MEASURING INTERSECTORAL TECHNOLOGY SPILLOVERS: ESTIMATES FROM THE EUROPEAN AND US PATENT OFFICE DATABASES

Contents

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ABSTRACT This paper "resents several new methods for measuring intersectoral knowledge spillovers, and applies these methods in an analysis of productivity growth in manufacturing for a cross-country, cross-sectional sample for the 1980s. It is argued that existing methods of measuring such intersectoral knowledge spillovers are mostly aimed at measuring so-called `rent spillovers'. The methods developed here are aimed at measuring knowledge spillovers--an additional aspect of the spillover process. The empirical analysis shows that there are indeed differences between these two types of spillover measure.

KEYWORDS: R&D spillovers, patents, productivity growth

1. Introduction

Despite recent efforts, technology is still an ill-measured phenomenon in economics. The most frequently used statistical measures of technology (patent counts and R&D data) suffer from all sorts of problems. (Pavitt (1985), Griliches (1979,1990) and Soete and Verspagen (1991) are a few examples of contributions that discuss the usefulness of the different indicators.) Theoretical advances in what might be called the field of the `economics of technological change' (encompassing such broadly distinct topics as endogenous growth theory, diffusion theory and parts of industrial economics, to name only a few) have helped in applying the commonly used data on patents and R&D in a more ingenious way to economic trends and problems, such as productivity growth and international trade. One important aspect of technological change that has inspired empirical research on measuring technology more adequately is the existence of public aspects, or externalities, of technology.

The idea that a technological innovation is not only useful to its innovator but also to other economic agents, and that these other economic agents do not always pay a `full' price for the use of the innovation, i.e. the existence of externalities, has recently inspired a complete rewriting of neoclassical growth theory (Grossman & Helpman, 1991; Romer, 1990). In the more empirical literature on the relationship between productivity growth and technology indicators such as R&D, this notion goes back to at least Griliches (1979) and Scherer (1982), with Scherer presenting a measure of `indirect'

R&D used in a sector, and showing that this indirect R&D significantly affected productivity development in a cross-section of US industries.

The externalities connected with an innovation might take different forms. Griliches (1979) proposed the (analytical) distinction between so-called `rent spillovers' and `knowledge spillovers'. The first of these two types relates to the tendency that supplier firms, under competitive pressure, typically are not able to raise prices proportionally to quality improvements in their product. Therefore, the quality-to-price ratio will generally rise, leading to spillovers for the firms who use the intermediary product or investment good. Knowledge spillovers are more directly related to the knowledge embodied in the innovation, and not necessarily to the economic transaction (as in the case of rent spillovers). An example of knowledge spillovers is when one invention might lead to a new idea for a different inventor.

`Pure' knowledge spillovers are difficult to measure. This paper presents several attempts to quantify these spillovers, by using the specific ways in which the European Patent Office (EPO) and the US Patent Office (USPO) classify patents. These methods are aimed at identifying and quantifying additional sources of knowledge spillovers, as compared with the methods already available in the literature.

The rest of the paper is organized as follows. Section 2 describes the methods used in more detail, and presents the raw results of the analysis on the basis of EPO and USPO data. Section 3 applies the results of these methods to the relationship between productivity and R&D, which is a main application area in the field of knowledge spillovers. A simple regression model will be estimated, which includes direct and indirect R&D in the explanation of growth rates of total factor productivity (TFP) in a cross-sectional, cross-country panel. The results will also be compared with one specific example of a broad class of other measures of spillovers found in the literature, i.e. the so-called `Yale method', as described by Putnam and Evenson (1994). The final section summarizes the results and concludes on the empirical relevance of the methods of identifying technological spillovers between sectors developed in this paper.

2. Measuring Technology Spillovers: A `Technology Perspective'

Perhaps the most effective method for measuring technology spillovers in the literature is by means of setting up a matrix with innovation or patent data classified by the user and producer industries. According to this method, which was originally proposed by Scherer (1982),(n1) spillovers flow from the innovation producing sector to the innovation-using sector. Typically, this approach simplifies to identifying the product or process that will result from an invention, and subsequently identifying the (main) economic sector in which this product or process will be used. For example, a patent that relates to fertilizers will be assigned to the chemical industry as the producing sector, and to the agriculture sector as the using sector.

This method is also the basis for the so-Galled `Yale matrix', which is constructed on the basis of data from the Canadian Patent Office. As well as assigning International Patent Classification (IPC) codes to a patent, the Canadian Patent Office (exclusively in the world) assigns principal user and producing sectors to each patent, so enabling the researcher to calculate a matrix such as that proposed by Scherer (1982) directly from the patent office data, without having to make inferences on the relationship between IPC codes and industrial sectors. The Yale matrix is presented in the paper by Putnam and Evenson (1994). The method described by DeBresson et al. (1994) is also based on the user-producer principle, although this method uses data on innovations rather than data on patents.

Although the approaches mentioned so far have proven to be useful in measuring spillovers, such as leading to significant estimates of the relationship between productivity growth and technology spillovers, there are at least two reasons why one may argue that they tend to ignore important aspects of the spillover process. First, because they are based on user-producer relationships, they tend to overlook spillover relationships that are more explicitly based on technological linkages between sectors. For example, the technical knowledge in a patent on fertilizers may be useful to a broad range of economic sectors, although the fertilizer itself will probably not be applied outside the agricultural sector. One may think of sectors such as rubber and plastic products or the glass industry, which, by the chemical nature of their technology base, may benefit from technical knowledge on fertilizers, although their relationships in terms of user-producer interactions with the fertilizer industry will be marginal.

The second problem with the user-producer method of measuring technological spillovers stems from the fact that, at least in as far as patent data are used to construct the spillover matrix, the underlying technological knowledge is actually appropriated by the knowledge producer. Again, using the example of fertilizers, the producer of the innovation, if the patent application is granted, may claim the sole use of the knowledge in the patent, so will be able to charge a mark-up over marginal costs to cover R&D costs. In such a case, if there were spillovers (between producer and user of the innovation) at al!, then they would most certainly contain important rent spillovers in addition to pure knowledge spillovers, because they are related to the economic transaction, rather than by a pure technological link (see van Meijl, 1995, 1997). Despite these problems, one may argue that the Yale- or Scherer-type matrix captures at least some aspects of pure knowledge spillovers, if only because economic linkages in the form of user-producer relationships may `guide' technological search efforts by firms to a certain extent.

An alternative approach by Jaffe (1986) was based on a more explicit `technological perspective'. Jaffe constructed a measure of the technological distance between firms, on the basis of the distribution of firms' patenting activities over technology fields. He then assumed that spillovers can be measured by the stock of knowledge developed by other firms, where each firm's input into this total stock of external knowledge is weighted by its technological distance from the spillover-receiving firm. Goto and Suzuki (1989) used a similar method.

Jaffe's method is clearly distinct from the user-producer-oriented methods described earlier. Although both methods are aimed at measuring knowledge spillovers, one should not compare them as alternative ways of measuring the same process. A more useful interpretation of the differences between the two methods is that they place different emphasis on different aspects of the complicated process of knowledge spillovers. Jaffe's technological method tends to stress technology-based linkages between firms or sectors, whereas the user-producer method tends to stress transaction-based linkages.

The different methods developed in this paper (following Jaffe) adopt a `technology perspective' to measuring spillovers. In light of the foregoing, it should be seen as a complement, and not a substitute, for the user-producer methods developed by Scherer (1982) and Putnam and Evenson (1994). The methods developed here all use patent statistics to measure technology flows. One of the problems with patent statistics is that the different national and international patent offices use different procedures to evaluate and classify patent applications. This implies that each system used provides different opportunities for measuring economic aspects of patents, such as spillovers, while none of these methods individually will enable the measurement of all aspects of spillovers.

From this point of view, this paper uses the two most widely used patenting databases available in the world, i.e. the USPO and EPO databases. As will be described in detail, both databases are quite different, from the point of view of measuring spillovers, so that the different matrices that will arise are expected to measure different aspects of technology spillovers, even if a broad technological perspective underlies both methodologies.

The measurements based on the EPO database take as the point of departure the distinction between different types of knowledge which may be described in a patent document. According to the description of the IPC (WIPO, 1989, p. 26):

Patent documents

(a) comprise `invention information' i.e. technical information as defined by the claims, with due regard given to the description and the drawings (if any). The classification symbols allotted should not be restricted to the place or places in the Classification which cover only one aspect of a technical subject identified. Due regard should also be given to further places in the Classification where non-trivial other aspects of that technical subject may need to be classified;

(b) may comprise `additional information' i.e. 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.

Thus, two forms of classification are typically distinguished: one form for the `claimed' knowledge (or `invention information') and the other form for non-appropriable knowledge (or `additional information'). It is clear from the quote that, even in the first (`claimed') classification, there is room for spillovers. The second type of knowledge, because it is not appropriable, is almost by definition a spillover. In this case, one may think, for example, about descriptions of certain characteristics of a previously known material. These characteristics themselves cannot be claimed in a patent, but a device which makes use of these characteristics can be (the device would be classified under `invention information' and the material's characteristics under `additional information').

In the case of the EPO, the main application of the claimed knowledge in a patent is assigned to a single technological class, while other, related knowledge is classified into (multiple) supplementary classes. Supplementary classes may contain invention information (claimable) and additional information (unclaimable).

The processing of the European patent data was carried out using a concordance table which maps four-digit IPC codes into one or multiple International Standard Industrial Classification (ISIC) (rev. 2) industrial sectors (see Verspagen et al., 1994).2 Two different matrices were constructed on the basis of approximately 650000 European patent applications over the period 1979-94 (note that data for the most recent, say, 3 years are scarce, as a result of a lag in information processing at the EPO). The first of these matrices (Table 1) is constructed on the basis of the distinction between main and supplementary IPC codes for claimable knowledge. This matrix assumes that the main IPC code into which a patent is classified provides a good proxy of the producing sector of the knowledge, and that the listed supplementary IPC codes (taken as partially unintended `by-products' of the main goal of the invention) given an indication for technology spillovers to other industrial sectors (see also Grupp (1996) for a similar idea). This matrix makes use of approximately 60% of the 650000 records in the EPO database (the other records do not have supplementary IPC codes).

The second matrix (Table 2) is constructed using information on the main classification of claimable knowledge and the (supplementary) codes for unclaimable knowledge. In this case, the main IPC code is again seen as a good proxy for the producing sector of the invention; however, in this case, the spillovers relate specifically to the unclaimable aspects of the patent description. Then, the number of available records with information is much smaller, so that the second matrix is based only on 2.5% of all patents in the database (again, other records do not have information on supplementary IPC classes).

A third spillover matrix (Table 3) was constructed on the basis of the US patent data. In the US system, the first page of a patent document lists citations to other patents (or to scientific publications). Cited patents and the patent application itself are classified into one or multiple US patent classes, which are different from the international patent classes used in the EPO system. The USPO also uses a concordance table between the US patent classes and US SIC scheme, which is a variant of the ISIC industrial activity classification system.(n3)

In the US patent database used here, each patent is assigned to two series of SIC codes: one series for the `original' US patent classes and the other series for all classes, i.e. the original classes as well as the `original' classes for patents cited on the front page. This provides an obvious opportunity to measure spillovers by means of patent citations, assuming that spillovers flow from the cited patent sector (SIC) to the citing patent sector (SIC). A matrix was set up in this way, where fractional counts were used (i.e. a patent is counted as 1/(ao), where a is the number of `all SICs' and o is the number of `original SICs). Note that this method tends to overestimate the values on the diagonal, because there is no way to distinguish between `original' and `cited' SICs in the series for `all SICs'.

Therefore, a SIC that occurs in both series may or may not represent `citation spillovers', while it is always counted as such. Another disadvantage of the US data is that there are three sectors for which there are no data, although these sectors are present in the IPC-ISIC concordance: wood and products, paper and printing, and other manufacturing. In contrast to the EPO data, the US data concern only granted patents. To achieve comparability with the EPO data, only data from the period 1980-92 were used.

Tables 1-3 present matrices A and B for the EPO data and the US patent matrix respectively. All three matrices have been constructed by dividing the number of patents in each cell by its row total, so that the cells hold the fraction of total patents in the sector (row) that generates spillovers to another sector (column). Perhaps the most striking feature of all three matrices is the fact that there are several `generic' sectors, in the sense that these sectors receive technology spillovers from a broad range of other sectors (i.e. the columns for these sectors generally have high values). These sectors are electrical machinery (column 1), chemicals (column 3), metal products (column 12), instruments (column 13) and machinery (column 15). Note also that, as in the matrix of Scherer (1982) and the Yale matrix, the diagonal elements have relatively high values.

To compare the results in the three matrices with each other and with the Yale matrix described earlier, Table 4 gives correlation coefficients for individual rows and columns, as well as for the overall matrices (i.e. simply correlating all elements from the same cell from two matrices). The diagonal elements of the matrices have been set to zero while calculating the coefficients, to avoid spurious correlation. In combinations where the US patents matrix was used, correlations were made for 19 rows and/or columns; otherwise, for 22 rows and/or columns.

The version of the Yale matrix that was used is described fully in Putnam and Evenson (1994). Using the data supplied by the Canadian Patent Office, Putnam and Evenson (1994) constructed a matrix which gives the (ex post) probability that a patent manufactured in industry i will be used by industry j.(n4) They used data for 1978-89, so the period is roughly comparable with the periods used here. The matrix presented by Putnam and Evenson (1994) includes many primary and tertiary sectors, such as agriculture, mining and many services sectors. These sectors mainly turn up as `user sectors'. In the method used to calculate matrices A and B, and in the database of the USPO, patents are always assigned to the `industry of manufacture of the knowledge', even in the case of a supplementary patent class or cited patent. For this reason, primary and tertiary sectors were not included in Tables 1-3. To keep the results comparable, all data from the Yale matrix that will be used in the remainder of this paper were normalized by dividing through all cells by the row total for manufacturing columns only. The resulting sectors are similar to those in Tables 1 and 2.

However, it should be kept in mind that, by doing this, an important feature of the Yale-Canada methodology, i.e. measuring spillovers from manufacturing to services, is omitted. This is related to the distinction between rent spillovers (or user-producer spillovers) and `pure' knowledge spillovers. Spillovers from manufacturing and services might be characterized as mainly consisting of rent spillovers; hence, the three matrices developed here do not measure this aspect very well, which implies an important disadvantage compared with the Yale-Canada methodology.

What emerges from Table 4 is that, in general, the correlation between matrix A and matrix B is quite high. In all three categories of correlations, the combination A-B yields the highest coefficient. The Yale matrix, although always positively correlated with the other three matrices, seems to be somewhat distinct, especially with respect to matrices A and B. For the total matrix, the correlation between the Yale matrix and the other matrices is never significant, while, for column correlations, it is only significant in the case of the US matrix. Thus, the US patent matrix seems to form an `intermediate' case between matrix A and matrix B, on the one hand, and the Yale matrix, on the other hand. When considered along the row dimension only, all correlations are significant. In general, correlation coefficients for columns are lower than for rows.

3. R & D, Productivity and Spillovers

One of the main applications of technology spillover matrices has been to the case of productivity growth (Scherer, 1982; Wolff & Nadiri, 1993). The general finding in this literature is that the impact of `indirect' R&D (i.e. R&D performed in other sectors, calculated on the basis of a spillover matrix) on productivity growth is positive and significant. In many cases, the finding is even that the impact of indirect R&D is greater than that of direct R&D (Mohnen, 1992). The comparison between the two types of R&D is difficult, however, because direct and indirect R&D are highly collinear in many cases, making inference in nested regression models difficult. In this section, a simple, heuristic model for the relationship between productivity growth and direct and indirect R&D will be used. A comparison between indirect measures of R&D based on the four different spillover matrices will be made.

The analysis starts from an assumed Cobb-Douglas production function, written in labour-intensive, dynamic format as

(1) q - l = c + Alpha(k-l) + Mul + Rho + Gamma r_i

where q, l and k denote the growth rates of output, labour input and the capital stock respectively. r and r_i denote the growth rates of two distinct knowledge stocks, with r relating to knowledge generated in the sector itself and r_i consisting of `indirect' knowledge, or spillovers. Alpha is the elasticity of output with respect to capital and Mu is defined as Alpha + Beta-1, where Beta is the elasticity of output with respect to labour (thus, if Mu = 0, then constant returns to scale with respect capital and labour hold).

Next, following Terleckyj's (1974) basic contribution, one may write the growth rate of the direct knowledge stock as

(2) r = R&D/Q Q/R

where R&D denotes the R&D expenditures in the sector, Q is the output and R is the direct knowledge stock. A similar expression can be written for the indirect knowledge stock, substituting for direct R&D expenditures by indirect R&D expenditures.

On multiplying equation (2) by Rho(or Gamma for indirect knowledge), one obtains the R&D intensity (R&D over output) multiplied by the rate of return to direct (or indirect) knowledge investments (because the elasticity of output with respect to the knowledge stock divided through by the ratio of the knowledge stock to output can be interpreted as a rate of return). Therefore, equation (1) can be rewritten as

(3) q - l = c + Alpha(k-l) + Mul + $m_d i_d$ + $m_s i_s$

where i_d and i_s are the direct and indirect (spillover) R&D intensities, respectively, and m_d and m_s are their respective rates of return.

The model in equation (3) is called the unrestricted model, which can be further restricted in several ways. First, a model which will be called the CRS (constant returns to scale) model is obtained by setting Mu to zero, i.e.

(4) q - l = c + Alpha(k-l) + $m_d i_d$ + $m_s i_s$

Second, the CRS model can be further restricted by assuming that Alpha can be inferred from the data, i.e. that it can be estimated as 1-Sigma, where Sigma is the share of labour in income. In this model, TFP growth becomes the dependent variable, i.e.

(5) q - l - Alpha(k-l) = TFP = c + $m_d i_d$ + $m_s i_s$

These are the basic equations that will be estimated, using each of the four different matrices discussed previously as measures to calculate indirect R&D. The two R&D intensity variables are measured as Sigma_tR&D/Sigma_t Q (where Q denotes value added and Sigma_t indicates a sum over the period 1979-89(n5)). Indirect R&D flows in sector i are calculated as Sigma_i equal to $_i$ m_{ji} (where j indicates the 22 sectors and m is an element from matrix A, matrix B, the US patents or the Yale matrix(.(n6) In calculating indirect R&D flows, the diagonal elements of the spillover matrices (m_{ii})

have been set to zero to avoid collinearity with the direct R&D measure. This implies that the estimated rate of return on direct R&D includes intrasectoral spillovers, i.e. that it is an intrasectoral `social' rate of return.

TFP is measured as

$$TFP= 1n\ Q_{1989} - 1n\ Q_{1979} - Alpha(1n\ L_{1989} - In\ L_{1979}) - (1- Alpha)(1n\ K_{1989}-1n\ K_{1979})/10$$

where L denotes the labour input used, K is the capital stock and is the wage share in value added.(n7) This measure of TFP growth is admittedly crude, because it does not adjust for underutilization of (quasi-)fixed inputs, and the capital stock input used is based on a fairly crude method. However, given the nature of the analysis, and keeping in mind the intended coverage of a large number of sectors and countries, the development of a more sophisticated measure is not possible.

The main source of the data is the OECD,(n8) but the price indices used to deflate R&D (i.e. the GDP deflator) and investment were taken from the Penn World Tables (version 5.5).(n9) The countries included in the analysis are Canada, Denmark, Finland, France, Germany, Italy, Japan, the UK and the US.

To give a crude impression of the dependencies in the data, Table 5 shows correlation coefficients between the variables in the model. Indirect R&D variables are subscripted by A, B, U or Y to indicate the matrix used in the calculations (i.e. matrices A, B, US patents and Yale). There are several interesting features in Table 5. First, the correlation between direct and indirect R&D measures, although positive, is not very high. The Yale measure of indirect R&D yields the highest correlation with direct R&D. Second, the indirect measures of R&D have fairly high correlation coefficients with respect to each other. Perhaps surprisingly, the correlation between the Yale matrix and the US patent matrix results are lowest in this part of the table. Finally, the correlation coefficients between TFP growth and labour productivity growth, on the one hand, and indirect R&D, on the other hand, are higher than for direct R&D; however, these coefficients are generally low (indirect R&D based on matrices A and B yields the highest coefficients). Overall, the danger for collinearity does not seem to be great, except in cases with more than one measure for indirect R&D in the same equation.

In the regressions that were carried out, the assumption of equal coefficients between countries and sectors was relaxed. To this end, the regression constants are assumed to vary between countries, whereas the regression slopes are assumed to vary between three broad groups of sectors. This specification is admittedly ad hoc. Slightly different specifications have been implemented, however, such as adding a country-specific element to the slope, instead of the constant. The results did not point to significantly different conclusions. Given the choice to abstract from the time dimension in the data set (this would undoubtedly introduce huge problems with regard to non-stationarity in the data and identifying an adequate lag structure), a more adequate specification is difficult to implement.

The three groups of sectors for which the slope is allowed to vary are set up according to the current OECD classification of ISIC sectors into low-, medium-and high-tech sectors. This classification is based on the R&D value added ratio in each sector, with high (low) values classified into the high-(low-)tech group. The group of high-tech sectors consists of electronics, computers, aerospace, drugs and medicines, and instruments. Medium-tech sectors are chemicals, motor vehicles, other transport,(n10) rubber and plastic products, machinery and electrical machinery. Other sectors are classified as low-tech sectors.

The three different models introduced earlier were estimated for each of the four different measures of indirect R&D. Inspection of the results showed that some of the significance levels of the estimated coefficients were quite sensitive to the inclusion of around 10 `influential' observations, defined as observations for which the diagonal of the `hat' matrix was greater than two times the number of estimated coefficients divided by the number of observations. From a theoretical point of view, there is no strict reason to exclude such `influential' observations, which is why the results for all observations are presented here. Appendix A documents the same estimations, excluding the influential observations. These are generally somewhat less significant, but are also higher. Finally, the country dummies are not documented explicitly.

The results are documented in Table 6. They confirm the expectation that the estimated coefficients differ between sectors. For the unrestricted model, we find that, for all sectors, the coefficient on the growth rate of labour (l) is negative, indicating decreasing returns to scale with regard to labour and capital. In the low-tech and medium-tech sectors, the negative signs are significant. Among the direct and indirect R&D variables, the only variables that are significant are the coefficients for indirect R&D in low-tech industries (not for the Yale measure), and the EPO A and US measures in medium-tech industries.

However, the results for the unrestricted model seem somewhat problematic, because the values of the coefficients for I in the low-tech sectors are implausibly low, whereas the values for the indirect R&D variables in these industries are rather high (they point to rates of return of the order of magnitude 350-900%). Therefore, the CRS model seems a reasonable alternative: in the high-tech sectors, the restriction that it imposes is not rejected in a t-test and, in the low-and medium-tech sectors, not imposing the restriction leads to results that are implausible from a theoretical point of view.

The CRS model yields significant estimates for the growth rate of the capital/ labour ratio in all three groups of industries. The values obtained for this parameter seem reasonable from a theoretical point of view. For direct R&D, no significant estimates are obtained, except in low-tech industries for EPO B. With the exception of the high-tech industries, the signs are positive, as expected. For indirect R&D, the results are significant for three out of four cases in medium-tech industries (Yale is the exception), two out of four cases in low-tech industries (Yale and US patents are the exceptions), and two of the four cases for high-tech industries (EPO B and US are the exeptions here). In all these significant cases, the estimated rates of return are quite high, ranging from 1.5 to 3.

The TFP model drops the capital/output ratio from the right-hand side of the equation, while using TFP growth as the dependent variable. This equation shows a clear difference with respect to the order of magnitude of the estimated coefficients on indirect R&D. Significant coefficients are found for all four measures of indirect R&D in low- and medium-tech industries, but for none in high-tech industries. Direct R&D is (still) not significant in any equation.

A final model--not introduced previously--drops the insignificant direct R&D variables from the equation, leaving only the indirect R&D variables and the undocumented country dummies as explanations for TFP growth. This is termed the restricted TFP model in Table 6. The results for this estimation show that, in general, leaving out direct R&D does not tend to yield higher or lower coefficients, or to give more significant coefficients for indirect R&D.

Summarizing, it appears that indirect R&D is a strong determinant of productivity growth, either measured in terms of labour productivity growth or in terms of TFP growth. Its impact, as measured in the current framework, is certainly much stronger than the impact of direct R&D. There are also differences between the different measures of indirect R&D that have been used in the analysis. The measure based on US patent citations yields relatively high rates of return (highest in low- and high-tech industries), whereas the Yale measure generally yields low rates of return, except in medium-tech industries, where this measure ranks highest. The two measures based on interdependencies in the EPO patent data yield intermediate values for the rates of return.

The differences between the estimated rates of return on indirect R&D can also be expressed in terms of `social rates of return' to R&D (see, for example, Mohnen & Lepine, 1991). Because no significant estimation results were obtained for direct R&D, the social rates of return calculated here are so-called `extrasectoral' rates of return to R&D, i.e. they do not include the direct effect of R&D or the indirect effect within the sector from which the R&D originates. The construction of this rate of return starts from the assumption that an extra `dollar' of R&D is distributed over the different R&D-performing sectors according to the existing sectoral distribution of R&D, and the expression for it is

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where m, as before, is an element of one of the four different spillover matrices, and the derivative of output with respect to indirect R&D (JR) (the rate of return to indirect R&D) is obtained from the above estimations of the restricted TFP model. The sectoral shares of R&D and output are calculated as the mean of the 1984 values for seven of the nine countries in the sample (excluding Canada and Denmark, because of missing values).

The calculations for the extrasectoral social rate of return indeed show that there are differences between the different spillover matrices, although they are small. The highest values are obtained for the EPO B and US matrices: 15.2% and 14.0% respectively. The Yale matrix yields a value of 11.7% and the EPO A matrix gives a value of 10.4%.

4. Conclusions

The questions that emerge from the foregoing analysis are as follows. Do the results in Section 3 lead to the conclusion that the methods for measuring knowledge spillovers presented in Section 2 are useful undertakings? Also, do the results point out that matrices A and B, the US patent matrix and the Yale matrix actually measure different aspects of the knowledge spillover process, or can they be regarded as different ways of measuring the same thing?

With regard to the first question, the argument in Section 2 was that methods such as the Yale matrix or the matrix developed by Scherer (1982) measure knowledge spillovers related to economic transaction, rather than spillovers related to technological linkages between sectors. It was argued that such a `transaction-based' approach leads to the danger of confusing rent spillovers with pure knowledge spillovers.

The comparison in Section 3 between the transaction-based Yale matrix and the technology based matrices A and B, as well as the US patents matrix developed in this paper, led to the conclusion that there are indeed differences between these matrices. The overall correlation between cell values in the matrices is low, although positive. Comparing the cell values row by row or column by column yields higher correlation coefficients, although those obtained for columns (i.e. from where sectors get their spillovers in particular) are low. This seems to indicate that there is at least some use in constructing a technology-based spillover matrix to be able to compare the results with the more traditional transaction based approach. It must be kept in mind, however, that such pure knowledge spillovers are mostly restricted to the manufacturing sector and that, for example, technology flows from manufacturing to services are not captured. The Yale matrix does measure flows from manufacturing to services or agriculture, which is an important advantage.

The results in Section 4 indicate that, as a result of collinearity, a direct comparison between the different measures of indirect R&D, by means of the inclusion of multiple measures in the same equation estimating productivity growth, is not very practical. This seems to indicate that there is at least some overlap between the various methods with regard to what is being measured. Various models were used to estimate the rates of return to direct and indirect R&D, with the latter measured by four different matrices. The estimations indicate that there are indeed differences between the different measures. The Yale matrix measure yields a relatively high rate of return in medium-tech sectors, but not so in the other sectors. The measure based on US patent citations yields relatively high rates of return. The two measures based on EPO patent data yield intermediate values for the rates of return. In terms of extrasectoral social rates of return, the EPO B and US data yield high values compared with the other two measures.

With regard to the differences between the technology-based estimates, recall that there are considerable differences between these matrices, both in terms of methodologies and of the underlying database. The matrix B is explicitly based on non-appropriable aspects of the knowledge described in a patent application, whereas the matrix A is based on the appropriable aspects of this knowledge. Thus, one might expect that the knowledge captured in matrix B flows more freely between sectors, but also that it is possibly less directly relevant for production. The relatively high estimated social rate of return for the matrix B must be seen in this light. The US patents matrix is based on patent citations, which might be regarded as a form of very directly relevant knowledge. Therefore, the higher values for this measure are not surprising. In the high-tech sectors, the matrix A and the US patent measures are the only two that are significant, indicating the importance of these types of technological linkage to other sectors in this group, as compared with transaction-based linkages.

Is there a `final verdict' on the technology-based matrices versus the transaction-based Yale matrix? It has already been stressed that a direct comparison is difficult, because of collinearity and, perhaps more importantly, because an important aspect of the Yale matrix, i.e. flows between manufacturing and primary and tertiary sectors, was omitted from the analysis. Therefore, the results can only point out that the technology-based measures are an important contribution. It is not the outcome or the aim of the analysis to reject the user-producer-oriented matrices, such as the Yale matrix, as a less adequate measure of technology spillovers. Any serious analysis that aims to provide a complete picture of the issue of knowledge spillovers must take into account both aspects.

Notes

(n1.) "Each patent was individually examined to determine the industry of origin . . . , the industry(ies) in which use was anticipated, and whether the invention involved an internal process, or externally-sold product" (Scherer, 1982, p. 627).

(n2.) This concordance table assigns IPC codes to the ISIC sector(s) where the patent most likely originates (i.e. in terms of the Canadian Patent Office methodology, the `producing' sector). In cases where multiple originating sectors seemed possible, weights were assigned to each of these, on the basis of the technological description of the IPC class.

(n3.) The concordance between US patent classes and US SICs is known to lead to slightly different results as compared with the concordance between international patent classes and ISIC as applied in the case of EPO patents above. See, for example, European Commission (1994) for a comparison. There is no a priori reason to favour one,of the two systems, although a case study for the chemicals sector has shown that the IPC-ISIC concordance may lead to better results in that particular sector (see European Commission, 1994, methodological appendix).

(n4.) Putnam and Evenson (1994) discuss two different methods of measuring spillovers on the basis of the same data. In the method used here, a matrix which has patent counts by `manufacturing' and `using' industry is normalized by dividing through by the row totals, i.e. by the total of the `manufacturing' sector. The second method of Putnam and Evenson estimates the probability that a patent used by industry j is manufactured in industry i. This is obtained by dividing through each cell in the matrix of patent counts by its column total. The second of these methods is conceptually more different from the method used in Tables 1 and 2. Moreover, Putnam and Evenson (1994) conclude: "Our best out-of-sample estimates with [the second method] tended to have an overall reliability about the same, or somewhat worse than, our best estimates using [the first method]". This is why the analysis in the remainder of this paper will only use their first method.

(n5.) R&D is measured in constant prices, where the GDP deflator was used to create these from current values. This also applies for Q, except that the sectoral producer price indices were then used. For the subsectors in ISIC classes 352, 382 and 383, no disaggregated price indices were available. In these cases, the three-digit price indices were used for the four-digit subsectors.

(n6.) For indirect R&D based on the US patents matrix, R&D flows from sectors 20-22 in Tables 1 and 2 have been set to zero. These sectors are left out of the regressions presented in the case of the US patents matrix measures for indirect R&D.

(n7.) K is calculated as a perpetual inventory: $K_t = 0.9K_{t-1} + I_t$. K_{1975} *is estimated by dividing through* I_{1976} *by 0.15 (this is consistent with the assumed depreciation rate of 10% and the assumption that the growth rate of the capital stock in 1976 relative to 1975 was 5%).* I_t *is deflated using a price index for investment goods. Beta is measured as Sigma W/Sigma Q, where Sigma indicates a summation*

over the period 1979-89 and W is the wage bill. In this case, both Wand Q are measured in current prices.

(n8.) STAN and ANBERD databases.

(n9.) Producers' price indices used to deflate value added were taken from the STAN database.

(n10.) In the OECD scheme, this sector is classified as low tech, but this seems less adequate for countries such as France, where R&D related to the train a grande vitesse (TGV) falls under this heading. Classifying this sector under low tech does not significantly change the results. However, the example does show the extent to which any classification into high-, medium- and low-tech sectors includes arbitrary elements. This again adds to the crudeness of the results in this section, as in most other literature on this subject.

Table 1. Patent spillover matrix A, EPO patents 1979-94, main IPC code by supplementary IPC code

	1	2	3	4	5	6
1 Electrical	0.440	0.355	0.008	0.000	0.000	0.000
2 Electronics	0.187	0.629	0.017	0.001	0.000	0.000
3 Chemicals	0.013	0.009	0.531	0.137	0.025	0.000
4 Drugs	0.001	0.000	0.261	0.369	0.006	0.000
5 Refined oil	0.046	0.005	0.371	0.070	0.191	
6 Ships, boats	0.012	0.001	0.004	0.000		0.290
7 Automotive	0.027	0.007	0.019	0.001	0.000	0.003
8 Aerospace	0.028	0.014	0.008			0.029
9 Other transport	0.065	0.005	0.002			0.004
10 Ferrous metals	0.030	0.001	0.035	0.002	0.001	0.000
11 Non-ferrous metals	0.043	0.008	0.069	0.007	0.003	0.000
12 Metal products	0.052	0.016	0.027	0.004	0.002	0.002
13 Instruments	0.035	0.038	0.071	0.111	0.005	0.000
14 Computers	0.027	0.075	0.006	0.001	0.000	0.000
15 Machines	0.024	0.007	0.069	0.014	0.003	0.002
16 Food, etc.	0.003	0.002	0.284	0.263	0.0001	0.000
17 Textiles	0.013	0.012	0.085	0.005	0.001	0.000
18 Rubber, plastic	0.156	0.007	0.046	0.005	0.005	0.000
19 Glass, etc.	0.020	0.008	0.135	0.008	0.001	0.001
20 Paper, printing	0.024	0.006	0.105	0.022	0.003	0.001
21 Wooden products	0.018	0.004	0.074	0.008	0.000	0.001
22 Other manufacturers	0.031	0.042	0.026	0.002	0.001	0.003

	7	8	9	10	11	12
1 Electrical	0.012	0.001	0.006	0.002	0.007	0.038
2 Electronics	0.001	0.001	0.005	0.001	0.001	0.011
3 Chemicals	0.001	0.000	0.001	0.004	0.004	0.018
4 Drugs	0.000		0.000	0.000	0.000	0.003
5 Refined oil	0.001		0.000	0.005	0.005	0.042
6 Ships, boats	0.444	0.010	0.049	0.000	0.000	0.038
7 Automotive	0.368	0.004	0.080	0.001	0.002	0.085
8 Aerospace	0.133	0.433	0.015		0.001	0.062
9 Other transport	0.479	0.003	0.275	0.000	0.001	0.044
10 Ferrous metals	0.007		0.000	0.187	0.461	0.095
11 Non-ferrous metals	0.007	0.000	0.001	0.322	0.298	0.085
12 Metal products	0.026	0.002	0.004	0.009	0.012	0.478
13 Instruments	0.005	0.002	0.002	0..01	0.002	0.026
14 Computers	0.004	0.000	0.002	0.000	0.000	0.008
15 Machines	0.039	0.003	0.004	0.006	0.007	0.110

16 Food, etc.	0.001		0.000	0.000	0.000	0.019
17 Textiles	0.006	0.002	0.004	0.091	0.002	0.042
18 Rubber, plastic	0.093	0.001	0.023	0.001	0.002	0.119
19 Glass, etc.	0.005	0.001	0.001	0.001	0.005	0.107
20 Paper, printing	0.004	0.001	0.001	0.003	0.008	0.034
21 Wooden products	0.006	0.002	0.016	0.000	0.001	0.247
22 Other manufacturers	0.008	0.001	0.006	0.004	0.001	0.041

	13	14	15	16	17	18
1 Electrical	0.059	0.020	0.029	0.001	0.002	0.001
2 Electronics	0.065	0.056	0.010	0.000	0.002	0.000
3 Chemicals	0.043	0.004	0.085	0.013	0.018	0.002
4 Drugs	0.023	0.000	0.031	0.025	0.002	0.000
5 Refined oil	0.106	0.004	0.111	0.005	0.003	0.000
6 Ships, boats	0.035	0.002	0.088		0.004	0.001
7 Automotive	0.033	0.003	0.194	0.001	0.005	0.044
8 Aerospace	0.077	0.006	0.153		0.000	0.005
9 Other transport	0.041	0.003	0.061	0.000	0.001	0.001
10 Ferrous metals	0.021	0.001	0.123	0.000	0.003	0.000
11 Non-ferrous metals	0.015	0.002	0.092	0.000	0.002	0.001
12 Metal products	0.051	0.004	0.187	0.004	0.003	0.004
13 Instruments	0.510	0.044	0.085	0.011	0.003	0.001
14 Computers	0.075	0.761	0.012	0.000	0.001	0.000
15 Machines	0.060	0.005	0.528	0.029	0.020	0.002
16 Food, etc.	0.039	0.000	0.091	0.274	0.007	0.000
17 Textiles	0.050	0.003	0.249	0.006	0.286	0.016
18 Rubber, plastic	0.144	0.007	0.142	0.006	0.126	0.034
19 Glass, etc.	0.049	0.002	0.212	0.003	0.004	0.001
20 Paper, printing	0.105	0.041	0.163	0.003	0.088	0.006
21 Wooden products	0.092	0.004	0.096	0.003	0.017	0.020
22 Other manufacturers	0.110	0.189	0.121	0.009	0.076	0.004

	19	20	21	22
1 Electrical	0.009	0.005	0.001	0.005
2 Electronics	0.004	0.001	0.000	0.008
3 Chemicals	0.039	0.011	0.000	0.014
4 Drugs	0.001	0.003	0.000	0.002
5 Refined oil	0.029	0.007	0.000	0.004
6 Ships, boats	0.004	0.002	0.001	0.015
7 Automotive	0.039	0.057	0.005	0.023
8 Aerospace	0.005	0.004	0.003	0.024
9 Other transport	0.003	0.003	0.002	0.007
10 Ferrous metals	0.024	0.002		0.004
11 Non-ferrous metals	0.020	0.016		0.010
12 Metal products	0.038	0.034	0.016	0.024
13 Instruments	0.05	0.022	0.001	0.019
14 Computers	0.001	0.006	0.001	0.019
15 Machines	0.020	0.016	0.002	0.030
16 Food, etc.	0.002	0.004	0.000	0.010
17 Textiles	0.015	0.026	0.002	0.083
18 Rubber, plastic	0.012	0.016	0.025	0.029
19 Glass, etc.	0.366	0.042	0.007	0.020
20 Paper, printing	0.011	0.283	0.003	0.087
21 Wooden products	0.017	0.204	0.108	0.061
22 Other manufacturers	0.009	0.034	0.003	0.282

Note: Rows denote `spillover-generating' sectors; columns are `spillover-receiving' sectors; empty cells must be read as `true' zeros; the value 0.000 indicates a positive value rounded to zero.

Table 2. Patent spillover matrix B, EPO patents 1979-94, main IPC code by (uclaimable) `additional information' supplementary IPC code

	1	2	3	4	5	6
1 Electrical	0.161	0.392	0.014	0.003	0.007	0.004
2 Electronics	0.285	0.227	0.121	0.008		
3 Chemicals	0.008	0.005	0.599	0.176	0.007	0.000
4 Drugs	0.001	0.000	0.241	0.654	0.006	
5 Refined oil	0.076	0.034	0.365	0.152	0.008	
6 Ships, boats	0.011					0.485
7 Automotive	0.045	0.017	0.048	0.001	0.002	0.013
8 Aerospace			0.083			0.083
9 Other transport	0.071	0.011	0.006			
10 Ferrous metals	0.087	0.013	0.062	0.008		
11 Non-ferrous metals	0.029	0.023	0.043	0.009		
12 Metal products	0.038	0.059	0.080	0.025	0.004	0.006
13 Instruments	0.012	0.019	0.172	0.282	0.010	0.001
14 Computers	0.037	0.115	0.022	0.004		
15 Machines	0.014	0.006	0.345	0.037	0.004	0.003
16 Food, etc.		0.002	0.410	0.318		
17 Textiles	0.007		0.294	0.041	0.003	
18 Rubber, plastic	0.040		0.097	0.027		
19 Glass, etc.	0.029	0.031	0.126	0.008	0.007	0.030
20 Paper, printing	0.010		0.148	0.080		
21 Wooden products	0.031	0.011	0.107	0.010		0.002
22 Other manufacturers	0.015	0.012	0.097	0.006		

	7	8	9	10	11	12
1 Electrical	0.010		0.005	0.004	0.005	0.049
2 Electronics	0.003		0.07	0.002	0.010	0.031
3 Chemicals	0.002	.0001	0.001	0.001	0.001	0.012
4 Drugs				0.000		0.003
5 Refined oil				0.034		0.050
6 Ships, boats	0.205	0.010	0.074			0.012
7 Automotive	0.290	0.23	0.044	0.001	0.001	0.102
8 Aerospace	0.333					
9 Other transport	0.667		0.059			0.026
10 Ferrous metals	0.021			0.279	0.251	0.094
11 Non-ferrous metals	0.001		0.010	0.342	0.106	0.146
12 Metal products	0.039	0.006	0.008	0.015	0.024	0.364
13 Instruments	0.002	0.001	0.002	0.003	0.001	0.019
14 Computers	0.007		0.002	0.001	0.01	0.004
15 Machines	0.048	0.002	0.009	0.007	0.002	0.106
16 Food, etc.				0.001		0.006
17 Textiles	0.009		0.006		0.004	0.023
18 Rubber, plastic	0.012					0.075
19 Glass, etc.	0.006	0.001		0.002	0.007	0.087
20 Paper, printing				0.003		0.046
21 Wooden products	0.005	0.002	0.020			0.108

22 Other manufacturers	0.034	0.006	0.009		0.003	0.098

	13	14	15	16	17	18
1 Electrical	0.077	0.198	0.040	0.001	0.002	0.001
2 Electronics	0.082	0.158	0.012	0.002	0.001	
3 Chemicals	0.056	0.003	0.042	0.017	0.033	0.002
4 Drugs	0.21	0.000	0.047	0.021	0.002	
5 Refined oil	0.093	0.017	0.099	0.050		0.003
6 Ships, boats	0.080		0.081			
7 Automotive	0.051	0.029	0.237	0.001	0.006	0.008
8 Aerospace			0.500			
9 Other transport	0.070		0.071			
10 Ferrous metals	0.032	0.008	0.103			0.007
11 Non-ferrous metals	0.042	0.001	0.166			
12 Metal products	0.064	0.004	0.161	0.003	0.005	0.003
13 Instruments	0.331	0.008	0.074	0.036	0.004	0.001
14 Computers	0.048	0.747	0.007			
15 Machines	0.055	0.006	0.269	0.021	0.010	0.004
16 Food, etc.	0.056		0.029	0.170	0.000	0.001
17 Textiles	0.058		0.089	0.002	0.396	0.005
18 Rubber, plastic	0.182		0.032		0.422	0.029
19 Glass, etc.	0.083	0.007	0.159	0.007	0.002	0.000
20 Paper, printing	0.060	0.035	0.152	0.014	0.282	0.005
21 Wooden products	0.072		0.060	0.002	0.033	0.010
22 Other manufacturers	0.166	0.051	0.140		0.079	0.008

	19	20	21	22
1 Electrical	0.008	0.003	0.005	0.010
2 Electronics	0.027	0.006		0.010
3 Chemicals	0.016	0.010	0.000	0.008
4 Drugs	0.000	0.003	0.000	0.002
5 Refined oil	0.017			0.001
6 Ships, boats				0.041
7 Automotives	0.016	0.025	0.003	0.034
8 Aerospace				
9 Other transport		0.006	0.001	0.011
10 Ferrous metals	0.025	0.003		0.008
11 Non-ferrous metals	0.017	0.019		0.046
12 Metal products	0.035	0.017	0.012	0.029
13 Instruments	0.003	0.013	0.001	0.006
14 Computers	0.001	0.006		0.001
15 Machines	0.020	0.016	0.003	0.013
16 Food, etc.	0.002	0.002		0.004
17 Textiles	0.008	0.023	0.001	0.030
18 Rubber, plastic	0.026	0.006	0.021	0.032
19 Glass, etc.	0.335	0.037	0.004	0.031
20 Paper, printing	0.013	0.129	0.002	0.021
21 Wooden products	0.032	0.406	0.054	0.036
22 Other manufacturers	0.009	0.031	0.002	0.233

Notes: Rows denote `spillover-generating' sectors; columns are `spill-over-receiving' sectors; empty cells must be read as `true' zeros; the value 0.000 indicates a positive value rounded to zero.

Table 3. Patent spillover matrix for US patents 1980-92, on the basis of co-references

	1	2	3	4	5	6
1 Electrical	0.644	0.129	0.008	0.000	0.001	0.000
2 Electronics	0.055	0.815	0.003	0.000	0.000	0.000
3 Chemicals	0.005	0.006	0.752	0.098	0.016	0.000
4 Drugs	0.001	0.000	0.451	0.467	0.001	
5 Refined oil	0.002	0.005	0.139	0.001	0.754	0.000
6 Ships, boats	0.005	0.013	0.001	0.000	0.004	0.074
7 Automotive	0.020	0.016	0.002	0.000	0.000	0.002
8 Aerospace	0.015	0.012	0.011	0.000	0.000	0.004
9 Other transport	0.018	0.004	0.001	0.000	0.000	0.066
10 Ferrous metals	0.013	0.008	0.011	0.000	0.002	0.001
11 Non-ferrous metals	0.022	0.061	0.022	0.000	0.001	0.000
12 Metal products	0.024	0.024	0.013	0.000	0.0003	0.004
13 Instruments	0.040	0.056	0.012	0.011	0.001	0.000
14 Computers	0.014	0.149	0.001	0.000	0.000	0.000
15 Machines	0.027	0.011	0.017	0.001	0.007	0.002
16 Food, etc.	0.001	0.000	0.051	0.020	0.000	
17 Textiles	0.009	0.008	0.135	0.002	0.010	0.006
18 Rubber, plastic	0.015	0.024	0.157	0.002	0.004	0.001
19 Glass, etc.	0.025	0.043	0.043	0.001	0.004	0.001

	7	8	9	10	11	12
1 Electrical	0.005	0.003	0.001	0.000	0.002	0.022
2 Electronics	0.002	0.001	0.000	0.000	0.001	0.006
3 Chemicals	0.000	0.001	0.000	0.001	0.001	0.005
4 Drugs	0.000	0.000	0.000		0.000	0.000
5 Refined oil	0.000	0.001	0.000	0.001	0.000	0.009
6 Ships, boats	0.009	0.017	0.011	0.000	0.000	0.052
7 Automotive	0.436	0.104	0.051	0.000	0.000	0.046
8 Aerospace	0.146	0.488	0.024	0.001	0.001	0.023
9 Other transport	0.184	0.049	0.452	0.004	0.000	0.043
10 Ferrous metals	0.004	0.005	0.011	0.537	0.131	0.092
11 Non-ferrous metals	0.000	0.004	0.000	0.118	0.588	0.043
12 Metal products	0.018	0.006	0.006	0.004	0.003	0.596
13 Instruments	0.002	0.002	0.001	0.000	0.001	0.022
14 Computers	0.006	0.001	0.001	0.000	0.000	0.003
15 Machines	0.030	0.022	0.007	0.003	0.003	0.052
16 Food, etc.	0.000	0.000		0.000	0.000	0.007
17 Textiles	0.003	0.002	0.001	0.001	0.000	0.048
18 Rubber, plastic	0.014	0.003	0.003	0.003	0.003	0.154
19 Glass, etc.	0.003	0.002	0.001	0.004	0.004	0.132

	13	14	15	16	17	18
1 Electrical	0.087	0.011	0.072	0.000	0.002	0.007
2 Electronics	0.053	0.041	0.012	0.000	0.001	0.005
3 Chemicals	0.021	0.000	0.015	0.003	0.006	0.061
4 Drugs	0.067	0.000	0.003	0.005	0.000	0.004
5 Refined oil	0.012	0.000	0.061	0.000	0.002	0.007
6 Ships, boats	0.007	0.004	0.114		0.007	0.013
7 Automotive	0.013	0.020	0.265		0.001	0.022
8 Aerospace	0.013	0.014	0.240		0.001	0.004
9 Other transport	0.016	0.029	0.176		0.001	0.012

10 Ferrous metals	0.017	0.001	0.109	0.000	0.002	0.033
11 Non-ferrous metals	0.021	0.000	0.088		0.001	0.043
12 Metal products	0.052	0.003	0.139	0.001	0.005	0.073
13 Instruments	0.794	0.012	0.037	0.000	0.001	0.006
14 Computers	0.047	0.725	0.049	0.000	0.000	0.002
15 Machines	0.040	0.013	0.735	0.003	0.003	0.016
16 Food, etc.	0.006	0.000	0.055	0.8473	0.001	0.019
17 Textiles	0.031	0.004	0.056	0.002	0.417	0.206
18 Rubber, plastic	0.038	0.003	0.088	0.002	0.023	0.401
19 Glass, etc.	0.040	0.003	0.089	0.001	0.021	0.164

	19
1 Electrical	0.005
2 Electronics	0.004
3 Chemicals	0.008
4 Drugs	0.001
5 Refined oil	0.006
6 Ships, boats	0.003
7 Automotive	0.003
8 Aerospace	0.002
9 Other transport	0.003
10 Ferrous metals	0.023
11 Non-ferrous metals	0.014
12 Metal products	0.027
13 Instruments	0.004
14 Computers	0.001
15 Machines	0.009
16 Food, etc.	0.001
17 Textiles	0.054
18 Rubber, plastic	0.061
19 Glass, etc.	0.419

Notes: Rows denote `spillover-generating' sectors; columns are `spillover- receiving' sectors; empty cells must be read as `true' zero; the value 0.000 indicates a positive value rounded to zero.

Table 4. Correlation coefficients between the `Yale matrix', the US patents matrix, matrix A and matrix B (diagonal elements set to zero), for individual rows, columns and the complete matrices

	Mean of rows			Mean of columns		
	Matrix B	US matrix	Yale matrix	Matrix B	US matrix	Yale matrix
Matrix A	0.86(a)	0.73(a)	0.49(a)	0.74(a)	0.62(a)	0.30
Matrix B		0.68(a)	0.44(a)		0.58(a)	0.29
US matrix			0.53(a)			0.38(a)

	Total matrix		
	Matrix B	US matrix	Yale matrix
Matrix A	0.82(a)	0.61(a)	0.19
Matrix B		0.60(a)	0.16
US matrix			0.16

(a) 10% significance in a two-tailed t-test for sample correlation.

Table 5. Correlation matrix between R&D ad TFP variables

Legend for Table:

A = i_d
B = $i_{s,A}$
C = $i_{s,B}$
D = $i_{s,U}$
E = $i_{s,Y}$

	q-l	k-l	l	A	B	C	D	E
k-l	0.10							
l	-0.31	-0.09						
1_d	0.09	0.18	0.32					
$I_{s,A}$	0.29	0.13	-0.11	0.24				
$i_{s,B}$	0.33	0.06	-0.02	0.31	0.85			
$i_{s,U}$	0.24	-0.01	-0.09	0.31	0.93	0.72		
$i_{s,Y}$	0.17	-0.01	0.13	0.36	0.74	0.77	0.62	
TFP	0.83	0.17	-0.39	0.05	0.35	0.38	0.31	0.20

Note: Number of observations is 166, except for correlations where $i_{s,U}$ is present (number of observations is 140).

Table 6. Regression results for four different models

Low tech

Dep. var.	Type i_s	k-l	l	i_d	i_s
Unrestricted model					
q-l	EPO A	0.082	-0.651(***)	0.558	2.848(**)
q-l	EPO B	0.069	-0.569(***)	0.814	2.365(***)
q-l	US	0.086	-0.735(***)	-0.357	8.606(**)
q-l	Yale	0.091	-0.665(***)	0.466	2.615
CRS model					
q-l	EPO A	0.278(***)		0.870	3.254(**)
q-l	EPO B	0.245(**)		1.202(**)	3.087(***)
q-l	US	0.364(***)		0.100	6.359
q-l	Yale	0.298(**)		0.717	4.487
TFP model					
TFP	EPO A			-0.047	0.422(**)
TFP	EPO B			-0.016	0.428(***)
TFP	Us			-0.144	1.156(**)
TFP	Yale			-0.053	0.676(*)
Restricted TFP model					

TFP	EPO A				0.371(**)
TFP	EPO B				0.412(***)
TFP	Us				0.858(*)
TFP	Yale				0.448

Medium tech

Dep. var.	Type i_s	k-l	l	i_d	i_s
Unrestricted model					
q-1	EPO A	0.303(***)	-0.444(**)	0.782	0.504(**)
q-1	EPO B	0.267(***)	-0.495(***)	1.053	0.333
q-1	US	0.312(***)	-0.424(**)	0.846	0.703(**)
q-1	Yale	0.257(***)	-0.523(***)	1.013	1.043
CRS model					
q-1	EPO A	0.390(***)		0.419	0.907(***)
q-1	EPO B	0.361(***)		0.682	0.887(*)
q-1	US	0.384(***)		0.423	1.203(***)
q-1	Yale	0.348(***)		1.196	1.540
TFP model					
TFP	EPO A			0.109	0.145(***)
TFP	EPO B			0.097	0.184(***)
TFP	Us			0.092	1.171(***)
TFP	Yale			0.116	0.464(***)
Restricted TFP model					
TFP	EPO A				0.181(***)
TFP	EPO B				0.228(***)
TFP	Us				0.212(***)
TFP	Yale				0.576(***)

High tech

Dep. var.	Type i_s	k-l	l	i_d	i_s
Unrestricted model					
q-1	EPO A	0.389(***)	-0.008	-0.363	1.505
q-1	EPO B	0.413(***)	-0.082	-0.411	0.868
q-1	US	0.464(***)	-0.044	-0.566	1.851
q-1	Yale	0.457(***)	-0.061	-0.521	1.352
CRS model					
q-1	EPO A	0.418(***)		-0.406	1.549(*)
q-1	EPO B	0.434(***)		-0.458	0.957
q-1	US	0.483(***)		-0.672	1.967
q-1	Yale	0.491(***)		-0.588	1.570(**)

TFP model			
TFP	EPO A	-0.003	0.122
TFP	EPO B	0.014	0.060
TFP	Us	-0.029	0.199
TFP	Yale	0.012	0.049
Restricted TFP model			
TFP	EPO A		0.103
TFP	EPO B		0.068
TFP	Us		0.107
TFP	Yale		0.046

Dep. var.	Type i_s	n	F	Adj. R^2
Unrestricted model				
q-1	EPO A	166	9.10(***)	0.50
q-1	EPO B	166	9.73(***)	0.51
q-1	US	140	7.10(***)	0.47
q-1	Yale	166	8.13(***)	0.46
CRS model				
q-1	EPO A	166	6.68(***)	0.37
q-1	EPO B	166	7.76(***)	0.41
q-1	US	140	5.21(***)	0.34
q-1	Yale	166	5.53(***)	0.32
TFP model				
TFP	EPO A	166	3.87(***)	0.20
TFP	EPO B	166	5.44(***)	0.27
TFP	Us	140	2.82(***)	0.16
TFP	Yale	166	2.97(***)	0.14
Restricted TFP model				
TFP	EPO A	166	4.81(***)	0.20
TFP	EPO B	166	6.91(***)	0.28
TFP	Us	140	3.39(***)	0.16
TFP	Yale	166	3.65(***)	0.15

Note: (*) Significant at 10% level; (**) significant at 5% level; (***) significant at 1% level in a two-tailed t-test, using heteroscedasticity consistent standard errors. Country dummies not explicitly documented.

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Appendix A: Regression results for the four different models, samples excluding `inferential observations'

Low tech

Dep. var.	Type i_s	k - l	l	i_d	i_s
Unrestricted model					
q - l	EPO A	0.104	-0.633(***)	0.295	4.001(***)
q - l	EPO B	0.052	-0.509(***)	0.637	3.658(***)
q - l	US	0.123	-0.727(***)	-0.261	9.392(**)
q - l	Yale	0.107	-0.650(***)	0.166	3.479
CRS model					
q - l	EPO A	0.277(***)		1.119	4.222(***)
q - l	EPO B	0.148		1.201	5.090(***)
q - l	US	0.375(***)		-0.697	9.850(*)
q - l	Yale	0.262(**)		0.867	3.587
TFP model					
TFP	EPO A			0.084	0.592(***)
TFP	EPO B			-0.030	0.708(***)
TFP	US			-0.110	1.506(**)
TFP	Yale			0.109	0.357
Restricted TFP model					
TFP	EPO A				0.787(***)
TFP	EPO B				0.674(***)
TFP	US				1.355(**)
TFP	Yale				0.637

Medium tech

Dep. var.	Type i_s	k - l	l	i_d	i_s
Unrestricted model					
q - l	EPO A	0.388(***)	-0.297	1.233	-0.705
q - l	EPO B	0.310(***)	-0.271	1.369	-0.276
q - l	US	0.434(***)	-0.287	1.111	-0.792
q - l	Yale	0.374(***)	-0.237	1.094	-1.338
CRS model					
q - l	EPO A	0.508(***)		0.070	0.131
q - l	EPO B	0.449(***)		0.088	0.044
q - l	US	0.421(***)		0.490	0.621
q - l	Yale	0.480(***)		0.259	-1.291
TFP model					
TFP	EPO A			0.110	0.239
TFP	EPO B			0.171	0.128
TFP	US			0.095	0.316(*)

TFP	Yale			0.076	0.391
Restricted TFP model					
TFP	EPO A				0.328(**)
TFP	EPO B				0.284(***)
TFP	US				0.424(***)
TFP	Yale				0.710(**)

High tech

Dep. var.	Type i_s	k - l	l	i_d	i_s
Unrestricted model					
q - l	EPO A	0.432(***)	0.393	-0.546	1.378
q - l	EPO B	0.454(***)	0.351	-0.693	0.687
q - l	US	0.361(**)	0.391	-0.455	4.324
q - l	Yale	0.519(***)	0.370	-0.846	0.959
CRS model					
q - l	EPO A	0.501(***)		-0.517	1.279
q - l	EPO B	0.356(**)		-0.367	1.493(**)
q - l	US	0.343(**)		-0.300	4.465(**)
q - l	Yale	0.466(***)		-0.648	4.525
TFP model					
TFP	EPO A			-0.001	0.168
TFP	EPO B			0.012	0.128(**)
TFP	US			-0.005	0.180
TFP	Yale			0.012	-0.003
Restricted TFP model					
TFP	EPO A				0.249(**)
TFP	EPO B				0.136(*)
TFP	US				0.276(*)
TFP	Yale				0.146

Dep. var.	Type i_s	n	F	Adj. R^2
Unrestricted model				
q - l	EPO A	155	8.11(***)	0.48
q - l	EPO B	154	8.25(***)	0.49
q - l	US	131	6.41(***)	0.45
q - l	Yale	155	7.10(***)	0.44
CRS model				
q - l	EPO A	156	6.06(***)	0.36
q - l	EPO B	155	7.39(***)	0.41
q - l	US	132	4.24(***)	0.30
q - l	Yale	155	4.66(***)	0.29

TFP model

TFP	EPO A	156	2.89(***)	0.15
TFP	EPO B	156	4.40(***)	0.23
TFP	US	130	1.63(*)	0.06
TFP	Yale	157	1.89(**)	0.07

Restricted TFP model

TFP	EPO A	156	4.21(***)	0.19
TFP	EPO B	160	6.06(***)	0.26
TFP	US	134	2.47(***)	0.11
TFP	Yale	159	2.76(***)	0.11

Notes: Original sample size for equations with EPO- and Yale-based indirect R&D measures is 166; for US-based indirect R&D measures it is 140. Observations for which the diagonal of the `hat' matrix was greater than two times the number of estimated coefficients divided by the number of observations were classified as `influential' and excluded from the regression. Regressions including all observations are documented in the appendix. (*) Significant at 10% level; (**) significant at 5% level; (***) significant at 1% level in a two-tailed t-test, using heteroscedasticity-consistent standard errors. Country dummies not explicitly documented.

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