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Using patent statistics as knowledge base indicators in the biotechnology sectors: An application to France, Germany and the U.K.

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In order to formulate firm, national or regional technology policy, it is necessary to have indicators that can measure technological competence. This paper develops a set of indicators using patent statistics to compare the "knowledge base" of individuals, laboratories, firms or nations. These indicators are then applied to the patent applications in France, Germany and the U.K. in the biotechnology sectors. The paper shows that France is lagging behind Germany and the U.K. in technology stocks (or its patent applications) in all biotechnology fields. However it is the leader in the technology network supporting the foods industry. It has a comparative advantage in terms of either technology stock counts or networks in Genetic Engineering, Pharmaceuticals, Foods, Chemicals, Cell Culture and Biocatalysis. Germany is leading in many sectors, but in all sectors in which it is a leader, it is a specialized leader, i.e. its technology networks need to be more extensive. It has a comparative advantage in terms of either technology stock counts or networks in all sectors except Genetic Engineering, Pharmaceuticals, Agriculture and Cell Culture. The U.K. is the leader in the important field of Genetic Engineering and in terms of the entire technology networks in the biotechnology sectors. It has a comparative advantage in terms of either technology stock counts or networks in Genetic Engineering, Pharmaceuticals, Agriculture and Purification.

Introduction

In order to formulate the technology strategy of a firm or the technology policy of a nation, it is necessary to have indicators that can measure the technological competence or the knowledge base of the firm or nation. In the scientometrics literature there has been an extensive discussion on the formulation, use and mis-use of technological competence and competition indicators (*Narin* and *Olivastro,* 1988; *Moed,* 1999; *Noyons*, 1999; *Banerjee* et al., 2000, *Ramani* and *de Looze,* 2000). As of now there is no consensus on the range of these indicators that can involve R&D expenditures,

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publications, patents, creation of new firms, market sales etc. Different indicators can give rise to different ranking. Nevertheless, this exercise is indispensable for the formulation of firm strategy and public policy.

Let us define an agent as a knowledge producer, i.e., either an individual researcher, a laboratory, an institution or a nation. The two central questions addressed by this paper are: how can we construct a model of the technological knowledge base of an agent from its patent applications? Suppose, such a model can be constructed, how can the knowledge base of two agents be compared to identify the "agent specific structure" and the "competitive position" of each agent? With the above objective in mind, the present paper develops a set of competence indicators using patent statistics to rank and compare the knowledge base of agents. These indicators are then applied to the patent applications of three European countries in the biotechnology sectors.

The present paper makes three kinds of contributions to the scientometrics literature on competition indicators. Firstly, it presents a simple model of the knowledge base embodied in the patent applications of an agent. Secondly, it assembles standard measures that are dispersed in the literature and shows how they can be used to understand the different facets of a knowledge base and compare two different knowledge bases. The originality of our contribution does not lie in the indicators themselves, for they are well known, but in the manner in which they are formulated, utilized and interpreted. They show that competitive positions can have different facets and the different facets can yield different rankings. Thirdly, the application of our indicators to patent depositions in France, Germany and the U.K. give us some insight on the strategic positions of these countries in the biotechnology sectors. Most existing comparative studies on patent applications in the biotechnology sectors focus on the relative positions of the countries in the triad namely the USA, Europe and Japan. Though convenient for international comparisons, this hides the reality that Europe is made up of a group of heterogeneous countries, each with its distinct national system of innovation and evolutionary trajectories in the biotechnology sectors. Thus, a more detailed and quantitative analysis of the investment trends in biotechnology at a national level would be useful. France, Germany and the U.K. have been chosen because they are the leading countries of Europe in terms of their R&D expenditure and patent applications in all fields (*Mustar*, 1999).

Methodology*

Patents as indicators of new technology creation

Patents applications were chosen as the indicator of new technology creation as they clearly reflect the commitment of agents to the new technology and they contain a large quantity of information. Firms, laboratories and individuals can apply for a patent to protect a new technology, to signal technological competence or simply to mark technological territory. Whatever the strategic motivations, a patent can be applied for, only if it has an industrial utilisation as a target. Other indicators such as R&D expenditures, the structure of R&D personnel, the creation of new firms etc. that permit the evaluation of investment in new technology creation could also have been considered. However, to our knowledge, the biotechnology sectors are so extensive that it is not possible to recover data on such indicators at a dis-aggregated level, by firm, laboratory or country. In fact, *Griliches* (1990) in his survey on the uses of patent statistics to measure research and innovative capacity concludes: “In spite of all the difficulties, patents statistics remain a unique resource for the analysis of the process of technical change. Nothing else even comes close in the quantity of available data, accessibility, and the potential industrial, organizational and technological potential” (*Griliches*, 1990, p.1702). A wide range of information on the scientific fields and industrial sectors to which a patent is pertinent is included in the patents, and it is a clear indication of the technology strategy of the patentee.

U.S. patent statistics were used by *Pavitt* and *Patel* to analyse the relative competitiveness of countries and to construct “an index of revealed technology advantage” (*Pavitt* and *Patel*, 1988). At the same time, some authors noted that as indicators of new technology creation, patent applications do not cover the different industrial sectors in an equally efficient manner (*Pavitt*, 1988; *Schankerman*, 1991). In fact, firms do not deposit as many patents in the food sector as in chemistry, pharmacy or electronics. Therefore, our analysis is pertinent to new technology creation in the biotechnology sectors to the extent that such knowledge is patented and it is possible to compare patent applications in each field in the biotechnology sectors.

This is indeed the case, because given the innovative and lucrative nature of the science and technology involved, it is necessary for firms to ensure protection through patenting. Otherwise, if the products are released into the market place they can be

* This section is partly based on a forthcoming article by *Ramani* and *de Looze* entitled “Country-specific characteristics of patent applications in France, Germany and the U.K. in the biotechnology sectors” forthcoming in *Technology Analysis and Strategic Management.*

easily imitated. New knowledge cannot be guarded as a secret between employers and scientists because these sectors are characterized by the mobility of researchers between firms (and universities). Therefore, barring fields like “diagnostics” in which innovations have short lives (e.g. 5 years) most new technology is protected by patents. The positive “signalling” impact of patent applications is also considered to be particularly strong in the biotechnology sectors, not only for the big firms but also for SMEs (*Lemarie* et al., 2000).

Caveats regarding the use of patents

The implications of our study is however subject to three caveats. Our data base contains patent depositions that have been published. These patents may or may not have been actually granted. In Europe, a patent application is usually published within 18 months of application, whether it is granted or not. For the purposes of our study, this does not pose a problem since we are using patent applications as an indicator of knowledge creation rather than market competition. Secondly, we are trying to distinguish the nation specific features of France, Germany and the U.K. in the biotechnology sectors by examining the patents that were first deposited in these countries. Our data base excludes patent applications by French, German and British agents that were not deposited first in France, Germany or the U.K. However, this does not seem to be a significant limitation as most European firms and laboratories tend to deposit their patents initially in their own country. Thirdly, we are identifying the national competencies in terms of patent applications and our findings cannot be used to make predictions on the present economic impact or the future value of the patents of the three countries concerned. The actual economic value of a patent depends on the capacity of the innovating agent to exploit the patent and generate revenue through selling the patent or licensing the patent to others and such investigations are beyond the scope of this paper.

Co-word analysis in scientometrics: a brief introduction

The origins of scientometrics can be traced to the 1960s in the U.S.A. In 1964, Garfield had created the *Science Citation Index* (or SCI) at the Institute for Scientific Information (or ISI) in Philadelphia, U.S.A. under the aegis of the National Science Foundation. The objective of the SCI was to provide an index, which permitted the rapid identification of the most important authors in a scientific domain, using references from publications (citing) and the aggregate bibliographies (cited) obtained from these publications. This new method of presenting the publications of researchers created a new culture that some referred to as the "culture of citations" (*Wouters*, 1999). Using the database of ISI, Garfield and Small developed a methodology to identify research frontiers in various scientific fields using citations and co-citations.

At the same time as when he created the SCI, Garfield also began interrogations on patent references which eventually led to the creation of heavy and unwieldy methods for the treatment of patent citations (citations of literature, patent to patent citations, citations of authors, citation of examiners, citations of technologies involved etc.). It was difficult to apply the citations method developed for publications on patents for several reasons. In patent texts, citations can be present in different sections, they can refer to publications or to other patents, and finally, they can be ranked according to different criteria of importance. Indeed, the investigations along these lines were never completed by ISI. However, very recently, the Derwent company brought out a new product that contains all the citations included in patents. Even more recently (summer, 2000), Derwent connected this database to the *Science Citation Index* on the *Web of Science* of the ISI. In this manner, the dream of Garfield came to be finally realized.

Narin is another pioneer, who has worked extensively on the methodology of "citations" (*Carpenter* et al., 1981; *Narin* et al., (1987); *Narin* and *Olivastro*, 1988; *Albert* et al., 1991). Initially, he used the SCI to identify the frontiers of various fields and he made a number of suggestions for the improvement of the SCI so that it could signal the creation of various types of knowledge better, notably the distinction of papers between science based and application oriented. Among his many contributions to the field, an important one with respect to patents, is his examination of citations of scientific data or scientific knowledge within patents. He has developed methods involving citations from one patent to another and from a patent to publications and shown that the creation of new technology is strongly determined by the creation of new knowledge in the sciences. More recently, he has developed a method based on citations and the technology cycle time (and patented it as a business method) to identify the leaders in an industrial sector, as he finds that certain patent indicators have a strong positive relationship with stock market evaluations.

During the 1980's in France, sociologists from the school "Ecole des Mines", were studying how to analyse emerging systems. Their objective was to characterize evolving systems, through identification of the role of the different variables and the actors associated with the variables. In this context, they began to examine the role of words and networks of words in literal texts describing evolving systems (*Callon* et al., 1986). This interrogations on words gave rise to the creation of a methodology close to that of the SCI. The distinguishing feature of the French method, termed "co-word analysis", was that the citation-co-citation method was applied to the *words* themselves in the literal text and not only to *authors.* This gave rise to two advantages as compared to the "co-citation analysis" developed by the ISI. Firstly, it could be applied to any corpus of words, including the patent texts, unlike the ISI method, which could only be applied to citations on their own data base. Secondly, citations pertain to events of the past, whereas there can be literal texts that describe the present, which bring us closer to the reality being formed. Thus, the above methods can be used to analyze the present in order to predict the future more credibly. The co-word analysis has been further developed by a number of authors (see *Van Raan*, 1988; *Wouters*, 1999; for surveys). As the treatment and analysis of literal texts becomes more and more automated with computers and linked with linguistic treatment of information, the applicability of this method also increases.

In economic analysis, the co-word method can be used to study multidimensional systems or multidimensional variables, which are in the form of "textual data". Consider a multidimensional variable v with n components $(v_1, v_2, ..., v_n)$. Suppose that in a data base, there are m number of observations of this multidimensional variable v. Then, the m observations of the n-dimensional variable v, form a scatter plot in n-dimensional space. The application of the co-word analysis, reduces this scatter plot in n-dimensional space to a graph in 2-dimensional space. Such a network is made up of n nodes, where each node corresponds to one of the n components of the variable v. The nodes are connected through arcs. For instance, the nodes which are connected to a particular node v_k through arcs, are those with which the component v_k has a positive joint frequency in the database. Thus, the structure of the multidimensional variable v is cast as a network map in which the position of each component is portrayed. The limitation of this method is that only pair wise joint frequencies are considered and represented. In other words, it does not consider the joint frequencies of more than two components (not three, not four etc.).

In the context of the present work, we were inspired by the "co-word analysis" and its two central concepts of "density" and "centrality". However, instead of representing data in n-dimensional space in terms of a graph, we do it in terms of a matrix. Then given our definition of a knowledge base and the central assumption of the paper, we show how characteristics of networks like "density" and "centrality" determine the evolution of a knowledge base when there is investment in new technology creation.

A model of a knowledge base from patent applications

Every patent is attributed a set of technology classes by the patent office. The number of patent applications to which a technology is affiliated can be considered as a measure of the stock of knowledge of the patentee in that technology. How do these knowledge stocks change when an agent invests in R&D or new knowledge creation? Technology does not develop in a vacuum. Whenever there is an investment in R&D in a particular technology, it generates knowledge in that technology and such knowledge may also spillover to other technologies as an externality (i.e., freely). Similarly, any technology can also benefit from knowledge spillovers from other technologies. In other words, the creation of new knowledge in a field by an agent depends not only on the magnitude of the investment in knowledge creation in that field, but also on knowledge spillovers from other fields. These spillovers depend on the nature of the network between the different fields, through which there is a circulation and transfer of knowledge. Thus, we can define the knowledge base embodied in a set of patents as follows.

Definition: *The knowledge base embodied in a set of patents can be characterized by two sets of elements:*

(i) Technology stocks: For each technology, the number of patent applications in that particular technology.

(ii) Technology networks: For each technology, the vector of co-occurrences or joint frequencies with other technologies.

Let us formalize the above definition more. Consider a set of n agents, where an agent is indexed by i or j =1,2,…,n. Let the total number of patent applications of agent i (that are published) be given by P_i. Each patent of agent i is associated with one or more of m technology fields, indexed by j or k = 1,2,…,m. In other words, corresponding to each patent application (that is published) there exists a technology vector with m components. A component is 1 if the patent is affiliated to the corresponding technology. It is equal to 0 otherwise. These technology affiliations are attributed by the patent office. From the technology vectors associated with P_i, we can define the knowledge base of agent i as follows:

$$\textit{Knowledge base matrix of agent } i = M_i = \begin{bmatrix} f_1^i & c_{12}^i & . & c_{1m}^i \\ c_{21}^i & f_2^i & . & c_{2m}^i \\ . & . & . & . \\ c_{m1}^i & c_{m2}^i & . & f_m^i \end{bmatrix}$$

Where:

Stock of technology k of agent i = f_k^i *= number of patent applications of agent i which are affiliated to technology k.*

Network of technology k of agent i = $cv_k^i = (c_{k1}^i, c_{k2}^i, ..., f_k^i, ..., c_{km}^i)$;

and c_{kl}^i *= number of patent applications of country i to which both technologies k and l are affiliated or the joint frequency of technologies of k and l in the patent applications of country i,* P_i.

Thus, the knowledge base matrix is symmetric (i.e., $c_{kl}^i = c_{lk}^i$) with as many columns and rows as the number of technologies, i.e., *m*. The diagonal terms represent the technology stocks and the off diagonal terms form the technology networks. The k^{th} row (or k^{th} column) of this matrix is given by the technology network vector cv_k^i with $k = 1,2,...,m$. The term c_{kk}^i is nothing but the frequency of technology *k* i.e., f_k^i. A component c_{kl}^i is also referred to as the co-occurrence of technologies *k* and *l*. Let us define technologies *k* and *l* to be connected if their joint frequency is positive i.e., $c_{kl}^i > 0$. Then we make the following assumption:

Assumption 1*: Whenever there is knowledge creation in technology k, there is a spillover of knowledge with a positive probability to all the technologies with which it is connected (such that the sum of the probabilities over the connected nodes is less than or equal to 1).*

When an agent undertakes R&D investment, the direct result is the creation of new knowledge in a set of technologies. Thereafter, there is a second round of knowledge creation through spillovers (of the knowledge created through R&D investment) between different technologies. According to the above assumption, the incremental knowledge creation through spillovers is determined by the nature of the technology networks. Thus, the evolution of the knowledge base depends both on the direct impact of R&D investment and the subsequent impact of knowledge spillovers between technologies. The characteristics of the technology network, which influence the spillovers of knowledge will be detailed later.

In what follows, we present eight indicators of technological competence that are formulated from the knowledge base matrix constructed from patent applications. The first four indicators are based on technology stocks (i.e., f_k^i) and the other four indicators are based on technology networks (i.e., cv_k^i). In this paper, the agents considered are competing countries, and therefore, in the remainder of the paper, we will only refer to agents as countries. But the methodology developed here can be used to compare the patent applications of any other set of agents, such as firms, laboratories or individual researchers.

Indicators on competitive positioning of knowledge stocks. We now present the indicators that measure the competitive positioning of knowledge stocks, f_k^i, of the different technologies in the different countries.

Internal structure

1. Relative importance of technology k within country i =

$$\frac{\textit{number of patent applications of country i involving technology k}}{\textit{total number of patent of country i affiliated to all technologies}} \times 100 =$$

$$= \left[\frac{f_k^i}{f_1^i + f_2^i + \ldots + f_m^i} \right] \times 100$$

Note that $f_1^i + f_2^i + \ldots + f_m^i > P_i$, as most patents are affiliated to more than one technology. The above indicator ranks the areas of new technology creation of country i, in order of their importance. Higher the index of a technology, greater the importance given to it.

Competitive positions

2. Competitive index of country i in all technologies =

$$\frac{\textit{number of patent applications of country i}}{\textit{number of patent applications of all countries}} \times 100 =$$

$$= \left(\frac{P_i}{P_1 + P_2 + \ldots + P_n} \right) \times 100$$

This indicator ranks the countries in terms of their total number of patent applications. It is an indicator of the ranking of the knowledge base of the different countries. Greater is the competitive index of a country, better is its competitive position.

3. Competitive index of country i in technology k =

$$\frac{\textit{number of patent applications of country i involving technology k}}{\textit{number of patent applications of all countries involving technology k}} \times 100 =$$

$$= \left[\frac{f_k^i}{f_k^1 + f_k^2 + \ldots + f_k^n} \right] \times 100$$

This indicator ranks the countries in each of the *m* technologies. Greater the competitive index in a particular technology field, greater the lead in the same field.

4. Comparative advantage index of country i in technology k =

$$\frac{\textit{competitive index of country i in technology k}}{\textit{competitive index of country i in all technologies}} \times 100$$

While competitive indices give a global ranking, we know from standard microeconomic theory that a country can be a leader in all technology fields and yet have a comparative advantage only in some of them. Hence, we have the comparative advantage (or CA) index, which indicates relative strength in a technology whenever the index is greater than one. The comparative advantage index is adapted from the Revealed Technology Advantage Index (RTA index) constructed by *Pavitt* and *Patel*, (1988). A country is said to have a CA in a field if its CA index is greater than 1 in that field, otherwise not. The CA index specifies the areas of nation-specific advantage, in which a country is encouraged to invest more in the short run.

This finishes our presentation of the stock indicators. Policy makers can also examine if the technology that is the most important for country *i* (in terms of national strategy) is also the one in which it has a comparative advantage or whether country *i* has a retard or an advance in the technologies viewed as being the least important. These checks are useful for the formulation of technology policy to check for "coherence".

Indicators on competitive positioning of the technology networks. For each technology network, cv_k^i, $k = 1,2,\ldots,m$ in the knowledge base matrix of country *i*, M_i, three kinds of characteristics are considered:

- *Centrality of technology k in country i*: number of non-zero components of technology vector cv_k^i other than f_k^i.
- *Density of technology k in country i*: sum of the components of technology vector cv_k^i other than f_k^i.

- *Connectedness of two technologies k and l*: the co-occurence of the two technologies k and l, c^i_{kl} .

The centrality of a technology indicates the number of other technologies with which it is connected, or with which it can enjoy spillovers, whenever there is new knowledge creation. The density of a technology, on the other hand gives the intensity of the relationship of a technology with that of others. Higher the centrality of a technology, larger the number of technologies to which or from which there can be a possible knowledge transfer issuing from any new knowledge creation. Higher the density of a technology, greater is the possible knowledge spillovers for any investment in R&D, given the following assumption.

Assumption 2: *The magnitude of knowledge spillover between two technologies is proportional to the co-occurrence of the two technologies.*

We can also compare the co-occurrence matrices of two different countries, M_i and M_j. Here we distinguish two more features:

- *Centrality of network* M_i: number of non-zero components in any one set of off-diagonal terms.
- *Density of network* M_i: sum of the non-zero components in any set of off-diagonal terms.

Since the knowledge base matrix M_i is a symmetric matrix, the number of technologies which are connected can be ascertained from any one set of off-diagonal terms. The density of the matrix is simply the sum of any one set of off-diagonal terms. Again, greater the centrality of the knowledge base matrix in a country, higher the number of technologies which can benefit from spillovers following new knowledge creation in the system. Finally, greater the density of the knowledge base matrix in a country, greater is the magnitude of possible knowledge transfer for any investment in R&D.

We give a simple example to illustrate the above concepts. Suppose there are two countries i and j and three technology classes. Let the patent depositions in countries i and j give rise to the following 3×3 co-occurrence matrices:

$$M_i = \begin{bmatrix} 3 & 0 & 3 \\ 0 & 4 & 3 \\ 3 & 3 & 10 \end{bmatrix} \text{ and } M_j = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 4 & 2 \\ 0 & 2 & 2 \end{bmatrix}$$

In the above example, in country i, according to the knowledge base matrix M_i, the centrality and density of technology 1 (i.e. given by first row or first column), are 1 and 3 respectively. In country j , the centrality is 0 and the density is also 0. The centrality and density of matrix M_i are 2 and 6 respectively, while the centrality and density of matrix M_j are 1 and 2 respectively.

The matrix M_i can also be graphically depicted on a map, where the nodes represent the technologies and the nodes are connected to one another through arcs representing the co-occurrence or the joint occurrence of pairs of technologies. Here, the centrality of a technology node is given by the number of arcs issuing from this node, while the density of a technology node is given by sum of the co-occurrences associated with the arcs issuing from this node.

Now we can define the technology network counterparts of the four technology stock indicators given earlier. While the technology stock indicators reveal the competitive positioning of the different knowledge bases at the time of patent publication, the technology network indicators suggest how these knowledge bases are going to evolve over time in the future, when there is investment in R&D resulting in new knowledge creation. However, another simplifying assumption has to be made before we can attempt to interpret the meaning of the indicators.

Assumption 3*: The rate of returns to R&D investment in terms of new knowledge creation (i.e. patent applications) is the same for all technologies and in all countries. The ratio of the degree of spillovers between two nodes and their co-occurrence is the same for all technologies and in all countries.*

This assumption is plausible, if we are considering competitors with similar resource structures and similar access to knowledge (as in our case).

All the technology network indicators are given in terms of a 2-component vector, where the first component is "centrality" and the second component is "density". Since vectors can never be ordered completely,* we compare each component of the indicator with the average over all agents, adopting the following terminology.

- If the centrality component is higher than average and the density component is higher than average, then the corresponding network is said to be "well developed".
- If the centrality component is higher than average, but the density component is lower than average, then the corresponding network is said to be "extensive".
- If the centrality component is lower than average, but the density component is higher than average, then the corresponding network is said to be "intensive".

* Consider two vectors (6,7) and (3,4). It is possible to state that the first vector is greater than the second because each component of the first vector is greater than the corresponding element of the second vector (i.e. 6>3 and 7>4). However the two vectors (6,7) and (8,4) cannot be compared. The first component of the first vector is smaller than the corresponding element in the second vector; while the order is reversed for the second component.

- If the centrality component is lower than average and the density component is lower than average, then the corresponding network is said to be “less developed”.

The term “average” will be detailed further in each indicator, as given below.

Internal structure

5. Relative importance of technology k within country i in terms of its network =

$$\left(\frac{\textit{centrality of technology k in country i}}{\textit{Average centrality of all technologies}}\ ,\ \frac{\textit{density of technology k in country i}}{\textit{Average density of all technologies}}\right)$$

When the technology network *k* is “well developed” it means that following new knowledge creation in the innovation system, technology *k* receives (and sends) large spillovers of knowledge from (to) many other technologies. When the technology network *k* is “extensive” the spillover extends to a large number of technologies, but the magnitude of the spillover is relatively small. When the technology network *k* is “intensive” the spillover occurs only with a small number of technologies, but the magnitude of the spillover is relatively important.

The interpretation of this indicator can then be understood as follows. Suppose, country *i* invests the same amount in all technologies today, then in the future:

- If the network of technology *k* is “well developed”, then new knowledge creation (in the form of patents) is likely to be the highest in technology *k*.
- If the network of technology *k* is “extensive”, new knowledge creation will be positive and occur in a variety of technologies, but it will be less than in the previous case.
- If the network of technology *k* is “intensive”, then technology *k* is likely to be part of an emerging group of technologies.
- If the network of technology *k* is “less developed”, then new knowledge creation is likely to be the lowest in this technology.

Basically, the intuition behind the attribution of these somewhat ad-hoc categories such as “leading”, “emerging” etc. can be explained as follows. Consider the “well developed” network of a technology *k*. Since its network is highly central, technology *k* irrigates and is irrigated by a large set of other technologies. Furthermore, because the density is high as well, these connections are strong. Thus, whenever there is investment for new knowledge creation in the system, technology *k* is likely to enjoy the maximum benefits from spillovers and the new knowledge creation is likely to be the highest in this technology.

When a technology network is extensive, it means that this technology benefits from knowledge spillovers from a large variety of other technologies. However, given the low density, the magnitude of such spillovers is small, and hence, the new knowledge creation is less than in the previous case.

When a technology network is intensive, it is strongly connected to some technologies. It benefits from large knowledge spillovers, whenever there is knowledge creation in any of the connecting technologies. Thus, the connected technologies can be considered as a group of specialized technologies and developing in the same direction.

Finally, when the network of technology k is neither central, nor dense, it can develop only with further investment in that particular field. Since it is isolated, it does not benefit from spillovers. Thus, if there is equal investment in all technologies, the technology k is likely to develop less than others.

Competitive positions

6. Competitive index of the technology networks of country i =

$$\left(\frac{\textit{centrality of matrix } M_i \textit{ of country i}}{\textit{Average centrality of matrices of all countries}}, \quad \frac{\textit{density of matrix } M_i \textit{ of country i}}{\textit{Average density of matrices of all countries}}\right)$$

Suppose, all countries invest the same magnitude in all technologies, then:

- If the technology network of country i is "well developed" vis-à-vis the other countries, then new knowledge creation (in the form of patents) is likely to be the highest in country i.
- If the technology network of country i is "extensive", new knowledge creation will be positive and occur in a variety of technologies, but it will be less than in the previous case.
- If the technology network of country i is "intensive", then new knowledge creation in a group of connected and complementary technologies will be higher than the average of all technologies in country i.
- If the technology network of country i is "less developed", then new knowledge creation is likely to be the lowest in this country.

When the technology network is "well developed" or "less developed", it is possible to rank the returns to investment in new technology creation as being the highest or lowest respectively. In the other two cases, it is not possible to rank the returns to investment, but it is possible to characterize the nature of new knowledge creation.

When the technology network is "extensive", knowledge creation is diffused over all the technologies, given the high centrality. By the same logic, when the technology network is "intensive", large spillovers are confined to some sets of connected technologies. These connected technologies form a strong group of complementary technologies and will develop more than the other technologies, given the larger spillovers amongst them.

7. Competitive index of the network of technology k in country i =

$$\left(\frac{\textit{centrality of technolgy k in country i}}{\textit{Average centrality of technology k in all countries}}\ ,\ \frac{\textit{density of technology k in country i}}{\textit{Average density of technology k in all countries}}\right)$$

Suppose, all countries invest the same magnitude in all technologies, then:

- If the network of technology *k* in country *i* is "well developed" vis-a-vis the other countries, then new knowledge creation (in the form of patents) in technology *k* is likely to be the highest in country *i*.
- If network of technology *k* in country *i* is "extensive", new knowledge creation will be positive in technology *k*, but it will be less than in the previous case.
- If network of technology *k* in country *i* is "intensive", then new knowledge creation in technology *k* will be proportional to the new knowledge creation in the technologies with which it is connected and complementary.
- If network of technology *k* in country *i* is "less developed", then new knowledge creation in technology *k* is likely to be the lowest in country *i*.

The reasoning is the same as for indicator 6, applied to the context of a single technology.

8. Comparative advantage of the network of technology k in country i =

$$\frac{\textit{competitive index of tech k in country i with respect to other countries}}{\textit{competitive index of all technologies in country i}}$$

While the comparative advantage in terms of technology stocks indicates in which technologies a country is most efficient in creating patents, vis-à-vis the other countries, the comparative advantage in terms of technology networks indicates in which technologies a country is most efficient in creating spillovers, vis-à-vis the other countries.

- When the comparative advantage of country *i* is given by the "well developed" network of technology *k*, then country *i*'s strengths lie technology *k* being an *important* source of knowledge spillovers to a variety of other technologies.
- When the comparative advantage of country *i* is given by the "extensive" network of technology *k,* then country *i*'s strengths lie in the role of technology *k* as being the source of knowledge spillovers to a variety of other technologies.
- When the comparative advantage of the networks of country *i* is "intensive" in technology *k*, then country *i*'s strengths lie in the role of technology *i* as being an *important* source of knowledge spillovers to a few other technologies with which it is connected and complementary.
- When the comparative advantage of the networks of country *i* is "less developed" in technology *k*, then country *i* does not have any comparative advantage in terms of the technology network of this technology.

This finishes our description of the indicators. Now we move on to the application of these indicators to a data base on patent applications in France, Germany and the U.K.

Application of indicators and results

The data base and variables

From the *Derwent Biotechnology Abstracts* (or DBA from now on) we first extracted all the patent applications for the years 1992-1996[*]. Then a second extraction yielded a list of patent applications filed in France, Germany and the United Kingdom during the years 1992-1996. The final data base contained 2650 patent publications. For each patent application, the data base provided the following information: (i) the technologies to which the patent was affiliated; (ii) the name of the patentee; (iii) the country in which the patent was first deposited and (iv) the region for which protection was sought at the moment of publication of the patent. From the above database we used only the information on technology affiliations. However, we supplemented the database with more information on the patentees to construct the following two variables.

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[*] The data base *Derwent Biotechnology Abstracts* covers the publications and patents related to the biotechnology sectors from 1982 onwards. The DBA covers 40 patent issuing authorities and for non-US issued patents it includes the first patent that comes to its attention. The main identification fields of a patent are present (priority year, names of the depositors, names of the inventors, publication number etc.). The information is available on CD ROM with the information being updated every three months.

National Affiliation of patentee V1: In order to carry out national comparisons it is necessary to identify the "nationality" of each patentee. The data base DBA did not provide this information. A number of experts were consulted* and the Internet was also used to attribute one of four possible "national affiliations" to each patentee: British, French, German or other.

Type of technology concerned V2: The Derwent Biotechnology Abstracts attributed one or more of 12 possible technology classes to each patent application published by them. These technology affiliations were attributed by Derwent experts in the field. They were: Genetic Engineering and Fermentation (A), Biochemical Engineering (B), Analysis (C), Pharmaceuticals (D), Agriculture (E), Foods (F), Energy (G), Chemicals (H), Cell Culture (J), Biocatalysis (K), Purification (L) and Environment (M). Thus, the "Type of technology concerned" was formulated a multidimensional variable in the form of a 12-component vector corresponding to each patent application. Each component of the vector corresponded to one of the technologies. A component was taken to be "1" if the corresponding technology was present in the patent observation and it was taken to be "0" if it was absent.

For each type of national affiliation (as identified by V1), the knowledge base matrix was constructed. The diagonal terms of each of these matrices were then used to construct the following technology stock indicators.

Application of Technology Stock Indicators

The internal structure of patent applications is given in Table 1. It should be read vertically and the columns indicates the percentage of patent applications affiliated to each of the technologies or the structure of the technology stocks of each country. It reveals that the target sectors of investment are almost the same in the three countries. The common target sectors of the three countries are Genetic Engineering, Pharmaceuticals and Biocatalysis. Germany places a greater emphasis on Biocatalysis and a lower emphasis on Genetic Engineering and Pharmaceuticals than France or the U.K. Some nation specific features can also be noted. France is distinct in its interest in Cell Culture, while Germany is focussed on Environment. Finally, U.K. is marked by its investment in Agriculture.

* Whenever the affiliation could not be directly inferred from the patent information, the internet was used to identify the corporate headquarters of the firm or the location of the laboratories. When this method did not yield the national affiliation, one of the following experts was consulted: Jackie Senker, Paul Martin (SPRU), Thomas Reiss (FhG, ISI), Bernard Bettel (OEB) and Lionel Nesta (SERD/INRA). The final results were sent to them again for confirmation.

Table 1. Internal structure of technology affiliations of France, Germany and the U.K.+

Relative importance of technologies within each country	French patents	German patents	U.K. patents	Total patents
A Genetic Engineering and Fermentation	34.5 %	27.8 %	36.1 %	32.94 %
B Biochemical Engineering	2.1 %	5.5 %	0.9 %	2.76 %
C Analysis	0.6 %	1.7 %	0.8 %	1.17 %
D Pharmaceuticals	31.1 %	22.1 %	34.3 %	29.66 %
E Agriculture	3.7 %	3.9 %	7.0 %	5.08 %
F Foods	4.1 %	2.6 %	1.8 %	2.47 %
G Energy	0.9 %	2.2 %	0.9 %	1.36 %
H Chemicals	3.4 %	4.2 %	2.3 %	3.09 %
J Cell Culture	7.8 %	5.9 %	5.9 %	6.59 %
K Biocatalysis	7.6 %	12.4 %	7.0 %	8.60 %
L Purification	1.1 %	2.4 %	1.1 %	1.49 %
M Environment	3.0 %	9.3 %	1.8 %	4.79 %
Total	100 %	100 %	100 %	100 %

+ The four most important technologies in each country are shaded.

The competitive positions of the three countries is shown in Table 2. The table has to be read horizontally and each line gives the percentage (% of total) of patent applications in France, Germany and the U.K. for each technology. In other words, the table ranks the technology stocks in terms of the quantity produced by each nation. The first line of Table 2 illustrates the position of the three countries in the technology race. Germany with 39.77 % of the total patent participations is at the head, followed by the U.K. with 27.17 % and France with 22.34 %. This positioning of the three countries is slightly different from their global positioning. The Observatoire des Sciences et des Techniques (functioning under the aegis of the French government) has reported patent publications in all sectors for the different countries of Europe for two years, 1990 and 1997.*

* The Observatoire des Sciences et des Techniques, *Science & Technologie Indicateurs*, 2000, pp. 214–215; 463.

Table 2. Competitive positions of France, Germany and the U.K.*

	% of French patents	% of German patents	% of U.K. patents	Total number of patents
Competitive index in all technologies	22.34 %	39.77 %	27.17 %	6769
Competitive index in specific technologies in percentage	French patents	German patents	U.K. participations	Total number of patents
A Genetic Engineering and Fermentation	22.02%	30.72 %	38.52 %	2230
B Biochemical Engineering	16.04 %	72.19 %	11.76 %	187
C Analysis	11.39 %	51.90 %	25.32 %	79
D Pharmaceuticals	22.06 %	27.09 %	40.69 %	2008
E Agriculture	15.41 %	27.91 %	48.55 %	344
F Foods	34.73 %	38.92 %	26.35 %	167
G Energy	14.13 %	59.78 %	23.91 %	92
H Chemicals	22.97 %	49.76 %	25.84 %	209
J Cell Culture	24.89 %	32.74 %	31.61 %	446
K Biocatalysis	18.56 %	52.58 %	28.52 %	582
L Purification	15.84 %	57.43 %	26.73 %	101
M Environment	13.27 %	70.99 %	13.27 %	324

* For each technology the leading nation is highlighted in gray

Since patents are published 18 months after submission, the figures for 1997 fall within the time period studied in our paper. According to their report, Germany accounts for 40%, U.K. 14.3% and France 15.7% of all published patents involving European patentees. Thus, while France has about half the number of patent applications as Germany, it has more than the U.K. This is however not the case in our sample, which indicates a better positioning of the U.K. with respect to France, in the biotechnology sectors.

The highest investment in the dominant technology, i.e., Genetic Engineering is by the U.K. (38.52%), followed by Germany (30.72%) and then France (22.02%). The U.K. is also the leader in Pharmaceuticals and Agriculture, the sectors in which there has been a maximum integration of the Genetic Engineering technology. Germany is leading in all the other technologies, which means that France is leading in none of the technologies.

Table 3. Comparative advantage of France, Germany and the U.K.

	Areas of comparative advantage of technology stocks
France	1. Foods. 2. Cell Culture 3. Chemicals and Pharmaceuticals
Germany	1. Biochemicals and Environment. 2. Purification and Energy. 3. Analysis, Chemicals and Biocatalysis. 4. Foods.
U.K.	1. Agriculture. 2. Pharmaceuticals 3. Genetic Engineering.

Then the comparative advantage (CA) of the three countries, which reveals the technologies in which each nation is most efficient in creating patents or technology stocks vis-à-vis the others, is identified in Table 3. The actual figures are given in the appendix in Table A1. The table reveals why the U.K. is the undoubtedly the European leader in biotechnology at the moment. It has developed a CA in Genetic Engineering, the most important technological field, and the two industrial sectors Pharmaceuticals and Agriculture, in which Genetic Engineering is most used. In other words, it has captured the most important biotech markets. Germany, with its traditional CA in chemical engineering has in addition, developed a CA in biotechnology fields linked to chemical engineering such as Biochemical Engineering, Analysis, Foods, Chemicals, Biocatalysis and Purification. France exhibits a CA in Pharmaceuticals, Foods, Chemicals and Cell Culture and is at a borderline with respect to Genetic Engineering (with a CA of 1).

Application of Technology Network Indicators

Using the off-diagonal terms of the knowledge base matrix of each country, the technology network indicators were constructed as follows. The internal structure indicates the state of development of each technology node, vis-à-vis other technology nodes, in a country.

Table 4. Internal structure of technology networks in each country

Technology nodes	French patents	German patents	U.K. patents	Total
A Genetic Engineering and Fermentation	well developed	well developed	well developed	well developed
B Biochemical Engineering	less developed	less developed	less developed	less developed
C Analysis	less developed	less developed	less developed	less developed
D Pharmaceuticals	well developed	well developed	well developed	well developed
E Agriculture	extensive network	less developed	well developed	less developed
F Foods	extensive network	less developed	extensive network	less developed
G Energy	less developed	less developed	extensive network	less developed
H Chemicals	extensive network	extensive network	extensive network	less developed
J Cell Culture	less developed	less developed	well developed	Intensive network
K Biocatalysis	extensive network	well developed	extensive network	well developed
L Purification	less developed	less developed	less developed	less developed
M Environment	extensive network	extensive network	extensive network	extensive network

The second, third and fourth columns concern the three countries, while the last column of Table 4, captures the importance of each technology network in the database. Table 4 confirms the results of Table 1 (based on frequency counts) that Genetic Engineering and Pharmaceuticals are the most developed technologies in the three countries. In all three countries these fields are the most dense, indicating that they have attracted the maximum R&D and industrial investment. They are also the most central technologies, benefiting from spillovers from the greatest number of outside fields.

Then Table 4 also supplements Table 1 in terms of the level of development of each technology and the manner in which the different countries have invested. For instance, Biocatalysis emerges as being globally “well developed” only because Germany has invested in it and developed it well. In France and the U.K., while Biocatalysis is among the technologies that is being invested upon highly, it does not emerge as a “well developed” technology. The field of Cell Culture is among the top four investment areas according to the technology stock counts in France (Table 1). However, in terms of density and centrality this technology is to be watched over (Table 4). The same holds for Environment in Germany. Though Environment is a high investment sector for Germany, its technology network is relatively underdeveloped. Another new feature is Cell Culture, which is not among the four top technologies of investment of the U.K., is shown to have a "well developed" technology network in this country.

Table 5. Competitive position of the technology networks of France, Germany and U.K.

Technology	France	Germany	U.K.
Competitive index in all technologies	Extensive network	Less developed	Well developed
Competitive index in specific technologies			
A Genetic Engineering and Fermentation	Extensive network	Less developed	Well developed
B Biochemical Engineering	Extensive network	Intensive network	Extensive network
C Analysis	Extensive network	Intensive network	Extensive network
D Pharmaceuticals	Extensive network	Less developed	Well developed
E Agriculture	Less developed	Less developed	Well developed
F Foods	Well developed	Less developed	Well developed
G Energy	Less developed	Extensive network	Extensive network
H Chemicals	Extensive network	Intensive network	Extensive network
J Cell Culture	Extensive network	Less developed	Well developed
K Biocatalysis	Extensive network	Intensive network	Extensive network
L Purification	Less developed	Extensive network	Well developed
M Environment	Less developed	Intensive network	Less developed

Next, we come to the results on the competitive positions of the technology networks, which reveal the state of development of a technology network in a country with respect to others, as shown in Table 5. The actual values of the centrality and the density indicators are given in the appendix in Table A2.

Table 5 again complements the information based on technology stock counts given in Table 2. It shows the nature of the leadership with respect to the technology networks of the three countries. While Germany emerges as a leader in biotech patenting when stocks are considered, it turns out to be a follower when technology networks are examined. The centrality and density of its networks are below those in France and Germany.

France, which was shown to be a follower in all fields, when only technology stock counts were considered, now emerges better. It is the leader in Foods but a follower in the very closely related sector of Agriculture. It is a potential leader in the technology poles such as Genetic Engineering, Pharmaceuticals and Biocatalysis, in which it has developed extensive networks.

Germany is leading in fewer fields (than shown in Table 2). For example, it is no longer a leader in Foods, Energy, Cell Culture and Purification. In all fields, in which Germany is a leader, it is a specialized leader. This means that Germany has created a specialization around these fields, which are less connected to other technologies than in France or the U.K. A majority of these technologies are not important as of now (recall Table 4), but if they become more important in the near future Germany will have a leading advantage in them.

In terms of the overall technology networks, the U.K. is the leader. More specifically, except in Environment, the U.K. is a potential leader with extensive networks or the actual leader with "well developed" networks in every biotechnology field.

Finally, we come to the comparative advantages (CA) of the technology networks of the three countries. The CA index indicates the technologies in which the countries should be encouraged to invest if they want to improve the generation and circulation of knowledge spillovers. It calls for investment in technologies with a "well developed" network to increase the variety and magnitude of spillovers; investment in technologies with an "extensive" network for diffusion of spillovers over many sectors; and investment in technologies with an "intensive" network to generate spillovers within a set of connected and complementary technologies. Table 6 shows the CA of each country in terms of technology networks and it complements the information provided by Table 3. The actual values are given in Table A3 in the appendix.

Table 6. Comparative advantage of technology networks

		Comparative advantages in terms of technology networks
France	1.	"Well developed" networks in Genetic Engineering, Foods, Chemicals and Biocatalysis.
	2.	"Extensive" networks in Analysis and Pharmaceuticals.
	3.	"Intensive" network in Biochemical Engineering.
Germany	1.	"Well developed" networks in Biochemical Engineering, Energy, Chemicals, Biocatalysis and Purification.
	2.	"Extensive" networks in Cell Culture and Environment.
	3.	"Intensive" network in Analysis.
U.K.	1.	"Well developed" networks in Agriculture and Purification.
	2.	"Extensive" networks in Analysis, Foods, Energy and Environment.
	3.	"Intensive" networks in Genetic Engineering and Pharmaceuticals.

Though France does not have any CA in Genetic Engineering when the frequency of patent applications is considered, it has a CA in this field in terms of its technology network. This shows that France can take into account its potential in this sector and strive to become a leader.

Though the German technology networks in Biochemical Engineering, Chemicals and Biocatalyis, are less extensive than in the other two countries, its technology networks in these domains exhibit a CA in being "well developed" vis-à-vis the others. Thus, from being a specialized leader in these fields, if it invests more, it can become a leader. According to technology stock counts, Germany had a CA in Foods. This is no longer valid at the level of networks. Again, according to technology stock counts, Germany had a CA in Analysis, while Table 6 indicates that in terms of its technology network, the CA lies in only in the density and not the centrality.

The U.K. had a CA in Genetic Engineering, Pharmaceuticals and Agriculture, when the frequency of patent applications was considered. According to Table 6, it also has a CA in terms of the density of its technology networks in Genetic Engineering and Pharmaceuticals. The U.K. is also having a CA in other fields such as Purification, Energy, Environment and Foods.

Conclusions

Indicators of technological competence are useful if they: (i) rank the competitive positions of the agents; (ii) enable comparisons of their internal structure and (iii) are easy to interpret and lead to identification of "catching up" strategies for the followers. The objective of this paper was to develop such indicators from the information given in patent applications. The knowledge base of a patentee was represented by two types of components. The first type indicated the stock of patent applications in each technology. The second type identified the network or the connections of each technology with the other technologies. Indicators based on the stock components gave an insight on the competitive positions by quantifying the proximity of agents in terms of the stocks of patent applications in the different technologies. Similarly, indicators based on the networks embodied in the patent applications, identified the nature and positioning of the technology networks in terms of their centrality and density.

These indicators were then applied to the patent applications in France, Germany and the U.K. in the biotechnology sectors. It was shown that the two types of indicators yielded different and complementary insight on their competitive positions, confirming the utility of each type. In particular, the paper highlighted the following results on their strategic positions.

- France is lagging behind Germany and the U.K. in knowledge stocks in all biotechnology fields. However it is the leader in the technology network supporting the foods industry. It has a comparative advantage in terms of either technology stock counts or networks in Genetic Engineering, Pharmaceuticals, Foods, Chemicals, Cell Culture and Biocatalysis. These are the fields on which it must concentrate in the short run.
- Germany is leading in many sectors, but in all sectors in which it is a leader, it is a specialized leader, i.e. its technology networks need to be more extensive. It has a comparative advantage in terms of either technology stock counts or networks in all sectors except Genetic Engineering, Pharmaceuticals, Agriculture and Cell Culture. Thus, its comparative advantage does not lie in the thrust areas of France and the U.K. By focussing on the fields in which the other European leaders do not have a comparative advantage, it can become an uncontested leaders in the same. In the long run, it has to decide if and how to close its gap with the other European leaders in Genetic Engineering.
- U.K. is the leader in technology networks in the biotechnology sectors. It has a comparative advantage in terms of either technology stock counts or networks in Genetic Engineering, Pharmaceuticals, Agriculture and Purification. Thus, if the present situation continues, then the U.K. should maintain its leading position among the Europeans.

A number of extensions of the present work can be envisaged. The model developed in this paper, of the knowledge base of an agent based on his patent applications, was very simple. Furthermore, comparisons of knowledge bases required some simplifying assumptions. The nature of the results in the absence of these assumptions rests to be examined. The validity of some of the assumptions can also be tested empirically. Patent data contain information on factors other than technology classes, such as the region of protection. This can also be combined with information on technology classes to get a more comprehensive vision of the process by which patents are created. Patent information can be combined with other indicators of new technology creation as well, to understand the nation specific features of the national systems of innovation of European countries. The data considered in this paper was aggregated over time, since only five years were considered. Larger databases can be used to identify the evolutionary trends in indicators. Finally, extensions of this paper can apply these indicators to analyze the knowledge base of individual researchers, laboratories and firms.

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Appendix

Table A1. Comparative advantage based on frequencies

Comparative advantage in specific technologies	French patents	German patents	U.K. patents
A Genetic Engineering and Fermentation	1.0	0.8	1.1
B Biochemical Engineering	0.8	2.0	0.3
C Analysis	0.5	1.4	0.7
D Pharmaceuticals	1.1	0.7	1.2
E Agriculture	0.7	0.8	1.4
F Foods	1.7	1.1	0.7
G Energy	0.7	1.6	0.7
H Chemicals	1.1	1.4	0.7
J Cell Culture	1.2	0.9	0.9
K Biocatalysis	0.9	1.4	0.8
L Purification	0.8	1.6	0.8
M Environment	0.6	2.0	0.4

Table A2. Competitive positions based on centrality and density

	France		Germany		U.K.	
	centrality	density	centrality	density	centrality	density
Competitive index in entire technology network	1.13	0.77	0.64	0.94	1.23	1.30
A Genetic Engineering and Fermentation	1.27	0.88	0.58	0.73	1.15	1.39
B Biochemical Engineering	1.05	0.79	0.90	1.88	1.05	0.33
C Analysis	1.29	0.50	0.43	1.50	1.29	1.00
D Pharmaceuticals	1.27	0.74	0.58	0.66	1.16	1.60
E Agriculture	0.87	0.17	0.53	0.86	1.60	1.97
F Foods	1.43	1.14	0.26	0.73	1.30	1.13
G Energy	0.96	0.38	0.72	2.22	1.32	0.39
H Chemicals	1.20	0.93	0.67	1.27	1.13	0.79
J Cell Culture	1.04	0.97	0.78	0.83	1.17	1.20
K Biocatalysis	1.15	0.81	0.76	1.44	1.09	0.75
L Purification	0.00	0.00	0.90	1.44	2.10	1.56
M Environment	0.92	0.41	0.83	2.06	1.25	0.54

Table A3. Comparative network advantage based on centrality and density

	Comparative network advantage					
	centrality			density		
	France	Germany	U.K.	France	Germany	U.K.
A Genetic Engineering and Fermentation	1.14	0.92	0.96	1.17	0.79	1.08
B Biochemical Engineering	0.95	1.43	0.88	1.06	2.02	0.26
C Analysis	1.16	0.68	1.07	0.67	1.61	0.78
D Pharmaceuticals	1.14	0.92	0.96	0.99	0.71	1.24
E Agriculture	0.78	0.85	1.33	0.23	0.92	1.53
F Foods	1.29	0.41	1.09	1.52	0.79	0.87
G Energy	0.86	1.14	1.10	0.51	2.39	0.31
H Chemicals	1.08	1.06	0.94	1.25	1.37	0.61
J Cell Culture	0.94	1.24	0.98	1.29	0.90	0.93
K Biocatalysis	1.03	1.21	0.91	1.08	1.55	0.58
L Purification	0.00	1.43	1.75	0.00	1.55	1.21
M Environment	0.83	1.32	1.04	0.54	2.21	0.42

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