

Key Sectors of Innovation

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Abstract

One way to proxy the outcome of the R&D process is to count the number of patents a firm has generated. However, there are several problems with the use of the number of patents as an indicator of R&D-output (Griliches, 1990). However, the correlation between changes in R&D spending and generated patents is quite high (Pakes and Griliches, 1984). Different uses of patents as indicators of technological progress range from 'simple' patent counts (Johnson *et al.*, 1995) to the use of 'specific' input-output techniques to measure the interaction between sectors in the innovative process. The purpose of this paper is to examine whether the techniques that are applied to input-output tables can also be used for the typical analysis of the specific data on patents and innovations. The data used in this study denote make and use of patents or innovations by sector. By applying the techniques developed, it is possible to pinpoint the sectors that are the most important for innovative activities and the sectors that generate the highest number of patents due to interaction with other sectors. Since these specific data are scarce only Canada is investigated empirically.

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1 Introduction

Economic growth matters. The economic backwardness on some continents leaves millions of people in depriving circumstances, whilst the very fast growth on other continents is simply staggering. It is difficult to grasp why some countries that are in a backward situation hardly grow at all while other countries which, on a first glance, are in the same situation grow very fast. By analyzing countries at a macro level, important information may be lost. In this paper, a closer look is taken at the sectoral data on innovative activity and patents.

If one assumes that the economic structure can be accurately described by a Cobb-Douglas functional form, simple derivations show that the extent of economic growth can be split into three categories, labour, capital and technological progress. The amount of productive labour increases through an increase in population, the amount of capital increases through investment and technological progress occurs through investment in R&D. The amount of productive labour and capital can be 'easily' measured but the increase in technology is hard to measure. Firms conduct R&D, they invest money to increase their productive capacity and to develop new products or new ways of producing. The outcome of this process however is hard to measure. One way to proxy the outcome of the R&D process is to count the number of patents the firm has generated. Numerous studies have been conducted to quantify the relationship between the inputs of the R&D process and the outcome of the process as indicated by the number of patents. However, even at a first glance, there are several problems with the use of patents as an indicator of output. 'Not all inventions are patentable, not all patents are patented and the inventions that are patented differs greatly in quality', Griliches (1990). Pakes and Griliches (1984) show that there is quite a strong relationship between R&D and the number of patents granted, at a cross-sectional level. About 90% of the variance in the number of patents can be explained by changes in R&D spending. If one uses time-series data only 30% of this variance can be explained by changes in spending, but the relationship between changes in R&D spending and generated patents is still quite remarkable.

Different uses of patents as indicators of technological progress range from 'simple' patent counts (Johnson *et al.* (1995)) to the use of 'specific' input-output techniques to mea-

sure the interaction between sectors in the innovative process. Evenson and Englander (1995), for example, employ a model for economic growth and convergence, using data on patents at the industry level. The number of patents generated is used as a proxy for the *outcome* of the R&D process. The empirical fit is reasonably well. This method contrasts with the 'standard' case in research on economic growth (see e.g. Barro and Sala-i-Martin (1995), chs. 6 and 7), in which the *inputs* in the R&D process are used to quantify the technological progress. It might seem strange to use the inputs in a process as a proxy for the output but, as Griliches (1994) points out, there are numerous problems in using patents or innovations as proxies for technological progress. Data on patents and innovations are not always available and there are some doubts about the relation between patents and inventions. During the period from 1965 to 1985 the number of domestic patent applications declined in the US while the R&D expenditures by companies rose. Griliches points to several possible solutions as diminishing returns to investment or too little capacity at the Patent Office. This study on the other hand supposes that the data on patents and innovations can be handled as if they represent a transactions table. The empirical results may indicate which sectors are of most importance for the innovation process. The analysis can indicate the extent to which interaction takes place between sectors. Verspagen (1995) uses patent statistics to measure the so-called *knowledge spillovers* of technological spillovers. He develops a model to estimate the relationship between (direct and indirect) R&D and productivity growth. Patent data are used as a proxy of R&D.

The purpose of this paper is to examine whether the techniques that are applied to input-output tables can also be used for the typical analysis of the specific data on patents and innovations. The data used in this study are on patents or innovations generated in a sector and used in other sectors. If input-output techniques can be applied to the data on patents and innovations, it is possible to pinpoint the sectors that are the most important for innovative activities and which sectors generate the most patents due to the interaction with other sectors. Since data are scarce only one OECD country is empirically investigated, Canada.

The rest of the paper is organized as follows. In the second section some attention is given to the data that are available. The third section discusses the basics of input-output

analysis. The fourth section indicates the way input-output analysis can be applied to the patent and innovation data. In the fifth section the data are analyzed, using the concepts that were derived in the third and in the fourth section. In the last section some conclusions are drawn.

2 The Data: an Outline

The data which are used in this study are taken from Johnson *et. al.* (1995). In Johnson *et. al.* (1995) several data sets are analyzed. Of these data sets two are used in this study. One covers the number of innovations in Canada in the period from 1945 to 1978 and one covers the number of Canadian patents issued in Canada in the period from 1978 to 1981. This last data set covers only about six percent of all patents generated in that period, more specifically only the patents that were patented by Canadians. The rest of the patents were patented by foreigners, fifty-eight percent of the patents were issued to American inventors.

The matrices are non-square. The supplier industries make up the rows and are labelled *industry of manufacturing* (IOM). The user industries make up the columns and are labelled *sector of use* (SOU). The elements (i,j) in the matrices are the number of patents generated in sector i and used in sector j or the number of innovative activities generated in industry i and used in industry j . If we denote the matrices by Q , the element q_{ij} thus represents the number of patents or innovations that are generated in sector i and used in sector j . Some remarks on the classification of the patents and innovations in the IOM's and the SOU's are made in Putnam and Evenson (1994) and in Johnson *et. al.* (1995).

Verspagen (1995) points out two potential problems if one uses these data sets to measure technological spillovers. These problems arise because the data sets only indicate the flow from producing to using sectors. One potential problem is that because the matrices strictly focus on producer-user relations, spillover relations that are based on technological spillovers (the so called knowledge-spillovers) are overlooked. A second possible problem is that there will be rent-spillovers as well as knowledge-spillovers because the economic transaction related to the patent grant is measured. Nevertheless we use these matrices because they are readily available.

Table 1: Input-output table.

sector						final	
	1	...	j	...	n	demand	total
1	z_{11}	...	z_{1j}	...	z_{1n}	f_1	x_1
\vdots	\vdots	\ddots	\vdots	\ddots	\vdots	\vdots	\vdots
i	z_{i1}	...	z_{ij}	...	\vdots	f_i	x_i
\vdots	\vdots	\ddots	\vdots	\ddots	\vdots	\vdots	\vdots
n	z_{n1}	...	z_{nj}	...	z_{nn}	f_n	x_n
value added	v_1	...	v_j	...	v_n		
total	x_1	...	x_j	...	x_n		

3 Intersectoral Dependencies

This section discusses measures for intersectoral dependencies (or linkages) within the standard input-output framework. These are applied in the next section to input-output tables of patents and innovations. The input-output table in money terms is given in Table 1.

Z denotes the $n \times n$ matrix of intermediate transactions, its typical element z_{ij} gives the delivery from sector i to sector j . f denotes the $n \times 1$ vector of final demands, covering private and government consumption and investments, and (net) exports. v' is the $1 \times n$ vector of values added, covering payments for labour and capital, indirect taxes minus subsidies, and profits. By construction, the i th column sum equals the i th row sum and gives the total output x_i . Hence we have the following identities for the row and column sums, respectively.

$$x = Ze + f, \tag{1}$$

$$x' = e'Z + v', \tag{2}$$

where e denotes the $n \times 1$ summation vector, consisting of ones.

The analysis of sectoral interdependencies starts from the intermediate deliveries, adopting two alternative viewpoints (see Augustinovic, 1970). For the buyer's dependence, the relevant question is "Where do the inputs come from?" This question is directed backwards and considers the columns of the matrix Z . The seller's dependence is reflected by the question "Where do the outputs go to?". The direction is forward looking and analyzes the intermediate deliveries rowwise. Normalization of the intermediate deliveries according to the two viewpoints yields the coefficient matrices. Normalization of the columns gives the input matrix,¹

$$A = Z\hat{x}^{-1}. \quad (3)$$

The typical element $a_{ij} = z_{ij}/x_j$ denotes the fraction of the total inputs (i.e. x_j) that is bought from sector i . The input coefficient describes the (additional) input from sector i required per (additional) unit of product j . Normalization of the rows gives the output matrix,

$$B = \hat{x}^{-1}Z. \quad (4)$$

Its typical element $b_{ij} = z_{ij}/x_i$ denotes the fraction of the output (i.e. x_i) that is sold to sector j . The output coefficient describes the (additional) output to sector j per (additional) unit of product i .

The simplest backward linkages are the direct linkages. They are measured as the column sums of the input matrix A . The direct backward linkage of sector j is given by

$$DBL_j = \sum_i a_{ij}. \quad (5)$$

It is interpreted as the additional amount of inputs (taken over all sectors) required directly for an additional unit of output in sector j and reflects the direct dependence of sector j on intermediate inputs.

The total (or direct plus indirect) backward linkages are obtained as the column sums of the Leontief inverse $L = (I - A)^{-1}$, which are also known as the output multipliers. That is for sector j as

$$\sum_i l_{ij}. \quad (6)$$

¹A hat, for example in \hat{x} , is used to denote the diagonal matrix with elements x_i on its main diagonal and all other entries equal to zero.

Using equation (3), equation (1) can be written as $x = Ax + f$. When f is specified exogenously the solution to this (demand-driven) input-output model yields $x = (I - A)^{-1}f = Lf$. The interpretation of (6) then is the additional output, in all sectors together, required directly or indirectly for an additional unit of final demand in sector j . Using the power series expansion of the Leontief inverse, i.e. $L = I + A + A^2 + A^3 + \dots$, the production required for satisfying Δf can be separated into three parts. First the initial effect Δf , second the direct effect $A(\Delta f)$, and third all indirect effects $(A^2 + A^3 + \dots)(\Delta f)$.

For the application to invention input-output tables, the total backward linkages seem to be less appropriate as will be indicated in the next section. An alternative is to consider how much additional production is required if sector j decides to increase its own production by one unit. Directly, this sector then needs additional inputs from any sector (including itself). These additional inputs have to be produced, which induces the indirect effects in the second and higher rounds. Denote the initial increase of production in sector j by e_j .² The additional inputs required directly are given by Ae_j and all indirect requirements amount to $(A^2 + A^3 + \dots)(e_j)$. The total output increase induced by an initial output increase in sector j of one unit thus yields $(A + A^2 + A^3 + \dots)(e_j) = (L - I)e_j$. That is, sector i ($i \neq j$) increases its output by l_{ij} and sector j (further) increases its output by $l_{jj} - 1$. The total output increase in all sectors induced by an initial increase of one unit in sector j is given as

$$TBL_j = \sum_i l_{ij} - 1. \quad (7)$$

Since we shall not use the linkages in (6), we shall term those in (7) as total backward linkages. Given the exogenous change of the output in sector j as a starting-point, (7) can also be interpreted as an output-to-output multiplier.³

The forward linkages take the output coefficients matrix B as their starting point. The direct forward linkages are given by the row sums,

$$DFL_i = \sum_j b_{ij}. \quad (8)$$

² e_j is the j th unit vector, i.e. $(0, \dots, 0, 1, 0, \dots, 0)'$.

³This multiplier is related to the output-to-output multiplier defined in Miller and Blair (1985, p. 328). The difference is that the total output increase in sector j (i.e. the induced increase $l_{jj} - 1$ plus the initial increase) is set at one in their approach. The output increase for sector i then amounts to l_{ij}/l_{jj} .

DFL_i denotes the intermediate deliveries per unit of output. The total forward linkages are obtained again by taking also the indirect effects into account, using $G = (I - B)^{-1} = (I + B + B^2 + B^3 + \dots)$. Equations (2) and (4) yield

$$x' = x'B + v'. \quad (9)$$

When the vector v' is given exogenously, the outputs may be determined endogenously as

$$x' = v'(I - B)^{-1} = v'G. \quad (10)$$

The model in (9) is known as the supply-driven input-output model, originating from Ghosh (1958). The inverse matrix G is termed the Ghosh inverse. The total forward linkages are, similar to (6), given by the row sums of G ,

$$\sum_j g_{ij}. \quad (11)$$

The typical interpretation of (11) stems from (10), and is as follows. $\sum_j g_{ij}$ gives the (additional) output, taken over all sectors, due to an (additional) unit of value added in sector i . The supply-driven input-output has been hotly debated. A major point of critique was put forward in Oosterhaven (1988, 1989). Suppose for simplicity that v' consists of labour inputs only. Exogenously specifying $\Delta v_j = 1$ and $\Delta v_i = 0$ ($\forall i \neq j$) results in an increase of the output in each sector. Thus the output in any sector i ($\neq j$) is increased using the same amount of labour. Gruver (1989) even shows that in the production process no input is essential, in the sense that each input can be substituted for any other input. The plausibility of the interpretation of the supply-driven input-output model in terms of quantities thus becomes very questionable.⁴ It should be emphasized that the output coefficients themselves are not implausible. In the next section, it will be indicated that the Oosterhaven critique does not apply to the supply-driven analysis of patents and innovations.

⁴Recently, Dietzenbacher (1997) has shown that the implausibility of the supply-driven model vanishes once it is interpreted as a price model. In that case, the supply driven model is equivalent to the standard Leontief price model. The interpretation is that g_{ij} describes the change in the output *value* of sector j , induces by a one dollar increase in the value added of sector i . Since quantities are assumed fixed, all changes in the output *values* are caused by price changes.

The measure for the total forward linkages differs from (11) and is, similar to (7), given as

$$TFL_i = \sum_j g_{ij} - 1. \quad (12)$$

This expression gives the output increase in all sectors, induced by an initial output increase in sector i .

4 Invention Input-Output Analysis

This section discusses the possibilities for applying standard input-output analysis to tables with patent and innovations data. The use of invention input-output coefficients was introduced in Evenson and Johnson (1997). Their analysis, however, focussed on the descriptive nature of these coefficients. Here we go one step further and incorporate also other elements of input-output analysis. Our main purpose is to find appropriate measures of the contribution of a particular sector to the innovation process.

The central idea is that knowledge spills over from one sector to another. An invention in sector i that is used in sector j , may trigger off or be beneficial to research in sector j . The research activities are thus advanced and yield new inventions in sector j . In their turn, sector j 's inventions affect the inventions in, say, sector k . Hence, sector i indirectly influences the inventive activities in sector k . To measure the extent and the effects of these direct and total spillovers, we use the invention output coefficients b_{ij} , defined as the percentage of sector i 's inventions that are used in sector j . The direction of reasoning is forward, answering the question "Where do inventions go to?"

In the same fashion, invention input coefficients are defined. In this case, the underlying idea is that inventive research in sector j often defines part of the research agenda in sector i . Inventions in sector j build forth on and thus require preceding inventions in sector i . The invention input coefficients a_{ij} measure how many inventions of sector i have been used for generating the inventions in sector j . The coefficients are scaled to measure the average use per invention in sector j .

Before we discuss the linkage measures, two difficulties that occur for invention input-output analysis should be mentioned. First, the input (or the output) coefficients are typically assumed to be constant. This assumption is unlikely to hold over time and is rather restrictive when a simulation experiment or an impact study is to be carried out, or when forecasts are to be made. It should be borne in mind, however, that it is our aim to measure intersectoral inventive dependencies for a given data set. For that purpose, we ask ourselves what the effect is of some small change if the coefficients had been the same.

Second, the patent and innovation data do not match the format of the input-output table (Table 1) exactly. Both the ‘final demand’ vector f and the ‘value added’ vector v are lacking. The invention input-output table that we use in our empirical analysis records ‘intermediate deliveries’ amongst 25 (basically manufacturing) industries. Next to this, it also gives the use of inventions by another 8 (essentially service) industries, which do not generate inventions themselves. In standard input-output analysis, the main reason for sectoral production is to satisfy final demand. According to the format of the invention input-output table we could, of course, define the deliveries to the service industries as the ‘final demand’ block. That would imply, however, that the ‘demand’ for inventions by the service industries (whatever this means) would drive the entire model. The total backward linkages as in (6) would then be interpreted as the total number of inventions required for the use of one invention in any of the service industries. We are very reluctant to adopt such an interpretation of the ‘final demand’ block.⁵ Therefore we use the total linkage measure as in (7) which is not based on final demand vectors. The lack of a value added vector can be overcome with more ease. The vector v' denotes the creative surplus, defined as the difference between the number of inventions generated and used, for each sector.

The direct backward linkages DBL_j in (5) denote the ratio between the use of inventions and the generation of inventions in sector j . They measure how much inventions are used on average per invention in industry j . If DBL_j is smaller (larger) than one, this industry generates more (less) inventions than it uses and the creative surplus is positive (negative). The direct backward linkages also reflect the incoming technological spillovers (also spill-

⁵In addition, it turns out that the ‘final demand’ equals zero for some industries.

ins) of industry j .

The total backward linkages TBL_j in (7) indicate the average number of (additional) inventions that would be triggered off by one (additional) invention in industry j . In terms of incoming spillovers, a_{ij} reflects the direct spill-ins from i . Indirect spill-ins from industry i are given by $\sum_k a_{ik}a_{kj}$, since the direct spill-in a_{kj} embodies spill-ins from i (to the amount of a_{ik}). Higher order terms yield $\sum_h \sum_k a_{ih}a_{hk}a_{kj}$ and so forth. All direct and indirect spill-ins of industry j are captured by the elements of column j of the matrix $(L - I)$.

The row sums of the output matrix B give the direct forward linkages. They measure the fraction of industry i 's inventions that is used by industries that generate inventions. DFL_i reflects the direct outgoing technological spillovers (or spill-outs) from industry i to industries which take part in the invention process.

Taking also the indirect outgoing spillovers into consideration yields that the spill-out of industry i to industry j is given by element (i, j) of $G - I$. The direct spill-out from i to j is given by b_{ij} , the indirect spill-outs from i to j via one other industry k are given by $\sum_k b_{ik}b_{kj}$, and so forth. The total forward linkages are thus obtained by the row sums of $G - I$. An alternative interpretation of G and $G - I$ stems from the supply-driven input-output model. Then, g_{ij} measures the average (additional) number of inventions generated in industry j , due to one (additional) unit of creative surplus in industry i . The implausibility of the supply-driven model in the standard input-output context, viz. that this cannot be achieved without any additional creative surplus in industry j , does not hold in the invention input-output context. An additional creative surplus in industry i initially leads to an additional invention in this industry. The total forward linkages TFL_i then indicate how many further inventions are induced by this.

5 An Application to the Yale Technology Concordance

The linkage measures have been calculated for the Yale Technology Concordance, covering data for innovations (1945-78) and patents (1978-81), both in Canada. Table 2 reports the direct linkages, both backward and forward, as obtained from equations (5) and (8). The direct backward linkages denote the ratio between the innovations (or patents) used and

Table 2: Direct linkages between sectors.

sector	innovations				patents			
	<i>DBL</i>	rank	<i>DFL</i>	rank	<i>DBL</i>	rank	<i>DFL</i>	rank
1	9.29		1.00					
2	0.95		0.95					
3	2.61	(1)	0.93	(2)	70.50	(1)	0.50	(16)
4	0.50	(10)	0.32	(19)	0.79	(16)	0.66	(11)
5	0.14	(18)	0.29	(20)	0.72	(17)	0.81	(6)
6	0.40	(13)	0.77	(5)	0.53	(19)	0.87	(3)
7	0.14	(18)	0.13	(23)	2.55	(4)	0.12	(23)
8	0.44	(12)	0.76	(6)	2.33	(5)	0.83	(4)
9	0.60	(9)	0.56	(12)	1.44	(9)	0.94	(1)
10	1.17	(6)	0.82	(4)	1.12	(12)	0.88	(2)
11	0.61	(8)	0.39	(17)	0.87	(15)	0.45	(18)
12	0.24	(15)	0.25	(22)	1.10	(13)	0.74	(8)
13	0.96	(7)	0.72	(9)	1.73	(7)	0.53	(14)
14	1.73	(3)	0.98	(1)	2.61	(3)	0.78	(7)
15	0.35	(14)	0.54	(13)	0.27	(22)	0.33	(21)
16	0.07	(22)	0.28	(21)	0.38	(20)	0.61	(13)
17	0.14	(18)	0.45	(15)	1.02	(14)	0.83	(4)
18	0.12	(21)	0.75	(7)	0.24	(23)	0.65	(12)
19	2.50	(2)	0.69	(10)	4.63	(2)	0.67	(10)
20	0.46	(11)	0.74	(8)	2.28	(6)	0.70	(9)
21	0.23	(17)	0.52	(14)	0.55	(18)	0.46	(17)
22	0.24	(15)	0.42	(16)	1.25	(10)	0.44	(19)
23	1.50	(5)	0.86	(3)	1.67	(8)	0.53	(14)
24	1.69	(4)	0.66	(11)	1.24	(11)	0.41	(20)
25	0.01	(23)	0.33	(18)	0.28	(21)	0.21	(22)

generated. A ratio smaller than one indicates that more inventions are generated than used in this industry. For the 25 industries in the innovation data set, three sectors have a ratio larger than 2, nine industries have a ratio between 0.5 and 2, and the remaining 13 industries all have a ratio smaller than 0.5. About 50% of the industries generate more than twice as much innovations than they use. For the 23 industries in the patent case we find that six industries have a ratio larger than 2, 13 have a ratio between 0.5 and 2, and only four industries have a ratio smaller than 0.5. The patent data clearly indicate a much smaller creative surplus than the innovation data. Observe also that for almost all industries the direct backward linkages are larger for the patent than for the innovation data.

The direct forward linkages cannot be larger than one, by definition. For the innovation data we find that for nine out of 25 industries more than 50% of its innovations are used by non-inventing industries, implying relatively small (direct) spillovers within the innovating process. For the patent data, this holds for seven out of 23 industries.

For the purpose of interpreting the direct linkage measures in terms of incoming or outgoing technology spillovers, it should be noted that the results in Table 2 are somewhat misleading. For example, DBL_j measures how much additional inventions would be used for an additional invention in industry j . The numbers of innovations range from 28 (ships) to 724 (machines), and from 2 (mining) to 1359 (machines) in the case of patents. Therefore it is unlikely that the probability of an additional innovation manufactured in “ships” is equal to that in “machines”. In contrast to assuming an additional invention in an industry, we assume that innovation activities can be stimulated and result in a 1% increase of the current number of inventions.⁶ The weighted direct backward linkages ($DBLW_j$) are equal to the number of inventions (divided by 100) used by industry j , and the direct forward linkages ($DFLW_i$) equal the number of industry i 's inventions (divided by 100) as used by all inventing industries. That is,

$$DBLW_j = 0.01 \sum_i a_{ij} x_j \quad \text{and} \quad DFLW_i = 0.01 \sum_j b_{ij} x_i.$$

⁶A more appropriate weight would be obtained by taking industrial R&D expenditures into account. If x_i denotes the number of inventions and c_i the R&D expenditures in industry i , the ratio x_i/c_i reflects the number of inventions per dollar. Taking a billion dollar increase in the R&D budget of an industry as the starting-point would imply that the ratios x_i/c_i were to be used as weights. Lack of data, however, prevents us from doing so.

The total (backward and forward) linkages are weighted in the same way,

$$TBLW_j = 0.01 \sum_i l_{ij} x_j \quad \text{and} \quad TFLW_i = 0.01 \sum_j g_{ij} x_i.$$

The weighted linkages are reported in Table 3 for the innovation data and in Table 4 for the patent data. The most striking result in these tables is the large difference between the direct and the total linkages. Note that this outcome does not depend the weighting scheme that is used, any other set of weights would yield exactly the same ratios $TBLW_j/DBLW_j$ and $TFLW_j/DFLW_j$. In Table 3, for example, the average ratio between the total and the direct backward linkages is four. The total forward linkages turn out to even five times as large as the direct forward linkages, on average. For an assessment of the full effects of an increase in the number of inventions it is therefore important to take the indirect effects into account as well. These are on average three (four) times the size of the direct effects for the backward (forward) linkages.

The differences between the rankings of the industries are fairly small. In Table 3, the ranking of $DBLW_j$ and $TBLW_j$ differ by six or more places in only one case (industry 8, petroleum). Also for the forward linkages such a large difference between the direct and total rankings is observed only once (industry 9, aircraft). For “petroleum” the large difference can be explained from the fact that it largely depends on innovations from “mining” (industry 3). In its turn, “mining” has very strong backward linkages which thus upgrades the backward linkages of “petroleum”. The difference between the rankings of the direct and total forward linkages for “aircraft” is induced by the fact that this industry’s innovations are used almost exclusively by itself or by non-innovating industries.

The differences between the rankings for the direct and the total linkages are somewhat larger for the patent data. We find a difference in ranking of six or more places for four industries (6, 9, 12, 17) in case of backward linkages and in one industry (9, aircraft) in the case of forward linkages. It turns out that the diagonal element of the input matrix (and thus also of the output matrix) is extraordinarily large (0.94).

Key sectors have been defined as sectors that have forward as well as backward linkages that are above average. The underlying idea was that a stimulus in these industries with strong linkages could initiate a further development due to the interactions (both forward

Table 3: Weighted linkages between sectors, innovations data.

sector	innovations							
	DBL_w .	rank	TBL_w .	rank	DFL_w .	rank	TFL_w .	rank
1	2.88	(4)	25.66	(2)	0.31	(23)	1.92	(21)
2	2.10	(5)	10.14	(6)	2.11	(3)	14.24	(3)
3	3.42	(2)	23.12	(3)	1.21	(9)	9.09	(5)
4	0.86	(12)	1.40	(17)	0.56	(19)	2.07	(20)
5	0.41	(17)	0.53	(22)	0.84	(14)	3.62	(16)
6	2.10	(5)	6.34	(8)	4.05	(2)	20.90	(2)
7	0.34	(19)	1.62	(15)	0.31	(22)	0.60	(24)
8	0.22	(23)	2.18	(13)	0.38	(21)	2.86	(19)
9	1.92	(7)	4.67	(9)	1.79	(5)	4.31	(13)
10	0.91	(11)	3.81	(10)	0.64	(18)	3.00	(18)
11	0.17	(24)	0.31	(24)	0.11	(25)	0.53	(25)
12	0.24	(22)	0.73	(20)	0.26	(24)	1.19	(23)
13	1.05	(10)	3.72	(11)	0.79	(16)	3.78	(15)
14	1.49	(9)	10.11	(7)	0.84	(14)	5.61	(10)
15	0.57	(15)	1.70	(14)	0.87	(13)	5.15	(11)
16	0.28	(20)	1.17	(18)	1.11	(11)	7.00	(7)
17	0.36	(18)	0.44	(23)	1.15	(10)	4.27	(14)
18	0.85	(13)	2.30	(12)	5.43	(1)	29.32	(1)
19	4.78	(1)	30.07	(1)	1.32	(7)	5.68	(9)
20	0.82	(14)	1.62	(15)	1.32	(7)	6.03	(8)
21	0.47	(16)	1.02	(19)	1.07	(12)	5.08	(12)
22	0.26	(81)	0.59	(21)	0.46	(20)	1.81	(22)
23	2.93	(3)	15.59	(4)	1.67	(6)	8.92	(6)
24	1.71	(8)	12.38	(5)	0.67	(17)	3.21	(17)
25	0.07	(25)	0.12	(25)	1.94	(4)	11.14	(4)

Table 4: Weighted linkages between sectors, patents data.

sector	patents							
	DBL_w .	rank	TBL_w .	rank	DFL_w .	rank	TFL_w .	rank
1								
2								
3	1.41	(7)	4.49	(7)	0.01	(23)	0.02	(23)
4	2.42	(3)	7.44	(3)	2.04	(4)	6.98	(4)
5	3.16	(2)	9.96	(2)	3.53	(2)	14.85	(2)
6	1.49	(6)	2.70	(12)	2.43	(3)	5.70	(6)
7	0.84	(13)	1.84	(16)	0.04	(22)	0.46	(18)
8	0.14	(23)	0.47	(23)	0.05	(21)	0.16	(22)
9	0.26	(22)	6.38	(5)	0.17	(17)	3.06	(8)
10	1.98	(4)	18.85	(1)	1.55	(7)	12.15	(3)
11	0.27	(21)	0.77	(22)	0.14	(19)	0.26	(21)
12	0.43	(20)	2.73	(11)	0.29	(12)	1.13	(11)
13	0.52	(17)	0.99	(20)	0.16	(18)	0.34	(20)
14	0.47	(18)	1.08	(19)	0.14	(20)	0.41	(19)
15	1.60	(5)	2.80	(10)	1.93	(5)	5.12	(7)
16	1.13	(9)	2.65	(13)	1.79	(6)	6.39	(5)
17	0.61	(15)	2.93	(8)	0.50	(9)	2.26	(9)
18	3.25	(1)	5.38	(6)	8.78	(1)	23.43	(1)
19	1.25	(8)	6.66	(4)	0.18	(16)	0.54	(16)
20	0.91	(11)	2.83	(9)	0.28	(14)	0.89	(12)
21	0.79	(14)	1.28	(18)	0.66	(8)	2.04	(10)
22	0.60	(16)	1.31	(17)	0.21	(15)	0.50	(17)
23	0.95	(10)	2.00	(14)	0.30	(11)	0.77	(13)
24	0.88	(12)	1.88	(15)	0.29	(13)	0.58	(15)
25	0.44	(19)	0.89	(21)	0.33	(10)	0.68	(14)

Table 5: Key sectors.

Innovations		
	FW > 6.45	FW ≤ 6.45
BW > 6.45	key sectors: 2, 3, 23	1, 14, 19, 24
BW ≤ 6.45	6, 16, 18, 25	4, 5, 7, 8, 9, 10, 11, 12, 13, 15, 17, 20, 21, 22
Patents		
	FW > 3.85	FW ≤ 3.85
BW > 3.85	key sectors: 4, 5, 10, 18	3, 9, 19
BW ≤ 3.85	6, 15, 16	7, 8, 11, 12, 13, 14, 17, 20, 21, 22, 23, 24, 25

and backward) with other industries. An advantage of using the weighted linkage measures $TBLW_j$ and $TFLW_i$ that the linkages have the same average. For the innovation data the average total linkage is 6.45, for the patent data it is much smaller, 3.85. The industries can thus be classified into four categories, depending on whether the total linkages are below or above average. The results are given in Table 5.

For the innovation data, we find three key sectors (forestry, mining, and paper & printing), eight industries with either the forward or the backward linkages above average, and 14 industries in which both linkages are below average. For the patent data the numbers are four (electrical machines, electrical equipment, motor vehicles, and other machines), six, and 13, respectively. If research in some industry is stimulated so as to yield, for example, a 1% increase in the number of its inventions, this induces the largest (or at least above average) effects when the stimulus takes place in a key sector. This holds irrespective of the viewpoint one adopts with respect to the propagation of the effects, i.e. using the backward or the forward type of reasoning.

A point that requires further attention is the weak correlation between the results for the two data sets (see also Johnson and Evenson, 1997). Note, for example, that three of the four

key sectors for the patent data are reported as industries weak linkages (both forward and backward) for the innovation data. Although the simple column sums of A and the simple row sums of B show some resemblance, the patterns within the matrices do not. The spread in the matrix of patents is much larger than in the matrix of innovations. Since we measure the interactions between industries, this leads to quite different results.

6 Concluding Remarks

We can conclude that input-output techniques can be applied to the available data on innovations and patents. The empirical investigation can show what sectors are of most importance in the sense that they generate the highest number of innovations or patents in reaction to an increase in demand. The most important sectors in the economy appear to be, as far as innovations are concerned: forestry, mining, and paper & printing, and, as far as patents are concerned: electrical machines, electrical equipment, motor vehicles, and other machines. These sectors are not the ones that generate the highest numbers of innovations or patents.

By applying input-output techniques to the patents and innovations data, we are able to obtain more information about sectors, more specifically we can show the magnitude of the interaction that takes place between sectors due to exogenous changes. This information is much more useful than the use of the number of patents or innovations a sector uses or generates as an indicator of the importance of a sector.

References

- AUGUSTINOVICS, MARIA (1970): "Methods of International and Intertemporal Comparison of Structure," in *Contributions to Input-Output Analysis*, ed. by Anne P. Carter, and András Bródy, pp. 249–269. North-Holland, Amsterdam.
- BARRO, ROBERT J., AND XAVIER SALA-I-MARTIN (1995): *Economic Growth*. Mc-Graw-Hill, New York.
- DIETZENBACHER, ERIK (1997): "In Vindication of the Ghosh Model: A Reinterpretation As a Price Model," *Journal of Regional Science*, 37(4), 629–651.
- EVENSON, R. E., AND A. S. ENGLANDER (1995): "International Growth Linkages Between OECD Countries," mimeo.
- EVENSON, ROBERT E., AND DANIEL JOHNSON (1997): "Introduction: Invention Input-Output Analysis," *Economic Systems Research*, 9, 149–160.
- GHOSH, AMBICA (1958): "Input-Output Approach in an Allocation System," *Economica*, 25, 58–64.
- GRILICHES, ZVI (1990): "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature*, 28(4), 1661–1707.
- (1994): "Productivity, R&D and the Data Constraint," *American Economic Review*, 84(1), 1–23.
- GRUVER, GENE W. (1989): "On the Plausibility of the Supply-Driven Input-Output Model," *Journal of Regional Science*, 29, 441–450.
- JOHNSON, DANIEL, AND ROBERT E. EVENSON (1997): "Innovation and Invention in Canada," *Economic Systems Research*, 9, 177–192.
- JOHNSON, DANIEL, ROBERT E. EVENSON, AND CHRIS DEBRESSON (1995): "Innovation and Invention in Canada," mimeo.

- MILLER, RONALD E., AND PETER D. BLAIR (1985): *Input-Output Analysis: Foundations and Extensions*. Prentice-Hall, Englewood Cliffs, NJ.
- OOSTERHAVEN, JAN (1988): "On the Plausibility of the Supply-Driven Input-Output Model," *Journal of Regional Science*, 28, 203–217.
- (1989): "The Supply-Driven Input-Output Model: A New Interpretation but Still Implausible," *Journal of Regional Science*, 29, 459–465.
- PAKES, ARIEL, AND ZVI GRILICHES (1984): "Patents and R&D at the Firm Level: A First Look," in *R&D, Patents and Productivity*, ed. by Zvi Griliches, pp. 55–72. University of Chicago Press, Chicago.
- PUTNAM, JONATHAN, AND ROBERT E. EVENSON (1994): "Inter-Sectoral Technology Flows: Estimates from a Patent Concordance With an Application to Italy," mimeo.
- VERSPAGEN, BART (1995): "Measuring Inter-Sectoral Technology Spillovers: Estimates from the European and US Patent Office Databases," Research Memorandum, 2/95-007, MERIT, Maastricht.