The Empirical Performance of a New Interindustry Technology Spillover Measure

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ABSTRACT

This paper investigates whether a new, easy to construct measure of interindustry knowledge spillovers could be used as an alternative to the existing more sophisticated but rather inflexible (especially with respect to the number of industries that can be distinguished) methods already in use. First, the method is shown to measure pure knowledge spillovers, contrary to earlier input-output based measures picking up with rent spillovers. Second, the measure is computed for the U.S. in 1987 to identify a number of technological clusters. Finally, using a database for American firms, the new measure is shown to yield estimates of spillover impacts similar to the existing knowledge spillover measures, but sometimes strongly different from rent spillover measures. A further novel aspect is the eldi me-5(f).27 Tm-

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1. Introduction

Technology has become an omnipresent topic in economic growth theory. At first this was only true for neo-Schumpeterian and evolutionary growth theories, since the mid-eighties this also applies to mainstream growth theory. Even before technology became so prominent in the mainstream theory, pioneers in the empirical field like Terleckyj (1974), Griliches (1979) and Scherer (1982) were aware of the influence an industry's technology generation can exert on the productivity of other industries, through so-called technology spillovers. In the eighties and nineties, many studies confirmed their main finding that technology spillovers have significant productivity effects.

Although the significance of the spillover effects is beyond doubt, the estimated rates of return to Research and Development (R&D) investment, considered to be the major input in technology generation, vary over a large range. This variation does not seem to be caused by differences in countries, industries and time periods considered alone, but also by the different spillover measurement methods that are applied. Los (1997) offers a survey of methods and argues that two broad classes of methods may be distinguished, based on the distinction between so-called 'rent spillovers' and 'knowledge spillovers', concepts originally introduced by Griliches (1979). According to Griliches (1992) and Los (1997), the input-output based measures of interindustry technology spillovers adopted by Terleckyj (1974), Sveikauskas (1981) and Wolff and Nadiri (1993) mainly refer to rent spillovers. In order to measure *knowledge* spillovers, one has always relied on methods that utilize patent data (Jaffe, 1986, Verspagen, 1997a,b), R&D classified to product fields (Goto and Suzuki, 1989) or data on the disciplinary composition of R&D staffs (Adams, 1990). In this paper, we introduce a knowledge spillover measure that is easily computable from input-output tables and investigate its empirical performance vis-à-vis existing measures.

The paper is organized as follows. The next section is devoted to a very short discussion of the basic distinction between rent spillovers and knowledge spillovers. Section 3 reviews input-output based spillover measures developed so far. In Section 4, we introduce the new knowledge spillover measure, show that two strands of economic theory can provide a justification for its use and conclude that the measure has some important practical advantages over more direct measures. Section 5 provides an empirical analysis of the most important technological interindustry linkages within the American economy in 1987 as they are identified by the new method. In Section 6, the measurement method is applied to the U.S. panel data on which Los and Verspagen (1997) based their study at the firm level, in order to see whether productivity effects estimates differ from those obtained using alternative spillover measures. To correct for potential cointegration, the three-step Engle-Granger-Yoo estimation framework (Engle and Yoo, 1991) is applied. The final section contains a short summary of the results and some conclusions with regard to the usefulness of the proposed measure for future research.

2. Two Kinds of Spillovers

In a widely cited paper, Griliches (1979) pointed out the basic difference between 'rent spillovers' and 'knowledge spillovers'. Rent spillovers relate to the fact that producers of product innovations are often unable to set a price for the improved product that reflects the quality increase relative to the old product, due to competition. This would not be problematic, if both input and output deflators were as advanced as they could fully correct for quality differences. Although hedonic price indices are available for some products (e.g. computers) in the U.S., researchers in the field of productivity have to rely on more conventional deflators if they are involved in economywide studies.[1] This implies that statistical deficiencies, together with competition, 'shift' rents connected to product innovations from the innovator to the user. Hence, productivity increases in the innovation producing industry will be measured in the industries buying the product innovation.[2]

Knowledge spillovers have a completely different nature. They arise from the fact that knowledge has some public good characteristics: the use of a 'unit' of knowledge by one research employee does not prevent other researchers from using it (knowledge is nonrival) and knowledge can be appropriated only to a certain extent (knowledge is partly nonexcludable).[3] As Los (1997) points out, a useful distinction between two classes of knowledge spillovers can be made. The first class, having a strong intraindustry nature, enhances imitation of innovations. 'Reverse engineering' by competitors and imperfect patent protection are the most important sources of 'imitation-enhancing' knowledge spillovers, but they can also emerge from the mobility of R&D employees for example.

Many R&D employees are not necessarily tied to one industry, however. In general, ideas from one industry may well induce new ideas in another industry, imitation playing no role at all. Los (1997) denotes this second class of knowledge spillovers by 'idea-creating' spillovers. These spillovers can also emerge from public information contained by patents and from scientific and professional journals and conferences. Other channels of 'idea-creating' knowledge spillovers are connected to supplier-buyer relationships: during trade negotiations or after sale services, knowledge may be exchanged from supplier to buyer and vice versa.[4] It should be noted that the spill

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1 Although they surely outperform conventional deflators, even hedonic deflators are not able to measure quality improvements perfectly, see Trajtenberg (1990).

2 See Griliches (1979), Van Meijl (1995) and Los (1997) for more comprehensive treatments of the rent spillover concept. Triplett (1996) provides an excellent empirical example of the disturbing effects connected to the use of conventional price deflators on productivity estimates.

3 Verspagen (1997b) argues that both rent spillovers and knowledge spillovers are important elements in the advanced endogenous growth theories, like Romer (1990). The switch from the assumption of perfect competition in the older models (e.g. Romer, 1986) to monopolistic competition and product varieties has been an immediate consequence of the notion that no firm would undertake any R&D if the full rents would spill over to buyers (as is the case if markets are perfectly competitive). Knowledge spillovers were at the heart of the older generation of models already, being the sole cause of the increasing returns to scale at the macro level that enable the economy to stick to a positive growth rate in output per worker.

4 For a more elaborate discussion of spillover channels, see Los (1997).

of knowledge does not affect the amount of knowledge present in the originating firm.

Although there is a basic difference between 'imitation-enhancing' and 'idea-creating' knowledge spillovers (at least at a theoretical level), the differences between rent spillovers and knowledge spillovers are more fundamental.[5] Therefore, it is important to determine which of these two kinds of spillovers are emphasized by a particular technology spillover measure, before the outcomes of empirical research with the measure are interpreted.

3. Input-Output Based Spillover Measures

In the last decades, the number of empirical studies concerning the productivity effects of technology spillovers has sharply increased. Mohnen (1990) and Nadiri (1993) offer good surveys of the results obtained for various countries, periods and aggregation levels. In general, spillover effects are found to be very significant and positive,[6] but the magnitude of the estimated effects appears to vary over a rather large range of values. One of the causes of this variation is the diversity of interindustry spillover measurement methods used. Los (1997) provides a survey of these methods, which have as a common feature that the amount of technology obtained through spillovers ('indirect R&D', *IRE*) is measured by a weighted sum of other industries' R&D expenditures (*RE*):

$$IRE_j = \sum_i \omega_{ij} RE_i \qquad \forall i \neq j, \tag{1}$$

in which i and j denote the spillover producing and spillover receiving industries, respectively. The weights ω_{ij} indicate to what extent the R&D undertaken by industry i may be considered to be part of industry j's technology stock. Many authors based the weights on input-output tables, following the pioneering contributions of Brown and Conrad (1967) and Terleckyj (1974).[7] These authors set their weights equal to the output coefficients, obtained by dividing the cell values through by the corresponding row sums. The common idea behind this method is that the 'statistical benefit' industries obtain through R&D embodied in intermediate goods is proportional to the parts of the output of the innovating industry they buy, through rent spillovers.[8] In some studies, capital flow matrix output coefficients are included in order to account for the fact that capital goods are carriers of rent spillovers, too. Wolff and Nadiri (1993) consider several input-output table based

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5 Griliches (1992) even argues that rent spillovers are no 'real' spillovers, as they occur as a part of a transaction between the firms or industries involved.

6 Schumpeterian 'creative destruction' might also yield negative spillovers. See the theoretical model by Aghion and Howitt (1992).

7 See, for instance, Terleckyj (1980), Sveikauskas (1981), Odagiri (1985), Goto and Suzuki (1989), Wolff and Nadiri (1993) and Wolff (1997).

8 Griliches and Lichtenberg (1984) show that, under the (strong) hypothesis that R&D improves an industry's outputs sold to all buying industries to the same extent, quality mismeasurement leads to overestimations of total factor productivity in the user industries proportional to the output coefficients.

sets of weights (like input coefficients, Leontief inverse coefficients and backward linkage measures), but stress the knowledge spillovers related to supplier-buyer relationships. Van Meijl (1995) argues that rent spillovers and knowledge spillovers from supplier to buyer can not be disentangled in economy-wide studies. Following him in that respect, and observing some confusion concerning the interpretation of some alternative measures not discussed here, Los (1997) proposes a classification of measurement methods according to the emphasis on either rent spillovers and supplier-buyer knowledge spillovers, or knowledge spillovers related to the relevance of produced knowledge to the R&D activities in other industries. As may have become clear from the discussion above, the input-output table based measures developed so far should be classified into the former category.

In the conclusions of his review, Los (1997) pleas for measures stressing the second kind of spillovers based on data of a lower degree of aggregation than usual. In the next section, such a method will be introduced taking advantage of the relatively low level of aggregation present in many present-day input-output tables. The new method utilizes the ‘technology dimension’ of input-output tables, instead of the ‘trade dimension’ on which the known input-output table based methods focus.

4. A New Measure of Knowledge Spillovers

Knowledge has entered production functions as a productive factor, like physical capital and labor. From an empirical point of view, however, there is a basic difference between these factors: capital and labor inputs can be measured relatively well, the non-tangible nature of knowledge prohibits its straightforward measurement. Often, the input of the knowledge production process, R&D investment, is used as a proxy for its output, knowledge. The intrinsic uncertainty about the outcome of the production process renders this proxy rather unreliable, but the problem is aggravated further when we take into account that knowledge itself is an input in the knowledge production process and has public good properties. We have to use a weighted sum of R&D performed in other industries (like in Eq. 1) to approximate an industry’s knowledge obtained through spillovers. In the knowledge spillover case, however, the ω_{ij}’s should not be based on trade statistics but on magnitudes that provide insight into the relevance of industry *i*’s knowledge for industry *j*’s knowledge production process.

First, we will present a new, easy way of constructing a set of ω’s and show how differents strands of theory support this method. Afterwards, the advantages and disadvantages of the new method compared to existing ones will be set forth.

A new measure of knowledge spillovers

The method proposed below is a member of a class of measures originating with Jaffe (1986). He introduced the concept of a ‘potential spillover pool’, which consists of all knowledge that can not be appropriated by the firms that have generated this knowledge. The public knowledge in the pool is accessible to every firm in the economy. However, not all knowledge is relevant to every firm. For instance, recent insights concerning the air streams around aircraft wings is likely to have no impact on the R&D efforts of a wooden furniture manufacturing firm, while a producer of trucks may think of new opportunities to lower their drag. The more similar two firms' technological activities are, the more they may benefit from each other's public knowledge.

Our measure is meant to capture interindustry instead of interfirm knowledge spillovers.[9] As is well-known (e.g. Leontief, 1989), a column of an input coefficient matrix derived from an input-output table is a strongly simplified representation of the corresponding industry's technology, giving the amounts of the various inputs needed to produce one value unit of that industry's output. Therefore, similarity measures of two industries' production technologies can be derived from such columns.[10] We propose a related measure in line with Jaffe (1986), the cosine between a pair of input coefficient vectors:[11]

$$\omega_{ij} = \frac{\sum_{k=1}^{n} a_{ik} \cdot a_{jk}}{\sqrt{\left(\sum_{k=1}^{n} a_{ik}^2 \cdot \sum_{k=1}^{n} a_{jk}^2 \right)}} , \qquad (2)$$

in which the vectors are denoted by a_i and a_j and the number of inputs by n. If two industries have similar input compositions, ω_{ij} will be close to one. In this case, both industries' indirect R&D stocks (Eq. 1) include each other's R&D almost completely. Two industries with strongly different input structures (and therefore, by assumption, different technologies) hardly contribute to each other's indirect R&D stock, as Eq. 2 yields a very small value in this case.

Having introduced the new measure, we should hurry to judge its merits from a theoretical point of view: is there any argument for assuming that industries with similar input structures engage in similar R&D projects, thereby benefiting from each other's contributions to the 'potential spillover pool'? In order to answer this question, we briefly refer to two theories from completely different strands of economic theorizing.

First, some theories with a strong *neoclassical* flavor show how optimizing firms without uncertainty (reflected in a so-called 'innovation possibility frontier') will direct their R&D efforts at a lower use per unit of output of a particular input, the higher the cost share of this particular factor (the classic contribution is Kennedy, 1964).[12] As a consequence, firms with roughly the same input structures (in value

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[9] Note that a firm can obtain both 'idea-creating' as well as 'imitation-enhancing' spillovers from the potential spillover pool. If the concept of a potential spillover pool is applied at the industry level, the latter class of knowledge spillovers does not play a role anymore.

[10] Blin and Cohen (1977) used this feature to construct measures of technological similarity, computing Euclidean distances between pairs of input coefficients vectors. Their ultimate aim was to find a good algorithm to aggregate n-dimensional input-output tables into m-dimensional tables, independent from the particular values of m and n.

[11] See Oksanen and Williams (1992) for a recommendation of the cosine measure as a measure of similarity.

[12] In these contributions, only two factors of production (physical capital and labor) are distinguished. The analysis, however, can easily be extended to any number of (intermediate) inputs.

terms) will engage in roughly similar R&D projects, according to these so-called 'induced innovation' theories.[13] Extending the reasoning from firms to industries, similarity of industrial input structures would imply some similarity of technological activities, which would generate relatively large knowledge spillovers between those industries. It should be mentioned, however, that the induced innovation theories do not consider R&D aimed at product innovation at all, while many empirical studies (e.g. Scherer, 1982) show that product-oriented R&D accounts for more than half of total R&D in many countries.

Second, an influential part of *evolutionary* growth theory explicitly addresses the directions in which firms search for technological progress. In their seminal contribution, Nelson and Winter (1982) replace the neoclassical assumptions of full rationality and optimizing behavior by the concepts of bounded rationality and satisficing. Firms are assumed to decide on the basis of 'routines'. Regarding technological change, firms only decide to search for alternative techniques if a predetermined aspiration rate of return on capital is no longer attained. This search can focus either on imitation of more profitable technologies used by other firms or on 'world new' (but incremental) innovation. In the case of the search for innovation, which is most interesting regarding our industry-level point of view, new technologies which are 'close' to the one in use already are assumed to be discovered and implemented with a higher probability than technologies which are 'distant' even if the performance of the latter would be superior. This is an immediate consequence of the bounded rationality hypothesis. Nelson and Winter (1982) define 'close' and 'distant' as 'having similar input structures' and 'having different input structures'.[14] Therefore, knowledge from firms (or industries) with similar input structures may be relatively productive for a firm searching for an innovation.

Despite this support, it should theoretically be preferred to use more direct measures of technological activity than the current technology. Alternative knowledge spillover measures utilize patent data or R&D classification data. To make clear why the new measure may fill a gap, we will now briefly review these measures, before we turn to its empirical performance.

Comparison with alternative knowledge spillovers measures

In the empirical literature on knowledge spillover measurement, two classes of methods may be distinguished. The most recent methods, introduced by Verspagen (1997a) and applied by Los and Verspagen (1997) and Verspagen (1997b) in firm-level and intercountry studies respectively, are based on the information contained in patent documents. The first two methods determine the most probable industry in which the producer of each of the patented processes and products ('the spillover producer') operates, as well as the industries most likely to use the information ('the spillover receiver').[15] This yields 'patent information input-output matrices', of which

[13] For a comprehensive survey of these theories, see Thirtle and Ruttan (1987).

[14] Like Kennedy (1964), Nelson and Winter (1982) describe technologies by their physical capital and labor requirements. Again, nothing seems to preclude extensions to more than two inputs in our case.

[15] Note that these methods determine the users of the *information* provided in the patent document, not the users of the patented innovation itself. Scherer (1982), Englander *et al*. (1988) and Mohnen

output coefficients can easily be computed. These coefficients are used as weights ω_{ij} in Eq. 1. The third method in Verspagen (1997a) utilizes a special feature of U.S. Patent Office documents, the citation of related patents in each document. The holders of cited patents are considered to be spillover producers, the holder of the patent itself to be a spillover receiver. In the Verspagen paper the number of industries distinguished is 19 or 22, depending on the particular spillover matrix.

Another, somewhat older, class of measures follows Jaffe (1986). He introduced our Eq. 2, but defined the *a* vectors in an alternative way. Each vector consisted of elements representing the share of a particular patent class in the total of patents granted to the firm in a certain period. Jaffe's (1986) approach has elicited a number of variants, the changes to the original being induced by data availability and/or research goals.[16] With regard to the topic of this paper (knowledge spillovers at the industry level), the study by Goto and Suzuki (1989) is the most interesting one. They used a product field classification (n=30) of R&D investment (instead of patent classes) in order to determine the position of Japanese industries in technological space and utilized Eq. 2 to assess the impact of R&D performed in the electronics industry on other industries. Although there are no major conceptual problems connected with this method, the empirical implementation seems to be restricted to countries in which a product field classification of R&D investments exists (at least if one is not willing to assume that interindustry technological proximities are roughly equal across countries). Furthermore, an aggregation of R&D investment into 30 product classes may be far too rough to approximate 'technological proximity' well.[17] Another problem arises if one wants to repeat the productivity effects estimation for a new time interval. Either one has to rely on the assumption that all R&D activity in all industries has been directed to the same product fields as before, or one has to perform a new survey in order to see how R&D has been redirected in the meantime. These practical disadvantages of the Goto and Suzuki (1989) method also hold concerning Jaffe's (1986) measure.

As we focus on interindustry 'idea-creating' knowledge spillovers, the imposed symmetry of the proposed spillover matrix seems artificial: why should a dollar of R&D in industry *i* be as relevant to industry *j* as a dollar of *j*'s R&D is to *i*? Indeed, Los (1997) argues that Jaffe-like spillover measures have an emphasis on symmetrical 'imitation-enhancing' knowledge spillovers, but he shows at the same time that Verspagen's (1997a) measure focusing on 'idea-creating' spillovers has a rather high degree of symmetry, too. The theoretical differences between the two groups of knowledge spillover measures seem larger than their empirical differences.

The practical inconveniences tied to the existing knowledge spillover methods are avoided by the method we propose. Columns of input coefficients are straightforwardly derivable from input-output tables. Nowadays, almost all countries of the world publish input-output tables at a regular basis, enabling researchers to perform both international and intertemporal analyses. Moreover, statistical agencies tend to lower the level of aggregation of the tables published,

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and Lépine (1991) used methods based on the latter notion, thereby (sometimes unconsciously) stressing rent spillovers (see Los, 1997, and Los and Verspagen, 1997).

16 See Jaffe (1988, 1989), Goto and Suzuki (1989) , Adams (1990) and Park (1995).

17 Jaffe (1986) distinguishes 49 patent classes.

thereby alleviating the heterogeneity problems paramount in traditional input-output analysis as well as in the aforementioned measures of technological proximity. Last but not least, the number of national statistical agencies collecting and publishing R&D investment data is steadily growing. It seems plausible to assume that both the classification systems and the levels of aggregation used will be made more and more comparable to those used with respect to traditional national accounts and input-output data.

Despite the theoretical considerations in favor of the proposed measure, it must be admitted that an industry's input structure is a less 'direct' measure of the nature of its technological activity than the patent profiles, R&D investment profiles and patent information classifications used by Jaffe (1986), Goto and Suzuki (1989) and Verspagen (1997a), respectively. From a practical point of view, however, the input structures measure seems a worthwhile alternative to those methods. In order to assess the quality of the input coefficients based measure, the next sections contain a report of two empirical exercises.

4. Empirical Performance

We will evaluate the quality of the proposed measure on the basis of two empirical studies. First, in this section, we will have a look at the elements of a proximities matrix consisting of ω_{ij}'s according to Eq. 2, in order to see whether the magnitudes of the elements are in line with common sense. In the next section, we compare estimation results of the productivity effects of technology spillovers based on the proposed measure with some other measures to investigate whether it can be considered as a reasonable alternative to some of them or not.

Interindustry technological distances

Our empirical applications of the new measure are based on the commodity-by-commodity input-output table of the United States for 1987 derivable from the table of total (direct and indirect) requirements published on computer disk by the Bureau of Economic Analysis.[18] The choice for a U.S. table is suggested by two considerations. First, as we argued above, we think one of the main advantages of the new measure is the possibility to obtain indirect knowledge stocks at a relatively low level of aggregation. The BEA tables for the U.S. distinguish 91 industries, which is a rather high number compared to most input-output tables. Second, an industry's technological activity is not likely to depend on the origin of its various inputs. Therefore, we should look at imported inputs as well as domestic inputs. Input-output tables normally contain only one row or column for imports, without a classification of the industry of origin.[19] The U.S. are a country that does not depend heavily on imports, which implies that the omission of imported inputs will cause only small biases.

[18] See also Lawson and Teske (1994).

[19] For some countries, additional tables are available in which imports are assigned to a number of industries or commodities. One of those commodities is "noncomparable imports" which can include very different inputs.

We decided to calculate the cosines of 'truncated' input coefficients columns, which means that we did not include the coefficients for primary inputs. The reason for this decision is the enormous heterogeneity in the recorded values. Expenditures for engineers, secretaries, low-skilled manual workers and high-skilled managers are lumped together into one input category and the same happens to payments for the use of very different sorts of capital goods. Although we immediately admit that these problems are also tied to intermediate input categories, we think that heterogeneity is far less a problem for these categories, at least with regard to our use of input-output tables. So we determined the cosines of each pair of industrial 91-elements input coefficients vectors. The resulting 'proximities' matrix is in Appendix B, a list of industries corresponding to the industry numbers can be found in Appendix A.

Examination of the proximities matrix shows that, although there are some counter-intuitively high and low elements, the general pattern seems to be quite plausible: many high values are found in blocks in the neighborhood of the main diagonal, which is a consequence of the SIC-related ordering of industries in the input-output table. In order to provide a better overview of the technological clusters of manufacturing industries that are identified by the proposed measure, we provide a diagram generated by a so-called multi-dimensional scaling (MDS) algorithm.[20] This technique, mostly used by marketing researchers to reveal the position of products or product varieties in 'customer perception space', projects the (n-1)-dimensional space containing n points, with interpoint distances given, onto a space of lower dimension, preserving the original interpoint distances as good as possible.[21] In our case, we decided to define the 'technological distance' between two industries i and j as $1-\omega_{ij}$, one minus the cosine of the two input coefficients vectors.[22] Figure 1 presents the two-dimensional 'map' of technological space, resulting from MDS applied to the interindustry distance data.

It is hard, or even impossible, to give an interpretation of the two dimensions. But more important for our purposes, the diagram clearly identifies a number of technological clusters. Cluster I consists of food and textiles manufacturing industries (12-17) and footwear and leather products (32). Cluster II, denser than the first one, can be characterized as "chemicals and plastics". Cluster III is related to the manufacturing of paper products. Cluster IV, having a central position in the figure, mainly consists of electric products, while Cluster V is strongly 'machines-related'. Cluster VI is rather heterogeneous, containing both various metal producing industries as well as "computers and office equipment" and "audio, video and communication equipment". Interesting solitary industries (as identified by the MDS plot) are "petroleum refining" (30), "lumber and wood products" (18), "motor vehicles" (56) and "aircraft and parts" (58).

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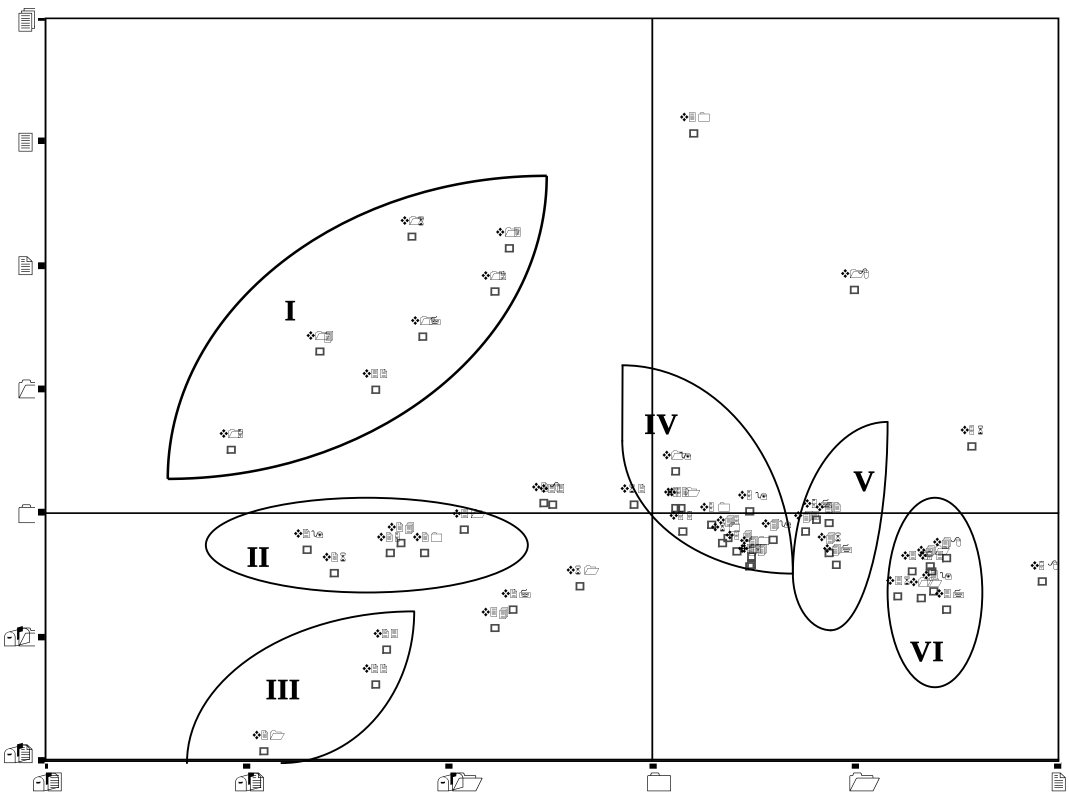
[20] Schmoch et al. (1996) present a similar diagram for their application of the Jaffe measure on German industries.

[21] For details on MDS, see Green *et al.* (1989).

[22] MDS has several variants, one of them treating the distances as measurable on the ordinal level. We used this variant, so the exact construction of the distance measure does not influence the configuration as long as the distance measure is a monotone decreasing function of ω.

Figure 1: Multi-Dimensional Scaling representation of 52 manufacturing industries in technological space.*



* See Appendix A for industry classification numbers.

A closer look at Figure 1 reveals that some industries are close to each other, although no one would expect them to benefit from each other's R&D. For example, the distance between "drugs" (27) and "stone and clay products" (34) is very small. In the table of Appendix B, however, a proximity of only 0.165 is recorded for this pair of industries. Apparently, the 'true' distance between these industries has been distorted by the MDS algorithm, in reducing the 51-dimensional space with true distances to the two-dimensional space plotted in the figure.[23] The same applies for "primary nonferrous metals manufacturing" (36) on the one hand, and "computers and office equipment" and "audio, video and communication equipment" (53) on the other one, all present in cluster VI. In a few other cases, the measure itself seems to generate intuitively strange proximities, like in the case of cluster IV industry "primary iron and steel manufacturing" (35), having ω's of more than 0.5 for many other industries in the same cluster, like "household appliances" (51) and "electric lighting and writing equipment" (52). It is impossible, however, to decide whether

[23] These distortions are the most important reason to present an MDS plot for manufacturing industries only. The MDS output reports an 'RSQ' of 0.75 in this case, indicating that 75% of the variation in the 'true' distances is reflected in the two-dimensional representation. Applying MDS on all 91 industries reduces RSQ to 0.64. The most important (but also expected) conclusion of the latter exercise should be that two 'superclusters' are identified: one corresponding to manufacturing, the other to services. Primary industries are scattered over the plot, which (after examination of the proximities matrix) turns out to be the consequence of reducing the number of dimensions.

the measure or our intuition is wrong, for pairs of industries like these.[24] In our view, the most important conclusion of this investigation into the technological linkages as identified by the proposed method should be that, despite a few counterintuitive results, the big majority of elements in the proximities matrix seem to justify its use as a measure of knowledge spillovers.[25]

5. Productivity Effects Estimation

Although the generation and diffusion of knowledge have entered mainstream economics only recently (well-known exceptions being Uzawa, 1965, and Shell, 1967), their important productivity effects have been recognized since a long time. Both the emergence of 'endogenous growth' theories (Romer, 1986, 1990, and Grossman and Helpman, 1991) and the strongly improved performance of various statistical agencies in gathering and publishing economic and technological data have caused an upsurge of empirical research in the relationship between innovative activity and economic performance. Following pioneering efforts by Terleckyj (1974) and Scherer (1982), the estimation of the influence of spillover effects have complemented the studies focusing on the productivity effects of technology developed by firms, industries or countries themselves. In this section, estimates of spillover effects obtained with the method proposed in this paper will be compared with estimates based on existing methods.

Estimated equations

Both the database and the method of analysis are identical to the firm level study by Los and Verspagen (1997). We will estimate the extended Cobb-Douglas production function

$$Q_{it} = A(IR)_{it}^{\eta} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} e^{u_{it}}, \tag{3}$$

in which Q is output, K the stock of physical capital, L the labor input, R the 'own' R&D stock and IR the R&D stock obtained through technology spillovers. A is a constant and u a stochastic error term with zero mean. The indices i and t indicate the firm and the year under consideration, respectively. The elasticities α, β, γ and η, assumed to be constant across the sample, are the parameters to be estimated. To

[24] Using more direct data on technological activity (information contained in patent documents), Verspagen (1997a) finds that "electrical products" ranks about fifth (out of 21) as receiver of knowledge spillovers from "ferrous metal manufacturing", while the rank of the latter industry as receiver of knowledge spillovers from "electrical products" varies (across his three measures) from five to a joint 21. This variation, as well as the higher level of aggregation, renders inference on the correctness of the high proximity value impossible.

[25] We also investigated the sensitivity over time. Comparisons on the basis of U.S. input-output tables for 1963 and 1967 showed that the for all industries Pearson's correlation coefficients between rows of proximity values were in excess of 0.8, and 80% of the industries showed coefficients over 0.95. Comparisons for a longer interval (1963-1987) showed more instability: 70% of the industries had correlation coefficients over 0.8, only 20% coefficients between 0.95 and one. The latter results may (partly) be a reflection of technological change.

reduce heteroscedasticity and multicollinearity, Eq. 3 is usually written in labor intensive form, after taking logarithms (indicated by lowercase letters):

$$(q_{it} - l_{it}) = a + \eta(ir)_{it} + \alpha(k_{it} - l_{it}) + \gamma(r_{it} - l_{it}) + (\mu - 1)l_{it} + u_{it}\ , \tag{4}$$

in which the dependent variable is labor productivity and μ is defined as $\alpha+\beta+\gamma$, the returns to scale with respect to all firm-specific inputs.[26] Los and Verspagen (1997) show that there is some preliminary evidence that the variables in their sample are not stationary (in the time series dimension), but seem to be cointegrated. As is well known in time series econometrics (Hendry, 1986), coefficient estimates based on Eq. 4 are (super)consistent, but biased. The corresponding t-values and the adjusted R^2's have an (often strong) upward bias. To solve this problem, Engle and Granger (1987) proposed a two-step procedure (also known as the error correction model, ECM). The first step is simply to estimate the cointegration equation Eq. 4. In the second step, Eq. 4 is rewritten in first differences ($\Delta x_t = x_t - x_{t-1}$) and the residuals of the first step, u_{it}, (lagged one period) are added to the set of independent variables:

$$\Delta(q - l)_{it} = \eta_s \Delta(ir)_{it} + \alpha_s \Delta(k - l)_{it} + \gamma_s \Delta(r - l)_{it} + (\mu_s - 1)\Delta l_{it} + \zeta u_{it-1} + \varepsilon_{it}\ . \tag{5}$$

A significantly negative sign of the estimated coefficient for the lagged residual (ζ) is an indication for cointegration in the original level specification, Eq. 4. The subscripts s denote that Eq. 5 estimates short-run parameters. In order to find unbiased normally distributed estimators for the long run parameters, which are more interesting from our point of view, we apply a third step introduced by Engle and Yoo (1991). This step estimates (in the time series dimension):

$$\hat{\varepsilon}_{it} = \eta_3(-\hat{\zeta}(ir)_{it-1}) + \alpha_3(-\hat{\zeta}(k - l)_{it-1} + \gamma_3(-\hat{\zeta}(r - l)_{it-1} + (\mu_3 - 1)(-\hat{\zeta} l_{it-1}) + v_{it}\ , \tag{6}$$

in which the left-hand-side variable is the residual from the second step and hats denote estimated coefficients. Now, under the assumptions of a unique cointegration vector and weak exogeneity of the right- hand-side variables in the short run ECM, the sums of the estimators in the first step (the level estimation, Eq. 4) and the corresponding estimators of Eq. 6 are normally distributed unbiased estimators of the long-run relation. The standard deviations are estimated without bias by the standard error of the estimators in Eq. 6.

[26] To analyze the sensitivity of the obtained estimation results, constant returns to scale will sometimes be imposed by setting μ equal to one.

Construction of Variables

The databases and the construction of variables are extensively discussed in Los and Verspagen (1997), so only the most important topics will be repeated here. The first database used, made available by Bronwyn Hall through the NBER-server, consists of annual data for nearly seven thousand American firms. For some of those firms, data are available for the period 1974-1991, other firms are not covered for the full time interval. In this paper, a non-random sample from the database will be used. It should be noted that we restrict the estimations to manufacturing firms, thus enabling ourselves to make comparisons with results obtained by Los and Verspagen (1997). This decision reduces the size of the sample substantially. The sample consists of those firms that are covered for at least ten consecutive years and do not exhibit too large jumps which are probably due to mergers. The (unbalanced) sample consists of 680 firms, and 9223 observations. All variables, except *IR*, are constructed from these samples. Output *Q* is 'approximated' by sales in millions of US$, because no better indicator for value added is available.[27] For the stock of physical capital *K*, we use 'net plant, property and equipment' (in millions of US$). Labor input *L* is measured by the number of employees (in thousands), because data on hours worked and/or skill levels are not available. *R*, the own R&D stock, is constructed from the annual data on R&D expenditures (in millions of US$) applying the well-known 'perpetual inventory method', with a depreciation rate of 15%. To be sure that estimations will not be influenced by errors with respect to the initialization of the R&D stocks, the first two years for each firm are excluded from the samples. Furthermore, *R* is included into the regressions with a lag of one year to alleviate biases due to simultaneity. *Q*, *K* and *R* are expressed in constant prices.[28]

The various *IR* variables we want to compare with each other are constructed on the basis of industry-level, deflated R&D expenditures in the U.S., available in OECD's STAN database. Defining RE_{it} as the R&D expenditures of industry i in year t, the indirect R&D expenditures of firm k operating in industry j are constructed according to a firm-level equivalent of Eq. 1:

$$IRE_{kjt} = \sum_i \omega_{ij} RE_{it} \ . \tag{7}$$

Note that when $i = j$, the R&D expenditures by firm k itself are excluded from RE_{it} to avoid double-counting. The indirect R&D stocks are then obtained according to the perpetual inventory model, again assuming a 15% depreciation rate.

In this section, six spillover measures (corresponding to different sets of ω's) are considered. Two are taken from Los and Verspagen (1997). The first of them, *IRT*, is obtained by simply setting all ω's equal to one and may be regarded as a 'baseline measure', originally proposed by Bernstein (1988) in a study focusing on intraindustry technology spillovers. The second measure was introduced in Verspagen (1997a) and will be denoted by *IR2*. This measure explicitly relates to knowledge spillovers, being based on the assignment of probable producers and

[27] Cuneo and Mairesse (1984) find that that estimates using either value added or sales do not differ significantly.

[28] See Los and Verspagen (1997) for the deflators used.

users of technical information present in patent documents of the European Patent Office.[29] The third measure (*IRC*) is the one proposed in this paper. To make the measure both compatible with the STAN data and comparable with *IR2*, we had to recalculate our measure on the basis of a 21-industry input-output table of manufacturing industries only.[30] This table was obtained by aggregating the 91-industry U.S. 1987 input-output table on the basis of the concordance between 4-digit SIC codes and input-output industries attached to the 1987 U.S. tables. This caused trouble in two of the 52 manufacturing industries, represented by SIC codes belonging to two or three STAN classes. We decided to assign 1/3 of the inputs and outputs of “ordnance and accessories” (11) to “metal products”, “aerospace” and “other transport” each, and half of the inputs and outputs of “furniture and fixtures” (19) to “metal products” and “wood products” each.[31] The application of Eq. 2 on the 21-industry input-output table leads to the proximities matrix in Appendix C, representing the ω’s needed to construct *IRC*. As a variant, we defined *IRN* as the indirect technology stock obtained by applying Eq. 7 on the *IRC* ω’s, normalized to add up to one over each row.[32] In this way, the assumed specificity of knowledge is equal to *IR2*’s (see Los, 1997, for a discussion of ‘single industry specificity’ and ‘full generality’ of knowledge spillovers): in *IRN*, each ‘unit of knowledge’ is assumed to be relevant to one spillover receiving industry only. The fifth indirect R&D stock (*IRO*) is based on the same 21-industry input-output table for the U.S. in 1987, but is the traditional measure on the basis of output coefficients. As we have argued in Section 3, such a measure mainly captures rent spillovers. The cell values are divided through by the total outputs of the corresponding row industries. An immediate consequence of this choice is that the ω_{ij}’s do not add to one for each i, representing the fact that the rents of some quality improvements are predominantly appropriated by service industries, consumers, and foreign countries. Wolff and Nadiri (1993) and Wolff (1997), emphasizing the knowledge flows from suppliers to buyers, also propose to use input coefficients as weights. Although we think knowledge spillovers and rent spillovers are mixed up in this approach, *IRI* is constructed along these lines.[33,34]

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29 The choice for Verspagen’s (1997a) *IR2* measure instead of his *IR1* is rather arbitrary. Generally, *IR1* and *IR2* yield comparable results in estimations like the ones presented here (see Los and Verspagen, 1997).

30 Note that the inputs of primary and tertiary industries are ‘moved’ to the primary input block. This implies that they play no role at all in the determination of the proximities ω and, consequently, the firms’ *IRC*s. An alternative course would be to leave these input coefficients unchanged in the intermediate block, but then discrepancies across industries concerning the levels of aggregation would be unavoidable.

31 This is an admittedly crude solution. Examination of other trade or production statistics would have yielded a ‘better’ aggregated table, but we do not think this effort would serve the goals of this paper.

32 Note that the equality between ω_{ij} and ω_{ji} (present in *IRC*) vanishes in the construction of *IRN*.

33 In Verspagen’s (1997a) *IR2* measure some R&D benefits a 22nd industry, “ships and boats manufacturing”. The STAN database on R&D investments and the U.S. input-output tables do not distinguish such an industry. Therefore, firms in this industry are added to “other transport” and no attention should be paid to the row and column corresponding to “ships” in Appendix C’s matrix.

34 Note that we implicitly assume homogeneity of firms within an industry, for all spillover measures.

Estimation results

Like Los and Verspagen (1997), we will present the estimation results for the total sample as well as for three subsamples. The construction of these subsamples roughly corresponds to the division of industries into high-tech, medium-tech and low-tech as currently in use with the OECD. The high-tech subsample consists of those firms operating in "electronics", "drugs", "aerospace", "instruments" and "computers". The firms with SIC codes relating to "electrical products", "chemicals", "motor vehicles", "other transport", "machines" and "rubber and plastics" are included in the medium-tech subsample. Firms in other industries are assigned the low-tech status.[35] The 'fixed effects' estimates of the level equation (Eq. 4) for the various samples, *IRC* being the specific indirect spillover measure, are in Table 1.

Table 1: 'Fixed effects' estimates for level specification. (unbalanced samples).

	NI	NOB	*k/l*	*r/l*	*l*	*irc*
Total	680	8543	0.140	0.010	-0.112	0.601
			0.134	0.033		0.572
High-tech	245	2958	0.079	0.112	-0.019	0.396
			0.076	0.119		0.384
Med-tech	224	2886	0.142	-0.001	-0.057	0.929
			0.141	0.009		0.910
Low-tech	211	2699	0.225	0.004	-0.098	0.417
			0.231	0.020		0.406

NI: number of firms; NOB: number of observations; *RES*: lagged residual from level estimation.

Two sets of results are presented: with and without imposed constant returns to scale. We do not present *t*-values and R^2's because the estimators have nonnormal distributions due to the non-stationarity of variables. If one would insist on inference-making on the basis of this fixed effects specification, all results would be significant at the usual levels, except those for own R&D in the med-tech and low-tech samples and the returns to scale parameter for high-tech firms. The values are in line with earlier studies in this field, like Griliches and Mairesse (1984). Note the estimated decreasing returns to scale (the estimates for μ-1 are negative), common in time-series estimations. Another well-known phenomenon is the sensitivity of the results to the assumption of constant returns to scale. Own R&D turns out to have more positive effects in this case, even in medium-tech and low-tech industries. The estimated productivity effects of indirect R&D (*IRC*) are somewhat lower than in the unrestricted equation, particularly for high-tech firms.

[35] The OECD classification is based on average R&D to value added ratios. This is a rather crude criterion which, for example, causes the "other transports" industry to be low-tech. Bearing in mind the huge R&D efforts of consortia in the field of rail transportation (Verspagen, 1995), we think firms in this industry should better be included in the medium-tech category. Of course, this adjustment does not remove all undesired heterogeneity in the categories. A firm specialized in the field of high-tech superconducting ceramics will still be in the low-tech "glass, stone, etc." industry.

On the basis of the level estimates in Table 1, we performed the second and third step of the Engle-Granger-Yoo procedure. The corresponding ECM-specification (Eq. 5) yielded significantly negative estimates for ζ (the lagged residual coefficient), ranging from -0.311 to -0.421. This supports the assumption of cointegration and justifies the third step that yields the corrected long-run relationship estimates documented in Table 2.

Table 2: Engle-Granger-Yoo corrected estimates (unbalanced samples).*

	k/l	*r/l*	*l*	*irc*
Total	0.129	0.004	-0.027	0.682
	(7.40)	(0.40)	(1.52)	(19.4)
	0.126	0.033		0.718
	(7.37)	(3.87)		(21.0)
High-tech	0.061	0.086	0.069	0.427
	(2.44)	(3.24)	(2.16)	(6.83)
	0.059	0.131		0.459
	(2.42)	(5.55)		(7.89)
Med-tech	0.136	-0.005	0.035	1.169
	(3.53)	(0.33)	(1.31)	(16.1)
	0.136	0.005		1.177
	(3.65)	(0.36)		(16.9)
Low-tech	0.214	-0.005	-0.048	0.435
	(8.53)	(0.43)	(2.11)	(9.78)
	0.212	0.016		0.453
	(8.75)	(1.70)		(10.5)

*Numbers of observations: see Table 1.

The most important differences between the results in Table 1 and Table 2 are in the estimates with respect to the returns to scale parameter. For the total sample, the implausible decreasing returns to scale have disappeared. The same is true for the medium-tech sample. For the high-tech sample we find increasing returns to scale, partly as a result to the positive estimate of the elasticity for own R&D. Despite the small deviations from constant returns to scale, the results for the restricted estimations are different, in particular with respect to the productivity effects of own R&D. The physical capital estimates are not affected by a priori constant returns to scale but are still rather low, which might be caused by mismeasurement: reliable indicators of capacity utilization are not available. The impacts of knowledge spillovers appear to be highly significant, although the variation across sectors seems to be remarkable. Medium-tech firms seem to be the main beneficiaries of those spillovers, while high-tech firms tend to depend to a larger extent on their own technological activity and the productivity of low-tech firms turns out to be simply less technology-dependent.

From the point of view of this paper, the most interesting thing to see is how *IRC* performs compared to the alternative measures. Ideally, we would like to estimate an equation simultaneously including a measure of knowledge spillovers (*IR2, IRC* or *IRN*) and a measure of rent spillovers (*IRO* or *IRI*). In practice, this turns out to be impossible, due to the serious multicollinearity in the time series dimension (even between first differences) apparent from Table 3.

Table 3: Correlation coefficients between first differences of six alternative measures of indirect R&D stocks (unbalanced samples).

	irc	*irn*	*iro*	*iri*	*irt*
ir2	0.58	0.57	0.41	0.43	0.52
irc		0.97	0.83	0.86	0.78
irn			0.76	0.80	0.83
iro				0.99	0.43
iri					0.47

Given this impossibility, we estimated the equations with one *IR* variable at a time. In general, the estimates for the elasticities with respect to physical capital and own R&D, as well as the estimates for the returns to scale parameter and the lagged residual coefficient are rather stable, no matter which spillover variable is included. Therefore, we report in Table 4 only the estimated elasticities (obtained by the Engle-Granger-Yoo procedure) with respect to the various spillover variables.

Table 4: Engle-Granger-Yoo corrected indirect R&D elasticity estimates for various spillover measures (unbalanced samples).*

	irc	*irn*	*ir2*	*iro*	*iri*	*irt*
Total	0.682	0.626	0.591	0.466	0.538	0.623
	(19.4)	(20.1)	(17.6)	(12.0)	(14.0)	(20.5)
High-tech	0.427	0.403	0.355	0.445	0.449	0.425
	(6.83)	(6.89)	(4.75)	(8.07)	(7.92)	(6.24)
Med-tech	1.169	1.052	0.703	0.293	0.772	0.955
	(16.1)	(17.1)	(10.7)	(2.50)	(6.69)	(16.5)
Low-tech	0.435	0.387	0.350	0.447	0.458	0.354
	(9.78)	(9.85)	(6.80)	(8.50)	(9.05)	(9.93)

* *t*-values in brackets; unrestricted estimates.

The differences between the estimates for the various indirect R&D stocks are only marginal, except for the medium-tech sample. The mainly rent spillover-oriented *IRO* yields a remarkably low estimate, while *IRC* and *IRN* show very high estimates. On the basis of these results, however, we cannot decide whether our spillover measures perform like other knowledge spillover measures but unlike input-output based rent spillover measures: there is simply too little variation. The estimated short-run dynamics due to indirect R&D, obtained from the second step error correction specification (Eq. 5), provides more clues (Table 5).

For the total sample, all *IR* measures yield significantly positive estimates again. Two remarkable results should be pointed out: first, the estimated elasticities for the knowledge spillover measures (*IRC*, *IRN* and *IR2*) and the unweighted indirect technology stock (*IRT*) are about twice as high as those for the rent spillover measures (*IRO* and *IRI*). This difference is even more apparent in the medium-tech subsample, in which *IRO* and *IRI* yield negative or insignificant estimates. Second, we find that the estimates for the elasticity with respect to the *IR* variables are very sensitive to the exclusion of the labor (returns to scale) variable from the equation.

The differences, which are far less severe for the long-run estimates in Table 2, are the most striking for the high-tech subsample.

Table 5: ECM estimates for alternative measures of indirect R&D (unbalanced samples).*

	irc		*irn*		*ir2*		*iro*		*iri*		*irt*	
	U	R	U	R	U	R	U	R	U	R	U	R
Total	0.551	0.367	0.527	0.366	0.547	0.379	0.246	0.065	0.313	0.132	0.545	0.393
	(14.3)	(9.27)	(15.2)	(10.3)	(14.7)	(9.92)	(6.45)	(1.68)	(8.20)	(3.37)	(15.7)	(11.0)
High-tech	0.559	0.236	0.522	0.228	0.576	0.241	0.493	0.222	0.496	0.218	0.588	0.250
	(8.59)	(3.90)	(8.70)	(4.07)	(8.03)	(3.59)	(8.87)	(4.26)	(8.68)	(4.07)	(8.54)	(3.90)
Med-tech	0.653	0.514	0.660	0.540	0.639	0.533	-0.423	-0.591	-0.114	-0.278	0.655	0.549
	(8.56)	(6.61)	(9.85)	(7.90)	(10.7)	(8.77)	(4.55)	(6.28)	(1.26)	(3.05)	(10.7)	(8.75)
Low-tech	0.315	0.238	0.287	0.218	0.176	0.086	0.090	0.008	0.148	0.072	0.290	0.231
	(4.84)	(3.48)	(4.97)	(3.59)	(2.66)	(1.24)	(1.30)	(0.11)	(2.15)	(1.01)	(5.42)	(4.11)

**t*-values between brackets; U: unrestricted estimation; R: estimation with a priori imposed constant returns to scale in *K*, *L* and *R*.

The most important conclusion of the estimates presented in this section is that the proposed measure seems to provide a good alternative to *IR2*, one of the knowledge spillover measures introduced by Verspagen (1997a). Furthermore, the results obtained with *IRC* (and *IRN*) are generally different from those obtained with *IRO* and *IRI*, the existing input-output based measures which were argued to measure a different aspect of interindustry technology effects.

6. Conclusions

In the first part of the paper, we introduced a new measure of interindustry knowledge spillovers. It was argued that existing measures of knowledge spillovers are rather inflexible concerning the number of industries and the time periods that are considered, due to the nature of the data needed to construct them. The new measure does not have this disadvantage, because its basic data (input-output tables) are widely available. Although some theoretical arguments were presented that support the measure, existing methods are clearly more straightforward measures of knowledge flows from industry to industry. Existing input-output based measures were argued to focus primarily on rent spillovers, a conceptually different notion of technology spillovers. Therefore, the new measure could fill a gap in the case it would yield results comparable to the existing, more sophisticated knowledge spillover measures.

The second part of the paper was devoted to empirical analyses to evaluate whether the measure generated plausible outcomes. First, a rather desaggregated U.S. input-output table was used to compute an actual spillover matrix. This matrix enabled us to distinguish a number of technological clusters which, in general, appeal to intuition. The second, and most elaborate, empirical exercise compared estimation results obtained with several technology spillover measures. A large cross-section time series sample of American manufacturing firms was used to estimate the impact of indirect R&D. Although many well-known problems concerning the estimation of various output elasticities in the time series dimension could not be solved, evidence was found that the new measure is likely to be a good alternative to existing knowledge spillover measures: the estimated elasticities are of the same order of magnitude as those obtained with the alternatives and differ from input-output based rent spillover measures with respect to short-run dynamics. The most important conclusion of this paper is that the proposed measure seems to be a flexible, easy-to-construct-and-adapt measure of knowledge spillovers, which may prove to be a worthwhile alternative to current measures.

In our opinion, the proposed measure opens up some interesting directions for future research. First, up till now, most productivity studies either are restricted to the impacts of technology spillovers on manufacturing industries or evaluate the effects of rent spillovers on service industries only. The new measure enables researchers to study whether knowledge about how to run a bank in a more efficient way influences the productivity in the real estate and insurance industries, or not. Of course, a host of problems should be solved (like how to measure inputs or outputs of this knowledge creating process, how to measure productivity in services industries in an adequate way, etc.), but the increasing importance of services and government industries in developed countries seems to justify more intense empirical work on the subject. Second, a number of studies have recently appeared that investigate whether international technology spillovers have significant effects or not. In an influential study in this field, Coe and Helpman (1995) used a spillover measure comparable to *IRI* in this paper to weight R&D performed by different countries. As Verspagen (1997b) already observed, they hereby seem to confuse the two notions of technology spillovers. Verspagen himself used a spillover measure with a strong resemblance to the knowledge spillover measure *IR2*, but had to assume that the weights are equal within and across the countries studied. This seems to be a reasonable assumption as long as developed (OECD) countries are studied, but must be questioned when other countries are included into the analysis. In principle, the proposed measure is able to correct for differences in technology within industries across countries, due to the fact that different technologies are likely to be reflected in differing input coefficients derivable from input-output tables. Again, data availability is likely to be the limiting factor, as the reliability of the proposed measure probably increases as the level of aggregation of input-output tables decreases.

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Appendix A: Industry Classification U.S. IO Tables

1	Livestock and livestock products
2	Other agricultural products
3	Forestry and fishery products
4	Agricultural, forestry, and fishery services
5	Metallic ores mining
6	Coal mining
7	Crude petroleum and natural gas
8	Nonmetallic minerals mining
9	New construction
10	Maintenance and repair construction
11	Ordnance and accessories
12	Food and kindred products
13	Tobacco products
14	Broad and narrow fabrics, yarn and thread mills
15	Miscellaneous textile goods and floor coverings
16	Apparel
17	Miscellaneous fabricated textile products
18	Lumber and wood products
19	Furniture and fixtures
20	Paper and allied products, except containers
21	Paperboard containers and boxes
22	Newspapers and periodicals
23	Other printing and publishing
24	Industrial and other chemicals
25	Agricultural fertilizers and chemicals
26	Plastics and synthetic materials
27	Drugs
28	Cleaning and toilet preparations
29	Paints and allied products
30	Petroleum refining and related products
31	Rubber and miscellaneous plastics products
32	Footwear, leather, and leather products
33	Glass and glass products
34	Stone and clay products
35	Primary iron and steel manufacturing
36	Primary nonferrous metals manufacturing
37	Metal containers
38	Heating, plumbing, and fabricated structural metal products
39	Screw machine products and stampings
40	Other fabricated metal products
41	Engines and turbines
42	Farm, construction, and mining machinery
43	Materials handling machinery and equipment
44	Metalworking machinery and equipment
45	Special industry machinery and equipment
46	General industrial machinery and equipment
47	Miscellaneous machinery, except electrical
48	Computer and office equipment
49	Service industry machinery
50	Electrical industrial equipment and apparatus
51	Household appliances
52	Electric lighting and wiring equipment
53	Audio, video, and communication equipment
54	Electronic components and accessories
55	Miscellaneous electrical machinery and supplies
56	Motor vehicles (passenger cars and trucks)
57	Truck and bus bodies, trailers, and motor vehicles parts
58	Aircraft and parts
59	Other transportation equipment
60	Scientific and controlling instruments
61	Ophthalmic and photographic equipment
62	Miscellaneous manufacturing
63	Railroads and related services; passenger ground transportation
64	Motor freight transportation and warehousing
65	Water transportation
66	Air transportation
67	Pipelines, freight forwarders, and related services
68	Communications, except radio and TV
69	Radio and TV broadcasting
70	Electric services (utilities)
71	Gas production and distribution (utilities)
72	Water and sanitary services
73	Wholesale trade
74	Retail trade
75	Finance
76	Insurance
77	Owner-occupied dwellings
78	Real estate and royalties
79	Hotels and lodging places
80	Personal and repair services (except auto)
81	Computer and data processing services
82	Legal, engineering, accounting, and related services
83	Other business and professional services, except medical
84	Advertising
85	Eating and drinking places
86	Automotive repair and services
87	Amusements
88	Health services
89	Educational and social services, and membership organizations
90	Federal Government enterprises
91	State and local government enterprises

Appendix B: 91-industry U.S. 1987 proximities matrix (shaded cells in upper right part indicate values > 0.4)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47
1	1.00	0.47	0.28	0.61	0.06	0.06	0.10	0.09	0.06	0.06	0.04	0.82	0.31	0.23	0.03	0.02	0.05	0.03	0.07	0.06	0.02	0.03	0.04	0.06	0.06	0.04	0.08	0.11	0.05	0.02	0.05	0.22	0.06	0.06	0.06	0.04	0.03	0.04	0.03	0.06	0.04	0.06	0.07	0.06	0.07	0.06	0.06
2	0.47	1.00	0.62	0.63	0.17	0.23	0.58	0.28	0.21	0.21	0.12	0.25	0.19	0.15	0.05	0.06	0.11	0.10	0.21	0.14	0.06	0.14	0.13	0.12	0.40	0.08	0.17	0.18	0.07	0.05	0.13	0.09	0.18	0.15	0.15	0.09	0.08	0.12	0.09	0.16	0.12	0.18	0.19	0.19	0.21	0.17	0.18
3	0.28	0.62	1.00	0.19	0.12	0.10	0.07	0.16	0.23	0.23	0.08	0.23	0.05	0.05	0.03	0.03	0.06	0.08	0.13	0.08	0.02	0.09	0.07	0.09	0.11	0.06	0.15	0.14	0.06	0.05	0.07	0.16	0.08	0.07	0.09	0.05	0.04	0.07	0.06	0.10	0.07	0.10	0.11	0.10	0.11	0.09	0.10
4	0.61	0.63	0.19	1.00	0.13	0.13	0.09	0.17	0.18	0.18	0.10	0.44	0.27	0.20	0.05	0.06	0.11	0.08	0.19	0.13	0.05	0.10	0.10	0.11	0.61	0.08	0.18	0.17	0.06	0.04	0.11	0.11	0.16	0.11	0.15	0.08	0.08	0.11	0.09	0.15	0.12	0.18	0.18	0.17	0.20	0.16	0.14
5	0.06	0.17	0.12	0.13	1.00	0.32	0.19	0.66	0.25	0.25	0.17	0.08	0.05	0.11	0.09	0.05	0.08	0.13	0.26	0.25	0.05	0.10	0.13	0.39	0.25	0.32	0.22	0.30	0.24	0.06	0.22	0.11	0.37	0.27	0.49	0.29	0.17	0.24	0.24	0.32	0.25	0.32	0.30	0.34	0.32	0.32	0.30
6	0.06	0.23	0.10	0.13	0.32	1.00	0.23	0.42	0.19	0.19	0.12	0.07	0.05	0.07	0.05	0.05	0.08	0.09	0.19	0.16	0.04	0.08	0.09	0.15	0.13	0.12	0.15	0.18	0.09	0.05	0.13	0.08	0.19	0.20	0.28	0.10	0.07	0.12	0.09	0.17	0.14	0.26	0.22	0.19	0.23	0.22	0.17
7	0.10	0.58	0.07	0.09	0.19	0.23	1.00	0.25	0.09	0.09	0.12	0.03	0.04	0.03	0.03	0.03	0.04	0.04	0.11	0.06	0.02	0.13	0.09	0.16	0.11	0.09	0.11	0.11	0.08	0.24	0.08	0.05	0.13	0.10	0.10	0.04	0.04	0.07	0.06	0.10	0.06	0.08	0.10	0.14	0.14	0.10	0.14
8	0.09	0.28	0.16	0.17	0.66	0.42	0.25	1.00	0.33	0.33	0.20	0.11	0.08	0.13	0.10	0.07	0.12	0.12	0.28	0.32	0.10	0.18	0.20	0.42	0.44	0.33	0.26	0.38	0.26	0.09	0.26	0.15	0.47	0.59	0.39	0.24	0.16	0.20	0.17	0.30	0.23	0.34	0.36	0.33	0.37	0.34	0.30
9	0.06	0.21	0.23	0.18	0.25	0.19	0.09	0.33	1.00	1.00	0.20	0.09	0.07	0.07	0.05	0.06	0.11	0.49	0.60	0.28	0.07	0.17	0.13	0.16	0.17	0.12	0.32	0.23	0.11	0.06	0.17	0.11	0.29	0.45	0.32	0.18	0.23	0.33	0.27	0.35	0.28	0.40	0.41	0.41	0.40	0.34	0.37
10	0.06	0.21	0.23	0.18	0.25	0.19	0.09	0.33	1.00	1.00	0.20	0.09	0.07	0.07	0.05	0.06	0.11	0.49	0.59	0.28	0.06	0.17	0.13	0.16	0.17	0.12	0.32	0.23	0.11	0.06	0.17	0.11	0.29	0.45	0.30	0.18	0.21	0.31	0.25	0.34	0.27	0.39	0.40	0.39	0.39	0.32	0.36
11	0.04	0.12	0.08	0.10	0.17	0.12	0.12	0.20	0.20	0.20	1.00	0.07	0.08	0.05	0.05	0.04	0.07	0.08	0.27	0.11	0.03	0.11	0.09	0.13	0.11	0.11	0.16	0.20	0.09	0.03	0.13	0.08	0.18	0.14	0.31	0.25	0.30	0.31	0.26	0.36	0.31	0.30	0.32	0.33	0.34	0.33	0.36
12	0.82	0.25	0.23	0.44	0.08	0.07	0.03	0.11	0.09	0.09	0.07	1.00	0.17	0.13	0.04	0.04	0.07	0.06	0.13	0.13	0.06	0.09	0.10	0.10	0.11	0.07	0.16	0.24	0.11	0.02	0.10	0.37	0.17	0.09	0.11	0.06	0.06	0.07	0.06	0.11	0.07	0.12	0.12	0.11	0.13	0.10	0.09
13	0.31	0.19	0.05	0.27	0.05	0.05	0.04	0.08	0.07	0.07	0.08	0.17	1.00	0.13	0.04	0.03	0.06	0.04	0.13	0.10	0.05	0.13	0.12	0.07	0.07	0.06	0.10	0.17	0.04	0.02	0.07	0.06	0.17	0.07	0.09	0.04	0.05	0.06	0.05	0.10	0.06	0.10	0.11	0.10	0.11	0.08	0.09
14	0.23	0.15	0.05	0.20	0.11	0.07	0.03	0.13	0.07	0.07	0.05	0.13	0.13	1.00	0.91	0.67	0.88	0.05	0.31	0.17	0.05	0.04	0.06	0.14	0.09	0.19	0.09	0.18	0.30	0.02	0.50	0.19	0.13	0.10	0.10	0.07	0.04	0.05	0.05	0.10	0.05	0.08	0.09	0.10	0.11	0.08	0.08
15	0.03	0.05	0.03	0.05	0.09	0.05	0.03	0.10	0.05	0.05	0.05	0.04	0.04	0.91	1.00	0.57	0.78	0.05	0.28	0.21	0.08	0.05	0.08	0.19	0.11	0.27	0.08	0.24	0.48	0.02	0.73	0.19	0.14	0.11	0.08	0.07	0.03	0.04	0.04	0.09	0.04	0.06	0.06	0.10	0.09	0.07	0.07
16	0.02	0.06	0.03	0.06	0.05	0.05	0.03	0.07	0.06	0.06	0.04	0.04	0.03	0.67	0.57	1.00	0.74	0.03	0.26	0.09	0.03	0.04	0.05	0.04	0.04	0.06	0.06	0.09	0.07	0.01	0.16	0.15	0.07	0.06	0.06	0.04	0.03	0.04	0.03	0.06	0.04	0.07	0.07	0.07	0.08	0.06	0.06
17	0.05	0.11	0.06	0.11	0.08	0.08	0.04	0.12	0.11	0.11	0.07	0.07	0.06	0.88	0.78	0.74	1.00	0.06	0.43	0.16	0.04	0.06	0.09	0.10	0.09	0.12	0.12	0.18	0.12	0.02	0.27	0.26	0.14	0.09	0.10	0.07	0.05	0.07	0.06	0.11	0.08	0.12	0.12	0.11	0.14	0.12	0.10
18	0.03	0.10	0.08	0.08	0.13	0.09	0.04	0.12	0.49	0.49	0.08	0.06	0.04	0.05	0.05	0.03	0.06	1.00	0.73	0.38	0.03	0.05	0.06	0.10	0.09	0.08	0.09	0.14	0.08	0.02	0.11	0.07	0.24	0.11	0.12	0.07	0.05	0.10	0.07	0.15	0.08	0.13	0.15	0.12	0.15	0.11	0.10
19	0.07	0.21	0.13	0.19	0.26	0.19	0.11	0.28	0.60	0.59	0.27	0.13	0.13	0.31	0.28	0.26	0.43	0.73	1.00	0.43	0.07	0.15	0.16	0.20	0.18	0.16	0.28	0.39	0.13	0.05	0.28	0.23	0.39	0.22	0.50	0.23	0.38	0.51	0.45	0.61	0.43	0.52	0.54	0.51	0.52	0.49	0.48
20	0.06	0.14	0.08	0.13	0.25	0.16	0.06	0.32	0.28	0.28	0.11	0.13	0.10	0.17	0.21	0.09	0.16	0.38	0.43	1.00	0.88	0.67	0.83	0.35	0.25	0.34	0.22	0.39	0.31	0.04	0.35	0.15	0.34	0.26	0.21	0.12	0.08	0.12	0.09	0.20	0.11	0.17	0.17	0.19	0.21	0.16	0.14
21	0.02	0.06	0.02	0.05	0.05	0.04	0.02	0.10	0.07	0.06	0.03	0.06	0.05	0.05	0.08	0.03	0.04	0.03	0.07	0.88	1.00	0.72	0.88	0.11	0.08	0.11	0.09	0.11	0.09	0.01	0.15	0.04	0.08	0.13	0.06	0.04	0.04	0.05	0.04	0.07	0.04	0.05	0.06	0.07	0.07	0.06	0.05
22	0.03	0.14	0.09	0.10	0.10	0.08	0.13	0.18	0.17	0.17	0.11	0.09	0.13	0.04	0.05	0.04	0.06	0.05	0.15	0.67	0.72	1.00	0.93	0.14	0.14	0.12	0.22	0.21	0.08	0.02	0.12	0.07	0.14	0.15	0.11	0.05	0.08	0.07	0.06	0.11	0.07	0.10	0.13	0.13	0.14	0.11	0.15
23	0.04	0.13	0.07	0.10	0.13	0.09	0.09	0.20	0.13	0.13	0.09	0.10	0.12	0.06	0.08	0.05	0.09	0.06	0.16	0.83	0.88	0.93	1.00	0.22	0.17	0.21	0.20	0.28	0.16	0.03	0.19	0.09	0.19	0.17	0.13	0.08	0.09	0.09	0.07	0.13	0.08	0.12	0.14	0.14	0.17	0.12	0.12
24	0.06	0.12	0.09	0.11	0.39	0.15	0.16	0.42	0.16	0.16	0.13	0.10	0.07	0.14	0.19	0.04	0.10	0.10	0.20	0.35	0.11	0.14	0.22	1.00	0.58	0.96	0.32	0.77	0.83	0.27	0.37	0.21	0.59	0.31	0.29	0.13	0.08	0.10	0.11	0.24	0.09	0.14	0.15	0.20	0.25	0.13	0.13
25	0.06	0.40	0.11	0.61	0.25	0.13	0.11	0.44	0.17	0.17	0.11	0.11	0.07	0.09	0.11	0.04	0.09	0.09	0.18	0.25	0.08	0.14	0.17	0.58	1.00	0.51	0.24	0.46	0.44	0.21	0.23	0.15	0.42	0.39	0.24	0.11	0.08	0.10	0.09	0.19	0.09	0.15	0.16	0.17	0.20	0.13	0.13
26	0.04	0.08	0.06	0.08	0.32	0.12	0.09	0.33	0.12	0.12	0.11	0.07	0.06	0.19	0.27	0.06	0.12	0.08	0.16	0.34	0.11	0.12	0.21	0.96	0.51	1.00	0.29	0.78	0.89	0.05	0.44	0.20	0.55	0.26	0.23	0.10	0.06	0.07	0.08	0.20	0.06	0.11	0.11	0.17	0.21	0.10	0.09
27	0.08	0.17	0.15	0.18	0.22	0.15	0.11	0.26	0.32	0.32	0.16	0.16	0.10	0.09	0.08	0.06	0.12	0.09	0.28	0.22	0.09	0.22	0.20	0.32	0.24	0.29	1.00	0.42	0.23	0.05	0.22	0.15	0.33	0.17	0.21	0.11	0.09	0.13	0.13	0.22	0.13	0.22	0.22	0.22	0.27	0.20	0.21
28	0.11	0.18	0.14	0.17	0.30	0.18	0.11	0.38	0.23	0.23	0.20	0.24	0.17	0.18	0.24	0.09	0.18	0.14	0.39	0.39	0.11	0.21	0.28	0.77	0.46	0.78	0.42	1.00	0.69	0.07	0.48	0.32	0.64	0.29	0.29	0.15	0.12	0.17	0.14	0.34	0.16	0.29	0.29	0.29	0.36	0.24	0.22
29	0.05	0.07	0.06	0.06	0.24	0.09	0.08	0.26	0.11	0.11	0.09	0.11	0.04	0.30	0.48	0.07	0.12	0.08	0.13	0.31	0.09	0.08	0.16	0.83	0.44	0.89	0.23	0.69	1.00	0.04	0.69	0.21	0.46	0.27	0.20	0.10	0.07	0.07	0.08	0.18	0.06	0.08	0.09	0.16	0.17	0.08	0.08
30	0.02	0.05	0.05	0.04	0.06	0.05	0.24	0.09	0.06	0.06	0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.05	0.04	0.01	0.02	0.03	0.27	0.21	0.05	0.05	0.07	0.04	1.00	0.04	0.03	0.06	0.04	0.05	0.03	0.02	0.03	0.02	0.04	0.03	0.04	0.05	0.05	0.05	0.04	0.04
31	0.05	0.13	0.07	0.11	0.22	0.13	0.08	0.26	0.17	0.17	0.13	0.10	0.07	0.50	0.73	0.16	0.27	0.11	0.28	0.35	0.15	0.12	0.19	0.37	0.23	0.44	0.22	0.48	0.69	0.04	1.00	0.19	0.31	0.22	0.20	0.15	0.10	0.15	0.12	0.25	0.13	0.20	0.20	0.23	0.24	0.19	0.18
32	0.22	0.09	0.16	0.11	0.11	0.08	0.05	0.15	0.11	0.11	0.08	0.37	0.06	0.19	0.19	0.15	0.26	0.07	0.23	0.15	0.04	0.07	0.09	0.21	0.15	0.20	0.15	0.32	0.21	0.03	0.19	1.00	0.19	0.11	0.12	0.07	0.05	0.08	0.06	0.13	0.08	0.13	0.13	0.13	0.15	0.11	0.10
33	0.06	0.18	0.08	0.16	0.37	0.19	0.13	0.47	0.29	0.29	0.18	0.17	0.17	0.13	0.14	0.07	0.14	0.24	0.39	0.34	0.08	0.14	0.19	0.59	0.42	0.55	0.33	0.64	0.46	0.06	0.31	0.19	1.00	0.44	0.35	0.17	0.12	0.18	0.15	0.30	0.16	0.24	0.25	0.30	0.33	0.23	0.23
34	0.06	0.15	0.07	0.11	0.27	0.20	0.10	0.59	0.45	0.45	0.14	0.09	0.07	0.10	0.11	0.06	0.09	0.11	0.22	0.26	0.13	0.15	0.17	0.31	0.39	0.26	0.17	0.29	0.27	0.04	0.22	0.11	0.44	1.00	0.32	0.13	0.11	0.16	0.14	0.23	0.14	0.19	0.19	0.27	0.22	0.19	0.22
35	0.06	0.15	0.09	0.15	0.49	0.28	0.10	0.39	0.32	0.30	0.31	0.11	0.09	0.10	0.08	0.06	0.10	0.12	0.50	0.21	0.06	0.11	0.13	0.29	0.24	0.23	0.21	0.29	0.20	0.05	0.20	0.12	0.35	0.32	1.00	0.34	0.68	0.86	0.88	0.88	0.75	0.79	0.74	0.82	0.72	0.79	0.75
36	0.04	0.09	0.05	0.08	0.29	0.10	0.04	0.24	0.18	0.18	0.25	0.06	0.04	0.07	0.07	0.04	0.07	0.07	0.23	0.12	0.04	0.05	0.08	0.13	0.11	0.10	0.11	0.15	0.10	0.03	0.15	0.07	0.17	0.13	0.34	1.00	0.76	0.42	0.21	0.41	0.35	0.20	0.25	0.34	0.34	0.34	0.49
37	0.03	0.08	0.04	0.08	0.17	0.07	0.04	0.16	0.23	0.21	0.30	0.06	0.05	0.04	0.03	0.03	0.05	0.05	0.38	0.08	0.04	0.08	0.09	0.08	0.08	0.06	0.09	0.12	0.07	0.02	0.10	0.05	0.12	0.11	0.68	0.76	1.00	0.86	0.74	0.80	0.71	0.59	0.57	0.68	0.59	0.66	0.76
38	0.04	0.12	0.07	0.11	0.24	0.12	0.07	0.20	0.33	0.31	0.31	0.07	0.06	0.05	0.04	0.04	0.07	0.10	0.51	0.12	0.05	0.07	0.09	0.10	0.10	0.07	0.13	0.17	0.07	0.03	0.15	0.08	0.18	0.16	0.86	0.42	0.86	1.00	0.96	0.96	0.84	0.82	0.78	0.85	0.72	0.81	0.82
39	0.03	0.09	0.06	0.09	0.24	0.09	0.06	0.17	0.27	0.25	0.26	0.06	0.05	0.05	0.04	0.03	0.06	0.07	0.45	0.09	0.04	0.06	0.07	0.11	0.09	0.08	0.13	0.14	0.08	0.02	0.12	0.06	0.15	0.14	0.88	0.21	0.74	0.96	1.00	0.91	0.81	0.81	0.74	0.85	0.68	0.78	0.77
40	0.06	0.16	0.10	0.15	0.32	0.17	0.10	0.30	0.35	0.34	0.36	0.11	0.10	0.10	0.09	0.06	0.11	0.15	0.61	0.20	0.07	0.11	0.13	0.24	0.19	0.20	0.22	0.34	0.18	0.04	0.25	0.13	0.30	0.23	0.88	0.41	0.80	0.96	0.91	1.00	0.81	0.82	0.81	0.86	0.77	0.81	0.82
41	0.04	0.12	0.07	0.12	0.25	0.14	0.06	0.23	0.28	0.27	0.31	0.07	0.06	0.05	0.04	0.04	0.08	0.08	0.43	0.11	0.04	0.07	0.08	0.09	0.09	0.06	0.13	0.16	0.06	0.03	0.13	0.08	0.16	0.14	0.75	0.35	0.71	0.84	0.81	0.81	1.00	0.89	0.78	0.81	0.76	0.80	0.79
42	0.06	0.18	0.10	0.18	0.32	0.26	0.08	0.34	0.40	0.39	0.30	0.12	0.10	0.08	0.06	0.07	0.12	0.13	0.52	0.17	0.05	0.10	0.12	0.14	0.15	0.11	0.22	0.29	0.08	0.04	0.20	0.13	0.24	0.19	0.79	0.20	0.59	0.82	0.81	0.82	0.89	1.00	0.84	0.82	0.77	0.83	0.77
43	0.07	0.19	0.11	0.18	0.30	0.22	0.10	0.36	0.41	0.40	0.32	0.12	0.11	0.09	0.06	0.07	0.12	0.15	0.54	0.17	0.06	0.13	0.14	0.15	0.16	0.11	0.22	0.29	0.09	0.05	0.20	0.13	0.25	0.19	0.74	0.25	0.57	0.78	0.74	0.81	0.78	0.84	1.00	0.83	0.87	0.87	0.76
44	0.06	0.19	0.10	0.17	0.34	0.19	0.14	0.33	0.41	0.39	0.33	0.11	0.10	0.10	0.10	0.07	0.11	0.12	0.51	0.19	0.07	0.13	0.14	0.20	0.17	0.17	0.22	0.29	0.16	0.05	0.23	0.13	0.30	0.27	0.82	0.34	0.68	0.85	0.85	0.86	0.81	0.82	0.83	1.00	0.87	0.85	0.89
45	0.07	0.21	0.11	0.20	0.32	0.23	0.14	0.37	0.40	0.39	0.34	0.13	0.11	0.11	0.09	0.08	0.14	0.15	0.52	0.21	0.07	0.14	0.17	0.25	0.20	0.21	0.27	0.36	0.17	0.05	0.24	0.15	0.33	0.22	0.72	0.34	0.59	0.72	0.68	0.77	0.76	0.77	0.87	0.87	1.00	0.90	0.78
46	0.06	0.17	0.09	0.16	0.32	0.22	0.10	0.34	0.34	0.32	0.33	0.10	0.08	0.08	0.07	0.06	0.12	0.11	0.49	0.16	0.06	0.11	0.12	0.13	0.13	0.10	0.20	0.24	0.08	0.04	0.19	0.11	0.23	0.19	0.79	0.34	0.66	0.81	0.78	0.81	0.80	0.83	0.87	0.85	0.90	1.00	0.80

Appendix B (continued): 91-industry U.S. 1987 proximities matrix (shaded cells in upper right part indicate values > 0.4)

	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70
1	0.05	0.07	0.08	0.08	0.08	0.04	0.06	0.08	0.04	0.06	0.02	0.09	0.06	0.05	0.09	0.06	0.08	0.05	0.05	0.08	0.02	0.02	0.03
2	0.13	0.18	0.22	0.21	0.23	0.11	0.18	0.23	0.11	0.16	0.06	0.26	0.18	0.16	0.22	0.20	0.23	0.20	0.20	0.34	0.09	0.11	0.13
3	0.07	0.10	0.13	0.11	0.13	0.05	0.10	0.12	0.06	0.10	0.04	0.15	0.10	0.09	0.13	0.21	0.14	0.14	0.21	0.15	0.04	0.03	0.13
4	0.13	0.19	0.23	0.22	0.23	0.10	0.15	0.22	0.11	0.18	0.06	0.22	0.16	0.15	0.22	0.18	0.15	0.11	0.17	0.15	0.04	0.09	0.11
5	0.11	0.25	0.31	0.28	0.29	0.10	0.24	0.29	0.10	0.27	0.09	0.31	0.21	0.19	0.26	0.27	0.20	0.22	0.20	0.46	0.07	0.03	0.17
6	0.10	0.20	0.22	0.21	0.22	0.09	0.17	0.21	0.09	0.18	0.06	0.26	0.16	0.15	0.20	0.25	0.15	0.16	0.17	0.24	0.05	0.04	0.73
7	0.07	0.08	0.12	0.09	0.11	0.06	0.12	0.12	0.02	0.07	0.05	0.19	0.13	0.09	0.14	0.17	0.13	0.23	0.14	0.46	0.12	0.17	0.11
8	0.15	0.31	0.39	0.33	0.36	0.14	0.32	0.36	0.13	0.27	0.11	0.37	0.25	0.27	0.35	0.35	0.33	0.29	0.31	0.52	0.10	0.05	0.28
9	0.16	0.40	0.41	0.41	0.40	0.15	0.27	0.35	0.14	0.33	0.11	0.52	0.28	0.22	0.41	0.20	0.26	0.18	0.21	0.22	0.07	0.04	0.12
10	0.16	0.39	0.40	0.40	0.39	0.14	0.27	0.34	0.14	0.32	0.11	0.51	0.27	0.21	0.40	0.20	0.25	0.17	0.21	0.22	0.07	0.04	0.12
11	0.20	0.32	0.45	0.38	0.36	0.38	0.43	0.44	0.13	0.31	0.91	0.31	0.47	0.35	0.37	0.13	0.09	0.13	0.32	0.20	0.10	0.05	0.08
12	0.08	0.13	0.16	0.16	0.17	0.07	0.12	0.16	0.07	0.11	0.04	0.13	0.12	0.14	0.20	0.06	0.08	0.10	0.09	0.08	0.02	0.01	0.04
13	0.05	0.10	0.15	0.15	0.14	0.06	0.09	0.14	0.05	0.10	0.04	0.10	0.11	0.13	0.19	0.05	0.05	0.06	0.07	0.11	0.03	0.01	0.03
14	0.06	0.10	0.12	0.19	0.21	0.05	0.10	0.13	0.05	0.09	0.03	0.13	0.13	0.11	0.27	0.06	0.05	0.05	0.05	0.08	0.02	0.01	0.04
15	0.04	0.09	0.11	0.21	0.23	0.05	0.09	0.13	0.04	0.09	0.03	0.12	0.14	0.14	0.31	0.04	0.06	0.06	0.05	0.07	0.02	0.01	0.03
16	0.05	0.08	0.10	0.11	0.11	0.04	0.07	0.09	0.05	0.07	0.03	0.09	0.10	0.07	0.19	0.04	0.04	0.05	0.05	0.07	0.02	0.01	0.02
17	0.09	0.14	0.16	0.20	0.20	0.08	0.14	0.17	0.09	0.12	0.04	0.16	0.16	0.13	0.29	0.06	0.06	0.08	0.07	0.08	0.03	0.01	0.04
18	0.07	0.16	0.15	0.20	0.17	0.07	0.12	0.14	0.08	0.14	0.04	0.31	0.12	0.10	0.30	0.08	0.08	0.06	0.07	0.09	0.02	0.01	0.05
19	0.20	0.50	0.56	0.65	0.57	0.20	0.40	0.48	0.20	0.45	0.16	0.59	0.38	0.31	0.62	0.19	0.16	0.19	0.16	0.22	0.06	0.03	0.11
20	0.11	0.20	0.26	0.28	0.26	0.12	0.22	0.28	0.10	0.18	0.06	0.25	0.20	0.62	0.39	0.13	0.16	0.09	0.11	0.17	0.04	0.02	0.11
21	0.04	0.07	0.11	0.09	0.08	0.04	0.06	0.10	0.03	0.05	0.02	0.07	0.08	0.56	0.16	0.04	0.07	0.03	0.04	0.05	0.01	0.01	0.03
22	0.08	0.11	0.19	0.13	0.14	0.09	0.12	0.18	0.05	0.10	0.07	0.12	0.17	0.50	0.25	0.11	0.10	0.16	0.16	0.26	0.07	0.05	0.06
23	0.09	0.14	0.21	0.18	0.18	0.10	0.16	0.22	0.08	0.13	0.05	0.14	0.17	0.58	0.28	0.10	0.11	0.09	0.11	0.16	0.05	0.03	0.06
24	0.09	0.17	0.20	0.22	0.23	0.09	0.25	0.31	0.08	0.14	0.05	0.17	0.16	0.32	0.28	0.15	0.14	0.12	0.14	0.17	0.04	0.02	0.14
25	0.09	0.16	0.20	0.20	0.21	0.09	0.19	0.25	0.09	0.15	0.05	0.17	0.15	0.23	0.25	0.13	0.25	0.13	0.11	0.15	0.04	0.02	0.13
26	0.07	0.13	0.15	0.20	0.21	0.08	0.24	0.29	0.08	0.12	0.03	0.13	0.14	0.31	0.26	0.08	0.08	0.07	0.06	0.10	0.03	0.01	0.08
27	0.16	0.23	0.29	0.29	0.31	0.15	0.27	0.33	0.13	0.21	0.08	0.24	0.24	0.29	0.36	0.15	0.11	0.25	0.19	0.22	0.08	0.05	0.09
28	0.18	0.32	0.38	0.47	0.45	0.20	0.42	0.50	0.20	0.30	0.09	0.31	0.31	0.43	0.50	0.16	0.17	0.17	0.19	0.17	0.06	0.03	0.11
29	0.05	0.12	0.13	0.22	0.24	0.06	0.18	0.23	0.06	0.11	0.03	0.14	0.13	0.26	0.28	0.09	0.12	0.06	0.07	0.06	0.03	0.01	0.07
30	0.03	0.05	0.06	0.06	0.06	0.03	0.05	0.06	0.03	0.04	0.01	0.06	0.04	0.04	0.06	0.10	0.07	0.08	0.14	0.11	0.01	0.01	0.06
31	0.13	0.24	0.28	0.43	0.44	0.14	0.28	0.34	0.13	0.24	0.07	0.28	0.25	0.30	0.46	0.12	0.18	0.13	0.11	0.14	0.05	0.02	0.08
32	0.08	0.14	0.17	0.20	0.19	0.08	0.16	0.20	0.09	0.13	0.04	0.15	0.14	0.15	0.25	0.07	0.08	0.07	0.08	0.09	0.03	0.01	0.04
33	0.14	0.28	0.35	0.40	0.53	0.14	0.32	0.38	0.15	0.25	0.09	0.33	0.26	0.34	0.43	0.19	0.17	0.15	0.16	0.25	0.10	0.02	0.19
34	0.08	0.20	0.28	0.24	0.23	0.08	0.17	0.22	0.09	0.20	0.07	0.20	0.17	0.22	0.30	0.16	0.37	0.12	0.12	0.21	0.08	0.02	0.17
35	0.16	0.61	0.70	0.72	0.62	0.14	0.28	0.43	0.13	0.55	0.17	0.56	0.34	0.24	0.47	0.24	0.14	0.17	0.14	0.24	0.06	0.02	0.26
36	0.14	0.48	0.59	0.32	0.54	0.12	0.41	0.56	0.07	0.38	0.23	0.31	0.25	0.16	0.59	0.09	0.12	0.13	0.08	0.11	0.03	0.01	0.07
37	0.13	0.62	0.73	0.59	0.65	0.11	0.34	0.51	0.08	0.54	0.24	0.46	0.29	0.14	0.56	0.07	0.07	0.08	0.06	0.07	0.02	0.01	0.04
38	0.15	0.67	0.74	0.76	0.69	0.13	0.31	0.44	0.14	0.61	0.20	0.60	0.33	0.18	0.47	0.14	0.12	0.10	0.09	0.10	0.04	0.02	0.08
39	0.11	0.57	0.62	0.70	0.57	0.10	0.19	0.31	0.12	0.54	0.16	0.51	0.27	0.14	0.34	0.11	0.09	0.08	0.07	0.10	0.03	0.02	0.06
40	0.19	0.70	0.79	0.84	0.75	0.19	0.42	0.55	0.19	0.65	0.22	0.64	0.41	0.28	0.57	0.19	0.14	0.17	0.14	0.19	0.07	0.02	0.12
41	0.17	0.67	0.72	0.70	0.63	0.14	0.28	0.43	0.20	0.60	0.22	0.75	0.32	0.18	0.42	0.14	0.09	0.13	0.10	0.12	0.05	0.02	0.08
42	0.20	0.64	0.71	0.76	0.63	0.18	0.32	0.46	0.23	0.64	0.17	0.78	0.37	0.25	0.47	0.17	0.13	0.17	0.15	0.17	0.06	0.02	0.10
43	0.23	0.75	0.77	0.81	0.69	0.20	0.37	0.51	0.21	0.63	0.18	0.72	0.42	0.28	0.49	0.22	0.13	0.18	0.16	0.19	0.08	0.03	0.11
44	0.21	0.74	0.80	0.78	0.71	0.18	0.34	0.50	0.18	0.64	0.22	0.64	0.41	0.27	0.53	0.21	0.16	0.19	0.17	0.24	0.09	0.04	0.11
45	0.28	0.85	0.85	0.84	0.75	0.23	0.42	0.58	0.20	0.61	0.21	0.70	0.47	0.33	0.56	0.25	0.13	0.21	0.19	0.24	0.10	0.04	0.12
46	0.22	0.78	0.78	0.79	0.68	0.18	0.33	0.48	0.17	0.62	0.19	0.68	0.39	0.25	0.48	0.20	0.11	0.20	0.14	0.21	0.07	0.03	0.10

	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91
1	0.01	0.05	0.09	0.09	0.05	0.03	0.09	0.10	0.10	0.10	0.05	0.05	0.07	0.05	0.42	0.09	0.05	0.15	0.16	0.10	0.03
2	0.07	0.19	0.37	0.42	0.21	0.21	0.49	0.54	0.39	0.45	0.22	0.28	0.33	0.21	0.19	0.36	0.19	0.53	0.53	0.27	0.12
3	0.02	0.15	0.22	0.17	0.13	0.11	0.22	0.16	0.23	0.20	0.09	0.21	0.20	0.10	0.29	0.19	0.11	0.17	0.20	0.12	0.11
4	0.02	0.14	0.26	0.15	0.09	0.05	0.11	0.13	0.20	0.21	0.12	0.14	0.19	0.15	0.13	0.20	0.12	0.18	0.17	0.18	0.10
5	0.10	0.36	0.31	0.36	0.16	0.06	0.14	0.18	0.40	0.35	0.15	0.20	0.25	0.14	0.13	0.25	0.12	0.30	0.24	0.25	0.34
6	0.03	0.17	0.23	0.24	0.12	0.04	0.16	0.21	0.24	0.26	0.11	0.15	0.19	0.12	0.11	0.22	0.09	0.26	0.23	0.18	0.15
7	0.25	0.20	0.37	0.68	0.21	0.10	0.61	0.81	0.42	0.60	0.26	0.37	0.37	0.26	0.20	0.32	0.26	0.73	0.77	0.27	0.19
8	0.18	0.41	0.39	0.39	0.30	0.08	0.19	0.26	0.50	0.42	0.26	0.26	0.36	0.21	0.16	0.33	0.15	0.39	0.33	0.34	0.35
9	0.03	0.18	0.40	0.29	0.21	0.08	0.09	0.13	0.31	0.41	0.15	0.43	0.36	0.18	0.12	0.38	0.14	0.25	0.20	0.18	0.11
10	0.03	0.18	0.39	0.28	0.21	0.08	0.09	0.12	0.31	0.40	0.15	0.43	0.36	0.18	0.12	0.38	0.13	0.24	0.19	0.18	0.11
11	0.04	0.15	0.25	0.24	0.10	0.04	0.10	0.15	0.21	0.29	0.17	0.17	0.26	0.13	0.09	0.21	0.10	0.21	0.18	0.13	0.12
12	0.02	0.06	0.14	0.11	0.04	0.02	0.02	0.04	0.12	0.11	0.06	0.04	0.10	0.08	0.66	0.10	0.06	0.16	0.17	0.11	0.04
13	0.01	0.04	0.17	0.14	0.07	0.03	0.02	0.06	0.10	0.12	0.07	0.05	0.10	0.09	0.07	0.10	0.05	0.08	0.12	0.06	0.02
14	0.02	0.07	0.10	0.06	0.03	0.01	0.02	0.03	0.10	0.12	0.04	0.04	0.08	0.05	0.05	0.08	0.03	0.09	0.06	0.05	0.06
15	0.02	0.06	0.08	0.07	0.04	0.02	0.02	0.04	0.08	0.10	0.04	0.03	0.06	0.05	0.04	0.06	0.03	0.08	0.05	0.07	0.04
16	0.01	0.03	0.09	0.07	0.03	0.01	0.02	0.04	0.10	0.14	0.04	0.04	0.06	0.04	0.04	0.07	0.04	0.07	0.07	0.04	0.03
17	0.02	0.06	0.14	0.08	0.06	0.02	0.03	0.05	0.14	0.17	0.07	0.06	0.10	0.07	0.06	0.11	0.04	0.12	0.08	0.07	0.04
18	0.02	0.10	0.15	0.08	0.04	0.02	0.03	0.05	0.09	0.10	0.05	0.04	0.08	0.06	0.06	0.13	0.04	0.09	0.07	0.08	0.05
19	0.03	0.19	0.39	0.24	0.16	0.05	0.09	0.16	0.32	0.33	0.16	0.20	0.29	0.16	0.14	0.34	0.12	0.28	0.21	0.16	0.12
20	0.06	0.18	0.25	0.20	0.08	0.03	0.04	0.07	0.23	0.22	0.13	0.09	0.18	0.58	0.11	0.16	0.06	0.24	0.17	0.18	0.11
21	0.01	0.05	0.11	0.11	0.04	0.01	0.01	0.03	0.11	0.10	0.07	0.05	0.09	0.61	0.04	0.06	0.02	0.11	0.10	0.08	0.03
22	0.02	0.11	0.45	0.32	0.24	0.08	0.10	0.20	0.36	0.37	0.36	0.38	0.47	0.74	0.10	0.19	0.15	0.33	0.53	0.28	0.07
23	0.02	0.11	0.29	0.21	0.13	0.05	0.06	0.12	0.24	0.26	0.24	0.17	0.27	0.73	0.09	0.15	0.08	0.27	0.37	0.20	0.06
24	0.25	0.27	0.19	0.16	0.08	0.03	0.05	0.09	0.19	0.21	0.08	0.12	0.19	0.16	0.09	0.15	0.07	0.33	0.13	0.14	0.18
25	0.23	0.20	0.21	0.13	0.12	0.03	0.04	0.07	0.23	0.19	0.09	0.10	0.19	0.14	0.10	0.15	0.06	0.23	0.13	0.25	0.13
26	0.06	0.22	0.12	0.10	0.05	0.02	0.03	0.05	0.12	0.17	0.06	0.09	0.14	0.14	0.06	0.09	0.05	0.30	0.08	0.08	0.14
27	0.05	0.18	0.41	0.30	0.18	0.06	0.09	0.15	0.34	0.40	0.18	0.39	0.39	0.21	0.15	0.24	0.15	0.48	0.24	0.18	0.14
28	0.05	0.22	0.34	0.22	0.10	0.04	0.05	0.11	0.28	0.36	0.17	0.14	0.28	0.21	0.24	0.27	0.10	0.43	0.22	0.17	0.12
29	0.03	0.17	0.09	0.06	0.04	0.01	0.03	0.05	0.07	0.12	0.04	0.05	0.11	0.10	0.09	0.08	0.03	0.24	0.07	0.12	0.10
30	0.63	0.05	0.07	0.04	0.03	0.01	0.02	0.03	0.06	0.06	0.03	0.03	0.05	0.03	0.03	0.07	0.02	0.06	0.04	0.03	0.03
31	0.04	0.15	0.19	0.13	0.08	0.03	0.04	0.08	0.18	0.21	0.11	0.09	0.16	0.14	0.09	0.17	0.06	0.23	0.12	0.18	0.10
32	0.02	0.08	0.15	0.11	0.06	0.02	0.03	0.06	0.14	0.23	0.08	0.07	0.13	0.08	0.50	0.12	0.07	0.20	0.15	0.09	0.05
33	0.23	0.29	0.33	0.25	0.10	0.04	0.08	0.13	0.33	0.28	0.13	0.10	0.22	0.15	0.13	0.24	0.09	0.31	0.20	0.21	0.21
34	0.11	0.21	0.22	0.20	0.13	0.04	0.06	0.11	0.22	0.23	0.10	0.10	0.17	0.15	0.10	0.17	0.07	0.19	0.15	0.35	0.15
35	0.14	0.25	0.28	0.22	0.09	0.03	0.09	0.13	0.27	0.24	0.11	0.11	0.21	0.11	0.12	0.21	0.09	0.20	0.17	0.16	0.21
36	0.04	0.10	0.13	0.09	0.05	0.02	0.02	0.04	0.12	0.12	0.06	0.05	0.09	0.07	0.06	0.11	0.04	0.10	0.07	0.13	0.07
37	0.02	0.05	0.11	0.07	0.03	0.02	0.02	0.04	0.07	0.09	0.06	0.04	0.08	0.08	0.05	0.10	0.03	0.08	0.08	0.08	0.03
38	0.03	0.12	0.17	0.10	0.06	0.02	0.06	0.08	0.14	0.14	0.08	0.08	0.13	0.08	0.07	0.20	0.04	0.13	0.11	0.12	0.09
39	0.03	0.11	0.14	0.11	0.06	0.02	0.05	0.06	0.12	0.14	0.06	0.10	0.11	0.07	0.06	0.15	0.04	0.10	0.09	0.09	0.08
40	0.05	0.20	0.27	0.19	0.11	0.04	0.09	0.13	0.23	0.24	0.13	0.12	0.20	0.12	0.11	0.31	0.08	0.22	0.16	0.15	0.14
41	0.03	0.11	0.17	0.10	0.06	0.03	0.05	0.07	0.13	0.15	0.09	0.07	0.14	0.07	0.08	0.21	0.04	0.13	0.10	0.10	0.08
42	0.04	0.15	0.26	0.17	0.09	0.04	0.06	0.10	0.20	0.23	0.13	0.10	0.20	0.11	0.12	0.27	0.07	0.20	0.15	0.14	0.10
43	0.04	0.17	0.30	0.19	0.10	0.04	0.08	0.12	0.22	0.25	0.15	0.12	0.23	0.13	0.13	0.33	0.08	0.21	0.18	0.13	0.12
44	0.05	0.18	0.33	0.25	0.13	0.06	0.10	0.16	0.26	0.29	0.16	0.17	0.27	0.14	0.13	0.29	0.10	0.25	0.21	0.18	0.14
45	0.04	0.19	0.34	0.23	0.14	0.05	0.10	0.16	0.26	0.31	0.17	0.16	0.28	0.16	0.14	0.31	0.10	0.27	0.21	0.15	0.14
46	0.04	0.15	0.27	0.18	0.10	0.04	0.08	0.12	0.21	0.24	0.14	0.13	0.23	0.12	0.11	0.24	0.08	0.20	0.16	0.13	0.11

Appendix B (continued): 91-industry U.S. 1987 proximities matrix (shaded cells in upper right part indicate values > 0.4)

	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91
47	0.18	0.67	0.77	0.68	0.67	0.18	0.38	0.53	0.16	0.68	0.26	0.59	0.40	0.26	0.56	0.20	0.13	0.23	0.16	0.26	0.09	0.04	0.11	0.04	0.19	0.39	0.28	0.18	0.05	0.13	0.20	0.33	0.31	0.18	0.25	0.34	0.15	0.12	0.32	0.13	0.25	0.24	0.17	0.16
48	1.00	0.27	0.37	0.31	0.31	0.44	0.48	0.42	0.12	0.20	0.10	0.24	0.49	0.38	0.28	0.11	0.06	0.12	0.13	0.10	0.07	0.05	0.06	0.02	0.09	0.19	0.09	0.07	0.02	0.05	0.08	0.13	0.29	0.30	0.09	0.21	0.11	0.08	0.15	0.04	0.15	0.12	0.10	0.06
49	0.27	1.00	0.84	0.87	0.78	0.22	0.44	0.60	0.24	0.58	0.22	0.65	0.47	0.30	0.59	0.20	0.12	0.15	0.14	0.16	0.06	0.02	0.10	0.03	0.14	0.27	0.16	0.07	0.03	0.05	0.09	0.19	0.25	0.13	0.10	0.21	0.12	0.13	0.29	0.07	0.24	0.15	0.12	0.09
50	0.37	0.84	1.00	0.86	0.87	0.45	0.66	0.81	0.25	0.66	0.30	0.67	0.68	0.52	0.78	0.25	0.16	0.23	0.26	0.29	0.12	0.05	0.15	0.05	0.19	0.41	0.31	0.18	0.06	0.09	0.17	0.32	0.40	0.24	0.17	0.34	0.20	0.17	0.35	0.12	0.28	0.24	0.19	0.14
51	0.31	0.87	0.86	1.00	0.87	0.35	0.57	0.68	0.27	0.62	0.22	0.69	0.59	0.45	0.67	0.20	0.16	0.18	0.17	0.18	0.06	0.03	0.11	0.04	0.17	0.33	0.18	0.11	0.03	0.05	0.10	0.26	0.33	0.19	0.11	0.26	0.15	0.15	0.36	0.08	0.30	0.18	0.16	0.09
52	0.31	0.78	0.87	0.87	1.00	0.32	0.58	0.73	0.28	0.62	0.24	0.65	0.54	0.42	0.72	0.22	0.16	0.19	0.20	0.24	0.09	0.04	0.13	0.04	0.18	0.38	0.23	0.15	0.06	0.09	0.14	0.32	0.34	0.20	0.16	0.29	0.16	0.16	0.39	0.10	0.30	0.22	0.19	0.12
53	0.44	0.22	0.45	0.35	0.32	1.00	0.87	0.68	0.14	0.22	0.16	0.21	0.91	0.77	0.35	0.08	0.06	0.10	0.10	0.11	0.10	0.09	0.05	0.02	0.08	0.18	0.13	0.07	0.02	0.04	0.08	0.15	0.38	0.31	0.09	0.30	0.15	0.08	0.16	0.06	0.16	0.12	0.08	0.05
54	0.48	0.44	0.66	0.57	0.58	0.87	1.00	0.87	0.21	0.41	0.22	0.40	0.90	0.78	0.58	0.18	0.11	0.19	0.15	0.22	0.11	0.09	0.10	0.04	0.20	0.29	0.20	0.14	0.04	0.10	0.15	0.30	0.47	0.34	0.16	0.37	0.19	0.12	0.31	0.09	0.32	0.21	0.14	0.15
55	0.42	0.60	0.81	0.68	0.73	0.68	0.87	1.00	0.28	0.56	0.27	0.52	0.79	0.69	0.73	0.19	0.16	0.20	0.21	0.26	0.10	0.08	0.11	0.04	0.19	0.39	0.27	0.16	0.06	0.08	0.15	0.31	0.46	0.31	0.18	0.38	0.23	0.16	0.36	0.12	0.34	0.23	0.19	0.12
56	0.12	0.24	0.25	0.27	0.28	0.14	0.21	0.28	1.00	0.79	0.07	0.34	0.19	0.16	0.22	0.11	0.10	0.06	0.07	0.07	0.02	0.01	0.05	0.01	0.17	0.14	0.07	0.03	0.02	0.01	0.03	0.11	0.13	0.08	0.04	0.11	0.06	0.06	0.72	0.03	0.13	0.07	0.19	0.03
57	0.20	0.58	0.66	0.62	0.62	0.22	0.41	0.56	0.79	1.00	0.19	0.61	0.39	0.29	0.55	0.19	0.19	0.18	0.15	0.17	0.07	0.02	0.09	0.04	0.22	0.30	0.20	0.08	0.04	0.05	0.09	0.21	0.24	0.14	0.10	0.21	0.11	0.11	0.67	0.07	0.21	0.15	0.27	0.09
58	0.10	0.22	0.30	0.22	0.24	0.16	0.22	0.27	0.07	0.19	1.00	0.19	0.26	0.17	0.24	0.07	0.04	0.09	0.32	0.13	0.05	0.02	0.04	0.02	0.08	0.15	0.13	0.09	0.03	0.05	0.08	0.13	0.15	0.09	0.09	0.14	0.07	0.05	0.12	0.05	0.12	0.10	0.08	0.06
59	0.24	0.65	0.67	0.69	0.65	0.21	0.40	0.52	0.34	0.61	0.19	1.00	0.40	0.28	0.52	0.33	0.16	0.22	0.17	0.23	0.11	0.04	0.17	0.04	0.28	0.33	0.23	0.10	0.04	0.20	0.24	0.29	0.31	0.16	0.16	0.26	0.15	0.15	0.40	0.10	0.31	0.26	0.19	0.22
60	0.49	0.47	0.68	0.59	0.54	0.91	0.90	0.79	0.19	0.39	0.26	0.40	1.00	0.81	0.54	0.16	0.12	0.17	0.17	0.24	0.13	0.10	0.09	0.04	0.16	0.35	0.29	0.14	0.06	0.10	0.17	0.28	0.50	0.35	0.19	0.41	0.22	0.14	0.28	0.12	0.31	0.23	0.15	0.11
61	0.38	0.30	0.52	0.45	0.42	0.77	0.78	0.69	0.16	0.29	0.17	0.28	0.81	1.00	0.53	0.15	0.12	0.22	0.20	0.22	0.10	0.09	0.10	0.03	0.17	0.36	0.27	0.18	0.07	0.07	0.14	0.30	0.46	0.32	0.18	0.40	0.49	0.12	0.25	0.12	0.30	0.22	0.17	0.10
62	0.28	0.59	0.78	0.67	0.72	0.35	0.58	0.73	0.22	0.55	0.24	0.52	0.54	0.53	1.00	0.20	0.22	0.35	0.30	0.31	0.11	0.05	0.12	0.04	0.19	0.47	0.40	0.20	0.07	0.09	0.19	0.35	0.49	0.22	0.20	0.35	0.25	0.19	0.32	0.15	0.32	0.29	0.28	0.12
63	0.11	0.20	0.25	0.20	0.22	0.08	0.18	0.19	0.11	0.19	0.07	0.33	0.16	0.15	0.20	1.00	0.24	0.26	0.48	0.36	0.18	0.05	0.61	0.08	0.78	0.32	0.27	0.15	0.07	0.58	0.51	0.44	0.26	0.16	0.17	0.27	0.14	0.10	0.33	0.11	0.24	0.39	0.24	0.76
64	0.06	0.12	0.16	0.16	0.16	0.06	0.11	0.16	0.10	0.19	0.04	0.16	0.12	0.12	0.22	0.24	1.00	0.18	0.32	0.26	0.09	0.03	0.14	0.03	0.19	0.26	0.21	0.18	0.08	0.10	0.15	0.21	0.23	0.13	0.15	0.21	0.13	0.08	0.29	0.07	0.21	0.19	0.77	0.07
65	0.12	0.15	0.23	0.18	0.19	0.10	0.19	0.20	0.06	0.18	0.09	0.22	0.17	0.22	0.35	0.26	0.18	1.00	0.55	0.45	0.15	0.06	0.12	0.04	0.14	0.46	0.29	0.42	0.08	0.15	0.26	0.44	0.32	0.23	0.32	0.42	0.16	0.13	0.32	0.16	0.30	0.31	0.31	0.11
66	0.13	0.14	0.26	0.17	0.20	0.10	0.15	0.21	0.07	0.15	0.32	0.17	0.17	0.20	0.30	0.48	0.32	0.55	1.00	0.49	0.16	0.05	0.28	0.05	0.19	0.41	0.28	0.28	0.10	0.13	0.20	0.29	0.27	0.20	0.20	0.32	0.15	0.12	0.35	0.11	0.22	0.27	0.33	0.13
67	0.10	0.16	0.29	0.18	0.24	0.11	0.22	0.26	0.07	0.17	0.13	0.23	0.24	0.22	0.31	0.36	0.26	0.45	0.49	1.00	0.31	0.11	0.21	0.12	0.43	0.60	0.72	0.62	0.35	0.48	0.60	0.68	0.62	0.45	0.47	0.57	0.29	0.20	0.42	0.26	0.51	0.60	0.36	0.38
68	0.07	0.06	0.12	0.06	0.09	0.10	0.11	0.10	0.02	0.07	0.05	0.11	0.13	0.10	0.11	0.18	0.09	0.15	0.16	0.31	1.00	0.07	0.12	0.03	0.22	0.28	0.24	0.20	0.07	0.19	0.23	0.27	0.26	0.28	0.17	0.28	0.14	0.06	0.14	0.11	0.20	0.24	0.12	0.21
69	0.05	0.02	0.05	0.03	0.04	0.09	0.09	0.08	0.01	0.02	0.02	0.04	0.10	0.09	0.05	0.05	0.03	0.06	0.05	0.11	0.07	1.00	0.03	0.02	0.05	0.15	0.15	0.09	0.03	0.12	0.16	0.12	0.17	0.10	0.13	0.15	0.68	0.06	0.08	0.96	0.15	0.20	0.07	0.05
70	0.06	0.10	0.15	0.11	0.13	0.05	0.10	0.11	0.05	0.09	0.04	0.17	0.09	0.10	0.12	0.61	0.14	0.12	0.28	0.21	0.12	0.03	1.00	0.28	0.55	0.19	0.16	0.13	0.07	0.38	0.33	0.30	0.17	0.10	0.09	0.15	0.08	0.06	0.19	0.07	0.15	0.25	0.14	0.53
71	0.02	0.03	0.05	0.04	0.04	0.02	0.04	0.04	0.01	0.04	0.02	0.04	0.04	0.03	0.04	0.08	0.03	0.04	0.05	0.12	0.03	0.02	0.28	1.00	0.23	0.10	0.11	0.04	0.02	0.10	0.12	0.18	0.12	0.05	0.05	0.07	0.04	0.03	0.07	0.04	0.11	0.13	0.06	0.19
72	0.09	0.14	0.19	0.17	0.18	0.08	0.20	0.19	0.17	0.22	0.08	0.28	0.16	0.17	0.19	0.78	0.19	0.14	0.19	0.43	0.22	0.05	0.55	0.23	1.00	0.27	0.33	0.16	0.23	0.74	0.60	0.51	0.30	0.12	0.18	0.25	0.14	0.10	0.31	0.13	0.28	0.42	0.22	0.96
73	0.19	0.27	0.41	0.33	0.38	0.18	0.29	0.39	0.14	0.30	0.15	0.33	0.35	0.36	0.47	0.32	0.26	0.46	0.41	0.60	0.28	0.15	0.19	0.10	0.27	1.00	0.70	0.50	0.15	0.30	0.53	0.81	0.74	0.42	0.73	0.87	0.45	0.24	0.55	0.36	0.63	0.65	0.44	0.22
74	0.09	0.16	0.31	0.18	0.23	0.13	0.20	0.27	0.07	0.20	0.13	0.23	0.29	0.27	0.40	0.27	0.21	0.29	0.28	0.72	0.24	0.15	0.16	0.11	0.33	0.70	1.00	0.39	0.15	0.49	0.73	0.66	0.81	0.36	0.63	0.63	0.38	0.26	0.43	0.36	0.65	0.74	0.33	0.31
75	0.07	0.07	0.18	0.11	0.15	0.07	0.14	0.16	0.03	0.08	0.09	0.10	0.14	0.18	0.20	0.15	0.18	0.42	0.28	0.62	0.20	0.09	0.13	0.04	0.16	0.50	0.39	1.00	0.23	0.23	0.38	0.65	0.42	0.43	0.45	0.52	0.24	0.12	0.39	0.18	0.33	0.39	0.23	0.11
76	0.02	0.03	0.06	0.03	0.06	0.02	0.04	0.06	0.02	0.04	0.03	0.04	0.06	0.07	0.07	0.07	0.08	0.08	0.10	0.35	0.07	0.03	0.07	0.02	0.23	0.15	0.15	0.23	1.00	0.49	0.27	0.15	0.14	0.10	0.13	0.17	0.08	0.04	0.22	0.06	0.15	0.16	0.07	0.06
77	0.05	0.05	0.09	0.05	0.09	0.04	0.10	0.08	0.01	0.05	0.05	0.20	0.10	0.07	0.09	0.58	0.10	0.15	0.13	0.48	0.19	0.12	0.38	0.10	0.74	0.30	0.49	0.23	0.49	1.00	0.90	0.48	0.42	0.17	0.28	0.32	0.19	0.14	0.29	0.21	0.49	0.66	0.19	0.70
78	0.08	0.09	0.17	0.10	0.14	0.08	0.15	0.15	0.03	0.09	0.08	0.24	0.17	0.14	0.19	0.51	0.15	0.26	0.20	0.60	0.23	0.16	0.33	0.12	0.60	0.53	0.73	0.38	0.27	0.90	1.00	0.65	0.63	0.29	0.44	0.50	0.30	0.20	0.39	0.30	0.69	0.85	0.29	0.58
79	0.13	0.19	0.32	0.26	0.32	0.15	0.30	0.31	0.11	0.21	0.13	0.29	0.28	0.30	0.35	0.44	0.21	0.44	0.29	0.68	0.27	0.12	0.30	0.18	0.51	0.81	0.66	0.65	0.15	0.48	0.65	1.00	0.74	0.36	0.63	0.76	0.38	0.25	0.52	0.33	0.63	0.67	0.35	0.47
80	0.29	0.25	0.40	0.33	0.34	0.38	0.47	0.46	0.13	0.24	0.15	0.31	0.50	0.46	0.49	0.26	0.23	0.32	0.27	0.62	0.26	0.17	0.17	0.12	0.30	0.74	0.81	0.42	0.14	0.42	0.63	0.74	1.00	0.47	0.72	0.77	0.43	0.25	0.48	0.34	0.72	0.73	0.35	0.26
81	0.30	0.13	0.24	0.19	0.20	0.31	0.34	0.31	0.08	0.14	0.09	0.16	0.35	0.32	0.22	0.16	0.13	0.23	0.20	0.45	0.28	0.10	0.10	0.05	0.12	0.42	0.36	0.43	0.10	0.17	0.29	0.36	0.47	1.00	0.57	0.69	0.31	0.12	0.24	0.17	0.49	0.47	0.23	0.08
82	0.09	0.10	0.17	0.11	0.16	0.09	0.16	0.18	0.04	0.10	0.09	0.16	0.19	0.18	0.20	0.17	0.15	0.32	0.20	0.47	0.17	0.13	0.09	0.05	0.18	0.73	0.63	0.45	0.13	0.28	0.44	0.63	0.72	0.57	1.00	0.88	0.37	0.16	0.35	0.33	0.58	0.56	0.29	0.15
83	0.21	0.21	0.34	0.26	0.29	0.30	0.37	0.38	0.11	0.21	0.14	0.26	0.41	0.40	0.35	0.27	0.21	0.42	0.32	0.57	0.28	0.15	0.15	0.07	0.25	0.87	0.63	0.52	0.17	0.32	0.50	0.76	0.77	0.69	0.88	1.00	0.45	0.21	0.46	0.35	0.67	0.65	0.41	0.20
84	0.11	0.12	0.20	0.15	0.16	0.15	0.19	0.23	0.06	0.11	0.07	0.15	0.22	0.49	0.25	0.14	0.13	0.16	0.15	0.29	0.14	0.68	0.08	0.04	0.14	0.45	0.38	0.24	0.08	0.19	0.30	0.38	0.43	0.31	0.37	0.45	1.00	0.13	0.23	0.73	0.40	0.51	0.25	0.11
85	0.08	0.13	0.17	0.15	0.16	0.08	0.12	0.16	0.06	0.11	0.05	0.15	0.14	0.12	0.19	0.10	0.08	0.13	0.12	0.20	0.06	0.06	0.06	0.03	0.10	0.24	0.26	0.12	0.04	0.14	0.20	0.25	0.25	0.12	0.16	0.21	0.13	1.00	0.16	0.15	0.32	0.35	0.14	0.09
86	0.15	0.29	0.35	0.36	0.39	0.16	0.31	0.36	0.72	0.67	0.12	0.40	0.28	0.25	0.32	0.33	0.29	0.32	0.35	0.42	0.14	0.08	0.19	0.07	0.31	0.55	0.43	0.39	0.22	0.29	0.39	0.52	0.48	0.24	0.35	0.46	0.23	0.16	1.00	0.19	0.44	0.42	0.32	0.14
87	0.04	0.07	0.12	0.08	0.10	0.06	0.09	0.12	0.03	0.07	0.05	0.10	0.12	0.12	0.15	0.11	0.07	0.16	0.11	0.26	0.11	0.96	0.07	0.04	0.13	0.36	0.36	0.18	0.06	0.21	0.30	0.33	0.34	0.17	0.33	0.35	0.73	0.15	0.19	1.00	0.30	0.36	0.14	0.12
88	0.15	0.24	0.28	0.30	0.30	0.16	0.32	0.34	0.13	0.21	0.12	0.31	0.31	0.30	0.32	0.24	0.21	0.30	0.22	0.51	0.20	0.15	0.15	0.11	0.28	0.63	0.65	0.33	0.15	0.49	0.69	0.63	0.72	0.49	0.58	0.67	0.40	0.32	0.44	0.30	1.00	0.78	0.35	0.20
89	0.12	0.15	0.24	0.18	0.22	0.12	0.21	0.23	0.07	0.15	0.10	0.26	0.23	0.22	0.29	0.39	0.19	0.31	0.27	0.60	0.24	0.20	0.25	0.13	0.42	0.65	0.74	0.39	0.16	0.66	0.85	0.67	0.73	0.47	0.56	0.65	0.51	0.35	0.42	0.36	0.78	1.00	0.43	0.39
90	0.10	0.12	0.19	0.16	0.19	0.08	0.14	0.19	0.19	0.27	0.08	0.19	0.15	0.17	0.28	0.24	0.77	0.31	0.33	0.36	0.12	0.07	0.14	0.06	0.22	0.44	0.33	0.23	0.07	0.19	0.29	0.35	0.35	0.23	0.29	0.41	0.25	0.14	0.32	0.14	0.35	0.43	1.00	0.14
91	0.06	0.09	0.14	0.09	0.12	0.05	0.15	0.12	0.03	0.09	0.06	0.22	0.11	0.10	0.12	0.76	0.07	0.11	0.13	0.38	0.21	0.05	0.53	0.19	0.96	0.22	0.31	0.11	0.06	0.70	0.58	0.47	0.26	0.08	0.15	0.20	0.11	0.09	0.14	0.12	0.20	0.39	0.14	1.00

Appendix C: 22-industry U.S. 1987 proximities matrix*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1 Electrical Prod.	1.000	0.569	0.238	0.165	0.102	0.000	0.378	0.274	0.679	0.559	0.507	0.693	0.667	0.287	0.699	0.141	0.114	0.433	0.265	0.213	0.169	0.696
2 Electronics	0.569	1.000	0.137	0.093	0.050	0.000	0.207	0.234	0.365	0.092	0.200	0.203	0.944	0.465	0.192	0.075	0.068	0.270	0.093	0.087	0.101	0.420
3 Chemicals	0.238	0.137	1.000	0.314	0.302	0.000	0.121	0.038	0.154	0.187	0.071	0.146	0.171	0.032	0.104	0.127	0.096	0.750	0.384	0.258	0.112	0.300
4 Drugs	0.165	0.093	0.314	1.000	0.087	0.000	0.079	0.025	0.090	0.059	0.033	0.075	0.125	0.029	0.061	0.121	0.063	0.326	0.187	0.232	0.054	0.203
5 Refined Oil	0.102	0.050	0.302	0.087	1.000	0.000	0.049	0.019	0.070	0.081	0.038	0.057	0.062	0.015	0.045	0.034	0.030	0.204	0.167	0.074	0.053	0.110
6 Ships	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7 Automotive	0.378	0.207	0.121	0.079	0.049	0.000	1.000	0.118	0.614	0.183	0.113	0.273	0.246	0.084	0.369	0.080	0.130	0.221	0.099	0.053	0.137	0.261
8 Aerospace	0.274	0.234	0.038	0.025	0.019	0.000	0.118	1.000	0.530	0.149	0.218	0.248	0.286	0.101	0.235	0.031	0.031	0.059	0.042	0.022	0.042	0.208
9 Other Transport	0.679	0.365	0.154	0.090	0.070	0.000	0.614	0.530	1.000	0.465	0.255	0.597	0.457	0.158	0.799	0.115	0.118	0.211	0.184	0.071	0.289	0.420
10 Ferrous Metals	0.559	0.092	0.187	0.059	0.081	0.000	0.183	0.149	0.465	1.000	0.210	0.940	0.202	0.052	0.730	0.035	0.014	0.139	0.205	0.047	0.090	0.318
11 Non-fer. Metals	0.507	0.200	0.071	0.033	0.038	0.000	0.113	0.218	0.255	0.210	1.000	0.393	0.184	0.080	0.297	0.019	0.027	0.110	0.059	0.035	0.045	0.630
12 Metal Products	0.693	0.203	0.146	0.075	0.057	0.000	0.273	0.248	0.597	0.940	0.393	1.000	0.313	0.087	0.758	0.081	0.072	0.167	0.148	0.096	0.187	0.490
13 Instruments	0.667	0.944	0.171	0.125	0.062	0.000	0.246	0.286	0.457	0.202	0.184	0.313	1.000	0.475	0.307	0.121	0.126	0.278	0.141	0.245	0.118	0.466
14 Computers	0.287	0.465	0.032	0.029	0.015	0.000	0.084	0.101	0.158	0.052	0.080	0.087	0.475	1.000	0.107	0.024	0.024	0.089	0.020	0.037	0.024	0.167
15 Machines	0.699	0.192	0.104	0.061	0.045	0.000	0.369	0.235	0.799	0.730	0.297	0.758	0.307	0.107	1.000	0.075	0.044	0.162	0.131	0.076	0.126	0.396
16 Food etc.	0.141	0.075	0.127	0.121	0.034	0.000	0.080	0.031	0.115	0.035	0.019	0.081	0.121	0.024	0.075	1.000	0.045	0.124	0.134	0.227	0.048	0.155
17 Textiles	0.114	0.068	0.096	0.063	0.030	0.000	0.130	0.031	0.118	0.014	0.027	0.072	0.126	0.024	0.044	0.045	1.000	0.283	0.059	0.082	0.081	0.347
18 Rubber, Plastic	0.433	0.270	0.750	0.326	0.204	0.000	0.221	0.059	0.211	0.139	0.110	0.167	0.278	0.089	0.162	0.124	0.283	1.000	0.303	0.279	0.129	0.563
19 Glass, Stone, etc.	0.265	0.093	0.384	0.187	0.167	0.000	0.099	0.042	0.184	0.205	0.059	0.148	0.141	0.020	0.131	0.134	0.059	0.303	1.000	0.256	0.129	0.232
20 Paper, Printing	0.213	0.087	0.258	0.232	0.074	0.000	0.053	0.022	0.071	0.047	0.035	0.096	0.245	0.037	0.076	0.227	0.082	0.279	0.256	1.000	0.157	0.390
21 Wooden Prod.	0.169	0.101	0.112	0.054	0.053	0.000	0.137	0.042	0.289	0.090	0.045	0.187	0.118	0.024	0.126	0.048	0.081	0.129	0.129	0.157	1.000	0.322
22 Other Manuf.	0.696	0.420	0.300	0.203	0.110	0.000	0.261	0.208	0.420	0.318	0.630	0.490	0.466	0.167	0.396	0.155	0.347	0.563	0.232	0.390	0.322	1.000

*Industry classification similar to Verspagen (1997a). Zeroes in row and column 6 due to the aggregation of the "ships" industry into a broader industry in U.S. input-output tables. This does not cause problems because the firm database does not distinguish "ship manufacturing" firms.