturing.

Before concluding this section, a final word on the double-counting issue originally raised by Schankerman (1981) is in place. He argued that the double-counting of labour and physical capital employed in R&D (these are counted in R&D as well as in the 'traditional' production factors) would yield negatively biased estimated elasticities with respect to R&D. Cuneo and Mairesse (1984) and Hall and Mairesse (1995) found evidence supporting this while Verspagen (1995) concluded that in his sample of industries, although the bias has the predicted sign, it does not affect the results significantly. Unfortunately, our database does not provide us with the information needed to correct for double-counting, i.e., the composition of R&D expenditures at the firm level is unknown. Neither did we find this type of data for total U.S. business R&D expenditures in the OECD databases. Hence the only thing we can do is to refer to the findings of the above-mentioned studies to indicate the likely effects of our double-counting, when interpreting our estimation results.

4. Indirect technology stocks

The main difference between our study and most other studies on R&D and productivity at the firm level is in our focus on technology spillovers. In this section we explain the ways in which we constructed the indirect R&D stocks.

Table 2. Developments over time: means, standard deviations between brackets (unbalanced samples)

	1977				1982			
	High-tech	Med-tech	Low-tech	Total	High-tech	Med-tech	Low-tech	Total
NOB	169	182	176	527	194	205	202	601
log Q	4.85	5.95	5.84	5.56	4.97	5.76	5.82	5.52
	(2.42)	(1.96)	(1.91)	(2.16)	(2.38)	(2.01)	(2.02)	(2.17)
$\log(Q/L)$	4.15	4.41	4.47	4.35	4.23	4.47	4.54	4.41
	(0.35)	(0.44)	(0.62)	(0.50)	(0.30)	(0.42)	(0.59)	(0.47)
$\log(K/L)$	2.41	2.84	2.97	2.75	2.68	3.05	3.08	2.94
	(0.73)	(0.69)	(1.02)	(0.86)	(0.70)	(0.68)	(1.11)	(0.87)
$\log(R/L)$	2.27	1.61	−0.27	1.20	2.46	1.79	0.06	1.43
	(1.24)	(1.97)	(3.04)	(2.46)	(1.21)	(2.02)	(2.91)	(2.39)
	1986				1991			
	High-tech	Med-tech	Low-tech	Total	High-tech	Med-tech	Low-tech	Total
NOB	244	220	201	665	241	210	184	635
log Q	4.80	5.83	5.93	5.48	4.90	6.05	6.07	5.62
	(2.39)	(2.15)	(2.12)	(2.29)	(2.54)	(2.25)	(2.20)	(2.41)
$\log(Q/L)$	4.36	4.64	4.63	4.53	4.57	4.87	4.77	4.73
	(0.35)	(0.46)	(0.60)	(0.49)	(0.44)	(0.53)	(0.63)	(0.54)
$\log(K/L)$	2.84	3.13	3.22	3.05	2.82	3.24	3.36	3.11
	(0.83)	(0.70)	(1.15)	(0.91)	(0.83)	(0.72)	(1.22)	(0.96)
$\log(R/L)$	2.78	2.13	0.22	1.79	3.22	2.42	0.54	2.18
	(1.35)	(1.77)	(3.06)	(2.38)	(1.50)	(1.85)	(3.05)	(2.43)

NOB: Number of observations in sample.
Q, K and R in millions of 1985 US$, L in thousands of employees.

The first step is to identify the amount of indirect R&D available to a firm.[12] This implies that we need to decide which fraction of U.S. manufacturing industry R&D is relevant as 'indirect R&D' for each individual firm. A simple but crude measure is to take the unweighted sum of the R&D stocks of all other firms (see Bernstein, 1988), which comes close to Romer's (1986) theoretical notion of Eq. 1.[13] We will denote this magnitude by *IRT*. However, many refinements to this have been proposed in the literature, because of a widespread feeling that technology produced by some firms is more relevant than technology produced by other firms. Thus, in general, one may assume the following:

$$IRE_{kj}(t) = \sum_{i} \omega_{ij} RE_i(t), \tag{2}$$

where IRE_{kj} is the indirect R&D flow relevant for firm k operating in industry j, RE_i denotes R&D expenditures in industry i (when $i = j$, this excludes firm k's R&D expenditures), and ω_{ij} denotes the weight assigned to industry i's R&D expenditures in industry j. We construct our different measures of indirect R&D by calculating IRE_{kj} for various weighting schemes ω, and then applying the perpetual inventory method in the same way as we have applied it to the firm's own R&D. Thus, *IRT* can be seen as the result of this with all ω_{ij}s equal to 1.

Focusing on technology obtained through inter-industry rent spillovers, Terleckyj (1974), Sveikauskas (1981), Wolff and Nadiri (1993) and others utilized input-output and/or capital flows matrices to construct weights, (implicitly) assuming that an industry that buys relatively much from a certain industry will benefit relatively much from (product oriented) R&D in that industry. A related approach is chosen by Scherer (1982), Griliches and Lichtenberg (1984), Sterlacchini (1989) and Mohnen and Lépine (1991), who use matrices in which either patents or innovations are classified according to their industry of manufacture (rows) and origin of use (columns). We feel that output coefficients of such a patent matrix can serve as a relatively reliable measure of rent spillovers.[14] We use the so-called Yale patent matrix from Putnam and Evenson (1994), from which we delete all primary and tertiary industries before the weights are computed. The resulting stock-variable is denoted *IRY*.

We now turn to 'pure knowledge spillovers'. Jaffe's (1986) and Goto and Suzuki's (1989) approach to this was to position firms in 'technological space' using a vector containing the number of patents per technology field. According to Jaffe, the weights ω_{ij} should be proportional to the similarity between two firm's 'technological space vectors'. Given the lack of detailed patenting data for the firms in our samples, we use two distinct measures defined at the industry level that, in a broad sense, may be considered as

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[12] We decided to abstract from R&D performed by foreign, i.e., non-U.S. firms.

[13] However, unlike Romer (1986), we exclude the firm's own R&D from aggregate R&D in its own industry.

[14] Other authors, however, use this kind of matrices to measure knowledge spillovers (see e.g. Van Meijl, 1995). Although we agree that knowledge may be spilled over during trade negotiations and after sale services with respect to patented product innovations, we maintain that analyses based on these measures primarily pick up with rent spillovers.

alternatives to Jaffe's method, and which were introduced by Verspagen (1997).[15]

Both measures are derived from European Patent Office (EPO) documents. We assume that the EPO data capture general technological linkages between different technology fields or industrial sectors, and that we can therefore safely apply the results to U.S. manufacturing data. In the EPO documents, the knowledge described in a patent is assigned to a single 'main patent class', and multiple 'supplementary patent classes'. For the knowledge classified into the supplementary patent classes, a systematic distinction is made between 'invention information' and 'additional information'. Invention information (present in all documents) comprises knowledge that is claimed by the patentee. The main application area of this part of the knowledge is assigned to the single main patent class, while other, secondary application areas are assigned to the supplementary patent classes.

We use a concordance table (Verspagen *et al.*, 1994) which maps 4-digit International Patent Classification (IPC) codes onto one or more of the 22 ISIC (rev. 2) manufacturing industries. The first of our two measures uses about 60% of all approximately 650,000 EPO patent application documents in the period 1979–1994 to construct an invention information matrix, assuming that the main IPC code into which a patent is classified provides a good proxy for the industry that produces the knowledge and that the invention information classified into supplementary IPC codes (taken as partially unintended 'by-products' of the invention) gives an indication for knowledge spillovers to other manufacturing industries.[16,17] We thus obtain a matrix with patent counts, and by dividing through by the row totals (rows indicate knowledge generators, columns knowledge receivers), we construct the weights ω_{ij}. The resulting indirect knowledge stock is denoted *IR1*.

Our second measure exploits the distinction between claimed 'invention information' and non-claimable 'additional information', which is defined as "non-trivial technical information given in the description, which is not claimed and does not form part of the invention as such but might constitute useful information to the searcher." (WIPO, 1989, p. 26). This information is almost by definition spilled over to other firms, because it is not appropriable. In Verspagen (1997), a non-claimable information matrix is constructed similarly to the invention information matrix: the main IPC code is used to assign the inventing industry, but now only supplementary classes with 'additional information' are taken into consideration. This matrix is based on only 2.5% of the 650,000 patent documents, however, because the number of records

[15] The use of inter*industry* spillover measures in our *firm* level analysis amounts to the assumption that firms within an industry are homogeneous with regard to their technological activity (in the case of knowledge spillover measures) or their use of patented inputs (in the case of *IRY*, emphasizing rent spillovers).

[16] If patent protection against imitation were perfect, this kind of spillovers would not occur. The surveys by Levin *et al.* (1987) and Arundel *et al.* (1995), however, show that in many industries this protection is considered to be far from perfect. Our method, like Jaffe (1986), assumes that 'rates of appropriability' are constant across industries and firms.

[17] In case of n multiple supplementary classes, all these classes were assigned $1/n$ of the patent considered. This 'fractional counting' implicitly assumes that no part of the invention information is relevant to more classes. Therefore, the rows of the corresponding patent matrix sum to the number of patents assigned to the industry of main application.

Table 3. Summary statistics for the indirect R&D variables.* Means, standard deviations between brackets (unbalanced samples)

	log *IR1*	log *IR2*	log *IRY*	log *IRT*
Total	9.68	9.49	9.48	12.76
	(1.14)	(1.43)	(0.95)	(0.20)
High-tech	10.45	9.89	10.20	12.77
	(0.34)	(0.95)	(0.64)	(0.20)
Med-tech	10.13	10.39	9.72	12.76
	(0.75)	(1.23)	(0.52)	(0.20)
Low-tech	8.35	8.10	8.41	12.75
	(0.88)	(0.95)	(0.59)	(0.20)

* All variables in millions of 1985 US$.

with additional information is relatively small. Calculating the weights ω_{ij} similarly, the resulting indirect R&D stock is called *IR2*.

Table 3 presents some descriptive statistics on our *IR* variables, based on the restricted, unbalanced samples. The means for *IRT* appear to be much higher than for the other *IR* variables, due to the $\omega_{ij} < 1$ for *IRY*, *IR1* and *IR2*. The very small standard deviations for *IRT* are due to the fact that for each firm the own R&D stock is subtracted from the (much larger) social R&D stock, which is identical for all firms. Standard deviations for the three alternative measures are higher (even for subsamples), because firms operate in different industries, each of which has its 'own' social R&D stock.

Whether we should regard the various alternative measures of indirect R&D or knowledge spillovers as substitutes or complements remains an open question. *IR1* and *IR2* are obviously close to each other, because they are both constructed with the idea of 'pure knowledge spillovers' in mind. Still, the concepts underlying these two variables are quite different, and thus one might expect that they measure different aspects of knowledge spillovers. Both *IR1* and *IR2* might be regarded as complements to *IRY*, the latter one representing rent spillovers. Finally, a (somehow weighted) sum of *IR1*/*IR2* and *IRY* might be seen as a theoretically more sophisticated alternative to *IRT*.

5. The model and first estimation results

As mentioned in the introduction, this paper has two purposes. First, we would like to see whether or not the results of earlier studies into the relations between R&D and productivity (at the firm level) are confirmed when applying similar techniques to a large panel data set. Second, we would like to test some of the ideas in endogenous growth theory for their empirical relevance, by relating it to the empirical literature on technology spillovers. These purposes together led us to the basic model we rely on throughout the remainder of the paper.

In their panel data analysis of the impacts of own R&D, Griliches and Mairesse (1984), Cuneo and Mairesse (1984) and Hall and Mairesse (1995) base their estimations on

$$Q_{it} = Ae^{\lambda t}K_{it}^{\alpha}L_{it}^{\beta}R_{it}^{\gamma}e^{\varepsilon_{it}}, \tag{3}$$

which is a stochastic (e_{it} is a random disturbance) specification of the standard dynamic Cobb-Douglas production function, extended with own R&D as a factor of production. Although the Cobb-Douglas form is very restrictive, the use of more complex functional forms (e.g. CES or translog) did not alter the estimated output elasticities α and γ to a large extent (see Griliches and Mairesse, 1984, p. 342). Therefore, our point of departure will also be an extended Cobb-Douglas form. The most important difference of our specification compared to Eq. 3 is suggested by the endogenous growth theories discussed in Section 2. We will estimate

$$Q_{it} = A(IR)_{it}^{\eta} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} e^{\varepsilon_{it}}, \tag{4}$$

or, in logarithms:

$$q_{it} = a + \eta(ir)_{it} + \alpha k_{it} + \beta l_{it} + \gamma r_{it} + \varepsilon_{it}. \tag{5}$$

This specification explicitly models R&D efforts as the factor determining the level of technology, instead of the simple lapse of time as in Eq. 3. We have chosen a very simple specification of the function $F(\cdot)$, discussed in Section 2, which we think, however, is flexible enough to capture at least the basic effects of technology spillovers. A positive elasticity η would indicate a dominance of positive 'own R&D augmenting' effects over Schumpeterian 'creative destruction' (e.g., strongly R&D intensive firms pushing other firms out of the market, a process which Aghion and Howitt, 1992, term creative destruction), a negative η a dominance the other way round. In the previous section, we already discussed the various alternatives we developed with respect to the *IR* variable. To reduce problems of heteroscedasticity and multicollinearity we estimate Eq. 5 in labour intensive form,

$$(q_{it} - l_{it}) = a + \eta(ir)_{it} + \alpha(k_{it} - l_{it}) + \gamma(r_{it} - l_{it}) + (\mu - 1)l_{it} + \varepsilon_{it}, \tag{6}$$

in which μ is defined as $\alpha + \beta + \gamma$, the coefficient of returns to scale with respect to all the (rival as well as non-rival) firm-specific inputs.[18,19]

As our sample consists of panel data, the stochastic disturbance might be decomposed into a permanent firm-specific effect and a random transitory effect: $\varepsilon_{it} = v_i + w_{it}$. In a plain OLS-regression on all observations ('total' regression) both effects are taken into account. OLS using firm means over time of all variables ('between') eliminates the transitory effects, thus stressing the cross sectional dimension. Using deviations from the firm means over time as

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[18] In line with our earlier discussion on the possible expectations on CRS with respect to various factors, we could have chosen to define μ as $\alpha + \beta$ or $\alpha + \beta + \gamma + \eta$. This does not affect the estimated values (or t-statistics) for any of the elasticities α, β, γ, or η. The only difference is in the interpretation of μ.

[19] Note that an alternative approach would be to use total factor productivity as the dependent variable. This amounts to inferring α (as the share of property in value added) from the data, and subtracting the term involving α from the equation. This involves the implicit assumption of perfect competition (otherwise the property share may not be used to measure α), which we prefer to avoid. Moreover, as will be discussed at length below, there are certain problems associated with estimating α, for which we will suggest a solution.

the variables ('within') leaves only the transitory random effects, and stresses the time series dimension.[20]

Griliches and Mairesse (1984) pointed out that the estimation results for all the models discussed are likely to be biased due to simultaneity. Investment in physical capital, R&D expenditures and employment might well be influenced by productivity. Lacking sufficient factor price data necessary to estimate a complete system of simultaneous equations, they decided to estimate a two-equation semi-reduced form model, in which functions of R and K simultaneously determine output and employment. One disadvantage of this approach is the implicit assumption of perfect competition in all markets and short-run profit maximization, which is problematic from the point of view of new growth theory. To keep simultaneity problems to a minimum, and to take into account the lag between R&D investment and productivity gains, we included the R&D stocks (both 'own' and indirect) with a lag of one year into the estimated equations. However, this might not completely solve our simultaneity biases.

In Table 4, estimation results using within and between models for the restricted, unbalanced sample are presented. We do not document the estimation results for total, because this does not add much to the understanding. In the estimations, we split the total sample into the high-, medium- and low-tech subsamples described in Section 3. The most important phenomenon emerging from the estimation results is the difference between the between and within estimates. One difference between these two models is the much lower elasticity of capital found in the case of the within model, apparent in all three groups of sectors. Griliches and Mairesse (1984) and Cuneo and Mairesse (1984) found comparable results, at least regarding the elasticity with respect to physical capital α. This difference (also apparent in the adjusted R^2s) must be caused by specification errors, to which we will come back later.

Concerning the 'own R&D' elasticities, these are positive and significant for the total and high-tech sample for both the between and within model. The estimated elasticities for this variable are highest in high-tech industries for both models, as expected. The low insignificant estimates for the other sub samples may (partly) be caused by the double-counting problem discussed in Section 3. According to the between model, deviations from constant returns to scale are small, and most often not significant (in high-tech it is close to significant at the 10% level). The within model yields very large and significant decreasing returns to scale in the low- and medium-tech, as well as in the total sample, mainly through the low estimates of α. In high-tech, we find a moderately negative coefficient.

The estimated values of the output elasticities with respect to indirect R&D are rather mixed. In the cross section (between) dimension the estimates are often insignificant or have a negative sign. The only cases with significantly positive elasticities are *IRT* in the total sample, and *IRY* and *IRT* in low- and high-tech. Negative (and significant) estimates are found for *IR1* and *IR2* in the total sample, and *IR2* for high-tech. These results, which are contrary to our prior expectations, might well be due to a high degree of multi-collinearity between own R&D and indirect R&D. In a between setting, the variability

[20] We do not discuss the 'random effects' version of the within variant, because this did not prove to be preferable over the 'fixed effects' case according to the Hausman test.

Table 4. Estimation results, between and within estimates (unbalanced samples)*

Between estimation	a	α	γ	$(\mu - 1)$	$\eta(ir1)$	$\eta(ir2)$	$\eta(iry)$	$\eta(irt)$	NI	NOB	adj. R^2
Total sample	3.711	0.363	0.014	0.000	−0.029	−0.028	0.005	0.392	680	9223	0.49
	26.15	21.18	2.33	0.05	−2.25	−2.77	0.31	1.98			
High-tech sectors	2.691	0.180	0.039	0.015	0.103	−0.065	0.130	1.249	245	3203	0.23
	3.60	6.35	2.96	1.76	1.47	−3.08	4.57	5.41			
Medium-tech sectors	4.004	0.337	0.016	0.002	−0.045	−0.021	−0.008	−0.665	224	3110	0.31
	11.51	8.88	1.22	0.14	−1.37	−1.07	−0.18	−1.64			
Low-tech sectors	3.204	0.449	0.010	−0.016	0.002	−0.027	0.124	0.698	211	2910	0.68
	12.98	17.78	1.20	−1.06	0.08	−1.03	3.12	1.80			
Within estimation		α	γ	$(\mu - 1)$	$\eta(ir1)$	$\eta(ir2)$	$\eta(iry)$	$\eta(irt)$	NI	NOB	adj. R^2
Total sample		0.138	0.017	−0.114	0.558	0.590	0.422	0.560	680	9223	0.85
		19.70	4.44	−16.32	42.34	42.79	31.72	45.13			
High-tech sectors		0.083	0.102	−0.038	0.396	0.399	0.342	0.439	245	3203	0.71
		8.06	9.22	−2.91	15.82	13.26	15.89	15.72			
Medium-tech sectors		0.160	−0.004	−0.137	0.793	0.761	0.556	0.775	224	3110	0.83
		10.91	−0.68	−11.43	32.49	36.24	17.62	36.14			
Low-tech sectors		0.226	0.004	−0.119	0.354	0.308	0.309	0.329	211	2910	0.93
		18.52	0.83	−10.64	16.63	12.89	13.52	18.94			

* The indicated values for α, γ, $(\mu - 1)$, $\eta(ir1)$ and adj. R^2 are those estimated in the regression equation containing *ir1* as the measure for indirect R&D. The indicated values for, $\eta(ir2)$, $\eta(iry)$, and $\eta(irt)$ are those obtained including *ir2*, *iry*, and *irt* respectively, instead of *ir1*. Of course, the estimated output elasticities with respect to K, R and L are different, but only to a small extent. Due to space limitations we do not present them in this paper.

Table 5. Unit root tests for the variables in the regressions (balanced sample), based on Im *et al.* (1996), $p = 4$, time trend included

Variable	$q - l$	$k - l$	$r - l$	l
Statistic	−1.028	−1.085	−0.703	1.624
Variable	$ir1 - l$	$ir2 - l$	$iry - l$	$irt - l$
Statistic	−21.637	−13.054	−0.738	3.503

between firms with regard to indirect R&D is very small, following from our definition of indirect R&D.

In the time series (within) dimension, the effects of indirect R&D are all positive and (very) significant. According to these estimates, the productivity enhancing effects of spillovers clearly dominate negative effects of spillovers (so-called creative destruction). Comparing the magnitude of the elasticity, in each of the four within equations, the effects of indirect R&D according to the Yale measure (emphasizing rent spillovers) seem to be somewhat lower than for the three alternative measures, except in low-tech sectors.

Before we draw strong conclusions on the relevance of spillovers, however, we will adopt a dynamic specification in the next section, in order to test the robustness of the results.

6. Co-integration, the long run and error correction mechanisms

We do not wish to exclude the possibility that our variables are non-stationary. As is well-known (e.g. Hendry, 1986 and Banerjee *et al.*, 1993) regressing variables that are integrated of order one or higher on each other might lead to spurious correlations, and an upward bias of the estimated t-values and R^2. Given the relatively high R^2-values found in Table 4, we cannot rule this possibility out *a priori*. In order to investigate whether or not the regression results presented in the previous section suffer from such problems, this section takes up the issues of stationarity, co-integration and error-correction models.

The first step in our analysis is to investigate whether or not our variables do indeed contain a unit root. In order to test for this, we apply the procedure proposed by Im *et al.* (1996). The null hypothesis in this test is that a unit root is present in the data. A standard normally distributed test statistic is generated. Table 5 documents the results of this test for the variables in our model.

The statistics lead to acceptance of the null hypothesis of a unit root for the labor productivity, capital intensity, research intensity and labor (returns to scale) variables at all usual levels of significance. The results for the indirect R&D variables are mixed: for *IRY* and *IRT* a unit root seems to be present, while this hypothesis must be rejected for the alternative spillover variables. For these two variables (*IR1* and *IR2*), however, the root is estimated to be in the range between 0.97 and 1.[21] Banerjee *et al.* (1993) call this 'near-

[21] To obtain such estimates, a 'within' ADF regression (allowing for firm specific constants but assuming common 'slopes') was run.

integratedness' and argue that this kind of variables are best treated as if they were integrated of order one. Hence, although the test results are not clear-cut and the low power of unit root tests with small T should be borne in mind, the results of the tests presented in Table 5 support the view that standard 'within' productivity regressions might well suffer from spurious correlation.

In order to obtain unbiased normally distributed estimators for the long run parameters, a three-step procedure proposed by Engle and Yoo (1991) is applied. Since this procedure is an extension of an original idea by Engle and Granger (1987), the method will be referred to as the 'Engle-Granger-Yoo' procedure. The first step is to estimate a cointegration equation using the fixed effects 'within' estimator, i.e., the within estimates for Equation 6 from Table 4. We performed the Im *et al.* (1996) test on the residuals of these equations, and indeed conclude that we have cointegration (results not documented, but available from the authors on request).

In the second step, Equation 6 is rewritten in first differences, and the residuals of the first step (lagged one period) are added to the set of independent variables. This is often called an 'error correction model' (ECM).[22] A significantly negative sign of the estimated coefficient for the lagged residual is another indication for cointegration in the original level specification. Again, we do not document these results explicitly, but estimates showing significant negative signs on the residual are available from the authors.

The third step of the Engle-Granger-Yoo procedure uses results from the second step for an additional within-regression:

$$\begin{aligned}\hat{\varepsilon}_{it} &= \eta_1(-\hat{\zeta}(ir)_{it-1}) + \alpha_1(-\hat{\zeta}(k-l)_{it-1}) \\ &\quad + \gamma_1(-\hat{\zeta}(r-l)_{it-1}) + (\mu-1)_1(-\hat{\zeta}(l)_{it-1}) + v_{it}, \qquad (7)\end{aligned}$$

where the left hand side variable is the residual from the second step, and $\hat{\zeta}$ is the estimated coefficient on the lagged residual in the second step. Under the assumptions of a unique cointegration vector and weak exogeneity of the right hand side variables in the short run ECM, the sums of the estimators in the first step (Table 4) and the corresponding estimators of Eq. 7 are normally distributed unbiased estimators of the long-run relationship. The standard deviations are estimated without bias by the standard error of the estimators in Eq. 7.

Table 6 reports the results of the procedure. An important difference between the corrected results and the standard 'within' results presented in Table 4 lies in the estimates for the returns to scale parameter. The standard results showed three out of four (sub)sample results with strongly negative estimates for $(\mu - 1)$, indicating strong decreasing returns to scale. In Table 6, the estimates for $(\mu - 1)$ are much higher. In case of the high-tech sectors, we find significant increasing returns to scale. In general, the corrections do not have much influence on the estimated physical capital elasticities. The high-tech

[22] Note that the ECM could have included each of the differenced variables with many more lags allowing for richer dynamics. For now, the least complex form is chosen. Further, the ECM does not include an intercept since this would imply the inclusion of a deterministic trend. Hence, the ECM is estimated by a 'total', normal OLS procedure.

Table 6. Estimation results for Engle-Granger-Yoo three step procedure* (unbalanced samples)

	α	γ	$(\mu - 1)$	$\eta(ir1)$	$\eta(ir2)$	$\eta(iry)$	$\eta(irt)$	NI	NOB
Total sample	0.131	0.007	−0.029	0.624	0.680	0.483	0.623	680	9223
	7.51	0.71	1.65	19.0	20.0	14.1	20.5		
High-tech sectors	0.065	0.073	0.048	0.434	0.356	0.393	0.439	245	3203
	2.60	2.68	1.45	7.09	4.76	7.51	6.39		
Medium-tech sectors	0.156	−0.008	−0.039	0.951	0.949	0.711	0.955	224	3110
	4.04	0.57	1.22	15.0	18.6	8.02	18.2		
Low-tech sectors	0.218	−0.001	−0.066	0.373	0.328	0.346	0.336	211	2910
	8.06	0.11	2.69	7.98	6.16	6.96	8.95		

* The indicated values for α, γ, $(\mu - 1)$, $\eta(ir1)$ are those estimated in the regression equation containing *ir1* as the measure for indirect R&D. The indicated values for, $\eta(ir2)$, $\eta(iry)$, and $\eta(irt)$ are those obtained including *ir2*, *iry*, and *irt* respectively, instead of *ir1*. Of course, the estimated output elasticities with respect to *K*, *R* and *L* are different, but only to a small extent. Due to space limitations we do not present them here.

sectors are an exception to this, where we find a lower elasticity as compared to Table 4. Own R&D is no longer significant in the total sample, and shows a smaller, but significant positive value for the high-tech sectors.

The indirect R&D variables generally show higher elasticities in Table 6 than in Table 4. *IR2* in high-tech sectors (lower) is the one exception to this. With regard to the comparison between the different spillover measures, for the sample as a whole, and medium-tech sectors, the earlier pattern is confirmed: the rent spillover measure *IRY* yields lower estimates than the others. For high-tech and low-tech the differences are small, as before.

Concluding, it can be said that the production functions that we estimated in Section 5 tend to underestimate the long-run elasticities of indirect R&D. In other words, R&D spillovers seem to be even more important for productivity than would be argued on the basis of the conventional estimates (although the impact differs between manufacturing industries). This result bears importance as empirical evidence with regard to many of the recent theories on ‘endogenous’ economic growth, which we will discuss in the final section.

7. Summary and conclusions

In this paper, we tried to find evidence in favour of the important role many endogenous growth theorists (both mainstream and non-mainstream) assign to technology spillovers. We set up our framework in a way comparable to the studies in productivity growth at the firm level already available. This implies (among others) the use of an extended Cobb-Douglas production function and the use of R&D as a proxy for technological output. The most important ‘innovation’ over the existing studies is the inclusion of indirect R&D stocks, estimated using patent data. We used a large panel database of U.S. firms between 1974 and 1993, which provided us with the possibility to analyze the effects of direct and indirect R&D at a level more detailed than studies so far.

The results of our level estimates, presented in Section 5, are roughly in line with previous studies. The striking result (first obtained by Griliches and Mairesse, 1984) of strong decreasing returns to scale in the time series dimension was obtained again. With regard to knowledge spillovers, which is the main novelty introduced in our model relative to the earlier literature, the initial estimates we undertook on level data pointed out that the measures aimed at pure knowledge spillovers have somewhat higher estimates than the measure aimed at capturing so-called rent spillovers. However, because the various alternative measures for spillovers are highly collinear, we were not able to produce useful results for equations in which both types of spillovers are present.

In Section 6, we found evidence that many of the variables under consideration are integrated of order one, which renders the estimated standard deviations and the linked R^2s, as well as the estimated elasticities, biased and therefore unreliable. We used recently developed panel data tests on unit roots, indicating that the residuals of the level estimations are stationary, which points to cointegration. Cointegration also appeared from the Engle-Granger-Yoo three-step procedure we implemented. This procedure yields long-run estimates of the elasticities of R&D spillovers, and shows that they tend to be larger than the ones obtained using the 'usual' (within-level) estimates.

The estimates of elasticities with respect to indirect R&D showed that the choice for a particular spillover measure affects the results. In general, rent spillovers (obtained through the purchase of innovated products) seem to yield lower estimates of the elasticities, compared to pure knowledge spillovers (the latter are mainly stressed in endogenous growth theories).

With regard to the strong decreasing returns to scale, which are often found in the literature on R&D and productivity, and which were also found in our within level estimates, we find that these largely disappear in the Granger-Engle-Yoo long-run estimates. Griliches and Mairesse (1984) were the first to find the strong decreasing returns to scale feature. They devote a section to possible causes of these findings, one of which is their inability to deal with underutilization of physical capital. We tried to catch this effect using an unemployment proxy in the dynamic specification, but the returns to scale estimates did not change significantly, perhaps due to the macro nature of the proxy. The other five possible causes of bias mentioned by Griliches and Mairesse (1984, p. 358) are: the use of sales rather than value added as the measure for output, simultaneity in the determination of employment and output, ignorance of random errors in the measures for labour and capital, the wrong assumption of firms operating in competitive markets and the peculiar selectivity in their sample. We think we have provided some evidence that the latter two possible causes might be relatively unimportant, as we did not assume perfect competition, and made avail of a large data set with many firms across almost all manufacturing industries in the United States. The former three causes we can not address, because of data limitations. In addition to the discussion by Griliches and Mairesse, however, we find that the finding of strong decreasing returns to scale may simply be due to an estimation bias associated with non-stationarity of the data.

In this paper, we tried to find out whether firm level data support the most prominent features of endogenous growth theories. Modern endogenous growth theories deviate from the Solow-Swan growth model in two important aspects. First, the introduction of monopolistic competition relaxes the constant returns to scale assumption. We find some limited evidence that increasing returns to scale may hold in high-tech industries. Also, the crucial role of knowledge spillovers is strongly confirmed by our study. However, it should be stressed that our analyses can not be seen as 'tests' of any specific model, but should be regarded as an investigation into the implications of technology-driven growth models in a broad sense.

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