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Inter-Industry Technological Spillovers and the Rate of Return on R&D

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An Empirical Evaluation for Japanese, American, and British Manufacturing Industries

ABSTRACT

This paper provides an homogeneous comparison of the impact of inter-industry technological spillovers on productivity growth in Japan, the USA, and the UK. The three main results may be summarized as follows. (i) The input-output matrix is not a good proxy for the technological flows matrix; the latter weighting matrix leads to substantially higher estimates of social rates of return on R&D. (ii) Among the three countries under consideration, Japan benefits from the highest private and social rates of return on R&D. (iii) The lower private rates of return on R&D in the US and the UK are likely to be counterbalanced by relatively stronger inter-industry R&D spillovers effects. However, it is not sufficient for an equalization of the social rates of return among the three countries.

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by

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1. INTRODUCTION

The importance of sectoral specificities in the process of innovation and of technological diffusion is increasingly recognized as a prime component of technological competitiveness. The impact of R&D investment performed in a particular industry goes well beyond the improvement of its own productivity. Indeed, such investments, through the existence of inter-industry technological spillovers, are also profitable to other industries. So far, relatively few empirical studies have measured the amplitude of these spillovers. Evaluations have been performed mainly for US and Canadian industries and, to a lesser extent, for Japanese and English ones. Besides, as the materialization of technology transfer from one industry to the other may adopt different forms, authors have relied on different methodologies and data sources. *De facto*, these existing estimates of technological spillovers are hardly comparable, either across countries or, for a given country, across studies. The main objective of this paper is to evaluate empirically the magnitude of inter-industry spillovers and to provide a homogeneous comparison of these effects across Japan, the US, and the UK. From governments' viewpoint, international differences in the rate of inter-industry technological spillovers should yield useful information about the efficiency of industrial and technology policies and, more particularly, on policies implemented towards the improvement of R&D efforts in spillovers generating sectors.

The paper is organized as follows. As a first step we recapitulate and comment on the empirical methodologies already adopted to measure inter-industry technological flows. Four techniques are identified. The appraisal of advantages and drawbacks underlying each of these four techniques, as well as a feasibility exploration, lead to put in practice the techniques which make use of the input-output and the technological flows matrices. As the two analytical approaches are identical, we then analyse to what extent both kinds of matrices are similar. Since the computation of the technological flows matrix is labor and time consuming, it is of prime interest to assess whether or not it can be proxied by the input-output matrix. The comparison exercise uses both proximity indexes and correlation coefficients as regard to the distribution of each industry's output across other industries.

The second step is to present the database and to perform the econometric evaluation of the output elasticities of inter-industry R&D spillovers over the period 1978-90 in the three countries. The industrial breakdown is composed of 22 industries. From a classical Cobb Douglas production function, the evolution of total factor productivity is regressed on R&D capital stocks. The R&D variables are either the total R&D capital stock, or the R&D spillover capital stock. The R&D spillovers capital stock in Japan, the US and the UK, are computed from Scherer's technological flows matrix and from the respective national input-output matrices. Several hypotheses concerning the depreciation rate and the lag between R&D capital stocks and the induced productivity growth, are tested.

2. MEASUREMENT TECHNIQUES IN REGRESSION STUDIES

General surveys of the literature specialized in the assessment of the role of R&D investments in growth accounting, i.e. Capron (1992) and Mairesse and Mohnen (1995), highlight that R&D activities are a substantial source of productivity gains. However, large discrepancies are observed across studies as regards to the amplitude of the estimated rates of return on R&D. These divergences arise mostly from the diversity of estimation methods and data sources. Concerning the relatively few studies which deal with the evaluation of inter-industry R&D spillovers, disparities are wider.

Griliches (1979) identifies two main sources of externalities: rent spillovers and knowledge spillovers. Rent spillovers, formaly modeled by Griliches and Lichtenberg (1984) reflect the fact that prices do not embody completely product innovations or quality improvement resulting from R&D activities. This leads to a mismeasurement of higher quality intermediate inputs. Therefore, the analysis of output growth of a particular industry has to take into account the technological improvement of all the supplying industries. Knowledge spillovers, as initially defined by Arrow, arise because of the imperfect appropriability associated to innovation. It is characterized by both intra- and inter-industry diffusion of technology. Incorporating rent and knowledge spillovers allows to make the distinction between private and social rates of return on R&D. The private rate of return is linked to the profitability of an industry's total R&D activities while the social rate of return takes into account both the private rate of return and the benefits ensuing from other industries R&D investments. The surveys by Torre (1989), Debresson (1990), Mohnen (1990, 1994), and Griliches (1992) deal exclusively with the R&D spillovers literature. Two ultimate conclusions sort out of these surveys. First, inter-industry spillovers contribute significantly to productivity growth. This contribution is substantial and most probably greater than the contribution of intra-industry spillovers. Second, applied economists are still confronted with substantial problems about the evaluation of inter-industry technological flows, as regards to both the analytical concept and the data measurement.

In order to grasp these inter-industry technological diffusion effects, a variable of R&D spillover (S), the pool of outside knowledge, has to be measured. The easiest way is to consider that the aggregate level of knowledge capital is simply the sum of all industry-specific R&D capital. The main criticism of this approach is that it gives the same weight to R&D stocks in all industries. This chapter summarizes the existing methodologies which have been used to construct the S variable. Each methodology is characterized by a concept of technological link between industries. The first one relies on input-output tables and has been originally experienced by Terleckyj (1974). The second technique, firstly implemented by Scherer (1982), is derived from Smookler (1966)'s idea of a technological flows matrix. The third procedure is based on Jaffe (1986)'s technological proximity concept and the fourth is characterized by a cost of adjustment function which allows an estimation of technological spillovers between pairs of industries. Aiming at limiting the unavoidable overlaps with the above-mentioned surveys, the focus is essentially put on econometric studies at the industry level. Table 1 presents the literature on inter-industry technological spillover classified along five criteria, according to the methodology used for the evaluation of the spillover variables. The characteristics, advantages and drawbacks of these techniques are summarized in table 2. Since our interest lies in the estimation of inter-industry spillovers in the whole industrial system, studies about particular sectors are not included in this analysis[1].

[1] Other studies surveyed by Griliches (1992) and Mohnen (1990) concentrate on particular sectors (such as agriculture and the computer industry) or on particular innovations.

i. The weighting matrices

The first technique used to estimate the impact of inter-industry R&D spillovers is founded on the hypothesis that R&D expenditures diffuse proportionately to the level of intermediate input flows between industries. It is therefore limited to the evaluation of rent spillovers. The degree of inter-industry economic dependence is considered as being the main factor influencing the diffusion level of technological know-how across industries. This approach is justified by the fact that R&D intensive intermediate products are purchased at less than their full 'quality' price (see Griliches (1992)). It is therefore an improvement of input measurement problem, rather than knowledge spillovers, which is taken into account. If there is n industrial sectors, the R&D spillover variable for industry j is constructed as a weighted sum of the other industries' R&D capital stocks R_i :

$$S_j = \sum_{\substack{i \\ i \neq j}} a_{ij} \cdot R_i \qquad i, j = 1, \dots, n \qquad (1)$$

where a_{ij} pertains to the weighting matrix A and measures the share of industry i's output accounted for by the sales to industry j. This methodology, pioneered by Terleckyj (1974, 1980a, 1980b) for U.S. industries, has been the most widely used by other authors, as listed in the first part of table 1. Different weighting matrices (input-output or investment flows), different database structures, and different econometric specifications are the three main factors which prevent any comparison axercices either across studies or across countries. Indeed, these divergences may explain why the estimated impact of outside R&D vary from negative values in Japan (cfr. Yamada, Yamada, and Liu) to very high impact for the US (cfr Sveikauskas).

Refering to Schmookler (1966)'s original idea[2], Scherer (1982a) computed the first technological flows matrix for the USA, which allows to trace the diffusion of technology between industries without relying on intermediate inputs. Patent data are used to identify the origin and destination of technology. Here, the diagonal elements of matrix A indicate process innovation. The sum across a row gives the total amount of technology originating in an industry, while the sum along a column yields the total amount of technology used by an industry. The details of the time consuming and complex procedure required for creating this matrix are

[2] Schmookler's idea is actually an extention of the input-output analytical framework.

reported in Scherer (1982a , 1982b, 1984). The components a_{ij} now measure the share of industry i's R&D expenditure which is 'used' by industry j.

Still aiming at measuring inter-industry technological spillovers, some authors have relied on the analysis of innovations rather than patent data. Robson and al. (1988a, 1988b) have analyzed the diffusion of technology from a database of more than 4000 innovations introduced in the U.K. along the last 40 years. Scholtz (1989, 1990) focused on a survey over 5000 firms in West-Germany. These two innovation analyses implemented for the U.K. and West Germany were 'only' used to classify industries as regard to their use of internal or external technology (no social rates of return were estimated). Robson and al. (1988) find an identical structure between the U.K. and the U.S.A. (when their results are compared to Scherer's matrix). In both countries 6 'core sectors' are of major importance in the production of technology that gets used by much more industries. These 'core' sectors are Chemicals, Machinery, Mechanical engineering, Instruments, Electrical engineering, and Electronics. Scholtz's analysis for Germany yields a different structure of innovation, with the Aircraft industry being at the center of technology diffusion.

ii. Technological proximity and bilateral effects

Taking into account of non-incorporated knowledge (either in intermediate input or patent) is even more difficult. Since knowledge is essentially a public good, substantial technological spillovers should take place through its accumulation. Jaffe (1986, 1988)'s technological proximity concept is derived from the position of firms in a technological space. This technological space is characterized by the number of technological classes in which patent applications are classified. The position of firms is evaluated from their patent distribution across an arbitrary number of technological classes. From these frequences vectors F_i , an index a_{ij} of technological proximity between each pair of firms is calculated as follows:

$$a_{ij} = \frac{F_i\, F_j'}{\left[F_i\, F_i'\right]^{1/2} \left[F_j\, F_j'\right]^{1/2}} \qquad (2)$$

Table 1

Inter-Industry Technological Spillovers : Four Tracking Devices at the Industry Level

Authors	Database	Weights	Struct.	Model	γ
I-O and investment matrices					
Terleckyj (1974)	USA, 20 ind.	I/O flows investments flows	C.S.	$\dot{TFP}$, IR	45% 50%
Terleckyj (1974)	USA, 20 ind.	I/O flows, private RD	C.S.	$\dot{TFP}$, IR	183%
Mansfield (1980)	USA, 20 ind.	I/O flows	C.S.	$\dot{TFP}$, IR	27 to 54%
Sveikauskas (1981)	USA, 102 ind.	investment flows	C.S.	$\dot{TFP}$, IR	860%
Postner & Wesa (1983)	Canada, 13 ind.	I/O flows	n.a.	n.a.	18 to 26%*
Odagiri (1985)	Japan, 15 ind	I/O flows	C.S.	$\dot{TFP}$, RD	0%
Hanel (1988)	Québec, 12 ind.	I/O flows	C.S.	$\dot{LP}$, $\dot{IR}$	100%
Sterlacchini (1989)	U.K., 15 ind.	I/O flows	C.S.	$\dot{TFP}$, IR	7 to 12%
Goto & Suzuki (1989)	Japan, 50 ind. 45 ind. electronics	I/O flows	C.S.	$\dot{TFP}$, IR	80% 0%
Yamada, Yamada & Liu (1991)	Japan, 45 ind.	I/O flows Investments flows	n.a.	n.a.	-44 to 24% -16 to 37%
Wolff & Nadiri (1993)	USA, 50 ind.	I/O flows Investments flows	n.a.	n.a.	0% 11%
Mohnen & Ducharme (1995)	Canada, 25 ind.	I-O flows	T.S.C.S.	$\dot{TFP}$, IR	685%
Technological flows matrices					
Scherer (1982a, 1982b, 1984)	USA, 87 ind.	Tech. flows - USA	C.S.	$\dot{LP}$, IR	147%
Griliches & Lichtenberg (1984b)	USA, 193 ind.	Tech. flows - USA	C.S.	$\dot{TFP}$, IR	0 to 90%
Englander & al. (1988)	7 countries	Tech. flows - Canada	T.S.C.S.	TFP, RD	-11 to50%*
Mohnen & Lépine (1991)	Canada, 12 ind.	Tech. flows - Canada	T.S.	Dual	11 to 314%
Sterlacchini (1989)	U.K., 15 ind.	Innovation flows - UK	C.S.	$\dot{TFP}$, IR	11 to 32%
Hanel (1994)	Canada, 19 ind.	Tech. flows - Canada	n.a.	n.a.	0.6%
Mohnen & Ducharme (1995)	Canada, 25 ind.	I-O flows	T.S.C.S.	$\dot{TFP}$, IR	172%
Technological proximity	**Jaffe (1986)**				
Goto & Suzuki (1989)	Japan, 45 ind.	Patent space-electronic	C.S.	$\dot{TFP}$, IR	4%
Adams (1990)	USA, 18 ind.	Labor in Science fields	T.S.C.S.	$\dot{TFP}$, IR	1 to 8%
Odagiri (1996)	Japan, 4 ind.	I-O, patent space	T.S.	Dual	-45 to74%*
Bilateral effect					
Bernstein & Nadiri (1988)	USA, 5 ind.	Parameterized weights	T.S.	Dual	11 to 111%
Bernstein (1989)	Canada, 9 ind.	Parameterized weights	T.S.	Dual	37 to 94%
Bernstein & Nadiri (1991)	USA, 6 ind.	Parameterized weights	T.S.	Dual	18 to 111%
Other					
Levin & Reiss (1988)	USA, 116 lines	Parameterized weights	C.S.		59 to 77%

Table extended from Mohnen (1994, table 1); n.a. : the information has been taken from Mohnen (1994).
γ : Estimated rates of return on outside R&D, * indicates output elasticities. Struct. : Chacteristics of the empirical estimates; C.S. = cross section, T.S. = time series, T.S.C.S. = time series cross section. Model : empirical specification, dependent and explanatory variables; LP = labor productivity, TFP = total factor productivity, IR = R&D intensity, RD = R&D capital stock; the point mark above a variable means rate of growth.

For a given firm, the sum of other firms' R&D, weighted by this index, constitute its 'spillover pool'. The principle is similarly used at the industry level. The weighting components are by definition bounded between 0 and 1. The more two industries are technologicaly close to each other, the higher is a_{ij}. The R&D spillover variable is then computed from equation (1), with the components calculated as in equation (2). This approach is subject to the usual drawbacks arising from the use of patent data.

Unlike the three previous methodologies which rely on the primal approach, Bernstein and Nadiri (1988), use a cost of adjustment model derived from the dual approach. They evaluate bilateral spillovers between pairs of industries. In all previous studies, the R&D spillover was defined as a single aggregate. Here all industries may adopt a different behaviour, both as recipient or as source of technological spillover. The difference is that R&D spillovers and their effect are not separated, while in the first three methods a spillover stock is firstly estimated and then its return is estimated. No spillovers variable has to be computed since for industry i, the R&D expenditures of each other industry j is a potential source of spillover. The main problem underlying this procedure is that it requires long time series (around 30 years) for each sector. A second drawback (see Griliches (1992)) is that potential multicollinearity between the various R&D series may lead to biased spillover estimates.

iii. Technological vs input-output flows

Out of the four methodologies, which one is more efficient than the others? Their characteristics are summarized in table 2. Clearly, each of them has its own advantages and drawbacks. They stand on different hypotheses concerning the nature of knowledge and the embodiement of R&D transfers, which determines the weighting matrix. None of them can be rejected since they reflect particular facets of technology diffusion. However, if the focus is put on the industrial level, Jaffe's technological proximity concept may not be adequate. Technological spillovers between two industries can barely be supposed symmetric. the proximity coefficient is not an appropriate weighting measure because of its bilateral characteristic. It does not allow for asymmetric downstream and upstream inter-industry relationship. Concerning the bilateral effects methodology, allowing each industry to be a distinct technological source and receiver would be too high an ambition in our international comparison objective. Bernstein and Nadiri's studies are restricted to 5 or 9 industries, either in the U.S.A. or Canada, estimating therefore only a share of total inter-industry technological spillovers.

Table 2

Advantages and Drawbacks of the 4 Methodologies

	Input-Output flows	**Technological flows**	**Technological proximity**	**Bilateral effects**
Spillovers	Embodied in intermediate goods Rent spillovers	Embodied in patent or innovations Knowledge Spillovers	Disembodied Knowledge spillovers	Disembodied Knowledge spillovers
Hypothesis	Private good	Private good	Quasi-public good	Public good
Data sources	Easy Input-output flows	Difficult Analysis of patents or innovations	Easy Patent distribution	Difficult Long time series
Concept	Does not allow for different propensity to benefit across industries No upstream links	Best way to approximate technological flows	Inappropriate at the industry level, does not allow for asymetric upstream and downstream relations	Allows each industry to be a distinct spillover sender and receiver
Reliability	High	Patent data	Patent data	Econometrics

The remaining two approaches are similar in the sense that both of them consider R&D as a private, indivisible good. As illustred in table 1, the input-output flows and technological flows techniques have been extensively used in meso-economic studies of inter-industry spillovers. The former method has the main disadvantages of considering that R&D transfers from one industry to the other are only a function of the exchange of intermediate goods between the two industries. Further, it does not allow for new opportunities offered by an innovation in upstream industries. The latter technique has the advantage of taking into account knowledge spillovers between industries, both in the upstream and downstream dimensions. However, the main drawbacks are its dependence on patent data and the difficulties underlying its implementation. Three restrictions are implicitely imposed: (i) every patent has the same weight; (ii) the propensity to patent is equal from one industry to the other, and (iii) every innovation are patented. Regarding our objective of comparing inter-industry spillovers in six industrialized countries, the input-output matrix offers the advantage of an easy access to homogeneous data. This is not the case for the technological flows matrices. Even if recent years have seen the development of new matrices, their dissimilarities, as regard to the surveys and the hypotheses upon which they have been built, make them barely comparable across countries and undermine homogeneous international comparisons. However, there should be a similar structure of inter-industry technological flows across industrialized countries[3].

Most of the studies presented in table 1 have used either a technological flows matrix or an input-output matrix, as if the two methods were mutually exclusive. It is established, however, that two kinds of technological externalities take place between industries: the rent spillovers and the knowledge spillovers. While the former would be more appropriately endogenized by the input-output method, the latter would require the use of a technological flows matrix. Both approaches should not be isolated from each other since their particular designs are more suitable to one of the two types of spillovers. However, The technological flows matrix certainly catches some rent spillovers. And the input-output matrix should also reflect some knowledge spillovers. In any case, confronting the results of both methods would yield a more complete information than concentrating on only one technique.

Few studies contrast the sensitiveness of the estimates to the nature of the weighting matrices and the results of those who do such comparison are controversial. For instance, Terleckyj (1974), Wolf and Nadiri (1993), Yamada, Yamada and Liu (1991), find a spillover effect substantially and significantly greater when the weighting matrix is computed from investment flows rather than input-output flows. On the opposite, Hanel (1988)'s results favor the use of intermediate input flows as inducing a greater impact of external knowledge. Although Goto and Suzuki (1989) concentrate only on the japanese electronics industry, they estimate a higher impact with a technological proximity measure (Jaffe coefficient of closeness) than with the input-output matrix. Concerning the comparison of the technological flows matrix (or the

[3] Englander and al. (1988), in their comparison of industries across seven industrialized countries, implicitely assume that inter-industry technological flows are identical in each country. They use the Canadian technological flows matrix for each country. This hypothesis of identical technological diffusion framework across countries has been tested by Robson and al. (1988) who compared their own results for the U.K. to Scherer's matrix for the U.S.A. According to them, both countries have similar patterns of technology diffusion. However, as previously noted, Scholtz (1989) depicted a different structure for West Germany. It is unclear whether this divergence between Germany on the one hand and the U.K. and the U.S.A. on the other hand is the result of real substantial differences in inter-industry technological spillovers framework, or whether it is the fruit of conflicting hypothesis underlying the matrices construction. For instance, Scherer does not include patents applied by the U.S. government. The assumption is of importance since federally-financed research projects account for a substantial share of national R&D efforts in this country. No answer may be given unless uniform matrices are built for different countries.

innovation flows matrix) and the input-output matrix, four studies also yield diverging conclusions. While Sterlacchini (1989) finds a higher spillover effect with the innovation flows matrix, Mohnen and Ducharme (1991, 1995) obtain greater impacts with the input-output matrix. Hanel (1994) highlights similar impacts, whatever the matrix used. Finally, Van Meijl (1994) and Odagiri and Kinukawa (1996) provide clues that support the idea that the contribution as well as the channels of R&D spillovers is diverse, depending on source industries and receiving industries.

Identical structures of inter-industry links would mean that the input-output matrix, despite its drawbacks, is a good proxy for technological flows matrix, which are so difficult to implement. The next chapter is devoted to a statistical comparison of both types of matrices. An international comparison of Japanese, American, and British inter-industry profiles is provided.

3. STATISTICAL ANALYSES OF MATRICES SIMILARITIES

This chapter presents firstly two basic statistical tools which will be used for the comparisons of matrices. Then, the available input-output and technological matrices are briefly described. The results are analyzed in the third section. The comparison exercices concerns (i) input-output matrices and their technological counterparts in the U.S. and Japan; (ii) the stability of inter-industry structures from the early seventies to the mid-eighties in Japan and the U.S.; and (iii) the input-output structures of Japan, the U.S.A., and the U.K. in 1985. The first point aims at bringing some evidence about the use of input-output matrix as a proxy for technological flows matrix. The second intends to verify if Scherer's technological flows matrix for the U.S. in 1974 may still be used for the eighties. The last point should give an insight about whether or not any national input-output matrix may be used for other countries.

i. Statistical tools

In accordance with previous studies computing stocks of R&D spillovers, the comparison will be based on output distribution vectors (instead of input composition, which might be an alternative solution). For each industry, a vector composed by the distribution of its output across other sectors, is computed. For instance, its weighting component, a_{ij} (the same than in equation 1) measures the share of industry i's total output accounted for by the sales to industry j (x_{ij}):

$$a_{ij} = x_{ij} \Big/ \sum_j x_{ij} \text{ and } \sum_j a_{ij} = 1 \tag{3}$$

If two matrices have the same structure - i.e. similar vectors of weighting components for each industry -, both of them would lead to identical R&D spillovers variables. The question that arise is whether or not, for a given industry, these output distribution vectors from two distinct matrices are similar. Since the weighting components of each vector sum to 1, a proximity coefficient may be used to indicate how similar two vectors are. This proximity coefficient has been computed for each industry as in equation (2). The difference is that the frequences vector F_i of industry i is now composed by the distribution of its output across other industries. This coefficient ranges from 0 to 1. The greater the similarity of the two vectors, the closer the coefficient is to unity. For all pairs of matrices, this proximity coefficient may be computed for each of the n industries. The mean of those n coefficients will provide an insight on how similar the two matrices are.

In the construction of R&D spillovers variables the important components are those which correspond to a transfer to other industries. The diagonal elements, the intra-industry shipments, are not used (cfr. equation (1)). This element is relatively large in most industries, which may lead to high proximity coefficient, higher than the real proximity between the inter-industry components. To illustrate this concept, consider two countries composed by four industries and suppose that the output distribution vectors of industry 1 in the the U.S.A. (U) and in Japan (J) have the following form:

	S1	**S2**	**S3**	**S4**
SECT 1U	0.8	0.1	0.0	0.1
SECT 1J	0.8	0.0	0.2	0.0

In this case, the proximity coefficient will be equal to 0.7. However, the inter-industry shipments are totaly different, so would be the R&D spillovers variables computed from these two vectors. In order to test the extent to which the rate of intra-industry shipments may lead to wrong interpretations, this proximity coefficient should be compared to another measure of similarity. A correlation coefficient among the two vectors, excluding the intra-industry component, should compensate for this drawback inherent to the proximity coefficient. In our case, the correlation coefficient would be equal to -1, meaning that there are opposite inter-industry links. The next section present the matrices that were available for the present research and the results of the statistical analysis of similarities between these matrices.

ii. The statistical analysis

The matrices used for the comparison are listed in table 3. The 1972 input-output table of the U.S.A. comes from the Survey of Current Business (1979), published by the U.S. Department of Commerce - Economics and Statistics Administration; Bureau of Economic Analysis. All the other national input-output matrices, for Japan, the U.S., and the U.K. have been provided by the Research Institute of the Ministry of International Trade and Industry (MITI/RI).

Table 3

Availability and Characteristics of Input-Output and Technological Flows Matrices

COUNTRY	DATE	DIMENSION
Input-Output		
U.S.A.	1972	74 * 74 sectors
U.S.A.	1985	90 * 90 sectors
Japan	1970	90 * 90 sectors
Japan	1985	90 * 90 sectors
U.K.	1985	194 * 194 sectors
Technological flows		
U.S.A.	1972-4	41 * 53 sectors
R&D Repartition		
Japan	1971-2	31 * 34 sectors
Japan	1985-6	31 * 34 sectors
Homogeneous Matrices for comparison :		
22 industries * 19 sectors (17 manufacturing, 1 primary, one services)		

The only easily accessible technological flows matrix was the one of Scherer (1982a, 1982b, 1984). The Japanese matrices of intramural expenditure on R&D by industry and product line (Aggregated from companies with capital of 100 million yen or more) have also been included in the analysis. Detailed results of the statistical comparison by industry are presented in the appendix, in table A5 for the proximity coefficients and in table A6 for the correlation coefficients. For the sake of space, only the means across industries are shown in table 4. One mean is calculated over all industries and another one over the six 'core' technological sectors whose products are the embodiment of technologies that pervade most sectors inside the economic system (see Robson and al. (1988)). This second mean aims at analysing these particular sectors which are the main source of technological spillovers.

Table 4

Proximity and Correlation Indexes Between Pairs of Matrices

Comparisons	**Proximity**		**Correlation**	
	All sectors	**core sectors**	**All sectors**	**core sectors**
Techn. flows vs input-output				
U.S. tech vs U.S. I-O (1972)	.78	.88	.87	.92
Japan RD vs Japan I-O (1970)	.35	.52	.17	.18
Japan RD vs Japan I-O (1985)	.33	.60	.22	.36
Time dimension				
Japan I-O (1970) vs Japan I-O (1985)	.87	.83	.78	.78
U.S. I-O (1970) vs U.S. I-O (1985)	.87	.83	.93	.94
International comparison				
Japan I-O vs U.S. I-O (1972)	.84	.88	.80	.87
Japan I-O vs U.S. I-O (1985)	.93	.88	.89	.81
Japan I-O vs U.K. I-O (1985)	.84	.79	.85	.77
U.S. I-O vs U.K. I-O (1985)	.86	.88	.89	.89

cfr. Tables A5 and A6. The six 'core' sectors are: chemicals, machinery, mechanical engineering, instruments, electrical engineering, and electronics.

The two indicators of closeness do not lead automatically to the same conclusions, depending on the nature and the origin of the matrices considered. Table 4 is subdivided in three parts: the first one is concerned with the comparison of technological flows matrices and their input-output counterpart. The second one considers structural stability over time. The third sudivision shows the level of similarity between the inter-industry structures of Japan, the U.S., and the U.K in 1985. Regarding the proximity between the Japanese R&D distribution matrix and its input-output counterpart, the two indicators of similarity emphasize substantial differences. In each column, the indicators have the weakest value. This may mean that at the aggregated level, there is no synchronism between the sectors in which Japanese companies invest in R&D and the sectors they supply with intermediate inputs. The cause of such dissimilarity is indubitably linked to the fact that most of the R&D expenditures of firms are directed towards their main sector of activity. As noted earlier, this R&D repartition matrix only reflects a marginal share of inter-industry spillover potentials. Therefore, they will not be included in the empirical analysis.

Scherer's technological flows matrix, which is designed to reflect U.S. inter-industry knowledge spillovers, is compared with the 1972 U.S. input-output matrix. The mean proximity coefficient over the 22 industries is equal to .78, which is still a relatively weak proximity as regards to the other coefficients in the same column. However, the mean across the six main producers and senders of innovation is relatively high. The proximity index is close to 90%, the highest value in the second column. The correlation coefficient reflects a relatively higher similarity which also increases with the six core sectors. Table A5 in the appendix shows the variability across industries which can be associated to the proximity measures. For instance, in the column which compares the US input-output matrix to Scherer's technological flows matrix (column A7OT), motor vehicules and equipment, non metallic mineral products, and petroleum refineries, are three industries whose output distribution are substantially different from their technological distribution. If the focus is put on the correlation coefficient, other industries seem to be the sources of this divergence. The three weakest values are related to drugs and medecines, rubber and plastic product, and textile, apparels and leather. The fact that the proximity coefficient is weaker in some comparison and the correlation coefficient is weaker in others, illustrates the significant influence of the intra-industry coefficient.

The second part of table 4 shows the comparisons of input-output matrices between the years 1970 and 1985, both for the U.S.A. and japan. These figures should mirror the main structural changes that occured inside the two countries from the early seventies to the mid-eighties. Again, the two similarity indexes lead to different interpretations. The industrial structures have been relatively stable if we refer to the proximity index. Either in Japan or in the U.S., the high proximity value of .87 seems to provide clues that the countries have seen identical slight changes in their industrial structures. The correlation coefficient shows a different story: while the U.S.A. kept a fairly stable industrial structure, Japan seems to have known profound modifications (the average correlation coefficients between the industrial structures of 1970 and 1985 are equal to .93 for the U.S.A., and to .78 for Japan). This mutation is principally the result of deep changes in the structure of the output distribution vectors of three industries (cfr column J78O of table A6): Food, beverage and tobacco, non metallic mineral products, and other transportation equipment. In the USA, no industries have known such impotant changes (cfr. column A78O).

International comparisons of inter-industry structures are presented in the third part of table 4. The two similarity indexes provide us with similar illustrations. From the early seventies, to the mid-eighties, a strong convergence appears between the American and the Japanese inter-industrial structures (the proximity coefficient between the two countries goes from .84 in 1970 to .93 in 1985). Finally, the proximity coefficient shows that the U.K is more similar to the U.S.A. than to Japan. The Japanese industrial structure is even closer to the U.S.A. than the U.K. is. The correlation coefficient between the same countries slightly modifies the conclusions. The distance of Japan and the U.K. from the U.S.A. is identical (.89) but both countries are more distant from each other. Considering the six core sectors in 1985, similarity indexes deteriorate in most cases, and particularly with the correlation coefficients. This hinders the idea that a unique input-output matrix may be used for every countries.

For some comparisons tables A5 and A6 illustrates a strong variability of the coefficients across industries. These asymetries illustrate the limits of summarising a multidimentional space through one single coefficient. However, some comments, which have to be taken cautiously, may sum up the above analysis of similarities. First, input-output matrices do not seem to be a good proxy for technology flows matrices. However, similarities are much higher for the six core sectors. Therefore, the spillovers variables computed from the two matrices may be similar. Second, the analysis over time shows that the U.S. industrial structure has been fairly stable, as compared to the Japanese one. Third, the U.K. industrial structure seems very close to the U.S. In this respect, the U.S. technological flows matrix may be used for Japan and the U.K.; as far as it is assumed that if they have a similar industrial structure, they may have a similar structure of inter-industry technological flows. However, the higher dissimilarities which appear when the core sectors are considered, penalize such an assumption. The best way to give credence to the assumption that input-output matrices are good proxy for technological flows matrix is to perform an empirical test, which is feasible only in the case of the U.S.A. Regarding the assumption that a particular technological flows matrix may be used for several countries is, unfortunately, not feasible in the present study. The next two chapters concentrate on the econometric estimation of the impact of inter-industry technological spillovers. Chapter 4 is concerned with theoretical considerations, the econometric model, and data description. Chapter 5 provides the econometric results.

4. EMPIRICAL IMPLEMENTATION

i. Theoretical perspectives

The econometric studies which intend to estimate the contribution of R&D to the growth of productivity commonly rely on either a primal or a dual theoretical model. The primal approach requires the use of a production function, while the dual approach concentrates on a system of factor demand equations which allow for more flexible functionnal forms. The choice usually depends on the structure of the available database and on the assumed functionnal forms (see Mairesse and Mohnen (1995) for a survey). For the sake of comparability with all the studies which have relied on an aggregated stock of R&D spillovers (the ones listed in the first two parts of table 1), the present study will make use of the primal approach.

To assess the impacts of R&D and other traditional inputs on output, a Cobb-Douglas production function (see Griliches (1979), Terleckyj (1974), Griliches and Lichtenberg (1984), and Mairesse and Mohnen (1995), between others), which has a useful log additive form and therefore directly gives the inputs elasticities of output, is commonly used. Specifically, including the R&D capital stock as a distinct production factor along with conventional inputs, gives the following function :

$$Q(t) = A \cdot RD(t)^{\gamma} \cdot \prod_i X_i(t)^{\alpha^i} \exp(\beta t) , \tag{3}$$

where Q(t) = output; A = constant; RD(t) = R&D capital stock which represents the stock of knowledge an industry possesses at a certain point in time; $X_i(t)$ = the traditional production factors, i.e : labor input, physical capital stock, energy input and nonenergy intermediate materials input; and β is the rate of disembodied technical change. At the macro-economic and industrial level, the most prominent problem which arises when estimating the parameters γ and α^i 's is related to multicollinearity between the explanatory variables. This potential multicollinearity could reflects either the fact that human, physical and R&D capital tend to move together along a common trend, or the double counting statistical phenomenon between labor and physical capital on one side and R&D capital on the other side. Thus, from equation (3), a substantial part of the existing empirical studies do compute an index of total factor productivity (TFP(t)) as follows :

$$TFP(t) = Q(t) \,/ \prod_i X_i(t)^{\alpha^i} . \tag{4}$$

However, considering this last indicator as a dependent variable implies some restrictive assumptions about the structural form of the production function[4]. Combining (3) and (4), we obtain :

$$TFP(t) = A \cdot RD(t)^{\gamma} \cdot \exp(\beta t) \ , \tag{5}$$

$$\log TFP(t) = \log A + \gamma \log RD(t) + \beta t \tag{6}$$

[4] Computing a total factor productivity index is synonymous to set the output elasticities equal to their observed factor share and to impose the assumption of constant returns to scale, competitive markets, cost minimizing factor holding, and an elasticity of substitution between labor and fixed capital equal to one.

Differentiating (6) with respect to time and expressing the rate of growth of total factor productivity as follows :

$$\left[\mathrm{d}\log \mathrm{TFP(t)}\right] / \mathrm{dt} = \dot{\mathrm{TFP}} / \mathrm{TFP},$$

$$\frac{\dot{\mathrm{TFP}}}{\mathrm{TFP}} = \gamma\,\frac{\dot{\mathrm{RD}}}{\mathrm{RD}} + \beta\ , \tag{7}$$

γ being the elasticity of output with respect to the stock of R&D capital, equality (7) can be rewritten as

$$\frac{\dot{\mathrm{TFP}}}{\mathrm{TFP}} = \frac{\partial \mathrm{Q}}{\partial \mathrm{RD}} \cdot \frac{\mathrm{RD}}{\mathrm{Q}} \cdot \frac{\dot{\mathrm{RD}}}{\mathrm{RD}} + \beta = \rho\,\frac{\dot{\mathrm{RD}}}{\mathrm{Q}} + \beta \tag{8}$$

where $\rho = \partial Q / \partial RD$ is the long term excess rate of return[5] on R&D capital stock and RD/Q is the R&D capital stock intensity. The equations (6) or (7) give the elasticity of output with respect to the R&D capital stock which is viewed as a parameter and is constant across observations, as the elasticity is equal to the product of the excess rate of return on R&D capital into the R&D capital intensity. When the R&D capital intensity increases the marginal product of R&D decreases. On the other hand, the marginal product of equation (8) being a fixed parameter, the rate of return on R&D capital must be invariable across observations. These developments leave the choice to adopt either the total factor productivity approach (equations (6) to (8)), or the initial Cobb-Douglas production function (3) . The total factor productivity approach is often based on the estimation of the sole impact of R&D expenditures, the parameter being either the elasticity or the rate of return on R&D. It relies also on the assumption of constant returns to scale and reduces potential colinearity bias between labor, fixed capital stocks and R&D capital stocks. In the present empirical analysis, the equation (6) is adopted, in order to evaluate the output elasticities of both the R&D capital stocks.

[5] The "excess" term recalls the double counting effect between R&D on one hand and labor and physical capital on the other hand. It is called "long term" excess rate of return because it is calculated on the basis of stocks of R&D capital instead of R&D expenditures.

The studies based on technological flows matrices (see Scherer (1982a, 1982b, 1984), and Griliches and Lichtenberg (1984)) introduce the 'used R&D' (USERD) and the 'origin R&D' (ORIRD) capital stocks as the main determinants of productivity growth. The used R&D is the sum of 'own R&D' (the share of R&D which does not spill over to other industries, also called 'process R&D') and R&D spillovers. The origin R&D is the amount of R&D which spills over to other industries (also called 'product R&D').

ii. The variables

The total factor productivity variable for each country is computed as follows:

$$TFP_{it} = Q_{it} \,/\, (\, L_{it}^{\alpha} \cdot K_{it}^{1-\alpha} \,) \tag{9}$$

Q, L, and K are respectively the output proxy, the number of employees, and the fixed capital stock. α is the share of labor costs, constrained to be equal to 0.6[6]. Most variables have been constructed from data drawn out from the OECD databases (their sectoral breakdown and period availability for each country are presented in the appendix, table A1). All the variables (except the number of employees) are expressed in constant 1980 US \$. Q is proxied by value added and is deflated by country and industry specific production prices (cfr table A2 for availability of price indexes). Total sales could not be used because of the lack of homogeneous information about intermediate inputs; L is the number of employees; K is the fixed capital stock generated by the perpetual inventory method, which is defined in appendix A1. The annual flows of fixed investments are deflated by national gross fixed capital formation deflator (1980=100) as defined in the OECD's National Account Surveys. This computation of K implies that the stock of fixed capital depends on the assumed depreciation rate and on the annual rate of growth of investments during the period preceding the first year of evaluation of the stock. Industry and country specific depreciation rates have been found in Blades (1991) (cfr. table A4 in the

[6] We first tried to evaluate the share of total labor costs in value added, some inconsistencies appeared (in some cases total labor costs were larger than value added); we therefore assumed a constant share of 0.6.

appendix). The mean annual rate of growth, which precedes the benchmark year, covers the period 1973-1978.

RD is the total R&D capital stock, computed as the fixed capital stock on the basis of total R&D expenditures, deflated by the Gross Domestic Product Price Indices (1980=100) of countries as established by the OECD's National Account Surveys. We assume that different depreciation rates prevail in each sector, which is most certainly the case. Further, industry-specific lags between R&D activities and the productivity growth they cause are taken into account. The industry-specific lags and depreciation rates have been published for Japanese industries in 1985 by the Japan Science and Technology Agency (cfr. table A6 in the appendix) and are used for each country.

Table 5
The Construction of the R&D Variables

R&D variables		
Own R&D (W)	$W_i = RD \cdot a_{ii}$	$a_{ii} = X_{ii} / X_i$, $X_i = \sum_j X_{ij}$
R&D Spillovers (S)	$S_j = \sum_{i, i \neq j} a_{ij} \cdot RD_i$	$a_{ij} = X_{ij} / X_i$
ORIRD	RD - W	
USERD	S + W	

Xij is a transfer of either technology, or intermediate goods, or investment goods from industry i to industry j.

USERD, the R&D capital stock used by each industry, is equal to the sum of the process R&D capital stock (W) and the stock of R&D spillovers. R&D spillovers variables (S) are computed as in equation (1) from the estimated R&D capital stock of each industry, which are weighted by the cross-industry repartition coefficient of either the national input-output matrices, or Scherer's technological flows matrix. It is therefore assumed that the U.S. technological flows matrix prevails in the other countries. The national input-output matrices are dated from 1985; Scherer's technological flows matrix is from 1972. It might be regarded as obsolete but Mohnen and Ducharme (1995) have shown that the choice of a particular weighting matrix in the time dimension do not affect significantly the econometric results. Own (or process) R&D capital stock (W) is equal to the R&D capital stock, (RD), weighted by the intra-industry coefficient. Product R&D, approximated by the share of RD which spills over to other industries, is equal to the R&D capital stock (RD), minus process R&D (W). The computation of these R&D variables is illustrated in table 5.

iii. The econometric model

For each country, a panel database is composed by 20 to 22 industries over the period 1980-90 (the data availability is presented in the appendix, table A1). The estimations of output elasticities of R&D may be done on the basis of the following equation:

$$tfp_{it} = \beta_{1i} + \gamma_{rd} \cdot rd_{it} + e_{it} \qquad (10)$$

The variables tfp and rd are the logarithm of the corresponding capital letters defined in the previous chapter; $i = 1, ..., 22$ indicates industries and $t = 1, ..., T$ indicates years. β_{1i} is a constant for each industry and γ_{rd} is the output elasticity of R&D capital stock; e_{it} is the stochastic term and is assumed to have a zero mean, $E[e_{it}] = 0$, and constant variance, $E[e_{it}^2] = \sigma_e^2$. Refering to equation (10), the more general and unrestrictive case is to estimate a parameter for each industries , i.e. one regression for each industries. But in our case the degree of freedom would be too small (11 years). Some restrictions have to be imposed in order to benefit from more robust estimations. Hence, a possible solution is to estimate the samples of sectors stacked together to form a sample of about 231 observations, allowing therefore a global estimation for all industries as a whole. The error term is thus assumed to capture the differences over time and between industries.

This "restricted" regression model only enables empirical analysts to assess the effects of quantitative factors. However, when the overall homogeneity of the sample is rejected by the panel data, an easy way to take into account the heterogeneity across industries is to use the variable intercept model that covers both quantitative and qualitative variables and allows each industry to have a different intercept. Hsiao(1986) recalls that the fixed effect model allow to reduce the 'omitted variable bias' since it focus on the effects which can not be directly observed or measured. For the ith industry, the intercept could be desagregated as follows: $\beta_{1i} = \overline{\beta}_1 + \mu_i$, ; where $\overline{\beta}_1$ is the mean intercept and μ_i represents the difference from this mean for the ith industry. μ_i allows for the industrial heterogeneity contained in the temporal cross-sectional data and is by definition constant over time for a given cross-sectional unit. Because numerical problems may appear when introducing a dummy variable for each industry, an alternative expression derived by taking the partitioned inverse is often employed: it requires that equation (10) is averaged over time for each industry and the result substracted from (10). Then an ordinary least squares (OLS) regression is applied to the following equation :

$$tfp_{it} - \overline{tfp} = \gamma_{rd}\,(rd_{it} - \overline{rd_i}) + e_{it} \qquad (11)$$

The use of the variation of variables within each industry gives the estimator which is refered as the 'within estimator'.

5. ECONOMETRIC RESULTS

The econometric specifications (12) to (14) are to be estimated[7]. The first one is the 'common' production function, while the two others embody the external R&D. Specification (13) is similar to the specification used by Scherer (1982a, 1982b, 1984) and specification (14) has been widely used in the empirical literature. Table 6 presents the estimated parameters for the 'common' production function, with different hypotheses concerning the construction of the R&D capital stock. This procedure aims at analyzing the sensitiveness of the results to the depreciation rate and the lags applied to the R&D variable.

[7] Griliches and Lichtenberg (1984) expand specifications (13) and (14) towards a less constrained specification, with three R&D components. They divide the USERD variable into its two components: the R&D spillover capital stock (S), and the process R&D capital stock (W). Our panel data framework being given, such a procedure is not feasible. The share of the process R&D capital stock in total R&D capital stock (RD) is constant over time for a given industry; which yield a perfect correlation between RD, W, and ORIRD for each industry, and serious collinearity biases for the whole panel. Griliches and lichtenberg (1984) did not face this problem since they worked within a cross-section framework.

$$tfp_{it} = \beta_{1i} + \gamma_{rd} \cdot rd + e_{it} \tag{12}$$

$$tfp_{it} = \beta_{1i} + \gamma_{or} \cdot orird + \gamma_{us} \cdot userd + e_{it} \tag{13}$$

$$tfp_{it} = \beta_{1i} + \gamma_{rd} \cdot rd + \gamma_{s} \cdot s + e_{it} \tag{14}$$

The R&D capital stocks in the first three rows of table 6 are computed with different depreciation rates and no lags. The estimated output elasticities of R&D are sensitive to the depreciation rate used. In the UK and to a lesser extent in Japan, a zero depreciation rate leads to a higher coefficient than a 15% or an industry-specific depreciation rate. In the U.S. it leads to a lower coefficient. The differences across countries are very important with the no depreciation rate hypothesis, the elasticities ranging from 21% in the USA to 85% in the UK. When the 'popular' 15% depreciation rate is used, the elasticities across countries get closer to each other, with an 18% value for the UK and a 48% value for Japan.

Table 6
Total Factor Productivity Regressions - The Basic Model

		JAPAN 1980-89, n = 200		**USA 1980-90, n = 231**		**UK 1980-90, n = 231**	
δ	lags	γ_{rd}	Adj.R^2	γ_{rd}	Adj.R^2	γ_{rd}	Adj.R^2
δ = 0%	t	.518*[.027]	.934	.211*[.005]	.845	.845*[.072]	.925
δ = 15%	t	.478*[.026]	.929	.245*[.006]	.826	.183*[.071]	.878
$\delta = \delta_i$	t	.471*[.025]	.930	.244*[.006]	.831	.294*[.077]	.882
$\delta = \delta_i$	t-1	.479*[.026]	.927	.247*[.006]	.834	.254*[.078]	.880
$\delta = \delta_i$	t-2	.454*[.026]	.926	.250*[.006]	.837	.233*[.079]	.879
$\delta = \delta_i$	t-3	.457*[.026]	.925	.253*[.006]	.839	.246*[.080]	.879
$\delta = \delta_i$	t-4	.461*[.027]	.923	.256*[.006]	.841	.291*[.079]	.882
$\delta = \delta_i$	t-l_i	.452*[.025]	.935	.250*[.006]	.838	.219*[.078]	.879

The dependent variable is a two years moving average (t and t-1) of log (total factor productivity). All equations include unreported country-specific constants. Standard errors between brackets; * indicates the estimated coefficients which are significantly different from zero at a 10% probability threshold.
δ is the depreciation rate used to compute the R&D capital stocks, δ indiced by i means that industry-specific depreciation rates are used. The l_i are an industry-specific lags of R&D capital stocks. Cfr. table A3 in the appendix. For the number of industries available in each country, cfr. table A1.

Turning to the industry-specific depreciation rates, the parameters do not vary substantially as compared to the 15% hypothesis, except in the UK. The output elasticites of R&D converge further across the three countries, from 24% in the USA to 47% in Japan. Concerning the lags, different pictures appear in each country. From the one year lag to the four year lag, the estimated parameter constantly increases in the USA, slightly decreases in Japan, and decreases only until the two years lag in the UK.

At this point it is worth noticing that the classification of countries as regards to their output elasticity of R&D is sensitive to the assumptions about the depreciation rates and the lags. Our preferate estimates are presented in the last row of table 6, when industry-specific lags and depreciation rates are used. Japan benefits from the highest output elasticity of R&D, the US has a coefficient equal to nearly a half of the Japanese one. The UK has the lowest elasticity but is very close to the US. This sort of comparison has to be considered very cautiously because the classification of countries may vary with the assumed depreciation rates and lags. However, we may infer from table 6 that in Japan the output elasticity of R&D is significantly higher than in the US and the UK.

Are these estimated elasticities overstimated by failure to properly take into account the existence of inter-industry spillovers? Table 7 shows the estimated paramaters of specifications (13) and (14). For each country the results are presented in three rows and two columns. The first row presents the parameters of specification (13), with product R&D (ORIRD) and used R&D (USERD) as determinants of total factor productivity. The second row contains the parameters of specification (14), with total R&D (RD) and R&D spillovers (S) as determinants of total factor productivity. The first column is characterized by the use of Scherer's technological flows matrix as the weighting matrix and the second column is characterized by the use of the national input-output matrix.

For the three countries, the results show that USERD, the used R&D capital stock, is associated with a significant and substantial impact on total factor productivity. Scherer (1982a, 1982b) obtains similar results for the US industries. The product R&D variable (ORIRD) plays a powerful negative role in the U.S. when it is computed through Scherer's technological flows matrix. This should be implausible and is contrary to Scherer's results. However, very high elasticities of used R&D capital stock seem to offset these negative impact of ORIRD. Turning to specification (14), the results highlight strong and positive effects of the R&D spillover variable in the three countries. The R&D capital stock variable is no more significant in the USA and is much smaller in Japan, as compared to the bottom line of table 6. This may be due to the presence of multicollinearity between the R&D variables. Multicollinearity may also partly explain the negative coefficient associated to ORIRD in the US. Concerning the sensitivity of the estimates to the nature of the weighting matrix, it seems that the technological flows matrix and the national input-output matrices yield different results in the US and the UK; in Japan the results are more similar.

Table 7
Total Factor Productivity Regressions - The Impact of R&D Spillovers

	JAPAN 1980-89		USA 1980-90		UK 1980-90	
Weighting Matrix	Scherer	I - O	Scherer	I - O	Scherer	I - O
γ_{or}	.248*[.109]	.266*[.081]	-.496*[.156]	-.155 [.104]	-.101 [.107]	-.016 [.075]
γ_{us}	.213*[.111]	.210*[.087]	.890*[.185]	.385*[.098]	.635*[.152]	.819*[.103]
R^2 Adj.	.928	.929	.853	.848	.887	.907
γ_{rd}	.189*[.075]	.229*[.071]	-.066[.077]	-.056[.078]	.125*[.066]	.217*[.066]
γ_{s}	.294*[.080]	.261*[.078]	.368*[.097]	.294*[.075]	1.06*[.110]	.837*[.089]
R^2 Adj.	.932	.938	.849	.863	.916	.914

Cfr. table 6.

In the line of Griliches and Lichtenberg (1984) study, in which they compare the differentiated impact of process R&D (W), product R&D (ORIRD) and spillovers R&D (S), one may wonder whether the two components of USERD, W and S, are equally 'potent' in generating productivity growth. Similarly to the analytical framework of Griliches (1986), let us assume that while the analysis is in term of the USERD variable only, its own R&D (W) component should have been weighted more, given a ϕ premium. Then, the right variable would be $USERD^* = S + (1+\phi)W = USERD\,(1+\phi\, q)$, where q = W/USERD is the share of own R&D in USERD, USERD = S + W. Then the term $\gamma_{us} \log USERD^*$ may be approximated by:

$\gamma_{us} \log \text{USERD}^* \cong \gamma_{us} \log \text{USERD} + \gamma_{us} \phi\, q$. The size and the magnitude of the premium ϕ will therefore be inversely proportional to the mix term q. Table 8 presents the estimates of the parameters of the two following specification:

$$tfp_{it} = \beta_{1i} + \gamma_{us} \cdot \text{userd} + e_{it} \tag{15}$$

$$tfp_{it} = \beta_{1i} + \gamma_{us} \cdot \text{userd} + \gamma_{W/USERD} \cdot (W / \text{USERD}) + e_{it} \tag{16}$$

Table 8
The Differentiated Effects of Spillover R&D and Process R&D

	JAPAN 1980-89		**USA 1980-90**		**UK 1980-90**	
Weighting Matrix	Scherer	I - O	Scherer	I - O	Scherer	I - O
γ_{us}	.458*[.026]	.483*[.027]	.301*[.007]	.239*[.005]	.533*[.106]	.810*[.094]
R^2 Adj.	.927	.925	.847	.848	.887	.907
γ_{us}	.466*[.026]	.497*[.030]	.359*[.019]	.244*[.006]	.703*[.102]	.827*[.091]
$\beta_{W/USERD}$	-.667[.529]	.883[.703]	-1.53*[.457]	-.832*[.495]	-2.56*[.416]	-1.39*[.372]
R^2 Adj.	.927	.925	.854	.849	.904	.912
Own RD premium : ϕ	non signif.	non signif.	-4.26	-3.4	-3.64	-1.68

Cfr. table 6.

Specification (15) takes into account only the USERD variable; we therefore implicitely assume that ORIRD has no significant impact, as in Scherer's results for the US. Specification (16) allows to compare the impacts of S and W. The first row of table 8 gives the results of specification (15) in which the output elasticities of USERD are different from the estimates that include ORIRD (cfr. first row of table 7). The fact that these coefficients are not stable is another indice of the potential presence of multicollinearity biases. The second row includes the coefficients of specification (16). There is one major point to be made about these estimates. In the US and the UK the sensitivity coefficients associated to the ratio (W/USERD) are negative and significant, with both weighting matrices. This means that the own R&D capital stock (W) has a negative premium relatively to the R&D spillover capital stock (S). In other words, the impact of imported product R&D is larger than the impact of the own R&D in both countries. In

Japan, as in Griliches and Lichtenberg (1984)' study for US industries, both variables have a similar impact on total factor productivity since no significant premium seems to be associated to W.

A last point concerns the leading questions adressed in this paper. Are there similar social rates of return in the countries under consideration? Is there a significant difference between the results obtained through the input-output matrix and through the technological flows matrix? Table 9 provides some clues towards these issues, it presents the estimated private and social excess rates of return on R&D in the three countries, which are computed by dividing the significant output elasticities of tables 6, 7, and 8 by the corresponding R&D intensities (the ratio of R&D capital stocks to value added).

Consider first the private rates of return on R&D (cfr. column 1 of table 9) estimated without taking into account R&D spillovers. The Japanese industries have a private rate of return on R&D (215%) four times as high as in the U.S. (52%) or in the UK (53%). The social rates of return on R&D efforts are computed from specification (13) and (15). The former includes USERD and ORIRD; its estimated parameters might be biased due to the presence of multicollinearity. The latter does not suffer from this bias but does not take into account ORIRD. The classification of the three countries with respect to the amplitude of their social rate of return on R&D is not sensitive to the nature of the weighting matrix and to the specification used. In the columns (2) to (5), Japan has the highest social rates of return on RD. The UK holds an intermediate position and the US has always the weakest value.

If the classification of countries is not altered by the nature of the weighting matrix, the amplitude of the estimated social returns seems in turn to be sensitive. As Scherer's technological flows matrix has been computed for the USA, the comparative analysis should focus on this country in order to compare the results derived from the technological flows matrix and the input-output matrix. With both specifications (13) and (15), the social rate of return is substantially smaller when the inter-industry spillovers are computed from the input-output matrix rather than the technological flows matrix. This is exactly the opposite relation that Mohnen and Ducharme (1995) found for Canadian industries.

Table 9
Evaluation of Social Gross Excess Rates of Return on R&D activities

	Private rates of return	**Social rates of return**					
	Spec. (12) : rd	Specification (13) : orird + userd		Specification (15) : userd		Social rate / private rate	
Weighting matrices :	(1)	Scherer (2)	I-O (3)	Scherer (4)	I-O (5)	Scherer (6)	Scherer (7)
						(4) / (1)	(5) / (1)
JAPAN	2.15	3.55	3.18	3.82	3.72	1.7	1.8
USA	.52	2.54	1.43	1.37	0.88	4.9	2.6
UK	.53	3.18	2.93	2.67	2.89	6.0	5.0

The social gross excess rates of return are computed by dividing the significant output elasticities of table 6, 7 and 8 (depending on the specification considered) by the corresponding R&D capital stock intensities.

To what extent has Japan benefited from inter-industry spillovers? Is its high social rate of return due to a high private rate of return or to substantial inter-industry R&D spillovers. In other words, a last important point to be made would be to evaluate the relative importance of inter-industry spillovers. Columns (6) and (7) of table 9 give the ratio of the social rate of return to the private rate of return on R&D, originating from specifications (13) and (15), respectively. There are some evidence that, with a value equal to 1.7 in Japan and to 5 and 6 in the US and the UK respectively, the relative importance of inter-industry R&D spillovers has been much weaker in Japan than in the US or in the UK. That is, a weaker private rate of return on R&D is likely to be offset by relatively stronger inter-industry R&D spillovers. However, even if the latter are relatively larger, they do not allow for an equalization of social rates of return across countries.

6. CONCLUSIONS

This paper aimed at providing an homogeneous international comparison of inter-industry technological spillovers in Japan, the USA, and the UK. The main limitation was the absence of comparable technological flows matrices in the different countries in order to compute R&D

spillover capital stocks. Therefore, the US technological flows for the three countries, as well as national input-output matrices, have been used in each country. The statistical analysis as well as the econometric estimates do not support the hypothesis that input-output matrices are a good proxy for technological flows matrices.

The main empirical results may be recapitulated in four points. First, regardless the impact of inter-industry R&D spillovers, Japanese industries have the highest private rate of return on R&D; the UK and the USA standing in a substantially weaker position with this respect. Second, in the US and the UK a negative premium is associated to the impact of process R&D as compared to spillover R&D. In Japan the two R&D variables have the same impact. Third, the social rate of return on R&D is weaker when R&D spillovers are computed through the national input-output matrix rather than the technological flows matrix. Fourth, the highest social rate of return on R&D takes place in Japan. The UK industries stand in an intermediate position and the US industries benefit from the weakest social return on R&D. Further, and in accordance with the second point, weaker private rates of return on R&D seem to be offset by stronger R&D spillovers. However, these relatively higher impact of R&D spillovers do not allow for an international equalization of the social rates of return on R&D.

These results bring about three particular issues. (i) Why is there such a difference across countries as regards to private and social rates of return? (ii) If the UK and Japan had their own technological flows matrices, would the results yield similar international differences in the relative importance of private and social rates of return on R&D? (iii) How would the introduction of international R&D spillover effects affect these conclusions?

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APPENDIX A1 : <u>STOCK EVALUATION FROM ANNUAL INVESTMENT FLOWS</u>

The stocks formulation used in this seminar to evaluate R&D and fixed capital stocks could be represented as follows. The stock at time t is equal to the new investment at time t plus the stock at time t-1 less the retirements of capital which depends on the depreciation rate :

$$K_t = I_t + (1-\delta)\,K_{t-1}$$
$$K_t = I_t + (1-\delta)\,I_{t-1} + (1-\delta)^2\,I_{t-2} + (1-\delta)^3\,I_{t-3} + \dots$$

Then, if we assume a constant annual rate of growth of the past investments :

$$K_t = I_t + (1-\delta)\,\lambda\,I_{t-1} + (1-\delta)^2\,\lambda^2\,I_{t-2} + (1-\delta)^3\,\lambda^3\,I_{t-3} + \dots$$

$$K_t = I_t\,\left(1 + \frac{\lambda\,(1-\delta)}{1-\lambda\,(1-\delta)}\right)$$

$$K_t = I_t\,\left(\frac{1}{1-\lambda(1-\delta)}\right)$$

where K_t = Fixed Capital stock at time t.

I_t = New investment at time t.

δ = Depreciation rate (constant over time).

$\lambda = \dfrac{1}{1+\eta}$ *and* η = Mean annual rate of growth of I_t.

The same formulation has been employed to calculate the R&D stocks.

Table A1. Database description

ISIC	Abbreviation	Industries	COUNTRIES		
			USA	UK	JAP
3000	**MANTOT**	Total Manufacturing			
3100	**FDT**	Food, Beverage, & Tobacco			
3200	**TC**	Textile, Wear. App, Leather			
3300	**WCF**	Wood & Wood Products			
3400	**PP**	Paper & Paper Products			
3500	**CHEMIC**	Chemicals			
3510+3520-3522	**CH**	Chemicals & Chemicals Products			
3522	**DR**	Drugs & Medecines			
3530+3540	**PE**	Petroleum Refineries			
3550+3560	**RP**	Rubber Products			
3600	**SCG**	Non Metallic min. Products			
3700	**BASMET**	Basic Metals			
3710	**FM**	Iron Steel			
3720	**NFM**	Non Ferrous Metal			
3800	**METPRO**	Metal Products, Mach. & Equipments			
3810	**FMP**	Metal Products			
3820-3825	**MAC**	Machinery			
3825	**OC**	Office, Computer, Account Mach			
3830-3832	**EM**	Electrical Machinery			
3832	**EE**	Radio, Tele, Comm., Equipement			
3841	**SH**	Shipbuilding	**n.a.**		
3843	**MV**	Motor vehicle			
3845	**AE**	Aircraft			**n.a.**
3842+3844+3849	**OTR**	Other transport equipment		**n.a.**	**n.a.**
3850	**IN**	Professional goods			
3900	**OTMAN**	Other manufacturing			
Available period			**1978-90**	**1978-90**	**1978-89**
Number of industries (does not include aggregated sectors: ISIC 35, 37, and 38)			**21**	**21**	**20**

Table A2. "Replacement" industries for unavailable data on industrial output price index (a)

ISIC	Abbreviation	Industries	COUNTRIES		
			USA	UK	JAP
3000	**MANTOT**	Total Manufacturing			
3100	**FDT**	Food, Beverage, & Tobacco			
3200	**TC**	Textile, Wear. App, Leather			
3300	**WCF**	Wood & Wood Products			
3400	**PP**	Paper & Paper Products			
3500	**CHEMIC**	Chemicals	-	-	-
3510+3520-3522	**CH**	Chemicals & Chemicals Products			
3522	**DR**	Drugs & Medecines			**CH**
3530+3540	**PE**	Petroleum Refineries			
3550+3560	**RP**	Rubber Products			**CHEMIC**
3600	**SCG**	Non Metallic min. Products			
3700	**BASMET**	Basic Metals	-	-	-
3710	**FM**	Iron Steel			
3720	**NFM**	Non Ferrous Metal			
3800	**METPRO**	Metal Products, Mach. & Equipments	-	-	-
3810	**FMP**	Metal Products			
3820-3825	**MAC**	Machinery			
3825	**OC**	Office, Computer, Account Mach	**GER (b)**	**GER (b)**	**GER (b)**
3830-3832	**EM**	Electrical Machinery			
3832	**EE**	Radio, Tele, Comm., Equipement	**EM**	**EM**	**EM**
3841	**SH**	Shipbuilding			
3843	**MV**	Motor vehicle			
3845	**AE**	Aircraft	**MV**	**MV**	**MV**
3842+3844+3849	**OTR**	Other transport equipment	**MV**	**MV**	**MV**
3850	**IN**	Professional goods	**EM**	**EM**	**EM**
3900	**OTMAN**	Other manufacturing	**MANTOT**	**MANTOT**	**MANTOT**
Availability of original price index, over 22 desaggregated industries			**0,73**	**0,73**	**0,64**

(a) The "replacement" manufacturing price index is choosen as the most tightly correlated with the "missing" industry price index in other countries.

(b) Office machines and computers is the only industry were the production price index has been stable or downward along the period.
As we belief that such evolution has been similar in other countries, we applied the German price index to all other countries.

Table A3. Industry specific lags between investment in R&D and the introduction of a new technology, and industry specific depreciation rates of R&D investments in Japan.

	R&D period before Introduced technology	Average Life of Technology Royalty-earning period	Implied depreciation rates
All industries	2,40	9,73	0,10
Agriculture, forestry, and fisheries	2,00	5,60	0,18
Construction	2,10	8,86	0,11
Food	2,00	16,60	0,06
Textile	2,00	8,70	0,11
Pulp and paper	1,40	11,20	0,09
Chemicals	2,70	12,60	0,08
Oil, fat, and paint	2,53	7,60	0,13
Pharmaceuticals	5,40	10,00	0,10
Other chemical industries	3,20	10,60	0,09
Oil and coal products	2,20	13,00	0,08
Rubber goods	1,30	8,00	0,13
Ceramics	2,20	14,00	0,07
Steel	1,70	12,20	0,08
Nonferrous metals	2,60	13,30	0,08
Metal products	2,50	9,80	0,10
Industrial machinery	1,60	13,80	0,07
Electrical machinery	2,90	7,70	0,13
Communications, electronics, and electrical inst	1,80	6,90	0,14
Automobiles	2,60	9,48	0,11
Other transportation equipment	2,20	7,04	0,14
Precision instruments	2,10	4,06	0,25
Other manufacturing industries	1,70	6,10	0,16
Transportation, communications, and utilities	2,80	6,68	0,15

Source : White Paper on Science and Technology 1985 - New Development of R&D and the Era of Cooperation - by Science and Technology Agency, December 1985

Table A4. Average Service Lives of Machinery Equipment (excluding vehicles) in Manufacturing Activities (years) and Corresponding Depreciation Rates : delta = 1/Average Service Live of Machinery Equipment (%)

	USA		Japan		UK		Average	
	Years	delta	Years	delta	Years	delta	Years	delta
Arithmetic Average	17	5,88	11	9,09	26	3,85	19	5,26
Food, beverages and tobacco	20	5,00	11	9,09	26	3,85	20	5,00
Textile, clothing and leather	15	6,67	10	10,00	25	4,00	18	5,56
Wood and wood products	13	7,69	10	10,00	23	4,35	18	5,56
Paper, paper products, printing etc.	16	6,25	12	8,33	32	3,13	19	5,26
Chemicals	16	6,25	8	12,50	29	3,45	18	5,56
Chemicals and chemical products	16	6,25	8	12,50	29	3,45	18	5,56
Drugs and medecines	16	6,25	8	12,50	29	3,45	18	5,56
Petroleum and coal products	22	4,55	13	7,69	23	4,35	20	5,00
Rubber and Plastic products	14	7,14	9	11,11	24	4,17	17	5,88
Non-metallic mineral products	19	5,26	9	11,11	24	4,17	19	5,26
Basic metals	27	3,70	13	7,69	26	3,85	21	4,76
Iron and steel	27	3,70	13	7,69	26	3,85	21	4,76
Non ferrous metals	27	3,70	13	7,69	26	3,85	21	4,76
Metal products, mach. & equipments	14	7,14	10	10,00	25	4,00	19	5,26
Metal products	24	4,17	11	9,09	26	3,85	20	5,00
Non-electrical machinery	25	4,00	12	8,33	25	4,00	19	5,26
Office, computer, account. mach.	14	7,14	10	10,00	25	4,00	19	5,26
Electrical machinery	14	7,14	10	10,00	25	4,00	19	5,26
Radio, telecom. equipment	14	7,14	10	10,00	25	4,00	19	5,26
Shipbuilding	17	5,88	11	9,09	27	3,70	19	5,26
Motor vehicules	14	7,14	11	9,09	27	3,70	18	5,56
Aircraft	17	5,88	11	9,09	27	3,70	19	5,26
Other transport equipment	17	5,88	11	9,09	27	3,70	19	5,26
Instruments	14	7,14	11	9,09	24	4,17	18	5,56
Other manufacturing industries	17	5,88	11	9,09	24	4,17	18	5,56

Sources : Adapted from BLADES D.W., "Capital Measurement in the OECD Countries : an Overview", in "Technology and Productivity - The Challenge for Economic Policy", OECD, TEP - The Technology Economy Programme, 1991, pp. 159.

Table A5 : Proximity indexes for the distribution of output or technology across industries

	Time comparison			Output and Technology			International Output				
	A78O	J78O	J78T	A7OT	J7OT	J8OT	AJ7O	AJ8O	AU8O	JU8O	AJ7T
Food, beverage, and tobacco	0,83	0,84	1,00	0,84	0,84	0,53	0,97	0,96	0,87	0,98	0,91
Textile, apparels, and leather	0,99	1,00	0,95	0,99	0,69	0,44	1,00	0,99	0,94	0,96	0,70
Wood, wood products, and furnitures	0,89	1,00	***0,99***	0,81	***0,13***	***0,18***	0,92	1,00	0,97	0,97	***0,87***
Paper, products, and printing	0,79	0,98	1,00	0,97	0,63	0,54	0,90	0,99	0,98	0,99	0,94
Chemicals excluding drugs	0,88	0,97	1,00	0,98	0,80	0,65	0,97	0,91	0,91	0,92	0,87
Drugs and medicines	0,93	1,00	1,00	0,96	0,01	0,01	0,89	0,98	0,28	0,12	0,22
Petroleum refineries and product	0,97	0,99	0,97	0,35	0,11	0,24	0,94	0,99	0,99	1,00	0,92
Rubber and plastic products	0,96	0,94	***0,99***	0,68	***0,13***	***0,18***	0,84	0,98	0,98	0,96	***0,87***
Nonmetallic mineral products	0,99	1,00	0,96	0,39	0,16	0,12	0,99	1,00	1,00	1,00	0,98
Ferrous metals	0,90	0,30	1,00	0,53	0,99	0,18	0,68	0,98	0,94	0,96	0,98
Nonferrous metals	0,75	0,93	0,91	0,92	0,65	0,71	0,85	0,89	0,94	0,91	1,00
Metal products	0,99	0,99	0,87	0,88	0,07	0,17	0,93	0,95	0,92	0,86	0,52
Nonelectrical machinery	0,61	0,86	0,99	0,65	0,39	0,12	0,75	0,93	0,82	0,70	0,23
Office and computing equipment	0,94	0,75	***0,97***	0,95	***0,73***	***0,93***	0,88	1,00	0,94	0,95	***0,33***
Electrical machines excl. communicatio	0,87	0,64	0,98	0,94	0,35	0,79	0,93	0,88	0,88	0,96	0,28
Radio, T.V., communication equipment	0,74	0,92	***0,97***	0,76	***0,73***	***0,93***	0,97	0,61	0,91	0,34	***0,33***
Motor vehicules and equipment	0,84	1,00	1,00	0,53	0,00	0,06	0,39	0,85	1,00	0,82	0,16
shipbuilding	***0,84***	1,00	***0,94***	***0,83***	***0,03***	***0,06***	***0,83***	0,98	0,46	0,64	***0,07***
Aircraft, missiles, spacecraft, and ordna	0,68	0,26	***0,94***	0,69	***0,03***	***0,06***	0,29	0,67	0,66	1,00	***0,07***
Other transportation equipment	***0,84***	1,00	***0,94***	***0,83***	***0,03***	***0,06***	***0,83***	1,00	0,70	0,68	***0,07***
Professional goods	0,96	0,86	0,98	0,99	0,13	0,16	0,78	0,95	0,82	0,85	0,18
Other manufacturing	0,94	0,90	0,99	0,74	0,13	0,18	0,85	0,99	0,99	0,97	0,87
minimum	0,61	0,26	0,87	0,35	0,00	0,01	0,29	0,61	0,28	0,12	0,07
maximum	0,99	1,00	1,00	0,99	0,99	0,93	1,00	1,00	1,00	1,00	1,00
mean	0,87	0,87	0,97	0,78	0,35	0,33	0,84	0,93	0,86	0,84	0,56
6 "core" sectors (3)	0,83	0,83	0,98	0,88	0,52	0,60	0,88	0,88	0,88	0,79	0,37

1. Italic and bold numbers : More aggregate level of classification, cfr Table A1.
2. Between each pair of matrices, the proximity index is computed for each industry,
as regard to the repartition frequences of output across the 19 manufacturing industries and services.
3. The 6 "core" sectors : Mean across the six "core" sectors, as defined by Robson, Townsend, and Pavitt (1988).
These sectors are : Chemicals, Machinery, Electrical machines, Instruments, Computers,
Communication and electronic components.
4. A = USA, J = Japan, U = the UK, 7 = 1972, 8 = 1985, O = input-output matrix, T = Technological flows matrix.
5. Proximity index between industry J and industry A, the inter-industry output repartition frequences vectors
Fj and Fa are used as follows : Pja = FjFa' /[[(FjFj') (FaFa')] exp1/2] .
It is unity for industries whose output repartition vectors are identical; bounded between 0 and 1 for all pairs.

Table A6 : Correlation coefficient of output distribution frequences (without intra-company shipments)

	Time comparison			Output and Technology			International Output				
	A78O	J78O	J78T	A7OT	J7OT	J8OT	AJ7O	AJ8O	AU8O	JU8O	AJ7T
Food, beverage, and tobacco	0,998	0,112	0,972	0,997	0,262	0,006	0,087	0,985	0,935	0,982	-0,041
Textile, apparels, and leather	0,962	0,978	0,992	0,681	-0,097	-0,088	0,903	0,839	0,825	0,972	-0,051
Wood, wood products, and furnitures	0,997	0,999	***0,962***	0,988	***-0,03***	***0,143***	0,996	0,999	0,995	0,995	***0,003***
Paper, products, and printing	0,923	0,991	0,939	0,955	0,047	0,148	0,895	0,997	0,988	0,985	-0,034
Chemicals excluding drugs	0,954	0,991	0,056	0,912	0,375	0,102	0,892	0,853	0,921	0,791	0,314
Drugs and medicines	0,886	0,999	0,676	0,084	0,847	0,953	0,666	0,754	0,998	0,715	0,300
Petroleum refineries and product	0,984	0,994	0,860	0,999	0,192	0,163	0,966	0,996	0,995	0,997	-0,050
Rubber and plastic products	0,919	0,918	***0,962***	0,667	***-0,03***	***0,143***	0,834	0,959	0,957	0,888	***0,003***
Nonmetallic mineral products	0,998	-0,117	0,757	0,928	0,233	0,069	-0,107	0,997	0,998	0,997	0,418
Ferrous metals	0,978	0,948	0,915	0,939	0,792	0,746	0,905	0,968	0,925	0,961	0,322
Nonferrous metals	0,920	0,842	0,500	0,967	0,692	0,454	0,804	0,789	0,947	0,790	0,910
Metal products	0,996	0,992	0,653	0,931	0,055	0,095	0,933	0,941	0,894	0,857	-0,002
Nonelectrical machinery	0,929	0,869	0,145	0,838	-0,004	-0,097	0,857	0,913	0,764	0,640	-0,252
Office and computing equipment	0,991	0,989	***0,992***	0,988	***0,091***	***0,599***	0,977	0,999	0,976	0,974	***-0,060***
Electrical machines excl. communicatio	0,872	0,546	0,975	0,933	0,233	0,928	0,937	0,858	0,853	0,979	-0,067
Radio, T.V., communication equipment	0,913	0,415	***0,992***	0,839	***0,091***	***0,599***	0,771	0,305	0,970	0,349	***-0,060***
Motor vehicules and equipment	0,999	0,999	0,887	0,995	-0,135	-0,057	0,999	0,998	0,998	0,999	-0,172
shipbuilding	***0,826***	1,000	***0,931***	***0,817***	***-0,07***	***-0,05***	***0,817***	1,000	0,998	0,998	***-0,060***
Aircraft, missiles, spacecraft, and ordna	0,602	1,000	***0,931***	1,000	***-0,07***	***-0,05***	1,000	0,604	0,597	0,997	***-0,060***
Other transportation equipment	***0,826***	-0,072	***0,931***	***0,817***	***-0,07***	***-0,05***	***0,817***	0,874	0,176	0,008	***-0,060***
Professional goods	0,975	0,846	0,834	0,994	0,287	0,015	0,768	0,944	0,843	0,877	-0,073
Other manufacturing	0,977	0,885	0,962	0,964	-0,029	0,143	0,867	0,989	0,995	0,973	0,003
minimum	0,60	-0,12	0,06	0,08	-0,14	-0,10	-0,11	0,31	0,18	0,01	-0,25
maximum	1,00	1,00	0,99	1,00	0,85	0,95	1,00	1,00	1,00	1,00	0,91
mean	0,93	0,78	0,81	0,87	0,17	0,22	0,80	0,89	0,89	0,85	0,06
Number of significant coef.	22	19	20	21	3	6	20	21	21	20	2
6 "core" sectors (3)	0,939	0,776	0,666	0,918	0,179	0,358	0,867	0,812	0,888	0,768	-0,033

1. Italic and bold numbers : More aggregate level of classification, cfr Table A1.
2. Between each pair of matrices, the correlation coefficient is computed for each industry, as regard to the repartition frequences of output across the other 18 manufacturing industries and services.
3. The 6 "core" sectors : Mean across the six "core" sectors, as defined by Robson, Townsend, and Pavitt (1988). These sectors are : Chemicals, Machinery, Electrical machines, Instruments, Computers, Communication and electronic components.
4. A = USA, J = Japan, U = the UK, 7 = 1972, 8 = 1985, O = input-output matrix, T = Technological flows matrix.
5. Coefficients over 0,4 are significantly different from zero at a 5% probability threshold.