THE VALUE OF PATENTS*

Alfonso Gambardella
Bocconi University, Milan
agambardella@unibocconi.it

Dietmar Harhoff
Universität München, München
harhoff@bwl.uni-muenchen.de

Bart Verspagen
Eindhoven University of Technology, Eindhoven
b.verspagen@tm.tue.nl

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Abstract

This paper estimates the determinants of the private economic value of patents from a novel and unusually comprehensive dataset built from a questionnaire survey of European EPO patents. We find that the resource investments made in the research leading to the patent are an important determinant of the value of patents. We also find that the characteristics of the individual inventor (his past patents, motivation) are a more important determinant of the private value of patents than the characteristics of the organization in which he is employed (e.g. its past patents), or the location in which the invention is carried out. Our study then supports the view that the invention business is about investments of resources and human capital more than special organizational designs or local spillovers. To validate our measure, we find that it is correlated with all the most commonly employed proxies of the value of patents.

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1. INTRODUCTION

The search for valid estimates of the economic value of patents has raised significant attention among economists and policy makers. This is paralleled by an increase in the relevance of intangibles (including inventions and know-how) for firm value over the last two decades, leading to new questions in accounting as to how firm value can be measured and reported reliably (e.g. Lev 2001). Moreover, as the number of patent applications has surged in Europe, Japan and the US (Kortum and Lerner, 1999, and EPO Annual Report, 2003), economists have become more and more dissatisfied with using simple application or grant numbers as an indication of R&D output.[1] The underlying cause for these concerns is a fundamental property of the patent value distribution which is skewed to the left. This implies that a small number of valuable patents largely determine the overall value of patent portfolios.[2]

Against this background, this paper estimates the economic value of patents by employing a unique and comprehensive dataset drawn from a large scale survey of European inventors. The PatVal-EU survey collected data on more than 9,000 patents (out of 27,000 questionnaire submissions), including their value and a broad set of characteristics describing the context of the invention. These are patents with priority date 1993-1997 applied for to the European Patent Office, and such that the address of the first inventor listed in the patent is in France, Germany, Italy, the Netherlands, Spain or the UK. The survey data are obtained from questionnaire responses produced by the first inventor or, if the first inventor was not available, by any other inventor on the patent whose address is in one of our six countries. Details of the survey are provided in Giuri, Mariani *et al.* (2006).

Most empirical studies on the value of patents have used indirect measures. Renewal studies have made use of the fact that it is expensive to holders of European patents to renew patent

[1] Griliches (1990, p. 1702) concludes: "These findings, especially the large amount of skewness in this distribution, lead to rather pessimistic implications for the use of patent counts as indicators of short-run changes in the output of R&D."

[2] See Scherer (1965), Griliches (1990), Harhoff, Scherer, and Vopel (2003a) and Silverberg and Verspagen (2004).

protection for an additional year. The pioneering papers in this field were contributed by Pakes and Schankerman (1984), Pakes (1986), and Schankerman and Pakes (1984). Another approach has been to use proxy variables, such as citations, and more recently, in the European setting, the filing of a legal opposition to the patents (Harhoff, Scherer and Vopel 2003b). Forward citations account for the visibility and importance of the patent. As Trajtenberg (1990) has shown, citation measures are correlated with a patent social value. Given the costs of legal battles, only privately valuable patents are worth opposing, as shown theoretically by Harhoff and Reitzig (2004). Lanjow and Schankerman (2004) have developed a combined index that uses a set of indirect measures to infer patent value from the correlation structure of observable patent characteristics, but does not build on observed patent value data.

We follow Harhoff, Scherer and Vopel (2003a) and estimate the present value of the patent from the inventor answers to the following question: *"What is your best guess of the minimum price at which the owner of the patent would sell the patent right to an independent party on the day in which the patent was granted?"* We offered a menu of ten interval responses: less than €30K ; 30-100K; 100-300K; 300K-1M; 1-3M; 3-10M; 10-30M; 30-100M; 100-300M; more than 300M. The central contribution of the paper is to estimate the determinants of this value measure, which we articulate around five sets of factors: i) characteristics of the *organization* in which the patent was developed; ii) characteristics of the *inventors*; iii) characteristics of the *patent*; iv) characteristics of the *competitive environment*; v) characteristics of the *location* in which the patent was developed. To our knowledge, this is the first attempt to determine the impact of such a comprehensive set of determinants on the value of patents.

Our analysis presents several novelties with respect to previous research. First, our survey enables us to assess the effect of factors that were ignored in previous studies, which employed mainly variables collected from patent documents. For example, this is the first attempt that we know of to study the effects of inventor characteristics (e.g. age, past productivity, educational degree) on the value of patents.[3] In addition, this enables us to understand empirically the relative importance of our five sets of determinants. For example, how important are the technological characteristics of a patents in determining its value? That is, is patent value largely determined by the sector or type of technology, or are there differences depending on the individual inventor, the organization or the location? How important are the inventor characteristics vis-à-vis the type of applicant organization? Work by Lotka (1926) and subsequent research have suggested that the productivity distribution of scientists and inventors displays huge heterogeneity and skewness. However, the impact of the organizational setting of invention has not been given much attention in this literature. That is, do more valuable patents depend on “star” inventors, or are they explained mainly by organizational characteristics, like the greater resources provided by the large firms or the more creative atmosphere of the small firms? Interestingly enough, the latter situation suggests that shopping for talents would not be crucial for an organization, as the proper organizational setting can turn most individuals with suitable characteristics into good inventors, while the opposite is true in the former case.

Since our analysis hinges critically on a new survey-based measure of the patent value, we evaluate it against alternative indicators. First, we find that it is highly correlated with some standard indirect indicators of patent value employed by the literature, viz. forward citations, backward citations, the number of patents filed with different authority that refer to the same invention (family size), and the number of claims in the patent. Second, the individual inventors may not know about the value of the patent as much as the managers who are responsible for their development. In our survey there are 354 French patents whose value question was submitted to both the inventor and to a manager responsible for the development of the patent. On comparing the two distributions we find that the investors slightly overestimate the value of their patents.

[3] Previous work has been confined to the use of indicators available in patent databases – such as the inventor productivity as measured by patented inventions. See, for example, Ernst, Leptien, and Vitt (2000).

We present several estimations of our data. First, because we know the boundaries of our value intervals we estimate an interval probit regression, which is an ordered probit regression in which the ordered probit constants are known and they are set equal to the boundaries of the value measure in the questionnaire. Second, we run an instrumental variable (IV) regression using the mid-point of the value intervals as the dependent variable, and instrumenting for the resources (man-months) employed in the research leading to the patent. Both the interval regressions and the IV regressions use sampling weight to account for potential biases in our questionnaire responses. Finally, we employ all the patents applied for in Europe in 1993-1997 and run a sample selection regression in which the selection equation accounts for the probability that the patent is in the sample of the value regression.

We find that all these regressions produce strikingly similar results. In particular, the two main determinants of patent values are: i) the resources invested in the project; ii) the skills and motivation of inventors. First, this suggests that the invention process may not be as serendipitous as it is often thought. Higher patent values are more likely the higher the amount of resources invested in the project. This also means that classical measures like R&D can be good predictors of the values of patents, as for example early studies like Hausman, Hall and Griliches (1984) had found. Second, individual features are important determinants of the value of patents. Interestingly, they seem to be relatively more important than organizational designs or the nature or type of patenting organization.

The next Section discusses the nature of our value measure. Section 3 presents the variables employed in our analysis. Section 4 validates our survey measure of patent value. Section 5 presents the empirical results. Section 6 concludes. The Appendix explains the construction of the sampling weights.

2. VALUE OF PATENT AND VALUE OF PATENTED INVENTION

To clarify the nature of our measure of patent value, this section shows that it is affected both by factors that influence the value of the patented invention and by factors that influence the private value of the patent right.

Our measure compares a situation in which the patent holder keeps the patent right with one in which she gives it out to another party. In the latter case she is not the only user of the invention. Define $V \equiv \Pi(x, p, z) - C(x)$ to be the present net value of the invention. The function $\Pi(\cdot)$ is the discounted sum of annual variable profits from selling the invention. This is a reduced form with all its optimized variable inputs in the background. The inventor organization also carries out R&D activities x to produce the invention, which affects Π and has cost $C(x)$. The variable p measures the effect of keeping the patent right. For example, a firm with alternative assets to protect the innovation, or in highly differentiated markets, would face fewer losses from giving out the patent right because it can protect the innovation in other ways or because other users employ the invention in distant businesses. We set conventionally $p = 0$ if the patent holder gives out the patent right. We assume that the extent of protection provided by the patent, i.e. the magnitude of p, is exogenous to the decision maker, while she can choose whether to give out the patent right or not, i.e. whether to set $p = 0$. Finally, z is a set of exogenous variables affecting value.

We adopt the conventional assumptions that $\Pi_x > 0$, $\Pi_{xx} < 0$, $C_x > 0$, $C_{xx} \geq 0$. In addition, we assume that all the cross-partials $\Pi_{ij} \geq 0$, where subscripts denote derivatives and $i,j = x, p, z$ with $i \neq j$. This simply states that the endogenous and exogenous factors that enhance innovation do not reduce the marginal value of patenting. This is a natural assumption as holding an exclusive right on the patent does not typically reduce the incentives to perform R&D or to create innovations.

The manager chooses x optimally. This yields $x^*(p, z) \geq x^{**}(0, z)$ according to whether she plans to give out the patent right or not. In the latter case x^{**} is smaller because of our assumption about the cross-partials. In turn, this yields $V^{*}(x^{*}, p, z) \geq V^{**}(x^{**}, 0, z)$. The value measure that we use in this paper is $V' \equiv V^{*} - V^{**}$. This is because, as noted in the introduction, we asked the inventors to indicate the minimum price at which the owner of the patent would sell the patent right at the moment of grant, which is the difference in value associated with having an exclusive patent right or not. The distance V' does not decrease with p or z because $V_p^{*} \geq 0$, $V_p^{**} = 0$, and $V_z^{*} \geq V_z^{**}$, where the latter follows from our assumption about the cross-partials and from $x^{*} \geq x^{**}$. Thus, our measure of patent value does not decrease with variables that measure the importance of patent protection, p, viz. the *patent premium* as Arora, Ceccagnoli and Cohen (2003) put it, or with variables that measure the quality of the patented invention, z.

3. DATA AND VARIABLES

2.1 Dependent Variable

Table 1 defines all the variables that we employ in our analysis. Table 2 presents descriptive statistics. Table 3 reports descriptive statistics for the 30 ISI technology class dummies in which our patents were classified (see Giuri, Mariani *et al.*, 2006 for details on this classification).

TABLES 1, 2 AND 3 ABOUT HERE

From the PatVal-EU survey, we obtained 7,752 responses to our question about the value of the patent. The 1-10 VALUE index accounts for each of the ten progressive intervals defined in the previous section. Figure 1 reports the distribution of answers. The distribution is skewed to the left, and it conforms to other assessments of the value of patents in the literature (Harhoff *et al.*, 1999; Scherer and Harhoff, 2000; Scherer, Harhoff and Kukies, 2000). We also produced a second variable, VALUEM, which is the mid-point of each value interval.

FIGURE 1 ABOUT HERE

As Table 2 shows, the sample average of VALUEM is over 10 million euros. The median is 650 thousand euros. The high average is pushed up by the few patents in the extreme right classes. We claim however that the scale that we set in our questionnaire is not unreasonable. First, from Figure 1 less than 1% of patents for which we obtained a response had a declared value higher than 300 million euros (our highest class). We checked these patents and while we cannot completely rule out odd answers quite a few of them regarded some pharmaceutical products, which are generally quite valuable, or other major product innovations. Second, is a value of patent higher than 300 million euros really abnormal? Suppose that a patent provides a monopoly power on a product for about 20 years. This is roughly the length of patent life plus some adjustment years for competition to pick this up. Assume a 5% discount rate and a constant flow of profits from this asset. Simple calculations show that an asset worth 500 million euros commands a constant annual flow of profits of slightly less than 40 million euros. Some pharmaceutical products have annual sales in the order of hundreds million euros, and a 40 million euros rent seems a conservative order of magnitude of the profits of a very small share of highly valuable patents.

Another reason why there may be a potential upward bias of our measure is that respondents may be reluctant to state that their patents have zero value. However, if we set VALUEM equal to zero rather than 15 and 65 thousand euros for the first two value classes, the sample average of VALUEM would simply fall from 10.391 million euros to 10.379, a negligible change. If we set the third class to zero as well, instead of 200 thousand euros, the sample average would fall to 10.337 millions, again a negligible change. Moreover, in the latter case 45.8% of the sampled patents would have zero value, which makes it the mode of the distribution. Alternatively, if we set the share of patents in the two top classes to zero, and redistribute these patents to the lowest class, our sample average becomes 3.2 million euros. If we reallocate the patents in the top three classes to the lowest one, the sample average becomes 1.9 million euros. These are smaller averages, yet of a similar order of magnitude. Moreover, Scherer and Harhoff (2000) sample of

772 patents filed in Germany in 1977 produced an average value of about 5 million Deutsche Marks, or about 2.5 million euros. Since their patents are 16-20 years older, then by assuming a 5% inflation rate this amounts to about 6 million euros 18 years later. As discussed in Giuri, Mariani *et al.* (2006) the PatVal-EU survey slightly oversampled the more valuable patents, which suggests that we are again well within similar orders of magnitudes.

Our measure may still include non-economic elements in the utility of the patent holder, like the desire of preventing others from using one's own invention or similar non-economic attitudes. A patent holder who is reluctant to give out the patent right may state a high value. Also, our measure is not the actual realization of a market transaction involving the patent, as there may be no buyers of the patent at that price. Yet, if the owner is not willing to part herself from the patent at a lower price, it means that she may be able to make at least that much, or more generally this is her reservation price, which for the reasons just noted may encompass both monetary and non-monetary aspects.

To be sure, we can provide some control on the questionnaire responses because German inventors have a more precise idea of the economic value of their patents. The German Employees Inventor Compensation Act establishes that German employers can claim the patent rights from an inventor by providing him with a fair compensation (see Harhoff and Hoisl, 2006, for details). This means that German inventors have something concrete to hang their PatVal-EU answers. A specific PatVal-EU question asked whether the inventor were compensated for their inventions, and 62% German inventors in our sample were compensated for their patents against shares well below 30% for all the other countries. This suggests that they may be better aware of the economic value of their patents. The sample average of VALUEM for the German patents is 5.6 million euros, which is slightly more than half of the 10.391 average of the full sample reported in Table 2. While confirming that German inventors are more conservatives in their assessments, their estimates are just slightly more than 50% higher, which again suggests that the orders of magnitudes are note dramatically different.

2.2 Covariates

Characteristics of the Applicant Organization

We distinguish our applicant organizations according to whether they are firms or research institutions (UNIV, GOV, OTHER), and among firms we test for differences across firm size (SMALL, MEDIUM, LARGE). It is often argued that the marginal cost of patenting is smaller in large firms. Because they hold more patents, they make fixed investments for applying and administering them. This makes patenting less costly at the margin. We then expect that they also patent less valuable inventions. The dummy INDIVIDUAL captures the idea that the individual inventors face an even greater cost of patenting than small firms and hence they patent only valuable inventions.

We also expect research institutions to hold less valuable patents. There are two potential reasons. First, they may produce economically less valuable inventions. This is because compared to firms they do not have sizable downstream complementary assets, which typically raise the value of inventions. Second, they enjoy lower private value from patents – i.e. our variable p in Section 2. These institutions are not in the business of profiting from innovation, and hence they exert fewer efforts on making profits from it. At the same time, the lack of resources for long and costly development activities implies that they enjoy fewer benefits from private appropriation of their inventions.

The variable PATAPP captures the inventive experience of the organization. Among other things, it enables us to compare the impact of the organization inventive experience with that of the inventor, as measured by the number of patents applied for by the inventor which we will discuss below. We employed the number of patents of the applicant in our PatVal-EU sample. Alternatively, we could count the number of patents of our applicants in the full EPO dataset. The problem is that while we cleaned all the applicants in our sample for subsidiaries and affiliates, and coded all the subsidiaries with the same applicant name, this would be a massive work in the full EPO database. Moreover, since we are dealing with a large sample of 1993-

1997 patents, the error from using our sample is small.

Characteristics of the Patent or the Invention Process

We employed WORDS and IPC4 as measures of the generality of the patent. The use of WORDS was suggested by some patent lawyers. They pointed out that a broad patent can be described in few words, while a narrow patent has to define the object more precisely to distinguish it from other inventions. Similarly, a broad patent spans many technologies. It will then list a larger number of IPC classes.

Another proxy for the generality of patents is the number of claims (e.g. Lerner, 1995). But the number of claims is probably endogenous in our analysis. Applicants put greater efforts in protecting more valuable patents by adding more claims. Variables like the number of countries in which the protection was applied for would have the same problem. As discussed in the introduction, we employ the number of claims and the family size of the patent as alternative indicators of our value measure. By contrast, WORDS and IPC4 are not as endogenous. Lawyers may put greater efforts to reduce the number of words of a more valuable patent, but this is more difficult to do given the patent characterstics and given the fact that patent characterstics have to be spelled out properly in order to define the technology. In short, given the nature of the technology, there is less room for manoevering the number of words stregically, and probably less room than with the choice of the number of claims. The IPC classes are also more exogenous. The applicants indicate the number of classes when they apply for the patent, but they are revised by patent examiners. In our data the number of IPC classes associated with the patents diminish during the application revision process, which suggests that patent examiners revise them. We then employed the latest available number of IPC classes introduced in the patent document, which fully captures the revisions by patent examiners.

The dummies BASKNOW, PATKNOW, and CUSKNOW are additional controls for the type of research leading to the patented invention. The first dummy accounts for the importance of more basic and academic knowledge in the development of the patent, as it combines the role of universities and the scientific literature as a source of knowledge for the invention. The other two dummies account for technological research (patents), and more pragmatic knowledge brought about by specific customers or users.

The MANMONTH dummies measure the amount of resources employed for producing the invention. Alternatively we employed MMANMONTH. We expect that the greater the resources involved the larger the expected value of the patent. The MANMONTH dummies however are potentially endogenous. Following our framework in Section 2, they may reflect the project-specific investment *x*. We take this into account in our estimation, and also estimate an instrumental variable version of our model. As instruments we employed AVMM_IPC3, PROJECT, INTFUND, and GOVFUND.

The variable AVMM_IPC3 is a natural instrument for man-months. We assume that all projects in the same technological classes have common characteristics, and in particular their scale and the resources that they require are correlated. Clearly, apart from a technology-class component they have a project-specific component. It is the latter that may be correlated with the value of patents. For example, the fact that a patent is valuable may emerge during the R&D process, and applicants may pour additional resources when they realize that the project has potential. Thus, AVMM_IPC3, which is not affected by the project-specific component, is likely to be correlated with the man-months employed in the project, but not with its potentially endogenous shock. We employ the other three variables to account for project-specific variability not affected by the value of the patent as man-months. The decision to launch a structured project is taken at the start of the project. It is therefore less likely to be affected by shocks arising during the innovation process. Also, a more structured project is likely to be correlated with project-size compared to a by-product innovation of other projects or activities. Similarly, internal funds are more likely to be employed by larger firms which in turn launch larger projects. Finally, government support often supports larger projects as well, which firms may be unable to carry out themselves. Most importantly, we will see in our empirical analysis that these variables are highly insignificant in a regression in which the man-month dummies are also present as regressors, while they become significant when the man-month dummies are removed. This suggests that they may not have a direct effect on patent value, but an indirect one via project size.

Characteristics of the Inventor

To our knowledge, no study has examined the effects of inventor characteristics on value or other aspects of the inventive activity. In particular, we are interested in understanding the extent to which inventor characteristics affect the value of patents after we control for characteristics of the organization or other factors. Zucker, Darby, and Armstrong (2002), among others, have pointed out the importance of "star" scientists in affecting the innovative performance of biotechnology firms. More generally, there is increasing attention to the role of individual talents in affecting the growth of firms, industries or regions.

Apart from the inventor age and degree, YEARINORG and PATINV compare the impacts of the experience of the inventor inside the organization and his own innovation experience measured by the number of previous patents that he filed. The latter variable is obtained from the inventor himself as a response to a specific question about his number of past patents in our PatVal-EU survey. We could have obtained this information from the EPO patent database. However, searching for the inventor names is not an easy matter, and several mistakes can be made because of mispelled names, as Trajtenberg (2004) pointed out. We then preferred to use our survey measure. We used size classes rather than the actual number of patents declared by the inventors because of some unusually high responses and more generally to reduce the vagaries of subjective assessments.[4]

Finally, we take MONEY, CAREER, and PRESTIGE as proxies for the efforts of the inventors

[4] However, when using the actual number of past inventor patents the empirical results did not change.

in the innovation process. The rationale is that individuals who respond to monetary, career, or reputation incentives are more motivated. In one way or another there are always monetary, career and reputation rewards after one patents. Reputation follows quite naturally. Similarly, patenting is likely to boost one's career. Not all companies or institutions offer money for patents, but it is likely that a patent leads, at least indirectly, to some higher income in the future, if anything because of the greater visibility or the career advance. Thus, individuals who are not motivated by any of these three factors are less likely to put effort in the invention process. At the same time, an individual motivated by all three factors may exert more effort than one who only cares about two or one of them, or who cares less about any of them, because she has more reasons to exert such effort.[5]

Characteristics of the Competitive Environment

While most of the covariates discussed so far are more likely to reflect factors that affect the value of the patented inventions, which we labelled as *z* in Section 2, COMMEXPL and PREVIMIT are more likely to account for the value of patenting, *p*. Patents are more valuable in a tight competitive environment, or more generally when imitation is easier. By contrast, if the firm has other assets to protect the innovation, or other potential users of the patent operate in distant markets (whether technically or geographically), the patent holder will not loose much from giving it out.

The problem is that it is not easy to find measures of potential competition or imitation on the particular innovation that is patented. One would have to find specific competitors of the firm in the products that may spring from the technology. This means that one needs first to find which products have sprung from it, and then the competitors in that domain. We therefore thought that asking the innovators was the easiest thing to do. A company facing many potential

[5] As noted, PatVal-EU offered another variable, viz. a dummy equal to 1 if the inventor actually received a compensation for the patent. However, this variable may be endogenous. Companies may tend to reward their inventors when the patents are more valuable, as implied for instance by the German Inventor Act discussed earlier.

competitors would state that it patents because of the fear of imitation, i.e. our dummy PREVIMIT. Another variable potentially measuring such a competition effect is COMMEXPL, since it reflects whether the patent owner patented the invention because of the need of securing benefits from its commercial exploitation. Again, a high score on this motivation suggests that the company faces potential competitors, and cannot protect its rents through means other than patent.

We also constructed a measure of the share of patents held by the top 1, 4, or 8 patent holders in the IPC4 class of the patent. This is a measure of the potential technological competitors of the firm. However, this variable did not turn out to be particularly powerful in our estimations. As noted, this may be because the competitors we really need to control for are not the technological competitors of the firm, but the product competitors, which may be different from the latter. For example, other patent applicants in the same field may include universities or other firms supplying complementary technologies. Also, it may reflect technological differentiation in that domain, whereby different companies patent different technologies in fairly distinct subfields.

Characteristics of the Location

The most natural variables to assess the effect of a location on the value of patents are its GDP per capita (GDPPOP) and the number of patents (PATLOC). We used the NUTS3 territorial level from the official EU territorial classification, which corresponds to the provincial level in Europe. We also used the NUTS3 population and area (POP and AREA) as additional controls. The four variables are obtained from the latest version of the REGIO database, which is the official Eurostat data for territorial units in Europe. We also employed NUTS3 patents in high-tech industries in lieu of and together with PATLOC, but the results did not change.

4. VALIDATING OUR VALUE MEASURE

4.1 Correlations with Other Indicators

To validate our value measure we compared it with some common alternative indicators of the importance of patents (e.g. see Lanjouw and Schankerman, 2004; Hall, Jaffe and Trajtenberg, 2001). We start by regressing four indicators on dummies for our VALUE intervals, and our country, technology, and application year dummies. The four indicators are: forward citations (CITES); backward citations (REFS); the number of claims in the patent (CLAIMS); the number of patents filed with different patent authorities referring to the same invention, commonly labelled as "family size" (STATES). Table 4 presents descriptive statistics for the four indicators. Table 5 shows the results of our regressions. Since the four indicators are non-negative integers we run negative binomial regressions.

TABLES 4 AND 5 ABOUT HERE

From Table 5 both CITES and REFS exhibit an increasing trend as we move towards higher value intervals. The trend is particularly well defined for CITES. For the other indicators the impacts of the highest VALUE classes become more erratic. However, from Figure 1, the share of the observations in the VALUE classes 8-10 is only 3.6% and it is 7.3% if one also includes the VALUE class 7. Thus, the trend in the impacts of the VALUE classes on our indicators is smooth for a vast majority of observations.

The correlation between our VALUE indicator and the other indicators is confirmed by Table 6, where we run an interval regression with the VALUE dummies as the dependent variable and our four indicators, along with technology, country and time dummies as regressors. The ordered probit constants of the interval regressor were set equal to the boundaries of our VALUE intervals. To reduce heteroskedasticity we used the logs of our indicators as regressors. Correspondingly, we set the interval regression boundaries to be the logs of the boundaries of our questionnaire intervals, i.e. log(1)-log(30) for the first class, log(30)-log(100) for the second, etc.. All four indicators have a positive and statistically significant impact.

TABLE 6 ABOUT HERE

In Tables 5 and 6 the German dummy is small and insignificant in the CITES and REFS equations, whereas it is negative and significant in the VALUE equation. This corroborates our earlier conjecture that German inventors do not boost their assessments of VALUE, as implied by the negative impact of the German dummy on VALUE not paralleled by a negative impact on the more objective measures CITES and REFS. We find the same pattern for the French dummies. Unlike the other countries, in which the questionnaire was administered by academic units, the French questionnaires of the PatVal-EU survey were managed by a Statistical Department of the Ministry of Science and Education (*Ministère de la jeunesse, de l'éducation nationale et de la recherche*). The greater experience of the Statistical Department of the French *Ministère* may have helped collect less inflated measures of patent value.

4.2 Comparing Inventor and Manager Responses

A potential limitation of VALUE is that it is reported by inventors. Especially in large firms, or even in academic settings, managers may provide more accurate estimates of the value of a patent. The trade-off here is that if one wants to conduct a survey at the scale of PatVal-EU, it is quite costly to seek for each patent the most suited individual to answer such a question. The problem is aggravated by the fact that, for each patent, one has to look for the right individual who could provide the best response. Moreover, since we are dealing with patents that are some years old, such individuals might have left the company. Thus, even if inventors may offer less precise answers, it was not at all clear that we did not introduce other biases by seeking other respondents to the value question or if we made judgments about who such people are. The inventors appeared the easiest and most obvious individuals who knew about the patent and could provide a "good" guess systematically and on a large scale.

At any rate, for a sample of 354 French patents the question about the value was asked independently to the inventor and a manager. Again we exploited the better experience of the French unit to look for the proper manager inside the applicant organization who could provide the best answer to the value question. Figure 2 shows the distributions of the two value classes. Figure 3 shows the distribution of the difference between the 1-10 number of the class picked by the inventor and the manager. The two distributions in Figure 2 overlap to a great extent. Figure 3 shows that in slightly more than two-third of the patents the inventors and managers missed each other by at most one contiguous class (difference between –1 and 1), and for almost 90% of the patents they missed each other by at most two contiguous classes (-2; 2).

FIGURES 2 AND 3 ABOUT HERE

Tables 7-8 compare the two distributions more formally. Table 7 shows that the inventors report a higher mean response than managers.[6] Table 8 reports statistical tests. It shows that a two tail t-test of differences in the mean responses cannot be rejected for a p-value smaller than 10%. In fact, while the inventors may boost the results of their work, it is harder to think that the managers may over-estimate the value of patents. It may then be reasonable to employ a one tail t-test of the nul hypothesis against the alternative that the mean response of the inventors is higher than that of the managers. Table 8 shows that in this case the nul hypothesis of equality of the means is rejected at $p < 5\%$. Table 8 reports other tests. In all of them we never reject the nul hypothesis. In particular, we cannot reject the hypothesis of equality of the standard deviations of the two distributions, and the Kolmogorov-Smirnov and Wilcoxon rank-sum (Mann-Whitney) test do not reject the hypothesis that the two distributions are equal. In sum, our results show that the inventors slightly overestimate the economic value of their patents. However, such an overestimation is not particularly severe.

TABLES 7-8 ABOUT HERE

[6] Recall that the number values are 1-10 for the ten classes. The descriptive statistics, and all the tests in Tables 7-10 below are computed by using these numbers.

We performed some additional tests. Compared to smaller firms or other organizations (universities, research labs) the inventors in large companies may be less informed about the value of their patents because of the greater organizational distance and the more intensive specialization of tasks. As a result, the gap in response ought to be wider. Table 9 corroborates this hypothesis. The inventors in large firms exhibit a higher average difference in their assessment of patent value with respect to managers in other organizations. Table 10 tests some other hypotheses. It first shows that the equality of mean responses between inventors and managers is rejected for the large firms (two-tail at $p < 10\%$, one tail at $p < 5\%$), while it cannot be rejected for the other organizations. In addition, one cannot reject the hypothesis that the average difference in the inventor-manager responses in large firms are equal to other organizations, and one cannot either reject the hypothesis that the standard deviations of the two distributions of the differences are equal. Finally, one cannot reject the hypothesis of the equality of the distributions of the differences according to the Kolmogorv-Smirnov and the Wilcoxon rank-sum (Mann-Whitney) test. While the lack of significance of these tests may stem in part from their small number of observations, it is also a consequence of the fact that the differences are probably not highly pronounced.

TABLES 9-10 ABOUT HERE

To summarize, the slight overestimate of the inventor assessment of the value of their patents compared to managers seems to be produced by inventors in large firms. This also helps better understand our earlier remark about the fact that inventors in smaller firms or other organizations are more likely to be biased in their assessment of patent values. Our results suggest that this is not the case, and that their evaluations are even closer to those of their managers. Yet, in these other organizations the managers are themselves more directly and closely involved with the invention and they may be themselves biased in their evaluations. For example, in a small start-up the inventor and manager probably work close to each other, and similarly in a university researchers and managers of the technology transfer office discuss a great deal about the potential value of the patent. Again, we cannot rule out this hypothesis. However, the average values of the 1-10 numbers for the value classes chosen by inventor and managers in the case of large firms are, respectively, 3.57 and 3.39 vis-à-vis 3.41 and 3.34 for all other organizations. Thus, the absolute value of the manager evaluation in other organizations is even lower than in large firms, which suggests that on average managers in small firms or universities do not overestimate the value of patents vis-à-vis managers in large firms. Of course, these averages do not control for several other factors that may affect the expected value of patents in different organizations. However, they suggest that simple statistics in the data do not entail a substantial overevaluation of the value classes in smaller firms or non-profit research centers compared to large firms.

5. REGRESSION RESULTS

5.1 Interval Regressions

Table 11 presents our interval regression estimations. We used a log-log specification, where apart from the dummies, all the continuous covariates are in logs. Correspondingly, we measured the boundaries of the value classes in logs, that is log(1), log(30K), log(100K), up to log(300M). All our interval regressions below are corrected by using sampling weights for potential biases in the PatVal-EU sampling. The Appendix explains how the sampling weights were constructed. In addition, we employ robust standard errors and we clustered by firm to account for the possibility that patents of the same firms may have correlated errors. The clustering is by ultimate parent firms, which we obtained by searching for the ultimate parent companies of all the firms in our sample by using *Who Owns Whom* and other company directories.

TABLE 11 ABOUT HERE

We estimate four specifications of our regression. The first column of Table 11 uses the

MANMONTH dummies along with the PROJECT, INTFUND and GOVFUND dummies. In this regression PROJECT, INTFUND and GOVFUND are insignificant. The second column of Table 11 uses the same regressors as in the first column, but the MANMONTH dummies. As noted, the MANMONTH dummies may be endogenous, and here we are basically running a reduced form regression where we assume that the MANMONTH dummies are explained by all the other covariates in the model. Now PROJECT and GOVFUND become significant. None of the other covariates change dramatically between the two columns. This suggests that PROJECT and GOVFUND may be proxying for the MANMONTH dummies. The third column uses log(AVMM_IPC3) in lieu of PROJECT, INTFUND, GOVFUND, and the MANMONTH dummies. The forth column adds the former three dummies back into the equation. Thus, the fourth column is our full specification when the MANMONTH dummies are excluded. In what follows we will discuss the results of this final specification. However, the results look similar across the four columns.

Impact of Characteristics of the Organization

Table 11 shows that, all else held constant, the patents held by individuals are more valuable. The baseline dummy in the regression is LARGE. The small firm dummy is also positive, but insignificant. A caveat to the individual inventor result is that they may be more jelous, protective, or excited about their inventions, and hence overstate the value of their patents. However, it also conforms to the hypothesis that because of the costs of patenting and managing patent portfolios more generally, an individual faces a higher marginal costs of patenting, and hence she patents only valuable inventions. We also find that universities and government research labs patent less valuable inventions than firms, which confirms our earlier conjecture, viz. they may produce less valuable inventions or enjoy a lower private value of patents.

Interestingly, the number of patents of the organization, PATAPP, does not seem to matter. As we shall see below, the experience of the individual inventors turns out to be more important than that of the organization.

Impact of Characteristics of the Patent or the Invention Process

Both WORDS and IPC4 are statistically insignificant, which suggests no impact of our measures of the generality of the invention. We also find that a higher number of applicants (DAPPL), as a proxy for formal collaborations, is not important.

By contrast, the important factor here is the scale of the research project. In the first column of Table 11, the MANMONTH dummies are significant and their coefficients progressively increase as we move from the smaller to the higher dummies, which denote higher man-months. In the second and fourth column, PROJECT and GOVFUND are positive and significant. As noted, since they were not significant when we had the MANMONTH dummies in the regression, this suggests that they are proxying for the scale of the project. The elasticity of AVMM_IPC3 in the third and fourth column is not negligible, even though it is not significant. However, we shall see that this variable raises the significance of MMANMONTH when used as an instrument for the latter.

The result that projects of larger size produce more valuable patents is intriguing also because it nails down the role of serendipity in research, which is often raised to point out its vagueness and unpredictability. Our finding is that the fuzziness of research should not be exaggerated. While invention has some natural uncertainty, there is a systematic correlation between the scale of resources invested in the project and the value of its output.

We also find that science and customers are important sources of knowledge that raise the value of patents. Both dummies BASKNOW and CUSKNOW are positive and significant. Interestingly, the patent literature as a source of knowledge, PATKNOW, is less significant. The importance of science is probably capturing the fact that new fields, or fields in which basic knowledge is more important are also potentially more valuable, either because they are at early development stages, or because science provides a framework for conducting industrial research. The importance of customers is also well known and it has been documented for a long time (e.g. Freeman and Soete, 1997; Von Hippel, 1988). Innovations that use customers as a guidance are probably better designed for the market and find wider and better opportunities.

Table 11 also shows that other things being equal patents by German and French inventors are less valuable. This confirms our earlier remark that the German and French dummies may capture non-economic factors boosting the value of patents declared by inventors from other countries. However, both the German and French dummies discount our estimated log-value of patents by relatively small amounts, about -0.8 for Germany and -1.2 for France, which correspond to 45% and 30% smaller values, other things being equal. The average predicted value of patents in our sample is 4.4 million euros. The German dummy would then discount it to about 2 millions and the French dummy to about 1.3 millions. Again, the order of magnitudes are in the same ball park.[7]

The application year dummies are not jointly significant. There is no reason why patents in different years ought to have a different expected value other things being equal, and given that we control for sectors and technologies. By contrast, we find differences across technologies. Although we do not report the dummies for the technological sectors, the highest impacts are in industries in which we know that patents are typically most valuable – e.g. pharmaceuticals and biotechnology, semiconductors, and the chemical technologies (e.g. Levin *et al*, 1987; Hall and Ziedonis, 2001).

Impact of Inventor Characteristics

Inventor characteristics are a critical determinant of the value of patents. Table 11 first shows that gender (MALE) does not matter. By contrast, the past patenting experience of the inventor, PATINV, is an important predictor of the value of patents. This compares to the earlier result that the inventive experience (number of patents) of the organization did not matter: the

[7] The average prediction of the dependent variable, 4.4 millions, is smaller than the sample average of 10.391 millions. As discussed in Giuri, Mariani et al. (2006) the PatVal-EU survey slightly oversampled important patents. The interval regressions correct this potential bias by using sampling weights, and therefore produces a lower average. In addition, we cannot rule out that the distribution of patent values may be more skewed than the log-normal. If so, our log-normal assumption creates more symmetry than what is actually in the data, which may further reduce the predicted average compared to the sample average.

inventive efficiency of the organization does not seem to be a good substitute for individual talents. The experience of the individual within the same organization, YEARINORG, is significant and has the expected effect, i.e. people hired in more recent years are less likely to produce valuable patents. Thus, both individual talent and his experience within the organization matter.

Individual motivations also matter. The dummies MONEY, CAREER, and PRESTIGE, are positive and generally significant. To be sure, it may be that more motivated individuals boost the evaluations of their patents. While we cannot rule out this possibility, we do not think it is important. When we discard these covariates from our regressions, the impact of the other covariates does not change. As discussed earlier, our interpretation is that the motivational dummies account for individual efforts, and their significance suggests that such individual efforts are important for innovation.

We also find that there is some age profile in the invention process. Other things being equal, the probability of making valuable inventions is higher for individuals older than 30, and drops after 60. Table 11 also shows that there is a small but systematic increase in the estimated coefficients of the dummies for the academic degree of inventors as we move from lower to higher degrees. Yet, these effects are not statistically significant. While the degree is probably most important for younger inventors, our sample, which includes inventors of any age, gives more weight to factors like the inventor talent, experience, and motivation, as well as the resources available for the project.

Impact of Competitive Environment and Inventor Location

Our measures for the competitive environment surrounding the patented invention are positive and quite significant. This corroborates our earlier statement that patents are more valuable when there are competitors around. This is because in this case owning a patent can considerably change the ability of the innovator to profit from innovation.

Finally, locational characteristics do not matter. One interpretation of this result is that geographic spillovers and locational advantages are probably important in specific sectors, like biotechnology or other special high-tech domains. However, when looking at a wider spectrum of industries altogether, as we are doing in this paper, the industries in which such localization advantages are important for innovation become negligible. Another possibility is that spillovers and other location advantages are less important in Europe than in the US or elsewhere. Yet another interpretation arises from our framework in Section 2. Geographical factors may affect the value of the patented invention, but not the marginal value of holding a patent. That is, the difference in value between holding *vs* not holding a patent does not change according to the location in which the invention is produced.

5.2 Robustness checks

We present two robustness checks. First, we run our value equation by using log(VALUEM) as the dependent variable and by instrumenting for log(MMANMONTH), which is used in lieu of the MANMONTH dummies. All the other covariates are the same as in Table 11. We show the results obtained by using log(AVMM_IPC3) as the only instrument excluded from in the value equation, and those obtained by also excluding PROJECT, INTFUND, and GOVFUND. The results are in Table 12. Practically all the results of Table 11 are confirmed. Only BASKNOW and CUSKNOW loose significance compared to the interval regression estimation. The impact of log(MMANMONTH) is positive and significant after instrumenting for it. The significance is more pronounced when we also drop PROJECT, INTFUND, and GOVFUND from the value equation. The three dummies are not significant in the value equation when we include them in the second column of Table 12, which suggests that using them as exclusion restrictions does not make a major difference. At the same time, while the elasticity of MMANMONTH becomes less significant in the second column, its magnitude changes only negligibly. Ultimately, we estimate that by doubling the man-month resources devoted to a project the value of the patent increases by slightly more than 31%.

TABLE 12 ABOUT HERE

Our second robustness check is a sample selection equation in which we regress log(VALUEM) on the same covariates as in the previous estimations, and we add a selection equation using the universe of EPO patents applied for in 1993-1997. The selection estimates the probability that a patent in the universe of 1993-1997 EPO applications is an observation of the value equation. Because of missing values in some PatVal-EU variables, not all of the surveyed PatVal-EU patents are part of the value equation. Our selection includes these observations as well on the ground that there may not only be potential selection biases for the non-surveyed patents, but also for the patents not included in the sample of our value equation. At any rate, we also run our sample selection equation by dropping the patents that were suveyed, but that were missing in the sample, and the results did not change.

To identify selection we employed in the selection equation CITES, REFS, CLAIMS and STATES, along with our country, technology, and application year dummies. As well known, the selection equation needs to be identified through variables that are present in it, but not in the regression. After all, CITES, REFS, CLAIMS, and STATES span different dimensions of the value of a patent, and given the large set of covariates in the value regression, it is not unreasonable to exclude them from the latter, as they may replicate the span of factors already defined by the regression covariates. Moreover, unlike the PatVal-EU variables, data on the four indicators (and on the country, technology, and application year dummies) are available for all 1993-1997 EPO patent applications. The results of this estimation are in Table 13, and they are strikingly similar to the previous estimations.

TABLE 13 ABOUT HERE

5.3 Illustrative predictions

To illustrate our results, we estimate how the value of patents change with changes in our covariates. As a benchmark we computed the median of the predicted value of the first regression in Table 12 by applying to all observations the constant for Germany. This median value is 388.2 thousand euros. It reflects the conservative view that the smaller German dummy provides a basis for discounting non-economic factors affecting PatVal-EU responses.

Assume that this median value corresponds to an observation with the median level of MMANMONTH of 4.5 from Table 2. Compare it to an observation identical in all respects but with MMANMONTH equal to the 75th percentile, which is 18 from Table 2. Given the estimated elasticity of MMANMONTH in Table 12 this raises the median value of patent from 388.2 to 599.9 = 388.2*$(18/4.5)^{0.314}$. Compare it now with an observation that differs only because the past patents of the inventor, i.e. PATINV, are equal to the 75th percentile rather than the median, i.e. 3 instead of 2 from Table 2. This raises the value of the patent from 388.2 to 425.6 = 388.2*$(3/2)^{0.227}$. The increase is smaller, which depends largely on the fact that the shift of PATINV from the median to the third quartile is not sizable, as implied by the well known skewed distribution of the researcher performance (Lotka, 1926). We also find that the invididual experience within the organization is not that important. If the median patent value corresponds to the 75th percentile in YEARINORG rather than the median, it drops from 388.2 to just 366.6 = 388.2*$(1989/1983)^{-18.95}$.

Most interestingly, the impacts of the inventor motivations seem to be quite relevant. Suppose that our median patent was produced by inventors not motivated by money, career or prestige, and consider an identical patent whose inventor is motivated by MONEY. This raises the patent value from 388.2 to 451.9 = 388.2*exp(0.152). If the inventor is also motivated by CAREER concerns, the patent value raises to 529.3 = 451.9*exp(0.158); and if she is also concerned about PRESTIGE, the patent value becomes 584.9 = 529.3*exp(0.1), which is as large as the increase in patent value computed earlier because of a change in resources from the median to the 75th percentile of MMANMONTH. Quite interestingly, in the invention business individual motivations can be as important as sizable increases in resources. This exercise also suggests that if the median patent is held by a university or a government research lab instead of a large firm it has a much lower private value, 170.6 = 388.2*exp(-0.822) in the former case and 222.4 = 388.2*exp(-0.557).

6. CONCLUSIONS

We employed an unusually comprehensive dataset of inventor responses to questions about the economic value of patents. We find that, other things being equal, two factors raise the value of patents: i) the resources invested in the process; ii) the inventor characteristics. The former suggests that innovation may be less seredipitous than often thought. Systematic investments in resources do lead to more valuable research outputs. Important inventor characteristics not only include the inventor ability (past patents), but also her experience in the inventing organization and her motivations. Interestingly, all these individual factors matter more than the inventive ability of the employer organization (its past patents), organizational design (e.g. large *vs* small firms), or local externalities. We also confirm the well known result that users are important sources of valuable innovations, and that the private value of patent is higher when there are potential risks of imitation. Finally, other things being equal, patents by universities and non-profit research institutions are less valuable, which may be either because they are less concerned about protection or because they produce less valuable inventions.

Appendix: Construction of the Sampling Weights

[…. To be written]

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Table 1: Description of variables employed in the empirical analysis

Variable	Description
VALUE	Index equal to 1-10 for the following PatVal-EU classes of patent values: ≤€30K; 30-100K; 100-300K; 300K-1M; 1-3M; 3-10M; 10-30M; 30-100M; 100-300M; ≥300M
VALUEM	Mid point of VALUE (15K; 65K; 200K; 650K; 2M; 6.5M; 20M; 65M; 200M; 650M)
Characteristics of the Applicant Organization	
INDIVIDUAL	Dummy = 1 if the applicant is a person rather than an organization, or if under "type of employer" the respondent reported words such as "individual", "individual researcher", "consultant", "professional studio"
SMALL, MEDIUM, LARGE	Dummies = 1 if the inventor employer is a firm with, respectively, ≤ 100 employees (and not an INDIVIDUAL); 101-250; or > 250
UNIV, GOV, OTHER	Dummies = 1 if the inventor employer is, respectively, a university; the government or a government research lab; any other employee
PATAPP	Total number of patents of the applicant in the PatVal-EU sample
Characteristics of the Patent or the Invention Process	
Sector, application year, and country dummies	30 industry dummies (see Table 3); 6 dummies for application years 1993-1998[(*)]; 6 dummies for whether the address of the first inventor was in France, Germany, Italy, Netherlands, Spain, UK
DAPPL	Dummy = 1 if there is more one applicant to the patent
WORDS	Number of words in the main claim of the patent
IPC4	Number of IPC 4-digit classes associated to the patent
BASKNOW	Dummy = 1 if the inventor of the patent checked 4 or 5 to the question "How important were university labs and faculty as sources of knowledge for the research that led to the patented inventions?", or to the question "How important was the scientific literature as a source of knowledge for the research that led to the patented inventions?" (1-5 response scale, 1 = not important, 5 = very important)
PATKNOW	Dummy = 1 if the inventor of the patent checked 4 or 5 to the question "How important was the patent literature as a source of knowledge for the research that led to the patented inventions?" (1 = not important, 5 = very important)
CUSKNOW	Dummy = 1 if the inventor of the patent checked 4 or 5 to the question "How important were customers or product users as sources of knowledge for the research that led to the patented inventions?" (1 = not important, 5 = very important)
MANMONTH1-8	8 dummies for man-months required for producing the patented invention (≤1; 1-3; 4-6; 7-12; 13-24; 24-48; 48-72; ≥72)
MMANMONTH	Mid-point of the man-month intervals above
AVMM_IPC3	Average of MMANMONTH for the sample patents in the same IPC3 class of the patent
PROJECT, INTFUND, GOVFUND	Dummies = 1 if, respectively: i) the patented invention was the outcome of a structured project aimed at producing that invention, rather than a by-product of other research or the unexpected outcome of other activites; ii) the financing of

	the research leading to the patent came from internal funds of the applicant (including affiliated organizations); iii) the financing of the research leading to this patent came from Government Research Programmes or other government funds
Characteristics of the Inventor	
AGE1-5	5 age class dummies (less than 30; 30-40; 40-50; 50-60; greater than 60)
DEGREE1-5	5 academic degree dummies (secondary school or less; high school; BA; Master; PhD)
MALE	Dummy = 1 for male inventor
YEARINORG	Year in which the inventor joined the employer organization in which the research leading to the patent was conducted
PATINV	1-19 size classes for the number of patents of the inventor. Class 1 = 1-5 patents (including the current patent); 2 = 5-10; 3 to 13 = from 10-20 to 110-120 (by 10); 14 to 17 = 120-140 to 180-200 (by 20); 18 = 200-300; 19 = more than 300
MONEY	Dummy = 1 if the inventor of the patent checked 4 or 5 to the question "How important are to you monetary rewards as a motivation for patenting?" (1-5 response scale, 1 = not important, 5 = very important)
CAREER	Dummy = 1 if the inventor of the patent checked 4 o 5 to the question "How important are to you career advances as a motivation for patenting?" (1 = not important; 5 = very important)
PRESTIGE	Dummy = 1 if the inventor of the patent checked 4 o 5 to the question "How important are to you prestige and reputation as a motivation for patenting?" (1 = not important; 5 = very important)
Characteristics of the Competitive Environment	
COMMEXPL	Dummy = 1 if the inventor of the patent checked 4 or 5 to the question "How important was to obtain exclusive rights to exploit the invention economically as a reason for patenting it?" (1-5 response scale, 1 = not important, 5 = very important)
PREVIMIT	Dummy = 1 if the inventor of the patent checked 4 or 5 to the question "How important was to prevent imitation as a reason for patenting this invention?" (1-5 response scale, 1 = not important, 5 = very important)
Characteristics of the Location	
GDPPOP	1994-1996 average GDP per capita of the NUTS3 region of the inventor address in the patent
POP	1994-1996 average population of the NUTS3 region of the inventor address in the patent
AREA	area of the NUTS3 region of the inventor address in the patent
PATLOC	1994-1996 average number of patents of the NUTS3 region of the inventor address in the patent

Table 2: Descriptive statistics

	Mean	*St.Dev.*	*Min*	*P25*	*Median*	*P75*	*Max*	*N.obs.*
VALUE	3.840	1.809	1	2	4	5	10	7752
VALUEM	10391.6	63302.2	15	65	650	2000	650000	7752
INDIVIDUAL	0.059	0.235	0	0	0	0	1	7752
SMALL	0.109	0.312	0	0	0	0	1	7585
MEDIUM	0.09	0.286	0	0	0	0	1	7585
LARGE	0.701	0.458	0	0	1	1	1	7752
UNIV	0.031	0.174	0	0	0	0	1	7585
GOV	0.021	0.144	0	0	0	0	1	7585
OTHER	0.014	0.116	0	0	0	0	1	7585
AGE1	0.044	0.205	0	0	0	0	1	7647
AGE2	0.311	0.463	0	0	0	1	1	7647
AGE3	0.325	0.468	0	0	0	1	1	7647
AGE4	0.268	0.443	0	0	0	1	1	7647
AGE5	0.052	0.221	0	0	0	0	1	7647
DEGREE1	0.029	0.167	0	0	0	0	1	7668
DEGREE2	0.125	0.331	0	0	0	0	1	7668
DEGREE3	0.171	0.376	0	0	0	0	1	7668
DEGREE4	0.227	0.419	0	0	0	0	1	7668
DEGREE5	0.448	0.497	0	0	0	1	1	7668
MALE	0.98	0.14	0	1	1	1	1	7712
YEARINORG (^)	1980.7	10.412	1923	1973	1983	1989	2003	7592
PATAPP (^)	32.718	70.953	1	1	1	23	286	7752
PATINV (^) (+)	2.665	2.439	1	1	2	3	19	7379
COMP	0.422	0.494	0	0	0	1	1	6521
MONEY	0.409	0.492	0	0	0	1	1	7072
CAREER	0.379	0.485	0	0	0	1	1	6972
PRESTIGE	0.538	0.499	0	0	1	1	1	7189
BASKNOW	0.433	0.496	0	0	0	1	1	7454
PATKNOW	0.409	0.492	0	0	0	1	1	7391
CUSKNOW	0.513	0.5	0	0	1	1	1	7466
WORDS (^)	163.2	101.8	5	98	145	204	1595	7749
IPC4 (^)	1.435	0.7	1	1	1	2	7	7752
APPL (*)	0.07	0.256	0	0	0	0	1	7752
MANMONTH1	0.129	0.336	0	0	0	0	1	7285
MANMONTH2	0.212	0.409	0	0	0	0	1	7285
MANMONTH3	0.194	0.395	0	0	0	0	1	7285
MANMONTH4	0.18	0.384	0	0	0	0	1	7285
MANMONTH5	0.151	0.358	0	0	0	0	1	7285
MANMONTH6	0.084	0.277	0	0	0	0	1	7285

MANMONTH7	0.019	0.138	0	0	0	0	1	7285
MANMONTH8	0.03	0.172	0	0	0	0	1	7285
MMANMONTH	12.64	18.26	1.5	1.5	4.5	18	90	7285
AVMM_IPC3	12.953	4.912	1.5	8.733	11.64	15.571	36	7285
PROJECT	0.372	0.483	0	0	0	1	1	7523
INTFUND	0.894	0.308	0	1	1	1	1	6978
GOVFUND	0.083	0.276	0	0	0	0	1	6978
COMMEXPL	0.704	0.456	0	0	1	1	1	6941
PREVIMIT	0.720	0.449	0	0	1	1	1	6856
GDPPOP (^)	22726.3	9158.7	8677.9	16977.2	19569.4	24401.2	76910.8	7387
POP (^)	767.6	828.3	19.9	260.9	532.7	998.8	5009.3	7442
AREA (^) (Km2)	1887.7	2221.3	35.6	308.5	1116.9	2284.4	17252	7442
PATLOC (^)	128.0	140.6	0.723	35.653	78.743	152.193	575.1	7386
UK	0.176	0.381	0	0	0	0	1	7752
DE	0.396	0.489	0	0	0	1	1	7752
IT	0.136	0.343	0	0	0	0	1	7752
ES	0.017	0.129	0	0	0	0	1	7752
FR	0.14	0.348	0	0	0	0	1	7752
NL	0.135	0.341	0	0	0	0	1	7752
YR93	0.025	0.157	0	0	0	0	1	7752
Y394	0.282	0.45	0	0	0	1	1	7752
YR95	0.258	0.437	0	0	0	1	1	7752
YR96	0.231	0.421	0	0	0	0	1	7752
YR97	0.154	0.361	0	0	0	0	1	7752
YR98	0.05	0.218	0	0	0	0	1	7752

(^) Absolute value of the variable (not in logs). (*) Number of patent applicants. (+) Classes 1-19

Table 3: ISI technological class dummies, descriptive statistics

Technology ISI Classes (30 Technology Class Dummies)	*Mean*	*St.Dev.*	*N.Obs.*
Electrical devices, electrical engineering, electrical energy	0.074	0.262	7752
Audio-visual technology	0.019	0.138	7752
Telecommunications	0.030	0.170	7752
Information technology	0.022	0.148	7752
Semiconductors	0.010	0.100	7752
Optics	0.018	0.133	7752
Analysis, measurement, control technology	0.059	0.237	7752
Medical technology	0.027	0.162	7752
Organic fine chemistry	0.057	0.232	7752
Macromolecular chemistry, polymers	0.052	0.221	7752
Pharmaceuticals, cosmetics	0.018	0.135	7752
Biotechnology	0.007	0.085	7752
Materials, metallurgy	0.034	0.181	7752
Agriculture, food chemistry	0.012	0.108	7752
Chemical and petrol industry, basic materials chemistry	0.034	0.181	7752
Chemical engineering	0.033	0.179	7752
Surface technology, coating	0.016	0.125	7752
Materials processing, textiles, paper	0.056	0.230	7752
Thermal processes and apparatus	0.022	0.148	7752
Environmental technology	0.016	0.124	7752
Machine tools	0.035	0.185	7752
Engines, pumps, turbines	0.028	0.166	7752
Mechanical Elements	0.046	0.209	7752
Handling, printing	0.076	0.266	7752
Agricultural and food processing, machinery and apparatus	0.021	0.145	7752
Trasport	0.070	0.255	7752
Nuclear engineering	0.004	0.066	7752
Space technology weapons	0.006	0.078	7752
Consumer goods and equipment	0.051	0.220	7752
Civil engineering, building, mining	0.043	0.204	7752

Table 4: Alternative indicators, descriptive statistics

	Mean	*St.Dev.*	*Min*	*P25*	*Median*	*P75*	*Max*	*N.obs.*
CITES	1.487	2.256	0	0	1	2	40	7752
REFS	4.397	2.249	0	3	4	6	18	7752
CLAIMS	10.82	7.018	1	6	9	13	131	7752
STATES	8.825	4.835	1	5	7	12	19	7752

Table 5: Relations between CITES, REFS, CLAIMS, STATES, and the VALUE classes 1-10 (Negative Binomial Regressions)

	Dependent Variables			
	CITES	*REFS*	*CLAIMS*	*STATES*
CONST	-0.114	1.393***	2.377***	1.920***
	(0.393)	(0.000)	(0.000)	(0.000)
VALUE2	0.047	0.038	-0.020	0.046
	(0.547)	(0.141)	(0.525)	(0.118)
VALUE3	0.140**	0.039	0.031	0.081***
	(0.047)	(0.116)	(0.299)	(0.007)
VALUE4	0.288***	0.058**	0.088***	0.111***
	(0.000)	(0.019)	(0.004)	(0.000)
VALUE5	0.397***	0.077***	0.151***	0.145***
	(0.000)	(0.004)	(0.001)	(0.000)
VALUE6	0.529***	0.093***	0.173***	0.179***
	(0.000)	(0.002)	(0.000)	(0.000)
VALUE7	0.575***	0.130***	0.218***	0.172***
	(0.000)	(0.001)	(0.000)	(0.000)
VALUE8	0.596***	0.139**	0.190***	0.301***
	(0.000)	(0.013)	(0.001)	(0.000)
VALUE9	0.795***	0.117*	0.111	0.275***
	(0.000)	(0.074)	(0.263)	(0.001)
VALUE10	0.703***	0.117*	-0.008	0.249***
	(0.006)	(0.085)	(0.921)	(0.000)
DE	-0.001	-0.014	-0.222***	-0.110***
	(0.988)	(0.448)	(0.000)	(0.000)
IT	-0.165**	-0.005	-0.233***	-0.068*
	(0.017)	(0.841)	(0.000)	(0.091)
ES	-0.360***	0.033	-0.566***	0.075
	(0.004)	(0.638)	(0.000)	(0.129)
FR	-0.018	0.021	-0.204***	0.025
	(0.764)	(0.357)	(0.000)	(0.329)
NL	-0.176***	0.023	-0.239***	0.012
	(0.002)	(0.468)	(0.000)	(0.875)
Overdispersion, α	0.123***	-4.050***	-1.480***	-1.940***
	(0.002)	(0.000)	(0.000)	(0.000)
N. Observations	7752	7752	7752	7752
Log-Lik. Function	-5.99E+04	-8.33E+04	-1.22E+05	-1.10E+05

P-values based on robust standard errors in parentheses.* $p < 10\%$; ** $p < 5\%$; *** $p < 1\%$. All equations include 29 technology class dummies (one omitted) and application year dummies. Overdispersion parameter α for Neg. Bin. is *variance = [1+α·exp(mean)]·mean*, viz. $\alpha=0 \Rightarrow$ Poisson. Sampling weights to account for potential non-response bias. Observations clustered by patent applicants.

Table 6: Relations between the VALUE classes 1-10 and CITES, REFS, CLAIMS, and STATES (Interval Regression)

	Dependent Variable VALUE CLASSES
CONST	4.876*** (0.000)
LOG(1+CITES)	0.349*** (0.000)
LOG(1+REFS)	0.166** (0.011)
LOG(CLAIMS)	0.176*** (0.000)
LOG(STATES)	0.372*** (0.000)
DE	-0.854*** (0.000)
IT	-0.297*** (0.002)
ES	0.371* (0.086)
FR	-1.075*** (0.000)
NL	-0.310*** (0.006)
N. Observations	7752
Log-Lik Function	-7.51E+04

P-values based on robust standard errors in parentheses.* p < 10%; ** p < 5%; *** p< 1%. Includes 29 technology class dummies (one omitted) and application year dummies. Sampling weights account for potential non-response bias. Observations are clustered by patent applicants.

Table 7: Comparing the responses to the value question by French inventors and managers, VALUE classes 1-10

Value reported by	*Mean*	*Std. Error*	*Std. Dev.*	*Min*	*P25*	*Median*	*P75*	*Max*
Inventors	3.520	0.089	1.680	1	2	3	4	10
Managers	3.370	0.086	1.625	1	2	3	4	10
Difference	0.150	0.086	1.608	-5	-1	0	1	7

N. of obs. = 354.

Table 8: Means, standard deviations, distributions. Tests of differences in the responses by French inventors and managers, VALUE classes 1-10

Test	*p-value*
t-test for difference between means in inventor vs manager responses (H_0: Mean diff. = 0)	
• two tail test	0.084*
• one tail test (mean inventors > mean managers)	0.040**
Two tail F-test for difference between St.Dev. (H_0: Diff. in St.Dev. = 0)	0.534
Two sample Kolmogorov-Smirnov test for equality of distributions	0.754
Two-sample Wilcoxon rank-sum (Mann-Whitney) test for equality of distributions	0.286

N. of obs. = 354. * Null hypothesis rejected at p < 10%. ** Null hypothesis rejected at p < 5%

Table 9: Differences across organizations in the responses of French inventors and managers, VALUE classes 1-10

Difference in value classes by (N. of obs.)	*Mean*	*Std. Error*	*Std. Dev.*	*Min*	*P25*	*Median*	*P75*	*Max*
Large firms (207)	0.188	0.113	1.630	-5	-1	0	1	6
All others (143)	0.077	0.136	1.628	-5	-1	0	1	7

Large firms = Firms with > 250 employees.

Table 10: Tests for differences in the responses by French inventors and managers by organization types, VALUE classes 1-10

Test	*p-value*
t-test for zero difference between inventor and manager responses, large firms vs others (H_0: mean diff. = 0)	
• Large firms (207 obs.)	
o two-tail test	0.098*
o one-tail test (mean inventors > mean managers)	0.049**
• All others (143 obs.)	
o two-tail test	0.573
o one-tail test (mean inventors > mean managers)	0.286
Two tail t-test for equal difference in inventor-manager mean responses between large firms and all other organization types (H_0: mean diff. for large firms = mean diff. for all others)	0.530
Two tail F-test for equal standard deviations of the distributions of the differences in inventor-manager responses by large firms and others (H_0: st. dev. of diff. for large firms = st. dev. of diff. for all others)	0.989
Two sample Kolmogorov-Smirnov test for equality of the distributions of the differences in inventor-manager responses for large firms and all others	0.992
Two-sample Wilcoxon rank-sum (Mann-Whitney) test for equality of the distributions of the differences in inventor-manager responses for large firms and all others	0.475

* Null hypothesis rejected at p < 10%. ** Null hypothesis rejected at p < 5%

Table 11: Interval regression estimation, dependent variable VALUE (1-10)

	Model I	*Model II*	*Model III*	*Model IV*
CONST	140.76**	102.85	139.24**	118.63*
	(0.031)	(0.109)	(0.032)	(0.075)
INDIVIDUAL	0.561***	0.633***	0.715***	0.664**
	(0.003)	(0.000)	(0.000)	(0.001)
SMALL	0.114	0.078	0.148	0.083
	(0.352)	(0.509)	(0.226)	(0.503)
MEDIUM	-0.175	-0.154	-0.193*	-0.189
	(0.118)	(0.174)	(0.088)	(0.103)
UNIV	-0.936***	-0.862***	-0.710***	-0.852***
	(0.000)	(0.000)	(0.001)	(0.000)
GOV	-0.517**	-0.481**	-0.403*	-0.485**
	(0.024)	(0.030)	(0.054)	(0.033)
OTHER	0.270	0.145	0.299	0.315
	(0.518)	(0.723)	(0.458)	(0.444)
AGE2	0.238	0.301**	0.229*	0.285**
	(0.129)	(0.046)	(0.144)	(0.063)
AGE3	0.153	0.267	0.169	0.213
	(0.362)	(0.104)	(0.315)	(0.198)
AGE4	0.248	0.352**	0.242	0.303*
	(0.153)	(0.039)	(0.165)	(0.077)
AGE5	0.039	0.286	0.055	0.164
	(0.877)	(0.251)	(0.824)	(0.508)
DEGREE2	0.191	0.171	0.213	0.206
	(0.416)	(0.429)	(0.368)	(0.387)
DEGREE3	0.265	0.272	0.346	0.322
	(0.203)	(0.164)	(0.101)	(0.127)
DEGREE4	0.278	0.282	0.325	0.308
	(0.191)	(0.158)	(0.119)	(0.147)
DEGREE5	0.351*	0.421**	0.489**	0.441**
	(0.085)	(0.030)	(0.017)	(0.032)
MALE	0.154	0.147	0.176	0.167
	(0.556)	(0.568)	(0.495)	(0.516)
LOG(YEARINORG)	-18.98**	-13.05	-17.84**	-15.18*
	(0.036)	(0.121)	(0.036)	(0.082)
LOG(PATAPP)	-0.019	-0.017	-0.026	-0.017
	(0.310)	(0.388)	(0.200)	(0.387)
LOG(PATINV)	0.233***	0.153***	0.164***	0.163***
	(0.000)	(0.004)	(0.002)	(0.002)
MONEY	0.133*	0.175**	0.135*	0.139*
	(0.074)	(0.018)	(0.068)	(0.064)
CAREER	0.141*	0.140*	0.194***	0.167**
	(0.054)	(0.054)	(0.008)	(0.024)
PRESTIGE	0.142*	0.129*	0.142*	0.132*
	(0.067)	(0.097)	(0.072)	(0.093)
BASKNOW	0.065	0.208***	0.212***	0.199***
	(0.355)	(0.002)	(0.003)	(0.005)
PATKNOW	-0.023	0.002	0.019	0.003
	(0.750)	(0.975)	(0.798)	(0.964)
CUSKNOW	0.126*	0.165**	0.152**	0.162***
	(0.065)	(0.011)	(0.020)	(0.014)
COMMEXPL	0.582***	0.675***	0.635***	0.648***
	(0.000)	(0.000)	(0.000)	(0.000)
PREVIMIT	0.198**	0.196**	0.178**	0.211**
	(0.016)	(0.016)	(0.027)	(0.011)
LOG(WORDS)	0.007	0.042	0.043	0.047
	(0.910)	(0.484)	(0.457)	(0.431)
LOG(IPC4)	-0.105	-0.080	-0.083	-0.084
	(0.198)	(0.328)	(0.303)	(0.308)

DAPPL	0.082	0.197	0.194	0.180
	(0.584)	(0.188)	(0.197)	(0.232)
MANMONTH2	0.164	--	--	--
	(0.171)			
MANMONTH3	0.630***	--	--	--
	(0.000)			
MANMONTH4	0.838***	--	--	--
	(0.000)			
MANMONTH5	1.013***	--	--	--
	(0.000)			
MANMONTH6	1.243***	--	--	--
	(0.000)			
MANMONTH7	1.556***	--	--	--
	(0.000)			
MANMONTH8	1.760***	--	--	--
	(0.000)			
LOG(AVMM_IPC3)	--	--	0.194	0.198
			(0.204)	(0.204)
PROJECT	-0.018	0.196***	--	0.183**
	(0.807)	(0.009)		(0.014)
INTFUND	0.078	0.094	--	0.052
	(0.584)	(0.465)		(0.722)
GOVFUND	0.049	0.298**	--	0.287**
	(0.715)	(0.024)		(0.033)
LOG(GDPPOP)	0.028	0.067	0.042	0.057
	(0.846)	(0.656)	(0.771)	(0.702)
LOG(POP)	0.028	0.061	0.039	0.060
	(0.734)	(0.459)	(0.640)	(0.478)
LOG(AREA)	-0.005	-0.008	-0.001	-0.008
	(0.900)	(0.857)	(0.977)	(0.860)
LOG(PATLOC)	-0.042	-0.066	-0.047	-0.058
	(0.441)	(0.238)	(0.398)	(0.310)
DE	-0.711***	-0.830***	-0.813***	-0.806***
	(0.000)	(0.000)	(0.000)	(0.000)
IT	-0.129	-0.165	-0.064	-0.110
	(0.440)	(0.308)	(0.702)	(0.511)
ES	0.116	0.198	0.207	0.133
	(0.722)	(0.522)	(0.521)	(0.684)
FR	-1.245***	-1.200***	-1.178***	-1.164***
	(0.000)	(0.000)	(0.000)	(0.000)
NL	-0.060	-0.133	-0.071	-0.077
	(0.658)	(0.334)	(0.615)	(0.578)
Sigma	1.952***	2.000***	1.996***	1.992***
	(0.000)	(0.000)	(0.000)	(0.000)
N. Observations	4657	4888	4849	4657
Log of Lik. Function	-4.24E+04	-4.49E+04	-4.46E+04	-4.28E+04

P-values based on robust standard errors in parentheses. * p < 10%; ** p < 5%; *** p < 1%. All equations include 29 technology class dummies (one omitted) and application year dummies. Sampling weights to account for non-response bias. Observations are clustered by patent applicants.

Table 12: Instrumental variable regression, dependent variable log(VALUEM)

	Model I	*Model II*
CONST	147.91**	150.80**
	(0.016)	(0.015)
INDIVIDUAL	0.595***	0.583***
	(0.001)	(0.002)
SMALL	0.169	0.178
	(0.134)	(0.116)
MEDIUM	-0.044	-0.042
	(0.696)	(0.710)
UNIV	-0.822***	-0.807***
	(0.000)	(0.000)
GOV	-0.557**	-0.553**
	(0.021)	(0.025)
OTHER	0.216	0.198
	(0.488)	(0.530)
AGE2	0.242*	0.235
	(0.089)	(0.101)
AGE3	0.207	0.200
	(0.167)	(0.187)
AGE4	0.278*	0.272*
	(0.091)	(0.099)
AGE5	0.096	0.077
	(0.672)	(0.739)
DEGREE2	0.245	0.252
	(0.292)	(0.279)
DEGREE3	0.316	0.316
	(0.156)	(0.157)
DEGREE4	0.368*	0.373*
	(0.090)	(0.086)
DEGREE5	0.400*	0.391*
	(0.067)	(0.079)
MALE	0.140	0.149
	(0.519)	(0.496)
LOG(YEARINORG)	-18.95**	-19.34**
	(0.019)	(0.018)
LOG(PATAPP)	-0.001	-0.001
	(0.938)	(0.976)
LOG(PATINV)	0.227***	0.239***
	(0.000)	(0.000)
MONEY	0.152**	0.151**
	(0.022)	(0.023)
CAREER	0.158**	0.154**
	(0.021)	(0.028)
PRESTIGE	0.100	0.103
	(0.109)	(0.105)
BASKNOW	0.099	0.077
	(0.183)	(0.439)
PATKNOW	-0.052	-0.058
	(0.424)	(0.390)
CUSKNOW	0.091	0.088
	(0.136)	(0.172)
COMMEXPL	0.562***	0.552***
	(0.000)	(0.000)
PREVIMIT	0.243***	0.238***
	(0.000)	(0.000)
LOG(WORDS)	-0.017	-0.023
	(0.743)	(0.688)
LOG(IPC4)	-0.121	-0.125
	(0.101)	(0.094)
DAPPL	0.009	-0.004
	(0.939)	(0.973)

LOG(MM)	0.314***	0.383
	(0.001)	(0.104)
PROJECT	--	-0.064
		(0.647)
INTFUND	--	0.164
		(0.191)
GOVFUND	--	0.040
		(0.832)
LOG(GDPPOP)	0.064	0.057
	(0.604)	(0.648)
LOG(POP)	0.030	0.025
	(0.628)	(0.706)
LOG(AREA)	-0.002	-0.003
	(0.954)	(0.945)
LOG(PATLOC)	-0.062	-0.060
	(0.171)	(0.197)
DE	-0.751***	-0.739***
	(0.000)	(0.000)
IT	-0.113	-0.112
	(0.414)	(0.418)
ES	0.151	0.138
	(0.564)	(0.598)
FR	-1.062***	-1.084***
	(0.000)	(0.000)
NL	-0.011	-0.010
	(0.930)	(0.939)
N. Observations	4657	4657
Log of Lik. Function	-1.65E+04	-1.65E+04

P-values based on robust standard errors in parentheses. * p < 10%; ** p < 5%; *** p < 1%. Instruments for LOG(MM) excluded from the log(VALUEM) equation: LOG(AVMM_IPC3); PROJECT; INTFUND; GOVFUND. In the second equation only LOG(AVMM_IPC3) is excluded. All equations include 29 technology class dummies (one omitted) and application year dummies.

Table 13: Sample selection equation, dependent variable log(VALUEM). Selection: Valid PatVal-EU observations vs all EPO patents applied for in 1993-1997

Regression	*Model I*	*Model II*	*Selection equation*	*Model I*	*Model II*
CONST	154.19***	136.08**	CONST	-1.191***	-1.174***
	(0.009)	(0.025)		(0.000)	(0.000)
INDIVIDUAL	0.710***	0.695***	LOG(1+CITES)	0.102***	0.107***
	(0.000)	(0.000)		(0.000)	(0.000)
SMALL	0.227**	0.170	LOG(1+REFS)	0.034*	0.043**
	(0.032)	(0.114)		(0.060)	(0.027)
MEDIUM	-0.074	-0.059	LOG(CLAIMS)	-0.016	-0.014
	(0.483)	(0.590)		(0.207)	(0.281)
UNIV	-0.618***	-0.720***	LOG(STATES)	-0.023	-0.039**
	(0.001)	(0.000)		(0.114)	(0.011)
GOV	-0.458**	-0.510**	DE	0.261***	0.139***
	(0.037)	(0.028)		(0.000)	(0.000)
OTHER	0.280	0.301	IT	-0.116***	-0.116***
	(0.405)	(0.369)		(0.000)	(0.000)
AGE2	0.222	0.261*	ES	-0.039	-0.028
	(0.111)	(0.060)		(0.538)	(0.662)
AGE3	0.203	0.242*	FR	-0.709***	-1.263***
	(0.169)	(0.099)		(0.000)	(0.000)
AGE4	0.255	0.302*	NL	0.317**	0.308***
	(0.109)	(0.056)		(0.000)	(0.000)
AGE5	0.069	0.154	ATHRO	-0.384***	-0.406***
	(0.755)	(0.489)		(0.000)	(0.000)
DEGREE2	0.259	0.255	SIGMA	2.096***	2.113***
	(0.215)	(0.227)		(0.000)	(0.000)
DEGREE3	0.378**	0.359*	N. Observations	45984	46176
	(0.048)	(0.063)			
DEGREE4	0.396**	0.392**	Log Lik. Function	-2.46E+04	-2.38E+04
	(0.028)	(0.033)			
DEGREE5	0.514***	0.470**	DAPPL	0.097	0.070
	(0.005)	(0.011)		(0.462)	(0.601)
MALE	0.115	0.105	LOG(AVMM_IPC3)	0.212	0.210
	(0.642)	(0.674)		(0.124)	(0.137)
LOG(YEARINORG)	-19.67**	-17.30**	PROJECT	--	0.136**
	(0.012)	(0.031)			(0.036)
LOG(PATAPP)	-0.006	-0.001	INTFUND	--	0.147
	(0.747)	(0.947)			(0.240)
LOG(PATINV)	0.167***	0.171***	GOVFUND	--	0.272**
	(0.000)	(0.000)			(0.028)
MONEY	0.151**	0.157**	LOG(GDPPOP)	0.074	0.077
	(0.024)	(0.022)		(0.565)	(0.559)
CAREER	0.197***	0.178**	LOG(POP)	0.039	0.060
	(0.004)	(0.012)		(0.509)	(0.327)
PRESTIGE	0.095	0.088	LOG(AREA)	0.003	-0.007
	(0.126)	(0.166)		(0.945)	(0.862)
BASKNOW	0.207***	0.195***	LOG(PATLOC)	-0.065*	-0.076*
	(0.002)	(0.004)		(0.137)	(0.091)
PATKNOW	-0.019	-0.035	DE	-0.996***	-0.989***
	(0.773)	(0.592)		(0.000)	(0.000)
CUSKNOW	0.119**	0.124**	IT	-0.017	-0.042
	(0.047)	(0.043)		(0.906)	(0.777)
COMMEXPL	0.614***	0.614***	ES	0.244	0.174
	(0.000)	(0.000)		(0.425)	(0.572)
PREVIMIT	0.220***	0.253***	FR	-0.547***	-0.508***
	(0.001)	(0.000)		(0.001)	(0.002)
LOG(WORDS)	0.015	0.013	NL	-0.233**	-0.252**
	(0.784)	(0.811)		(0.073)	(0.055)
LOG(IPC4)	-0.107	-0.108	N. Observations of the regression	4849	4657
	(0.143)	(0.146)			

P-values based on robust standard errors in parentheses. * p < 10%; ** p < 5%; *** p < 1%. ATHRO = 0.5*log[(1+rho)/(1-rho)]; which is negative for rho < 0 and positive otherwise, where rho is the correlation coefficient of the errors between the two equations.

Figure 1: Distribution of patent values

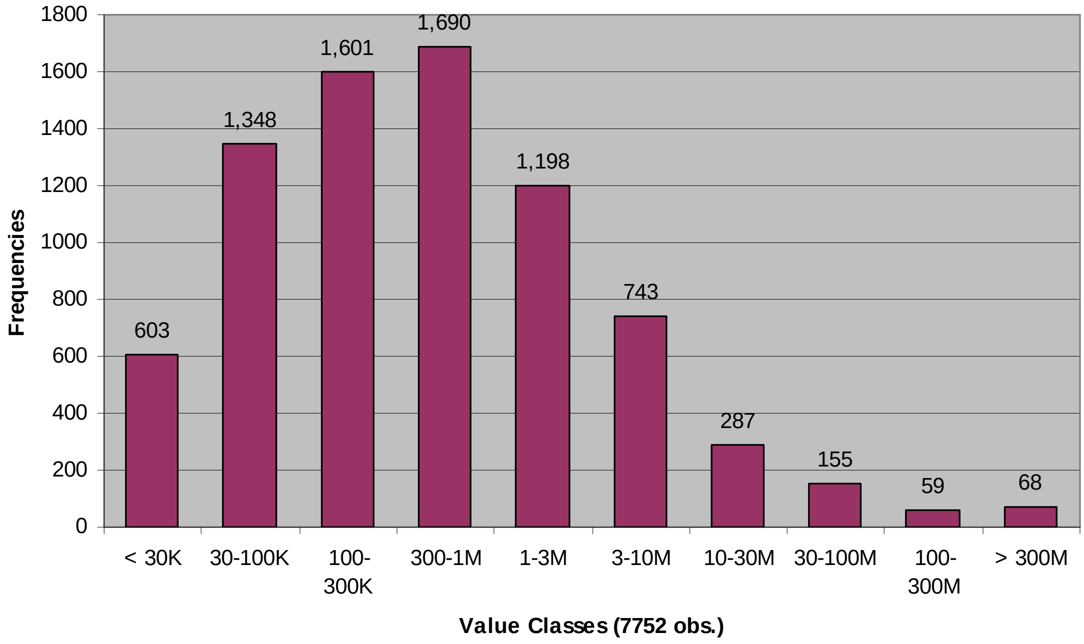

Figure 2: Distribution of patent values, responses by French inventors and managers

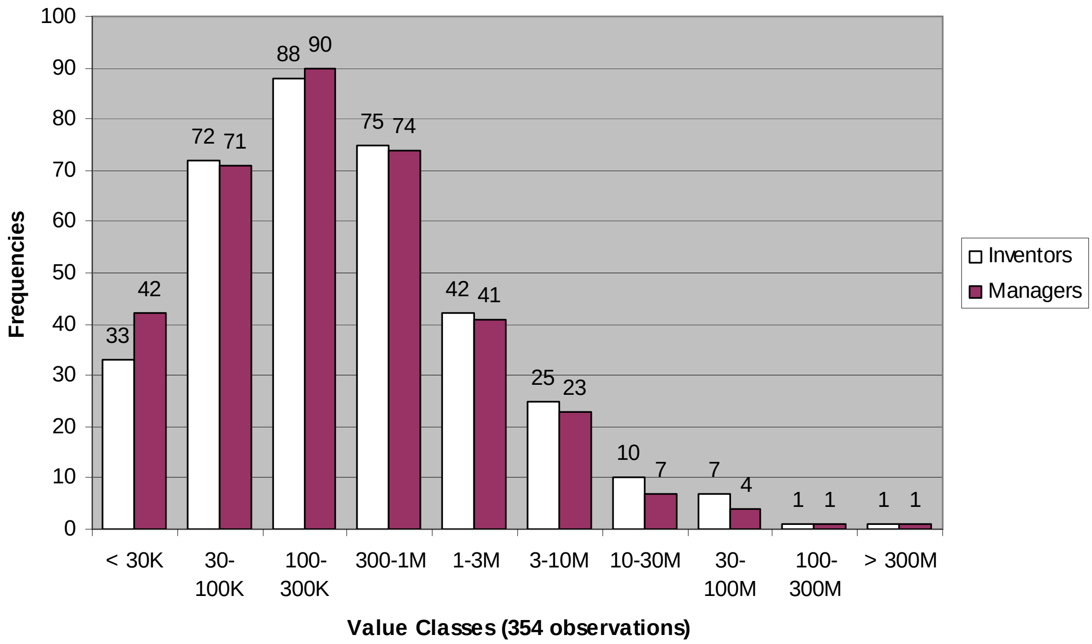

Figure 3: Differences in the responses of Inventors and Managers