Does patenting increase the private incentives to innovate? A microeconometric analysis

Emmanuel DUGUET* and Claire LELARGE**

FEBRUARY 2005

* EPEE – Université d'Evry Val d'Essonne - 4 boulevard François Mitterrand - 91025 EVRY Cedex. Email: emmanuel.duguet@univ-evry.fr.
** Département des Études Économiques d'Ensemble - Division « Marchés et Stratégies d'Entreprise » - Timbre G230 - 15, bd Gabriel Péri - BP 100 - 92244 MALAKOFF CEDEX. Email: claire.lelarge@insee.fr

Does patenting increase the private incentives to innovate?
A microeconometric analysis

Abstract

This paper examines whether patenting increases the private incentives to innovate in manufacturing. To study this issue, we build a model in which the value of an innovation depends both on the type of innovation implemented (product, process) and on whether it is patented or not. We obtain a three-equation model that links the values of product and process innovations to the value of patent protection. This model and the feature of the data imply the estimation of a censored trivariate Probit model. We reach two main conclusions. First, the value of patent rights increases the incentives to innovate in products but not in processes and, conversely, the value of product innovations only – and not the one of process innovations – increases the incentives to patent. Second, we find that the distributions of product innovations and of patent values are skewed contrary to the values of process innovations. A significant share of the skewness in product values would come from the efficiency differences of intellectual property rights between the different activities.

Introduction

Since information has the characteristics of a public good, it is generally agreed that the market will fail to provide a sufficient production of knowledge. The production of knowledge by private agents is affected by several imperfections that prevent an optimal R&D investment by the market. Knowledge has non-rivalry and non-exclusion properties that drive the private return on knowledge below its social return. Therefore, R&D has been a long-standing field of state intervention in advanced countries. Different types of policy measures have been implemented in order to stimulate the production of knowledge. A first type of intervention is to create public research institutions in order to encourage fundamental research, which is the source of many industrial applications. A second type of measure aims at reducing the private cost of R&D: this includes R&D subsidies to firms (David, Hall and Toole, 2000; Duguet, 2004), R&D tax credit (Hall and Van Reenen, 2000), support to cooperative R&D (D'Aspremont and Jacquemin, 1988; Jorde and Teece, 1990; Cassiman and Veugelers, 2002). A third set of measures aims to encourage research by increasing the private return on R&D. One manner to reach this objective is to set a patent system in order to weaken the non-exclusion property of knowledge, by granting property rights on immaterial goods. The choice between these systems, or their specific combination in each country, will depend on the common beliefs about the efficiency of a direct state intervention versus a law system whose use is let to market participants.[1] The evaluations that have been

---

[1] The use of the R&D tax credit is also left to the discretion of market participants, but it can be changed by the state according to a policy, contrary to property rights that are more stable over time. The direct interventions allow for active innovation policies, while the patent system lets the initiative of innovation decisions to the market participants.

performed on subsidies and tax credit conclude that these measures are efficient (in the sense that they increase total R&D investments); the issue of the evaluation of the patent system has been less investigated.

Another motivation for this paper is based on empirical considerations (Figures 1 and 2): the use of patents has considerably increased over the last two decades in the most technologically advanced countries. The interpretation of this evolution is however ambiguous. It is possible that the increase of the number of patents results from an increase of the number of patentable innovations and, in this case, the reinforcement of patents rights that occurred over the same period could have had a positive effect on innovation. But another interpretation is also conceivable: this rise in the number of patents could express strategic considerations related to patent applications, like preventing litigation or the will to improve the bargaining power in technological negotiations (Duguet and Kabla, 1998). In the latter case, the reinforcement of patent rights could have been neutral on welfare, or even negative if we account for the social cost of the patent system.

Figure 1: Number of patent applications in Europe

4
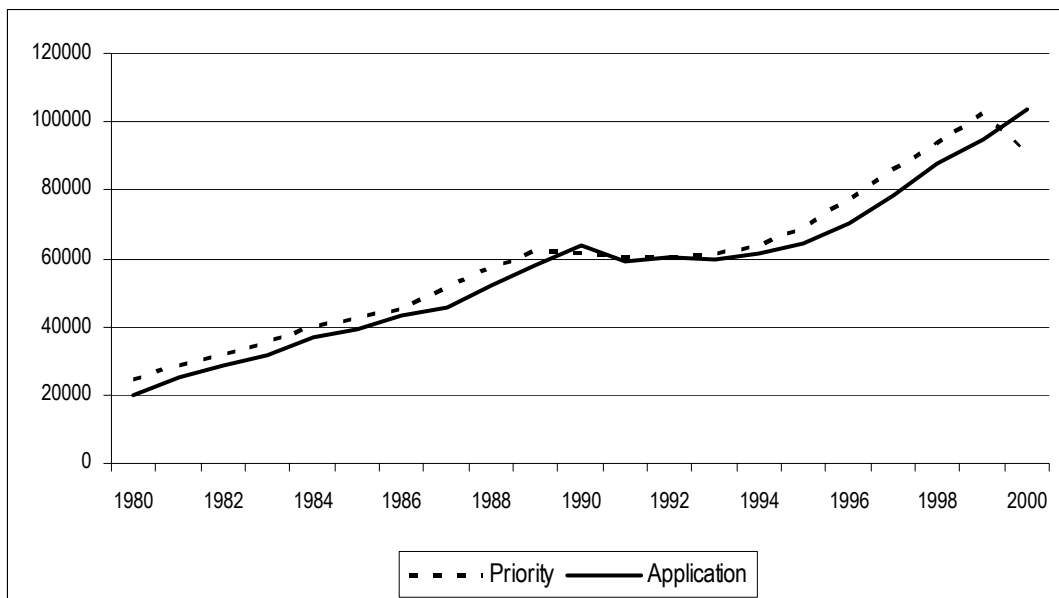
From a social viewpoint, the design of a patent system should result from a trade-off between the social costs and benefits. The gains of the reinforcement of intellectual property rights (IPRs) result from the rise of the number of innovations and from a greater diffusion of knowledge during the patent life; the costs of the patent system include the inefficiencies related to market power and the cost of the judicial system. In the literature, this situation has often been summarized by the trade-off between dynamic efficiency (new products, new processes) and static efficiency (competitive pricing). From the firms' point of view, patent applications are interesting when the ability of the patent system to prevent imitation is sufficiently strong to compensate the legal and "bearing" costs of the patents.

Figure 2: Number of patents granted in the United States
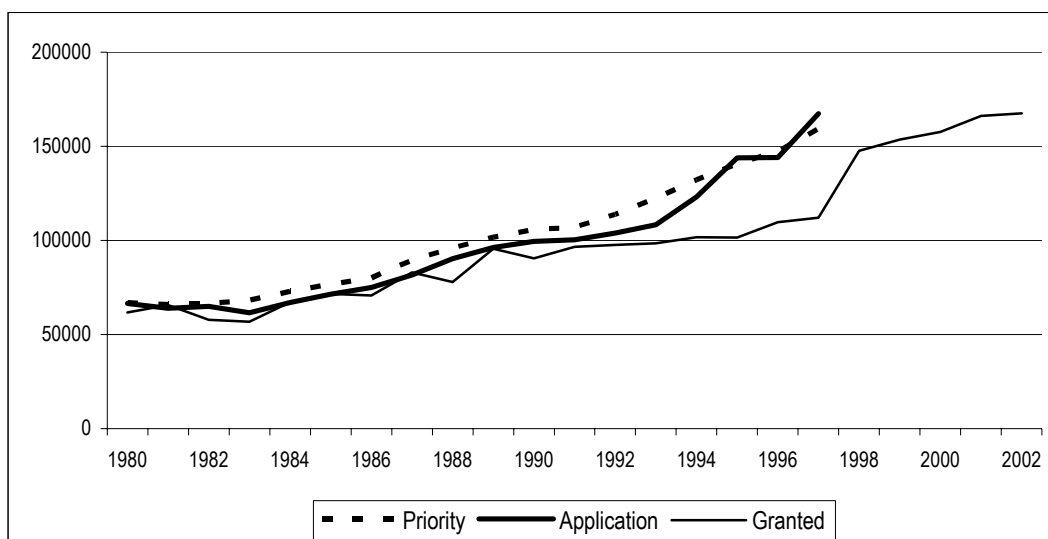
The empirical studies conducted on this topic remain cautious. The results obtained so far seem however to depend strongly on the activity considered. Overall, a first set of studies concludes that the patent system would have had a positive effect on innovation in pharmaceuticals and chemicals (Grabowsky and Vernon, 1986; Park and Ginarte, 1995 at the aggregate level, Arora, Ceccagnoli and Cohen, 2003 and, in a lesser extent, Branstetter and Sakakibara, 2001). A second set of studies stresses that the differences in property

rights modify the choice of the country of application and the direction of technological change, that is the domain in which firms' R&D investments are performed. Moser (1999), from nineteenth century data, shows that the firms that operate in countries where there is no patent system tend to direct their innovations in the activities where secrecy is efficient compared to patenting. Lerner (2001) finds that, over the period 1850-2000, the countries that have reinforced their property rights have attracted more innovations from the other countries but have not made more innovations of their own. Last, a third set of studies reach conclusions that are less favorable to the patent system. Hall and Ziedonis (2004) show that the doubling of the patent to R&D ratio in the semiconductor industry would result mostly from the will to avoid litigation, a conclusion similar to that of Duguet and Kabla (1998) on French manufacturing. These strategic considerations are also omnipresent in the studies by Levin et al. (1987) and Cohen, Nelson and Walsh (2000). In service activities, Bessen and Hunt (2004) conclude that the extension of property rights to software would have led to a decrease of R&D investment at the firm level. The latter conclusion, unfavorable to the patent system, meets other considerations on the potentially harmful effects of patent rights on innovation output when knowledge is cumulative. Thus, Bessen and Maskin (2002) emphasize that an activity like software has achieved a remarkable development *without* a patent system.

This paper scrutinizes the effect of the patent system on the innovation output of the French manufacturing firms. The restriction to manufacturing corresponds to the field of patent rights in France. Compared with the previous literature, we develop the analysis in two directions. Our first contribution is to study the causality that goes from the value of patents to the value of innovations – or the contribution of patenting to the output of research investments – while the previous studies have focused on the other causality. We do it in a setting that allows for a simultaneous determination of the values of patenting and of innovations. Our second contribution is to allow for differences of appropriation behavior depending on the type of innovation considered (products, processes). Thus, we extend the previous empirical works, which suggest that the patents would be more efficient at protecting products rather than

processes; the latter being more efficiently protected by secrecy. Our model allows for testing that assumption.

We reach two main conclusions. First, patent protection increases the incentive to innovate in products but not in processes. Conversely, process innovations do not contribute to increase patenting once product innovation is accounted for. Second, while the distribution of the values of processes is symmetric, the distributions of the product and patent values are skewed. A large part of product innovations have a small value and a small part a large value. This skewness partly originates in the skewness of the efficiency of property rights among lines of business.

In the first section, we present a model that accounts for the interdependence between the value of patents and the values of product and process innovations. The second section presents the data and the estimation method is detailed in section 3. It accounts for the fact that one can observe a patent when a firm has innovated only (selection bias) and allows for testing the validity of the model (overidentification) constraints. The results are discussed in section 4.

I - Model

The model that follows represents one way to interpret our econometric application. It gives a justification to the simultaneity relationships between the decisions to innovate and to patent, and settles the identification constraints of the system that we estimate later. Other models may be compatible with our estimation.

We consider a firm facing a three-step decision process. In the first step, the firm decides whether to invest in innovation activities or not; in the second step, the innovation output is known and its importance, denoted μ, depends on the amounts invested in research. In the third step, the firm decides whether it applies for a patent, knowing both the value of its innovation and its appropriability (a random variable denoted ε).[2] We solve this problem by backward induction.

Decision to patent

At the last step, the value of innovation without protection, denoted μ, and the appropriability disturbance, denoted ε, are known. The firm compares the values of its innovation with and without a patent protection. The value of a patented innovation can be written:

$$V(\mu, \varepsilon) = \left(1 + P\left(\varepsilon, \mu, X_{appro}\right)\right) \times \mu ,$$

where P(.) is the patent premium and X_{appro} a set of explanative variables related to the appropriability of innovations at the firm level. The patent premium can be interpreted as the percentage gain of the innovation value attributable to the patent system:

---

[2] This random variable reflects the variations of market power granted by the patent. It could be interpreted as "success" as far as the considered innovation need to be "novel" to be patentable (novelty requirement) For instance, the actual life of a patent may vary from one line of business to another, depending on the quantity of information disclosed in the patent document. If the information has a strong diffusion and the innovation is perfectible, the competitors can leapfrog the patented innovation and make it obsolete.

$$P = \frac{V}{\mu} - 1 \,.$$

Extending Arora, Ceccagnoli and Cohen (2003), we assume that the patent premium can depend on the quality of the innovation. For our application, we will assume later than:

$$P\left(\varepsilon, \mu, X_{appro}\right) = \varepsilon + \alpha_{brev}\mu + X_{appro}\beta_{appro} - 1 \,.$$

The firm will patent when the patent premium is positive:

$$P\left(\varepsilon, \mu, X_{appro}\right) > 0 \Leftrightarrow \varepsilon > 1 - \alpha_{brev}\mu - X_{appro}\beta_{appro} \,.$$

Research investment

At the second step, the firm has not yet observed whether its innovation is successful or not (i.e., the value of ε) but has an idea on its distribution. We denote $\Phi(.)$ the cdf and $\phi(.)$ the pdf of this distribution (assumed to be gaussian in the application). We also assume that the quality of the innovation depends on the amount of R&D invested, denoted r, in the following manner:

$$\mu = f\left(r, X_{inno}\right),$$

where X_{inno} denotes the determinants of innovation different from research investments. The firm chooses its amount of R&D, r, by maximizing its expected profit, denoted $\overline{\Pi}$:

$$\overline{\Pi} = \int_{P>0} \underbrace{\left(P\left(\varepsilon, \mu, X_{appro}\right) + 1\right)\mu}_{V} \, \phi(\varepsilon) \, d\varepsilon + \int_{P\leq 0} \mu \, \phi(\varepsilon) \, d\varepsilon - r$$

under the constraint $\mu = f\left(r, X_{inno}\right)$. It is useful to define the expected patent premium, denoted z:

$$z = \alpha_{brev}\mu + X_{appro}\beta_{appro} - 1$$

so that the expected profit can be written:

$$\overline{\Pi} = \mu\left(1 + \phi(z) + z\,\Phi(z)\right) - r\,.$$

The first-order condition defines the optimal R&D investment:

$$\frac{\partial\mu}{\partial r} \times \left[1 + \phi\left(z^*\right) + z^*\Phi\left(z^*\right)\right] + \frac{\partial z}{\partial R} \times \mu^*\Phi\left(z^*\right) = 1$$

$$\Leftrightarrow \frac{\partial\mu}{\partial r}\left[1 + \phi\left(z^*\right) + z^*\Phi\left(z^*\right) + \alpha_{brev}\mu^*\Phi\left(z^*\right)\right] = 1$$

with $\mu^* = f\left(r^*, X_{inno}\right)$ and $z^* = \alpha_{brev}\mu^* + X_{appro}\beta_{appro} - 1$. The previous relationship implicitly defines the optimal amount of R&D and therefore the quality μ^* of the innovation. This amount depends on the environment of the firm that can be decomposed into two parts: first, the innovative environment summarized by the variables in X_{inno} and, second, the institutional environment summarized in the X_{appro} vector. The latter includes the appropriation possibilities in the firm's line of business. It is important for estimation to remark that the appropriability conditions intervene in the first-order condition through the expected patent premium z^* only. Using the innovation function $\mu = f(r, X_{inno})$, we get the following two-equation system at the optimum:

$$\begin{cases} \mu^* = \mu^*\left(z^*, X_{inno}\right) \\ z^* = z^*\left(\mu^*, X_{appro}\right) \end{cases}$$

One contribution of this study is to measure the firm-level incentives that patents provide to innovation; this effect is measured by $\partial\mu^*/\partial z^*$. Notice that the quantity that is commonly estimated in the previous literature is close to $\partial z^*/\partial\mu^*$. Furthermore, the previous equations highlight the identification conditions essential for the estimation to follow. The appropriation condition X_{appro} affects innovation output through the patent premium only, and the innovative environment affects the patent premium through the value of innovation only.

Therefore we have at least one variable that intervenes in one equation and not in the other; needless to say that this exclusion constraints needs to be tested. The estimation method we use – namely, asymptotic least squares – allows for testing these overidentification constraints directly. On our data, these restrictions are accepted at conventional levels of significance.

Econometric model

In order to estimate the theoretical model we have to account for the following data constraints[3]. Firstly, the information on innovation output and on patent applications is available on the same period (1997-1999), so that we have to account for their simultaneity, at least for time aggregation reasons.[4] This innovation data comes from the FIT[5] survey. Secondly, the only information available is dichotomous; we know whether a firm has patented and whether it has innovated (in products or processes separately) so that we will need to estimate a three-equation Probit model. Thirdly, the matching of the innovation surveys with the standard R&D surveys would have made us lose a large number of firms due to differences of sampling. Therefore, we have used the CIS2[6] survey that provides information on the R&D expenditures over the period 1994-1996 and whose sampling is close to the FIT survey. We use the same theoretical model for products and for processes, which is possible because we focus on the patent premium; however, since we observe patenting only globally, we have to interpret the patent premium z^* as a global premium defined at the firm level and not at the innovation level. However, we show below that it is possible to decompose the patent premium between products and processes. Fourthly, we observe patenting when the firms have innovated only; therefore, we have to account for a selection bias.

---

[3] See below for a description of our data.

[4] See Mundlak (1961) for a discussion.

[5] FIT: Financement de l'Innovation Technologique (Funding of Technological Innovation). This survey was performed by Sessi (French Ministry of Industry) in 2000. It also provides information on the appropriation conditions.

[6] CIS for Community Innovation Survey. Therefore our data is comparable with the one of the other European countries. The CIS are coordinated across countries by EUROSTAT.

We account for these data limitations and use a linear version of the first order condition of our model:

$$\begin{cases} \mu_{prod}^* &= \alpha_{prod} z^* + X_{inno}\beta_{prod} + u_{prod} \\ \mu_{proc}^* &= \alpha_{proc} z^* + X_{inno}\beta_{proc} + u_{proc} \\ z^* &= \alpha_{brev}^{prod}\mu_{prod}^* + \alpha_{brev}^{proc}\mu_{proc}^* + X_{appro}\beta_{brev} - 1 \end{cases}$$

where $\left(\mu_{prod}^*, \mu_{proc}^*\right)$ are the values of product and process innovations and $\left(u_{prod}, u_{proc}\right)$ the usual disturbances of an econometric model. The third endogenous variable, the expected patent premium z^*, is not random. Since we observe the decision to patent only, we shall rewrite the model as a function of patent premium (which is random) P^*. Since $P^* = z^* + \varepsilon$, we obtain the following system:

$$\begin{cases} \mu_{prod}^* &= \alpha_{prod}P^* + X_{inno}\beta_{prod} + u_{prod} - \alpha_{prod} \times \varepsilon \\ \mu_{proc}^* &= \alpha_{proc}P^* + X_{inno}\beta_{proc} + u_{proc} - \alpha_{proc} \times \varepsilon \\ P^* &= \underbrace{\alpha_{brev}^{prod}\mu_{prod}^* + \alpha_{brev}^{proc}\mu_{proc}^* + X_{appro}\beta_{brev}}_{z^*} + \varepsilon \end{cases}$$

This formulation of the model shows that we certainly face endogeneity problems since the success disturbance ε intervenes in all the equations. This property is important for choosing the estimation method[7]. We observe the following binary variables:

$$Prod = \begin{cases} 1 & \text{if } \mu_{prod}^* > 0 \\ 0 & \text{otherwise} \end{cases}, \qquad Proc = \begin{cases} 1 & \text{if } \mu_{proc}^* > 0 \\ 0 & \text{otherwise} \end{cases},$$

$$Brev = \begin{cases} 1 & \text{if } P^* > 0 \text{ and } \max\left(\mu_{prod}^*, \mu_{proc}^*\right) > 0 \\ 0 & \text{otherwise} \end{cases}$$

---

[7] One has to account for cross correlations in the Reduced Form to get consistent first step estimators - see below for more precision on the estimation procedure. The disturbances ε, u_{prod} and u_{prod} can also be correlated if, for example, some unobserved heterogeneity drives both innovative and appropriation behaviours.

The three previous binary variables are endogenous. The definition of the third variable comes from the fact that one can observe a patent application ($P^* > 0$) only when the firm has innovated in product ($\mu_{prod}^* > 0$) and/or in process ($\mu_{proc}^* > 0$). This selection bias is important because the disturbances of the three equations are correlated. We explicitly account for it when we estimate the model.

II - The data

Sample construction

The sample results from the matching of the four following sources of firm-level data:[8]

1.   « Financement de l'Innovation Technologique » (FIT, "Funding of Technological Innovation") survey. It was collected by SESSI in 2000 in manufacturing, and provides global information over the period 1997-1999.

2.   Community Innovation Survey (CIS2). It was collected by SESSI in 1997 in manufacturing and provides information over the period 1994-1996.

3.   BRN administrative file. It is collected by the tax administration ("Direction Générale des impôts") and provides information about accounting data for the year 1996.

4.   Line of business industry census. It was collected by SESSI in 1996 among firms of 20 employees or more and includes the decomposition of a firm's sales, employment and exports for all its lines of business.

The FIT survey covers manufacturing firms with 20 employees or more, except food industry and construction. This definition corresponds roughly to the set of innovations that are patentable in France (services cannot be patented). However, the size threshold indirectly excludes a part of the start-ups. We take the three endogenous variable of our analysis from this data set: the product innovation dummy, the process innovation dummy and the patent application dummy. We also take from this survey one of the variables needed for the identification of the model: the firms' assessment on the patent system.[9]

---

[8] The matching is performed easily since all French firms have a national identification number whose use is compulsory (called the SIREN number). The surveys are also all compulsory.
[9] See the appendix for a detailed presentation.

The CIS2 is the French part of the Community Innovation Survey that is coordinated by EUROSTAT. The Community surveys are performed jointly by the members of the European Union. Notice that our survey *is not* micro-aggregated. We use the information on the innovation inputs over the period 1994-1996: internal R&D expenditures, external R&D expenditures, expenditures on equipment goods that incorporate innovations, as well as a product imitation rate at the line of business level (see appendix I).

Last, the data from BRN and EAE provide the firm-level accounting data for the year 1996: Sales, Lerner index, sales diversification index, Herfindahl index of sales concentration and an export dummy.

The four data sets have been matched from the SIREN identification of the firms. Our final sample includes 1027 firms, all engaged in (successful or unsuccessful) innovation activities.

Sample statistics

Tables 1 to 4 present some sample statistics. Overall, the firms that are involved in research activities have a median size of 191 employees. They export more than the fourth of their production. Table 2 summarizes the innovative output of these firms. The most innovative activities are electrical equipment, chemicals, electrical components, houseware and pharmaceuticals. The product and process innovations are strongly correlated, since 58% of the firms implement these both types of innovation together. Yet, a significant share of firms innovates in product only (21%). Process innovation without product innovation is less common (13%) but some industries depart from the average behavior. For instance, 45% of the firms in printing and publishing make process innovations only; the figure is 20% for wearing apparel and leather as well as metalworking. Notice tha innovation in the "old" industries is often motivated by the environmental regulations, which allow production only when the environmental damage is below a given threshold. Industries in advanced lines of business can also make a strong use of processes; for instance 17% of the firms in shipbuilding, aircraft and rail make process innovations only, even though the majority of innovators in this industry make both product and process innovations (Figure 3). These differences in innovation behaviors should have consequences on the patenting behavior of

the firms: indeed, the processes are more easily protected by secrecy than the products, so that the patenting rate should be smaller in the industries that innovate strongly in processes.

Table 1: Sample statistics

	1st Quartile	Median	3rd Quartile	Mean
% : Lerner index (Value added minus labor cost / Sales)	3.7	7.3	11.7	7.8
Value added / Sales	9.9	20.1	30.3	18.0
Exportations / Sales	3.6	19.8	45.4	27.3
Labor cost / Production	15.6	20.5	27.0	21.9
Thousands of Euros : Value added minus labor cost / Employees	3	9	16	12
Sales / Employees	88	122	171	143
Value added / Employees	36	45	58	50
Number of employees	58	191	580	669

Table 2: Innovation output by industry

|	Innovation (%)					Activity (%)		
Code : Industry	Product	Process	Product and Process	Product only	Process only	Non innovative	Moderately innovative	Strongly innovative
C1: Wearing apparel, leather	58	63	42	17	21	63	33	4
C2: Printing and publishing	45	82	37	8	45	39	47	13
C3: Pharmaceuticals	81	73	62	19	11	3	54	43
C4: Houseware	87	76	68	19	8	44	39	17
D0: Cars	79	79	66	13	13	23	41	36
E1: Shipbuilding, aircraft, rail	78	83	65	13	17	22	61	17
E2: Non-electr. machinery	85	63	56	29	7	33	55	12
E3: Electrical machinery	92	77	73	19	5	13	39	48
F1: Mineral products	71	70	55	16	14	71	19	10
F2: Textile	70	72	56	14	16	49	47	5
F3: Wood and paper	68	77	55	14	23	52	36	11
F4: Chemicals	88	69	64	24	5	33	44	23
F5: Metalworking	70	65	45	24	20	45	40	14
F6: Electrical components	88	79	67	21	12	16	49	34
Manufacturing	79	71	58	21	13	46	44	10

Figure 3: Innovation profile by industry
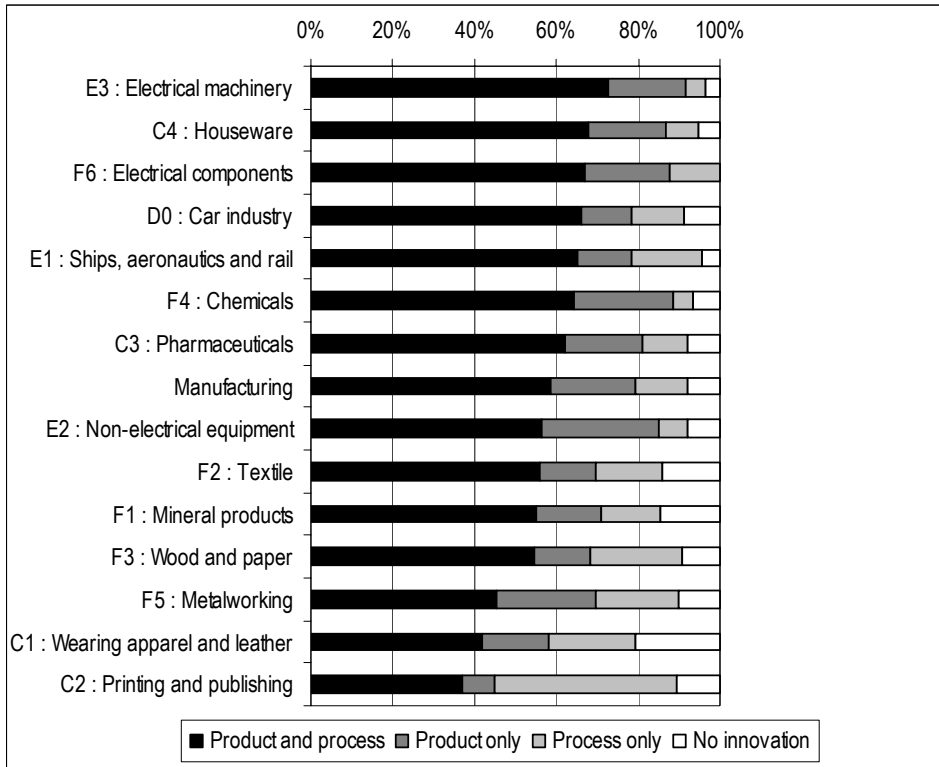
Table 3: IPR use and assessment by industry

Code : Industry	Patent application %	Intellectual property rights (patent) %		
		Not important	Weakly important	Important
C1: Wearing apparel. leather	12.5	58.3	16.7	25.0
C2: Printing and publishing	7.9	79.0	18.4	2.6
C3: Pharmaceuticals	70.3	29.7	48.7	21.6
C4: Houseware	54.7	36.0	40.0	24.0
D0: Cars	64.3	35.7	32.1	32.1
E1: Shipbuilding. aircraft. rail	56.5	26.1	34.8	39.1
E2: Non-electr. machinery	62.4	23.3	44.6	32.2
E3: Electrical machinery	67.9	27.4	45.2	27.4
F1: Mineral products	55.1	27.5	40.6	31.9
F2: Textile	32.6	55.8	18.6	25.6
F3: Wood and paper	47.7	52.3	20.5	27.3
F4: Chemicals	67.5	21.7	38.3	40.0
F5: Metalworking	51.1	38.2	30.8	30.9
F6: Electrical components	63.0	28.8	31.5	39.7
Manufacturing	56.1	33.5	36.0	30.5

The lines of business where firms patent the most are ones where the codification of knowledge is the easiest and where cooperation and technological negotiations are necessary to make significant advances. It is clearly the case when knowledge is strongly cumulative. The activities where firms patent the most are (Table 3) pharmaceuticals, electrical machinery, chemicals, electrical components and non-electrical machinery (more than 60%). Some activities, on the contrary, neglect patenting. It is the case of printing and publishing (8%) where 82% of the firms innovate in processes. It is also the case in wearing apparel and leather (12%) and in textile (32%), where other protections than patent exist (trademarks, textile models). Overall, 56% of the firms do patent, which is small for a sample of firms that all declare to be involved in research activities.[10]

Table 4: Innovation and assessment of IPRs

The amounts are in thousand Euros

	Sample Total	Product Innovators	Process Innovators	Both types Innovators	Patenting	Not Patenting
IPR protection considered as:						
- unimportant	33.5	28.9	33.7	28.8	15.8	55.7
- weakly important	36.0	37.9	36.1	38.5	43.8	26.4
- important	30.5	33.2	30.2	32.7	40.5	17.9
Several innovation projects (%)	61.6	68.5	66.6	72.3	77.6	43.0
Internal R&D						
Yes (%)	70.5	77.4	70.9	77.7	85.1	53.5
Mean expenditure	7 384	8 230	9 319	10 075	10 007	1 904
First quartile	152	152	152	152	228	76
Median	520	610	730	763	913	152
Third quartile	2 166	2 567	3 046	3 356	3 400	730
External R&D						
Yes (%)	29.4	32.4	31.3	34.5	40.6	15.2
Mean expenditure	3 160	3 543	3 607	3 906	3 939	543
First quartile	46	53	76	76	78	30
Median	152	152	152	183	152	76
Third quartile	656	761	762	762	762	259
Acquisition of innovative equipment						
Yes (%)	44.0	46.5	48.6	50.8	51.3	36.3
Mean expenditure	1 854	2 136	2 022	2 269	2 490	682
First quartile	76	76	76	91	91	76
Median	305	305	305	305	305	152
Third quartile	763	914	869	914	1 065	457

Table 4 presents the assessment of IPRs according to the type of innovations implemented and according to the patenting practices of firms. Overall, only a third of the firms in our

---

[10] However, this is a widespread result of innovation studies in general.

sample declare that IPRs are important. This figure is stable whatever the innovation profile of the firms. As expected, the firms that patent value the IPRs more than the other firms but they do not value it importantly: 60% of the patenting firms think that intellectual property is unimportant or weakly important against 82% for the non-patenting firms.

Table 5: Patent applications by innovating firms

In %	Product	Process	Product and Process	Product only	Process only
Patenting firms	93.7	76.6	70.3	23.4	6.3
Non-patenting firms	75.9	78.6	54.5	21.4	24.1
Difference	17.8	-2.0	15.8	2.0	-17.8
(standard error)	(3.18)	(3.86)	(4.45)	(3.86)	(3.18)
All firms	86.1	77.4	63.6	22.6	13.9

The Table 5 highlights the importance of product innovation in the decision to patent. Two interesting facts show up. Firstly, while the patenting firms innovate more often in products than the non-patenting firms, they do not innovate more in processes than the non-patenting firms. Secondly, while the patenting firms have the same probability to innovate in products *only* than the non-patenting firms, the patenting firms have a four times smaller probability to innovate in process *only* than the non-patenting firms. These two facts suggest that there is a positive association between product innovation and patenting.

The aim of our application is to study this issue more deeply, with regression methods, in order to see by which extent the innovations are patented and whether patenting influences the innovation output.

III - Model estimation

The selection bias

The structural model has the following form:

$$\begin{cases} \mu_{prod}^{*} &= \alpha_{prod}P^{*} + X_{inno}\beta_{prod} + u_{prod} - \alpha_{prod} \times \varepsilon \\ \mu_{proc}^{*} &= \alpha_{proc}P^{*} + X_{inno}\beta_{proc} + u_{proc} - \alpha_{proc} \times \varepsilon \\ P^{*} &= \alpha_{brev}^{prod}\mu_{prod}^{*} + \alpha_{brev}^{proc}\mu_{proc}^{*} + X_{appro}\beta_{brev} + \varepsilon \end{cases}$$

The latent variables in this model are not observable; we only observe the following dummy variables:

$$\begin{cases} Prod &= 1_{\left(\mu_{prod}^{*}>0\right)} \\ Proc &= 1_{\left(\mu_{proc}^{*}>0\right)} \\ Brev &= 1_{\left(P^{*}>0\right)} \times 1_{\left(\max\left(\mu_{prod}^{*},\mu_{proc}^{*}\right)>0\right)} \end{cases}$$

A selection bias appears for the patenting dummy. It is censored by the following dummy variable:

$$1_{\left(\max\left(\mu_{prod}^{*},\mu_{proc}^{*}\right)>0\right)}$$

Only firms that have innovated answer to the question on patenting in the FIT and CIS2 questionnaires. If this selection was not taken into account we would have a selection bias because the disturbance of the patent equation is correlated with the disturbances of the innovation equations; our estimates will confirm it for product innovations.[11]

---

[11] To our knowledge, the only innovation study that accounts for this kind of problem is Monjon and Waelbroeck (2003).

The model estimation, related to Amemiya's method (see Lee, 1981 for an overview) is made in two steps:

1.   We estimate the reduced form of the model. Assuming that the vector of the disturbances is normal, we estimate this model by simulated maximum likelihood, using a GHK simulator.

2.   Using the reduced form estimator, we estimate the structural form of the model by asymptotic least squares (i.e., "minimum distance"). This step is also useful for testing the overidentification constraints of the model.

Simulated maximum likelihood

The reduced form of the latent model can be written:

$$\begin{cases} \mu^*_{prod} & = X\pi_1 + \eta_1 \\ \mu^*_{proc} & = X\pi_2 + \eta_2 \\ P^* & = X\pi_3 + \eta_3 \end{cases} \quad \eta = \begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{pmatrix} \quad iid \quad N[0,\Sigma], \quad \Sigma = \begin{pmatrix} 1 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & 1 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & 1 \end{pmatrix}$$

The log-likelihood is therefore equal to:

$$\ell = \sum_{i \mid max(Prod,Proc)=1} \ln Pr[Prod_i, Proc_i, Brev_i \mid X_i, \pi, \Sigma] + \sum_{i \mid max(Prod,Proc)=0} \ln Pr[Prod_i, Proc_i \mid X_i, \pi, \sigma_{12}]$$

The quantities that need a specific treatment are the ones that involve triple integrals. For instance, the probability that a firm makes both types of innovation and patents, denoted p_{111}, is equal to:

$$p_{111} = Pr\left[Prod_i = 1, Proc_i = 1, Brev_i = 1 \mid X_i, \pi, \Sigma \right]$$
$$= \int_{-X\pi_1}^{+\infty} \int_{-X\pi_2}^{+\infty} \int_{-X\pi_3}^{+\infty} \varphi_3\left(\eta_1, \eta_2, \eta_3 \mid X, \pi, \Sigma\right) d\eta_1 d\eta_2 d\eta_3$$

where $\varphi_3(.)$ is the trivariate standard normal density function. In order to evaluate the previous probability, we use Bayes' theorem:

$$
\begin{aligned}
p_{111} &= \Pr\left[\eta_1 > -X\pi_1, \eta_2 > -X\pi_2, \eta_3 > -X\pi_3\right] \\
&= \Pr\left[\eta_1 > -X\pi_1\right] \times \Pr\left[\eta_2 > -X\pi_2 \mid \eta_1 > -X\pi_1\right] \times \Pr\left[\eta_3 > -X\pi_3 \mid \eta_1 > -X\pi_1, \eta_2 > -X\pi_2\right]
\end{aligned}
$$

Since Σ is positive definite, there exists a lower triangular matrix Λ such that $\Sigma = \Lambda\Lambda'$ (Cholesky decomposition). Therefore, we can write:

$$
\begin{aligned}
\eta_1 &= \lambda_{11}v_1 \\
\eta_2 &= \lambda_{21}v_1 + \lambda_{22}v_2 \\
\eta_3 &= \lambda_{31}v_1 + \lambda_{32}v_2 + \lambda_{33}v_3
\end{aligned}
$$

where $v = (v_1, v_2, v_3)'$ is a standard normal vector. We have:

$$
\begin{aligned}
p_{111} &= \Pr\left[v_1 > -\frac{X\pi_1}{\lambda_{11}}\right] \times \Pr\left[v_2 > -\frac{X\pi_2 + \lambda_{21}v_1}{\lambda_{22}} \,\middle|\, v_1 > -\frac{X\pi_1}{\lambda_{11}}\right] \\
&\times \Pr\left[v_3 > -\frac{X\pi_3 + \lambda_{31}v_1 + \lambda_{32}v_2}{\lambda_{33}} \,\middle|\, v_1 > -\frac{X\pi_1}{\lambda_{11}}, v_2 > -\frac{X\pi_2 + \lambda_{21}v_1}{\lambda_{22}}\right]
\end{aligned}
$$

Now let $\tilde{v}_1$ be a normal variable truncated from below by $-X\pi_1/\lambda_{11}$ and $\tilde{v}_2$ a normal variable truncated from below by $-(X_2\pi_2 + \lambda_{21}v_1)/\lambda_{22}$, we get:

$$
p_{111} = \Pr\left[v_1 > -\frac{X\pi_1}{\lambda_{11}}\right] \times \Pr\left[v_2 > -\frac{X\pi_2 + \lambda_{21}\tilde{v}_1}{\lambda_{22}}\right] \times \Pr\left[v_3 > -\frac{X\pi_3 + \lambda_{31}\tilde{v}_1 + \lambda_{32}\tilde{v}_2}{\lambda_{33}}\right]
$$

We make $D = 50$ draws of $(\tilde{v}_1, \tilde{v}_2)$ and approximate p_{111} by the following quantity:

$$
\overline{p}_{111} = \frac{1}{D}\sum_{d=1}^{D}\Phi\left(-\frac{X\pi_1}{\lambda_{11}}\right)\Phi\left(-\frac{X\pi_2 + \lambda_{21}\tilde{v}_1^d}{\lambda_{22}}\right)\Phi\left(-\frac{X\pi_3 + \lambda_{31}\tilde{v}_1^d + \lambda_{32}\tilde{v}_2^d}{\lambda_{33}}\right)
$$

where $\Phi(.)$ is the cdf of the standard normal distribution. The other probabilities are approximated with the same method; the simulated likelihood is then maximized with the routines available under SAS-IML.

The obtained estimator is consistent for $D \to \infty$ and $n \to \infty$ (n being the number of observations). The GHK simulator has two particularly interesting properties. First, the simulated quantities are continuous with respect to the parameters and this facilitates the optimization. Second, empirical works (Hajivassiliou *et al,* 1996) have shown that the consistency can be achieved for a number of simulations that is much smaller than for other simulation-based methods.

Asymptotic least squares

The estimator of the censored trivariate Probit model obtained in the previous section is a simulated (pseudo) maximum likelihood estimator. Let $\hat{\pi} = (\hat{\pi}_1 {}', \hat{\pi}_2 {}', \hat{\pi}_3 {}')'$ be the vector of the first-order parameters of the reduced from, it is consistent and asymptotically normal:

$$\sqrt{n}(\hat{\pi} - \pi) \xrightarrow{\ d\ } N\left(0, J^{-1}IJ^{-1}\right) \text{ with } J = E\left(-\frac{\partial^2 \ell}{\partial \pi \partial \pi'}(\pi)\right) \text{ and } I = E\left(\frac{\partial \ell}{\partial \pi}(\pi)\frac{\partial \ell}{\partial \pi'}(\pi)\right)$$

In order to get back the parameters of the structural form of the model, we use the identification constraints of the model. For this, we introduce the exclusion matrices A_j that are defined by:[12]

$$X A_j = X_j \quad \text{with} \quad j \in \{prod, proc, brev\}$$

Equating the conditional expectations of the structural and of the reduced form of the model, we obtain:

---

[12] These matrices are made of 0 and 1. They indicate whether a variable is present (1) or absent (0) of the equation considered.

$$
\begin{aligned}
X\pi_1 &= \alpha_{prod}X\pi_3 + XA_{prod}\beta_{prod} \\
X\pi_2 &= \alpha_{proc}X\pi_3 + XA_{proc}\beta_{proc} \\
X\pi_3 &= \alpha_{brev}^{prod}X\pi_1 + \alpha_{brev}^{proc}X\pi_2 + XA_{brev}\beta_{brev}
\end{aligned}
$$

Since the X matrix is of full column rank, we obtain the following identification constraints:

$$
\begin{aligned}
\pi_1 - \alpha_{prod}\pi_3 - A_{prod}\beta_{prod} &= 0 \\
\pi_2 - \alpha_{proc}\pi_3 - A_{proc}\beta_{proc} &= 0 \\
\pi_3 - \alpha_{brev}^{prod}\pi_1 - \alpha_{brev}^{proc}\pi_2 - A_{brev}\beta_{brev} &= 0
\end{aligned}
$$

Let:

$$
\beta_1 = \begin{pmatrix} \alpha_{prod} \\ \beta_{prod} \end{pmatrix}, \beta_2 = \begin{pmatrix} \alpha_{proc} \\ \beta_{proc} \end{pmatrix} \text{ and } \beta_3 = \begin{pmatrix} \alpha_{brev}^{prod} \\ \alpha_{brev}^{proc} \\ \beta_{brev} \end{pmatrix},
$$

With these notations, it is possible to rewrite the identification constraints under a form that is linear according to the parameters of the structural form:

$$
\underbrace{\begin{pmatrix} \pi_1 \\ \pi_2 \\ \pi_3 \end{pmatrix}}_{\pi} = \underbrace{\begin{pmatrix} \pi_3 & A_{prod} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \pi_3 & A_{proc} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \pi_1 & \pi_2 & A_{brev} \end{pmatrix}}_{H} \underbrace{\begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix}}_{\beta}
$$

In the usual terminology of asymptotic least squares, π is called the auxiliary parameter (reduced form), and β is called the parameter of interest (structural form). In order to get a consistent and asymptotically normal estimator of the parameter of interest, we replace the auxiliary parameter by its estimator:

$$
\hat{\pi} = \hat{H}\beta + \omega,
$$

where ω is a random variable that appears because we have replaced π by $\hat{\pi}$. The covariance matrix of this error term is equal to:

$$V(\omega) = M \, V(\hat{\pi}) \, M' \quad \text{with} \quad M = \begin{pmatrix} 1 & 0 & -\alpha_{prod} \\ 0 & 1 & -\alpha_{proc} \\ -\alpha_{brev}^{prod} & -\alpha_{brev}^{proc} & 1 \end{pmatrix} \otimes I_g$$

where g is the number of explanative variables in the reduced form (i.e., the number of columns of X). The estimation of the auxiliary equation is performed in two steps. In a first step, we perform ordinary least squares (OLS) on the identification constraints in order to estimate M consistently. In a second step, we perform feasible generalized least squares (FGLS) using $\hat{V}(\omega) = \hat{M} \, \hat{V}(\hat{\pi}) \hat{M}'$ as the covariance matrix.

Eventually, since our model is overidentified, we test the overidentification constraints with the following statistic:

$$S = \hat{\omega}' \, \hat{V}(\hat{\omega})^{-1} \, \hat{\omega}.$$

Under the null assumption that the overidentification constraints are valid or, more precisely, that there exists an estimator compatible with the overidentification constraints, this statistic is asymptotically distributed according to a Chi squared distribution with $g - k$ degrees of freedom, where g is the number of (first-order) parameters of the reduced form and k is the number of (first-order) parameters of the structural form of the model. Our model appears compatible with the data (p-value: 0.865).

IV - Results

The estimates are presented in Table 6. The reduced form of the model is useful to compare our results with the previous literature on the innovation function. The firms that have the highest probability to patent are the ones that do the more internal and external R&D, that work on several research projects at the same time, that have a large size and achieve a high mark-up rate. Most of these determinants are similar to the ones of innovation output. One can distinguish the determinants of patenting from the determinants of innovation in the structural form of the model only. However, we notice that the degree of technological opportunities does not influence patenting even though it influences both types of innovation. These results mean that, once controlled for innovation inputs, the firms that operate in the most scientifically promising activities do not patent more than the firms that operate in older activities.

The reduced form of the product innovation equation provides results that are already known in the previous literature: the probability to innovate in products increases with internal research, the degree of technological opportunities, export but also with the importance of IPRs. Two other variables have an important effect on product innovation: working on several projects at the same time increases the probability to launch new products while, at the opposite, the probability to be imitated by competitors reduces product innovation. Both effects indicate that the value of product innovation may depend on patenting. However, the structural form of the model is needed in order to distinguish clearly the determinants of product innovation from the determinants of patenting.

Compared to product innovations, process innovations rely on a more informal research process based on the purchase of innovative equipment goods (embedded innovations). This is in line with previous studies that obtain a similar result for the improvement of processes (Duguet, 2002). The probability to innovate in processes increases with the size of the firms, the fact to work on several projects at the same time and with the degree of technological opportunities. An important difference with product innovation is that process

26

innovation does not depend on the importance of IPRs. The reason often advocated to explain this result is that process innovations are better protected by secrecy. Indeed, product innovations can be purchased by the competitors and reverse-engineered, contrary to processes that are kept in house (industrial espionage is more difficult, and illegal).

The structural form is useful since it allows studying the direct interactions between patenting and innovation. Therefore it provides a way to study the issue of patent data quality, especially when they are used to measure the innovation performance in international comparisons or over time for the same country.

Our results allow concluding that only product innovations have a significant effect on patenting. Thus, the firms prefer to rely on secrecy to protect their processes. A significant part of the processes are however patented too, but it is likely that these are patented when firms innovate both in products and processes - that is when these two types of innovations are complementary. Patent statistics are therefore biased in favor of product innovations. Patenting also increase with the importance of IPRs and with the specialization of the firm. The first result suggests both that when IPRs are more efficient firms patent more and that IPRs are sometimes needed for technological negotiations. The second result suggests that when a firm operates in several lines of business it has less to lose by non-patenting than a single activity firm (diversity as insurance). This effect is counterbalanced by the fact that diversified firms do more product innovation and therefore patent more. Overall, the firm-level explanative variables summarize a large amount of heterogeneity between firms since most industry dummies are not significant.

The existence of patent protection originates from the will to increase the private return on research and development. We find that this mechanism works for new products only. Since patent rights increase the private returns on products it should encourage the firms to do more research than they would do without a patent protection. This point is further confirmed by another econometric result on the product imitation rate. This rate is computed at the industry level and gives the percentage of firms that launch products that are new for them but that are not new for the market. This imitation rate has a negative effect on product

innovation, therefore appropriability problems remain.[13] The original model introduces this imitation rate in all the equations of the model; the only effect that is significant at the 5% level appears in the product innovation equation. We can conclude that product imitation reduces the private return of product innovation only. In our structural model, this result also implies an indirect reduction of patenting through the reduction of the number of product innovators. Overall, the patent system encourages the private R&D investment in products. The other determinants of product innovation are in line with the previous literature: research expenditure, technological opportunities and export increase the value of product innovation.

Process innovation follows different determinants. Patent has no significant influence on the probability to innovate in processes. This point comforts the result that we have found on the patent equation: since the process is not the motivation to patent it is not surprising that patenting does not affect directly the value of process innovation.[14] The firms that innovate in processes prefer relying on secrecy. Furthermore, we find that the disturbance of the process and patent equations are uncorrelated. Under our normality assumption, this implies that processes and patents are conditionally independent. The variables that increase the value of processes are the expenditures on innovative equipment goods, the fact to undertake several projects at the same time and the size of the firm. These results suggest that the processes that are patented would be the ones that are strongly associated to a new product. This also implies that an important part of technical knowledge does not pass through the patent system but needs other diffusion channels, like cooperation in R&D for example.

---

[13] This result is valid for several innovation output variables (see Crépon, Duguet and Kabla, 1996).

[14] Notice that there is always an indirect influence in a structural system. Here process innovations are complementary to product innovations. Therefore, even though there is no direct connection between processes and patents, there remains an indirect relationship between product and processes. In econometric terms, our result means that there is no relationship between patents and processes *once controlled fo*r product innovation.

Table 6: Model estimation

	Reduced form			Structural form		
	Patent	**Product**	**Process**	**Patent**	**Product**	**Process**
Patent	-	-	-	-	0.35** (0.12)	0,03 (0,12)
Product	-	-	-	0.77** (0.22)	-	-
Process	-	-	-	0.53 (0.41)	-	-
Importance of IPRs (ref. none)						
moderate	0.78** (0.13)	0.25** (0.11)	0.03 (0.12)	0.56** (0.16)	-	-
strong	0.99** (0.14)	0.38** (0.13)	0.01 (0.13)	0.71** (0.19)	-	-
Internal R&D (ref. None)						
moderate	0.24* (0.14)	0.43** (0.12)	-0.20 (0.14)	-	0.36** (0.12)	-0,19 (0,14)
strong	0.56** (0.15)	0.76** (0.15)	-0.04 (0.15)	-	0.55** (0.16)	-0,04 (0,17)
External R&D (ref. None)						
moderate	0.26* (0.15)	0.23 (0.16)	0.09 (0.15)	-	0.17 (0.12)	0,09 (0,14)
strong	0.38** (0.17)	-0.06 (0.16)	0.05 (0.14)	-	0.06 (0.13)	0,16 (0,14)
Equipment and machinery expend. (ref. None)						
moderate	0.10 (0.14)	-0.08 (0.14)	0.40** (0.14)	-	-0.16 (0.14)	0,40** (0,14)
strong	-0.05 (0.14)	-0.07 (0.12)	0.21* (0.12)	-	-0.12 (0.10)	0,18 (0,12)
Several innovation projects (ref. No)						
yes	0.35** (0.12)	0.23** (0.56)	0.28** (0.12)	0.01 (0.20)	0.12 (0.13)	0,28** (0,14)
Degree of techn. opportunities (ref. None)						
moderate	0.17 (0.12)	0.49** (0.10)	0.22** (0.11)	-0.32 (0.20)	0.43** (0.11)	0,21* (0,11)
strong	0.18 (0.14)	0.48** (0.14)	0.27* (0.15)	-0.33 (0.25)	0.41** (0.15)	0,27* (0,15)
Other firm-level characteristics:						
Ln(Sales)	0.23** (0.04)	0.06 (0.04)	0.12** (0.04)	0.12 (0.08)	-0.02 (0.05)	0,11** (0,05)
Mark-up rate	1.45** (0.69)	0.08 (0.61)	0.50 (0.63)	1.22 (0.92)	-0.50 (0.66)	0,47 (0,65)
Ln(Div Index)	0.04 (0.16)	0.39** (0.17)	0.26 (0.17)	-0.43* (0.26)	0.40** (0.18)	0,25 (0,17)
Exportation dummy	-0.10 (0.18)	0.28** (0.13)	-0.02 (0.17)	-0.33 (0.24)	0.34** (0.14)	-0,02 (0,17)
Ln(Herfindahl market concent.)	-0.03 (0.06)	-0.05 (0.05)	0.03 (0.06)	-0.01 (0.08)	-0.04 (0.05)	+0,03 (0,06)
Sectoral variables:						
Ln(Imitation rates)	-1.18 (0.77)	-1.49** (0.64)	-0.25 (0.73)	-	-1.04** (0.44)	-
C1 : wearing apparel and leather	-0.88** (0.44)	-0.23 (0.26)	-0.01 (0.35)	-0.74 (0.49)	0.10 (0.33)	0,02 (0,37)
C2 : printing and publishing	-0.57 (0.50)	-0.45* (0.24)	0.03 (0.36)	-0.30 (0.56)	-0.22 (0.32)	0,05 (0,36)
D0 : car industry	-0.13 (0.27)	-0.40* (0.21)	0.01 (0.25)	0.18 (0.35)	-0.36 (0.22)	0,02 (0,37)
E1 : shipbuilding. aircraft and rail	-0.50 (0.47)	-0.73** (0.30)	0.24 (0.45)	-0.09 (0.62)	-0.53 (0.36)	0,30 (0,45)
F3 : wood and paper	0.24 (0.24)	-0.25 (0.19)	0.35 (0.28)	0.20 (0.35)	-0.30 (0.20)	0,32 (0,28)
F5 : metalworking	-0.07 (0.15)	-0.35** (0.12)	-0.09 (0.15)	0.23 (0.21)	-0.32** (0.13)	-0,09 (0,14)
F6 : electrical components	-0.24 (0.20)	-0.44** (0.19)	0.02 (0.19)	0.07 (0.28)	-0.33 (0.21)	0,04 (0,19)
Intercept (ref. C3+C4+E2+E3+F1+F2+F4)	-4.11** (0.62)	-1.44** (0.56)	-1.62** (0.59)	-2.21** (0.99)	0.03 (0.67)	-1,41** (0,67)
Covariance matrix :						
Patent	1 (imposed)	0.14** (0.06)	0.00 (0.05)			
Product		1 (imposed)	0.12** (0.05)			
Process			1 (imposed)			
Log-likelihood		-2208.90				
Overidentification test:						
Statistic					3.915	
Degrees of freedom					8	
p-value					0.865	

** : significant at 5%. * : significant at 10%.

29

The estimations that we have performed also allow for taking a first look at the issue of the distribution of the returns on innovation. Since the contributions by Pakes and Schankerman (1986) and Scherer (1998), we know that the distributions of patent and innovation values are skewed, with some innovations highly valuable and many innovations of little value. In order to examine this issue on our data, we have computed the predictions of the latent variables of the patent, product innovation and process innovation equations. According to our theoretical model, these predictions represent a standardized estimation of the value of patenting and innovation at the firm level. Figure 4 below show the distributions of the latent variables $\left(\mu^*_{prod}, \mu^*_{proc}, P^* \right)$ on the same scale.

Figure 4: Standardized value of the Predicted Latent Variables

Legend : ——— Patenting   ------ Process Innovation
          .... Product Innovation
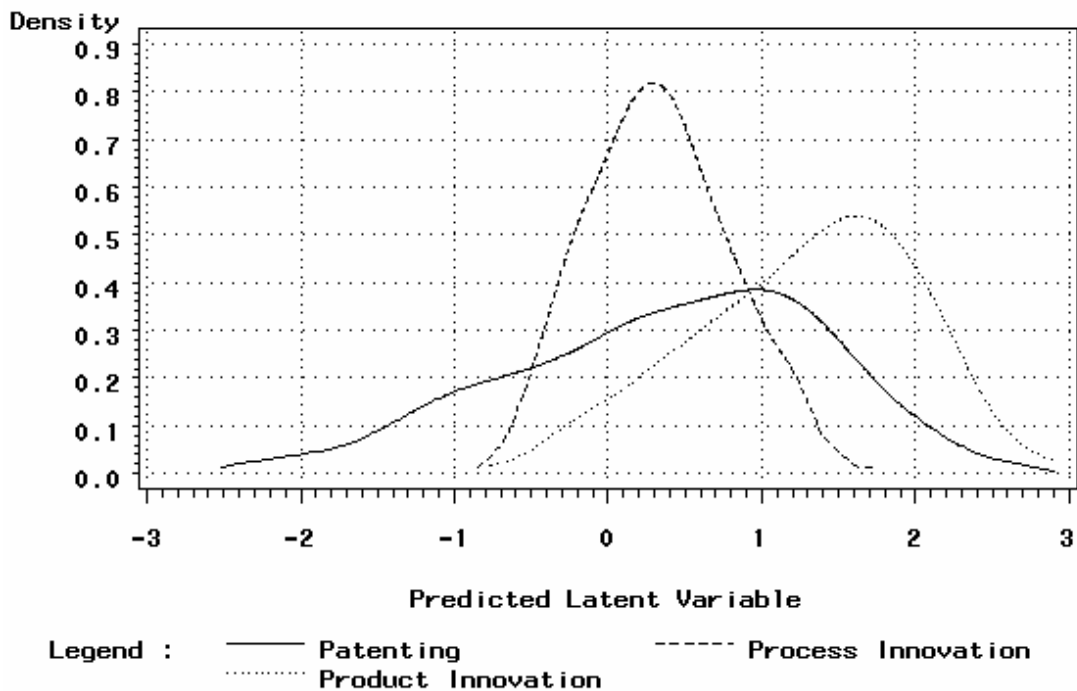
Three main results emerge from the analysis of Figure 4. First, the distribution of innovative processes' values is approximately symmetric. The surface representing the projects carried out (i.e., with a positive value) is important compared to the total of "potential" projects. Second, the distribution of innovative products' values is highly skewed, as in the previous literature. Here as well, a large number of the potential innovations are carried out. Third, the distribution of patent value is clearly influenced by the distribution of product innovation value and is also skewed. However, we find a difference between the product and patent value distributions: there are much less patents carried out (i.e., positive patent premium) than product innovations; this translates the fact that many product innovations are not patented. This result is in line with the previous studies by Levin et al. (1987), Duguet and Kabla (1998), who find that patenting is not the favorite appropriation mechanism of industrial firms. Technological advances, a rapid renewal of products, or good distribution networks are other means capable of increasing the private return on research.

Figures 5 and 6 allow us to analyze the sources of the asymmetry of patents' and product innovations' values within our sample. The estimates of the mode (Table 6) suggest that that this asymmetry is likely to result mainly either from the differences in the efficiency of patent rights from one firm to another, or from the differences of R&D efforts among firms (both variables are significant in the reduced patent and product equations, but not in the process equation). Figure 5 represents the distributions of the standardized predicted latent variables according to the assessment of firms about IPR efficiency, while Figure 6 represents them according to R&D intensity. The comparison of the estimated densities shows that the first variable (IPR efficiency) "explains" better the asymmetry of the distribution of patents while the second (R&D intensity) explains better the asymmetry of the distribution of product innovations.

Figure 5: Standardized value of the Predicted Latent Variables and IPR Importance

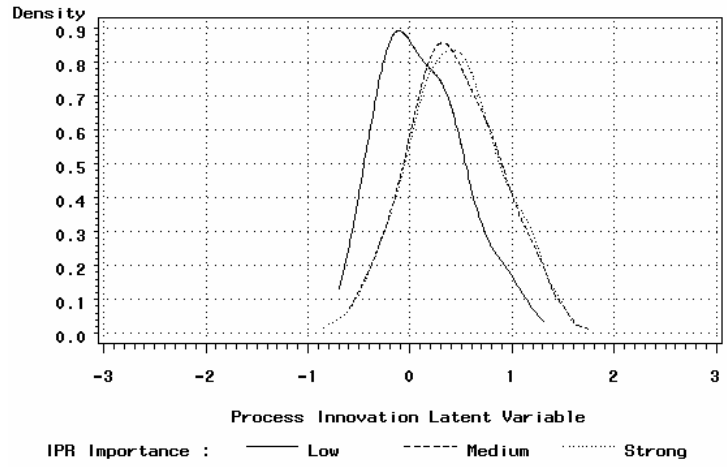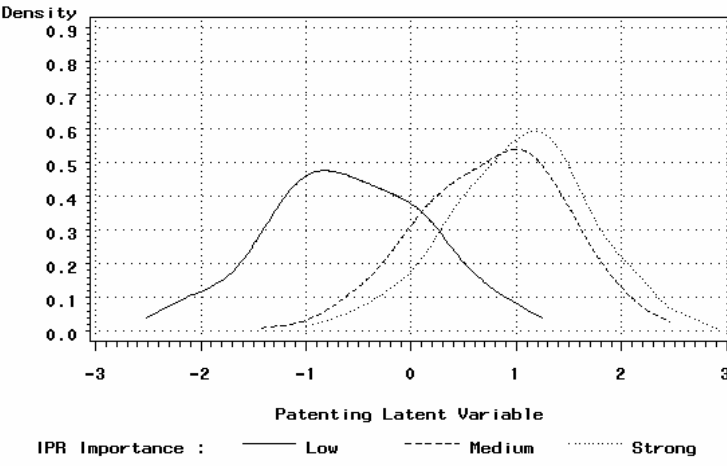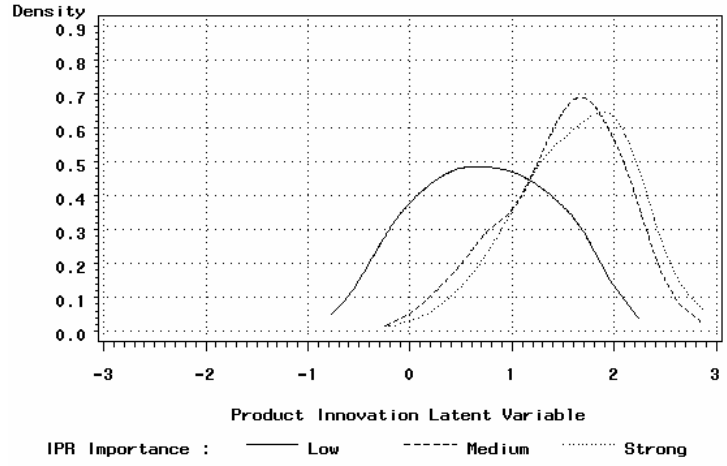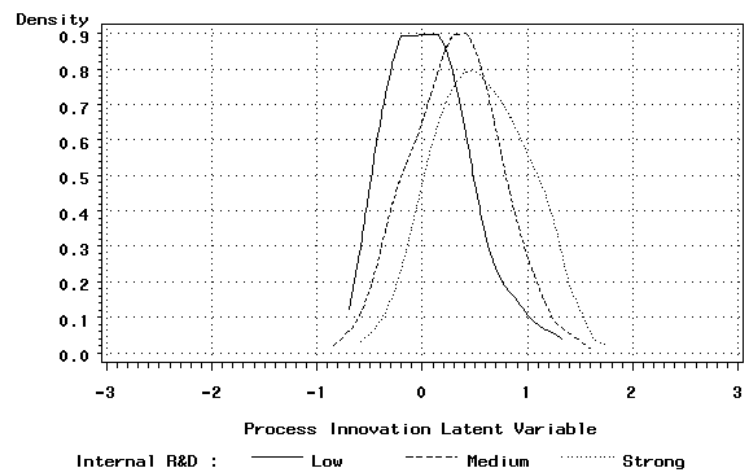*(Parzen-Rosenblatt density estimators with a Normal kernel and a Silverman window)*
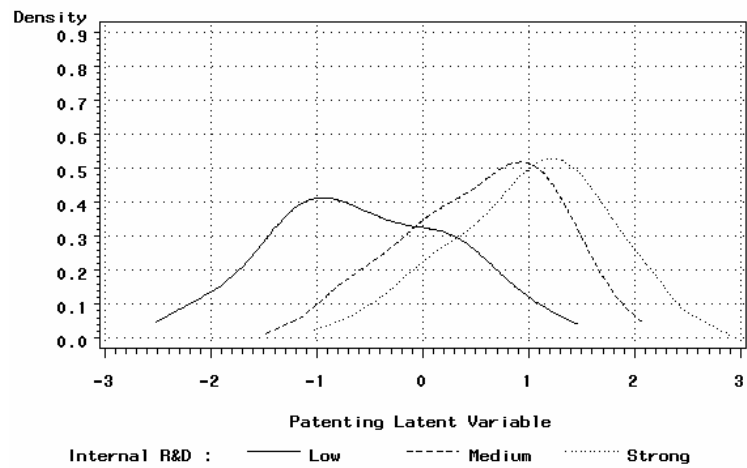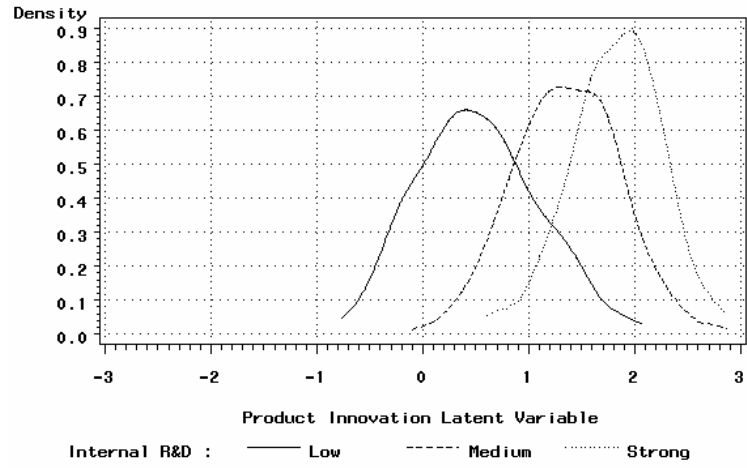
Figure 6: Standardized value of the Predicted Latent Variables and R&D Intensity

(Parzen-Rosenblatt density estimators with a Normal kernel and a Silverman window)

From a statistical point of view, this graphical analysis reflects the fact our structural system is well identified (in agreement with the overidentification test) although the variables are correlated. From an economic point of view, this suggests that the observed product innovations' distribution results partly from the various *ex post* appropriation strategy ("direct" effect of IPR) but also from the asymmetry in the incentives conveyed *ex ante* to the R&D activity of firms ("indirect" effect of IPRs and of other incentives).

Conclusion

This study throws some light on several issues related to the efficiency of the patent system and the information content of patent data.

It clearly appears that patenting is not automatic for all among manufacturing firms and that only some types of innovations are patented. We find that product innovations are the sole significant contributors to patenting. Process innovations, at the opposite, follow ways that draw aside industrial property rights. Conversely, the patent system significantly increases the private return on product innovation but is unable to influence the private return on process innovations. These results suggest examining theoretical models in which the patent rights would not protect processes – as is often assumed – but products. Our results also suggest that among the theoretical analyses performed so far, the ones that rely on product innovations should be more relevant to patenting analysis.

Another point deals with the interpretation of patent statistics.[15] Our analysis shows that in France these statistics are representative of product innovations but not of process innovations. Consequently, these statistics tend to overestimate the innovative output in the activities were patent rights are efficient. Therefore, the patent statistics exaggerate the innovation output of the countries that are strongly present in activities were knowledge is easy to describe in patent documents and that make new products (pharmaceuticals, chemicals, electronics, components) and to underestimate innovation output in the countries whose activities generate new processes (printing, shipbuilding, aircraft and rail, wood and paper).

---

[15] We do not discuss here the issue of the comparability of the patents systems of different countries.

References

ARORA A., CECCAGNOLI M. and W. M. COHEN (2003), « R&D and the Patent Premium ». NBER Working Paper W9431.

d'ASPREMONT C. and A. JACQUEMIN (1988), « Cooperative and Non Cooperative R&D in Duopoly with Spillovers ». *American Economic Review*, vol. 78, 1133-1197.

BESSEN J. and E. MASKIN (2002), « Sequential Innovation, Patents and Imitation ». MIT Working Paper, Department of Economics.

BRANSTETTER L and M. SAKAKIBARA (2001), « Do Stronger Patents Induce More Innovation ? », *RAND Journal of Economics*, vol 32, n°1, 77-100.

CASSIMAN, B. and R. VEUGELERS (2002), « R&D Cooperation and Spillovers: some empirical evidence from Belgium ». American Economic Review, 92, 4, 1169-1184.

COHEN W. M., NELSON R. R. and J. P. WALSH (2000), « Protecting their Intellectual Assets : Appropriability Conditions and Why Firms Patent or Not ? ». NBER Working Paper, n°7552.

CREPON B., DUGUET. E. and I. KABLA (1996). « A moderate support to schumpeterian conjectures from various innovations measures ». In A. Kleinknecht ed., *Determinants of Innovation : the message from new indicators (chapter 3)*, Mac Millan Press, London.

CREPON B., DUGUET E. and J. MAIRESSE (1998), « Research Investment, Innovation and Productivity : an Econometric Analysis ».*Economics of Innovation and New Technology*, 7(2), 115-158.

DAVID P, B. HALL AND A. TOOLE (2000). « Is public R&D a complement or a substitute for private R&D ? A review of the econometric evidence ». *Research Policy*, vol. 29, 497-529.

DUGUET E. (2002). « Innovation height, spillovers and TFP growth at the firm level : Evidence from French manufacturing ». *Economics of Innovation and New Technology*, Forthcoming. (http://emlab.berkeley.edu/users/bhhall/EINT/EINTMay04.html).

DUGUET E. (2004). « Are R&D subsidies a substitute or a complement to privately funded R&D? Evidence from France using propensity score methods for non experimental data ». *Revue d'Economie Politique*, 114(2), march-april, 263-292 (http://ssrn.com/paper=421920).

DUGUET E. and I. KABLA (1998), « Appropriation Strategy and the Motivations to Use the Patent System in France : An Econometric Analysis at the Firm Level ». *Annales d'Economie et de Statistique*, n°49-50, 290-327
(download at http://www.adres.prd.fr/annales/anciensnumeros/sommaires/index.htm#49/50)

GEWEKE J. (1989), « Efficient Simulation from the Multivariate Normal Distribution Subject To Linear Inequality Constraints and the Evaluation of Constraint Probabilities », *Duke University Working Paper*.

GINNARTE J.C. and W. G. PARKS (1998). « Determinants of Patent Rights: A Cross-National Study ». Research Policy, 26, 283-301.

GOURIEROUX C. and A. MONFORT (1991), « Simulation Based Inference in Models with Heterogeneity », *Annales d'Economie et de Statistiques*, vol. 20/21, pp.69-107.

GOURIEROUX C., MONFORT A. and A. TROGNON (1985), « Moindres Carrés Asymptotiques », *Annales de l'INSEE*, vol. 58.

GRABOWSKY H. and J. VERNON (1986), « Longer Patents for Lower Imitation Barriers: The 1984 Drug Act », *AEA Papers and Proceedings*, 195-198.

GUELLEC D. and C. MARTINEZ (2003), « Overview of Recent Trends in Patent Regimes in the United States, Japan and Europe » in *Patents Innovation and Economic Performance*, Proceedings of the OECD Conference on IPR, Innovation and Economic Performance, 28-29 Août 2003, OECD.

HAJIVASSILIOU V., MC FADDEN D. and P. RUUD (1996), « Simulation of multivariate normal rectangle probabilities and their derivatives. Theorical and computational results », *Journal of Econometrics*, 72, pp. 85-134.

HAJIVASSILIOU V., and A. BORSCH-SUPAN (1993), « Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models », *Journal of Econometrics*, vol. 58 (3), pp. 347-368.

HALL B. AND J. VAN REENEN (2000). « How effective are fiscal incentives for R&D ? A review of the evidence ». *Research Policy*, vol. 29, 449-469.

HALL B. H. and R. H. ZIEDONIS (2001), « The Patent Paradox Revisited : an Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995" ». *Rand Journal of Economics*, n° 32, pp. 101-128.

JORDE T. and D. TEECE (1990), « Innovation and Cooperation: Implications for Competition and Antitrust », Journal of Economic Perspectives, 4:3 (Summer), pp. 75-96.

KEANE M. (1994), « A Computationally Efficient Practical Simulation Estimator for Panel Data », *Econometrica*, 62 (1), pp. 95-116.

LEE L.-F.(1981). « Simultaneous equations models with discrete and censored dependent variables ». In C. MANSKI and D. Mc FADDEN eds., *Structural Analysis of Discrete Data with Econometric Applications*, MIT.Press, pp. 346-364.

LERNER J. (2001), « 150 Years of Patent Office Practice », Paper prepared for the Conference on the Law, Economics and History of Intellectual Property, Haas School of Business, Berkeley, California (hhtp://emlab.berkeley.edu/users/bhall/ipconf/lerner.pdf)

LEVIN R. C., KLEVORICK A. K., NELSON R. R. and S. G. WINTER (1987), « Appropriating the Returns to Industrial R&D », *Brookings Papers on Economic Activity*, 783-820.

LOLLIVIER S. (2003), *Econométrie avancée des variables qualitatives*. Polycopié de cours de l'ENSAE.

MONFORT A. (2003), « Modèles statistiques dynamiques à variables cachées », cours de l'ENSAE.

MONJON S. and P. WALBROECK (2003), « Assessing Spillovers from Universities to Firms: Evidence from French Firm-level Data ». *International Journal of Industrial Organization*, 21 (9), 1255-1270.

MOSER P. (2003). « How Do Patent Laws Influence Innovation? Evidence from Nineteenth-Century World Fairs ». NBER Working Paper w9909.

MUNDLAK Y. (1961). « Aggregation over time in distributed lag models ». International Economic Review, vol. 2, 154-163.

PARK W. G. and J. C. GINARTE (1997), « Intellectual Property Rights and Economic Growth ». *Contemporary Economic Policy*, XV, 51-61.

PAKES A. (1986), « Patents as Options: Some Estimates of the Value of Holding European Patent Stocks ». Econometrica, Vol. 54 (4), 755-84.

PAKES A. and M. SCHANKERMAN (1986). « Estimates of the Value of Patent Rights in European Countries During the Post-1950 Period ». Economic Journal (December), 1052-1076.

SAKAKIBARA M. and L. BRANSTETTER (1999), « Do Stronger Patents Induce More Innovation? Evidence from the 1988 Japanese Patent Law Reforms ». NBER Working Paper W7066.

SCHANKERMAN M. (1998), « How Valuable is Patent Protection ? Estimates by Technology Field », *The RAND Journal of Economics*, vol. 29 n°1, 77-107.

SCHERER F. M. (1998), « The Size Distribution of Profits from Innovation ». *Annales d'Economie et de Statistique*, n°49/50, 495-516.

TIROLE J., C. HENRY, M. TROMETTER, L. TUBIANA and B. CAILLAUD (2003), *Propriété Intellectuelle,* Rapport du CAE, 41.

Appendix I: Data sources

The innovation concept used in the two innovation surveys is defined in the Oslo Manual (OECD). The technological innovations include the technologically new products and processes, as well as the important technological improvements of products and processes. Either these innovations are new for the firm and not for the market ("incremental innovation"), or they are new for both the firm and its market ("radical innovation"). The definition used in the survey excludes design or organizational innovations, the changes of packaging and seasonal changes.

« Financement de l'Innovation Technologique (FIT) »
(Funding of Technological Innovation Survey)
We use the following items of the FIT survey:

1. In 1997, 1998 or 1999, has your firm launched products that were technologically innovative (or technologically improved) from your firm's viewpoint? (Yes/No).

2. Do you manage several technologically innovative projects in parallel? (Yes/No).

3. Knowledge leaking: How do you assess the risk that, at the end of each step of your technologically innovative projects, other firms can benefit freely from your results? "Patent (infringement, patenting around)" (irrelevant/very weak/weak/strong/very strong).

4. In 1997, 1998 or 1999, has your firm (or the group it belongs to) applied for at least one patent in France or in another country? (Yes/No).

5. Do you consider that your main line of business is technologically: not innovative/weakly innovative/moderately innovative/strongly innovative?

Second Community Innovation Survey (CIS2)

We use the answers from the following questions from CIS2:

1　Between 1994 and 1996, has your firm launched products that were technologically innovative (or improved) from your firm's viewpoint? (Yes/No).

2　Between 1994 and 1996, has your firm launched products that were technologically innovative (or improved) not only from your firm's viewpoint, but also for its market? (Yes/No).

3　In 1996, has your firm been involved in the following innovative activities? If yes, indicate the corresponding expenditures:

- Internal R&D;

- External R&D (including from another firm in your group);

- Purchase of machinery and equipments in relation to product and process innovations.

4　Between 1994 and 1996, has your firm applied for a least one patent in France or in another country? (Yes/No)

Explanative variables

1.　*Lagged product innovation, process innovation and patent application dummy variables.* Available in CIS2.

2.　*Importance of intellectual property rights.* This variable corresponds to the fourth question of the FIT survey. The reference value is « irrelevant »; the intermediate value regroups « very weak » and « weak »; the highest value regroups « strong » and « very strong ».

3. *Firm-level assessment of the technological opportunities in the line of business.* Corresponds to question 6 in the FIT survey. The reference value is « not innovative »; the intermediate value regroups « weakly innovative » and « moderately innovative », the strongest value is « strongly innovative ».

4. *Innovation input variables (internal R&D, external R&D, innovative equipment and machinery expenditures).* These variables are constructed from the third question of CIS2. For each variable the reference value is the absence of any investment; the intermediate value is reached when the ratio of the investment to sales is lower than the sample median (among strictly positive values); the highest value is reached when the ratio of the investment to sales is higher than the median (among strictly positive values).

5. *Size variable.* The logarithm of sales in 1996.

6. *Diversification*: the logarithm of the Herfindahl equivalent number of lines of business (equal to the inverse of the Herfindahl index). This index is computed from the decomposition of each firm's sales among its lines of business. For a firm *i* that operates in k_i lines of business, we get:

$$H_i = \sum_{k=1}^{k_i} \left(\frac{S_{i,k}}{S_i} \right)^2 \text{ and we use } \ln(DIV_i) = \ln(1/H_i).$$

Notice that when all the shares are equal $S_{i,k}/S_i = 1/k_i, \forall k = 1,...,k_i$, the equivalent number of activities DIV_i is equal to the real number of activities k_i. When a firm is not diversified, the equivalent number is equal to one.

7. *Average concentration index.* It generalizes the Herfindahl index to multi-products firms.

Let H_k be the concentration index of the line of business *k*:

$$H_k = \sum_{i=1}^{n_k} \left(\frac{S_{i,k}}{S_k} \right)^2$$

where n_k that operates on market k. The average concentration index is defined by the following formula:

$$H_i = \sum_{k=1}^{k_i} \frac{S_{i,k}}{S_i} \times H_k \ ,$$

therefore $1/H_i$ measures the equivalent number of firms on the average market where firm i operates. We include $\log(H_i)$ in our regressions.

8.   *Lerner index.* It is a firm level measure of market power:

$L_i = EBE/Sales$, where "EBE" (excédent brut d'exploitation) equals valued added minus labor cost. This is an accounting approximation of $(p-c)q/pq = (p-c)/p$. This variable reflects the capacity of the firm to price above its unit cost *c*.

9.   *Exportation dummy* (equals one when a firm exports).

10.   *Sectoral variables.* We include a full set of industry dummies at the two-digit level (NAF36) and a variable that aims to measure the probability to be imitated by competitors when one launches a new product (at the three-digit level in order to ensure identification). This variable is computed from CIS2 and should reveal the degree of competition between the innovative firms since it influences the degree of substitution between their innovative products. This variable is computed the following way and is a special case of Crépon, Duguet and Kabla (1996). Let:

- p_k the percentage of product innovators in industry *k* (three-digit decomposition);

41

- p_k^I the percentage of product imitators in industry *k.* They are defined as the firms that launched innovative products that were new for the firm *but not* for the market;

- p_k^M the percentage of real product innovators in industry *k.* They launched a product that is new *both* for them and for the market.

We have the identity: $p_k = p_k^I + p_k^M$ and the imitation rate equals:

$$TI_k = \frac{p_k^I + p_k^M/2}{p_k}\,.$$

The coefficient 1/2 comes from the fact that, in our data, the real product innovators are always almost product imitators too.[16] We also computed an imitation rate weighted by the sales of innovative products. The latter measure always gave us less good results in the regressions, possibly because of measurement error.

---

[16] This is the difference between Crépon et al. (1996) that worked on a larger data set. See this reference for a generalization of the previous formula.

Appendix 2: Variables on the efficiency of property rights

The variable about the assessment of the efficiency of industrial property rights relies on the answers to the following question in the FIT survey:

" How important do you consider the risk that, at the end of each stage of your research project, other firms can benefit freely from your results?

*Patent (infringement, patenting around): irrelevant, very weak, weak, strong, very strong ".*

We interpret this variable as expressing the degree of importance that the firms attribute to patent protection, as well as an appreciation on the efficiency of the patent system. However, since the question is not formulated exactly in this manner, our interpretation must be validated by other measures. Therefore, we have examined the correlation between the answers to the previous question and the following measures: the judgment on the efficiency of patents available in the Appropriation survey ("Yale 2") and the product imitation rate computed from CIS2 (1994-96). We find the following correlations between the average scores at the two-digit level:

Variables	Correlation coefficient
1993: Efficiency of patents to protect products (score 1-4)	0.59 (0.025)**
1993: Efficiency of patents to protect processes (score 1-4)	0.18 (0.536)
1993: Patents do not prevent imitation by competitors (score 1-4)	−0.32 (0.272)
1993: Patents disclose too much information (score 1-4)	0.49 (0.079)*
FIT: Knowledge leaking from exploratory research	0.90 (<0.001)**
FIT: Knowledge leaking from R&D	0.96 (<0.001)**

p-values between parentheses. **: significant at 5%; *: significant at 10%.

The Figure A.1 illustrates the previous correlations. The variable we use describing patent rights efficiency is positively correlated with the efficiency of patents variable available in the Appropriation survey ("Yale 2") and negatively correlated with the product imitation rate computed from CIS2. It is also positively correlated with the score on the fact that patent disclose too much information.

Figure A.1 Correlation between patent efficiency related indicators
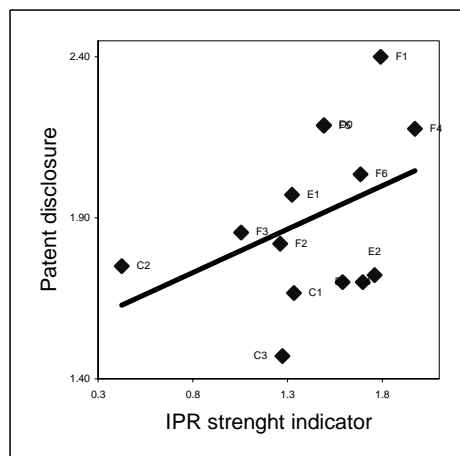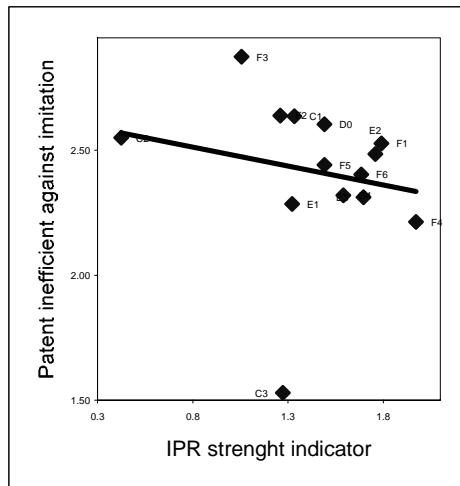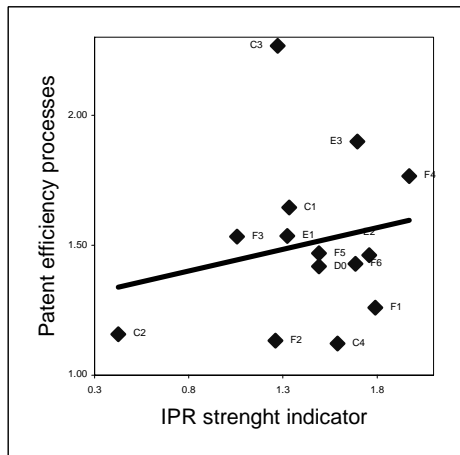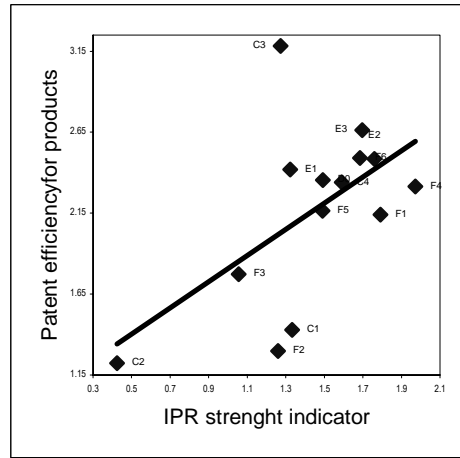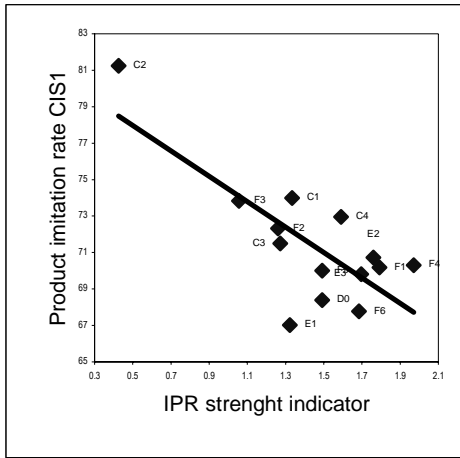
Appendix 3: Estimation controlling for lagged innovation

and patent dummies

This appendix presents the results we obtain when introducing the lagged dependent variables into the three regressions. The endogenous variables refer to 1997-1999 and the lags to 1994-1996. One objective of this additional regression is to capture potentially missing variables that could bias the estimates.

The results show that the lagged dependent variables capture a large part of the individual variations. Overall, the coefficients of the exogenous variables are lowered by this introduction. However the only deception is the patent equation, since the introduction of the lagged patenting variables cancels the effects of innovation. This could come from the data limitation that we observe only the fact that a firm patents and not the number of patents (not available at INSEE after 1994). However, a more positive result appears in the innovation equations. While lagged product innovation is highly significant, patenting has still a significant and positive effect on product innovation. Last, patenting has still no effect on process innovation. These two last results are therefore robust to an important change of specification.

	Reduced form			Structural form		
	Patent	Product	Process	Patent	Product	Process
Patent	-	-	-	-	0.36** (0.14)	0.08 (0.14)
Product	-	-	-	0.29 (0.34)	-	-
Process	-	-	-	0.63 (0.48)	-	-
Lagged patent	0.87** (0.13)	0.20 (0.14)	-0.09 (0.12)	0.95** (0.18)	-0.17 (0.19)	-0.21 (0.19)
Lagged product	0.08 (0.16)	0.70** (0.12)	0.03 (0.15)	-0.06 (0.29)	0.66** (0.13)	-0.02 (0.15)
Lagged process	-0.18 (0.14)	0.10 (0.12)	0.40** (0.12)	-0.37 (0.27)	0.13 (0.12)	0.38** (0.12)
Importance of IPRs (ref. none)						
moderate	0.74** (0.13)	0.23** (0.12)	0.07 (0.13)	0.62** (0.16)	-	-
strong	0.87** (0.14)	0.36** (0.13)	0.05 (0.13)	0.75** (0.19)	-	-
Internal R&D (ref. None)						
moderate	0.03 (0.16)	0.10 (0.13)	-0.28* (0.16)	-	0.16 (0.13)	-0.19 (0.15)
strong	0.21 (0.18)	0.37** (0.17)	-0.12 (0.17)	-	0.35* (0.17)	-0.04 (0.16)
External R&D (ref. None)						
moderate	0.20 (0.16)	0.10 (0.18)	0.06 (0.15)	-	0.09 (0.17)	0.10 (0.13)
strong	0.29 (0.18)	-0.13 (0.18)	0.05 (0.15)	-	-0.09 (0.17)	0.15 (0.13)
Equipment and machinery expend. (ref. None)						
moderate	0.16 (0.15)	-0.25 (0.16)	0.25* (0.15)	-	-0.29* (0.16)	0.28** (0.14)
strong	0.00 (0.15)	-0.26 (0.13)	0.04 (0.13)	-	-0.25* (0.13)	0.07 (0.12)
Several innovation projects (ref. No)						
yes	0.36** (0.12)	0.19 (0.11)	0.26** (0.12)	0.13 (0.21)	0.06 (0.14)	0.24* (0.14)
Degree of techn. opportunities (ref. None)						
moderate	0.19 (0.12)	0.42** (0.11)	0.21* (0.11)	-0.07 (0.22)	0.35** (0.12)	0.19* (0.12)
strong	0.22 (0.15)	0.44** (0.15)	0.24 (0.15)	-0.06 (0.26)	0.36** (0.17)	0.23* (0.15)
Other firm-level characteristics:						
Ln(Sales)	0.19** (0.04)	0.06 (0.04)	0.12** (0.04)	0.10 (0.08)	-0.01 (0.05)	0.10** (0.05)
Mark-up rate	1.11 (0.72)	0.16 (0.66)	0.53 (0.64)	0.84 (0.86)	-0.38 (0.70)	0.43 (0.65)
Ln(Div Index)	-0.03 (0.17)	0.34* (0.19)	0.30* (0.18)	-0.30 (0.27)	0.34* (0.19)	0.28 (0.17)
Exportation dummy	-0.12 (0.18)	0.24* (0.13)	-0.05 (0.17)	-0.14 (0.24)	0.28** (0.15)	-0.04 (0.17)
Ln(Herfindahl market concentration)	-0.04 (0.06)	-0.04 (0.05)	0.04 (0.06)	-0.05 (0.08)	-0.03 (0.06)	0.04 (0.06)
Sectoral variables:						
Ln(Imitation rates)	-0.82 (0.80)	-1.23* (0.68)	-0.20 (0.74)	-	-1.22** (0.63)	-
C1 : wearing apparel and leather	-0.67 (0.48)	-0.17 (0.28)	0.00 (0.37)	-0.63 (0.49)	0.08 (0.35)	0.07 (0.37)
C2 : printing and publishing	-0.49 (0.46)	-0.33 (0.25)	0.04 (0.34)	-0.49 (0.51)	-0.09 (0.33)	0.08 (0.34)
D0 : car industry	-0.10 (0.26)	-0.40* (0.24)	0.02 (0.25)	0.07 (0.33)	-0.38 (0.29)	0.01 (0.25)
E1 : shipbuilding, aircraft and rail	-0.49 (0.55)	-0.73** (0.31)	0.24 (0.45)	-0.41 (0.67)	-0.57 (0.38)	0.30 (0.45)
F3 : wood and paper	0.28 (0.25)	-0.37* (0.21)	0.34 (0.28)	0.12 (0.38)	-0.44** (0.21)	0.30 (0.45)
F5 : metalworking	0.00 (0.15)	-0.29** (0.12)	-0.09 (0.15)	0.13 (0.20)	-0.28** (0.14)	-0.09 (0.14)
F6 : electrical components	-0.33 (0.22)	-0.46** (0.19)	-0.01 (0.19)	-0.19 (0.28)	-0.36 (0.22)	0.04 (0.20)
Intercept (ref. C3+C4+E2+E3+F1+F2+F4)	-3.49** (0.65)	-1.48** (0.61)	-1.69** (0.61)	1.88 (1.09)	-0.31 (0.73)	-1.33** (0.67)
Variance :						
Patent	1 (imposed)	0.17** (0.06)	0.02 (0.05)			
Product		1 (imposed)	0.11** (0.05)			
Process			1 (imposed)			
Log-likelihood		-2152.15				
Overidentification test:						
Statistic					4.22	
Degrees of freedom					8	
p-value					0.837	
LRT significance of lagged variables:						
Statistic					113.5	
Degrees of freedom					9	
p-value					0.000	

** : significant at 5%. * : significant at 10%.