# R&D Spillovers and Productivity: Evidence from U.S. Manufacturing Microdata*

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Bart Los** and Bart Verspagen***

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**University of Twente, Faculty of Public Administration and Public Policy, P.O. Box 217, 7500 AE Enschede, The Netherlands. Corresponding author.
***MERIT, University of Maastricht, P.O. Box 616, 6200 MD Maastricht, The Netherlands.
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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.

(JEL-classification codes: 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 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, basically 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, 1995b) are based on patent documents of the European Patent Office.

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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 (1995b). Very recent examples of studies considering international technology spillovers are Bernstein and Mohnen (1995), Coe and Helpman (1995) and Park (1995).

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

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

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 is which different types of technology spillovers can be distinguished, and what their impact on economic growth and the production structure is. In 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

Until the late 1980s, economic theory on the relationship between growth and technological change was limited to a number of, mostly informal, frameworks outside the mainstream, such as Schumpeter's theory of 'basic innovations' and long waves (Schumpeter, 1939, Freeman, Clark and Soete, 1982) and Nelson and Winter's 'evolutionary theory' (Nelson and Winter, 1982). Mainstream theory was focusing mainly on the Solow-Swan growth model (Solow, 1956, 1957, Swan, 1956) in which technological change is reduced to an exogenous time trend, although there were isolated contributions like Uzawa (1965) and Shell (1967) in which a more realistic representation of technology was provided.

During the late 1980s, with the contribution of Romer (1986), the idea of 'endogenous technological change', so prominently present in the heterodox theories mentioned above, finally entered the mainstream. Romer (1986) and Lucas (1988) provided models (partly similar to Arrow, 1962) that maintain most of the neoclassical core ideas (rationally optimizing agents, perfect competition and the equilibrium concept), but endogenize technological change. In Lucas' models, human capital formation (education, training, etc.) decisions influence the level of technology, Romer focused on the decisions concerning the direct search for technology, R&D. Because this paper aims at measuring the impacts of R&D, our brief discussion of these so-called endogenous growth theories is limited to the ones based on R&D.[4]

Romer (1986) explicitly modeled R&D as a separate factor of production. The assumption of constant returns to scale with respect to the three factors labor, physical capital and R&D enabled him to stick to the neoclassical premises of perfect competition. His most important innovation over Solow's model is the introduction of knowledge spillovers into the model: knowledge (as a product of R&D) is assumed to have public good properties in the sense that the use of a 'unit of knowledge' 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). As a result, 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.

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[4] More extensive surveys are offered by Helpman (1992) and Verspagen (1992).

Later on, growth theorists (e.g. Romer, 1990, Grossman and Helpman, 1990, 1991b, Aghion and Howitt, 1992) formally introduced into their models a solution to a problem directly related to the fact that knowledge generated by R&D has some public good properties. No firm would undertake any R&D if markets were perfectly competitive, because any other firm would immediately imitate the process or product, achieving the same efficiency gain or quality improvement without incurring the R&D costs. Their 'answer' to this deficiency consisted of models in which two sectors are distinguished: a conventional production sector and an R&D sector. 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)[5] 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. Studies estimating the relation between productivity growth and R&D took a rather more pragmatic approach to modelling spillovers, mainly because the rather crude nature of available empirical data does not allow for sophisticated theoretical devices such as product differentiation. As suggested by the early overview of this literature in Griliches (1979), one possible approach is to estimate an extended Cobb-Douglas production function (assuming homogeneous output and inputs), similar to the one assumed by Romer (1986):

$$Q_{it} = AF(\sum_j R_{jt}) K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} , \qquad (1)$$

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

Although our setting of homogeneous output and inputs is perhaps not completely in line with the assumption of increasing returns to scale at the firm level, we do not wish to impose a restriction of constant returns to scale *a priori*, keeping in mind the more general assumptions on returns to scale from the 'later' new growth models. Thus, unlike Romer (1986), we do not impose any *a priori* restriction on the elasticities $\alpha$, $\beta$ and $\gamma$, we will rather let our estimation results indicate if constant returns with respect to either all factors ($\alpha + \beta + \gamma = 1$) (Romer, 1986) or only the traditional, non-rival factors ($\alpha + \beta = 1$) (see Romer, 1990, 1994) applies or not.

Turning to the issue of technology spillovers in our production function $F(.)$, 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 inno-

[5] The models by Grossman and Helpman (1991b) and Aghion and Howitt (1992) differ from the other models mentioned in incorporating Schumpeterian creative destruction: the production of a new blueprint renders old varieties obsolete, thereby causing negative technology spillovers. Therefore, the net externalities of R&D can not be assumed a priori to be positive.

vation 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 'mismeasurement'. 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 in fact interpret the price increases as inflation. In this case, the rent spillover would again spill from producer to user. In fact, 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.[6] Moreover, one can not speak of a true externality even in the case of rent spillovers not caused by mismeasurement, 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 assumption, Griliches' concept of pure knowledge spillovers is more central to the debate on endogenous growth, technology and increasing returns.[7] 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.[8]

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

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6 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.

7 This also holds for the non-mainstream contributions to this debate, as mentioned above.

8 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.

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. 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. 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), but we considered nppe more adequate. 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. This price index is an admittedly crude deflator for firm level variables as nppe. However, more desaggregated alternatives were not available (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). For labor 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 modeling 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 $w_\tau$ are exogenously fixed according to a geometrical lag: $w_\tau = (1-\delta)^\tau$, in which $\delta$ 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 basically 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.[9] A main disadvantage is that one cannot estimate the output elasticity with respect to R&D directly. Our goal to estimate the output elasticities implicit in Eq. 1 has led us to the decision to construct R&D stocks.

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

**TABLE 1 ABOUT HERE**

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 phenomena 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.

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9 For a short mathematical proof, see e.g. Griliches and Mairesse (1984, p. 342-344).

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

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 labor 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.

**TABLE 2 ABOUT HERE**

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 labor 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 hypothesis, while Verspagen (1995a) 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. The first step is to identify the amount of indirect R&D available to a firm. We decided to abstract from R&D performed by foreign, i.e., non-U.S. firms. Then 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.[11] 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 that the following:

$$IRE_{kj}(t) = \sum_i \omega_{ij} RE_i(t), \qquad (2)$$

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

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 $\omega_{ij}$ 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 $\omega$, 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 $\omega_{ij}$'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.[12] We use the so-called Yale patent matrix from Putnam and Evenson (1994), in which all primary and tertiary industries were deleted before the weights were 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 $\omega_{ij}$ should be proportional to the similarity between two firm's 'technological space vectors'. Given te 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 alternatives to Jaffe's method, and which were introduced by Verspagen (1995b).[13]

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

[12] 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.

[13] 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).

invention) gives an indication for knowledge spillovers to other manufacturing industries.[14,15] 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 $\omega_{ij}$. 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 (1995b), 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 with additional information is relatively small. Calculating the weights $\omega_{ij}$ 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.

**TABLE 3 ABOUT HERE**

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. But 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 dataset.

[14] 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.

[15] 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. As a consequence, the rows of the corresponding patent matrix sum to the number of patents assigned to the industry of main application.

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 $\alpha$ and $\gamma$ 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 (see Romer, 1994). We have chosen a very simple specification of the function $F(.)$, discussed in Section 2, which we think, however, is flexible enough to capture at least the basic effects of technology spillovers. A positive elasticity $\eta$ would indicate a dominance of positive 'own R&D augmenting' effects over Schumpeterian creative destruction, a negative $\eta$ 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 labor 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 $\mu$ 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.[16] In order to guarantee exogeneity of variables, we lag all R&D variables in the estimations by one year.

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 the

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

variables ('within') leaves only the transitory random effects, and stresses the time series dimension.[17]

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-equations semireduced 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 $\alpha$. This difference (also apparent in the adjusted $R^2$s) must be caused by specification errors, to which we will come back later.

**TABLE 4 ABOUT HERE**

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 subsamples 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 $\alpha$. 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. 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 creative destruction effects. 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.

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

Using calendar time (*year*) instead of indirect R&D, this variable turns up significantly in all within equations. We include this variable in order to be able to compare the results obtained with endogenous growth theory based spillover measures to results obtained by earlier studies, such as Griliches and Mairesse (1984). At first sight, the spillover measures seem to do as well as calendar time. Most of the coefficients are roughly similar, and the adjusted $R^2$s are also of the same magnitude. Note that due to multi-collinearity, we were not able to estimate equations including both *year* and one of the indirect R&D measures (multicollinearity is extremely high in the within dimension).

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, hence, misleading results. 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 test-procedures proposed in two papers by Levin and Lin (1992 and 1993). These test-procedures consist of estimating the well-known augmented Dickey-Fuller (ADF) statistics (Dickey and Fuller, 1979), making use of the panel nature of our dataset in order to increase the power of the test, relative to a pure time series context. The simplest of the three Levin and Lin test-statistics (L&L1-a) performs a simple OLS panel regression of the ADF regression equation. In terms of the above used terms, this is a total estimate of the ADF equation. The second L&L test-statistic (L&L1-b) assumes individual specific intercepts in the panel estimation of the ADF equation, i.e., a within estimate. Levin and Lin (1992) provide critical values of the *t*-statistics on the lagged test-variable, based on Monte Carlo experiments. In Levin and Lin (1993), a more complicated and general test procedure is presented. In this case, the ADF equation is estimated for each individual in the panel, opening up the possibility of individual-specific dynamics and a different number of lagged difference terms in the ADF equation. The residuals of the individual specific test equations are then used to derive a test-statistic for the hypothesis that all individual series together contain a unit root (L&L2).

We selected only firms for which data for the full period were available (the balanced sample), and ran the three L&L tests on the variables in our regressions. We included a constant and deterministic time trend in all our ADF equations, because these variables usually turned up significantly in the ADF-regressions we estimated. As it is a well-known fact that the power of the ADF-test is very sensitive for the inclusion of the correct number of lagged difference terms (e.g., Fox, 1995), we calculated tests for zero up till five lags (with only 15 observations per firm, we cannot include more lags). Note that in case of the first two L&L statistics (L&L1-a and b), the number of lags is fixed across individuals, while in L&L-2, the number may vary in principle. The L&L-2 statistics we document, however, are all based on a fixed number of lags across individuals. We did perform tests where we used the Schwarz-Bayesian information criterion to determine the ‘optimal’ number of lags for each firm individually, but these yielded similar results as the runs with fixed lag length (favoring a large number of lags in general).

**TABLE 5 ABOUT HERE**

The results are documented in Table 5.[18] The three different L&L tests do not point in the same direction. For L&L1-a, labor productivity, capital intensity and the indirect R&D stock for total R&D all appear to be stationary. It has to be noted, however, that the estimated coefficients on the lagged dependent variable in the ADF equations (i.e., the estimated root minus one) for these variables are small in absolute value (see the notes in the table). Banerjee *et al.* (1993, pp. 95 ff., 164 ff.) term this 'near integratedness', and conclude that, in finite samples, one might better treat such variables as non-stationary.

The other variables, own R&D and the EPO and Yale indirect R&D stocks, show mixed results, depending on the number of lagged difference terms in the ADF equation. Because the lagged difference terms in case of the equations with 4 or 5 lags are usually all significant, we interpret this 'mixed' result as pointing to non-stationarity of our variables. For the L&L1-b tests, the results are more homogenous. In this case, the results point out that all indirect R&D variables contain a unit root. Favoring the results with more lags over the ones with few lags, we find the same conclusion for labor productivity. The results for own R&D and the capital labor ratio point to stationarity, however.

The L&L2 tests generally point to the conclusion of stationarity as well, although the tests with four lags seem to point out that our variables, except own R&D, contain a root significantly larger than one. We do not have an explanation for the strange result obtained with the ADF equations with four lags. While searching for an explanation, we experimented with various artificially generated datasets, and we found that the L&L2 procedure did not yield the 'correct' conclusions in experiments in which the data were generated with a different lag structure than the one used in the Monte Carlo experiments reported by Levin and Lin.[19] Thus, although the L&L2 test-specification is more general (and indeed encompasses the two L&L1 specifications), we are not confident enough to entirely dismiss the possibility of non-stationarity on its basis. Thus, because the conclusion of the two L&L1 tests seems to be that we should treat our variables, perhaps with the exception of the capital labor ratio, as non-stationary, we proceed by implementing an error-correction model (ECM) to ensure the validity of the results obtained in the previous section.

As is well-known, the estimates for the elasticities in level specifications with non-stationary data, as in section 5, are biased (although 'super-consistent') in finite samples (see Banerjee *et al.*, 1993, p. 162), and so are their standard errors (and hence *t*-values) as well as the $R^2$ statistics. A possible way to obtain unbiased standard errors is by performing the Engle-

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[18] Note that the stationarity tests in the table for the indirect R&D variables were done on a labor intensive form of these variables, i.e., the logarithm of the labor input was subtracted. Performing the L&L1-a test on the non-labor intensive form of the indirect R&D variables yields roots slightly, but significantly larger than unity. Because the labor intensive form of these variables appear as I(1) from the L&L1-a tests, this does not have any consequences for the results on co-integration presented below.

[19] More specifically: Levin and Lin derived their 'adjustment factors' used in the calculation of their test-statistic from Monte Carlo experiments in which they generated data using the data generating process $y_t = py_{t-1} + at + c + e_t$. Although we did not perform extensive Monte Carlo experiments on this, we were able to generate test-statistics pointing to the 'correct' conclusion for the cases $p = 1$ and $p < 1$. Whenever we included lagged difference terms of $y$ in the above equation, however, we did not find the 'correct' conclusion on the sign of $p$ (even if we tested with an ADF form with the number of lags used in the data generating process).

Granger two-step procedure, which starts by estimating a co-integration relationship between levels of the variables, as we have done in section 5. The procedure then implements a short-run 'error correction model' (ECM). The ECM specification starts from the assumed long-run relationship, and by taking first differences, obtains a short-run version of it, which includes the short-run disturbance. As was shown by Engle and Granger (1987), one may substitute the (lagged) residuals from the level estimation in lieu of this short run disturbance. A (significantly) negative sign on these residuals points to co-integration in the level estimations, and the resulting standard errors for the independent variables are unbiased. One may also include other (stationary) variables in the modeling of the short-run disturbance.

We implement the Engle-Granger two-step procedure by taking residuals from the within estimations in Table 4, and include those in an ordinary least squares (total) estimation of the same model in first differences. Note that this first difference model no longer includes constants (except in the cases where a linear trend appears in our level estimations), so we no longer estimate a within variant of the model. Nevertheless, the resulting model is comparable to the within models in Section 5, because firm-specific effects are eliminated by taking first differences, and hence the time series dimension of the data determines the results.

The results from the ECM estimations are documented in Table 6. In all four cases, the lagged residual indeed has the significantly negative sign expected in the case of co-integration. The capital labor ratio is also significantly positive in all cases, and shows parameter values almost equal to the ones obtained in the within level regressions. The coefficient on labor input, however, is much smaller than in the case of level estimations, most notably for the high- and medium-tech sectors. Direct R&D is significant and positive in high-tech sectors only, and has a negative and significant sign in medium-tech sectors, which is contrary to our theoretical priors. Indirect R&D is always significant with positive signs, except for rent spillovers (*IRY*) in medium- and low-tech industries. The values of the coefficients for the indirect R&D variables are generally somewhat smaller than in the within level estimations. As in the level estimations, the estimated elasticities for *IRY* rank lowest.

**TABLE 6 ABOUT HERE**

Concluding, it can be said that the production functions that we have estimated in Section 5 can be viewed as reasonable approximations of the long-run relationships between inputs and output of manufacturing firms. Indirect R&D has an important role to play with regard to the development of productivity over the long run, 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.

Before we proceed to that discussion, however, we turn to a brief analysis of the so-called productivity slowdown, which occurred in the second half of the 1970s (see e.g. Griliches, 1988). In Table 7, we document some ECM-estimation results for two subperiods, the first (1977-1983) roughly corresponding to the slowdown period, the second (1984-1991) to the recovery. In order to avoid disturbances caused by unbalanced samples, we used the balanced sample. The results are remarkable. The estimated output elasticities with respect to capital increase over time in both the medium-tech and the low-tech sectors. In the high-tech sector, the estimated elasticity with respect to own R&D increases from an insignificant 0.04 in the first subperiod to a high and significant 0.13 in the second.

**TABLE 7 ABOUT HERE**

Moreover, the effects of indirect R&D seem to have increased a lot, especially in the medium-tech sector. For the total sample, the elasticities of *IR1*, *IR2* and *IRT* increased by a factor of about four, while the elasticity for *IRY* increased by a factor of about three. Thus, again, the beneficial effects of knowledge spillovers, $\eta(ir1)$ and $\eta(ir2)$, are estimated to be (slightly) more important than the effects of rent spillovers, $\eta(iry)$, although both types of spillovers clearly gain importance in time. Our analysis thus shows that increasing technology spillovers are a factor in the productivity upswing in the second half of the 80s.

We offer two interpretations for the apparent increase in these coefficients. First, the $\gamma$'s show that own R&D has become more productive, which might have had positive effects on spillovers as well, and second, the exchange of knowledge might have increased. We can only speculate as to why the increase of the estimated elasticities on indirect R&D are somewhat different between different variables (*IR1*, *IR2*, *IRT* vs. *IRY*). It might be the case that information technology has a role in this: one may argue that its impact was more direct in the process of science and technology itself (knowledge spillovers) as compared with manufacturing (rent spillovers).

To provide a final indication of the different effects of the four indirect R&D stocks on output, we use the definition of the estimated elasticities in computing the ratio of the increase in *IRT* to the increase in each of the three alternative indirect R&D stocks necessary to attain an identical percentage increase in output:

$$\frac{d(IRT)}{d(IRx)} = \frac{\eta(irx)}{\eta(irt)} \cdot \frac{IRT}{IRx}, \tag{7}$$

in which *IRx* denotes either *IR1*, *IR2* or *IRY*. This ratio can alternatively be seen as the ratio of the (private) rates of return to the two measures of indirect R&D. The first factor of the right hand side is calculated from the estimated elasticities reported in Table 6, the second factor is approximated as the ratio of the two sample means. Table 8 presents the values obtained.

**TABLE 8 ABOUT HERE**

A value of about one would indicate that the impact of the indirect R&D stock under consideration is about equal to the impact of *IRT*. The higher a value, the higher the relative impact. Clearly, the relative impacts of the various seem to vary greatly. Only in the total sample and the low-tech sector, the impacts of *IR1* and *IR2* are about equal. In general, the impacts of all three indirect R&D stocks are much larger than IRT's, which leads us to the conclusion that the use of IRT as a spillover variable may yield serious underestimations of the importance of technology spillovers. More generally, the large differences between the reported values within the rows of Table 8 indicate that estimated rates of return to indirect R&D are likely to be highly dependent upon the chosen spillover measure. Both the estimated elasticities and these relative impacts confirm that the common conclusion from industry level studies that spillover measurement methods matter, also holds for studies at the firm level.

## 7. Summary and Conclusions

In this paper, we tried to find evidence in favor 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, 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 some (although not unambiguous) evidence that many of the variables under consideration are integrated of order one, which renders the estimated standard deviations and the linked $R^2$s, 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 two-step procedure we implemented, yielding significantly negative estimates of the error coefficient in an error correction model. Cointegration would imply that the level estimates can be seen as a kind of equilibrium long run relationship. The estimates obtained using an error correction specification showed that own R&D has only significant positive effects in high-tech manufacturing, a common result in firm level time series studies. Indirect R&D also appears to be somewhat less influential than in the long run, but still very important for high-tech and medium-tech firms.

Estimations on period subsamples (1977-1983 and 1984-1991, respectively) showed that elasticities with respect to physical capital were much higher in the later period following the productivity slowdown years. Own R&D appeared to be insignificant in both periods, with the (important) exception of high-tech firms in 1984-1991. Irrespective of the spillover measure applied to construct indirect R&D stocks, technology spillovers seem to have become important determinants of productivity growth, even in low-tech firms.

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 be less important than knowledge spillovers that are so important in endogenous growth theories. This conclusion was strengthened by the calculation of relative impacts (on output) of indirect R&D stocks according to different spillover measures. A simple unweighted addition of all R&D performed outside the firm appeared to yield roughly the same estimated elasticities as the two measures of knowledge spillovers. However, the low output impacts relative to the more sophisticated measures, should be conceived as a warning to assess the social returns to R&D investments on such a crude measure.

With regard to the validity of our estimation results, we need to stress a surprising finding: the quite strong decreasing returns to scale we found in our within level estimates and the dynamic specification. Griliches and Mairesse (1984) found similar results in their within estimates. Griliches and Mairesse (1984) 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 labor 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 dataset 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 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. Due to data limitations and/or well-known specification problems, we were not able to find evidence for increasing returns to scale at the firm level. The crucial role of knowledge spillovers, however, is strongly confirmed by our study. It should be stressed that our analyses can not be seen as ‘tests’ of any specific model (mainstream or not), but should be regarded as investigations into the implications of technology-driven growth models in a broad sense.

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

| | NI | | NOB | | log $Q$ | | log $Q/L$ | | log $K/L$ | | log $R/L$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample | 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 US$, $L$ in thousands of employees.

**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 US$, *L* in thousands of employees.

**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 US$.

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

| Between estimation | a | $\alpha$ | $\gamma$ | $(\mu-1)$ | $\eta(ir1)$ | $\eta(ir2)$ | $\eta(iry)$ | $\eta(irt)$ | | 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** | | $\alpha$ | $\gamma$ | $(\mu-1)$ | $\eta(ir1)$ | $\eta(ir2)$ | $\eta(iry)$ | $\eta(irt)$ | *year* | NI | NOB | adj. $R^2$ |
| Total sample | | 0.138 | 0.017 | -0.114 | 0.558 | 0.590 | 0.422 | 0.560 | 0.026 | 680 | 9223 | 0.85 |
| | | 19.70 | 4.44 | -16.32 | 42.34 | 42.79 | 31.72 | 45.13 | 44.76 | | | |
| High-tech sectors | | 0.083 | 0.102 | -0.038 | 0.396 | 0.399 | 0.342 | 0.439 | 0.021 | 245 | 3203 | 0.71 |
| | | 8.06 | 9.22 | -2.91 | 15.82 | 13.26 | 15.89 | 15.72 | 15.59 | | | |
| Medium-tech sectors | | 0.160 | -0.004 | -0.137 | 0.793 | 0.761 | 0.556 | 0.775 | 0.036 | 224 | 3110 | 0.83 |
| | | 10.91 | -0.68 | -11.43 | 32.49 | 36.24 | 17.62 | 36.14 | 35.75 | | | |
| Low-tech sectors | | 0.226 | 0.004 | -0.119 | 0.354 | 0.308 | 0.309 | 0.329 | 0.015 | 211 | 2910 | 0.93 |
| | | 18.52 | 0.83 | -10.64 | 16.63 | 12.89 | 13.52 | 18.94 | 18.66 | | | |

*The indicated values for $\alpha$, $\gamma$, $(\mu-1)$, $\eta(ir1)$ and adj. $R^2$ are those estimated in the regression equation containing *ir1* as the measure for indirect R&D. The indicated values for, $\eta(ir2)$, $\eta(iry)$, $\eta(irt)$ and $\eta(year)$ are those obtained including *ir2*, *iry*, *irt* and *year* 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).

| | L&L1-a | | | | | | L&L1-b | | | | | | L&L2 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Number of lags in ADF | | | | | | Number of lags in ADF | | | | | | Number of lags in ADF | | | | | |
| Variable | 5 | 4 | 3 | 2 | 1 | 0 | 5 | 4 | 3 | 2 | 1 | 0 | 5 | 4 | 3 | 2 | 1 | 0 |
| *q - l* * | -5.8 | -6.6 | -6.7 | -8.8 | -9.4 | -11.7 | -19.8 | -21.3 | -21.5 | -23.1 | -24.7 | -31.4 | -4.3 | 7.6 | 3.4 | -6.9 | -16.0 | -19.1 |
| *k - l* ** | -3.0 | -3.4 | -5.1 | -5.6 | -7.2 | -7.5 | -27.0 | -27.5 | -31.4 | -30.9 | -32.2 | -30.8 | -27.1 | 8.7 | -7.7 | -6.4 | -15.5 | -15.1 |
| *r - l* *** | 0.3 | -0.9 | -2.2 | -3.0 | -4.1 | -4.3 | -22.4 | -25.8 | -30.2 | -30.9 | -32.2 | -29.1 | -9.1 | -1.3 | -21.8 | -26.5 | -24.7 | -18.0 |
| *l* ## | -2.3 | -2.3 | -2.6 | -3.2 | -4.0 | -4.6 | -15.5 | -15.3 | -16.5 | -18.8 | -18.6 | -18.7 | 1.0 | 11.2 | -4.0 | -4.4 | -7.0 | -7.6 |
| *ir1 - l* ## | -0.8 | -1.1 | -1.5 | -2.3 | -3.2 | -4.2 | -15.9 | -15.6 | -16.8 | -19.3 | -19.1 | -19.2 | -5.0 | 6.0 | -2.5 | -4.1 | -5.1 | -7.9 |
| *ir2 - l* ## | -0.7 | -0.9 | -1.3 | -2.0 | -2.9 | -3.7 | -16.6 | -16.1 | -17.1 | -19.3 | -19.1 | -19.1 | -20.9 | 5.5 | -2.8 | -5.6 | -5.7 | -8.0 |
| *iry - l* ### | -0.7 | -1.0 | -1.4 | -2.0 | -2.8 | -3.7 | -15.8 | -15.6 | -16.8 | -19.1 | -18.7 | -18.4 | -4.9 | 10.9 | -2.9 | -5.5 | -6.2 | -7.0 |
| *irt - l* ## | -2.3 | -2.3 | -2.6 | -3.3 | -4.1 | -4.7 | -15.9 | -15.7 | -16.7 | -19.4 | -19.3 | -19.4 | 1.2 | 11.0 | -4.0 | -4.4 | -7.0 | -7.6 |

Dark cells point to roots significantly smaller than one.

* in L&L-1a, last lag not significant in 5 - 3, values of estimated roots in L&L-1a are less than 0.05 smaller than unity, in L&L1-b las

** in L&L-1a, last lag always significant, values of estimated roots in L&L-1a are less than 0.05 smaller than unity, in L&L1-b last la

*** last lag not significant in L&L1-a and L&L1-b for lag 5, values of estimated roots in L&L-1a are less than 0.05 smaller than unit

# last lag always significant in L&L1-a, in L&L1-b not significant in lags 5 and 4.

## last lag always significant, values of estimated roots in L&L-1a are less than 0.05 smaller than unity.

### in L&L-1a, last lag always significant, values of estimated roots in L&L-1a are less than 0.05 smaller than unity, in L&L1-b last

**Table 6:** Estimation results for ECM specification*, based on within level estimates of the residuals, ECM estimations by OLS (total), no constants included (unbalanced samples).

| | $\alpha$ | $\gamma$ | $(\mu-1)$ | res(-1) | $\eta(ir1)$ | $\eta(ir2)$ | $\eta(iry)$ | $\eta(irt)$ | year | NOB | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Total sample | 0.138 | -0.003 | -0.288 | -0.314 | 0.496 | 0.547 | 0.254 | 0.545 | 0.026 | 8543 | 0.28 |
| | 19.62 | -0.52 | -28.96 | -37.05 | 14.01 | 14.71 | 7.37 | 15.68 | 16.29 | | |
| High-tech sectors | 0.085 | 0.053 | -0.254 | -0.310 | 0.466 | 0.576 | 0.400 | 0.588 | 0.027 | 2958 | 0.27 |
| | 8.45 | 3.00 | -11.67 | -22.12 | 7.65 | 8.03 | 7.63 | 8.54 | 8.95 | | |
| Medium-tech sectors | 0.198 | -0.025 | -0.259 | -0.311 | 0.633 | 0.639 | 0.023 | 0.655 | 0.032 | 2886 | 0.25 |
| | 13.19 | -2.95 | -14.33 | -20.29 | 9.43 | 10.68 | 0.30 | 10.66 | 11.47 | | |
| Low-tech sectors | 0.206 | 0.003 | -0.282 | -0.381 | 0.243 | 0.176 | 0.041 | 0.290 | 0.013 | 2699 | 0.37 |
| | 15.55 | 0.46 | -18.75 | -24.55 | 3.99 | 2.66 | 0.65 | 5.42 | 5.19 | | |

[*] Estimated coefficients for the lagged residual from the level estimates are listed in the column 'res'. The indicated values for $\alpha$, $\gamma$, ($\mu$-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*) , $\eta$(*irt*) and $\eta$(*year*) are those obtained including *ir2, iry, irt* and *year* 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. NI is no longer documented explicitly, but can be readily derived from Table 4.

**Table 7:** ECM-estimates on period subsamples* (balanced samples)

| | $\alpha$ | $\gamma$ | $(\mu-1)$ | res(-1) | $\eta(ir1)$ | $\eta(ir2)$ | $\eta(iry)$ | $\eta(irt)$ | year | NOB | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1977-1983 | | | | | | | | | | | |
| Total sample | 0.091 | 0.004 | -0.247 | -0.667 | 0.212 | 0.226 | 0.185 | 0.222 | 0.012 | 2910 | 0.42 |
| | 9.85 | 0.71 | -17.89 | -37.01 | 4.95 | 5.12 | 4.76 | 4.95 | 6.25 | | |
| High-tech sectors | 0.065 | 0.036 | -0.194 | -0.648 | 0.263 | 0.426 | 0.213 | 0.399 | 0.021 | 996 | 0.39 |
| | 5.60 | 1.34 | -6.26 | -21.33 | 3.28 | 5.04 | 3.28 | 4.41 | 5.43 | | |
| Medium-tech sectors | 0.077 | -0.006 | -0.208 | -0.696 | 0.191 | 0.115 | 0.174 | 0.144 | 0.010 | 1008 | 0.38 |
| | 3.65 | -0.62 | -8.61 | -22.19 | 2.61 | 1.60 | 2.28 | 1.95 | 3.08 | | |
| Low-tech sectors | 0.160 | 0.003 | -0.327 | -0.697 | 0.109 | 0.115 | 0.073 | 0.106 | 0.006 | 906 | 0.51 |
| | 6.90 | 0.49 | -12.32 | -21.66 | 1.42 | 1.44 | 1.02 | 1.36 | 1.70 | | |
| 1984-1991 | | | | | | | | | | | |
| Total sample | 0.183 | -0.008 | -0.325 | -0.448 | 0.818 | 0.919 | 0.500 | 0.892 | 0.036 | 3880 | 0.35 |
| | 16.30 | -0.63 | -18.31 | -30.52 | 15.32 | 16.06 | 9.16 | 17.60 | 15.49 | | |
| High-tech sectors | 0.078 | 0.133 | -0.199 | -0.439 | 0.463 | 0.567 | 0.380 | 0.676 | 0.027 | 1328 | 0.32 |
| | 4.84 | 3.27 | -4.47 | -18.35 | 4.85 | 4.75 | 4.53 | 6.21 | 5.61 | | |
| Medium-tech sectors | 0.350 | -0.041 | -0.285 | -0.481 | 1.200 | 1.166 | 0.543 | 1.216 | 0.050 | 1344 | 0.37 |
| | 15.12 | -2.38 | -10.23 | -18.49 | 12.32 | 14.21 | 4.38 | 14.25 | 12.53 | | |
| Low-tech sectors | 0.243 | -0.014 | -0.389 | -0.500 | 0.653 | 0.533 | 0.413 | 0.543 | 0.019 | 1208 | 0.44 |
| | 11.64 | -0.84 | -13.51 | -17.92 | 6.64 | 4.57 | 3.62 | 7.05 | 5.43 | | |

*The indicated values for $\alpha$, $\gamma$, $(\mu$-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, $\eta(ir2)$, $\eta(iry)$ , $\eta(irt)$ and $\eta(year)$ are those obtained including *ir2*, *iry*, *irt* and *year* 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. Note that we do include the 1983 values in the calculations of 1984 first differences.

**Table 8:** Estimated impacts on output, relative to *IRT* (unbalanced samples).

| | *IR1* | *IR2* | *IRY* |
|---|---|---|---|
| Total | 13.10 | 13.81 | 8.43 |
| High-tech | 7.85 | 14.19 | 7.35 |
| Med-tech | 11.43 | 7.44 | 0.66 |
| Low-tech | 47.24 | 43.87 | 9.34 |