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ON ESTIMATING A KNOWLEDGE PRODUCTION FUNCTION AT THE FIRM AND SECTOR LEVEL USING PATENT STATISTICS

by
Shyama V. Ramani[a*], Mhamed-Ali El-Aroui[b], Myriam Carrère[c]

[a] INRA (Institut National de la Recherche Agronomique)
65 Bd de Brandebourg, 94205 Ivry sur Seine Cedex, France
and
Ecole Polytechnique, 1 Rue Descartes, 75005 Paris, France.
email : ramani@ivry.inra.fr

[b] LARODEC, ISG de Tunis
41 Av. de la Liberté, Bardo, 2000 Tunisie
email: Mhamed.Elaroui@isg.rnu.tn

[c] INRA (Institut National de la Recherche Agronomique),
Université Pierre Mendes France, BP 47,
Grenoble, 38040 France
email: carrere@grenoble.inra.fr

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Abstract

This paper proposes a definition of the knowledge base of an agent using only patent statistics. It then develops a model of a knowledge production function that can be estimated at a firm level and at a sector level using the knowledge base matrix. It identifies the impact of own knowledge base, absorptive capacity to exploit intersectoral spillovers, and absorptive capacity to exploit intrasectoral spillovers, on new technology generation. It permits a study of the dynamics of knowledge generation without having to take recourse to additional information on the R&D activities of firms. Finally, the paper illustrates the method with the case study of new biotechnology-based knowledge creation by firms in the foods sector.

Key-words *knowledge production function, patents.*

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***Please address your correspondence to:** Shyama V. Ramani, Department of Economics, INRA, 65 Bd de Brandebourg, 94205 Ivry sur Seine Cedex, France.

ON ESTIMATING A KNOWLEDGE PRODUCTION FUNCTION AT A FIRM AND SECTORAL LEVEL USING PATENT STATISTICS

1. Introduction

Several path breaking empirical works studying the determinants of inventive activity have developed models of firms investing in R&D in order to generate knowledge via an explicit or implicit knowledge production function (Grilliches 1979; Nelson 1987; and Jaffe 1986). Four questions concerning the estimation of knowledge production functions on which a consensus is yet to emerge are: How can the impact (on innovation creation) of a firm’s knowledge base, accumulated over time, be measured? How can the multidimensional nature of a knowledge base be taken into account? How can the firm specific capacity to absorb spillovers be measured? How can the differences between the dynamics of innovation creation at the firm level and at the industry be distinguished? The present paper attempts to contribute to this debate positively by proposing a model of a knowledge production function, which can be constructed using patent statistics, the most readily available indicator of innovative activity.

Most microeconomic models of the knowledge production function, consider data on indicators of inventive activity such as R&D expenditures or patents, as equilibrium values to be plugged in as inputs to estimate a knowledge production function. The focus then shifts to the measurement of the impact of the different inputs on new technology generation or augmentation of factor productivity. A few also consider knowledge capital as a factor of production and consider its accumulation over time (Gambardella, 1995). In this case, knowledge capital is assumed to be a scalar quantity, like any another factor of production and is represented by patent or publication counts.

Standard models of R&D competition and knowledge creation are very pertinent for contexts, where the results of R&D investment can be evaluated ex-ante. This is often the case in mature sectors, where learning patterns of firms are similar. On the other hand, in the case of emerging sectors, R&D investment cannot be calculated to maximize profit, because the relation between R&D investment and increase in profit itself is unclear. Moreover, firms are likely to be marked by firm specific learning capacities as determined by their resources and managerial vision, since they are operating in an environment of technological and market uncertainty. Here the evolutionary approach, where firms base their R&D expenditure on past success seems more pertinent.

In the above context, the present paper makes three types of contributions to the industrial organization literature on the knowledge production function. First, it proposes an evolutionary model of the knowledge production function that is pertinent for hi-tech sectors, where technology evolves rapidly. Second, unlike the standard models of knowledge production, which rely on data on R&D activities such as R&D expenditure that are difficult to obtain, the present paper offers a model that can be entirely estimated just using patent statistics. Third, our knowledge production function can be used to study the dynamics of knowledge evolution both at a firm and sector level.

The originality of the model developed in this paper lies in its combination (with consequent adaptation) of four approaches that have been used in the economics of innovation.

Largely inspired by the evolutionary economics school of thought, in our model, firms are considered to practise routines rather than being direct profit maximizers (Nelson and

Winter, 2002). Furthermore, they are characterized by firm specific absorptive or learning capacities that evolve over time giving rise to firm specific evolution of knowledge base. Spillovers have no influence on firm strategy and are considered purely from the technological point of view.

Second, the technological positioning of a firm is represented in terms of a multidimensional knowledge base, taking into account the technology affiliations of patents as well as absolute patent counts. This kind of approach is similar to that of Jaffe (1986), Jaffe and Trajtenberg (1999) and Hu and Jaffe (2003), where measures of technological proximity are constructed using information on the technological affiliations of patents. At the same time, our model is different because the information on the technological affiliations of patents is not used to construct measures of proximity, but to build firm specific measures of learning.

Third, the firm's absorptive capacity as given by its knowledge base determines its capacity to exploit spillovers (Cohen and Levinthal, 1989). The standard assumption that firms benefit equally from spillover pools is dropped.

Finally, the indicator and the time of *knowledge creation* is distinguished from that of *knowledge diffusion.* Patent applications represent the knowledge creation by a firm. However, such knowledge is diffused outside of the firm only when patents are published (and sometimes even within the firm). Thus, spillovers are considered to stem from patent publications and not from patent applications.

The rest of the paper is organized as follows. Section 2 introduces the conceptual framework for the representation of 'knowledge base' of an economic actor, using patent statistics. Section 3 contains the methodology for estimating the knowledge production function of a firm and a sector. Section 4 illustrates the method by examining the nature of biotech-based new knowledge creation by firms in the foods sector using patent statistics. Section 5 concludes.

2. Representation of a knowledge base

A knowledge creating agent can be a firm, a laboratory or an individual. For the purposes of this theoretical exposition, we will simply refer to agents as firms. A firm invests in R&D expenditure and produces a knowledge output in terms of patent applications in a variety of technology fields. This gives rise to its knowledge base.

After a period of time, patents are published and the information contained in them is diffused in the public domain both within and outside of the firm. Such information forms pools of spillovers in the different technology fields, which are exploited by firms to produce new patent applications in the next period according to their absorptive capacities.

Patent publications are also the indicator used by firms to decide on their next period's R&D investment. Greater is the number of patent publications in a particular field, higher is the R&D investment in that field.

The knowledge production function of a firm then depends on two factors: the marginal productivity of own R&D expenditure and the capacity to exploit spillover pools created by the R&D expenditures of other firms. Under the assumptions of the model, both the marginal productivity and the absorptive capacity of firms depend on the knowledge base of the firm. Thus, knowledge generation by a firm not only depends on its present R&D expenditure, but also on its past R&D expenditures, as well as on the past R&D investments of other firms.

Consider an economy with *N* knowledge creating agents given by *i* = 1,2,…..*N*. Let us further suppose that there are *M* distinct generic technologies or sector specific technologies in which the firms are engaged in research. Then, let *k* represent the subject technology that is being considered. Let *t* stand for the time period considered. Let $x_{i,t}^{k}$ be the R&D expenditure of firm *i* in technology area *k* in year *t*. We define the '*R&D strategy*' or the '*R&D program*' of firm *i* in period *t* as the vector of its R&D expenditures in the different technology areas. Let $x_{i,t}$ be the R&D program of firm *i* in period *t*. It is given by the vector $x_{i,t} = (x_{i,t}^{1}, x_{i,t}^{2}, ..., x_{i,t}^{k}, ... x_{i,t}^{M})$. Thus, firm *i* can be using several technologies and be active in several sectors.

The R&D investment generates new knowledge, which results in patent applications by the firm. *It is to be noted that a patent application can be affiliated to more than one technology class.* For example, a patent application could be affiliated to the foods sector, agriculture as well as environment. In this case, the same patent will account for '*knowledge generation*' by the firm in the foods, agriculture and environment sectors during that year. Let us indicate the '*knowledge created*' by firm *i* in period *t* as $PA_{i,t}$, where $PA_{i,t} = \left(PA_{i,t}^{1}, PA_{i,t}^{2}, ..., PA_{i,t}^{M}\right)$ is a vector whose components are the number of patent applications of firm *i* in year *t* in the various technology domains. Given the possibility of affiliation to more than one technology class, the total number of patent applications by a firm can be less than the sum of patent applications affiliated to the different technology classes, i.e. $PA_{i,t} \leq \sum_{k} \left(PA_{i,t}^{1} + PA_{i,t}^{2} + ... + PA_{i,t}^{k} + ... + PA_{i,t}^{M}\right)$.

In reality, the '*knowledge created*' within a firm is not diffused either within the firm or outside of the firm immediately. Knowledge takes time to diffuse. We assume that '*knowledge diffusion*' takes place within the firm completely and is accessible to other firms as well once patent applications are published. This usually happens after 18 months of filing for a patent application in most countries outside of the U.S.A. In the U.S.A., till recently patents were published only upon being granted, but now patents seeking world wide protection are published after 18 months also. Let knowledge that is diffused by firm *i* at time *t* within the firm and outside of the firm be given by its vector of patent publications, $PP_{i,t}$ = ($PP_{i,t}^{1}, PP_{i,t}^{2}, ..., PP_{i,t}^{M}$).

We can now develop a definition of a '*knowledge base*' of a firm. We start with the assumption that the knowledge base of a firm consists of two components, first, its firm-specific capacity to create knowledge as given by its patent applications, and second, its absorptive capacity to exploit knowledge created by other firms and in other sectors. Then we propose a representation of the knowledge base of a firm in the form a matrix, whose elements correspond to the two components referred to above.

Let $PS_{i,t}^{k}$ stand for the stock of patent applications of agent *i* in technology *k*, at time *t*. Then, $PS_{i,t}^{k}$ is the sum of the patent applications in technology *k*, from time 0 to *t*, discounted by a rate of depreciation $\delta \in (0,1)$ indicating that knowledge created in the past becomes less useful or obsolescent over time:

$$PS_{i,t}^{k} = PA_{i,t}^{k} + \delta^{1} PA_{i,t-1}^{k} + \delta^{2} PA_{i,t-2}^{k} + ... + \delta^{t} PA_{i,0}^{k}.$$

We now enumerate the frequency of technology affiliations in the stocks of patent applications to any two technology classes. Let *l* represent another technology, other than technology k, the spillovers from which are the object of exploitation by firms to create knowledge in technology k. Suppose the number of patent applications of firm i, over the years 0 to t, which are related to both technology classes k and l is given by $ta_{i,t}^{kl}$. Then $ta_{i,t}^{kl}$ gives the number of patent applications in the patent stocks of firm at year t, which are affiliated to both technology classes k and l. It is taken as an indicator of the absorptive capacity of the firm to exploit knowledge created in sector l to be applied in sector k or vice versa.

Let the knowledge base of firm i in period t be given by $KB_{i,t}$ and defined as a symmetric matrix with M rows and M columns, where the diagonal terms are the patent stocks of firm i in the different technologies and the off-diagonal terms are the technology affiliations between pairs of technologies present in the patent stocks of firm i as follows:

$$KB_{i,t} = \begin{bmatrix} PS_{i,t}^{11} & ta_{i,t}^{12} & . & ta_{i,t}^{1M} \\ ta_{i,t}^{21} & PS_{i,t}^{22} & . & ta_{i,t}^{2M} \\ . & . & . & . \\ ta_{i,t}^{M1} & ta_{i,t}^{M2} & . & PS_{i,t}^{MM} \end{bmatrix}$$

Thus, the knowledge base of a firm is a function of the stock of patent applications in the different technology classes and the frequency of affiliation between any two technology classes that evolves over time as patent applications are accumulated. As will be further detailed, the diagonal terms determine the learning from *intrasectoral spillovers*, while the off-diagonal ones influence the learning from *intersectoral spillovers*.

3. Estimating the knowledge production function

3.1 At the firm level for technology field k

When firms invest in R&D expenditure, a part of the knowledge generated by such investment will be accessible without costs to other firms as an externality. Let s^k be the rate of spillovers from R&D expenditure in any sector $k = 1, 2, ..., k, ..., M$. In any time period t, let the total R&D investment by all firms in area k, be given by $x_t^k = \sum_{i=1}^{N} x_{i,t}^k$. Then the economy wide R&D investment in period t, ($x_t^1, x_t^2, ..., x_t^M$) will generate M pools of spillovers in the M technology domains as given by $\left(s^1.x_t^1, s^2.x_t^2, ..., s^k.x_t^k, ..., s^M.x_t^M\right)$. Each firm i can exploit the spillovers created by all firms excluding itself according to its absorptive capacity.

In order to trace the evolution of the knowledge base of a firm and the evolution of knowledge generation in a sector, we make four important assumptions:

Assumption 1: R&D investment by a firm in a technology field k is an increasing function of the knowledge diffused within the firm in the past, i.e. the number of patent publications in the previous time period in field k.

Assumption 2: The marginal productivity of own R&D expenditure in a particular technology area is constant and the same for all firms in the economy.

Assumption 3: The absorptive capacity of firm i to exploit the spillover pool of technology k to create new knowledge in area k is an increasing function of the previously acquired patent stocks of firm i in sector k.

Assumption 4: The absorptive capacity of firm *i* to exploit the spillover pool created by R&D expenditures in area $l \neq k$ to generate knowledge in area *k* is an increasing function of the number of patent applications in the patent stocks which are affiliated to both technology *l* and *k*.

For simplicity, we assume constant returns to scale for the processes referred to above. These assumptions enable us to define the knowledge production function of firm *i* in terms of patent applications.

Recalling assumption 1, let each firm *i* decide its R&D expenditure in area *k* as an increasing function of its past success in terms of patent publications in the same area, i.e:

(1) $$x_{i,t}^k = a_0 + a_1.PP_{i,t-1}^k \text{ with } a_0 > 0 \text{ and } a_1 > 0 .$$

According to the above firm routine, in any time period *t*, given the economy wide R&D investment profile, ($x_t^1, x_t^2, ..., x_t^M$) any firm *i* generates knowledge along three routes.

First, there is a direct impact of the R&D expenditure of firm *i* in sector *k*. Using assumption 2, let us suppose that b^k is the constant marginal productivity of the firm's own R&D expenditure in sector *k*. Then the direct impact of own R&D expenditure of firm *i* on knowledge generation will be given by $b^k.x_{i,t}^k$.

Second, there is an indirect impact issuing from the exploitation of the pool of intrasectoral spillovers $s^k.\sum_{j \neq i}\left(x_{j,t}^k\right)$ or spillovers created in sector *k* by the R&D expenditures of other firms. Consider an agent distinct from firm *i*, say firm *j*, that is also engaged in R&D. In what follows, firm *i* is the 'user firm' (using and creating spillovers), while firm *j* refers to a supplier firm (creating spillovers that are used by firm *i* that is being modeled). When any other firm *j* spends $x_{j,t}^k$ in area *k*, it contributes to the spillover pool of technology *k* by $s^k.x_{j,t}^k$, where s^k is the intra-sectoral spillover rate. Let $b_{i,t}^{kk}$ indicate the absorptive capacity of firm *i* to exploit the spillover pool of technology *k* to create new knowledge in area *k*. Recalling assumption 3, $b_{i,t}^{kk}$ is an increasing function of the previously acquired patent stocks of firm *i* in sector *k*, and is given by $b_{i,t}^{kk} = z^k.\dfrac{PS_{i,t-1}^k}{\sum_i PS_{i,t-1}^k} = z^k.\dfrac{PS_{i,t-1}^k}{PS_{t-1}^k}$ where z_k is a positive real number.

Third, when any firm *i* spends $x_{i,t}^l$ in another area *l*, it creates a spillover of knowledge $s^l.x_{i,t}^l$ related to technology *l* that could be applicable to technological area *k*. The combined R&D program of all the firms gives rise to technology pools of spillovers $\sum_{l \neq k} s^l.\sum_i x_{i,t}^l$ pertaining to other sectors $l \neq k$, which nevertheless could be applicable to technology field *k*. Let $b_{i,t}^{kl}$ indicate the absorptive capacity of firm *i* to exploit the intersectoral spillover pool created by R&D expenditures in area *l* to generate knowledge in area *k*. By assumption 4, it is an increasing function of the firm *i*'s patent applications that are affiliated to both sectors *k* and *l* and defined as $b_{i,t}^{kl} = z^{kl} . \frac{ta_{i,t-1}^{kl}}{\sum_i ta_{i,t-1}^{kl}} = z^{kl} . \frac{ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}}$ where z^{kl} is a positive real number.

Thus, even if the marginal productivity of R&D expenditure remains constant at b^k for all firms, the knowledge generating capacity of each firm evolves according to its absorptive capacity accumulated over the past to exploit pools of spillovers as given by $b_{i,t}^{kk}$ and $b_{i,t}^{kl}$.

This gives us the production function for new knowledge creation in area *k* as follows.

(2) $$PA_{i,t}^k = b^k . x_{i,t}^k + b_{i,t}^{kk} . s^k . \sum_{j \neq i} \left(x_{j,t}^k \right) + \sum_{l \neq k} \left(b_{i,t}^{kl} . s^l . \sum_i x_{i,t}^l \right)$$

$$b^k > 0; 1 > s^k > 0; 1 > s^l > 0; \text{ for all } k \text{ and } l.$$

Substituting the value of $x_{i,t}^k$ from equation (1) into equation (2) we can rewrite the knowledge production $PA_{i,t}(x_{i,t}, x_{j,t}, s, KB_{i,t-1})$ as follows (see appendix for details):

(3) $$PA_{i,t}^k = b_0 + a_1 . b^k . PP_{i,t-1}^k + a_1 . b_{i,t}^{kk} . s^k . \sum_{j \neq i} \left(PP_{j,t-1}^k \right) + a_1 . \sum_{l \neq k} \left(b_{i,t}^{kl} . s^l . PP_{t-1}^l \right)$$

where $b_0 = b^k a_0 + (N-1) b_{i,t}^{kk} s^k a_0 + \sum_{l \neq k} N b_{i,t}^{kl} s^l a_0$ and $PP_{t-1}^l = \sum_i PP_{i,t-1}^l$

Furthermore, substituting the values of $b_{i,t}^{kk}$ and $b_{i,t}^{lk}$ in terms of patent stocks, the knowledge production function at the firm level, becomes:

(4) $$PA_{i,t}^k = b_0 + a_1 . b^k . PP_{i,t-1}^k + a_1 . z^k . \frac{PS_{i,t-1}^k}{PS_{t-1}^k} . s^k . \sum_{j \neq i} \left(PP_{j,t-1}^k \right) + a_1 . \sum_{l \neq k} \left(z^{kl} . \frac{ta_{i,t-1}^{kl}}{ta_{t-1l}^{kl}} . s^l . PP_{t-1}^l \right)$$

An econometric estimation of the knowledge production function based on patent statistics would involve a further reduced form as follows (see appendix for details):

(5) $$PA_{i,t}^k = \alpha_0 + \alpha_1 . PP_{i,t-1}^k + \alpha_2 . \frac{PS_{i,t-1}^k}{PS_{t-1}^k} . \sum_{j \neq i} \left(PP_{j,t-1}^k \right) + \sum_{l \neq k} \left(\alpha^l . \frac{ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}} . PP_{t-1}^l \right)$$

with $\alpha_0 = b_0$; $\alpha_1 = a_1 . b^k$; $\alpha_2 = a_1 . z^k . s^k$ and $\alpha^l = a_1 . s^l . z^{kl}$ $\; l = 1, 2, \ldots k-1, k+1, \ldots M$.

At a firm level, an estimation of equation (5) would not be able to distinguish the magnitude of the spillover rates (s^k, s^l), from the marginal productivity parameter (a_1) and the absorption capacity parameters (z^k, z^{kl}). Herein lies the weakness of the present model. However, since all these parameters are positive, an estimation of the knowledge production function of a firm in a sector would reveal the impact of 'own knowledge base in technology field *k*' (as given by sign of α_1), 'capacity to absorb knowledge generated by other firms in the same technology field *k*' (as given by sign of α_2), and 'capacity to absorb knowledge generated by all firms in a field *l* other than *k*' (as given by sign of α^l) on the firm's capacity to generate knowledge in field *k* (or $PA_{i,t}^k$). We would also be able to rank the importance of the impact of these three factors on the knowledge production function of the firm.

3.2 The knowledge production function at the k sector level

Aggregating equation (5) over agents *i*, the knowledge production function at a sectoral level, can be written as follows (see appendix for details):

$$PA_t^k = \beta_0 + \beta^k . PP_{t-1}^k + \sum_{k \neq l} \beta^l . PP_{t-1}^l . \qquad (6)$$

where : $PA_t^k = \sum_i PA_{i,t}^k$; $PP_t^k = \sum_i PP_{i,t}^k$; $PP_t^l = \sum_i PP_{i,t}^l$;

and $\beta_0 = N.\alpha_0$; $\beta^k = \alpha_1 + (N-1).\alpha_2$; $\beta^l = \alpha^l$.

An estimation of the knowledge production function at the level of sector *k* suffers from the same drawback as the one at the firm level in that the estimation of parameters of marginal productivity of firms, spillovers and absorptive capacities cannot be distinguished. At the same time, it is again possible to distinguish between the nature of the contribution of 'spillover pool of technology field *k* or intra-sectoral spillovers' (as given by the sign of β^k) and the nature of the contribution of 'spillover pool of a technology field $l \neq k$ or intersectoral spillovers from area *l*' (as given by the sign of β^l) to knowledge generation in technology domain *k*.

The advantages of the evolutionary approach are even clearer now. In a standard R&D competition model, the values of the R&D expenditure, x_i, would be a function of the parameters of market demand, the R&D expenditures of other firms and production costs. The capacity to absorb spillovers $b_{i,kk}^t$ and $b_{i,kl}^t$ would still be a function of the structure of patent stocks of the firm. Then, the knowledge production function would have to be estimated using information on the patent stocks, the parameters of market demand, R&D expenditures of firms and production costs and it is well known that comprehensive information on the last three variables is very difficult to obtain at an aggregate level.

4. Case Study: Knowledge production function of firms in the bio-foods sector

4.1 The context

The foods sector refers to firms and other organizations that are involved in the processing and transformation of primary agricultural products into final consumable commodities. A puzzle about the foods sector that fascinates economists is the fact that it produces a significant number of process and product innovations, while investing little in R&D. It is claimed that such achievements are due to an efficient exploitation of spillovers from complementary sectors like pharmaceuticals, chemicals and agriculture (Connor, 1988; Galizzi and Venturini 1996; Wilkinson, 1998). The machine tools sector and the electrical products have also provided significant knowledge spillovers (Johnson and Evenson, 1999). Even though innovation creation in the foods industry has been made possible in a large measure through knowledge spillovers from other industrial sectors, Wilkinson (1998) points out that it has always been oriented to satisfy the needs and current trends of the consumer's market.

Similar results have been put forth at the firm level. Alfranca, Rama and von Tunzelmann (2001) and Wilkinson (1998) find that the leaders of the foods industry, the giant multinationals, spend much more on R&D than the rest of the firms in the food industry. New technology creation is also higher among firms that already have a record of innovation. Even so, the food leaders do not invest much in basic research (as compared to their counterparts in the chemical or pharmaceutical industries), instead their in-house R&D capabilities are geared to exploit opportunities for knowledge transfer from other industries.

An examination of the temporal pattern of innovation in the world's largest food and beverage multinationals by Alfranca et al. (2001, 2004) reveals that though innovative spells (i.e. maximum number of successive years that the firm has at least one new patent) are very short, the majority of patents in the multinational agri-food sector have been granted to companies, which have innovated persistently over long periods of time. Firms with longer innovative spells have a higher average annual production of patents. At the sectoral level, creation of new technology in terms of utility and design patents increases with past research efforts and patent creation by other multinationals in the same sector. However, at the firm level, patenting in other firms in the same sector does not induce technical innovation or new designs.

Despite the march of innovation, as Galizzi and Venturini (1996) explain, innovation creation in the food industry has always been constrained by one factor: "consumer's risk aversion". For the most part, consumers are willing to swallow medicines produced by new technology. However, they are more risk averse with respect to their daily consumption of food. They are not willing to consume products that are radically different from present products. They are also not so willing to consume new products that have been produced by a radically new technology.

Modern biotechnology (i.e. techniques that involve manipulation or change in the genetic patrimony of cells of living organisms) have revolutionized the agro-food chain for a little more than a decade and their integration in the agro-food supply chain has aroused heated discussions in many parts of the world. Some topical problems related to the use of biotechnology in foods sector are: risks posed by the incorporation of genetically modified organisms (GMO) in the agro-foods chain, consumer reticence, impact on potential epidemics, the opportunities and dangers presented by biotechnology as a means of eradicating starvation in developing countries, impact of globalization and differences between national legislations on technology transfer, etc. (Gaisford et al., 2001; Tourte, 2001). Thus, it is not surprising that in the agro-food chain, biotechnology has been successfully integrated only in the upstream segments giving rise to products such as genetically modified crops. The derivatives of such genetically modified crops reach the food sectors in the form of oils, flours and additives.

The agribusiness firms have responded to the unforeseen strength of consumer resistance to the incorporation of biotechnology in foods in a variety of ways. Large, upstream agbiotech firms like Monsanto have vertically disintegrated, separating their agbiotech division from the rest of their operations. Large, downstream food firms like Nestle have taken measures to assure their consumers that regulation concerning GMOs is being followed and that information is being provided to consumers on the presence of GMOs in any of their products.

Even as the food industry becomes more focused on demand conditions, with biotechnology, the foods sector has more technological opportunities on the supply side from which to develop innovations (Menrad, 2004). However, little is known about the responses of agribusiness firms in the knowledge market and about the trends in the accumulation and utilisation of their knowledge and technology involving biotechnology. Thus, it is interesting to take a backstage look at the integration of biotechnology in the food sectors by examining food patents involving biotechnology and examine which of the three factors is inducing technological innovation the most: own knowledge base, exploitation of intrasectoral spillovers from the foods sector, or exploitation of intersectoral spillovers from other non-food sectors. And the knowledge production function described in the previous section is an ideal tool to attempt to answer such questions.

4.1 Description of data

The data for the analysis was compiled from the "Derwent Biotechnology Abstracts" (hereafter DBA) developed by the Derwent Information Ltd for the years 1978-1998[1]. Experts at Derwent analyze patent applications in 40 national and international patent offices in order to select those involving biotechnology. For each patent application, the DBA indicates the year of initial application, the year of publication, the names of the patentees (and their affiliations after 1995), the region of protection sought at the time of application, the region of protection sought at the time of publication and the associated technology fields.

At the highest level of aggregation, the DBA attributes one or more of the following technologies to each patent: genetic engineering and fermentation (*a*), biochemical engineering (*b*), analysis (*c*), pharmaceuticals (*d*), agriculture (*e*), foods (*f*), energy (*g*), chemicals (*h*), purification (*i*)[2], cell culture (*j*), biocatalysis (*k*), and environment (*m*). An extraction of patent applications affiliated to the field "foods" yielded 4339 food patent depositions by 1406 patentees out of which only 35 were not affiliated to at least one other non-food category. The distribution of the patentees by type was as follows: 77.8% were firms, 17.6% were laboratories and 4.6% were individuals.

The evolution of the total number of biotech based food patent applications over the years 1978 to 1998 is shown in figure 1. Three stages can be clearly distinguished. First, there is an emergence and infancy stage between 1978 and 1985, which is characterized by a very low and stable flow of patents of only 6 applications a year on average. This low level of patenting activity is evidently due to the novelty of biotechnology, when organizations were not aware or were not sure of the potential of biotechnology. This is followed by a short high growth stage between 1986 and 1988. This spurt of growth is likely to have been due to a rising awareness of the potential of biotechnology combined with a bandwagon effect to invest in biotechnology. Finally, during the period 1988-1998, patent applications fluctuate around an average of 380, without any sharp and sustained falls or increases, indicating a trend towards stabilization.

We focused on the stabilization phase (1988-1998) containing 4179 patent applications or 96.3% of the total patent applications in our database and organized the information as a balanced panel data, indicating the number of patent applications by each one

[1] After 1998 DBA was purchased by Thomson Scientific and prices became prohibitive and hence we were not able to purchase the database for the years thereafter.
[2] In the DBA purification is indexed by *l* and not by *i*.

of the 1337[3] patentees and in each one of the 11 years considered. The distribution of patentees according to the number of their patent applications is given in figure 2. Only 68 firms out of the 1337 patentees applied for more than 10 patents during this period and all ten top patentees are firms[4]. Furthermore, an ANOVA analysis showed that the average annual numbers of patent applications, *PA*, are not significantly different at the 5% confidence level across the 11 years (1988-1998), but there is a significant difference in *PA* between the 1337 observed firms (see table 1). In other words, at the sectoral level, the number of patent applications in the foods sector does not vary much from year to year in the stabilization phase, but at the firm level there are significant differences in the innovation capacity of the patentees. This implies that there is a great deal of heterogeneity in the patenting behaviour of firms, and this heterogeneity is not changing rapidly, thus confirming the results of Alfranca et al. (2001, 2004).

4.2 Estimation of the knowledge production function

Given that the data pertains to only eleven years, only ten observations were available for the estimation of the knowledge production at a sectoral level, which are too few for a credible approximation of reality. Therefore, estimation was attempted only at the firm level.

Let us replace the generic sector *k* used in subsection 3.1 by the foods sector denoted by *f* . Then the knowledge production function of firms in the foods sector, which was given earlier by equation (5), can now be rewritten as:

$$PA_{i,t}^{f} = \alpha_0 + \alpha_1.PP_{i,t-1}^{f} + \alpha_2.Z_{i,t-1} + \sum_{l \neq f} \alpha_l.U_{i,t-1}^{l} \; ; \qquad (7)$$

where $Z_{i,t} = \frac{PS_{i,t}^{f}}{PS_{t}^{f}} \sum_{j \neq i} (PP_{j,t-1}^{f})$ represents the knowledge stocks involved in the exploitation of intrasectoral spillovers in the foods sector or the firm's *intrasectoral spillovers absorption*; and $U_{i,t}^{l} = PP_{t}^{l} \frac{ta_{i,t}^{fl}}{ta_{t}^{fl}}$; $l \in \{a,b,c,d,e,g,h,i,j,k,m\}$ represents the knowledge stocks involved in the exploitation of intersectoral spillovers issuing from a sector *l* other than foods, and used in foods sector or the firm's *intersectoral spillovers absorption*.

Hence, the knowledge production function at the firm level is a function of its knowledge base in the foods sector $PP_{i,t-1}^{f}$; the intrasectoral spillovers absorption $Z_{i,t-1}$ and the intersectoral spillovers absorption $U_{i,t-1}^{l}$, $l \in \{a,b,c,d,e,g,h,i,j,k,m\}$. Therefore, as a first step, the above stocks were computed for each of the 1337 patentees of the studied decade. The statistical characteristics of the variables are presented in table 1.

Second, the Pearson correlation indices between the dependent variable PA_{t}^{f} and the regressors were calculated. The highest correlation was found to be with intrasectoral spillovers absorption Z_{t-1} (0.63) followed by correlation with own knowledge base in the

[3] 69 patentees were removed from the initial database as they had no patent applications during the period 1988-1998.

[4] Top ten leaders with number of patents in foods within brackets : Ajinomoto (155); Kyowa Hakko (92); Novo (87); Mitsubishi Petro-Chem (73); Mitsubishi Chem (68); Hayashibara (46); Nestle (43); Snow-Brand (40); Roche (37); Unilever (35).

foods sector PP^{f}_{t-1} (0.55) , spillovers from genetic engineering U^{a}_{t-1} (0.53), spillovers from biocatalysis U^{k}_{t-1} (0.48), spillovers from chemicals U^{h}_{t-1} (0.34), and spillovers from pharmaceuticals U^{d}_{t-1} (0.27).

Given the linearity of the theoretical model (i.e. constant returns to scale and linearity of $x_{i,t} = x_{i,t}(PP_{i,t-1})$ and $PA_{i,t}(s, KB_{i,t-1}))$, in order to facilitate economic interpretation, it seemed appropriate to estimate the knowledge production function as *an ordinary least squares linear-model*[5]. A first model, Model I given by equation (7), was estimated (see table 2), representing the knowledge production function at the firm level as a linear pooled regression without taking into account firm specific effects. However, the results of the F-test (see last line of table 2) disproved the null hypothesis claiming absence of firm specific effects.

Hence, *linear models with firms' specific effects* were tried out. These refer to general methods for modelling firm-specific effects on patenting not explained by the regressors in panel data. It is widely accepted that innovation strategies are more firm-specific than other activities of the firm such as production and marketing and therefore consideration of firms' specific effects in estimations of outcomes of R&D activity is highly recommended[6].

Furthermore the firm-specific intercepts $\alpha_{0,i}$ may be considered to be deterministic, leading to a *fixed effects models* or taken to be random, calling a *random effects models*. In both cases, the knowledge production function estimated is:

$$PA^{f}_{i,t} = \alpha_{0,i} + \alpha_1.PP^{f}_{i,t-1} + \alpha_2.Z_{i,t-1} + \sum_{l \neq f} \alpha_l.U^{l}_{i,t-1} \qquad (8)$$

In firm-specific effects models, the identity of the firms is supposed to have an effect on whether it is likely or unlikely to have a patent application for a given year, but some authors like Cincera (1997) have argued that the random effects model may not be consistent in the case of knowledge creation data since the unobservable firms' heterogeneity is usually not independent of the regressors. The Haussman test is then used to examine whether the firms' specific effects are correlated to the regressors or not. The chi-square test statistic value so obtained ($X^2(13)$ =12833.83) in our model disproved the null hypothesis of consistent random effects and led us to reject it.

In the light of the above results, a second linear model, Model II (see equation (8) and estimation results in table 3) was constructed to incorporate fixed firm-specific effects. The Lagrange Multiplier test[7] was thereafter used to verify that the residuals were not auto-correlated. A number of interesting inferences can be made from table 3 on the nature of knowledge creation by patentees in the foods sector, which are mostly firms.

[5] Several other classes of *panel count data models* can be considered for panel data such as Poisson Panel models, Negative Binomial Panel Models and Zero-Inflated Poisson models, but these do not assume linear production functions. Furthermore, they often require additional assumptions (e.g. equidispersion or equal mean and variance of $PA^{f}_{i,t}$ in the case of Poisson regression).

[6]For example Cincera (1997) argues that "*in panel data, the presence of firm specific unobservable heterogeneity such as the aptitude of engineers to invent new products are not uncommon and these unobservables influence the way by which firms decide to apply for patents*".

[7] The obtained test statistic was $LM_{intra-i}$= - 0.33 which is smaller than the reference value 1.64.

Results of Model 2: Biotechnology based knowledge created by a firm in the foods industry:

- increases significantly with the number of past patent publication of the firm in the foods sector or the firm's own knowledge stock in the foods sector.
- increases significantly with U_{t-1}^{a}, U_{t-1}^{e} and U_{t-1}^{k} or the capacity of the firm to exploit spillovers emanating from the *a*-genetic engineering and fermentation, *e* –agriculture and *k*-bio-catalysis sectors.
- is not influenced by Z_{t-1}, or the capacity of the firm to exploit the spillovers generated within the foods sector.
- the knowledge production of firm *i* in foods sector decreases significantly with U_{t-1}^{g}, U_{t-1}^{h} and U_{t-1}^{j} i.e. the capacity of the firm to exploit spillovers from the *g*-energy, *h*-chemicals and *j*-cell culture sectors.

Interestingly, according to Model I, bio-food patent applications increase significantly with Z_{t-1}, or the capacity of the firm to exploit the spillovers generated within the foods sector, when no heterogeneity between firms is considered. But as Model II reveals, the impact of this explanatory variable becomes non significant when heterogeneity between firms is modelled by specific firms' intercepts. This means that when we assume that the behaviour of the firms can entirely deduced from the given explanatory variables as in Model I, the absorptive capacity of a firm to exploit intra-sectoral spillovers within the foods sector seems to determine its capacity to generate food patents. However, when we consider that in addition to the above explanatory variables, some hidden characteristics of patentees, the so called firm specific effects, (e.g. managerial vision) may have a significant impact on the innovation activity of a firm, as in Model II, then this absorptive capacity ceases to impact the innovative behaviour of firms.

Thus, the model confirms the intuition of the articles on the foods sector that firms in this industry benefit more from spillovers emanating outside of the industry, than from spillovers generated within the industry. At the same time, the model refines the intuition of experts by demonstrating that innovative firms in the foods sector are those that have a strong knowledge base themselves, which is no doubt a necessary condition for the development of absorptive capabilities. It is likely that the absorptive capacity of firms to exploit intrasectoral spillovers is a firm specific strategy.

5. Conclusion

This paper develops a model of a knowledge production function, pertinent for sectors where a firm's new technology generation depends on its past success, firms of similar sizes do not innovate at the same rate, and both intersectoral and intrasectoral spillovers determine the returns to R&D investment. It is also particularly relevant for industries in which the dynamics of innovation creation are likely to be different at the firm level and at the industrial level, such as in the foods sector, for which an illustration of the method is provided at the firm level.

The model tries to illustrate how the 'transformation of R&D expenditure' into 'patent applications' takes place via an 'agent specific knowledge production function' and an 'agent specific knowledge base'. Three distinctive features mark this model. First, both the knowledge production function and the knowledge base evolve over time as a function of the accumulation of stocks of patent applications. Second, the knowledge production functions corresponding to a particular technology can be aggregated over agents to get the knowledge production function at a sectoral level, retaining the evolutionary features. Third, the final form of the knowledge production functions for any technology class can be estimated both at a firm and sectoral level simply on the basis of patent statistics without having to take recourse to additional information on the R&D expenditures of firms, production costs or the parameters of market demand.

Two possible extensions of the present work can be envisaged. First, the present model can be reformulated in an equilibrium context with spillovers playing a strategic role. Second, quality adjusted measures of patent counts may also be considered (Harhoff et al. 1999).

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APPENDIX

A1: Computation of equation (3)

Consider the production function:

(2) $$PA_{i,t}^{k}=b^{k}.x_{i,t}^{k}+b_{i,t}^{kk}.s^{k}.\sum_{j\neq i}\left(x_{j,t}^{k}\right)+\sum_{l\neq k}\left(b_{i,t}^{kl}.s^{l}.\sum_{i}x_{i,t}^{l}\right)$$

We know that R&D expenditure is such that :

$$x_{i,t}^{k}=a_0+a_1.PP_{i,t-1}^{k} \quad (1)$$

Substituting the value of $x_{i,t}^{k}$ from (1) into (2) we get:

$$PA_{i,t}^{k}=b^{k}.\left(a_0+a_1.PP_{i,t-1}^{k}\right)+b_{i,t}^{kk}.s^{k}.\sum_{j\neq i}\left(a_0+a_1.PP_{j,t-1}^{k}\right)+\sum_{l\neq k}\left(b_{i,t}^{kl}.s^{l}.\sum_{i}\left(a_0+a_1.PP_{i,t-1}^{l}\right)\right)$$

$$PA_{i,t}^{k}=b^{k}a_0+(N-1)b_{i,t}^{kk}s^{k}a_0+\sum_{l\neq k}Nb_{i,t}^{kl}s^{l}a_0+b^{k}.a_1.PP_{i,t-1}^{k}+b_{i,t}^{kk}.s^{k}.a_1\left(\sum_{j\neq i}PP_{j,t-1}^{k}\right)+\sum_{l\neq k}\left(b_{i,t}^{kl}.s^{l}.a_1\left(\sum_{i}PP_{i,t-1}^{l}\right)\right)$$

Put $b_0=b^{k}a_0+(N-1)b_{i,t}^{kk}s^{k}a_0+\sum_{l\neq k}Nb_{i,t}^{kl}s^{l}a_0$ and $PP_{t-1}^{l}=\sum_{i}PP_{i,t-1}^{l}$

Then we can write:

$$PA_{i,t}^{k}=b_0+a_1.b^{k}.PP_{i,t-1}^{k}+a_1.b_{i,t}^{kk}.s^{k}.\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)+a_1.\sum_{l\neq k}\left(b_{i,t}^{kl}.s^{l}.PP_{t-1}^{l}\right)$$

A2: Computation of equation (5)

Consider the knowledge production function :

$$PA_{i,t}^{k}=b_0+a_1.b^{k}.PP_{i,t-1}^{k}+a_1.b_{i,t}^{kk}.s^{k}.\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)+a_1.\sum_{l\neq k}\left(b_{i,t}^{kl}.s^{l}.PP_{t-1}^{l}\right)$$

We know the absorption capacities are given by:

$$b_{i,t}^{kk}=z^{k}.\frac{PS_{i,t-1}^{k}}{\sum_{i}PS_{i,t-1}^{k}}=z^{k}.\frac{PS_{i,t-1}^{k}}{PS_{t-1}^{k}} \text{ and } b_{i,t}^{kl}=z^{kl}.\frac{ta_{i,t-1}^{kl}}{\sum_{i}ta_{i,t-1}^{kl}}=z^{kl}.\frac{ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}}$$

Let us substitute the absorption capacity values into the production function:

$$PA_{i,t}^{k}=b_0+a_1.b^{k}.PP_{i,t-1}^{k}+a_1.z^{k}.\left(\frac{PS_{i,t-1}^{k}}{PS_{t-1}^{k}}\right).s^{k}.\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)+a_1.\sum_{l\neq k}\left(\left(z^{kl}.\frac{ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}}\right).s^{l}.PP_{t-1}^{l}\right)$$

Put $\alpha_0=b_0$; $\alpha_1=a_1.b^{k}$; $\alpha_2=a_1.z^{k}.s^{k}$ and $\alpha^{l}=a_1.s^{l}.z^{kl}$ $l=1,2,\ldots k-1,k+1,\ldots M$.

Then we get:

(5) $$PA_{i,t}^{k}=\alpha_0+\alpha_1.PP_{i,t-1}^{k}+\alpha_2.\frac{PS_{i,t-1}^{k}}{PS_{t-1}^{k}}.\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)+\sum_{l\neq k}\left(\alpha^{l}.\frac{ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}}.PP_{t-1}^{l}\right)$$

A3: Computation of equation (6)

Consider the knowledge production function at the firm level:

(5) $$PA_{i,t}^{k}=\alpha_0+\alpha_1.PP_{i,t-1}^{k}+\alpha_2.\frac{PS_{i,t-1}^{k}}{PS_{t-1}^{k}}.\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)+\sum_{l\neq k}\left(\alpha^{l}.\frac{ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}}.PP_{t-1}^{l}\right)$$

Suppose we aggregate over agents we would get:

$$PA_{i,t}^{k}=\sum_{i=1}^{N}\alpha_0+\sum_{i=1}^{N}\left(\alpha_1.PP_{i,t-1}^{k}\right)+\sum_{i=1}^{N}\left(\alpha_2.\frac{PS_{i,t-1}^{k}}{PS_{t-1}^{k}}.\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)\right)+\sum_{i=1}^{N}\left(\sum_{l\neq k}\left(\alpha^{l}.\frac{ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}}.PP_{t-1}^{l}\right)\right)$$

A first simplification gives us:

$$PA_{i,t}^{k}=N.\alpha_0+\left(\alpha_1.\sum_{i=1}^{N}PP_{i,t-1}^{k}\right)+\left(\alpha_2.\left(\sum_{i=1}^{N}\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)\right).\left(\frac{\sum_{i=1}^{N}PS_{i,t-1}^{k}}{PS_{t-1}^{k}}\right)\right)+\left(\sum_{l\neq k}\left(\alpha^{l}.PP_{t-1}^{l}.\frac{\sum_{i=1}^{N}ta_{i,t-1}^{kl}}{ta_{t-1}^{kl}}.\right)\right)$$

But: $\sum_{i=1}^{N}PS_{i,t-1}^{k}=PS_{t-1}^{k}$ and $\sum_{i=1}^{N}ta_{i,t-1}^{kl}=ta_{t-1}^{kl}$

Therefore the above equation becomes

(5a) $$PA_{i,t}^{k}=N.\alpha_0+\left(\alpha_1.\sum_{i=1}^{N}PP_{i,t-1}^{k}\right)+\left(\alpha_2.\left(\sum_{i=1}^{N}\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)\right)\right)+\left(\sum_{l\neq k}\left(\alpha^{l}.PP_{t-1}^{l}\right)\right)$$

Note that $\left(\sum_{i=1}^{N}\sum_{j\neq i}\left(PP_{j,t-1}^{k}\right)\right)=(N-1).\sum_{i=1}^{N}PP_{i,t-1}^{k}=(N-1).PP_{t-1}^{k}$

So we can rewrite (5a) as:

$$PA_{i,t}^{k}=N.\alpha_0+\left(\alpha_1.PP_{t-1}^{k}\right)+\left(\alpha_2.(N-1).PP_{t-1}^{k}\right)+\left(\sum_{l\neq k}\left(\alpha^{l}.PP_{t-1}^{l}\right)\right)$$

which gives:

$$PA_{i,t}^{k}=N.\alpha_0+\left(\left(\alpha_1+\alpha_2.(N-1)\right).PP_{t-1}^{k}\right)+\left(\sum_{l\neq k}\left(\alpha^{l}.PP_{t-1}^{l}\right)\right)$$

Put $\beta_0=N.\alpha_0$; $\beta^{k}=\alpha_1+(N-1).\alpha_2$; $\beta^{l}=\alpha^{l}$; This gives the knowledge production function at the sectoral level as:

(6) $$PA_{t}^{k}=\beta_0+\beta^{k}.PP_{t-1}^{k}+\sum_{k\neq l}\beta^{l}.PP_{t-1}^{l}$$

Figure 1: Evolution of food patent applications

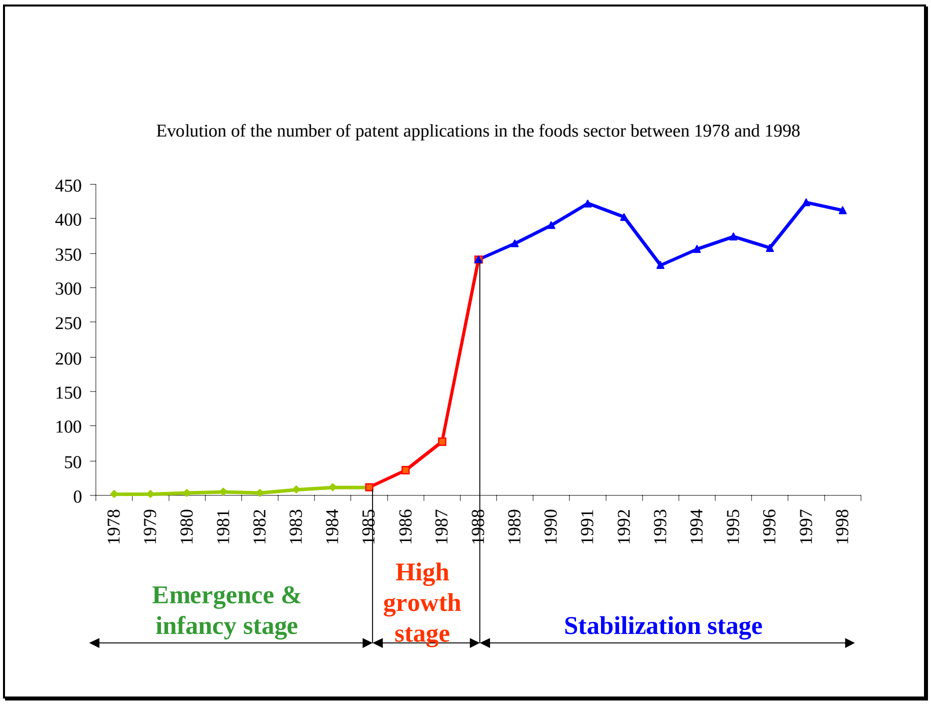

Figure 2: Distribution of patentees according to the number of their patent applications during 1988-1998

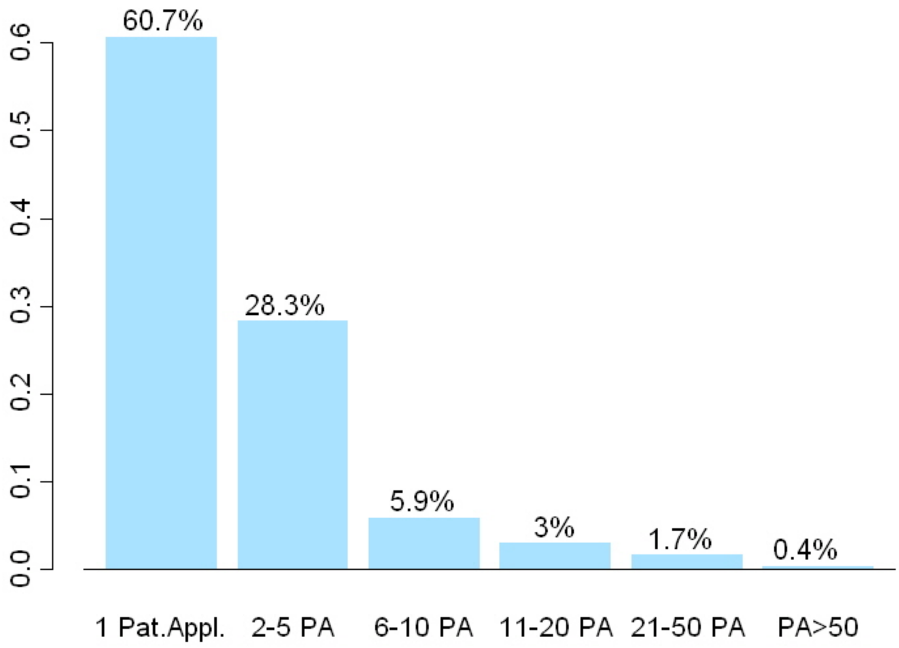

Table 1. Characteristics of the Panel sample
(1337 patentees observed during 11 years: 1988-1998)

					Analysis of firms' effects		
	Mean	**Min**	**Max**	**Std. Dev.**	**Between Std. Dev.**	**Within Std. Dev.**	**ANOVA p-value**
PA^f	0.2878	0	22	0.996	2.267	0.730	0.000
PP^f	0.2469	0	28	0.965	2.212	0.701	0.000
Z	0.2452	0	14.54	0.712	1.844	0.431	0.000
U^a	2.3949	0	238.52	9.906	20.975	7.757	0.000
U^b	0.2048	0	68.80	2.507	2.703	2.484	0.000
U^c	0.0976	0	212.00	3.505	3.770	3.474	0.000
U^d	1.7959	0	294.63	10.843	15.839	10.137	0.000
U^e	0.3807	0	117.21	4.014	5.557	3.804	0.000
U^g	0.1004	0	55.00	1.533	1.732	1.510	0.000
U^h	0.2176	0	75.38	1.847	3.241	1.620	0.000
U^i	0.1859	0	33.41	1.663	2.148	1.600	0.000
U^j	0.6912	0	420.00	8.370	11.652	7.923	0.000
U^k	0.9360	0	136.80	4.304	8.922	3.427	0.000
U^m	0.2636	0	81.20	2.367	2.817	2.312	0.000

Table 2: Model I - Linear Model (Pooled regression)[8]

Variable	*Intercept*	PP^f	Z	U^a	U^b	U^c	U^d	U^e	U^g	U^h	U^i	U^j	U^k	U^m
Coeff. estim.	0.081	0.226	0.395	0.015	-0.006	-0.002	3.10^{-4}	0.002	-0.016	0.010	-0.002	-0.002	0.022	-6.10^{-3}
Se	0.007	0.010	0.024	0.001	0.003	0.002	7.10^{-4}	0.002	0.004	0.004	0.004	8.10^{-4}	0.002	0.003
p-value	$<2.10^{-16}$	$<2.10^{-16}$	$<2.10^{-16}$	$<2.10^{-16}$	0.029	0.222	0.613	0.139	5.10^{-4}	0.011	0.682	0.047	$<2.10^{-16}$	0.065
Signif	***	***	***	***	*				***			*	***	
$R^2 = 0.425$		*DW* = 1.987												

F test for the existence of individual specific effects (H_0: No indiv. Speci. Effects) : F-value=2.237 with (1336,12020) deg. of freedom, p-value = 0.

[8] The sample is 1337 firms, annual data from 1988 to 1998. Coefficient estimates, Standard errors (*Se*) and p-values of parameter significance tests are given. Signif gives Significance codes of T-test: Coefficient significant at α=0.001 → ***, α =0.01 → **, α =0.05 → *
R statistical software with plm package (Yves Croissant yves.croissant@let.ish-lyon.cnrs.fr) was used for parameters estimation.

Table 3: Model II - Fixed Effects Model with specific firms' heterogeneity[8]

Variable	PP^f	Z	U^a	U^b	U^c	U^d	U^e	U^g	U^h	U^i	U^j	U^k	U^m
Coeff. estim.	0.127	0.027	0.010	-0.001	3.10^{-4}	4.10^{-4}	0.004	-0.017	-0.012	-4.10^{-4}	-0.002	0.014	8.10^{-4}
Se	0.010	0.025	0.001	0.002	0.002	6.10^{-4}	0.002	0.004	0.004	0.004	8.10^{-4}	0.002	0.003
p-value	$<2.10^{-16}$	0.286	$<2.10^{-16}$	0.577	0.862	0.495	0.021	9.10^{-5}	0.003	0.911	0.0231	10^{-9}	0.775
Signif	***		***				*	***	**		*	***	

Hausman Test : chi2(13) = 12833.83 (p-value=0)

F Test: F(1336,12020) = 2.237044 (p-value=0)

Table 4. Determinants of new technology creation at the firm level

	Own firm feedback loops	**Capacity to exploit intrasectoral spillovers**	**Capacity to exploit intersectoral spillover** Significant coeff. at α =0.05					
Variable	PP_{t-1}^{food}	Z_{t-1}	U_{t-1}^{a} *Genet.Eng. &Ferment.*	U_{t-1}^{e} *Agric*	U_{t-1}^{g} *Energy*	U_{t-1}^{h} *Chemicals*	U_{t-1}^{j} *Cell cult.*	U_{t-1}^{k} *Bio-cataly.*
Coeff. sign	+	**Not significant**	+	+	--	--	--	+