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Exploring the Spillover Impact on Productivity of World-Wide Manufacturing Firms

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ABSTRACT. – This paper analyzes the relationship between R&D activity, spillovers and productivity at the firm level. Particular attention is put on the formalization of technological spillovers. The analysis is based upon a new dataset composed of 625 worldwide R&D-intensive manufacturing firms whose information has been collected for the period 1987-1994. Given the panel data structure of the sample, ad hoc econometric techniques which deal with both firm's unobserved heterogeneity and weak exogeneity of the right hand-side variables are implemented. The empirical results suggest that spillover effects influence significantly firm's productivity. Nevertheless the effects differ substantially among the pillars of the Triad. The United States are mainly sensitive to their national stock of spillovers while Japan appears to draw from the international stock. On its side, Europe shows a tendency to internalize spillovers.

Évaluation de l'impact des externalités technologiques sur la productivité des entreprises manufacturières mondiales

RÉSUMÉ. – Cet article quantifie la relation entre la R&D, les externalités technologiques et la productivité au niveau de la firme. Une attention particulière est apportée à la formalisation des externalités. L'analyse se fonde sur un nouvel échantillon composé de 625 entreprises mondiales intensives en R&D dans le secteur manufacturier. L'information collectée couvre la période 1987 à 1994. Etant donné la structure de données de panel caractérisant l'échantillon, des méthodes économétriques prenant en compte l'hétérogénéité des entreprises et l'exogénéité faible des régresseurs sont mises en œuvre. Il résulte des estimations que les externalités influencent de manière significative la productivité des entreprises. Néanmoins ces effets apparaissent substantiellement différents au sein des piliers de la Triade. Les Etats-Unis sont principalement sensibles à leur propre stock national d'externalités tandis que le Japon semble puiser dans le stock international. De son coté, l'Europe montre des faiblesses à internaliser les externalités.

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1 Introduction

The purpose of this paper is to measure the impact of technological activity of firms on their economic performance as measured by output. More specifically, the stress is put on technological spillovers [1] which are often described as a main source of technology-push. These determinants are quantified from a new database composed of 625 worldwide R&D-intensive firms over the period 1987-1994. So, our main objective is to deal with the measurement of technological spillovers at the micro level on the basis of a new dataset gathering information from large companies representative of industrialized countries. To this end, Jaffe's methodology (1986, 1988), which associates econometrics and data analysis, has been adopted. The main contributions of the paper are the enlargement of the analysis to the international dimension and the extension of the appropriability hypothesis in the construction of spillovers to take into account the geographical origin of firms in addition to their technological proximity.

In the second section, we focus the attention on the alternative ways to appreciate the impact of technological spillovers on firms' technological activity with reference to the main approaches proposed in the literature. In the following section, we discuss the methodological framework necessary to characterize and to differentiate the technological determinants. A particular attention is paid to the way in which firms are classified into technological clusters. In the fourth section, we describe the international R&D database. Then, the econometric models to be estimated by panel data methods are presented and the empirical alternative results obtained from the sample discussed. We conclude by underlining the main observations resulting from the econometric analysis as well as some points deserving further research.

2 Measuring Technological Spillovers

The economics of innovation has for a long time emphasized the role played by exogenous technological factors, often designated as "technology push forces". Among these factors, one can distinguish technological opportunity and technological spillovers.

Technological opportunity can be defined as the difficulties or the costs linked with the innovation activity in a given area of technology. These costs may vary according to technological classes given that the characteristics

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[1] See GRILICHES [1992] and MOHNEN [1996] for a review of the empirical literature.

intrinsic to technology, on the one hand, and the available stock of scientific knowledge at a certain point of time, on the other hand, differ among fields of technological specialization. These differences are assumed to be reflected by technological opportunities which vary from a technological class to another and which makes the technological activity of a given firm more profitable in some fields.

As stressed by GRILICHES [1992], there is often a confusion about the two distinct notions of technological spillovers. The first kind of spillovers is related to new products and processes which embody technological change and are bought by other firms at less then their "full quality adjusted" prices. The second kind of technological spillovers can be defined as the potential benefits of the research activity of other firms for a given firm. These spillovers exist because of the "non rival and partially excludable" property of technology. A distinction can be made between the spillovers coming from the firm's industry and those which arise from other industries. According to the firm's country, a similar distinction can be made between the national and the international nature of these spillovers. The technological opportunity, as well as the technological spillovers, affect the costs of innovation. If the appropriability of knowledge is imperfect and if many firms are involved in similar technological activities, then the costs of innovation for a given firm are likely to be affected by these activities. For instance, if the technological spillovers and the firm's own R&D are complementary, then an increase of these spillovers should lead the firm to intensify its R&D effort.

Several approaches have been proposed in the literature in order to formalize technological spillovers. MOHNEN [1996] distinguishes five approaches that may be listed into two categories according to whether the R&D stocks of all other firms or industrial sectors are weighted or not. We are here only concerned with the second category in which the R&D stocks are weighted according to the technological linkage or proximity between firms or industrial sectors. This proximity can be alternatively calculated on the basis of the matrix of intermediate input purchases, patents or innovation flows [2] as well as on the basis of the firms' positions in the technological space. This last approach was developed by JAFFE (1986, 1988). The firm's position in the technological space is characterized by the distribution of its patents over patent classes. This way of formalizing technological spillovers suffers from the limits of the use of patents as indicators of the output of the innovation activity [3].

The firm's position in the technological space, as well as the distinction between a global and a local stock of technological spillovers are the key points of this approach which has been adopted in the present paper. Thanks to the international dimension of our database, Jaffe's methodology has been extended by considering the technological proximity among firms

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[2] See TERLECKIJ [1974, 1980], SCHERER [1982] and ROBSON et al. [1988] for more details about these approaches.

[3] For the relevance of patent statistics as an indicator of the technological output, see GRILICHES [1990] for instance.

as well as the geographic one. Hence, it is interesting to separate the national stock of spillovers from its international counterpart. Such an exercise should improve our understanding of how and to what extent R&D spillovers generated in one country affect the economic performances of other economies.

3 Locating Firms in the Technological Space

3.1. Technological Proximities and Total, Local and National Technological Spillovers

Locating firms into the technological space allows one to formalize the technological spillovers. Indeed, this way of formalizing spillovers is closely related to the notion of technological proximity: the closer two firms are in the technological space, the more the research activity of one firm is supposed to be affected by the technological spillovers generated by the research activities of the second firm. Hence, it is assumed that each firm faces a potential 'stock' of spillovers, which is a weighted sum of the technological activities undertaken by all other firms. In order to measure the technological closeness between firm i and j, Jaffe used the 'angular separation' between them, *i.e.* he computed the uncentered correlation between their respective vectors of technological position, $T_i = (t_{i1}, ..., t_{iK})$ and $T_j = (t_{j1}, ..., t_{jK})$:

$$P_{ij} = \frac{\sum_{k=1}^{K} T_{ik} T_{jk}}{\sqrt{\sum_{k=1}^{K} T_{ik}^2 \sum_{k=1}^{K} T_{jk}^2}} \tag{1}$$

This measure of closeness takes values between one and zero according to the common degree of research interest of both firms. In order to measure the distribution of the firm's research interests through the different technological areas, we use the patent distribution over 50 technological sectors according to the International Patent Classification (IPC). The patent distribution relies on the whole number of patent applications [4] filed to the European Patent Office during the period 1978-1994.

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[4] The patents considered here are those classified by date of application rather then by date of issue as is it the case in Jaffe's study. According to JAFFE [1986], patents classified by date of application are preferable because they reflect the moment when a firm makes out itself to have generated an innovation and because of the existence of long lags in a patent's application process.

In the following example, we observe that Solvay and Du Pont de Nemours are closer to each other than to Renault or Honda. This is quite normal given the nature of the research activities of these firms.

Example of Technological Proximity between Firms.

FIRM	NPA[a]	SOLVAY	DU PONT	RENAULT	HONDA
SOLVAY	284	1			
DU PONT DE NEMOURS	4412	.785	1		
RENAULT	636	.021	.058	1	
HONDA	618	.044	.063	.946	1

a: # of patent applications field to the European Patent Office during the period 1978-1994.

It should be observed that this measure is purely directional, *i.e.* it does not depend on the technological vector's length. Once the measure of closeness between firms i and j is calculated, the potential stock of technological spillovers of the i^{th} firm can be evaluated as follows:

$$S_i = \sum_{\substack{j \\ j \neq i}} P_{ij}\, K_j \tag{2}$$

where:

$S_i = \text{stock of spillovers of firm } i,$
$K_j = \text{R\&D capital stock of firm } j.$

This index of technological distance relies on the strong assumption that the appropriability conditions of knowledge are the same for all firms (JAFFE, 1988) [5]. Another drawback of this method is that firms which encounter a rather diversified technological activity will benefit to a lesser extent from the stock of spillovers. Indeed, the more the firm's R&D activities are diversified, the more its patent distribution over technological classes is uniform and the more the index of technological closeness is likely to be close to zero. A firm which is technologically diversified will be located in the central region of the technological space so that it will not be close to any firm. An alternative standpoint is to say that firms are aware of the research activities undertaken by only a few technologically similar firms. In that sense, even if all stocks of technological spillovers are relevant, they will probably not be taken into account completely due to imperfect information about the content of R&D realized by rivals. In order to examine this possibility, Jaffe divided the potential stock of spillovers into two distinct components obtained by applying a clustering method: a local stock which

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[5] According to SPENCE [1984], an imperfect appropriation can be defined as the proportion Φ of the output of each firm's technological activity that is disclosed. If $\Phi = 0$, then appropriability is perfect, if $\Phi = 1$, then R&D is a pure public good.

corresponds to the sum of R&D stocks of firms belonging to a same cluster of technological activities and an external stock which is computed from the other firms. Thanks to the international dimension of our sample, Jaffe's methodology has been extended by distinguishing, besides the local and external stocks, national stocks [6] from international ones. In this way, we will be able to appreciate to what extent geographical and cultural contiguity matters. Furthermore, in order to consider the technological as well as the geographical closeness, the potential stock of spillovers was dissociated into four components: the local national stock, the local international stock, the non-local or external national and international stocks.

3.2. **Firm's Attribution to Technological Clusters**

This section discusses the procedure which allows one to group the firms into homogeneous categories or clusters on the basis of their technological 'nearness'. Because of this closeness, firms belonging to a same cluster are assumed to face the same state of technological opportunity. Among the several techniques available to combine firms into clusters, the K-means clustering method is one of the most commonly used [7]. In the present paper, we experimented this technique as well as two others: the K-Means clustering with 'strong centers' and the agglomerative hierarchical clustering methods [8]. The algorithm, which has been used to combine firms into clusters, works on the factorial coordinates of a preliminary principal components analysis. The advantage of this method is that it uses an Euclidean distance between firms, which permits considering an objective criterion in order to evaluate the quality of the firms' partition. This distance is used for measuring how far apart two firms are in the factorial space. Besides the benefit of the orthogonality of factorial axes, another advantage of this method is that it does not take into account the last factorial axes which often carry random components. Given the nature of our data, the analysis of binary correspondence of the contingency table, *i.e.* the table of the firm's patent distribution across 50 IPC classes, has been performed to compute the factorial axes.

A common difficulty to all clustering techniques is to fix the number of clusters present in the data. Different procedures for determining the 'optimal' number of clusters have been proposed in the literature [9]. In this study, the three experimented clustering techniques are based on Ward's aggregation criterion. This criterion allows one to measure the quality of the firm's partition into technological clusters by considering the within and the without cluster inertia. The within cluster inertia represents the mean of the squared distances between the firms' cluster and its center of gravity, while the without cluster inertia consists in the mean of the squared

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[6] In this paper, we consider alternatively Europe and the European countries as specific geographic regions.

[7] JAFFE [1986] derived a modified version of this method which allows him to take the multinomial structure of the firm's patent distribution into account.

[8] See LEBART, MORINEAU and FENÉLON [1979] for a description of these methods.

[9] For an examination of some of these procedures, see Milligan and COOPER [1985].

distances between all cluster centers of gravity and that of the whole data sample. Ward's criterion for forming the clusters consists of maximizing the ratio between these two inertia in order to get the most homogenous and the most distant possible clusters. It should be noticed that such a ratio does not permit one to compare two partitions with a different number of clusters. Actually, the partition into $k+1$ clusters will always have a higher ratio of inertia than a partition into k clusters. Ultimately, the best possible partition would be the one which has as many clusters as the number of firms. In this case the ratio of inertia is equal to zero given that each firm is blended with its cluster center. To choose the number of clusters, a two step procedure has been applied. In a first step, the agglomerative hierarchical and the K-Mean with Strong Centers clustering methods have been identified as the best candidates as far as the measure of inertia is concerned. In a second step, we experimented different stocks of local spillovers constructed from different partitions into k clusters according to the agglomerative hierarchical method for k equal 15 to 29. These stocks have been systematically tested in the productivity regression model. The local stock based on k equal to 18 has appeared the most satisfactory both in terms of the regression's overall fit and the estimated standard error associated to the local stock coefficient. For these reasons, we decided to retain the partition with 18 clusters, against 21 clusters in Jaffe's analysis.

4 Data, Total Factor Productivity and Econometric Models for Panel Data

4.1. **Data and Variables**

The R&D database has been constructed with the view of setting up a representative sample of the largest firms at the international level that reported R&D expenditure during the last 10 years. The database consists of a balanced panel of 673 firms over the period 1987 to 1994. This dataset has been extracted from the *Worldscope* database which provides information on financial profiles for companies around the world [10]. For each firm, information is available for net sales, number of employees, capital stock, annual R&D expenditure and major industry group according to the Standard Industrial Classification (SIC-2 digits) [11]. The European Patent Office (EPO)

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[10] The *Worlsdcope* database is produced by Worldscope/Disclosure partners.

[11] More details regarding this information is provided in the Worldscope data definitions guide (1994).

is the second source of information. This office supplies the firm's patent applications across technological classes according to the International Patent Classification (IPC) for the whole period from 1978 to 1994.

A major task in constructing the sample has been the matching of patents to firms. In a first step, patents were assigned to firms on the basis of their generic names [12]. Second, many large firms have several R&D performing subsidiaries and it is not obvious to link the patents applied by these subsidiaries to the parent company [13]. Thanks to the software provided in the EPO database, it has been possible to minimize these issues to a great extent. Indeed, by choosing one or more criteria (such as firm's name or parts of it, country codes,...), the software retrieves all documents meeting these criteria. For instance, searching for the word 'Du Pont' gave 4599 patent documents (from 1978 up to 1994). Examining more in details the firm's full names reported in these documents, it appeared that 4191 patents were assigned to 'E.I. Du Pont De Nemours and Company' while 221 documents were attributed to foreign subsidiaries of the US parent company and 120 to 'Du Pont Merck Pharmaceutical Company'. Hence, 4412 patents have been retained for Du Pont de Nemours. This procedure has been repeated for each firm of the sample : for about four fifths of the sample there was only one firm's name in the retrieved documents. For the rest, firm's names which could be identified without any doubts as subsidiaries have been included in the matching process of generic names.

In order to allow for comparison, all variables have been converted to constant 1990 dollars. R&D expenditures have been deflated using the GDP deflators of respective countries, while the deflator of physical capital has been used for the capital stock [14]. Also, due the presence of outliers [15], a cleaning procedure has been applied to this subset of firms (for details, see annex 1) in order to reject firms whose variables displayed very high and often irrelevant variations. The final sample retained for estimations includes 625 firms. A substantial number of firms in the sample have more than one product line at the SIC two digit level. Furthermore, these firms are multinational so that a large amount of their sales is performed outside the domestic market. Since these firms are 'multiproducts' and have subsidiaries in several countries, the use of domestic output prices indexes at the 2 digit industry level for each country did not seem to be a relevant

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[12] For instance, Honda has been used for Honda Motor Co. LTD and Honda Giken Kogyo Kabushiki Kaisha.

[13] Ideally, one has to have a 'mapping' of the main firms to their subsidiaries. However it is not easy at all to construct an accurate mapping since by essence it changes over time.

[14] The capital stock measures correspond to the net property, plant and equipment of firms. 'Net' means that accumulated reserves for depreciation, depletion and amortization are not included. Information on capital annual expenditures is available as well. Hence it may have been possible to construct a capital stock according to the perpetual inventory method. However, this approach requires to know the rates of depreciation of physical capital which vary across firms and over time. Since this information is unavailable and capital expenditures are missing for some firms and years, this approach has not been considered.

[15] Mainly due to the process of mergers and acquisitions of firms over time. Indeed, 419 firms in our sample acquired at least one company during the period investigated.

approach to deflate net sales [16]. Instead, thanks to the availability of the shares of sales performed in the home country [17] and abroad, a more general price index has been performed according to the following formula:

$$(3) \quad WPI_i = d_i\, PI_i + (1 - d_i) \sum_{j \neq i}^{n} w_j\, PI_j \qquad \text{and} \qquad w_j = \frac{VA_j}{\sum_{j \neq i}^{n} VA_j}$$

where WPI_i is the weighted manufacturing price index used to deflate net sales of firm i,
d_i is the share of sales of firm i performed in its home country,
PI_i is the price index of added value for the whole manufacturing sector in firm's i home country,
$j = 1, ..., n$ and n is the number of countries considered in this study,
w_j is the share of added value of country j with respect to the sum of added value of the $(n - 1)$ countries.

Some variables have been constructed for the purpose of the analysis. The stock of R&D capital has been built on the basis of the permanent inventory method with a depreciation rate equal to 15 percent and an initial stock of R&D capital calculated by assuming a growth rate of R&D expenditure equal to 5 percent. The IPC classification allows one to identify the technological classes of patent applications. The IPC at the two digit level is composed of 118 technological classes. In order to ease the calculations, these 118 classes were grouped into 50 broader classes. On this basis, a table of contingency, *i.e.* a table reporting the distribution of the firms' patents across the 50 IPC classes, has been constructed. This table was used for computing the index of technological closeness [18] and consequently the stocks of spillovers.

The first column in Table 1 gives a view of the geographical and sectorial composition of the sample. With sixty per cent of firms, the United-States are largely over-represented in the sample. If we have a look at the sectorial distribution of firms, we observe that the weight of American firms is particularly important in some sectors: computer & office equipment, professional goods and software. European firms account for only sixteen percent while Japanese firms cover twenty one per cent of the sample. So, a main drawback of the sample is the under-representativeness of European firms. This is mainly a consequence of the miss of data availability for

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[16] It should be noticed that the Worldscope data are based on firm's consolidated accounts unless specified. This raises the question of the comparability of data. Due to the diversity of accounting practices across countries, it is not obvious how subsidiaries or affiliates should be aggregated. In order to aggregate data in the most possible accurate way, the terminology used in reported accounting information has been redefined in a generic standard way by the Worldscope analysts.

[17] For instance, for the Swedish firms of the sample, the average share of sales performed by these firms in Sweden is 13.7% while for the Japanese firms this figure is 79.6%.

[18] It might be objected that the measure of technological proximities that we get using European patents applied by non-European firms may be quite distorted or incomplete. Indeed it can be expected that the propensity of European firms to patent in Europe differs from that of U.S. firms and Japanese firms and that this propensity varies across fields for firms based in different continents. Yet in the absence of a "global" patent office, we have no choice but to use national or regional patent data.

these firms for the first years covered by the sample. Indeed, despite the availability of data for a larger sample of European firms for a shorter period, the panel so built allows to optimize jointly the number of firms as well as the number of periods.

TABLE 1

Sectorial and Geographical Characteristics of Variables (average over the period 1987-1994)

	Number of firms				Sales [b]	Employment [c]	Physical capital [b]	R&D capital [b]	R&D [b]	Spillovers [b]	R&D intensity [d]
	RW [a]	EU	JP	US							
Aircraft	0	5	2	10	5897	46	1355	1879	302	130589	5.1
Chemicals	0	15	25	37	3034	16	1123	776	127	83415	4.2
Computer	0	3	6	35	5598	32	1498	2275	426	106502	7.6
Construction	0	2	5	2	9003	65	1696	3162	619	78252	6.9
Drugs	3	13	19	19	3474	19	1198	1362	281	114782	8.1
Electrical	0	1	7	15	3993	26	1120	608	113	96669	2.8
Electronics	2	9	15	52	3003	22	798	1108	218	134997	7.3
Fabricated metal	1	4	6	16	2046	12	650	172	34	68370	1.7
Food	0	5	2	12	5564	38	1669	394	74	39326	1.3
Instruments	0	7	5	55	1452	11	430	495	94	109744	6.4
Machinery	0	9	11	38	2211	14	560	358	60	73479	2.7
Mining	1	4	0	11	20614	40	1248	1598	255	106463	1.2
Motor vehicles	0	11	6	14	15528	83	4156	3318	673	114262	4.3
Paper	0	1	2	16	2330	13	1632	153	27	54551	1.1
Primary metal	5	8	11	12	3383	15	1843	274	53	84054	1.6
Rubber	0	2	4	6	1500	12	542	227	39	76222	2.6
Software	0	0	0	14	519	3	101	232	62	99824	11.9
Stone	0	2	4	4	2200	16	1048	323	58	85220	2.6
Textiles	0	0	3	4	1364	5	398	100	22	69395	1.6
Wood	1	0	0	6	1533	13	486	87	17	24470	1.1
Average					4198	23	1477	979	187	98618	4.5
Rest of the world [a]	13				2113	12	1342	444	90	80712	4.3
Europe		101			7373	53	2404	1959	375	104076	5.1
Japan			133		3444	13	1023	808	157	111562	4.5
United-States				378	3687	20	1394	796	151	93221	4.1

a: Australia and Canada, b: Millions US dollars 1990, c: in thousands, d: %.

The next column in Table 1 shows the characteristics of the sample. The R&D intensity of industries goes from 1.1 percent in the wood and paper industries to 11.9 percent in the software industry. Regarding the R&D intensity of the different geographical areas, European and Japanese firms included in the sample are more R&D intensive than US ones, which is a consequence of the higher number of US firms. Table 2 gives a view of the representativeness of the sample comparatively to the business enterprise R&D expenditures of the different geographical areas. These percentages have to be interpreted cautiously as the data come from different sources. Nevertheless, these percentages show that despite only 625 firms are retained in this analysis they account for around 32 to 53 percent of the R&D outlays realized in the three main geographical areas.

TABLE 2

Representativeness of the Sample: R&D Realized by Firms as a Percentage of Business Enterprise R&D ^{a}**.**

	1987	1988	1989	1990	1991	1992
Rest of the world	17.5	16.9	16.6	20.7	18.3	18.3
Europe	40.1	43.0	43.4	44.7	46.2	47.6
Japan	34.8	33.6	33.7	32.2	34.2	37.5
United-States	46.4	48.8	51.7	52.6	52.8	53.4

a: OECD's ANBERD database.

4.2. **The Productivity Equation**

The R&D activity implemented by firms is expected to stimulate their productivity. Besides the impact of the firm's own R&D capital as well as the influence of labor and of physical capital stock on productivity, it is worth examining to what extent the spillover stocks improve firm's productivity. In order to answer this question, the Cobb-Douglas production function framework is used. Formally, we have:

$$\ln S_{it} = \alpha_i + \lambda_t + \beta_1 \ln L_{\mathrm{it}} + \beta_2 \ln C_{it} + \beta_3 \ln K_{it} + \gamma \ln X_{it} + \varepsilon_{it} \tag{4}$$

where ln is the natural logarithm,

L_{it} is the employment of firm i at time t ($i = 1$ to 625, $t = 1$ to 8),
K_{it} is the stock of R&D capital,
S_{it} is the net sales,
C_{it} is the stock of physical capital,
α_i is the firm's specific effect,
λ_t is a set of time dummies,
X_{it} is a vector of spillover components,
γ is its associated vector of parameters and
ε_{it} is the disturbance term.

Four alternative specifications of X_{it} have been considered:

– Specification I: Impact of the total stock of spillovers

$$\gamma \ln X_{it} = \gamma_T \ln \mathrm{TS}_{it}, \tag{5}$$

where TS is the total stock of spillovers.

– Specification II: Differentiated impact of the local and external stocks of spillovers

$$(6) \qquad \gamma \ln \mathrm{X}_{it} = \gamma_L \ln \mathrm{LS}_{it} + \gamma_E \ln \mathrm{ES}_{it},$$

where LS, ES are the local and external stocks of spillovers respectively.

– Specification III: Differentiated impact of the national and international spillover stocks

$$(7) \qquad \gamma \ln X_{it} = \gamma_N \ln \mathrm{NS}_{it} + \gamma_I \ln \mathrm{IS}_{it},$$

where NS, IS are the national and international spillover stocks respectively.

– Specification IV: Totally differentiated impact of the spillover stocks

$$(8) \quad \gamma \ln X_{it} = \gamma_{\mathrm{LN}} \ln \mathrm{LNS}_{it} + \gamma_{\mathrm{LI}} \ln \mathrm{LIS}_{it} + \gamma_{\mathrm{EN}} \ln \mathrm{ENS}_{it} + \gamma_{\mathrm{EI}} \ln \mathrm{EIS}_{it},$$

where LNS, LIS, ENS, EIS are the local national, local international, external national and external international spillover stocks respectively.

The R&D stock represents the firm's research activity. As GRILICHES and MAIRESSE [1984] pointed out, the omission of materials as a production factor in the equation above can lead to misspecifications and hence biases in the estimated coefficients. In order to avoid this issue, it is possible to use the added value instead of the sales. Some authors tested whether the use of sales versus added value give different results. The conclusion of GRILICHES and MAIRESSE [1984], CUNÉO and MAIRESSE [1984] and MAIRESSE and HALL [1996] is that the use of sales or added value as a dependent variable leads to similar results. On the other hand, SCHANKERMANN [1981] and HALL and MAIRESSE [1995] indicate that the estimated R&D elasticities are sensitive to the double-counting between R&D and capital expenditures as well as between total employees and the workers allocated to R&D activities. According to these authors, correcting for double-counting tends to slightly increase the R&D elasticity. Consequently, our results should be interpreted cautiously as materials are not included in the model and the R&D estimated coefficients are a measure of the 'excess' R&D elasticity of output.

4.3. **Econometric Panel Data Models**

To estimate the equations specified above, we used standard panel data estimation procedures which allows one to take into account firm's unobserved over time fixed effects. These effects take into account permanent differences among firms. For instance the ability of engineers to discover new inventions is a typical unobserved variable of firms. Actually, these unobservables are likely to be 'transmitted' to the R&D decision since firms facing higher abilities will generally invest more in research activities. Hence neglecting these effects as it is the case in cross-section estimates may lead to some omitted variable biases. In the context of panel data, it is possible to get around this issue by appropriate transformations of data in order to 'eliminate' unobserved fixed effects.

The fixed effects can be removed through the so-called within transformation which can be estimated consistently by OLS provided that the α_i are fixed over time and the regressors are strictly exogeneous [19]. Unfortunately, the strict exogeneity condition is a hypothesis which is hard to maintain in the productivity framework. According to GRILICHES [1995] for instance, when we want to measure the elasticities of the right hand side variables in the equation above, it is not clear to what extent the explanatory variables depend on past, current or future values of the dependent variables or inversely. In other words, does R&D for instance causes output or is it output which causes R&D ? A solution to this simultaneity problem is to use an instrumental variable approach, but quoting MAIRESSE and HALL [1996], applying this approach to the within transformation often invalidate the estimates because the only available instruments are generally lagged values of explanatory variables and in short panels, these variables are likely to be correlated with the disturbances, once the firms means have been removed. Another way to eliminate the unobserved fixed effects consists of first-differencing the productivity equation. An advantage of this transformation is that it does not longer require the strict exogeneity of regressors. However due to possible measurement errors in all the variables, this approach leads generally to estimates which are more biased towards zero than does the within correction (GRILICHES and HAUSMAN [1986]).

In order to allow for all effects to be present, i.e. correlated fixed effects and simultaneity, we performed our estimates using the same methodology as MAIRESSE and HALL [1996] [20]. The methodology departs by assuming the presence of correlated fixed effects with regressors in the productivity equation (so that this equation has to be first-differenced) and by assuming that only lag 2 or higher values of regressors are available as instruments (because later values are correlated with the error term). These assumptions imply the following set of orthogonality conditions between instruments and the error term:

(9) $E\left[X_{is}\,\Delta\varepsilon_{it}\right] = 0 \text{ where } i = 1, ..., N;\ s = 1, ..., t-2 \text{ and } t = 3, ..., T.$

These moment conditions are then estimated by means of the General Method of Moments. Relaxing the assumption of lag 2 or higher values of regressors as valid instruments, implies additional moment conditions. Testing the validity of these additional conditions allows one to determine if the regressors are lag 2, lag 1, weakly or strongly exogeneous. Furthermore, if the fixed effects are not correlated with the regressors, then it is appropriate to estimate the productivity equation in level. Here again, considering this equation in level rather in first-differences implies additional moment conditions whose validity can be tested in order to answer the question of correlated fixed effects.

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[19] Substracting individual means from equation above eliminates the fixed effects (provided that they are constant over time) but contaminates the ε_{it}'s with the disturbances from the other years, $\varepsilon_{i1}, ..., \varepsilon_{iT}$. Hence strict exogeneity of the regressors is required, i.e. $E\left[x_{is}\,\varepsilon_{it}\right] = 0$, $\forall\, s = 1, ..., T$ and $\forall\, t = 1, ..., T$.

[20] This methodology is based on that of ARELLANO and BOND [1991] and KEANE and RUNKLE [1992].

It should be noticed that though this GMM framework seems quite attractive in terms of the modelling possibilities it contains and the weak distributional assumptions it relies on, it nevertheless rests on an instrumental variable approach and as pointed out by GRILICHES and MAIRESSE [1995], the past levels as instruments for current growth rates of regressors such as R&D capital are likely to be quite poor and possess little resolving power.

5 Empirical Results

Estimates of the productivity equation are given in Table 3. We observe that the alternative estimation methods lead to different results, particularly for the spillover variables and GMM estimates. The coefficients obtained for the employment and the physical capital are significant. Yet, their values are inferior to those obtained in some studies, what can be explained by the fact that we use sales instead of added value. While materials were not introduced in the equation due to data unavailability, the coefficients are comparable to those obtained by studies using sales. If we suppose constant return to scale for traditional production factors, the elasticity for materials should be expected to be about .3 to .4.

Regarding the R&D capital elasticities, the estimates give coefficients whose values are globally higher than the measures reported in the literature, what can be explained by the high proportion of R&D-intensive companies in our sample. Indeed, a split of data into two subsamples has given R&D elasticities which are respectively .43 and .44 for high R&D-intensive firms against .12 and .22 respectively for other firms. The GMM estimates are comparable to within and first difference ones in two specifications. Discrepancies among GMM results can be explained by the different sets of instruments used to implement this procedure.

The total spillover stock elasticities are significant and higher than the own R&D elasticities. The distinction between the local and external components exhibits a higher elasticity of output with respect to the external spillover stock. This observation seems to indicate that the inter-industry spillover effects are relatively more important than the intra-industry ones, as far as we consider that there is a close relationship between industries and technological classes.

The breakdown of spillovers between their national [21] and international components puts forward the importance of foreign R&D activities. At the opposite, the national stock gives ambiguous and scattered results. The negative coefficients obtained for within and first difference estimates are astonishing. Yet, this result is not confirmed by the GMM estimate. When

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[21] When the measure of national stocks of European countries is based on the European entity instead of individual countries the estimates are to a large extent similar to the ones reported here.

Table 3

Productivity Estimates.

dependent Variable: ln S					sample: 625 firms × 8 years
WITHIN Level	est. s.e. [a]	OLS F.D.	est. s.e.	GMM-IV F.D.	est. s.e.
lnL lnC lnK lnTS	.50 (0.16)* .21 (.013)* .24 (.015)* 1.11 (.151)*	ΔlnL ΔlnC ΔlnK ΔlnTS	.41 (.029)* .17 (.022)* .32 (.043)* .94 (.277)*	ΔlnL ΔlnC ΔlnK ΔlnTS	.53 (.069)* .07 (.061) .13 (.048)* .80 (.302)*
	R_a^2 .993		R_a^2 .358	X^2 [d.f.] [b] Sim. [c]:	130.3 [76] $+L1$
lnL lnC lnK lnLS lnES	.49 (.016)* .21 (.013)* .24 (.015)* .25 (.042)* .59 (.125)*	ΔlnL ΔlnC ΔlnK ΔlnLS ΔlnES	.40 (.029)* .17 (.022)* .32 (.043)* .24 (.067)* .60 (.228)*	ΔlnL ΔlnC ΔlnK ΔlnLS ΔlnES	.41 (.018)* .15 (.012)* .25 (.017)* .26 (.049)* .37 (.155)*
	R_a^2 .993		R_a^2 .359	X^2 [d.f.] Sim. :	300.3 [195] S
lnL lnC lnK lnNS lnIS	.50 (.016)* .22 (.013)* .25 (.015)* –.31 (.050)* 1.03 (.122)*	ΔlnL ΔlnC ΔlnK ΔlnNS ΔlnIS	.41 (.029)* .17 (.022)* .33 (.042)* –.19 (.106)** .65 (.209)*	ΔlnL ΔlnC ΔlnK ΔlnNS ΔlnIS	.56 (.095)* .08 (.094) .22 (.080)* .13 (.209) .99 (.530)**
	R_a^2 .993		R_a^2 .359	X^2 [d.f.] Sim. :	108.0 [45] $+L3$
lnL lnC lnK lnLNS lnLIS lnENS lnEIS	.50 (.016)* .22 (.013)* .24 (.015)* –.06 (.025)* .19 (.035)* –.41 (.046)* .68 (.097)*	ΔlnL ΔlnC ΔlnK ΔlnLNS ΔlnLIS ΔlnENS ΔlnEIS	.41 (.029)* .17 (.022)* .32 (.043)* –.01 (.045) .15 (.060)* –.26 (.096)* .46 (.185)*	ΔlnL ΔlnC ΔlnK ΔlnLNS ΔlnLIS ΔlnENS ΔlnEIS	.82 (.088)* .01 (.083) .26 (.073) –.04 (.094) .15 (.131) –.21 (.175) 1.3 (.442)*
	R_a^2 .993		R_a^2 .359	X^2 [d.f.] Sim. :	143.4 [63] $+L3$

a: heteroskedastic-consistent standard errors in brackets, * (**) = statistically significant at the 5 (10)% level; b: overidentification test; c: predeterminancy of X_{it}: $W(S)$ =weak (strong) exogeneity, $+L3 = \text{lag}\,3$ and lower values of X_{it} as instruments

the spillover stock is completely disaggregated, the local national stock has no effect, what is not the case for the other components. Yet, only the international stocks influence positively the output while the external stock has a negative impact. There is no rational explanation for this unexpected effect and, consequently, it is worth turning to alternative specifications in order to see if such a result holds. Although it might be argued that it is a consequence of multicollinearity among the different stocks, their correlation coefficients are weak as can be seen from annex 2.

Table 4

Productivity Estimates: Opportunity Effects.

dependent Variable: Δln S				First differences
	est. s.e. [a]	est. s.e.	est. s.e.	est. s.e.
ΔlnL	.40 (0.29)*	.40 (.029)*	.41 (.028)*	.40 (.027)*
ΔlnC	.17 (.022)*	.17 (.022)*	.17 (.021)*	.17 (.021)*
ΔlnK	.32 (.043)*	.32 (.044)*	.32 (.041)*	.31 (.041)*
ΔlnTS	.79 (.298)*	.57 (.367)	.63 (.275)*	.27 (.369)
X^2 stat. [d.f.] on:	ind. effects 60.9 [18]*	technol. effects 51.1 [17]*	geogr. effects 228.6 [15]*	all effects 291.5 [50]*
R_a^2	.364	.363	389	392
ΔlnL	.40 (.028)*	.40 (.028)*	.41 (.027)*	.40 (.027)*
ΔlnC	.17 (.022)*	.17 (.022)*	.17 (.021)*	.17 (.021)*
ΔlnK	.32 (.043)*	.31 (.043)*	.32 (.040)*	.32 (.041)*
ΔlnLNS	–.01 (.048)	–.05 (.051)	.05 (.042)	.06 (.049)
ΔlnLIS	.15 (.065)*	.09 (.100)	.08 (.059)	.02 (.099)
ΔlnENS	–.28 (.102)*	–.28 (.104)*	.11 (0.91)	.05 (.099)
ΔlnEIS	.20 (.184)	.29 (.214)	–.08 (.183)	–.38 (.210)**
X^2 stat. [d.f.] on:	ind. effects 61.7 [18]*	technol. effects 59.2 [17]*	geogr. effects 240.5 [15]*	all effects 305.1 [50]*
R_a^2	.365	.365	.388	.393

a: heteroskedastic-consistent standard errors in brackets, * (**) = statistically significant at the 5 (10)% level.

In order to appreciate to what extent the introduction of opportunity effects influences the impact of spillovers, alternative results are reported in Table 4. It appears that, despite a diminution of its value, the elasticity of the total spillover stock remains significant when the sectorial and geographical dummies are introduced. On the other hand, the taking into account of technological opportunities destroys the significativeness of spillovers. The results obtained when we consider the different components of spillovers lead to temper this observation. Indeed, technological dummies as well as sectorial and geographical ones seem to contribute to the deterioration of results. A negative effect predominates when some significant coefficients are obtained. Regarding the coefficients obtained for the external national spillover stock, we observe that it remains significantly negative when sectorial and technological dummies are introduced and turns to be insignificant when geographical dummies are considered. Consequently, it can be suspected that the negativity of this coefficient is linked to a geographical specificity.

To verify this observation, we report in Table 5 the results obtained for the regressions realized for each geographical area. A first observation is that the coefficients obtained for the explanatory variables are significantly different among the three areas. The elasticities for the labor and the physical capital are similar in Europe and the United-States and significantly different in Japan. Regarding the own R&D stocks, the results are more

TABLE 5

Productivity Estimates by Geographic Area.

dependent Variable: ln S					
WITHIN Level	est. s.e. [a]	OLS F.D.	est. s.e.	GMM-IV F.D.	est. s.e.
US sample 3024 (2646) obs.					
lnL	.66 (0.30)*	ΔlnL	.47 (.031)*	ΔlnL	.51 (.012)*
lnC	.11 (.027)*	ΔlnC	.13 (.025)*	ΔlnC	.10 (.001)*
lnK	.18 (.024)*	ΔlnK	.28 (.039)*	ΔlnK	.25 (.013)*
lnNS	.69 (.179)*	ΔlnNS	.59 (.202)*	ΔlnNS	.56 (.075)*
lnIS	–.02 (.155)	ΔlnIS	–.43 (.273)	ΔlnIS	–.35 (.122)*
R_a^2	.995	R_a^2	.468	X^2 [d.f.] [b] Sim. [c]:	239.8 [195] S
JP sample 1064 (931) obs.					
lnL	.23 (.053)*	ΔlnL	.11 (.040)*	ΔlnL	.09 (.001)*
lnC	.28 (.033)*	ΔlnC	.18 (.035)*	ΔlnC	.12 (.001)*
lnK	.07 (.040)**	ΔlnK	.28 (.114)*	ΔlnK	.10 (.001)*
lnNS	–.17 (.149)	ΔlnLS	–.23 (.403)	ΔlnNS	.28 (.028)*
lnIS	.91 (.307)*	ΔlnIS	1.46 (.621)*	ΔlnIS	.97 (.065)*
R_a^2	.992	R_a^2	.221	X^2 [d.f.] Sim. :	122.9 [120] W
EU sample 808 (707) obs.					
lnL	.63 (.052)*	ΔlnL	.53 (.066)*	ΔlnL	.56 (.001)*
lnC	.18 (.035)*	ΔlnC	.09 (.040)*	ΔlnC	.11 (.001)*
lnK	.04 (.053)	ΔlnK	.22 (.105)*	ΔlnK	.15 (.001)*
lnNS	.13 (.140)	ΔlnNS	.13 (.281)	ΔlnNS	.12 (.032)*
lnIS	.32 (.269)	ΔlnIS	.06 (.565)	ΔlnIS	–.12 (.030)*
R_a^2	.996	R_a^2	.417	X^2 [d.f.] Sim. :	97.4 [95] $+L1$

a: heteroskedastic-consistent standard errors in brackets (except for JP and EU GMM estimates), * (**) = statistically significant at the 5 (10)% level; b: overidentification test; c: predeterminancy of X_{it}: $W\,(S)$ =weak (strong) exogeneity, $+L3 = \text{lag}\,3$ and lower values of X_{it} as instruments. For the GMM estimates, the variance-covariance matrix of orthogonality conditions has been held fixed across all tests and is based on the estimates of the corresponding specification in first differences and with lag 2 instruments.

controversial. The first-difference estimates are similar while the within estimates are significantly different and the GMM estimates are in an intermediary position.

Turning to the effects of spillovers, it appears that their influences are drastically different for each geographical area. In the United-States, the national stock affects significantly the output which it is not the case for the international stock. An opposite observation emerges for Japan which appears to benefit from the international stock. So, Japan seems to depend, to a large extent, on technologies developed outside while American firms are mainly turned to their domestic technologies. Interestingly, BERNSTEIN and MOHNEN [1995] in their study of the effects of international R&D spillovers on productivity growth of R&D intensive sectors, find that international spillovers exist from the U.S. to Japan, but not in the converse direction. BRANSTETTER [1996] too, reports some evidence that Japanese firms benefit positively from R&D undertaken by U.S. firms while no effect of Japanese R&D on U.S. firms' output growth is found. As far as Europe is concerned, no consistent effect is obtained for this continent. Consequently, the receptivity of European firms to new technologies can be questioned. These empirical observations are, to a large extent, in accordance with the positioning often emphasized for the three geographical areas. As a technological leader, the United-States is principally concerned by its own technological development. On its side, Japan has demonstrated that it was highly successful in implementing technologies developed outside, particularly in the United-States. The weakness of European countries in fast growing technological fields, their higher specialisation in slow growing or declining activities and a more defensive and/or passive behaviour regarding R&D intensive activities induce a lesser sensitiveness to spillovers. Consequently, the lesser R&D intensity of European countries combined to a weaker propensity to internalize technological spillovers might jeopardize its long term competitiveness.

To complete the analysis, we have used a similar approach to the one developed by JAFFE. Table 6 compares Jaffe's results [1988] with the ones obtained from our sample. It should be noticed that first, the productivity equation used by Jaffe directly estimates a rate of return to R&D rather than an elasticity. Second, in the preceding tables, the impacts of the local and external components of spillovers are estimated separately, while Jaffe quantifies the impact of the total stock and tries to find out if there is a significant premium for the local stock [22]. Finally, because of data availability, Jaffe estimated long differences between average years 1976-1978 and 1971-1973. Consequently, we have also calculated long differences between average years 1987-1989 and 1992-1994.

When industry effects are not taken into account, the spillover coefficients are not significant in the international sample as well as in the US sample. The return to R&D is similar to the measure obtained by Jaffe. The labor elasticity is also comparable to Jaffe's result, the main difference is observed for the capital stock elasticity in the international sample which is triple of the estimate obtained in the US sample and by Jaffe. The introduction of industry effects does not change drastically the value of estimates except for the spillover variables which turn to be significant. The coefficients are higher than the ones obtained by Jaffe and give evidence that there is a

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[22] Actually, Jaffe's specification is based on a perfect substituability hypothesis among the spillover stocks, while a unitary one is assumed in our previous specification. Alternatively, we have tried to estimate the value of the elasticity of substitution from a CES production function. Yet, the test has been unfortunately inconclusive.

Table 6

Productivity Estimates: Comparison with Jaffe [1988].

dependent Variable: ln S						long differences
	international sample (1993-1988) 625 obs		US sample (1993-1988) 378 obs		Jaffe sample (1977-1972) 434 obs	
	est. s.e. [a]	est. s.e.	est. s.e.	est. s.e.	est. s.e.	est. s.e.
ΔlnL	.55 (.129)*	.52 (.142)*	.76 (.050)*	.76 (.050)*	.72 (.047)*	.69 (.038)*
ΔlnC	.31 (.133)*	.34 (.144)*	.12 (.054)*	.14 (.052)*	.04 (.045)*	.13 (.047)*
RD/S	1.7 (.575)*	1.8 (.761)*	1.2 (.437)*	1.1 (.641)**	1.9 (.410)*	1.5 (.0460)*
ΔlnLS	–.14 (.178)	.28 (.131)*	.10 (.071)	.38 (.386)*	.04 (.049)	.10 (.051)**
Δln(ES/LS)	–.0045 (.006)	.0100 (.005)**	.0029 (.005)	.0179 (.007)*	.0003 (.001)	.0004 (.0003)
X^2 stat. [d.f.] on industry effects		39.8 [19]*		41.5 [19]*		6.2 [19]*
R_a^2	.683	.693	.783	.795	.618	.742

a: heteroskedastic-consistent standard errors in brackets, * (**) = statistically significant at the 5 (10)% level.

premium effect for external stock relatively to the local stock. The estimates for our sub-sample of US firms are remarkably close to the ones reported by Jaffe. The only important difference is about the local spillover component which is somewhat high in our sample. So, it seems that US firms have become closer technologically [23] and hence may benefit more from R&D performed by technological neighbors. The estimated coefficient associated to the R&D intensity variable implies a somewhat lower annual excess rate of returns of .23 against .34 in Jaffe's study. This result suggests that for the US firms the impact of own R&D has decreased over time.

5 Conclusion

The purpose of the paper has been to assess the importance of the main determinants of technological activity of international firms on productivity. Among the main determinants, the firms' own R&D capital as well as the technological spillovers were considered. Technological spillovers have been formalized by weighting the firms' R&D stocks according to their proximity into the technological space on the basis of the patent distribution of firms across technological classes. The new constructed dataset which

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[23] An alternative explanation may be found in the fact that we use European patents for US firms.

enlarges Jaffe’s study to the international scope is representative of a main part of R&D expenditures in industrialized countries. In order to provide a distinction between local and external components of the total spillover pool, three clustering procedures have been investigated. National and international spillover stocks have also been constructed on the basis of the geographic location of firms. Despite these improvements, such an approach has some limitations which are difficult to overcome. The main drawbacks of this methodology are the difficulty to take into account firms which do not apply for any patents as well as the risk of erroneous technological location for firms which applied for a small number of patents. These problems have really been encountered in the empirical analysis.

The estimates obtained have been performed by using ad hoc panel data estimation methods which control for specific hypotheses typically associated with this kind of data, namely, correlated firms’ unobserved fixed effects with regressors and weakly exogeneous explanatory variables. However the GMM techniques which seem to promise so much in theory has delivered less than might be hoped in the way of useful results. On the whole, results for traditional production factors appeared to be consistent with the findings of previous related studies. Some evidence about the effects of technological spillovers on productivity has also been found. The results lead one to conclude that the sensitivity of firms to spillovers differs significantly among the three geographical areas. Indeed, the United States, Japan and Europe seem to adopt very differentiated behaviors. While US firms are mainly concerned with their national spillover stock, Japanese ones are more receptive to the international stock and European ones do not seem to particularly benefit from both sources of spillovers. Furthermore, our results confirm to a large extent those obtained by Jaffe, our elasticity of productivity with respect to spillovers is higher and we cannot exclude that the external stock benefit from a premium effect.

In our opinion, the measure of technological spillovers is facing with lots of methodological problems. If the concept of technological space is very attractive, its measure is not direct and the choice of a distance metric can affect the nature of results. In a same vein, there is also the question of heterogeneity in technological space. Moreover, given the positioning of firms into the technological space, to what extent two firms benefit from spillovers from each other given the possible existence of asymmetrical information flows? The timing of spillover effects should also be considered. How much time take the spillovers to concretize in new products and processes and as a result in productivity? Because of lags in the diffusion of knowledge, spillover effects are probably not immediate. This last point is perhaps the main explanation why empirical studies encounter lots of difficulties to measure the real impact of spillovers.

So far, we do not have clear answers to these questions and there are consequently still lots of bottlenecks to overcome in the burgeoning literature on the relationship between productivity growth and technological spillovers.

ANNEX 1

The balanced panel of 673 firms from 1987 to 1994 was cleaned according to similar criterions as those used by HALL and MAIRESSE [1995], what led to remove 48 observations (7.1%):

a) Any observations for which R&D intensity was less than 0.2% or greater than 50% were removed. This eliminated 6 firms.

b) Any observations for which net sales per worker, capital stock per worker and R&D capital per worker was outside of three times the interdecile range above or below the median were removed This eliminated 15 firms.

c) Any observations for which the growth rate of net sales was less than minus 90% or greater than 300% or for which the growth rate of labor, capital and R&D stocks was less than minus 60% or greater than 240% were removed. This eliminated 27 firms.

ANNEX 2

Correlation Matrix of Spillover Components

	ΔTS	ΔLS	ΔES	ΔNS	ΔIS	ΔLNS	ΔLIS	ΔENS
ΔLS	.49							
ΔES	.79	.10						
ΔNS	.50	.29	.40					
ΔIS	.88	.29	.71	.27				
ΔLNS	.28	.61	.07	.38	.09			
ΔLIS	.43	.43	.19	.16	.42	.02		
ΔENS	.44	.11	.51	.74	.27	–.01	.18	
ΔEIS	.68	.05	.88	.23	.74	.04	.09	.29

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