Returns to Inventors

Work-in-progress, please do not quote

23.5.2008

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ABSTRACT

The return that inventors appropriate from their inventions forms a key incentive and remuneration mechanism for innovation. We utilize data of U.S. patents and their inventors linked to matched employer-employee data in Finland to estimate the effect of patenting on wages. Inventors get a temporary 3.4% wage increase in the year of the patent grant. In addition, there is a 5-6% increase in wages four years after the patent grant, which remains there for at least the following two years. The returns to inventors depend on the quality of the patent, and are nonlinear in the number of patents.

KEYWORDS: effort, incentives, inventors, patents, return, wages

JEL codes: O31, J31

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1 Introduction

The extent of the literature on innovation and invention reflects the established fact that technical progress is a key determinant of economic growth. This literature emphasizes that innovations are essentially a product of human activity, made possible by the skill and effort of individuals. In view of this, it is surprising that very little is known of how individual inventors are rewarded. The objective of this study is therefore to empirically examine the returns to inventors. To this end, we construct a dataset where U.S. (USPTO) patents and their inventors from the NBER patents and citations data file (Hall, Jaffe Trajtenberg, 2001) are linked to Finnish employee-employer data containing detailed information on personal characteristics and earnings as well as information on the employers from 1988 to 1999.

Inventors today mostly invent as a part of their job, as inventive activity is to a large extent organized in R&D laboratories in firms and other R&D performing organizations. Thus it is no surprise that the focus of existing research has been on innovation at the level of the innovating organization. However, a key to promoting innovation are not only the incentives that firms face, but also the incentives that individuals are provided with. These may take several forms: Rossman (1931) reports the survey responses of a group of over seven hundred inventors, including the most prominent inventors of the time, who were asked for their motives and incentives to invent. The most commonly cited reason was “love of inventing”, followed by “the desire to improve existing devices”. “Financial gain”, although clearly important, was only the third most frequently mentioned motive. There is clearly an element of current satisfaction ("on-the-job-consumption") that research activity provides in addition to any financial rewards, as also noted by Levin and Stephan (1991), and emphasized in biographies of past inventors (Rossman, 1931). Similar evidence is provided by Stern (1999), who finds that scientists employed by firms in fact "pay to be scientists", i.e., accept lower wages in return for being able to pursue individual research agendas and publish in scientific journals.

The importance of non-pecuniary incentives not-withstanding, economists have studied the role of monetary incentives in the innovative process. Aghion and Tirole's (1994) incomplete contracts - analysis, for example, normalizes the non-monetary incentives to a constant, and studies the effects of monetary incentives. The standard theoretical foundation for providing employees with (monetary) incentives comes from principal-agent models. These models suggest that compensation should be tied to an informative signal of the level of effort (Holmström, 1979). While incentive schemes have been subject to empirical research, they have been less studied in the context of innovation. One exception is Lerner and Wulf (2006), who analyze how corporate R&D managers' compensation affects innovation in firms. Their key finding is that when the corporate R&D head has substantial firm-wide authority over R&D decisions, long-term incentives such as stock options are associated with a higher level of innovation (more heavily cited patents, patents of greater generality and more frequent awards).

The provision of incentives is not the only reason why the labor market would reward inventors. For example, being a patent inventor may work as a signal of the individual's ability and productivity and so result in a wage premium. Furthermore, such signaling can lead to improved firm-worker matches, thus raising wages. Additionally, an invention represents knowledge, some of which is tacit and embedded in the individual, and this knowledge should earn a return in the labor market. A related point concerns knowledge spillovers: if firms want to prevent such spillovers, they may have to pay a wage premium to inventors in order to retain them. Evidence for this is provided by Møen (2005), who finds that while the technical staff in R&D-intensive firms first pays for the knowledge they accumulate on the job through lower wages in the beginning of their career, they later earn a return on these implicit investments through higher wages. Support for this view is also provided by Andersson et al. (2006), who find that firms with high potential payoffs from innovation pay more in starting salaries than other firms in order to attract star workers (workers with a history of higher wages and wage growth), and furthermore, that such firms also reward these workers for loyalty. Finally, the law on employee inventions in Finland (FINLEX, 29.12.1967/656) provides a basis to expect inventors to earn a return on the inventions they produce. While giving the right to the invention to the employer, the law also rules that the employee has the right to reasonable compensation from the employer for the invention, taking into account the value of the invention.

Monetary rewards to individuals' innovations may take various forms, including one-time bonuses, value-contingent payments, as well as wage increases. In any case, the returns ultimately show up in their wages. Thus the appropriate empirical approach to studying the individuals' returns to innovation follows the standard framework applied to study the returns to schooling, i.e. specifications similar to Mincer wage equations, where we use measures of invention generated from patent data. Patents offer a convenient, if not trouble-free, window on individual inventiveness and have been exploited in economic research at least since the 1950s (Schmookler 1957, Griliches 1992). We estimate the effect of patenting on wages over time, and investigate its dependence on the value of the innovation, proxied by a quality measure based on the citations received by the patent. Having access to panel data at the individual level, together with the variation over time in our variable of interest, enables us to control for unobserved individual heterogeneity, which is often a problem in exercises of similar nature, such as in estimating the returns to schooling (see e.g. Card 2001). Furthermore, the lag between the time of an invention and the patent grant enables us to treat granted patents as predetermined variables.

We find that inventors get a temporary increase in their wages in the order of about 3.4% in the year of the patent grant, presumably corresponding to a one-time bonus for being awarded a patent. In addition, there is a 5-6% increase in wages four years after the patent grant, which remains there for at least the following two years, possibly representing a permanent wage increase. We also find that the returns to being a (patent) inventor depend on the quality or value of the patent, and these quality-dependent returns are first realized three years after the granting of the patent, coinciding with the time it typically takes to learn the value of a patent (Pakes 1986, Lanjouw 1998).

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 presents the empirical framework. Section 4 presents the results. Section 5 concludes.

2 Data

2.1 Matching USPTO and FLEED data

Our source of information on inventions and inventors is the NBER patents and citations data file (Hall, Jaffe Trajtenberg, 2001) on U.S. Patent Office (USPTO) patents. While we are not the first to utilize the information on inventors contained in patent data[1], we go a step further than the previous studies and match inventor data to the employee records in a longitudinal employer-employee dataset of the Finnish working-aged population (FLEED) that resides at Statistics Finland. The FLEED contains detailed information on individuals and their characteristics, in particular their annual earnings, as well as firm-level information on their employers.

The NBER patent data contains the names of all inventors of a given patent, and information on their address (at a minimum, the municipality of residence). In Finland, each resident is given a unique identifier (the personal identity code), which is contained in the Finnish Population Information System (FPIS) together with basic personal information, including the address and municipality of residence. With the aid of the Population Information System, inventor information from the NBER patent data can be linked to their personal identity codes. These personal identity codes are also contained in the FLEED (in encrypted form), enabling the linking of inventor information with it.[2] The Finnish patents from the NBER data have also been linked to their assignees in the

[1] In the past few years, there have been some research projects making use of large scale inventors' data. Most notably, Trajtenberg et al. (2006) have developed a computerized matching procedure to identify inventors in the NBER patent data. Several other studies have used smaller samples of the patent data to identify inventors (REF).

[2] The process of linking the inventor records to personal identification codes was done at the Statistics Finland by their own personnel under strict confidentiality, and the researchers never had access to any information that would have enabled the identification of individual people from the data.

FLEED. This provides us with an additional link we can use to help us identify the inventors. In cases where the name and residence information in the inventor data matches more than one personal identity code from the FPIS, we also utilize the link between the patent inventor and the patent assignee, allowing us to search for the correct personal identity code from among the employees of the assignee firm. Altogether, this information helps us in solving a key issue that has hampered progress in studying inventors: the matching of inventors from patent documents to other data.

We use USPTO patents rather than Finnish patents, because they should be more valuable. Grönqvist (2007) has estimated that the average value of a Finnish patent is of the order of only 5000€, reflecting the small size of the Finnish market. Using USPTO data will also make our results comparable to other studies using the same data.

The data construction proceeded as follows. Using the full name and the municipality of residence on the inventor record (as well as the full address where available), together with the patent application year, the FPIS was searched for matching records and all matching personal identity numbers were linked to the inventor record. For some, this resulted in a unique match, while for others a number of potential identity numbers matched the inventor information. In order to determine the right identity for the inventor, we utilized the link between the patent inventor and the assignee firm to search the personal identity codes of all the employees in the assignee for matches with those linked to the inventor record.

For those individuals for whom more than one personal identity number was found from the population register, the identification of the correct individual was based on the assumption that they are employees of the patent assignee firm. While we expect this to hold true for the majority, in some cases this may lead to misidentification of the inventor. Thus we may have assigned a patent to some non-inventors, and at the same time failed to assign the patent to its proper inventor. If this is the case, it introduces some measurement error into our patent variable and biases our estimates downward.[3]

Unfortunately, though not surprisingly, we were unable to identify and link all the patent-inventor records to the employee records, for two reasons. First, for some inventor records, the search from the population register produced no match. This could be due to misspellings in the names or incorrect information for some other reason. Second, for some of those inventor records for which several matching identity numbers were obtained from the population register, more than one of these identity numbers were also found among the employees of the patent assignee firm. Without a unique match, we failed to identify and link the patent to any individual, so that these inventors are not included in our sample.

Taking from the NBER patents data all the patents whose assignee country code is FI, and which were applied for between 1988 and 1999, and linking these patents to their inventors, whose country code is FI, we end up with 8065 inventor-patent records. From these, we manage to identify and link 5905 records to the FLEED, consisting of 3253 individuals. For our empirical analysis, we limit the sample to observations from the year 1991 onwards, because the linking of inventors and patents to the FLEED is based on the application year of the patent, but our analysis uses the grant year of the patent. The typical lag from the patent application to the grant is between one and three years, so for most of the cases, we are able to match a patent inventor to a granted patent

[3] For the sake of robustness, we also run our regressions with a sample limited to only those inventors for whom a unique match was found from the population register.

from 1991 onwards. The resulting sample is an unbalanced panel, with 91% of the individuals appearing in the data for all the nine years, resulting in a total of 28212 observations. Removing from the sample observations for which there are missing values in any of the variables we need, we are left with a sample of 17297 observations on 2456 individuals.

2.2 Samples and descriptive statistics

The process described above generates our data on inventors, i.e., individuals that have at least one USPTO patent during our observation period. Table 1a presents some descriptive statistics for this sample for the years 1991, 1995, and 1999. We see that the inventors in this sample are predominantly male (92%), on average 39 years old in 1991 (45 years old in 1999), and employed by their current employer (tenure) for 8 years on average in 1991. The mean annual earnings in the sample is about 36 000 Euros in 1991 (all converted to 1999 money). Table 1b presents the levels and fields of education for the sample. The inventors are fairly highly educated, with more than half of the inventors having a masters degree or a doctorate. Most of the inventors have an engineering degree (78%).

[Tables 1a and 1b here]

In Figure 1 we present the histogram of the number of patents per inventor over our sample period. The great majority of them (60%) have just one patent over the whole time period, while about 20% have two patents and the most inventive of them as many as 25 patents. To gain further insight into this, Figure 2 presents a histogram displaying the frequency of observations with *n* patents. This distribution is also heavily skewed towards having zero patents: almost 14000 observations with zero patents in a given year (not shown in the figure), 2500 observations with one patent, and 400 with two patents.

[Figures 1 - 2 here]

3 The empirical framework

We estimate equations of the following form:

$$\ln(w_{it}) = X_{it}\beta + \sum_{j=0}^{\tau} \gamma_{j+1} patent_{i(t-j)} + \alpha_i + \mu_t + \varepsilon_{it}\,, \tag{1}$$

where *ln(w*$_{it}$*)* refers to the log of annual wage income, X_{it} is a vector of person- and firm-level characteristics, α_i is an individual-specific unobservable fixed effect, possibly correlated with the variable patent, μ_t is a vector of year dummies, and ε_{it} is the error term. Personal characteristics include the person's age and its square, a vector of 42 dummy variables for the level and field of education, gender, tenure with the current employer and its square, the number of months employed during the year, as well as an indicator if the person is an entrepreneur. Firm characteristics include the sector of the firm, the number of employees in the firm, and its location regionally (NUTS2: 5 location dummies[4]).

The variable $patent_{it}$ is a variable capturing the individual *i*'s inventions in period *t*. The simplest measure of invention we use is a patent count, i.e., the number of patents granted in a given year in which the individual is listed as an inventor. A number of studies have shown that there is substantial heterogeneity in the value of innovations, and that this distribution is highly skewed, e.g. by using patent counts and renewal decisions

[4] The NUTS 2 is a five-level regional classification system of the European Union. In Finland the five major regions are: Southern Finland, Western Finland, Eastern Finland, Northern Finland, and Åland.

(Pakes 1986, Lanjouw 1998, Grönqvist 2007), survey questions on patent value (Harhoff, Narin, Scherer and Vopel, 1999), and from patent citations (Trajtenberg 1990, Hall, Jaffe and Trajtenberg 2005). Given that the returns to firms from patents are highly variable, one might expect that the rewards that employers pay to inventors are also based on the value of the innovation. We therefore also explore the implications of patent value or quality on the inventors' wages by constructing a citation-weighted patent measure. Finally, inventions can affect wages in subsequent years, not just in the year of the patent grant. We therefore include τ lags of the patent variable in order to estimate any long-term wage effects of innovation. We experiment with as many lags as the data enables.

We use first-differencing to identify the effect of patenting on an individual's wage. The key aspect is that any unobservable individual time invariant factors are removed by differencing. Importantly, this relieves us of the ability bias typically encountered in the returns to schooling studies (see Card 2001 for a review of the schooling studies). The first-differenced wage equation is

$$y_{it} - y_{i(t-1)} = (X_{it} - X_{i(t-1)})\beta + \sum_{j=0}^{\tau} \gamma_{j+1}(patent_{i(t-j)} - patent_{i(t-j-1)}) + (\mu_t - \mu_{t-1}) + (\varepsilon_{it} - \varepsilon_{i(t-1)}), \quad (2)$$

where $i = 1,\ldots,N$, $t = 2 + \tau,\ldots,T$. Consistency of (2) requires that $E\left[\varepsilon_{it} - \varepsilon_{i(t-1)} \mid Z_{it} - Z_{i(t-1)}\right] = 0$, where $Z_i = \left[X_i \;\; patent_i\right]$. An alternative is to use the within-estimator. The consistency of the within-estimator would require the stronger assumption that $E\left[\varepsilon_{it} - \bar{\varepsilon}_i \mid Z_{it} - \bar{Z}_i\right] = 0$, for which a sufficient condition is the strong exogeneity condition $E\left[\varepsilon_{it} \mid Z_{i1},\ldots,Z_{iT}\right] = 0$. In our view, this assumption may be violated in our data. This would happen if the realization of patents in the future is correlated with the contemporaneous error term, or if the future wage shocks are correlated with the current period value of the patent variable. The former could happen for example through changes in jobs either within or between firms and the latter for example through labor markets treating patenting as a signal of (permanent or at least long-lasting) productivity. The occurrence of such events would invalidate the use of the within estimator, but still allow the use of the first-differenced version that does not require strong exogeneity of explanatory variables.

The lag between the years of patent application and granting of the patent is on average 2 years in our data. Therefore the effort into developing the innovation has been put in at least a couple, probably more, years before the granting of the patent, so anything in the contemporaneous error term should not be correlated with the innovation measure. It therefore seems reasonable that the data satisfies the assumptions underlying the first-difference estimator.

4 Results

4.1 Base specification

In Table 2 we present the results from estimating our base specification with the variable patent being the number of patents granted to individual *i* in year *t*. While our preferred estimation method is first-differencing, we also report the results from pooled OLS and fixed effects estimations for comparison. The pooled OLS estimate of the returns to inventors is 0.037, the fixed effects estimate is 0.018, and the first-difference estimate is 0.015. The magnitude of the OLS estimate reflects the upward bias generated from unobserved individual heterogeneity, as expected. These results indicate that the average increase in wages due to having an invention being granted a patent is around 1.5%.

[Table 2 here]

4.2 Including lags

We next investigate whether the effect of patenting on wage is a permanent increase in the wage level (e.g. a wage raise) or a temporary one (e.g. a bonus) by including lags of the patent variable. Including lags is also important because patent grants may be correlated over time and thus introduce an omitted variable bias when not included in the estimations.

We run a series of regressions where we include lagged values of the patent variable, experimenting with one to six lags. In Table 3 we present the results from the estimations with six lags. The estimations with fewer lags echo these results, and are presented in the appendix. In all the estimations, the coefficient of the current value of patent remains positive and significant, and in fact goes up (0.050 in OLS, 0.030 in FE, and 0.034 in FD). This suggests that there indeed is an omitted variable bias in the base specification results.[5] In addition, the fourth, fifth and sixth lags get a positive significant coefficient in the fixed effects and first differenced regressions, ranging from 0.05-0.06. These results indicate that, first of all, there is a temporary wage increase in the year of being granted a patent in the order of about 3%, and in addition to that, there appears to be a longer lasting, possibly permanent, effect increasing wages from 5 to 6 percent four years after the invention is patented. The fact that this wage increase comes a few years after the patent grant may be related to the fact that it typically takes three to four years to learn the value of the patent (see Pakes 1986 and Lanjouw 1998 for German, UK and

[5] Intuitively, what happens in the base specification is that the (fourth – sixth) years after the patent grant are wrongly allocated into the control group of "no patent grant" – years, raising the average wage earned while in the control group, and thereby inducing a downward bias in the base specification patent coefficient.

French patents and Grönqvist 2007 for Finnish patents). We investigate this next by using a proxy for the quality or value of the patent to see how it affects the returns to being a patent inventor.

[Table 3 here]

4.3 Accounting for the quality of the patent

The effect on wages of having made a patented invention is likely to depend on the value of the patent. Citations received by a patent has been shown to be a fairly good proxy for the value of the patent, so we run the regressions including lags of the number of citations received by the inventor's patents together with the current period patent count. Using citations suffers from the problem of truncation, as citations to a patent arrive over long periods of time, but we only observe them until the last year of the available data.[6] We adjust these citation counts using the results in Hall, Jaffe, and Trajtenberg (2001) to remove the effects of truncation. These adjustments provide us with an estimate of the total number of citations a given patent will receive in its lifetime. We acknowledge that these estimates will be somewhat noisy, because for the patents in our data we only observe citations for the subsequent 3-15 years. Typically, the prime citation years for a patent are roughly 3-10 years after the grant (Hall, Jaffe, and Trajtenberg, 2005). The less citation years we observe for a patent, the noisier these estimates are.

The results of these estimations are presented in Table 4. We find that between three and six years after the patent grant (and possibly permanently), the number of citations received has a positive effect on the inventor's wages, with every 10 citations

[6] Here we make use of the updates to the NBER patent data, available from Bronwyn H. Hall's website, allowing us to observe the number of citations received by the patents up until 2002.

received increasing the inventor's wage by around 2-5%. These results lend support to the notion that the returns to inventors depend on the value of the patent, and are realized three years after the patent grant once the value of the invention is learned. The immediate effect of the patent grant remains.

[Table 4 here]

4.4 Nonlinear effects

Finally, we investigate whether the returns to inventors depend on the number of patented inventions in a non-linear way. We include the number of patents invented in a given year as a categorical variable. The results, presented in Table 5, show that the effects of having 5-7 patent grants are particularly large, corresponding to wage differentials of 35%-80% relative to having no granted patents. The results indicate that there are particularly high returns for those inventors who get a large number of patents.

[Table 5 here]

5 Conclusions

The engine of economic growth is technological progress; the engine of technological progress is human inventiveness. We address the question of the returns to individual inventors by estimating the effect of obtaining a U.S. patent on the wages of Finnish inventors over subsequent years. Finland is one of the countries that has improved its rate of invention, measured by U.S. patents, the most over the last decades (Trajtenberg 2001). Understanding the role of monetary incentives in bringing this change about should offer lessons of more general applicability.

Our results indicate that, first there is a 3.4% temporary increase in wages in the year the patent is granted, probably representing a one-time bonus; second, there is a 5-6% increase in wages four years after the patent grant, which remains there for at least the following two years, possibly representing a permanent wage increase; third the returns to being a patent inventor depend on the quality or value of the patent as measured by the expected lifetime citations received by a patent. These quality-dependent returns are first realized three years after the granting of the patent, coinciding with the time it typically takes to learn the value of a patent. Finally, the immediate returns to inventors who invent frequently (five or more patents a year) are much higher than those to inventors who invent only once, with wages increasing by 35% for inventing five patents and by as much as 80% for inventing seven patents relative to no patents.

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Figure 1. Histogram of total number of patents per inventor

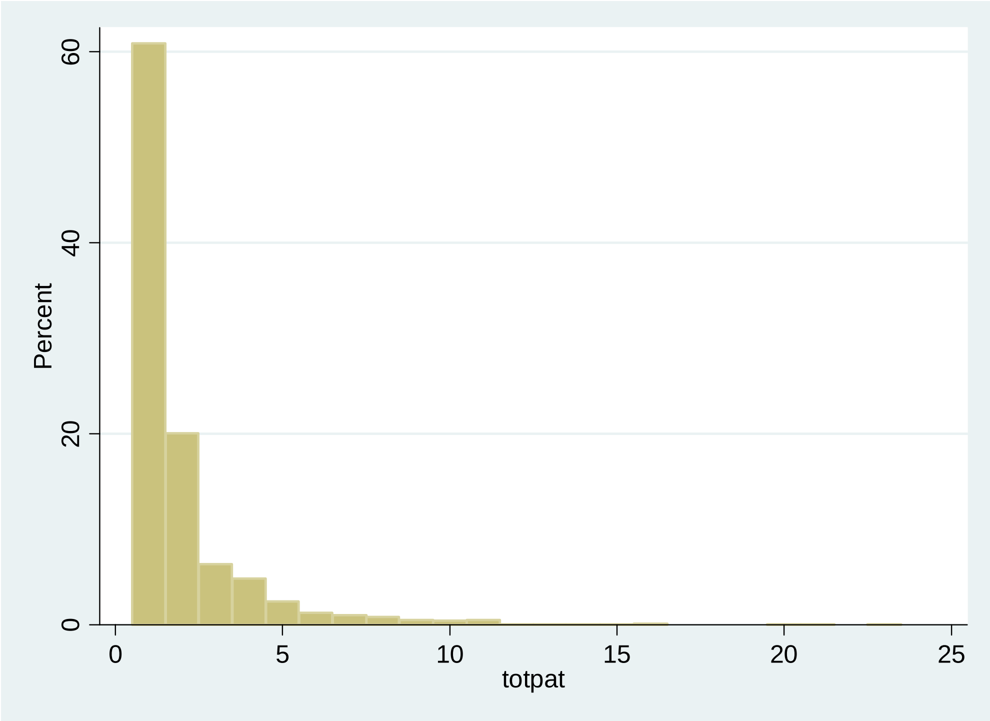

Figure 2. Histogram of the number of patents per observation

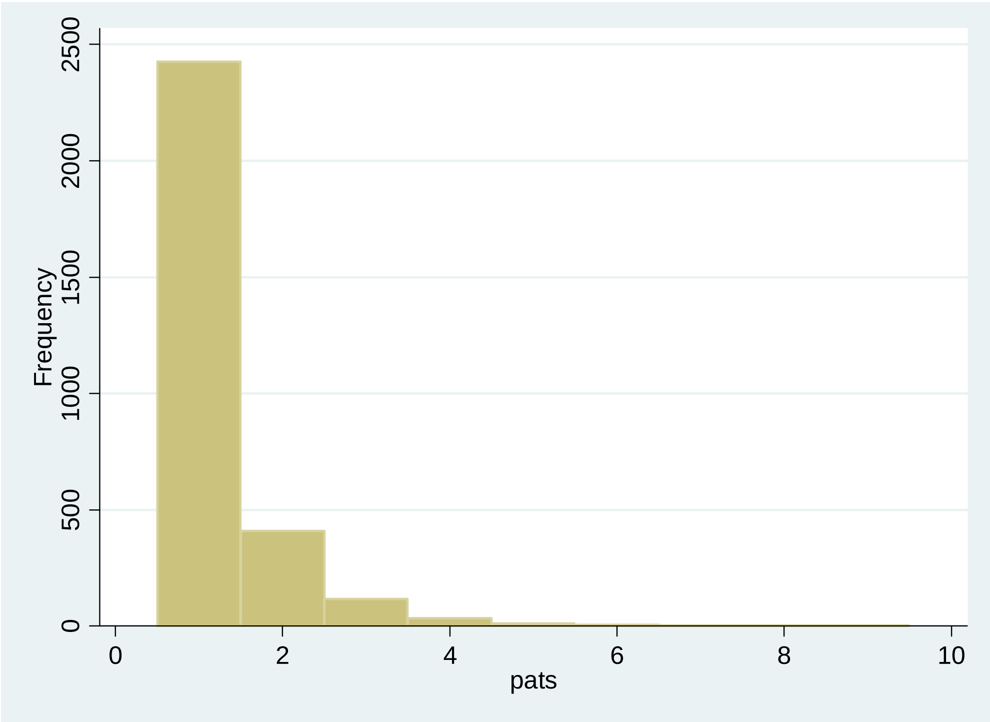

Table 1a. Descriptive statistics

Variable	1991	1995	1999
EARNINGS	35810	39061	69734
	19661	19800	224297
PATENTS	0.13	0.16	0.37
	0.40	0.46	0.75
AGE	39.28	41.80	45.10
	8.87	8.56	8.08
FEMALE	0.08	0.08	0.08
	0.27	0.28	0.28
TENURE	8.02	9.41	10.43
	7.83	8.17	8.85
MONTHS	11.83	11.81	11.63
	1.04	1.12	1.65
Observations	2657	2623	2524

Notes: *Earnings* is real annual work income (in 1999 Euros), *patents* is the number of patents granted, *age* is the age of the inventor, *female* is a dummy equal to one if the inventor is female, *tenure* is the number of years with the current employer, and *months* is the number of months in employment during the year.

Table 1b. Education of inventors

Levels of education	%
Upper secondary	8.54
Lowest level tertiary	9.02
Lower-degree level tertiary	21.8
Higher-degree level tertiary	43.1
Doctorate	13.1
Not known or unspecified	4.46

Fields of education	%
General Education	2.04
Humanities and Arts	0.43
Social Sciences and Business	1.34
Natural Sciences	10.7
Engineering	77.9
Agriculture and Forestry	0.81
Health and Welfare	2.09
Services	0.16
Not known or unspecified	4.46

Table 2. Base specification

	OLS	FE	FD
PATENTS	0.0369***	0.0178***	0.0152***
	0.0078	0.0059	0.005
AGE	0.104***	0.154***	
	0.0098	0.0083	
AGE^2	-0.00104***	-0.00122***	-0.00169***
	0.00012	0.000097	0.00023
TENURE	0.0113***	0.00314	-0.0104***
	0.0031	0.0025	0.0039
TENURE^2	-0.000163	0.000280***	0.000535***
	0.00012	0.000095	0.00015
FEMALE	-0.205***		
	0.023		
ENTREPRENEUR	-4.242***	-4.761***	-3.206***
	0.39	0.21	0.29
MONTHS	0.123***	0.0966***	0.0930***
	0.0083	0.0037	0.0038
FIRM SIZE	0.000872***	0.00227***	0.000667**
	0.00027	0.00019	0.00031
Constant	5.734***	4.600***	0.203***
	0.61	0.31	0.019
Observations	17297	17297	14347
Individuals		2456	2348
R-squared	0.44	0.28	.

Notes: All regressions include dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm's regional location, and year dummies. Standard errors below. OLS are the results from pooled OLS estimations with clustered standard errors, FE are the results from using the within (fixed effects) estimator, and FD are the results from the first-differenced regressions.

Table 3. Including lags

	OLS	FE	FD
PATENTS	0.0502***	0.0297**	0.0337***
	0.013	0.012	0.012
PATENTS (t-1)	-0.00248	-0.00537	0.00574
	0.018	0.014	0.016
PATENTS (t-2)	-0.0078	-0.0211	-0.0229
	0.016	0.017	0.019
PATENTS (t-3)	0.00176	0.0212	0.0143
	0.022	0.019	0.021
PATENTS (t-4)	0.0358**	0.0553***	0.0540**
	0.015	0.02	0.022
PATENTS (t-5)	0.0153	0.0613***	0.0524**
	0.015	0.019	0.021
PATENTS (t-6)	0.0148	0.0528***	0.0548***
	0.012	0.019	0.019
AGE	0.107***	0.264***	
	0.023	0.047	
AGE^2	-0.00104***	-0.00218***	-0.00199***
	0.00027	0.00052	0.00063
TENURE	0.00829*	-0.00479	-0.00425
	0.0046	0.0083	0.0088
TENURE^2	-0.000148	0.000507*	0.000441
	0.00016	0.0003	0.00032
FEMALE	-0.213***		
	0.036		
ENTREPRENEUR	-5.086***	-6.201***	-6.081***
	0.63	0.55	0.58
MONTHS	0.0192***	0.00766	0.00509
	0.0068	0.0087	0.0092
FIRM SIZE	0.000812*	0.00383***	0.00310***
	0.00048	0.00079	0.00084
Constant	6.928***	3.933***	0.241***
	0.82	1.39	0.057
Observations	5001	5001	3096
Individuals		1879	1738
R-squared	0.33	0.15	

Notes: All regressions include dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm's regional location, and year dummies. Standard errors below. OLS are the results from pooled OLS estimations with clustered standard errors, FE are the results from using the within (fixed effects) estimator, and FD are the results from the first-differenced regressions.

Table 4. With citations

	OLS	FE	FD
PATENTS	0.0402 ***	0.0278 **	0.0269 **
	0.0130	0.0140	0.0110
CITS (t-1)	0.0009	-0.0008	-0.0001
	0.0012	0.0015	0.0008
CITS (t-2)	0.0012	0.0008	0.0001
	0.0008	0.0017	0.0011
CITS (t-3)	0.0023	0.0031 *	0.0020 *
	0.0014	0.0018	0.0012
CITS (t-4)	0.0028 *	0.0031 *	0.0027 **
	0.0014	0.0018	0.0012
CITS (t-5)	0.0015	0.0042 **	0.0033 ***
	0.0013	0.0018	0.0012
CITS (t-6)	0.0021	0.0050 **	0.0043 ***
	0.0020	0.0024	0.0011
AGE	0.1090 ***	0.1950 ***	0.0000
	0.0230	0.0470	0.0000
AGE^2	-0.0011 ***	-0.0015 ***	-0.0015 **
	0.0003	0.0005	0.0006
TENURE	0.0078 *	-0.0017	-0.0019
	0.0042	0.0061	0.0087
TENURE^2	-0.00005	0.00038 *	0.00034
	0.00014	0.00020	0.00031
FEMALE	-0.2240 ***		
	0.0350		
MONTHS	0.0182 ***	0.0062	0.0033
	0.0065	0.0045	0.0087
FIRM SIZE	-0.0005	0.0002	0.0011
	0.0010	0.0028	0.0021
FIRM SIZE^2	0.00001	0.00003	0.00002
	0.00001	0.00002	0.00002
CONSTANT	7.8260 ***	4.679 ***	0.189 ***
	0.5000	1.25	0.056
Observations	4938	4938	3126
Individuals	1789	1789	1662
R-squared	0.24	0.09	

Table 5. Non-linear effects

	OLS	FE
PATENTS=1	0.0195*	-0.00219
	0.011	0.009
PATENTS=2	0.0721**	0.0429**
	0.029	0.021
PATENTS=3	0.150***	0.0618
	0.052	0.039
PATENTS=4	0.0167	0.0113
	0.1	0.072
PATENTS=5	0.195**	0.347***
	0.089	0.13
PATENTS=6	0.770**	0.551***
	0.35	0.16
PATENTS=7	0.853***	0.805***
	0.029	0.30
PATENTS=8	0.804***	0.472
	0.028	0.31
PATENTS=9	0.397***	0.115
	0.067	0.40
AGE	0.104***	0.154***
	0.0098	0.0083
AGE^2	-0.00104***	-0.00122***
	0.00012	0.000097
TENURE	0.0113***	0.00337
	0.0031	0.0025
TENURE^2	-0.000164	0.000271***
	0.00012	0.000095
FEMALE	-0.205***	
	0.023	
ENTREPRENEUR	-4.244***	-4.762***
	0.39	0.21
MONTHS	0.123***	0.0965***
	0.0083	0.0037
FIRM SIZE	0.000876***	0.00227***
	0.00027	0.00019
Constant	5.730***	4.596***
	0.61	0.31
Observations	17297	17297
Individuals		2456
R-squared	0.44	0.28

Notes: All regressions include dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm's regional location, and year dummies. Standard errors below. OLS are the results from pooled OLS estimations with clustered standard errors, FE are the results from using the within (fixed effects) estimator, and FD are the results from the first-differenced regressions.