THE VALUE OF PATENTS

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PRELIMINARY
Comments welcome

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Abstract

This paper estimates the determinants of the economic value of patents from an unusually comprehensive dataset built from a questionnaire survey of European EPO patents in France, Germany, Italy, Netherlands, Spain, and the UK. We find that the characteristics of the individual inventor (e.g. his past patents) are a more important determinant of the 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 human capital and talented individuals 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 for value or for the importance of patents.

JEL Classification: L20, O31, O33, O34

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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 (see, *inter alia*, Lev 2001). Moreover, as the number of patent applications has surged in Europe, Japan and the US (see e.g. 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 the PatVal-EU Final Report (2005).

Most empirical studies on the value of patents have used indirect measures to infer the value of patents. Renewal studies have made use of the fact that it is expensive to holders of European patents to renew patent protection for an additional year.[3] The pioneering papers in this field were contributed by Pakes and Schankerman (1984),

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).

3 Following the European examples, renewal fees were introduced into the U.S. patent system in 1980. See Griliches (1990, p. 1681).

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's 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 inventors' answer 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 survey responses represent our measure of the value of patents employed in this paper. While giving up the possibility of obtaining point estimates in the survey, our interval-based measure reduce vagaries compared to an open question as it provides the interviewees with a basis to anchor their responses.[4]

The central contribution of this paper is to present the estimates of an ordered probit regression that uses our value intervals as the dependent variable. Our regressors, which are drawn from PatVal-EU or other datasets, explore the impact of four sets of determinants: 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 *location* in which the patent was developed. To our knowledge, this is the first

[4] The PatVal-EU survey asked the inventor to answer the value question by using all the information about the patent that was available when they were answering. This yields more precise estimates than using only the information at the time of the grant. In the first place, the survey was conducted in 2004, seven or more years after the priority date of the most recent patents in the sample. Five-six years after the grant are enough to find out about the true value or the potential applications of most patents (see Pakes 1985), which also implies that there is presumably little additional information in our older 1993 patents compared to the 1997 ones. Moreover, it would have been harder for the inventors to remember what they knew about the patent seven or more years earlier, which could produce other biases.

attempt to determine the impact of such a comprehensive set of determinants on the value of patents.

Moreover, our analysis presents several novelties with respect to previous research on this issue. First, our survey enable us to assess the effect of factors that were ignored in previous studies, which employed variables collected from patent documents. For example, this is the first attempt that we know of to study the effects of the inventors' characteristics (e.g. age, past productivity, educational degree) on the value of patents.[5] In addition, this enables us to understand empirically the relative importance of our four 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 inventors' 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. Similarly, our analysis enables us to assess the relative importance of agglomeration economies, spillovers and local factors more generally. Several studies have noted the importance of local knowledge spillovers (e.g. Audretsch and Feldman, 1996). Others have diminished the importance of spillovers, and have argued that organizational experience and performance are most important even in areas that witness a significant rise of new firms (e.g. Klepper, 2004).

Since our analysis hinges critically on a new survey-based measure of the patent value,

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

we provide some assessment of this measure against alternative indicators. We check the validity of our measure in three ways. First, we regress five traditional indicators of patents value on our value intervals, and our value intervals on the five indicators, along with technology, application year and country dummies as controls. The five indicators are forward citations, backward citations, the number of patents filed with different authority that refer to the same invention (family size), the number of claims in the patent, and whether the patent was opposed by other parties. The first four are the same indicators employed by Lanjow and Schankerman (2004) to construct their patent quality index. As noted earlier, legal opposition is another indicator of the private value of a patent. We can fairly say that these are the five most common indicators of patent value employed by the literature. We find that our value dummies are correlated with all of them. Interestingly enough, our measure reproduces most closely the patent family size. As suggested by Lanjouw and Schankerman (2004) family size is the closest indicator to the monetary value of the patent because the increase in the number of applications for the same invention implies an increase in the patenting costs, which is incurred only if the applicant believes that the patent is worth more. Oppositions are also highly correlated with the monetary value of the patent, and we do find a good match of the value intervals with the oppostion dummy as well. In addition, the five indicators are jointly significant in an ordered probit regression with the value intervals as the dependent variable, and the technology, year, and country as control dummies. This suggests that the five indicators span different dimensions of the value of a patent.

In our second check, we construct a patent value index using the same methodology and indicators employed by Lanjow and Schankerman (2004) – i.e. the first four indicators mentioned above. As they note, this index captures the combined effect of the underlying indicators. We find that this index reproduces quite closely the variability of our patent value intervals. Finally, a third aspect of our patent value measure is that the individual inventors may not know about the value of the patent as much as the managers who are responsible for their development. The problem is probably not that severe in the case of the smaller firms or non-profit research labs, but it can be more serious in larger firms wherein the organizational distance between the inventor and the managers responsible for their development can be notable. 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 there is just a slight overestimate of the patent value by the inventors.

In the next Section we present the variables employed in our analysis. Section 3 presents our validation of the patent value measure. Section 4 discusses our empirical results. Section 5 concludes.

2. DATA AND VARIABLES

From our PatVal-EU survey, we obtained 7,624 responses to our question about the value of the patent. We employed these answers to construct a variable VALUE equal to 1-10 where each digit accounts for one of the ten progressive intervals defined in the previous section. Figure 1 reports the distribution of the 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).

FIGURE 1 ABOUT HERE

The regressors of our ordered probit estimation of the value of patents can be divided in four categories. These variables are described below. Table 1 presents descriptive statistics. Table 2 reports the descriptive statistics of the thirty ISI technology class dummies in which our patents were classified.

TABLES 1 AND 2 ABOUT HERE

Characteristics of the Applicant Organization

- INDIVIDUAL = dummy equal to 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”
- SMALLFIRM = dummy equal to 1 if the inventor’s employer is a firm with less than 100 employes (and not an INDIVIDUAL)

- MEDIUMFIRM = dummy equal to 1 if the inventor's employer is a firm with 100-250 employees
- LARGEFIRM = dummy equal to 1 if the inventor's employer is a firm with more than 250 employees
- UNIV = dummy equal to 1 if the inventor's employer is a university
- GOV = dummy equal to 1 if the inventor's employer is the government or a government research center
- OTHER = dummy equal to 1 for other inventor's employer types
- LPATAPP = log of the number of patents of the applicant in the PatVal-EU sample

The dummies for firm size test the hypothesis that the marginal cost of patenting is smaller for the large firms. Because they patent more, the large firms make fixed investments for applying and administering patents. This makes patenting less costly at the margin. We then expect that they patent less valuable inventions. The dummy INDIVIDUAL captures the idea that the individual inventors face an even greater cost of patenting and hence they patent only valuable inventions. The UNIV, GOV, and OTHER dummies account for the value of patents applied for by non-profit research organizations.

The variable LPATAPP 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. Another potential concern is that we use the experience of the applicant rather than that of the inventor's employer organization. From our questionnaire, in the vast majority of cases the two coincide. Even when they do not, the information about the applicants' inventive experience is relevant because the individual inventors typically work in tight connection with them – e.g. university professors consulting for them, as Breschi Lissoni, and Montobbio (2004) have shown, or the applicant supplies funds, machines, or other forms of support. Sometimes the inventors simply license the invention to the applicant which then applies for the patent without any previous links among them. These are likely to be few cases however.

Characteristics of the Patent or the Invention Project

- 30 dummies for specific industries/technologies. See Table 2 above.
- 6 dummies for application years 1993-1998[6]
- 6 dummies for whether the address of the first inventor of the patent was in France, Germany, Italy, Netherlands, Spain, or UK
- DAPPL = dummy taking the value 1 if there is more one applicant to the patent
- LWORDS = log of the number of words in the main claim of the patent
- LIPC4 = log of the number of IPC 4-digit classes associated to the patent
- BASKNOW = dummy equal to 1 if the inventor of this 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 equal to 1 if the inventor of this 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 equal to 1 if the inventor of this patent checked 4 or 5 to the question "How important were customers or product users as sources of

[6] While our survey covered EPO patents with priority date 1993-1997, in our survey we ended up with a few patents having priority date 1998.

knowledge for the research that led to the patented inventions?" (1 = not important, 5 = very important)

- MANMONTH1-8 = eight dummies for man-months required for producing the patented invention (less than 1; 1-3; 4-6; 7-12; 13-24; 24-48; 48-72; more than 72)

We employed LWORDS and LIPC4 as measures of the generality of the patent. The use of LWORDS was suggested by some patent lawyers. They pointed out that a broad patent can be described in few words. A narrow patent has to cover many more details, and it has to define the object more precisely to distinguish it from other (narrow) inventions. The lawyers we discussed this with also suggested that a good patent attorney always tries to minimize the words of the main claim. Similarly, a broad patent spans many technologies. It will then list a larger number of IPC classes.

Another proxy for the generality of the patent is the number of claims (see 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 a matter of fact, 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, LWORDS and LIPC4 are probably 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 the 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 these are revised by the patent examiners. In our data we noted that the number of IPC associated with the patent reduce during the application revision process, which suggests that the patent examiners revise them. In our analysis we use the latest available number of IPC classes introduced in the patent document, which captures the influence of the patent examiners.

The dummies BASKNOW, PATKNOW, and CUSKNOW are additioanl 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 dummies for man-months measure the amount resources employed for producing the invention. We expect that the greater the resources involved the larger the expected value of the patent. The MAN-MONTH dummies however are potentially endogenous. We then showed regressions using both the man-month dummies and, in alternative, some variables that are likely to capture the amount of resources employed for the project without facing an equally severe endogeneity problem:

- LINVENTORS = log of the number of inventors listed in the patent
- PROJECT = a dummy taking the value 1 if 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
- INTFUND = a dummy taking the value 1 if the financing of the research leading to the patent came from internal funds of the applicant (including affiliated organizations)
- GOVFUND = a dummy taking the value 1 if the financing of the research leading to this patent came from Government Research Programmes or other government funds

The number of inventors in the patent is correlated with the size of the project. However, it is less project-specific than the man-months expressly employed for it. This is because larger organizations employ more researchers, and compared to smaller firms or even to academia they have fixed research assets in place (incuding greater difficulties in dismissing researchers, especially in Europe). As a result, it is easier for them to organize larger research groups, and in turn a larger number of inventors listed in the patent can be taken as a proxy for the ability to organize larger projects. Similarly, projects that are planned and organized explicitly for a given purpose reflect planning capabilities and tighter organizational structures which are normally associated with the ability to carry out larger proejcts. The internal and government fund dummies have the same features. The use of internal funds is typical of the larger firms, and it is again more organization- rather than project-specific compared to MAN-MONTHS. Similarly, the government often funds large projects, which would not be funded privately on a similar scale. Again, this proxies for larger project while not being project-specific as much as the resources devoted to a particular line of research.

Characteristics of the inventor

- AGE1-5 = five age class dummies (less than 30; 30-40; 40-50; 50-60; greater than 60)
- DEGREE1-5 = five academic degree dummies (secondary school or less; high school; BA; Master; PhD)
- MALE = dummy equal to 1 for male inventor
- LYEARINORG = log of the year in which the inventor joined the employer organization in which the research leading to the patent was conducted
- LPATINV = log of 1-19 size classes, with 1 = 1-5 patents (including the current patent); 2 = 5-10; 3 to 13 = from 10-20 to 110-120; 14 to 17 = 120-140 to 180-200; 18 = 200-300; 19 = more than 300
- COMP = dummy equal to 1 if the inventor received compensation for the patent
- MONEY = dummy equal to 1 if the inventor of this 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 equal to 1 if the inventor of this 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 equal to 1 if the inventor of this 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)

To our knowledge, no study has examined the effects of the inventors' characteristics on value or other aspects of the inventive activity. In particular, we are interested in understanding the extent to which inventors' characteristics are important in affecting the value of the invention after we control for the 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. In this respect, our analysis will assess how much such individual factors matter.

The variables LYEARINORG and LPATINV compare the impacts of the experience of the inventor inside the organization and his own innovation experience, as 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 the same information more objectively from the EPO patent data base. However, searching for inventors' names is not at all an easy matter, and several mistakes can be made because of mispelled names and the like, as Trajtenberg (2004) has recently 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.[7]

Finally, COMP, MONEY, CAREER, and PRESTIGE measure factors that can affect the effort made by the inventor in the research process. We use COMP and MONEY as proxies for the pecuniary motive. The former accounts for whether the inventor actually received compensation for this particular patent, while the latter asks generically whether the inventor's incentives to patent are motivated by monetary rewards. Broadly speaking we introduced both variables in our regression because they may span different dimensions of the same motive. In fact, COMP might be endogenous (because if a patent is more valuable the applicant organization might offer rewards to the inventors). However, MONEY is more likely to reflect an overall attitude towards compensating the inventors in a given organization. At any rate, when using only

[7] However, when using the actual number of past inventors' patents the empirical results did not change.

MONEY in our value regressions the results did not change. Similarly, CAREER and PRESTIGE provide a generic view of whether the inventor is motivated by career or prestige.

Characteristics of the location

- LGDPPOP = log of the 1994-1996 average GDP per capita of the NUTS3 region of the inventor's address in the patent
- LPOP = log of the 1994-1996 average population of the NUTS3 region of the inventor's address in the patent
- LAREA = log of the area of the NUTS3 region of the inventor's address in the patent
- LPATLOC = log of the 1994-1996 average number of patents of the NUTS3 region of the inventor's address in the patent

The most natural variables to assess the effect of a location on the value of the patents are its GDP per capita and the number of patents. We used the NUTS3 territorial level from the official EU territorial classification, which corresponds to the provincial level in Europe. The NUTS3 territorial level covers a main city (the provincial capital) and its enlarged metropolitan area including smaller towns and the countryside. This territorial level distinguishes quite well between large metropolitan areas and smaller cities or more rural environments. 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 used LPOP and LAREA separately as controls. We also employed NUTS3 patents in high-tech industries in lieu of and together with LPATLOC, but the results did not change.

3. Validating our Value Measure

3.1 Correlations with Other Indicators

In this Section we compare our self-reported measure of the value of patents to some commonly employed alternative indicators of the importance of patents. We start by regressing five indicators on the dummies for our VALUE intervals, and the following controls: country dummies for Germany, France, Italy, Netherlands, Spain, and the UK; our 30 dummies for specific industries/technologies; dummies for application years. The five indicators are: forward citations (FCIT); backward citations (BCIT); the number of patents filed with different patent authorities referring to the same invention, commonly labelled as "family size" (FAMSIZE); the number of claims in the patent (CLAIMS); a dummy denoting whether the patent was legally opposed (OPPO). Table 3 presents descriptive statistics for the five indicators. Table 4 shows the results of our regressions. Since the former four indicators are non-negative integers we run negative binomial regressions. We run probit for the dycothomous OPPO variable.

TABLE 3 AND 4 ABOUT HERE

From Table 4 both FCIT and BCIT exhibit an erratic trend as we move towards higher value intervals. The trend however is increasing on average. For example, when we regress FCIT or BCIT on the VALUE index (taking values 1-10) rather than the dummies for each category, along with the controls, the coefficient of VALUE is positive and statistically significant at the 5% confidence level. Yet, the erratic impact mirrors the fact that FCIT and BCIT are more strongly correlated with the technological importance of the patent rather than its economic value.

This is confirmed by the smoother trend of the VALUE interval dummies in the other three regressions. Lanjow and Schankerman (2004), among others, maintain that the number of patent authorities in which a given invention is applied for has a direct implications on costs (because each application is paid for), and therefore reflects more closely the economic value of the patent. Similarly, more valuable patents are more likely to be opposed, and a larger number of claims reflects a more valuable patent because of the stronger protection that they provide. As a matter of fact, it is noteworthy that in Table 4, the coefficients of the value dummies increase progessively in the FAMSIZE equation as we move towards higher intervals. The trend is systematic, not only reflecting a smooth increase, but also suggesting that our intervals represent progressively higher levels of the patent value. Only the very highest intervals entail a reduced impact of FAMSIZE. But categories 9 and 10 of the VALUE variable represent only 1.5% of all the patents with a valid answer to value question in the PatVal-EU survey. Not only they may reflect excessively high responses, but we could have lumped the top VALUE intervals in the eighth or even earlier categories and then obtained a smooth increase throughout. The CLAIMS and OPPO regressions entail similar results. Again, the increase is smooth up to some of the final categories. Here again the intervals from 7 to 10 represent only 7% of the total patents with valid responses for the value question in the PatVal-EU sample.

The correlation between our VALUE indicator and the other indicators is confirmed by Table 5, where we run an ordered probit regression with the VALUE dummies as the dependent variable and all the five indicators as regressors. We also include the technology, country and time dummies as controls. All the five indicators have a positive and statistically significant impact. This suggests that they span different dimensions of the VALUE indicator. For example, FCIT may contain "news" about the value of the patent that were not predicted when the patent was applied for, and therefore are not captured by the number of claims or the family size which is decided around the time of the application. Moreover, FCIT is more likely to capture unexpected technical features that give value to the patent, while legal oppositions, which also occur after the patent is applied for, may capture more economic dimensions of news in the value of patents.

TABLE 5 ABOUT HERE

3.2 Common Factor

To further assess the nature of our measure we estimated a common component drawn from the alternative indicators of the importance of patents. We basically reproduced the exercise performed by Lanjow and Schankerman (2004). We employed the same four indicators (FCIT, BCIT, FAMSIZE, CLAIMS) that they employ to construct the patent quality index. Our goal is to assess its correlation with the VALUE indicator. To some extent, this is a redundant exercise because the correlations between the four indicators and VALUE was already established in Table 5. However, it is worth showing that the results are confirmed under a different methodology and different assumptions.

We start by regressing the logs of our four indicators on technology, country, and year dummies.[8] We then retrieved the 4x4 covariance matrix of the errors. By using the notation employed by Lanjow and Schankerman (2004) the indicators' equations can be expressed as $y_{ki} = \sum_j \beta_j x_{ji} + u_{ki}$, where i refers to the ith observation, y_{ki} is the kth indicator, $\beta_j x_{ji}$ is the set of observed determinants of y_{ki} (the βs are the OLS coefficients), and u_{ki} is the stochastic component. The latter can be expressed as $u_{ki} = \lambda_k q_i + \varepsilon_{ki}$, where q_i is the common component, λ_k is its impact on the kth indicator, and ε_{ki} is an error term independent of q_i. By normalizing q_i to have zero mean and unit variance, the generic element of the covariance matrix $\mathbf{\Lambda}$ across the four u_k errors is $[\lambda_l \lambda_m + \sigma_{lm}]$ where l, m = 1,2,3,4, and σ_{lm} is the covariance between the ε terms. The predicted value of the latent variable q given the four indicators y_k is $E(q \mid \mathbf{y}) = \boldsymbol{y\Lambda^{-1}\lambda}$, where, apart from $\mathbf{\Lambda}$, $\boldsymbol{y}$ is the $n \times 4$ matrix of the n observations for the 4 indicators, and $\boldsymbol{\lambda}$ is the 4×1 vector of λs.

To obtain an estimate of the λs we used the observed covariance structure given by $\mathbf{\Lambda}$. In fact, given that the generic element of $\mathbf{\Lambda}$ is $[\lambda_l \lambda_m + \sigma_{lm}]$ the four λs cannot be identified.[9] If we assumed that $\sigma_{lm} = 0 \ \forall l, m$ – i.e. no correlation among the εs across the four indicators – the λs would be overidentified. With four indicators we can identify up to two σ_{lm} beyond the λs. We follow Lanjow and Schankerman (2004) and assume that there is a non-zero correlations between the errors in the FCIT and FAMSIZE equations. When we retrieved the λs under this assumption we found that the correlation between the errors of the BCIT and FAMSIZE equations was negative. This implied that the signs of the λs were inconsistent when we tried to obtain their estimates. As a result, we also assumed a non-zero covariance between the εs of BCIT and FAMSIZE. In other words, we assumed that the negative correlation between the errors of the two equation did not arise because of the common factor, but because of the correlation between the other error component. With this assumption, we could identify exactly the four λs.

[8] We selected the sample to be the same for all four equations. These are the observations for which we had data on all the variables in all four equations. We ended up with 6140 observations. Since FCIT and BCIT have zero values, we used *log(1+FCIT)* and *log(1+BCIT)*.

[9] The identification of the λs depends only on the covariance part of the $\mathbf{\Lambda}$ matrix. See Lanjow and Schankerman (2004).

Table 6 presents our OLS estimation of the latent component E(q | $\mathbf{y}$) regressed on the VALUE interval dummies and the technology, country and year dummies. The latent component increases progressively with the VALUE intervals as expected. The progressive increase is even smoother and more systematic than the one observed earlier for FAMSIZE, which suggests that it is capturing additional elements of correlation with VALUE even when compared with FAMSIZE itself.

TABLE 6 ABOUT HERE

3.3 Comparing Inventor and Manager Responses

One potential limitation of our VALUE measure is that it is reported by the inventors. The inventors may not be the best person to make such an assessment. Especially in the larger 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 the inventors may offer some biased response, 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, we also attempted to test potential biases in the inventors' responses compared to managers. 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*). Unlike other participants, who were academic units, the Ministry had better opportunities to seek for the proper manager or individual inside a firm who could provide the best answer to the value question. For a sample of patents the question about the value was then asked independently to the inventor and to a manager. Specifically, we obtained a sample of 354 patents for which we had the two answers. 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 90% of the patents the 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 some descriptive statistics of the responses by the inventors and the managers. From Table 7, the inventors exhibit a higher mean response.[10] 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, pride and other psychological factors are likely to induce the inventors to boost the results of their work. If so, it is 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

We performed some additional test on the different responses of the French inventors and managers. One hypothesis is that compared to the smaller firms the inventors in the large companies are 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 should be wider in the larger firms. Table 9 corroborates this hypothesis. The inventors in the larger firms exhibit a higher average difference in the

[10] 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 from these numbers.

evaluation of their patents' value with respect to their managers than in the smaller firms. The Table also shows that the inventors in academia and other non-profit research institutions behave like the small companies. 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 small firms and research institutions. In addition, one cannot reject the hypothesis that, pairwise, the three average differences in the inventor-manager responses are equal, and one cannot either reject the hypothesis that, pairwise, the three standard deviations of the distributions of the differences are equal. Finally, one cannot reject the hypothesis of the equality of the distributions according to the Kolmogorv-Smirnov and the Wilcoxon rank-sum (Mann-Whitney) test.

TABLES 9-10 ABOUT HERE

In sum, the slight overestimate of the inventor's assessment of the value of their patents compared to the managers seems to be produced by the inventors in the large firms. This also helps better understand our earlier remark about the fact that the inventors in the smaller firms are more likely to be biased in their assessment of the value of their patents. Our results suggest that this is not the case, and that their evaluations are even closer to those of their managers. Yet, it could be that in the smaller firms the managers are themselves more directly and closely involved with the invention that they are biased in their evaluations. 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 the small-medium firms are, respectively, 3.264 and 3.189 vis-à-vis 3.575 and 3.386 for the large firms. Thus, the absolute value of the evaluation for the managers in the small firms is even lower. Of course, these averages do not control for several other factors that may affect the expected value of patents in large and small firms. However, it suggests that simple statistics in the data do not entail a substantial overevaluation of the value classes in the small firms *vs*. the larger ones.

4. Value of Patents: Regression Results

Table 11 presents our ordered probit results. In the first column of Table 11 we estimate a regression that uses all the variables discussed in the previous section, and the MANMONTH dummies in lieu of LINVENTORS, PROJECT, INTFUND and GOVFUND. The second column of Table 3 shows our regression with the latter variables instead of the former. The third column includes all five sets of regressors. This column shows that when we include all the regressors, the significance of LINVENTORS, PROJECT, and GOVFUND in the second column of Table 11 disappears. The MANMONTH dummies seem to capture their effect. This suggests that LINVENTORS, PROJECT, and GOVFUND are good proxies for MANMONTH. Since the results of the first two columns of Table 11 are fairly similar, we focus our discussion below on the second column of Table 11.

TABLE 11 ABOUT HERE

Impact of characteristics of the applicant organization

Table 11 shows that, all else held constant, the patents held by individuals or small firms are more valuable. The baseline dummy in the regression is LARGEFIRM. Both the individual and small firm dummies are positive and statistically significant. Moreover, the impact of the INDIVIDUAL dummy is higher than that of SMALLFIRM. While a caveat to this result is that the individual inventors may overstate the value of their patents, it also conform to the hypothesis that because of the costs of patenting and managing patent portfolios more generally, the large firms face smaller marginal costs for an additional patent, while the individuals or the small firms only patent valuable inventions. Our results also suggest that the medium firms behave like the large firms, while non-profit research organizations, particularly universities and government research labs, patent inventions that are even less valuable than those of the larger firms.

In fact, given the way we stated the question about the value of the patents, our results suggest that small firms and individuals will ask on average for a higher price to part from their patent rights, while the larger firms, and the more so the academic or government research labs, will charge a smaller price for their licenses. This reflects on the one hand the fact that, as noted, when they patent, the smaller firms and the individuals patent more valuable inventions. The universities and the government reseach labs, on the other hand, patent less valuable inventions than the firms. However, this may also reflect the fact that they do not have the resources, or the incentives, to undertake the long and costly innovation development activities to actually realize the economic value of their inventions. As a result, they are willing to give up the patent right at a lower price because to them the invention is not as valuable as to another organization that owns the proper assets for development and commercialization.

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

Impact of characteristics of the patent or the research process

Given all our controls, there is no impact left for the generality of the invention. In the second column of Table 11, both LWORDS and LIPC4 are statistically insignificant. We also find that whether there is one or more applicants to the patent (DAPPL), as a proxy for formal collaborations, is not important.

By contrast, the important factor here is the scale of the research project. All our four proxies for the size of the investment – LINVENTORS, PROJECT, INTFUND, GOVFUND – are positive and significant. Similarly, in the first column of Table 11, the MANMONTH dummies were significant and their coefficients increase as we move from the lower dummies, indicating smaller man-months, to the higher ones. The result that projects of larger size produce more valuable patents is intriguing also because it helps nail down the role of serendipity in research, which is often raised to point out its vagueness and unpredictability. Be that as may, the fuzziness of research should not be exaggerated. While invention has some natural uncertainty, yet there is a systematic correlation between the scale of the resources invested in the project and the value of its output. Moreover, the scale of the resources seem to be quite important compared to other elements that characterize the nature of the research output, like the generality of invention.

Table 11 also shows that other things being equal patents by UK inventors are on average more valuable. The application year dummies are not jointly significant. This is only to be expected. 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, and hence for technological opportunities in different areas. By contrast, we find differences across technologies. Table 12 reports the estimated sector dummies in the three regressions of Table 11. They are estimated as differences from the baseline sector "Electrical devices, electrical engineering, electrical energy". Most of the differences in the estimated coefficients of our technology class dummies are in the expected directions. Thus, for example, after our controls, pharmaceuticals and biotechnology are the two sectors with the highest dummy coefficient. It is well known that they are both industries in which patents are quite important to protect innovations (e.g. Levin *et al*, 1987; Gambardella, 1995; Arora and Gambardella, 1990). Another sector with a high impact of the technology dummy is semiconductors, which is also known to entail more valuable patents than in other industries (e.g. Hall and Ziedonis, 2001). Similarly, we know that patents are particularly effective in the chemical technologies, and we find that many chemical technology dummies exhibit a higher impact than other industries.

TABLE 12 ABOUT HERE

Impact of inventors' characteristics

Our results in Table 11 suggest that the inventors' characteristics are a critical determinant of the value of the patents. In this respect, our analysis strengthens the view that the invention process is a business wherein individual talents and competencies matter. While this may be natural, it is less obvious in a comparative perspective. Most notably, we find that, apart from the scale of the resources invested in the project, the individuals' characteristics are important relative to organizational or other factors. There are differences associated with large firms, small firms, universities, or across countries and technologies. But by and large our results suggests that the value of patents is to a good extent a matter of providing competent and expert individuals with the right amount of resources, and as we shall see, with proper motivations and incentives.

Specifically, Table 11 first shows that gender does not matter. The estimated coefficient of the MALE dummy entails that women are not better than men at making valuable patents. By contrast, the past patenting experience of the inventor, LPATINV, matters. There is some potential endogeneity here, even though the problem is probably less severe than if we were estimating, for instance, the impact of past patents on the probability of making a new patent. As we are willing to make the assumption that this endogeneity is not dramatic, we conclude that the inventive experience of the researchers is an important predictor of the value of patents. Moreover, this results compares to the earlier one about the inventive experience (number of patents) of the organization. Our empirical results show that it is the individual and not the organizational inventive experience that matters for the value of the patents – that is, the efficiency of the organization in the invention process does not seem to be a good substitute for the individuals' talents. We also find that the experience of the individual within the same organization, LYEARINORG, has the expected effect, i.e. people hired in more recent years are less likely to make valuable patents, even though the impact is statistically significant only at $p < 10\%$.

In addition, individuals' motivations matter. Inventors who are compensated for their patents make more valuable inventions, other things being equal. The impact of the COMP dummy is positive and statistically significant, and so is the MONEY motivation. Thus, both our measure of the pecuniary incentives to invent are sizable and statistically significant. The CAREER dummy is also sizable and significant, while the PRESTIGE dummy is less important. All in all, motivations seem to be important, and particularly the inventors put greater efforts into research projects that provide them with pecuniary or career rewards.

We also find that there is some age profile in the invention process. Other things being equal, the probability of making valuable inventions increases with age up to 50-60, and declines after 60. Interestingly enough, Table 11 shows that there is a small but systematic increase in the estimated coefficients of the dummies for the academic degree of the 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 inventors' experience, the motivation that is provided for their inventions, and the resources that they can deploy for the project.

Impact of inventions' location

Finally, Table 11 shows that the dummies for the NUTS3 locations are statistically insignificant. This suggests that the potential externalities that can arise in large metropolitan areas do not encourage more valuable patents, after the various controls that we use in this analysis.

5. CONCLUSIONS

We employ an unusually comprehensive dataset of inventors' responses to questions about the economic value of patents. We find that, other things being equal, the individual inventor's characteristics are an important determinant of the economic value of patents. For example, not only is the inventive experience of the inventor an important determinant of patent value, as compared for instance to the inventive experience of the organization, but other inventor's characteristics seem to matter. In particular, individual's incentives seem to produce more valuable patents, thus inventors respond to monetary rewards for patenting as well as to potential career advances. These incentives appear to spur valuable inventions more than academic motives, like the search for prestige and reputation.

Our study then suggests that compared to organizational design (e.g. large *vs* small firms), local externalities, or other project characteristics, the inventive activity is largely the province of talented individuals. Not only this explains the importance of human capital in recent years, but also the increasing attention by firms or other research organizations for attracting talents.

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Table 1: Variables employed in the empirical analysis, descriptive statistics

	Mean	*St.Dev.*	*Min*	*Max*	*N.obs.*
VALUE	3.835	1.797	1	10	7624
LARGEFIRM	0.696	0.460	0	1	7387
INDIVIDUAL	0.059	0.235	0	1	7624
SMALLFIRM	0.109	0.311	0	1	7460
MEDIUMFIRM	0.091	0.287	0	1	7460
UNIV	0.030	0.172	0	1	7460
GOV	0.020	0.140	0	1	7460
OTHER	0.014	0.117	0	1	7460
AGE1	0.043	0.204	0	1	7518
AGE2	0.310	0.463	0	1	7518
AGE3	0.325	0.468	0	1	7518
AGE4	0.269	0.444	0	1	7518
AGE5	0.052	0.222	0	1	7518
DEGREE1	0.029	0.168	0	1	7541
DEGREE2	0.123	0.329	0	1	7541
DEGREE3	0.173	0.378	0	1	7541
DEGREE4	0.230	0.421	0	1	7541
DEGREE5	0.445	0.497	0	1	7541
MALE	0.980	0.140	0	1	7584
YEARINORG (^)	1980.647	10.426	1923	2003	7465
PATINV (^) (+)	2.678	2.454	1	19	7251
PATAPP (^)	33.452	71.927	1	287	7624
COMP	0.421	0.494	0	1	6472
MONEY	0.407	0.491	0	1	6957
CAREER	0.378	0.485	0	1	6858
PRESTIGE	0.541	0.498	0	1	7071
BASKNOW	0.433	0.496	0	1	7328
PATKNOW	0.411	0.492	0	1	7265
CUSKNOW	0.515	0.500	0	1	7340
WORDS (^)	163.241	101.816	5	1595	7619
IPC4 (^)	1.432	0.697	1	7	7622
APPL (*)	1.081	0.317	1	4	7621
INVENTORS (^)	2.261	1.449	1	15	7622
PROJECT	0.372	0.483	0	1	7395
INTFUND	0.894	0.307	0	1	6911
GOVFUND	0.083	0.276	0	1	6911
MANMONTH1	0.131	0.337	0	1	7161
MANMONTH2	0.214	0.411	0	1	7161

MANMONTH3	0.193	0.395	0	1	7161
MANMONTH4	0.180	0.384	0	1	7161
MANMONTH5	0.150	0.357	0	1	7161
MANMONTH6	0.083	0.276	0	1	7161
MANMONTH7	0.019	0.137	0	1	7161
MANMONTH8	0.030	0.170	0	1	7161
GDPPOP (^) (	22765.2	9173.5	8677.9	76910.8	7263
POP (^) (	764.1	832.2	19.9	5009.3	7318
AREA (^) (Km2)	1858.3	2201.3	35.6	17252	7318
PATLOC (^)	127.6	140.3	0.723	575.1	7262
UK	0.179	0.384	0	1	7624
DE	0.402	0.490	0	1	7624
IT	0.138	0.345	0	1	7624
ES	0.017	0.130	0	1	7624
FR	0.129	0.336	0	1	7624
NL	0.133	0.340	0	1	7624

(^) Absolute value of the variable (not in logs)

(*) Number of patent applicants

(+) Classes 1-19

Table 2: ISI technological class dummies, descriptive statistics

Technology ISI Classes (30 Technology Class Dummies)	Mean	StDev	Min	Max	N.Obs.
Electrical devices, electrical engineering, electrical energy	0.074	0.262	0	1	7622
Audio-visual technology	0.019	0.138	0	1	7622
Telecommunications	0.030	0.169	0	1	7622
Information technology	0.023	0.149	0	1	7622
Semiconductors	0.010	0.099	0	1	7622
Optics	0.018	0.133	0	1	7622
Analysis, measurement, control technology	0.060	0.237	0	1	7622
Medical technology	0.027	0.162	0	1	7622
Nuclear engineering	0.057	0.231	0	1	7622
Organic fine chemistry	0.052	0.222	0	1	7622
Macromolecular chemistry, polymers	0.018	0.134	0	1	7622
Pharmaceuticals, cosmetics	0.007	0.085	0	1	7622
Biotechnology	0.034	0.180	0	1	7622
Agriculture, food chemistry	0.012	0.108	0	1	7622
Chemical and petrol industry, basic materials chemistry	0.034	0.182	0	1	7622
Materials, metallurgy	0.033	0.178	0	1	7622
Chemical engineering	0.016	0.125	0	1	7622
Surface technology, coating	0.056	0.231	0	1	7622
Materials processing, textiles, paper	0.022	0.146	0	1	7622
Environmental technology	0.016	0.124	0	1	7622
Handling, printing	0.036	0.186	0	1	7622
Agricultural and food processing, machinery and apparatus	0.029	0.167	0	1	7622
Thermal processes and apparatus	0.046	0.209	0	1	7622
Machine tools	0.077	0.266	0	1	7622
Engines, pumps, turbines	0.021	0.145	0	1	7622
Mechanical Elements	0.070	0.255	0	1	7622
Trasport	0.004	0.067	0	1	7622
Space technology weapons	0.006	0.076	0	1	7622
Consumer goods and equipment	0.051	0.220	0	1	7622
Civil engineering, building, mining	0.044	0.204	0	1	7622

Table 3: Alternative indicators, descriptive statistics

	Mean	*St.Dev.*	*Min*	*Max*	*N.obs.*
FCIT	0.929	1.847	0	42	7621
BCIT	4.033	2.485	0	19	5327
FAMSIZE	6.889	3.996	1	31	7618
CLAIMS	10.806	7.030	1	131	7618
OPPO	0.084	0.278	0	1	7621

Table 4: Relations between VALUE, FCIT, BCIT, FAMSIZE, CLAIMS, OPPO

	Dependent Variables.				
	FCIT (NegBin)	*BCIT (NegBin)*	*FAMSIZE (NegBin)*	*CLAIMS (NegBin)*	*OPPO (Probit)*
CONST	-1.545*** (0.000)	1.352*** (0.000)	1.727*** (0.000)	2.403*** (0.000)	-1.733*** (0.000)
VALUE2	0.057 (0.475)	0.060* (0.063)	-0.018 (0.473)	-0.024 (0.407)	0.079 (0.426)
VALUE3	0.027 (0.741)	0.051 (0.108)	0.048* (0.053)	0.011** (0.029)	0.220** (0.021)
VALUE4	0.101 (0.203)	0.058* (0.067)	0.105*** (0.000)	0.059** (0.042)	0.241*** (0.010)
VALUE5	0.157* (0.057)	0.075** (0.031)	0.152*** (0.000)	0.101*** (0.002)	0.282*** (0.004)
VALUE6	0.063 (0.558)	0.068* (0.074)	0.210*** (0.000)	0.132*** (0.000)	0.490*** (0.000)
VALUE7	0.200* (0.095)	0.153*** (0.006)	0.224*** (0.000)	0.193*** (0.000)	0.349** (0.011)
VALUE8	-0.049 (0.787)	0.047 (0.535)	0.421*** (0.000)	0.170*** (0.003)	0.347** (0.041)
VALUE9	0.638** (0.042)	0.051 (0.645)	0.370*** (0.000)	0.091 (0.309)	-0.002 (0.994)
VALUE10	0.179 (0.362)	0.157 (0.111)	0.289*** (0.000)	-0.045 (0.616)	-0.140 (0.681)
Overdispersion (α)	1.438*** (0.000)	0.060*** (0.000)	0.074*** (0.000)	0.225*** (0.000)	--
30 Technology Class Dummies	Yes (Sig.)	Yes (Sig.)	Yes (Sig.)	Yes (Sig.)	Yes (Sig.)
Country Dummies	Yes (Sig.)	Yes (Sig.)	Yes (Sig.)	Yes (Sig.)	Yes (Sig.)
Application Year Dummies	Yes (Not Sig.)	Yes (Not Sig.)	Yes (Not Sig.)	Yes (Not Sig.)	Yes (Not Sig.)
N. Observations	7617	5324	7618	7617	7583
Log-Lik Function	-9052.8	-11606.3	-18952.4	-23776.4	-2067.0

* $p < 10\%$; ** $p < 5\%$; *** $p < 1\%$; p-values based on robust standard error. Overdispersion parameter α for Neg. Bin. is variance = $[1+\alpha\cdot\exp(\text{mean})]\cdot\text{mean}$, viz. $\alpha=0 \Rightarrow$ Poisson.

Table 5: Relations between VALUE, FCIT, BCIT, FAMSIZE, CLAIMS, OPPO

	Dependent Variable *VALUE CLASSES* *(Ordered Probit)*
FCIT	0.025*** (0.001)
BCIT	0.016*** (0.010)
FAMSIZE	0.050*** (0.000)
CLAIMS	0.006** (0.015)
OPPO	0.158*** (0.001)
30 Technology Class Dummies	Yes (Sig.)
Country Dummies	Yes (Sig.)
Application Year Dummies	Yes (Not Sig.)
N. Observations	5323
Log-Lik Function	-10008.8

* $p < 10\%$; ** $p < 5\%$; *** $p < 1\%$; p-values based on robust standard error. Estimations include constant terms for each value class.

Table 6: Relations between the latent component *q* and VALUE

	Dependent Variable q (OLS)
CONST	4.403*** (0.000)
VALUE2	0.028 (0.600)
VALUE3	0.099** (0.056)
VALUE4	0.244*** (0.000)
VALUE5	0.393*** (0.000)
VALUE6	0.394*** (0.000)
VALUE7	0.526*** (0.000)
VALUE8	0.664*** (0.000)
VALUE9	0.705*** (0.000)
VALUE10	0.555*** (0.005)
30 Technology Class Dummies	Yes (Sig.)
Country Dummies	Yes (Sig.)
Application Year Dummies	Yes (Not Sig.)
N. Observations	5323
R^2	0.187

* $p < 10\%$; ** $p < 5\%$; *** $p < 1\%$; p-values based on robust standard error.

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

Value reported by	**Mean**	*Std. Err.*	*Std. Dev.*	*95% Conf. Interval*	*Quantiles* Min; Q1; Q2; Q3; Max
Inventors	3.494	0.088	1.650	3.322; 3.667	1; 2; 3; 4; 9
Managers	3.345	0.085	1.591	3.178; 3.511	1; 2; 3; 4; 9
Difference	0.149	0.085	1.608	-0.018; 0.318	-5; -1; 0; 1; 6

N. of obs. = 354. Q1-Q3=1st, 2nd, 3rd quartiles.

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 (H_0: mean diff. = 0)	
• two tail test	0.081(*)
• one tail test (mean inventors > mean managers)	0.040(**)
Two tail F-test for difference between St.Dev. (H_0: St.Dev. = 0)	0.500
Two sample Kolmogorov-Smirnov test for equality of distributions	0.754
Two-sample Wilcoxon rank-sum (Mann-Whitney) test for equality of distributions	0.285

N. of obs. = 354. (*) Nul hypothesis rejected at p < 10%; (**) Nul 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. Err.*	*Std. Dev.*	*95% Conf. Interval*	*Quantiles* Min; Q1; Q2; Q3; Max
LARGE (207)	0.188	0.113	1.630	-0.035; 0.412	-5; -1; 0; 1; 6
SME (106)	0.075	0.151	1.560	-0.225; 0.376	-4; -1; 0; 1; 6
OTHER (36)	0.083	0.286	1.713	-0.496; 0.663	-5; -1; 0; 1; 4

LARGE = Firms with > 250 employees (dummy LARGEFIRM in Table 1); SME = Small-Medium Enterprises, less than 250 employees (dummies SMALLFIRM, MEDIUMFIRM); OTHER = all other types (universities, govt research labs; dummies UNIVERSITY GOV, OTHER)

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 inventors and managers responses by organization type (H_0: mean diff. = 0)	
• LARGE (207 obs.)	
○ two-tail test	0.098(*)
○ one-tail test (mean inventors > mean managers)	0.049(**)
• SME (106 obs.)	
○ two-tail test	0.619
○ one-tail test (mean inventors > mean managers)	0.310
• OTHER (36 obs.)	
○ two-tail test	0.772
○ one-tail test (mean inventors > mean managers)	0.386
Two tail t-test for equal difference in mean responses of inventors and managers by pairs of organization types (H_0: mean diff. org.A = mean diff. org.B)	
• LARGE; SME	0.557
• LARGE; OTHER	0.724
• SME; OTHER	0.980
Two tail F-test for equal standard deviations by pairs of organization types (H_0: st. dev. of diff. org.A = st. dev. of diff. org.B)	
• LARGE; SME	0.601
• LARGE; OTHER	0.703
• SME; OTHER	0.498
Two sample Kolmogorov-Smirnov test for equality of distributions	
• LARGE; SME	0.590
• LARGE; OTHER	0.946
• SME; OTHER	0.959
Two-sample Wilcoxon rank-sum (Mann-Whitney) test for equality of distributions	
• LARGE; SME	0.454
• LARGE; OTHER	0.845
• SME; OTHER	0.780

(*) Nul hypothesis rejected at $p < 10\%$; (**) Nul hypothesis rejected at $p < 5\%$

Table 11: Ordered Probit Estimation, dependent variable VALUE (1-10)

	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value
INDIVIDUAL	0.231***	0.007	0.308***	0.000	0.240***	0.009
SMALLFIRM	0.125**	0.024	0.119**	0.031	0.123**	0.032
MEDIUMFIRM	0.018	0.759	0.054	0.361	0.029	0.639
UNIV	-0.504***	0.000	-0.474***	0.000	-0.487***	0.000
GOV	-0.353**	0.010	-0.328**	0.015	-0.323**	0.027
OTHER	-0.041	0.797	-0.041	0.807	0.003	0.984
AGE2	0.149*	0.054	0.180**	0.019	0.160**	0.044
AGE3	0.122	0.133	0.176**	0.029	0.131	0.117
AGE4	0.157*	0.074	0.220**	0.011	0.176**	0.049
AGE5	0.008	0.945	0.140	0.251	0.016	0.896
DEGREE2	0.041	0.721	0.018	0.869	0.032	0.785
DEGREE3	0.079	0.448	0.047	0.630	0.069	0.517
DEGREE4	0.062	0.540	0.033	0.737	0.055	0.604
DEGREE5	0.121	0.234	0.093	0.339	0.094	0.375
MALE	0.118	0.361	0.078	0.554	0.114	0.399
LYEARINORG	-10.521**	0.011	-7.002*	0.094	-9.177**	0.034
LPATAPP	-0.081	0.251	-0.009	0.328	0.008	0.381
LPATINV	0.120***	0.000	0.081***	0.002	0.122***	0.000
COMP	0.060*	0.097	0.080**	0.028	0.074**	0.046
MONEY	0.082**	0.024	0.117***	0.001	0.093**	0.014
CAREER	0.115***	0.002	0.099***	0.008	0.102***	0.007
PRESTIGE	0.048	0.154	0.048	0.160	0.053	0.134
BASKNOW	0.038	0.287	0.117***	0.001	0.057	0.121
PATKNOW	-0.024	0.482	-0.023	0.513	-0.033	0.353
CUSKNOW	0.061*	0.059	0.091***	0.005	0.069**	0.040
LWORDS	-0.019	0.513	-0.005	0.871	-0.023	0.437
LIPC4	-0.031	0.434	-0.041	0.301	-0.050	0.221
DAPPL	0.021	0.760	0.028	0.692	0.017	0.813
LINVENTORS	--	--	0.066**	0.026	-0.009	0.762
PROJECT	--	--	0.099***	0.004	-0.016	0.653
INTFUND	--	--	0.138**	0.022	0.126	0.048
GOVFUND	--	--	0.140**	0.031	0.028	0.668
MANMONTH2	0.115**	0.032	--	--	0.109*	0.054
MANMONTH3	0.351***	0.000	--	--	0.370***	0.000
MANMONTH4	0.471***	0.000	--	--	0.483***	0.000
MANMONTH5	0.535***	0.000	--	--	0.562***	0.000
MANMONTH6	0.678***	0.000	--	--	0.698***	0.000

MANMONTH7	0.692***	0.000	--	--	0.735***	0.000
MANMONTH8	1.013***	0.000	--	--	1.001***	0.000
LGDPPOP	0.011	0.871	0.039	0.575	0.028	0.696
LPOP	-0.011	0.727	0.028	0.378	0.003	0.930
LAREA	0.006	0.747	0.002	0.914	-0.001	0.980
LPATLOC	-0.017	0.465	-0.043*	0.076	-0.025	0.309
DE	-0.401***	0.000	-0.483***	0.000	-0.431***	0.000
IT	-0.074	0.303	-0.128*	0.066	-0.094	0.200
ES	0.053	0.721	0.066	0.638	0.036	0.809
FR	-0.694***	0.000	-0.752***	0.000	-0.826***	0.000
NL	-0.081	0.210	-0. 096	0.131	-0.079	0.230
30 Technology class dummies	Yes	Sig.	Yes	Sig.	Yes	Sig.
Application yr. Dummies	Yes	Not Sig.	Yes	Not Sig.	Yes	Not Sig.
N. of obs. Log of Lik. Function	4461 -8363.1		4398 -8353.5		4165 -7806.1	

Estimations include constant terms for each value class.

* p < 10%; ** p < 5%; *** p < 1%. p-values based on robust standard error.

Table 12: Estimated impacts of the technology class dummies from the ordered probits of Table 11

	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value
Audio-visual technology	-0.031	0.789	0.004	0.974	-0.050	0.685
Telecommunications	-0.081	0.424	-0.113	0.289	-0.159	0.138
Information technology	-0.183	0.104	-0.218**	0.058	-0.248**	0.040
Semiconductors	0.182	0.310	0.222	0.234	0.123	0.528
Optics	-0.018	0.892	0.099	0.456	0.010	0.941
Analysis, measurement, control technology	-0.077	0.355	-0.051	0.542	-0.119	0.168
Medical technology	0.090	0.404	0.114	0.291	0.082	0.459
Organic fine chemistry	0.128	0.142	0.238***	0.007	0.105	0.241
Macromolecular chemistry, polymers	0.087	0.284	0.199**	0.017	0.073	0.388
Pharmaceuticals, cosmetics	0.379***	0.007	0.463***	0.002	0.325**	0.026
Biotechnology	0.234	0.249	0.398**	0.037	0.229	0.271
Materials, metallurgy	0.165*	0.095	0.211**	0.040	0.127	0.220
Agriculture, food chemistry	0.079	0.608	0.255*	0.095	0.116	0.450
Chemical and petrol industry, basic materials chemistry	0.165	0.104	0.179*	0.075	0.113	0.276
Chemical engineering	0.231**	0.019	0.238**	0.014	0.212**	0.038
Surface technology, coating	-0.111	0.365	-0.016	0.893	-0.143	0.259
Materials processing, textiles, paper	0.150*	0.078	0.220**	0.011	0.131	0.136
Thermal processes and apparatus	-0.013	0.913	0.028	0.821	-0.045	0.716
Environmental technology	-0.013	0.921	0.031	0.817	-0.066	0.641
Machine tools	0.029	0.783	0.091	0.401	0.008	0.942
Engines, pumps, turbines	0.215**	0.028	0.152	0.137	0.155	0.126
Mechanical Elements	0.114	0.189	0.038	0.668	0.057	0.529
Handling, printing	0.006	0.939	-0.044	0.562	-0.041	0.592
Agricultural and food processing, machinery and apparatus	-0.358***	0.003	-0.217*	0.087	-0.330***	0.009
Trasport	0.093	0.244	0.085	0.297	0.046	0.578
Nuclear engineering	0.069*	0.784	0.179	0.496	0.056	0.827
Space technology weapons	0.339*	0.084	0.337	0.160	0.335	0.161
Consumer goods and equipment	-0.073	0.436	-0.071	0.445	-0.096	0.316
Civil engineering, building, mining	0.045	0.657	0.042	0.675	0.008	0.939

* $p < 10\%$; ** $p < 5\%$; *** $p < 1\%$. p-values based on robust standard error.

Figure 1: Distribution of patent values

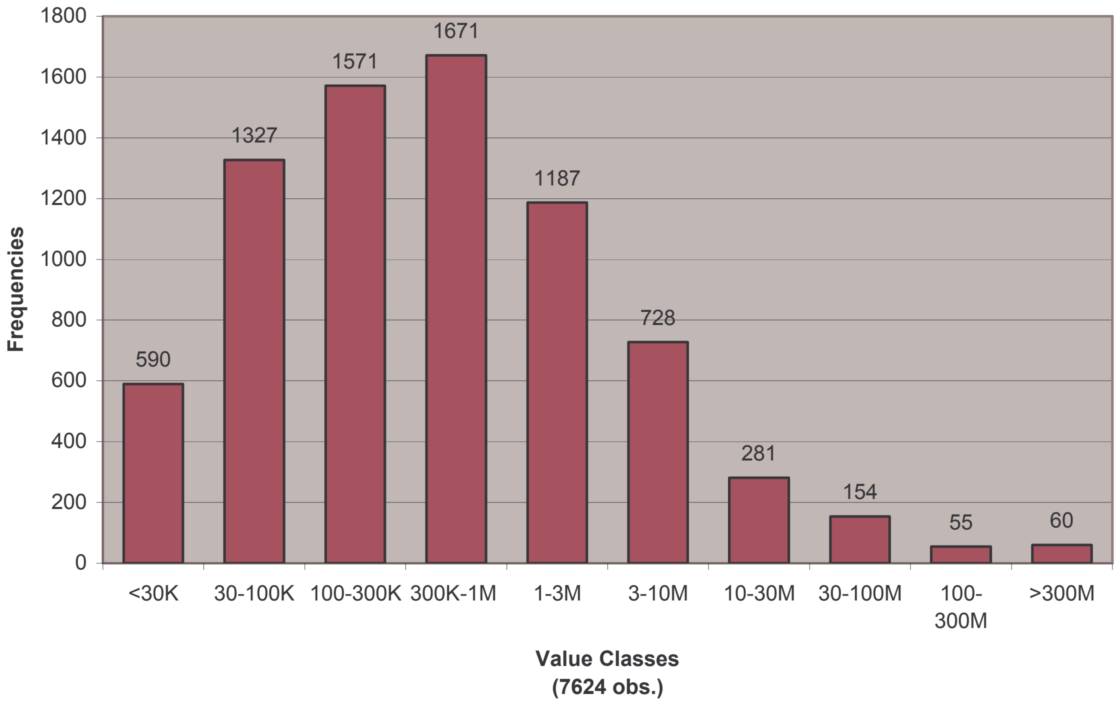

Figure 2: Distribution of patent values, responses by French inventors and managers

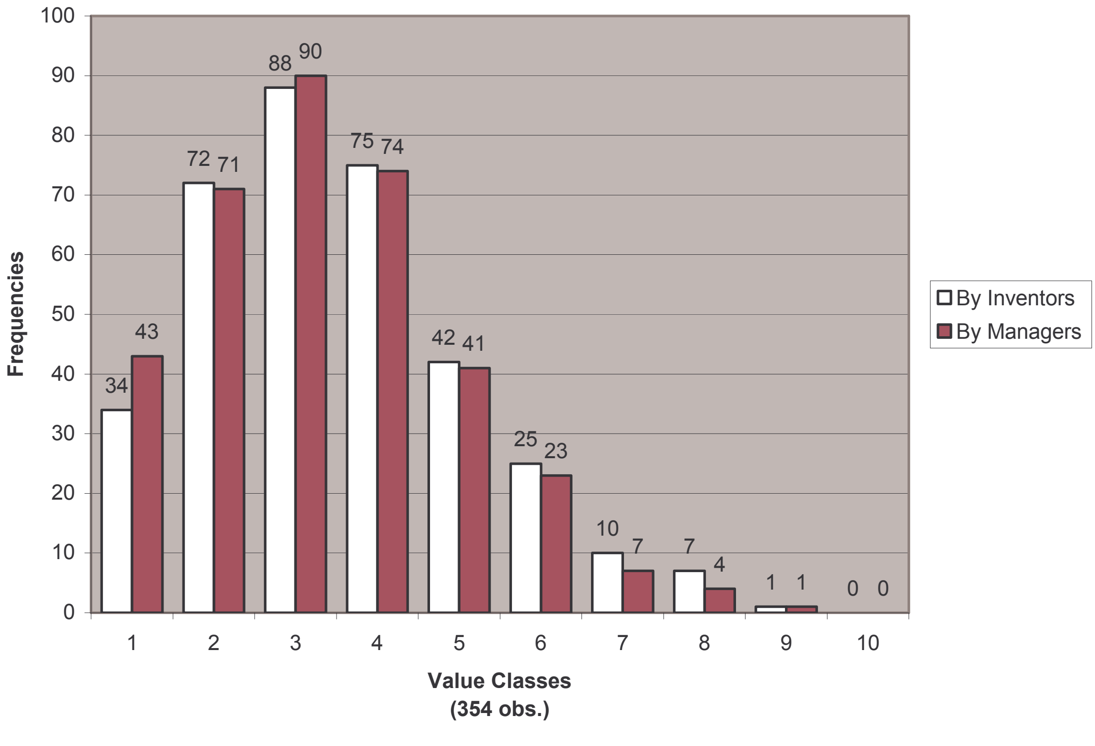

Figure 3: Differences in the responses of Inventors and Managers