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"Stacking" and "picking" inventions: The patenting behavior of European inventors

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Abstract

By using a sample of 793 inventors drawn from the PatVal-EU dataset, this paper explores three aspects of patent production at the individual inventor level: (1) the number of EPO patents that the inventors produce; (2) the average value of their inventions; (3) the production of the most valuable patents. By jointly estimating the three equations we find that the inventors' level of education, employment in a large firm, and involvement in large-scale research projects positively correlate with *quantity*. Yet, apart from the size of the research project, none of these factors *directly* influence the expected *value* of the inventions. They do, however, have an *indirect* influence, as we find that the number of patents explains the probability of producing a technological hit (the maximum value). Also, there is no regression to the mean in the invention process at an individual level, as the number of inventions that an inventor produces is not correlated with the average value.

Keywords: Inventor; Productivity; Number of patents; Patent value

1. Introduction

Invention and human capital are key factors for the growth of firms and for economic growth more generally. Yet, little is known about the key actors in this process – the industrial inventors – and the determinants of their productivity.

Traditional contributions focus on scientists and use scientific publications as a measure of their research output (for an overview, see Stephan, 1996). They show that the distribution of the scientists' productivity is skewed (Lotka, 1926; De Solla Price, 1963; Allison and Stewart, 1974; Turner and Mairesse, in press), and that age and vintage matter, with scientists becoming less productive as they get older (Oster and Hamermesh, 1998; Levin and Stephan, 1991; Cole, 1979). This holds after controlling for individual fixed effects that proxy for differences in motivation and ability. Our knowledge about industrial inventors is sparser. The difficulty to obtain information about individual inventors has prevented previous research from performing systematic empirical studies on this matter. The existing evidence is based on small samples, specific industries and firms (e.g., Narin and Breitzman, 1995; Ernst et al., 2000; Tijssen, 2002).

By relying on novel and detailed information from a large sample of European inventors (PatVal-EU, 2005), our paper explores the determinants of the *quantity* and *value* of the patents that they produce. In fact, inventors' productivity may take various forms. While the number of patents that they develop is one form, the inventors often acquire visibility for the technological

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and economic importance of their inventions, and sometimes their reputation depends on one or several, major achievements (Jones, 2005). This calls for an indicator of the technological and economic importance of the inventions. We start by using the number of citations that the patents have received within 5 years of their publication date (i.e., forward citations). Alternatively, by combining different patent indicators, we extract a composite index – i.e., a common component – that proxies for the technological and economic importance of the inventions, as in Lanjouw and Schankerman (2004). We then measure inventors' research output as follows:

1. Number of patents that the inventors contributed to inventing and that were applied for at the European Patent Office (EPO) in the period 1988–1998.
2. Average value of these inventions as measured by the average number of forward citations across each inventor's patents, and alternatively, by the average common component indicator.
3. Maximum value of the patents invented by the individual inventor, i.e., the inventor's patent with the largest number of forward citations, and alternatively, with the highest level of the common component indicator.

The empirical investigation uses a sample of 793 European inventors. Information on individual characteristics is drawn from the PatVal-EU survey that interviewed the inventors of 9017 EPO patents with a priority date in the years 1993–1997. Information on all the patents that the 793 individuals contributed to inventing and that were applied for at the EPO in 1988–1998 is collected from the EPO database. We jointly estimate three equations at the inventor level with (1)–(3) above as dependent variables. Our covariates are individual, firm, industry, and country characteristics. To identify the effect of the number of patents on the expected average and maximum value of the inventions we exploit information contained in the variance–covariance matrix of the residuals of the system of three equations.

The paper is organized as follows. We first provide an overview of the background literature in Section 2. Then we present the data, describe the estimation procedure, and show the results of the empirical tests (Sections 3–5). Section 6 summarizes the results and draws some conclusive remarks.

2. Background literature

The determinants of research productivity over a researcher's life cycle have been studied in the economic literature as well as in other disciplines. Pioneering work by Lotka (1926) shows that research productivity is concentrated among only a few individuals, regardless of the scientific field. Other authors confirm these findings and explain them with differences in the distribution of ability among scientists, and with the allocation of recognition and resources to the most productive individuals that make them even more productive – the "Matthew Effect" – whereby an initial success entails increasing productivity and reputation (Merton, 1968; Allison and Stewart, 1974; Cole, 1979; David, 1994).

Yet other authors show that age matters in many disciplines with older scientists becoming less productive (Dalton and Thompson, 1971; Goldberg and Shenhav, 1984). Levin and Stephan (1991), for example, examine the research productivity of scientists over their life cycle in six scientific areas, and find that it declines over time. Oster and Hamermesh (1998) follow the careers of 208 economists in the economic departments of 17 top research institutions who received PhD degrees between 1959 and 1983. They provide evidence that publishing diminishes with age. They also demonstrate the presence of persistent heterogeneity among individuals: the most productive economists early in their careers keep producing high-value research (though at a lower rate) as they become older. In a cross-section analysis of American scientists, Cole (1979) finds that age is concavely related to the quantity and quality of their productivity. Turner and Mairesse (in press) explore the differences in productivity among French condensed matter physicists between 1986 and 1997 in terms of the number and impact of their publications. They find a strong impact of individual and institutional characteristics. For the same sample of scientists, Hall et al. (2005) try to disentangle the impact of cohort, age, and period effects on researcher productivity.

Existing evidence about industrial inventors is much more limited compared to academic scientists, and it is based on small-scale samples, and specific industries and firms. Narin and Breitzman (1995) tested Lotka's inverse square law of productivity on a sample of inventors in the R&D departments of four companies in the semiconductor industry. Similarly, Ernst et al. (2000) studied the research productivity of inventors in 43 German companies, both in terms of quantity and value of their patents (see also Ernst, 1998 for a study at the firm level).[1] This literature confirms that the distribution of

[1] From a different point of view, Breschi et al. (2007) investigate the relationship between publishing and patenting by Italian academic inventors and find a strong and positive relationship between the two research outputs.

productivity among industrial inventors is skewed. However, because of the lack of information at the individual level, the reasons behind these disparities are not yet clear.

Our paper contributes to studying the relationship between the research output of the European industrial inventors and its determinants. An important novelty of our work is that, among other factors, it also controls for the characteristics of the individual inventors. As far as research productivity is concerned, while *quantity* is defined by the number of inventions that the inventors contributed to inventing, *value* is measured by two patent indicators that the literature shows to be correlated with the ex post economic value of the inventions.[2] For example, Trajtenberg (1990) shows that there is a close association between patent counts weighted by forward citations and the social value of inventions in the computer tomography scanner industry. Harhoff et al. (1999) demonstrate that the number of backward citations to previous patents and to the non-patent literature, and the number of forward citations received after the publication date is positively correlated with the value of the inventions. Schankerman and Pakes (1986) use patent renewal data to estimate the value of patent rights, while others use the number of countries in which the patent is applied for and the number of claims in the patent application as indicators of the value of the patents (see, for example, Putnam, 1996). Finally, patents that undergo opposition and annulment procedures are also shown to be more valuable (Harhoff and Reitzig, 2004).

We start by employing the number of forward citations received by the patents within 5 years of the publication date as a measure of their value. Then, in order to solve some of the problems that arise with the use of patent citations and to check for the robustness of the results, we follow the approach developed by Lanjouw and Schankerman (2004). We use multiple indicators of the patent value to construct a composite index that proxies for the technological and economic significance of the patents. As we shall see in the next section, this common component indicator reduces substantially the measured variance in patent value (Lanjouw and Schankerman, 2004) and is correlated with the actual monetary value of the patents (Gambardella et al., 2005).

[2] On the limitations of patent indicators see Griliches (1990), Almeida and Kogut (1999), Alcacer and Gittleman (2006), and Singh (2005).

3. Data sources and construction of variables

3.1. Data sources

Our major source of data is the PatVal-EU survey conducted in 2003–2004. The survey interviewed the inventors of 9017 patents granted by the EPO with a priority date of 1993–1997 and located in France, Germany, Italy, the Netherlands, Spain, and the United Kingdom. The PatVal-EU database provides critical information for our study on the age, education, career, and affiliation of a large sample of EPO inventors (for details and descriptive statistics see Giuri et al., 2005). We complemented the PatVal-EU dataset with data on all the EPO patents that the inventors in our sample applied for between 1988 and 1998. We chose this time window because the EPO data are not fully reliable before the end of the 1980s. Still, an 11-year window is large enough to capture a sizable portion of an inventor's career.

We focus on a sample of 793 PatVal-EU inventors that we selected by taking all the German, Italian, Dutch, and British inventors that responded to the PatVal-EU questionnaire on patents invented in five technological classes – Information Technology, Chemical Engineering, Civil Engineering, Optics, and Biotechnology – according to the ISI-INIPI-OST classification developed by the German Fraunhofer Institute of Systems and Innovation Research (ISI), the French patent office (INIPI), and the Observatoire des Sciences and des Techniques (OST). This classification translates the International Patent Classification (IPC) classes into 5 macro- and 30 micro-technological classes that mimic industrial sectors. We employed one micro-ISI-INIPI-OST technological class for each of the five macro-classes (Electrical Engineering, Instruments, Chemicals and Pharmaceuticals, Process Engineering, and Mechanical Engineering, respectively) and we checked the distribution of patents in the five micro-classes compared to the whole PatVal-EU sample. The characteristics of the inventors and the invention processes in the selected micro-classes did not differ substantially from those of the macro-classes from which they are drawn.[3]

[3] In order to construct a sample of inventors representative of the whole PatVal-EU population, we performed a series of Wald tests on the statistical significance of differences between the mean values of inventor and patent variables in different micro-technological classes and countries (see Greene, 2002, for the Wald test statistics). In general, the test shows no statistically significant differences across countries. Only inventors from the Netherlands are on average younger, and the share of graduated inventors is larger than in the other countries. As far as the technological classes are concerned, *Information Technol-*

We employed the database Delphion to collect all the patents of our 793 inventors, either applied for or granted by the EPO in 1988–1998. The search on Delphion was followed by a matching procedure to solve problems of homonymy that arise because quite a few inventors had the same first and last names as some inventors in our list, although they were not the same individuals. The matching software ran on two tables: a searching table with information on the 793 PatVal-EU inventors and a reference table with all the potential EPO matching patents extracted from Delphion.[4] The match between the EPO patents and the inventors was performed by using a set of weighted criteria: inventor's last name, first name, middle name, and technological class. The matching software browsed the reference table and reported the probability for each patent to be a "good match" with the inventor in the searching table. At the end of this process we checked the list of inventors manually in order to remove the patents invented by homonymous inventors. Other PatVal-EU information on the name of the applicant organization and the extent of inventors' mobility helped this check as well. Finally, we searched on the internet to solve the remaining doubtful cases.

This searching and cleansing procedure left us with data on 4376 patents invented by the 793 PatVal-EU inventors. For each patent we have information on the number of claims, the number of states in which the invention is patented, the name and location of the applicant organization, the IPC classes in which the patent was classified, and the number of forward and backward citations. The PatVal-EU survey provided us with data on the inventor who contributed to developing the patent and the organization in which he was employed at the time of the invention. Table 1 describes the composition of our sample of 793 inventors.

The share of women in the sample is low; it is larger in Biotechnology and smaller in Civil and Chemical Engineering, with no significant differences across countries. The average age of the inventors is 45, with some variation across countries and technologies. The more a technology is science-intensive, the larger its share of inventors with PhDs—e.g., in Optics and Biotechnology compared to Civil Engineering or to the overall share of 33.4%. In Italy only 5.1% of the inventors in the sample have a PhD degree. Table 1 also shows that the average number of patents per inventor in the database is 5.5, with a peak for German and Italian inventors (7.4 and 6.4, respectively).[5]

3.2. Productivity measures and regressors

The number of patents that the inventors contributed to inventing in 1988–1998 is our *quantity* measure (NPAT) of inventors' productivity. As far as *value* is concerned, we cannot use the monetary value of the patents as given by the PatVal-EU survey because this information is provided only for the surveyed patents, but it is not available for all the patents that compose our 4376 sample. Therefore, we employed two indicators that the literature on the measurement of patent value showed to be correlated with the technological and economic impact of the inventions.

The first one is the number of forward citations that a patent receives. A patent must cite all related prior patents, and the patent examiner eventually checks and changes them in order to ensure that all appropriate citations are included in the list. These citations identify the rights of the applicant, and they are a signal for the technological importance of a patent as a source of knowledge on which subsequent patents are built. We collected the total number of patents that cite the 4376 patents in our sample, and focused on the citations received within 5 years of the patent publication date to avoid "truncation" problems (i.e., more recent patents are less cited). We use these citations to construct two inventor-level measures of patent value.

The first one is the average value of each inventor's patents, and it is given by the average number of forward citations across the inventor's patents (AVCITE). Inventors, however, often acquire visibility for one or several major inventions (Jones, 2005; Zucker et al., 1998) that

ogy is the micro-class that better represents the average characteristics of patents and inventors in Electrical Engineering (macro-class I). In macro-class II (Instruments), inventors in *Nuclear Engineering* and *Optics* are respectively less and more mobile than those in the other micro-classes. In *Optics,* the estimated economic value of the inventions is higher than the average of the macro-class. In Chemicals and Pharmaceuticals (macro-class III), *Biotechnology* shows a share of inventors with a PhD degree higher than the average of the macro-class. No significant differences in inventor and patent characteristics emerge among the micro-classes in Process Engineering (macro-class IV) and Mechanical engineering (macro-class V).

[4] Delphion is an on-line database released by Thomson Corporation. It collects all the EPO patent applications issued since 1979. We thank Grid Thoma for downloading the European patents, either applied or granted, in which the first and last names of the inventors corresponded to one of our 793 inventors. The matching software is *SearchEngine v. 5.751* developed at the ZEW Research Institute by Thorsten Doherr.

[5] These data are consistent with OECD data that show that the share of population between 25 and 64 years old with a tertiary education degree is 24% in Germany and the Netherlands, 28% in the UK, and 10% in Italy (OECD, *Education at a Glance*, 2005). The distribution of patents is shown in Fig. 1.

Table 1
Gender, age, education, and number of patents applied for by the 793 inventors (1988–1998) (distribution by technological class and country)

	% of female inventors	Average age[a] (year)	% of inventors with university BSc or Master	% of inventors with PhD	Average no. of patents in 1988–1998
Information Technology (145)	1.4	41(9.5)	51.2	33.3	5.9 (9.3)
Optics (139)	5.0	42(8.9)	34.1	46.4	6.4 (6.9)
Biotechnology (53)	9.8	43(9.0)	15.4	48.1	4.6 (4.2)
Chemical Engineering (198)	1.0	46(9.8)	39.8	38.3	6.1 (8.5)
Civil Engineering (258)	0.8	48(9.1)	44.3	19.6	4.6 (5.8)
Germany (304)	2.9	47(9.6)	46.9	33.4	7.4 (8.5)
Italy (119)	2.3	44(10.8)	56.4	5.1	6.4 (10.3)
The Netherlands (162)	1.7	42(7.5)	13.8	54.4	3.5 (3.9)
UK (208)	1.9	45(10.1)	43.4	34.6	3.8 (4.3)
Total	2.3	45(9.7)	40.6	33.4	5.5 (7.4)

Note. The number of observations is in parentheses next to technological classes and countries.
[a] The age of the inventors is calculated as 1995 minus year of birth. Standard deviations in parenthesis.

lie at the very right-hand side of the patent value distribution. We decided to look also at the factors that explain the probability of inventing the "best" invention among those produced by the individual inventors. We measure the technological hits by the highest number of forward citations across each inventor's patents (MAXCITE). We therefore start by estimating a system of three equations in which NPAT, AVCITE, and MAXCITE are the dependent variables in our regression model.

However, these measures based only on the number of forward citations have some limitations (see Hall et al., 2001, for a survey). For example, citations cannot be made to or by inventions that are not patented, thus underestimating the actual importance of some of them. Second, patents applied for in different years and technological classes differ in their propensity to be cited, leading to changes in the number of citations per patent that stem from factors other than the actual changes in the technological impact of the inventions. Finally, there is also a different propensity to be cited according to the type and size of the organization that applies for the patent. For example, large firms might have larger portfolios of "citing patents" compared to smaller enterprises and universities, and this can affect the number of citations that their patents receive if self-citations (i.e., citations made by patents applied for by the same applicant) are included.[6]

[6] This potential bias cannot be solved by simply dropping self-citations from the citation list. This is because their role in measuring the value of the invention compared to independent cites is not clear. For example, some firms cite their own patents because they have large patent portfolios to cite, while others cite themselves because there are internal spillovers and cumulative processes of knowledge creation, or because they are exploiting technological trajectories in specialised niches.

In order to limit these problems, and to check for the robustness of the empirical results, we follow Lanjouw and Schankerman (2004) and use an alternative measure of patent value based on a composite patent index which proxies for both the technological and economic impact of the inventions. As discussed by Lanjouw and Schankerman, it reduces the variance in patent value compared to employing only one of the traditional value indicators, which suggests that there is a large information gain from employing multiple patent characteristics. The index is also cleaned from differences among patents that depend on country, time, and technological characteristics. Moreover, since only a fraction of the index is composed of forward citations, potential differences between applicants in the propensity to be cited are less severe. Finally, the monetary value of patents is highly correlated with a common component indicator similar to the one that we employ in this paper (see Gambardella et al., 2005).

By controlling for some observed patent characteristics, we derive the common factor as the unobserved characteristic of a patent that influences the following three indicators:

- *Forward citations*. This is the number of citations that a patent receives within 5 years of the patent publication date (as described above).
- *Backward citations*. We collected the number of prior patents cited by the 4376 patents. Backward citations are an indicator of others working on similar research fields, and therefore they signal the importance of the technological area.
- *Claims*. A claim describes the features of the invention, and defines the property rights protected by the

Table 2
Correlation between the errors of the three equations and parameter estimates

Errors of the three equations	Forward citations equation	Backward citations equation	Claims equation
Forward citations equation	1.000		
Backward citations equation	0.0282*	1.000	
Claims equation	0.102***	0.027*	1.000
Parameter estimates of the common factor model			
Variable (log)			
Forward citations (5 years after publication date)		0.21*** (0.082)	
Backward citations		0.04** (0.017)	
Number of claims		0.27*** (0.106)	

Note. To calculate the index we used dummies for the nationality of the inventors, the publication year, and the primary micro-technological class in which the patents are classified. Standard errors in parenthesis. Significant at: *0.1 level; **0.05 level; ***0.01 level.

patent. The inventor and the patent applicant may have an incentive to write as many claims as they can, but the examiner may require some of them to be dropped—the larger the number of claims, the broader and the greater the expected profitability of an invention.

From our sample of 4376 patents we retrieve the parameter estimates to construct the index (Q).[7] To do so we control for some observed characteristics of the patents: the nationality of the inventors, the publication year, and the primary micro-technological class in which the patents are classified. For each indicator k ($k = 1, \ldots, 3$) of the pth patent we perform the following multiple-indicator model with one latent common factor:

$$y_{kp} = \beta_0 + \beta' x_p + \lambda_k q_p + \varepsilon_{kp} \qquad (1)$$

where y_{kp} indicates the value of the kth indicator for the pth patent (in logs). The common factor is q with factor loadings λ_k, while x_p denotes the vector of observed controls. From the matrix of variance–covariance between the error terms of the three equations we derive the parameter estimates of the common factor model. The top part of Table 2 shows the correlation between the errors of the three equations. The bottom part shows the parameter estimates of the indicators that make up the index.

By employing this patent-level index we construct two other inventor-level measures of the average and maximum patent value. The average value is calculated as the average of the index across all the inventor's patents (AVQ). The "most important" invention among those produced by the individual inventor is measured by the inventor's highest value of the common component indicator across his patents (MAXQ). We then estimate a second set of equations where NPAT, AVQ, MAXQ are the dependent variables.

Figs. 1–3 show the distribution of NPAT, AVCITE, MAXCITE, AVQ and MAXQ across the 793 inventors. Consistent with other contributions on the productivity of individual scientists and inventors, these figures confirm that the distribution of the inventors' productivity is skewed with few inventors being very productive in terms of the *quantity* and *value* of the inventions that they produce.

Our regressors are inventor characteristics, characteristics of the organization in which they work, country and technological dummies. Table 3 lists and defines the variables.

Age, sex, and education are the inventor characteristics. The age of the inventors in 1995 is included in linear and in quadratic form (AGE and AGE^2). This is to mimic existing work in the literature that the effect of age on the researchers' productivity may first increase and then decline with age. Cole (1979), for example, studied the relationship between age and the quantity and quality (measured by means of citations) of publications of American scientists in six fields in 1965–1969. He found that, in general, age is curvilinearly related to such productivity measures: productivity first increases and peaks in the late 1930s–1940s (and 1950s for quality), and then it declines. The curve is less steep for the quality of the publications than for their quantity. The educational background proxies for the inventors' unob-

[7] We also constructed the index by employing four patent indicators: the three described in the text and family size, i.e., the number of countries in which the invention is patented. However, the correlation coefficients between the measurement error of the family size equation and the measurement errors of the backward citations and claims equations are close to zero and they are statistically not significant. This suggests that for our sample of patents we can use three patent indicators to construct the index, which provides exact identification. See Lanjouw and Schankerman (2004) for details.

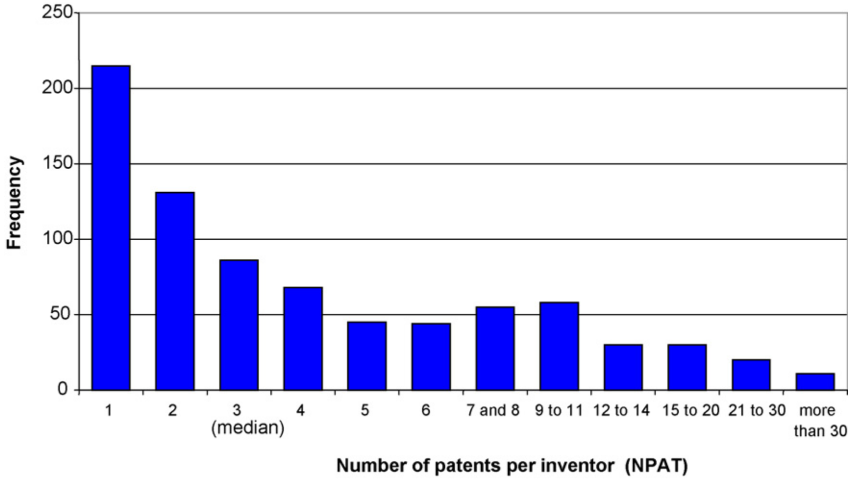

Fig. 1. Distribution of NPAT.

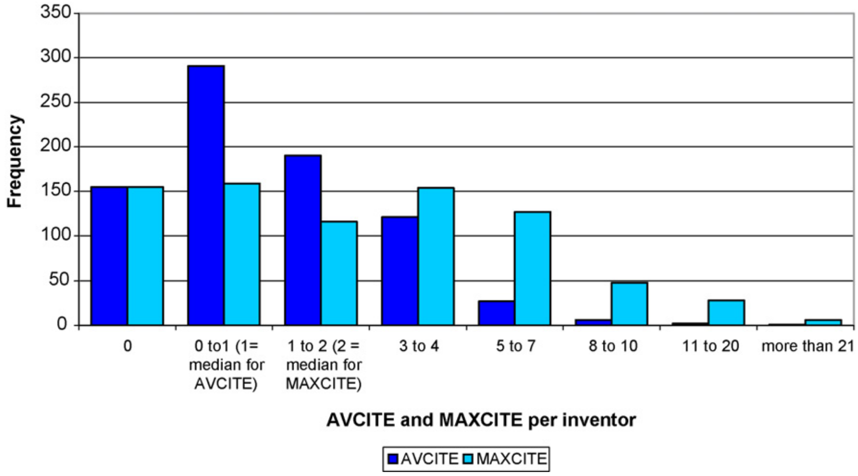

Fig. 2. Distribution of AVCITE and MAXCITE.

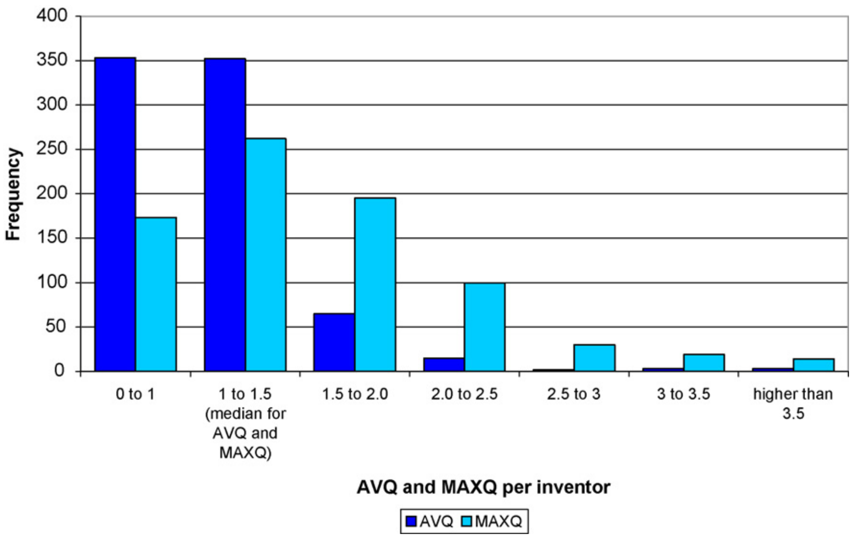

Fig. 3. Distribution of AVQ and MAXQ.

Table 3
List of variables

Productivity measures	
NPAT	Number of patents invented by each inventor. Publication date 1988–1998 (*Source*. EPO)
AVCITE	Average value of the patents invented by each inventor and applied for in 1988–1998. Measured by the average number of citations received by the inventor's patents within 5 years of the publication date (*Source*. EPO)
MAXCITE	Maximum value of the patents invented by the inventor among those applied for in 1988–1998. Measured by the highest number of citations received within 5 years of the publication date across each inventor's patents (*Source*. EPO)
AVQ	Average value of the inventor's patents applied for in 1988–1998. Measured by the mean of the common component index across each inventor's patents (*Source*. Elaborations from EPO data)
MAXQ	Maximum value of patents invented by the inventor among those applied for in 1988–1998. Measured by the highest common component index among each inventor's patents (*Source*. Elaborations from EPO data)
Inventors characteristics	
AGE and AGE^2	Age of inventors is 1995 minus year of birth (*Source*. PatVal-EU)
DEGREE	Dummy variable. Highest academic degree of inventor at the time in which he developed the PatVal-EU invention: Secondary School or lower (SecSc); High School (HighSc); University BSc or Master (Uni); PhD (PhD) (*Source*. PatVal-EU)
GENDER	Dummy variable. Male or female inventor (*Source*. PatVal-EU)
NINV	Number of inventors who take part in developing of a patent: average across each inventor's patents applied for in 1988–1998 (*Source*. EPO)
Characteristics of employer organization	
EMPL	Dummy. Type of employer organization: large firm (LARGE) with more than 250 employees; medium and small firms (SME) with less than 250 employees; universities and government institutions (GOV) (*Source*. PatVal-EU)
PATSORG	Number of patents granted to the applicant organization in the PatVal-EU sample (*Source*. PatVal-EU)
Controls	
TECH	Dummy variables for the macro-ISI-INIPI-OST technological classes in which the inventor's patents are classified: Electrical Engineering (ELENG), Process Engineering (PRENG), Mechanical Engineering (MECENG), Instruments (INST), Chemicals & Pharmaceuticals (CHEM). We used the technological class in which the majority of the inventor's patents falls
COUNTRY	Dummy variables for the country of the inventor: Germany (GER), Italy (IT), the Netherlands (NL), UK (UK)

Source. PatVal-EU dataset and EPO. *Note*. The characteristics of employer organizations are provided by the PatVal-EU survey. We checked whether the patents in our 1988–1998 sample were applied for at the EPO during the period in which the inventors were employed in the organization reported in the PatVal-EU survey. We found out that almost all our inventors did not change job during 1988–1998.

servable ability and for the knowledge that they embody and that was assimilated in the different stages of the scientific training. We employ the highest degree of education of the inventors among the following four types: Secondary School (SecSc), High School (HighSc), University BSc or Master (Uni), PhD (PhD). We expect the level of education to be positively correlated with the quantity and value of the patents that the inventors produce. Not only is this because inventors with better ability and scientific knowledge are expected to be more productive, but also because education might be a signal that the inventors and the employer organizations use to search for a good "match" between the research potential of the former and the characteristics of the latter.[8]

The type of employer organization and the number of patents that the applicant was granted by the EPO are the two organization characteristics included in the regressions. As far as the number of patents granted by the EPO to the applicant organizations is concerned (PATSORG), we use the data provided by the PatVal-EU database.[9] PATSORG is a proxy for the capacity to innovate and the propensity to file patents of the applicant organization. Moreover, the development of inventions often requires extensive resources in terms of technical equipment,

[8] See, for example, the seminal contributions by Arrow (1973) and Spence (1973) on the consequences of imperfect information. Also, Moore (1911) argues that "Large establishments are able to carry out the work of selection [of more capable individuals] because in consequence of their large capital and better organization, they offer opportunities for more capable individuals to reap the reward of their differential ability". Idson and Oi (1999) confirm that "the adoption of advanced technologies, employment of inherently more able individuals, and higher work standards go together to raise labour productivity [. . .]".

[9] We use the number of EPO patents granted to the organization and included in the PatVal-EU survey as we are interested in the distribution of patents across applicants rather than in the absolute number. Given the sampling methodology that we employed in the PatVal-EU survey, these data provide a good approximation of such distribution.

research laboratories, instruments, research assistants, and complementary expertise. The type of organization in which the inventor is employed partially proxies for the availability of such resources. We differentiate between large firms (LARGE), small and medium companies (SME), and public research organizations (GOV). Compared to SME and GOV, large firms might have the financial resources to engage in complex research projects, to produce a large number of inventions, and to apply for patent protection for many inventions. They are also likely to be endowed with a large pool of heterogeneous and specialised researchers that are involved in a wide number of larger research projects compared to smaller enterprises. We expect these characteristics to be positively correlated with the productivity of the individual inventors, both in terms of quantity and maximum value of the inventions. It is more difficult to predict the effect of these variables on the average value of the inventions. For example, if large companies have the financial strength and the human resources to apply for patent protection not only for important inventions, but also for less valuable ones, this might produce a decline in the average value of the patented inventions both at the company and at the inventor level. The net effect of the size of the firm on the average value will depend on the extent to which higher value inventions compensate for the number of low value patents that are applied for. By controlling for the size and type of the employer organization, we also separate the effect of the scale of the organization from its patent propensity, which otherwise would both be reflected by the same PATSORG variable.

We also include in the regression model a project-level measure of the resources available to the inventors for developing the inventions. This is the size of the research project leading to the patents: for each patent in the database we collect the number of inventors involved in the development of the invention, and for each inventor we compute the average size (NINV) of the research projects in which he participated. We expect a positive correlation between NINV and the *quantity* and *value* of the research performed by the inventors, which would suggest that the investment in large-scale research projects leads to better and larger inventive output, and that research teams matter for the development of a large number of high value inventions (see Andrews, 1979, and Lawani, 1986, for the relationship between researchers' productivity and collaboration in scientific research).

Finally, we control in all the regressions for the country of the inventors (COUNTRY) and for the macro-technological classes in which the patents are classified (TECH). Table 4 provides the descriptive statistics of the variables.

Table 4
Descriptive statistics

	Mean	S.D.	Minimum	Maximum
Productivity measures				
NPAT	5.51	7.40	1	87
AVCITE	1.40	1.75	0	24
MAXCITE	3.30	3.82	0	31
AVQ	1.11	0.39	0.37	3.93
MAXQ	1.54	0.69	0.37	6.43
Inventors characteristics				
AGE	45	9.71	18	73
DEGREE	3.26	0.82	1	4
GENDER	0.98	0.15	0	1
NINV	2.40	1.25	1	8.6
Characteristics of the employer organization				
LARGE	0.60	0.49	0	1
SME	0.30	0.46	0	1
GOV	0.11	0.32	0	1
PATSORG	33.44	72.95	1	286

Source. PatVal-EU dataset and EPO.

4. Specification and estimation: step 1

We start by estimating a set of three equations in a reduced form model by seemingly unrelated regressions (SUR).[10] We employ two specifications. The first one, which uses the measures constructed with the number of forward citations, jointly estimates the probability of NPAT, AVCITE, and MAXCITE:

$$\begin{cases} \mathrm{NPAT_i} = x_i'\alpha_1 + \varepsilon_{1i} \\ \mathrm{AVCITE_i} = x_i'\alpha_2 + \varepsilon_{2i} \\ \mathrm{MAXCITE_i} = x_i'\alpha_3 + \varepsilon_{3i} \end{cases} \tag{2}$$

The subscript 'i' denotes the inventor, while α_1, α_2 and α_3 are the coefficients to be estimated for the impact of the x_i organization and inventors' characteristics on the three dependent variables. All the variables are in logs. Table 5 presents the estimated results. Since NPAT and MAXCITE are count variables, we also show the results of these two equations by using negative binomial regressions.[11]

The estimated results in Table 5 suggest that inventors and firm characteristics produce a different impact on the expected *quantity* compared to the *value* of the inven-

[10] Given that the regressors are the same in all three equations, SUR yields the same estimates as separate OLS regressions.

[11] We use a zero-truncated negative binomial regression model for NPAT_i because the data are strictly positive (Cameron and Trivedi, 1998). Our definition of "European inventor" implicitly requires that the individual contributed to inventing at least one EPO patent. This is a necessary condition for the inventors to be included in our sample and interviewed in the PatVal-EU survey.

Table 5
Estimates of SUR and negative binomial regression (dependent variables: NPAT, AVCITE and MAXCITE (variables in logs))

	SUR			NegBin	
	NPAT	AVCITE	MAXCITE	NPAT	MAXCITE
Dependent variables: log of number of patents and forward citations					
AGE[a]	9.17*** (3.52)	−1.52 (2.66)	1.83 (3.26)	20.41*** (7.55)	3.31 (4.31)
AGE2[a]	−1.17** (0.47)	0.21 (0.35)	−0.22 (0.43)	−2.62*** (1.00)	−0.41 (0.57)
DEGREE: HighSc[a]	0.06 (0.17)	−0.17 (0.11)	−0.17 (0.15)	−0.09 (0.33)	−0.29 (0.22)
DEGREE: Uni[a]	0.12 (0.15)	−0.10 (0.10)	−0.03 (0.13)	0.22 (0.17)	−0.01 (0.19)
DEGREE: PhD[a]	0.33** (0.16)	−0.10 (0.10)	0.02 (0.13)	0.59** (0.29)	0.01 (0.20)
MALE[a]	0.54*** (0.21)	0.29* (0.14)	0.52*** (0.19)	0.77 (0.47)	0.72** (0.38)
NINV[a]	0.35*** (0.07)	0.09** (0.05)	0.21*** (0.06)	0.51*** (0.15)	0.34*** (0.08)
LARGE[a]	0.31*** (0.10)	0.12* (0.07)	0.23** (0.09)	0.36** (0.17)	0.28** (0.13)
SME[a]	0.07 (0.10)	0.04 (0.07)	0.08 (0.10)	0.09 (0.12)	0.05 (0.13)
PATSORG[a]	0.06*** (0.02)	0.02 (0.01)	0.05*** (0.02)	0.08*** (0.02)	0.05** (0.02)
Const.[a]	−18.37*** (6.53)	3.19 (4.98)	−3.58 (6.07)	−40.56*** (14.44)	−6.61 (8.03)
Log likelihood		−1360.69		−1866.81	−1729.84

Note. Robust standard errors in parentheses. All regressions include dummies for country of inventors and for the macro-ISI-INIPI-OST technological class of his patents. Coefficient significant at: *0.1 level; **0.05 level; ***0.01 level. Zero-truncated negative binomial regression for NPAT: $\ln(\alpha) = 0.45$ (1.08); R-squared = 0.20. Negative binomial regression for MAXCITE: $\ln(\alpha) = -0.38$ (0.08); R-squared = 0.12.
[a] # obs. 767.

tions. Specifically, they are positively correlated with the probability of producing a large number of inventions (NPAT), but many of them lose significance in the AVCITE and MAXCITE equations.

This is the case of AGE. As the inventors grow older, the probability of producing a large number of patents increases, but after a certain point the relationship becomes negative.[12] The same AGE variable, however, does not affect the probability of inventing valuable inventions (both average and maximum). Being a MALE is positively correlated with NPAT, AVCITE, and MAXCITE, though with a different level of statistical significance. The positive effect of MALE on the productivity measures might be due to the very low number of women in our sample and to the fact that, on average, male inventors can spend more time and effort in their job compared to women.

As expected, the academic degree of the inventors matters for producing a large number of inventions: the coefficient of PhD is positive and statistically significant on NPAT. Also the characteristics of the applicant organization are correlated with NPAT. The dummy LARGE is positive and statistically significant at the 0.01 level on the number of patents (it is significant at the 0.05 level in the negative binomial model); PATSORG is positive and statistically significant at 0.01. Finally, the size of the research project is positively correlated with NPAT, confirming that investment in large-scale research projects and collaboration among researchers are correlated with the number of patents being produced by the individual inventors. The negative binomial estimation confirms these results.

When we turn to the factors that affect the expected value of the inventions, however, Table 5 shows that, apart from MALE, inventors' personal characteristics are not correlated with the average and maximum value measures. Not even the inventors' academic degree matters for producing high value inventions.

Some firm characteristics are statistically significant in the *value* equations. The size of the research project (NINV) and the size of the firm (LARGE) are positively correlated with AVCITE, even though the statistical significance of the coefficients is only 5% and 10%, respectively. Employment in a LARGE firm, the size of the research project (NINV), and the number of patents granted to the organization (PATSORG) increase the probability of inventing a technological hit (MAXCITE). In reading these results, however, it is worth keeping in mind that we are measuring value in terms of the number of forward citations received by the patents. As we mentioned in Section 3.2, large firms own larger portfolios of citing patents compared to smaller enterprises. These large patent portfolios open the way to self-citations, which, in turn, contribute to the total number of citations received by the patents invented in large companies.

[12] We are aware of the potential source of selectivity bias in our paper (Cole, 1979; Levin and Stephan, 1991). However, since the inventor's life cycle is not the primary focus of our analysis, we do not include any correction to predict the likelihood that the inventors are active in the invention business.

Table 6
Estimates of SUR and negative binomial regression (dependent variables: NPAT, AVQ and MAXQ (variables in logs))

	SUR		
	NPAT	AVQ	MAXQ
Dependent variables: log of number of patents and value index			
AGE[a]	9.17*** (3.52)	0.21 (1.57)	2.72 (1.82)
AGE2[a]	−1.17** (0.47)	−0.03 (0.21)	−0.36 (0.24)
DEGREE: HighSc[a]	0.06 (0.17)	−0.07 (0.07)	−0.06 (0.08)
DEGREE: Uni[a]	0.12 (0.15)	−0.03 (0.06)	0.00 (0.07)
DEGREE: PhD[a]	0.33** (0.16)	−0.07 (0.06)	−0.01 (0.07)
MALE[a]	0.54*** (0.21)	0.17 (0.10)	0.33** (0.12)
NINV[a]	0.35*** (0.07)	0.07** (0.03)	0.15*** (0.03)
LARGE[a]	0.31*** (0.10)	0.03 (0.04)	0.08 (0.05)
SME[a]	0.07 (0.10)	0.04 (0.04)	0.05 (0.05)
PATSORG[a]	0.06*** (0.02)	−0.01 (0.01)	0.01 (0.01)
Const.[a]	−18.37*** (6.53)	−0.47 (2.93)	−5.36 (3.40)
Log likelihood −660.881			

Note. Robust standard errors in parentheses. All regressions include dummies for inventors' country and macro-ISI-INIPI-OST technological class. Coefficient significant at: *0.1 level; **0.05 level; ***0.01 level.
[a] # obs. 767.

To address the concerns associated with forward citations as a proxy for the importance of the inventions, and to check for the robustness of our results, we also employ the composite index. We estimate the same set of three equations with the logs of NPAT, AVQ, and MAXQ as dependent variables. The results in Table 6 confirm that inventor and firm characteristics are correlated with the probability of developing a large number of patents. Interestingly, however, when value is measured by the composite index the effect of firm characteristics (LARGE and PATSORG) vanishes. These results confirm our suspicion that the number of forward citations to patents applied for by large companies might be partly independent of the actual value of the cited inventions. In Table 6, apart from MALE, only the size of the research project (NINV) is positive and statistically significant on the average and maximum value of the inventor's patents.[13]

These results are intriguing, as they suggest a peculiar story arising from our data. Firm and personal characteristics influence the number of inventions that the inventors produce, but apart from the participation in large-scale research projects, they do not affect the value of the inventions at an inventor level. This is interesting and puzzling at the same time. We therefore move one step further in order to understand whether the effect of inventor and firm characteristics on *value* takes place indirectly through *quantity*. Our perception is that firm and inventor factors are correlated with *quantity*, which, in turn, explains *value*. The next section explores this hypothesis.

5. Specification and estimation: step 2

This section builds empirical evidence for the story that we envision about inventors' productivity. The story goes as follows. Highly educated inventors are employed in large companies that have the financial resources and research capabilities to develop and apply for a large number of patents. This is suggested by the estimated results of the NPAT equation, and it would also be consistent with anecdotal evidence that shows that the inventors are often evaluated and rewarded according to the number of patents that they contribute to inventing.

[13] In order to check for complementarity between PhD and LARGE we included the interaction between PhD and the type of employer organization (LARGE, SME and UNI) in our system of equations. The estimated results do not change compared to those in Tables 5 and 6, and the impact of the interacted variables is statistically not significant. This suggests that firm and personal factors have an independent effect on NPAT. We also checked for the robustness of our results by replacing AGE and AGE^2 with five age classes. We also dropped alternatively NINV, PATSORG, and LARGE, with no significant changes in the results shown in Tables 5 and 6. Finally, we included three motivations for inventing that the inventors reported in the PatVal-EU survey: economic compensation, reputation, and career advances. Career advances turned out to be positive and statistically significant on the value of the inventions. However, due to the phrasing of the questionnaire, the inventors might have misunderstood the question and interpreted it as the ex post reward from patenting rather than an ex ante motivation, i.e., career might be endogenous with respect to patent value. This is confirmed by the fact that when we drop it, the coefficient and statistical significance of AGE increase.

For example, in 2004, Siemens AG honoured 13 inventors responsible for about 600 patents invented in the same year. Similarly, the WIPO Award scheme, launched in 1979, grants prizes to inventors for their "outstanding research activities and numerous patented inventions" (Hoisl, 2005).

In turn, the *quantity* of inventions that the inventor produces might affect their *value*. This is true in the case of a technological hit, since the expected value of the maximum as an ordered statistic increases with the number of trials (see Mood et al., 1974). This is also possible, with a negative sign, for the average value of the inventions. Unless the value of the best inventions compensates for the large number of lower value patents, there could be regression to the mean in the average value of the inventions as their number increases. We therefore include in the two *value* equations an additional explanatory variable: the number of inventions (NPAT) that we expect to have a positive effect on MAXCITE (and alternatively on MAXQ). It is more difficult to predict the sign of the relationship between NPAT and AVCITE (and alternatively AVQ) as it depends on how much better inventions compensate for the large number of lower value patents.

Operationally, we propose a structure for our model in which NPAT enters the AVCITE and MAXCITE equations, and not vice versa. Specifically

$$\begin{cases} \mathrm{NPAT_i} = x_i'\alpha_1 + \varepsilon_{1i} \\ \mathrm{AVCITE_i} = x_i'\alpha_2 + \theta_2\mathrm{NPAT_i} + \varepsilon_{2i} \\ \mathrm{MAXCITE_i} = x_i'\alpha_3 + \theta_3\mathrm{NPAT_i} + \varepsilon_{3i} \end{cases} \tag{3}$$

By substituting the NPAT equation in the AVCITE and MAXCITE equations, the system above can be rewritten as follows:

$$\begin{cases} \mathrm{NPAT_i} = x_i'\alpha_1 + \varepsilon_{1i} \\ \mathrm{AVCITE_i} = (\alpha_2 + \theta_2\alpha_1)x_i' + \theta_2\varepsilon_{1i} + \varepsilon_{2i} \\ \mathrm{MAXCITE_i} = (\alpha_3 + \theta_3\alpha_1)x_i' + \theta_3\varepsilon_{1i} + \varepsilon_{3i} \end{cases} \tag{4}$$

Now, to retrieve θ_2 and θ_3 we need a variable that affects only NPAT with no influence on AVCITE and MAXCITE. Since we do not have a structural model that justifies such exclusion restriction, a possible solution is to estimate θ_2 and θ_3 from the variance–covariance matrix between the residuals of our three equations. To do so it is natural to allow the errors ε_2 and ε_3 of the two value equations to be correlated. Still, we assume the correlation between ε_2 and ε_3 on the one hand, and ε_1 on the other hand equal to zero.[14] By doing this we obtain the estimates of θ_2 and θ_3 and their standard errors as shown in the upper part of Table 7.

Table 7
Parameter estimates: θ_2 and θ_3

Computed with NPAT, AVCITE, MAXCITE as dependent variables	
θ_2	0.108*** (0.022)
θ_3	0.480*** (0.024)
Computed with NPAT, AVQ, MAXQ as dependent variables	
θ_2	0.016 (0.013)
θ_3	0.248*** (0.015)

Note. Robust standard errors in parentheses. Coefficient significant at: *0.1 level; **0.05 level; ***0.01 level.

As expected, θ_3 is positive and statistically significant. This confirms our story that, at the individual level, the larger the number of patents, the higher the probability to invent a technological hit. Surprisingly, also θ_2 is positive and statistically significant, which would suggest that the average value of the inventions increases with their number.

However, when we estimate θ_2 and θ_3 from the variance–covariance matrix between the residuals of the NPAT, AVQ, MAXQ equations as shown in the bottom part of Table 7, θ_2 is small and it is not statistically significant. This suggests that, when value is measured by means of the composite indicator to which forward citations contribute only partially, there is no regression to the mean in the invention process at the individual level. The value of the "best inventions" compensates for the many lower value patents that are produced during the process. Still, θ_3 is positive and statistically significant, which confirms the results above: the number of patents that the inventors produce is positively correlated with the maximum value.

The last question concerns the direct effect of inventor and firm characteristics on the two value measures once NPAT is included in the regressions. The Wald test for the α_2 and α_3 parameters shows that the direct effect of all our regressors is statistically not significant once NPAT is controlled for. In particular, the size of the firm (LARGE) completely loses its explanatory power in the two value equations. The same applies to PATORG that was statistically significant at the 0.01 level (0.05 in the negative binomial regression) in the MAXCITE equation. The Wald test shows that it is not directly correlated with any of the value indicators. Also, the average size of the research projects in which the inventor is

[14] *De facto* this assumes that we control for all the observed factors that simultaneously affect the three productivity measures. This is clearly a hypothesis, although we really control for major individual and institutional factors. Moreover, by including NPAT in the two value equations, shocks on NPAT do not enter the value equations via the error term.

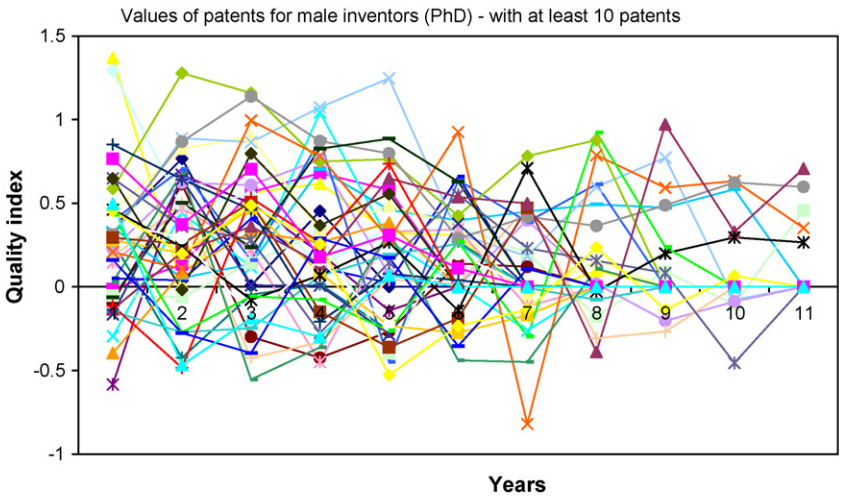

Fig. 4. Progression of patent value index (in logs) over time. Sample: male inventors with PhD who invented 10 or more patents in 1988–1998.

involved (NINV) is not correlated with the value of the patents.

Similarly, the Wald test for the α_2 and α_3 parameters in the AVQ and MAXQ equations shows that, once NPAT is included as a regressor, the other factors do not directly affect the expected average and maximum value of the inventions. Only NINV is still statistically significant at 0.05 on both AVQ and MAXQ, suggesting that investment in large-scale research projects and collaboration among researchers are positively correlated with both the number and the value of the inventions, when value is measured with the composite index.[15]

In sum, our story is that inventors with a high level of education and inventors employed in large firms are more likely to produce a large *quantity* of inventions. This might be because large firms provide the inventors with the financial resources and complementary expertise to develop and apply for many patents. Also, large firms might provide the inventors with the incentives to produce a large number of inventions, as they use this information to identify and reward productive inventors.[16] In turn, the larger the number of patents, the higher the probability of developing a valuable invention: more ideas are correlated with better ideas.

Moreover, our study shows that the number of the inventor's patents, together with investment in large research projects, are the only factors that, at the individual inventor level, impact directly on the maximum value of the inventions. Inventor and organizational characteristics are only indirectly important for *value*, as they positively influence the number of the inventors' patents. Finally, we find no regression to the mean in the average value as NPAT increases, suggesting that the average value of an inventor's patents is mostly determined by stochastic factors.

Still, we do not know whether the effect of NPAT on the maximum value is the result of a stochastic process where the larger the number of draws, the higher the probability of obtaining a success, or whether this is the output of a learning process through which knowledge accumulates and raises the probability of inventing a high value patent. Although it is not within the scope of this paper to analyze systematically this issue, Fig. 4 gives some insights into the "learning versus stochastic" process for producing high value patents. It depicts the progression of the patent value index (in logs) over 1988–1998 for a sub-sample of 39 male inventors employed in large firms, with a PhD degree and with more than 10 EPO inventions in the period.[17]

The horizontal axis shows the sequence of patents invented over time. The vertical axis reports the value of each invention by means of the composite value index. Each line identifies an inventor. As a first approximation it is hard to extrapolate a specific monotonic trend in patent value at the inventor level, either decreasing or increasing as the number of patents grows. Although these results are not conclusive, they would suggest

[15] Also MALE is positive and statistically significant at the 0.05 level on MAXCITE and at 0.10 on MAXQ, when we control for NPAT.

[16] As suggested by a Referee, strategic motivations like cross-licensing with partners or competitors might also lead to expand a firm's patent portfolio.

[17] For inventors with multiple patents in the same year we consider the patent with the highest value index. It does not change much, however, if we take the average value index of the multiple patents applied for in the same year.

that no learning process is at work in the relationship between quantity and value, and that the positive correlation between NPAT and MAXCITE (and MAXQ) is the output of a stochastic process, where the number of patents is correlated with the probability of finding a maximum.

6. Summary and conclusions

This paper estimated the impact of individual and organization characteristics on the expected *quantity* and *value* of the patents of European inventors. In so doing it used information on the individual characteristics of 793 inventors drawn from the PatVal-EU database and on 4376 EPO patents that they contributed to inventing in the period 1988–1998. *Quantity* is measured by the number of EPO patents that the inventors produced. Value is computed by means of the number of forward citations that the patents received within 5 years of the publication date, and alternatively, by a common component index as developed by Lanjouw and Schankerman (2004). With these indicators we constructed two measures of patent value at the level of individual inventor: the average value and the value of the best patent among those that he contributed to inventing.

Patent quantity and average and maximum values were then regressed on inventors' personal characteristics and the characteristics of the employer organization. By using seemingly unrelated regressions and the matrix of variance–covariance between the residuals of the three equations, our findings are twofold. First, the drivers of *quantity* differ from the factors that impact *value*. Specifically, inventors with a high level of education and employed in large firms are more likely to produce a large *quantity* of patents. Inventor and firm characteristics, however, do not impact directly on the expected *value* of the inventions, neither average nor maximum. They do only indirectly, as we find that the number of patents that the inventor produces is positively correlated with the *maximum patent value*. Second, we find no regression to the mean at the inventor level: as the number of patents per inventor gets larger, the *average value* of the inventions does not decrease.

It is worth noting that our findings do not diminish the importance of firm and individual characteristics in producing high-value inventions. Although indirectly through *quantity*, they affect *value*. This confirms that a key resource for fostering invention, both in terms of number and value, is the availability and employment of highly educated researchers, which, in turn, depends on investment in high level and postgraduate education and training. Moreover, the importance of the inventors' education and the fact that their productivity distribution is skewed reinforce the "retaining the best" policy (Narin and Breitzman, 1995): if ability is concentrated in a few key individuals, the organizations in which they are employed should do their best to retain them. This is particularly important if these individuals are responsible for both the *quantity* (directly) and *value* (indirectly) of the inventions developed by the organization, and if, at the inventor level, there is no regression to the mean in the average value of the inventions.

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