A Closer Look at Inventive Output - The Role of Age and Career Paths

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Abstract

Against the background of the aging of the economically active population accompanied by the current opinion of a decreasing productive efficiency with age, this paper is analyzing the age-output relationship of inventors. To do so, this study integrates both inventor related characteristics and external factors that may influence observable inventive output. Results of a fixed effects panel regression estimation show that different career paths of engineers in firms at least in part explain decreases in inventive output over time. This decrease would have otherwise been wrongly attributed to the relationship between output and age. Data for the analysis was derived from a survey of German inventors (N = 3,049) as well as from semi-structured interviews with inventors, R&D managers and human resource managers.

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1 Introduction

The end of the 19th century was characterized by outstanding and sustainable achievements in the German automobile industry, in particular, in engine construction. In 1876, Otto invented the "Otto Cycle Engine". In 1883, Daimler completed a prototype of the modern gas engine. Only two years later, Benz designed and built the first automobile powered by an "internal combustion engine". Finally, in 1897, Diesel invented the first "diesel fueled internal combustion engine", which was later called the "diesel engine". These four inventors had two things in common: (1) they were highly productive over their whole inventive career and (2) at the time they made the probably most important inventions of their lives, they were between 39 and 49 years old. This means that these inventions were made at later age, especially, when taking into account a much lower anticipated average life around 1900. This may implicate that great achievements require expert knowledge collected over decades and possibly also experience of life. Additionally, this could mean that the average inventive output needs not to decrease over time.

Studying Nobel Prize winners and famous inventors during the 20th century, Jones (2005) finds that young inventors are less productive compared to older ones. But there are also studies suggesting that a scientist's or engineer's output reaches a maximum at the age between 35 and 45 and declines afterwards (Vincent/Mirakhor 1972). Possible reasons for changes in the performance of researchers over time are (1) inventor related issues, e.g., motivation, experience or physical and mental performance or (2) external influences, e.g., incentive systems or career systems (Sauermann/Cohen 2007; Roberts/Biddle 1994; Stephan/Levin 1992).

Against the background of the aging of the economically active population accompanied by the current opinion of a decreasing productive efficiency with age, it will be interesting to analyze the age-output relationship of German inventors more closely. To do so, this study integrates both inventor related characteristics and external factors that may influence observable inventive output.

This paper moves beyond previous research by combining three data sources. First, it uses survey data on 3,049 German inventors, who hold at least one granted European patent. To trace the inventive output of each inventor over time, the EPOLINE database of the European Patent Office (EPO) was used. In particular, all patent applications with priority dates between 1977 and 1999 that listed one of the 3,049 inventors were extracted from the database. To validate the results of the following multivariate analysis, 24 interviews were conducted with R&D managers, inventors, IP managers, and human resource managers in firms active in different industries.

Citation counts are used as an output measure to overcome biases caused by strategic patenting behavior (Hall 2004). Since the number of citations a patent receives is a measure for its quality (Harhoff et al. 1999), citation counts seem to be rather independent of the increasing patenting activity. Additionally, including the number of claims per patent as a control variable allows controlling for an increasing number of citations per patent due to an increasing number of references appearing in the search report.[1]

To estimate the relationship between inventive output and age, a fixed effects panel regression will be conducted. To do so, the inventors' patent applications were sorted into groups according to the age of the inventor at the time of the application of the patent. In particular, nine five-year age groups were constructed which represent the time structure of the panel. Then the remaining variables were categorized according to this time structure (i.e., to the nine age groups). To accommodate different career paths of inventors over time, the sample is sub-divided into three groups: inventors who kept on inventing for their whole professional life, inventors who spent at least a major part of their professional life in inventive activity, and finally, inventors who stopped inventing after a short period of time.

Results reveal that the longer inventors remain in R&D, the higher their average inventive output. A possible interpretation may be that inventors who remain in R&D get more experienced and consequently increase their output. However, following the statements of the interviewees, it seems more reasonably to assume that the causality runs the other way around, inventors who generate more output stay in R&D, whereas less productive inventors leave R&D for another job, e.g., in sales. Additionally, results show that not taking different career paths of engineers into account leads to an underestimation of the output of older inventors. For instance, inventors who are promoted into management positions are no longer visible in terms of patents or citations, since they may no longer be part of R&D projects.

The remainder of this paper is divided into six sections. The following section provides an overview of the theoretical and empirical literature. The third section contains the description of the data used in the empirical part of this paper as well as the description of the dependent and the explanatory variables. Section 4 provides descriptive statistics. In section 5 a fixed effects panel regression estimation analyzes the age-performance relationship of inventors. Finally, section 6 discusses the results and provides implications for further research.

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[1] The patent examiner at the EPO conducts his search on prior art on the basis of the claims containing the scope of protection. An increasing number of claims per patent, hence, lead to an increase in the number of references in the search report. Since citations are calculated on the basis of the references, an increasing number of claims increases the number of citations.

2 Theoretical Background and Empirical Evidence

In the following, important results of two lines of research will be summarized. First, studies that analyze the relationship between age and output of researchers will be presented. Second, literature that deals with career paths of R&D personnel will be provided.

The relationship between age and output among technical personnel or scientists has been analyzed in a number of studies[2]. Early findings show an output maximum at the age of about 40 and a decline afterwards. This decline was explained by a decrease in motivation and risk-taking as well as by difficulties in keeping up with technological change (Dalton/Thompson 1971; Lehman 1966; Oberg, 1960). A recent study on European inventors conducted by Mariani and Romanelli (2006) confirms an inverted u-shaped relationship between the age of an inventor and the number of patents he produces. A second group of studies detected a curve with two modes, one before the age of 40, the second approximately at the age of 50 (Pelz/Andrews 1966; Vincent/Mirakhor 1972). These findings were criticized by Zuckerman and Merton (1972). Studying Nobel Prize winners, the authors showed that these scientists remained highly productive over time. A decline in productivity due to seniority was explained by differences between two groups: a small group of key scientists who increase or at least maintain their productivity level, and another, larger group showing a decrease in productivity over time. Stewart and Sparks (1966) analyzed the patent productivity of chemists and chemical engineers and also find no decline in productivity with age.

Jones (2005) uses data on Nobel Prize winners and 20th century great inventors. His analysis shows an upward trend in the age at which scientists and engineers begin their careers. A reason for this delayed start is an increase of the age at the time of the highest educational degree. Thus, scientists and engineers spend more time on education. This time shift is not compensated by a shift in the productivity of innovators beyond middle age. The combined effects lead to a decline of the overall innovative output of younger innovators. In particular, Jones observes a 30% decline in life-cycle output over the 20th century. Furthermore, the author finds that “the mean age of great achievement for both Nobel Prize winners and great technological inventors rose about 6 years over the course of the 20th century” (Jones 2005: 2).

Levin and Stephan (1991), who examined the research productivity of Ph.D. scientists in physics and earth science over their academic life cycle, come to different results. According to their data, the average research productivity decreases over time. The authors explain their finding by the fact that research activity may be "investment-motivated". This means that

[2] See Goldberg/Shenhav (1984) and Börsch-Supan et al. (2006) for a summary of the relevant literature on the relationship between age and productivity.

scientists do research hoping to receive future financial rewards from their achievements. Given a finite time horizon, research productivity should decrease over time (Diamond 1984).

Finally, Allison and Steward (1974) use survey data on 1,947 U.S. scientists working in university departments and find a highly skewed distribution of productivity among these scientists. Furthermore, the authors observe an increasing output inequality with age. A possible explanation for this finding is the fact that a number of scientists stop publishing at a certain point of their career, e.g., because they leave university. This finding is especially interesting, since not taking a change in the publication behavior into account would result in biased productivity measures. One could assume that not only the number of publications of scientists but also the number of patents produced by inventors in firms are influenced by their career decisions. For instance, inventors changing to administrative roles become invisible in terms of patents. To get a better understanding of the relationship between career paths and visible patent output, important literature on career paths of R&D personnel will be summarized in the following paragraph.

First of all, Allen and Katz (1985) find that career systems of engineers and scientists in the U.S. are completely different compared to career systems of managers. In general, career prospects are less promising for technical professionals compared to management positions. Therefore, engineers and scientists are often attracted by higher wages to undertake administrative roles. Since tacit knowledge, which is stuck in the heads of researchers, plays a major role in R&D (Dosi 1988), key inventors leaving R&D to take up a management position could harm the competitive position of a firm. A possible solution proposed by the authors are so-called “dual ladder” career systems providing more career chances for engineers (Allen/Katz 1985). The advantages and disadvantages of a dual ladder system had already been discussed in previous research, e.g., by Shepard (1958) and Cantrall et al. (1977).

Based on semi-structured interviews conducted in five R&D labs in the U.S. and U.K., Bailyn (1991) distinguishes four different R&D careers: (1) the managerial route, (2) the technical route, (3) the from project to project route, and (4) the technical transfer route. Whereas the "managerial route", which is the most attractive due to the highest compensation, moves technical personnel away from R&D to administrative tasks, the "technical route" makes advancement for R&D personnel possible without leaving R&D. "From project to project route" means that technical employees evolve from project to project, e.g., by receiving larger overall responsibility for the budget. Finally, "technical route transfer" means that the R&D professionals move out of R&D into another division of the firm. Which route to choose depends on both the characteristics of the firm and the skills of the R&D professional. The motives and preferences of 2,500 scientists and engineers are analyzed by Allen and Katz (1992). The authors find that only 21% of the R&D professionals opt for a technical career path. The others rather prefer a managerial career. Additionally, the higher the educational level of the respondents, the more likely scientists and engineers choose the technical career path. A reason for this result may be that individuals who have a Ph.D. prefer the technical ladder, since the reward system is more similar to the academic reward system, i.e. recognition is more important than status related incentives. Roberts and Biddle (1994) suggest that about 50% of the R&D professionals involved in technical work move to a management position after about 35 years.

The age-output related literature summarized above clearly shows that the age of researchers does influence their performance. However, the shape of the performance distribution is considerably influenced by the ingenuity of the researchers under consideration. In particular, whereas productivity increasers over time if star inventors are considered, the productivity distribution for average R&D employees seems to be inverted u-shaped,. Within this paper the following hypothesis is proposed:

H.1: The relationship between the age of an inventor and his inventive output is inverted u-shaped.

Additionally, the literature provides evidence of a career path related dependency of observable inventive output. Generally, many different career paths are open to R&D personnel. Actually, scientists and engineers who keep on inventing for their whole professional life seem to be rather rare. However, inventors changing to a management position or to a non-R&D unit within the firm become invisible in terms of patents. Therefore, the following relationship is expected:

H.2: The shape of the output distribution of inventors strongly depends on the career path the inventors choose.

3 Data Source and Description of the Variables

3.1 Description of the Data

The data used in this chapter were collected in the course of a project sponsored by the European Commission. The project called PatVal aims at creating a database of patent characteristics based on a survey of European inventors named in European (EP) patents and from information drawn from the patent documents[3]. This paper relies only on the German dataset. 10,500 EP patents listing inventors living in Germany were chosen by stratified random sampling based on a list of all granted EP patents with priority dates between 1993 and 1997 (15,595 EP patents). A stratified random sample was used in order to oversample potentially important patents.[4] The information was obtained using a questionnaire. The first inventor listed on the patent document was chosen as the addressee of the survey. Overall, answers were received from 3,049 different inventors, resulting in a response rate of 32%.

The data from the questionnaire were merged with bibliographic and procedural information on the respective patents obtained from the online EPOLINE database. The database contains information on all published EP patent applications as well as all published PCT applications since the founding of the EPO in 1978. The dataset corresponds to the EPOLINE data as of March 1st, 2003 and covers over 1,260,000 patent files with application dates ranging from June 1st, 1978 to July 25th, 2002. For this study, inventor address data were available up to 1999.

To trace the output of each inventor over time, the EPOLINE database was used to search for all patent applications belonging to the 3,049 inventors with priority dates between 1977 and 1999. The search procedure resulted in a total of 35,971 EP patent applications. To ensure that the matching worked well, data from the PatVal questionnaire providing information about the mobility of the inventor was used.

To collect additional information about career systems of engineers and about the relationship between different career paths and the inventive output, additional explorative interviews were conducted. The sample consists of 24 interviews which were conducted between June and December 2006, either personally or via telephone. To obtain comprehensive information about the career system of engineers and about inventive output, inventors, R&D managers, IP managers, and human resource managers were interviewed. The interviewees have been working in different industries, i.e. in biotechnology, engine technology, energy supply, semiconductors, mobile telecommunications, automotive engineering, aerospace, and medical technology. Since a purposive sample was used, the responses cannot claim to be representative for the population of German firms. Nevertheless, the answers will be used to properly interpret the results of the multivariate analysis and to derive accurate implications for R&D management.

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3 For further details on the PatVal project see Giuri, Mariani et al. (2007).

4 The sample of 10,500 patents hence includes all patents an opposition was filed against by a third party (1,048) and patents which were not opposed but received at least one citation (5,333), and a random sample of 4,119 patents drawn from the remaining 9,212 patents.

3.2 Motivation for the Measure of Inventive Output

Former empirical studies on inventor productivity used patent counts to measure inventive output (e.g., Narin/Breitzman 1995). Ernst et al. (2000) were one of the first to use patent quality as an output measure. In particular, the authors used the grant rate (number of patents granted divided by the total number of applications per inventor), the share of valid patents (share of patents for which the renewal fees had still been paid), the citation ratio (number of citations received divided by the total number of patents), and the share of US patents in the inventors' patent portfolios.

The results of Ernst et al. (2000) and also the work of Hall (2004), which provides determinants of the "patent explosion" observable in the U.S. since 1984, prove that output measures are at risk of being biased due to:

- differences in the organization of the inventive process across firms and due to
- a strategic shift in the patenting behavior of firms over time.

Both problems as well as their handling in the following regression model will be discussed below.

Organizational Differences

R&D is organized differently in large firms compared to small and medium firms. For instance, Kim et al. (2004) showed that inventors in large firms contribute less in any single R&D project but are involved in more projects at the same time. Additionally, large firms have more resources at their disposal to operate larger projects, to recruit more R&D staff, or to apply for more EP patens. This could lead to an overestimation of the output of inventors employed with large firms. Consequently, one has to control for the size of the applicant or for the availability of resources. To control for the size of the applicant, one could use the number of employees. However, firm size does not vary considerable over time unless the inventor changed his employer. The data reveal that more than 60% of the inventors have not changed their employer at all and only 15% of the inventors changed their employer more than once. Since variables that vary little over time have only small power in a fixed effects approach, the number of employees seems to be a rather inappropriate control variable.

In contrast, the size of the inventor team should be more appropriate. In particular, team size varies considerably over time, i.e. it could be different for each patent. Additionally, team size is positively correlated with firm size and also controls for the resources that were assigned to the project that resulted in the specific patent. Figure 1 shows the variation of team size with firm size. Whereas an inventor team consists of an average of two inventors in small firms, in large firms an average of four inventors are jointly responsible for an invention.

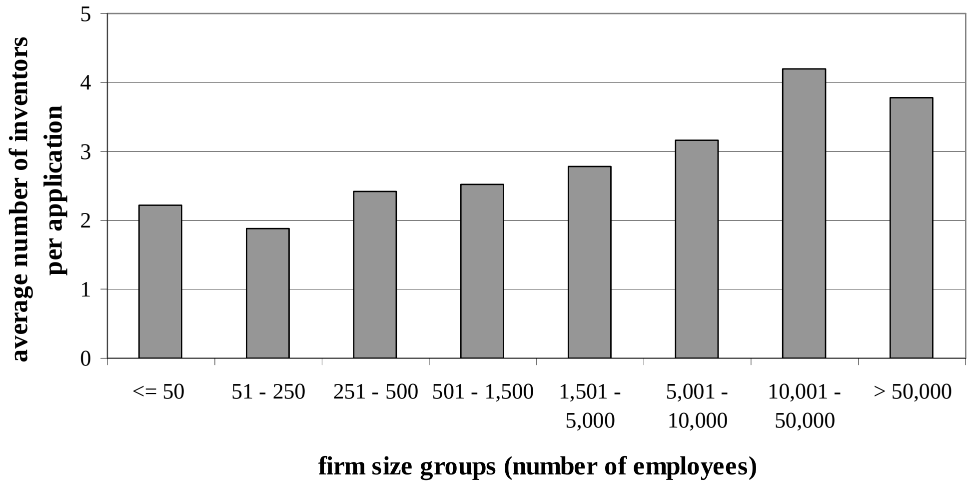

Figure 1: Average inventor team size by firm size (N = 28,542)

Furthermore, Figure 2 shows that the average size of inventor teams has remained almost stable over time.

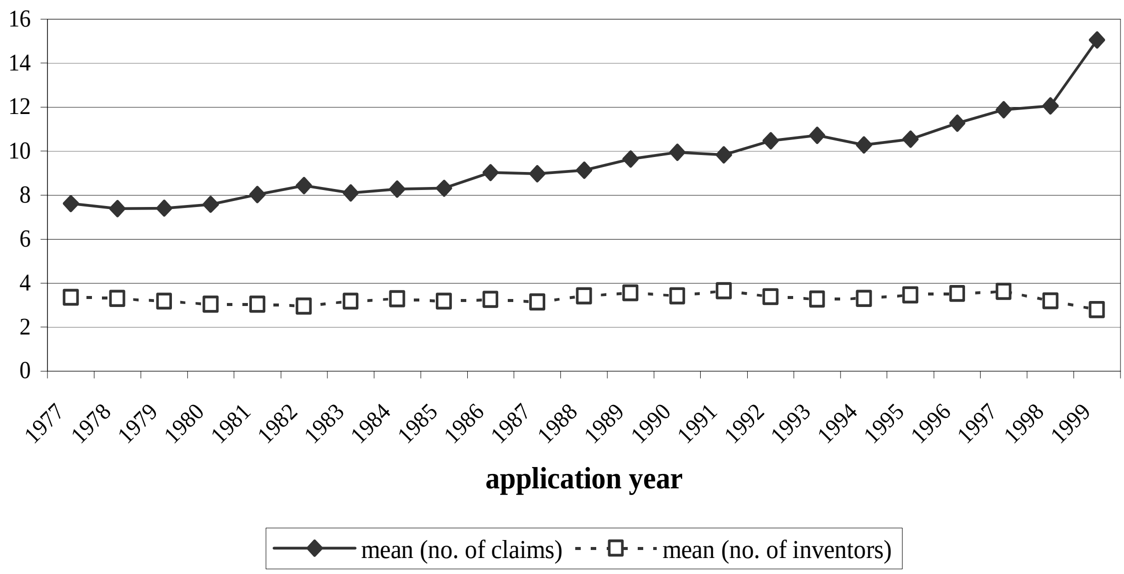

Figure 2: Yearly means of the number of claims specified in the patent applications and yearly means of inventor team size (N = 28,542)

Changing Patenting Activity

Over the last years, the annual number of patent applications increased both in the US (Hall 2004) and in Europe (Harhoff 2005, Harhoff 2006). One possible reason is that patenting has been extended to new technological areas such as genes, software, or business methods which were previously not patentable. Additionally, firms apply for more patents per unit of R&D expenditure due to strategic reasons. Hall (2004) uses U.S. patent data of about 1,400 U.S. manufacturing firms between 1980 and 1989 to explore the sources of patent growth in the U.S. since 1984. Results reveal that the increase of patent applications has taken place especially in the electrical, electronics, computing and scientific instruments industry. This “patent explosion” is assumed to be a result of a strategic shift in patenting behavior of U.S. firms in these industries (Hall 2004).

An increasing patenting activity over time leads to biased results when using uncorrected output measures, since younger inventors today (keeping all other variables constant) tend to patent more inventions than older inventors did in the past when they were the same age (Hall et al. 2005). To avoid these biases, an alternative output measure is employed. Following Ernst et al. (2000), who found that inventive quantity does not rule out inventive quality, the quality of the patent applications is used as a dependent variable. According to Harhoff et al. (1999) the number of citations a patent application received from subsequent patent applications within a certain period of time is an appropriate proxy for the quality of the application.

Not only the number of patent applications but also the number of citations has increased over time (Harhoff/Wagner 2005). However, this increase has to a large extent occurred as a result of the increasing number of claims per patent and not due to an increasing patent propensity of firms (see Figure 2). An application that seeks patent protection at the European Patent Office has to pass an examination process. During this examination process, a search report is prepared by the patent examiner. The search report contains patent and non-patent documents constituting the relevant prior art to be taken into account in determining whether the underlying invention is new and involves an inventive step. According to the Guidelines for Examination in the European Patent Office[5] the patent examiner should direct his search to the most important characteristics of the invention. Therefore, the search is conducted on the basis of the claims that describe the scope of protection for which patent protection is designated. An increasing number of claims per patent, hence, lead to an increase in the number of references included in the search report. Since references in the search report form

[5] See http://www.european-patent-office.org/legal/gui_lines/pdf_2005/index.html, access on February 12, 2007.

the basis for calculating the number of citations a patent received by a subsequent patent, an increasing number of claims indirectly increases the number of citations per patent. Therefore, in the following multivariate analysis, the number of claims will be included as a control variable. However, possibly the fact that examiners have to choose the patent and non-patent literature to be referenced in the search report from a larger pool of available literature (caused by an increasing number of patents and scientific articles) leads to more references in the search reports and, consequently, to more citations per patent in later years. To control for this possible time trend, additional time dummies indicating the priority year of the patent applications will be factored into the panel regression.

3.3 Description of the Variables

(quality adjusted) inventive output – As an output measure (dependent variable) the number of citations will be used. This variable includes the number of citations a patent application received within 5 years following the publication of the search report added up for the total number of patent applications per inventor. Due to the skewness of the output distribution (Lotka[6] 1926, Price[7] 1965) the logarithm of the dependent variable is employed. To accommodate zero values, one was added to the total number of citations before calculating the logarithm. In accordance with Price (1976), who counts the publication of a paper as its first citation "success", the application of an EP patent is supposed to be its first patent citation.

age of the inventor - The variable contains the age of the inventors in 1999. The information was obtained from the questionnaire.

claims - This variable contains the number of claims per patent. The claims define the scope of an invention for which patent protection is requested. Within the multivariate analysis, this variable is used to control for an increase in the number of references in the search report caused by an increase in the number of claims per application over time.

inventor team size - This variable provides information about the size of the inventor team, i.e., it contains the number of inventors mentioned on the patent document. Team size will be included in the regression to control for the allocation of resources in different R&D projects and also for firm size.

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6 Lotka formulated the "inverse square law of scientific productivity" (Lotka 126: 320). According to Lotka's Law, the number of researchers producing n scientific contributions is proportional to $1/n^2$.

7 Price (1965) formulated the "square root law of elitism" (Ernst et al. 2000: 186) suggesting that a scientific community in a particular research field contains an elite group of scientists, almost identical to the square root of all community members. This elite group is responsible for about 50 percent of the entire scientific output within this research field.

status - This variable provides information on the status of the patent applications. Two variables were included accounting for the share of applications that were either refused by the examiner or withdrawn by the applicant, for instance, due to the results of the search report. Additionally, the share of patent applications that were finally granted was factored into the regression.

opposition - The variable contains the share of granted patents that were opposed by a third party within the opposition term of nine months after grant. The status variables as well as the opposition variable are included to control for the value of the patent applications.

technical area - Based on their International Patent Classification (IPC) codes, the patent applications were classified into 30 technical areas. This classification was proposed by Schmoch (OECD 1994).

priority years - The following priority year dummies will be used as additional control variables in the panel regression to account for a changing patenting and citation behavior over time: priority year 1977-1981 (reference group), priority year 1982-1987, priority year 1988-1993, priority year >1993.

4 Descriptive Statistics

The empirical analysis is based on the responses of 3015[8] inventors who are responsible for a total of 35,210 EP patent applications. Table 1 presents selected descriptive statistics of the variables described in the previous section. The total number of patent applications per inventor received an average of 14.94 citations, ranging from 0 to 709. Each patent application received on average 1.06 citations. Additionally, the inventors' patent applications contain on average 10.65 claims. The number of claims per patent ranges between 1 and 55.6.

Furthermore, Table 1 provides information on the legal status of the patents. On average 75% of the applications had been granted by the EPO. 7% of the inventors' granted patents were opposed by a third party. On average 11% of the applications had been withdrawn by the applicant and 2% had been refused by the EPO. Statistics of the EPO reveal that on average 29.7% of EP patent applications between 1980 and 1990 had been withdrawn and 5.2% had been refused by the EPO (Harhoff/Wagner 2005). A possible reason for the low rates of withdrawal and refusal within this data is the fact that the dataset includes only patents of

[8] 3,015 of the 3,349 questionnaires were filled out completely with regard to the above described variables.

German inventors. The difference may especially arise due to a different behavior of German applicants in drafting patent applications. In particular, German applicants perform extensive search of prior art before filing a patent application. This should result in lower rates of withdrawal and refusal.

Variable	Mean	S. D.	Min.	Max.
number of citations (5 year window)	14.94	32.97	0	709
number of citations per patent (5 year window)	1.06	1.01	0	14
priority year				
1977 - 1981	0.03	0.08	0	0.84
1982 - 1987	0.08	0.15	0	0.83
1988 - 1993	0.31	0.30	0	1
> 1993	0.58	0.34	0	1
number of claims per patent	10.65	4.75	1	55.6
inventor team size	2.84	1.40	1	11
status of the patent appliations				
share of applications withdrawn	0.11	0.16	0	0.75
share of applications refused	0.02	0.05	0	0.5
share of applications granted	0.75	0.23	0.04	1
share of applications opposed	0.07	0.16	0	1
age of the inventor in 1999	50.18	9.95	28	83

Table 1: Descriptive Statistics (N = 3,015)

The responding inventors were between 28 and 83 years old in 1999 with a mean at 50.18 years. The size of the inventor team varies between 1 and 11 inventors and has its mean at 3 inventors per team.

Variable	no_cit (5yrs)	no_cit pp (5yrs)	no_ claims	age_ inv	share_ oppo	share_ withdr.	share_ refused	share_ granted	team_ size
no. of citations (5 yrs)	1.000								
no. of citations per patent (5yrs)	0.318*	1.000							
number of claims	0.170*	0.002	1.000						
age in 1999	-0.105*	0.036	-0.039*	1.000					
share_opposed	0.087*	-0.035	0.001	0.070*	1.000				
share_withdrawn	-0.008	0.150*	-0.038*	0.076*	-0.088*	1.000			
share_refused	0.028	0.050*	-0.003	0.057*	-0.021	0.072*	1.000		
share_granted	-0.077*	-0.182*	-0.083*	0.119*	0.145*	-0.621*	-0.239*	1.000	
inventor team size	0.226*	0.312*	0.028	-0.105*	-0.026	0.091*	0.014	-0.125*	1.000

* significant at 5% or lower

Table 2: Pearson correlation coefficient (N = 3,015)

Table 2 lists the Pearson correlation coefficients for interval scaled variables. The dependent variable “number of citations” is positively correlated with the number of claims, the number of patents opposed and the inventor team size. The number of citations is negatively correlated with the age of the inventors and the share of patents granted. The correlation coefficients of the explanatory variables are quite small. The strongest correlation (corr = 0.226) is observable between the variable “number of citations received” and inventor team size. Apparently, the qualitative output largely depends on firm size, i.e. on the availability of resources. This relationship will be further explored in the multivariate analysis.

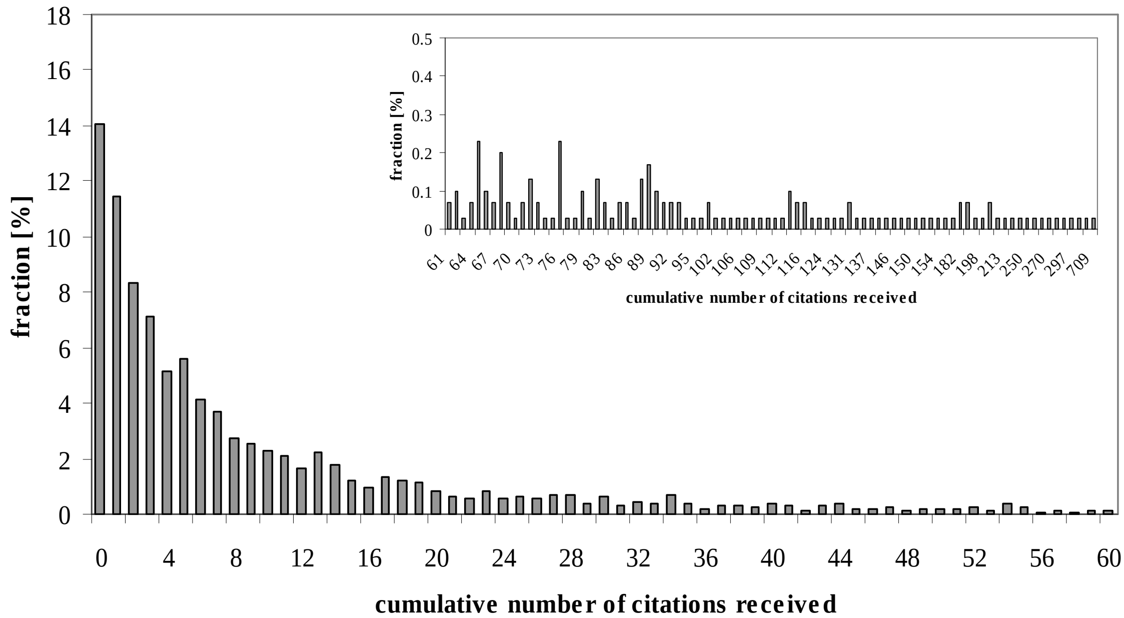

Figure 3: Distribution of the cumulative number of citations received (N = 3,015)

Figure 3 displays a histogram of the distribution of the citations the inventors received for their patent applications. The tail of the distribution (more than 60 forward citations) is displayed separately in the right hand upper corner. About 14% of the inventors generated patent applications that received no citations at all. 2% of the inventors are responsible for applications that received more than 100 cumulative citations.

5 Multivariate Specification and Results

To analyze the relationship between age and inventive output over time, in the following, a panel data analysis will be conducted. To do so, the inventors’ patent applications were sorted into groups according to the age of the inventor at the time of the application of the patent. In particular, nine five-year age groups were constructed: 25-29 years, 30-34 years, 35-39 years, 40-44 years, 45-49 years, 50-54 years, 55-59 years, 60-64 years, and >64 years.

The basic model (1) can be written as

$$y_{it} = \beta_1 x_{it} + c_i + u_{it} \qquad (1)$$

where i indexes the different individuals and t the different time periods. c_i denotes an unobserved individual effect, representing all factors affecting y that do not change over time, e.g., the educational degree of an inventor or his gender. u_{it} is called the idiosyncratic error term (Wooldridge 1999).

Two different methods exist that could be used for estimating the described unobserved effects panel data model: (1) the fixed effects estimator which uses the variation in explanatory variables over time to estimate regression coefficients. Inventor specific characteristics which are time invariant are automatically dropped from the equation procedure and regression analysis is employed to provide unbiased, consistent estimators. (2) The random effects estimator which makes assumptions about the unobserved individual effect c_i uses a GLS estimation. An advantage of the random effects model is that the coefficients of time invariant explanatory variables are estimated (Ruud 2000).

To decide, which method to use, a Hausman test was conducted. Since the test revealed that random effects estimators would be inconsistent[9], in the following a fixed effects approach will be employed.

Regression model (2) will be estimated:

$$\begin{aligned} \log(citation\ counts_{it} + 1) &= \beta_0 + \delta_{1m} * (d\_age)_{mt} + \delta_{2n} * (d\_priority)_{nit} + \beta_1 * (no\_claims)_{it} \\ &+ \beta_2 * (teamsize)_{it} + \beta_{3j} * (status)_{itj} + \beta_{4k} * (tech\_area)_{itk} + u_{it} \quad (t = 1,...,9) \qquad (2) \end{aligned}$$

where i denotes the different inventors and t indexes the time period. Age groups of the inventors m represent the nine time periods: 25-29 years, 30-34 years, 35-39 years, 40-44 years, 45-49 years, 50-54 years, 55-59 years, 60-64 years, and >64 years, which were factored into the regression as dummy variables. The time periods do not change across i, which is

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[9] The key consideration in choosing between a random effects and a fixed effects approach is whether c_i and x_{it} are uncorrelated which is an assumption of the random effects model. To test this assumption Hausman (1978) proposed a specification test based on the differences between the random effects and the fixed effects estimates. In particular, the null hypothesis tests if the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator (Wooldridge 2001). Results of the Hausman test show that H_0 has to be rejected (Chi2 = 223.96, p = 0.000) which means the random effects estimators are not consistent.

why they have no i subscript. n denotes the priority year dummies: prio_1977-1981, prio_1982-1987, prio_1988-1993, and prio>1993, j indexes the status variables (application granted, withdrawn, or refused, patent opposed) and k indexes different technical areas. Due to the fact that inventor specific characteristics which are time invariant are automatically dropped from the equation procedure, the level of education of the inventors could not be used as an independent variable. However, the data reveal that the level of education of the underlying inventors is considerably high. In particular, 86% of the inventors in the sample have a university degree. Therefore, it can be assumed that the education variable would not have too much explanatory power in a regression model due to a lack of variation in the variable. This is illustrated by Hoisl (2007), who uses the same sample and shows that the level of education does not have a significant impact on output quantity.

To accommodate for different career paths of inventors over time, the sample was sub-divided into three groups. The first group includes inventors who were observable for at least five periods (≥ 20 years) within the panel (hereinafter referred to as *long-term inventors*). The second group comprises inventors observable for three to four periods (10 to < 20 years) (hereinafter referred to as *medium-term inventors*). Inventors who were only observable during two periods (< 10 years) were sorted into the last group (hereinafter referred to as *others*). Whereas the *long-term inventors* (5 or 6 periods) represent inventors who kept on inventing for their whole professional life, the *medium-term inventors* (3 to 4 periods) include inventors who spent at least a major part of their professional life on inventing. Finally, *others* (2 periods) comprise three types of inventors: first inventors who stopped inventing and left R&D for another job, e.g., in sales or marketing. Second, inventors who were still at the beginning of their career in 1999 (inventors who were about 40 years old in 1999 or younger) and who could due to truncation of the data only be observed for two periods. Third, these inventors may also be in the middle or at the end or their inventive life cycle and may for a short period in time have produced patented output.

Before presenting the results, it should be mentioned that the interviewees pointed out that technical specialists from the beginning of their career spend between 30 and 50% of their working time on administrative duties or paperwork. This applies also to full-time inventors. The respondents also explained that inventive activity of R&D personnel may also decrease before an official change to a management position, for instance, if engineers take over a project management position. Finally, if employees have a management position they do no longer produce any inventive output.

Table 3 and Table 4 display the results of the fixed effects panel estimation. Model 1 (Table 3) only includes dummy variables for the age of the inventors. Model 2 (Table 4) additionally controls for an increasing number of citations over time by including the number of claims as a control variable. Additionally, control variables for the priority years of the patent applications and further determinants of inventive output are factored into the regression. Model (a) is estimated for the full sample of inventors. Models (b) - (d) refer to the three sub-samples described before.

First of all, the outcomes of Model 1(a) will be discussed using results based on the full sample of inventors (Table 3, column 1). Results suggest that inventors aged between 25 and 29 receive 68% less citations compared to the reference group (45-49 years). Inventors aged between 30 and 34 still receive 18% less citations. The early literature in this field proposes a maximum of productivity at the age of about 35 to 45 and a decline afterwards (Dalton/Thompson 1971; Lehman 1966; Oberg 1960). Model 1(a) does not confirm the findings of earlier research. The number of citations rather reaches its maximum at the age of 55 to 59. As from this age the number of citations received decreases.

	Model 1			
	(a)	(b)	(c)	(d)
dependent variable	**log(no. of citations + 1)**			
sub-samples	full sample	5 to 6	3 to 4	2
reference group: age: 45 - 49 years				
age: 25 - 29 years	-0.680***	-1.508***	-0.607***	-0.090
	[0.100]	[0.332]	[0.116]	[0.185]
age: 30 - 34 years	-0.181***	-0.922***	-0.094	0.232*
	[0.064]	[0.158]	[0.076]	[0.135]
age: 35 - 39 years	-0.116**	-0.540***	0.028	0.133
	[0.054]	[0.108]	[0.063]	[0.117]
age: 40 - 44 years	-0.110**	-0.212**	-0.088	0.055
	[0.045]	[0.096]	[0.054]	[0.089]
age: 50 - 54 years	0.112**	-0.011	0.120**	0.151
	[0.046]	[0.098]	[0.054]	[0.094]
age: 55 - 59 years	0.058	-0.094	0.104*	0.061
	[0.054]	[0.113]	[0.062]	[0.107]
age: 60 - 64 years	-0.098	-0.483***	0.020	0.081
	[0.080]	[0.161]	[0.088]	[0.157]
age: > 64 years	-0.068	-0.950***	0.100	0.260
	[0.142]	[0.298]	[0.153]	[0.306]
Constant	1.359***	2.020***	1.345***	1.064***
	[0.034]	[0.070]	[0.039]	[0.077]
Observations	7237	929	3538	1990
Number of inventors	3015	184	1056	995
F-test (n1, n2)	8.58 (8,4214)	10.13 (8,737)	6.27 (8,2474)	1.55 (8,987)
R-squared	0.020	0.098	0.020	0.013

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Robust fixed effects panel estimation (Model 1) (N_{full} = 7,237, N_{5_6} = 929, N_{3_4} = 3,538, N_2 = 1,990)

Additional information is provided when dividing the sample into the three sub-samples according to the number of periods the inventors were observable in the panel dataset. Models 1(b) to 1(d) (Table 3, columns 2 to 4) provide the regression results for the three sub-samples. Figure 3 displays the differences in the productivity-age relationship between the three sub-samples. The three curves present the logarithm of the medium number of citations the inventors received for patents applied for at the age of, e.g., 25 to 29 or 30 to 34.

The upper curve represents *long-term inventors* who were observable for five or six periods. As proposed by the literature, the relationship between productivity and age is inverted u-shaped and has its maximum at an age of about 45 years. The medium curve represents *medium-term inventors* who were observable for three to four periods. These inventors still spent a considerable share of their professional career in R&D (10 to < 20 years) but are supposed to have stopped inventing at a certain point in time. Figure 3 shows that *medium-term inventors* are at the age of 25 to 35 even more productive than the *long-term inventors* (5 to 6 periods). After the age of about 35 output quality of the *medium-term inventors* is much lower than that of the long-term inventors. This could mean that those inventors, who are characterized by a very high level of productivity and are promoted. These inventors may then stop inventing or at least spend only part of their time on inventive activities leading to a lower observable productivity compared to the long-term inventors. As from the age of 30 to 34, the output of the medium-term inventors is rather constant, i.e. the performance curve is no longer inverted u-shaped.

The interviewees confirmed this finding. In particular, eight interviewees reported that they already started their job in R&D with having a management career in mind. Additional, they affirmed that a change to a management position typically takes place at the age of about 35 years. Three interviewees confirmed that their management orientation even prompted them to obtain a doctoral degree. Finally, ten respondents reported that are very happy with their technical specialization and that they do not plan to move into a management position in the near future.

Finally, the lower curve represents *others* who were only observable for two periods (about 10 years). *Others* receive, almost as from the beginning of their career, less citations compared to the other two groups. These inventors could first of all drop out of the sample since they are unsuccessful inventors and change to an administrative position or another position within the firm (or leave the firm completely). One of the interviewees reported that this third group does exist in firms. Inventors who are less successful in making inventions initially stay in R&D and will be assigned to routine jobs or industrious but uninspired work. In the long run, these inventors change to jobs or into a role that more strongly suits their capabilities, e.g., account management, sales or consultancy.

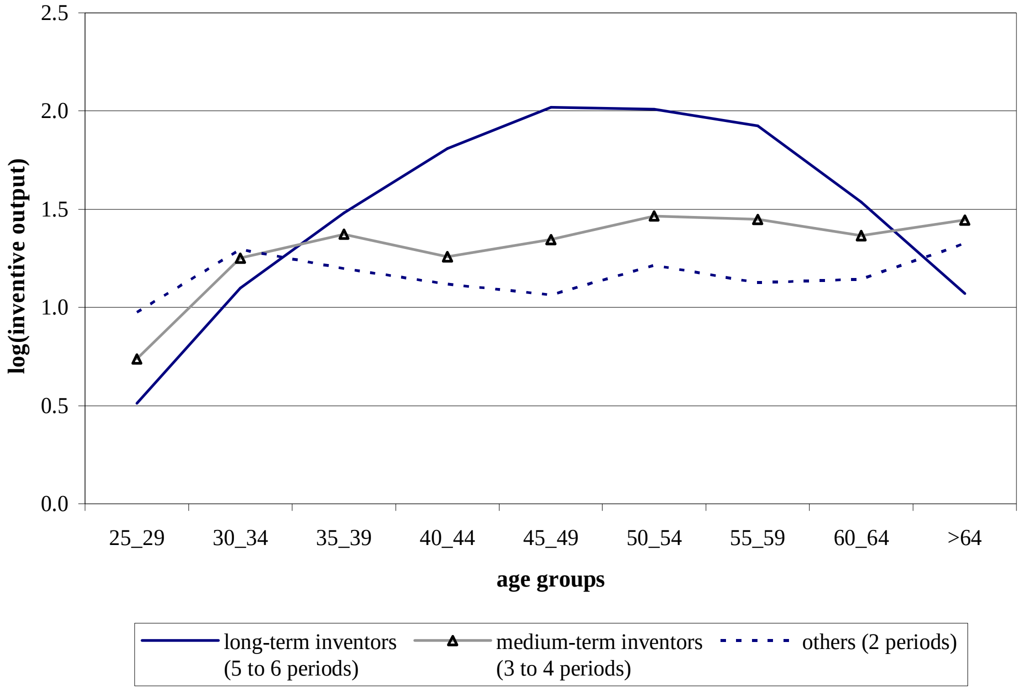

Figure 3: Productivity differences by age groups; subdivided into three groups by number of periods observed (N_{5_6} = 929, N_{3_4} = 3,538, N_2 = 1,990), graph of: $\log(no\_cit_{it} + 1) = \beta_0 + \delta_1 * d\_age25-29_t + ... + \delta_8 * d\_age > 64_t + u_{it}$ where the coefficient δ_1 is the percentage change in productivity between the reference group and the first age group. δ_2 to δ_8 have the same interpretation with respect to the remaining age groups. β_0 is the intercept for the reference group and $\beta_0 + \delta_1$ is the intercept for the first age group.

Second, inventors assigned to the third group (*others*) are also very young in 1999. Therefore, truncation of the data impedes observing these inventors any longer. Young inventors may be mistakenly sorted into sub-sample three (*others*). In the event these inventors are indeed on average more productive than the unsuccessful inventors, the first two or three age groups of the lower curve (including these young inventors) should suffer from an overestimation of productivity. Overall, it becomes clear that the patent applications of inventors remaining in R&D for a longer time receive more citations.[10]

10 Additionally, a robustness check was conducted. In particular, medium-term inventors and others were excluded who are characterized by a lack of patent applications for more than 2 periods (i.e., more than ten years) before the age of 45 and who were not observable in terms of patents before the age of 45. The reduced sample leads to the same results with respect to early years of inventive activity (age between 25 and 45). The exclusion of occasional inventors and of respondents who started inventive activity just before retirement led to similar results. However, the performance curve is characterized by a sharper decrease at later age. This robustness check provides evidence that the results are hardly influenced by the fact that certain inventors have not continuously produced inventive output.

	Model 2			
	(a)	(b)	(c)	(d)
dependent variable	**log(no. of citations + 1)**			
sub-samples	full sample	5 to 6	3 to 4	2
reference group: age: 45 - 49 years				
age: 25 - 29 years	0.038	0.048	0.143	0.118
	[0.174]	[0.585]	[0.215]	[0.282]
age: 30 - 34 years	0.395***	0.214	0.476***	0.423**
	[0.127]	[0.410]	[0.158]	[0.209]
age: 35 - 39 years	0.324***	0.261	0.419***	0.289*
	[0.091]	[0.268]	[0.112]	[0.159]
age: 40 - 44 years	0.147**	0.167	0.144**	0.159
	[0.058]	[0.155]	[0.070]	[0.105]
age: 50 - 54 years	-0.152**	-0.330*	-0.154**	-0.015
	[0.060]	[0.171]	[0.072]	[0.107]
age: 55 - 59 years	-0.400***	-0.678**	-0.372***	-0.298*
	[0.096]	[0.285]	[0.117]	[0.163]
age: 60 - 64 years	-0.693***	-1.254***	-0.574***	-0.473**
	[0.138]	[0.415]	[0.166]	[0.234]
age: > 64 years	-0.847***	-2.026***	-0.704***	-0.434
	[0.206]	[0.607]	[0.245]	[0.349]
reference group:(mean) priority year: 1977 - 1981				
(mean) priority year: 1982 - 1987	0.469***	0.719***	0.273***	0.581**
	[0.083]	[0.190]	[0.100]	[0.279]
(mean) priority year: 1988 - 1993	0.953***	1.154***	0.818***	0.906***
	[0.115]	[0.337]	[0.137]	[0.296]
(mean) priority year: > 1993	1.215***	1.750***	1.103***	1.134***
	[0.153]	[0.480]	[0.189]	[0.322]
(mean) no. of claims	0.009***	0.007	0.009**	0.011*
	[0.003]	[0.009]	[0.004]	[0.006]
(mean) no. of inventors	0.065***	0.024	0.069***	0.071***
	[0.014]	[0.036]	[0.017]	[0.023]
(mean) share withdrawn	0.329***	0.278	0.394***	0.22
	[0.084]	[0.233]	[0.103]	[0.140]
(mean) share refused	0.29	0.435	0.362*	0.033
	[0.177]	[0.467]	[0.205]	[0.335]
(mean) share grant	0.535***	0.774***	0.595***	0.356***
	[0.064]	[0.215]	[0.082]	[0.096]
(mean) share opposition	0.235***	0.304	0.228***	0.248*
	[0.075]	[0.225]	[0.087]	[0.138]
(mean) share technical areas	included	included	included	included
Wald test	n.s.	Chi2(5) =2.14 p=0.028	n.s.	n.s.
Constant	-0.298*	0.612**	-0.244	-0.602
	[0.154]	[0.290]	[0.180]	[0.375]
Observations	7237	929	3538	1990
Number of inventors	3015	184	1056	995
F-test (n1, n2)	17.83 (22,4200)	8.14 (22,723)	12.76 (22,2460)	4.08 (22,973)
R-squared	0.100	0.189	0.103	0.078

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Robust fixed effects panel estimation (Model 2) (N_{full} = 7,237, N_{5_6} = 929, N_{3_4} = 3,538, N_2 = 1,990)

The increase in inventive output observable for both medium-term inventors and others at the age of about 60 years may arise due to the fact that certain inventors started their inventive career at a later age that is these inventors were observable from the age of 45 to the age of 65. The increase may also be the result of a time trend. Therefore, the second model (Table 4) includes control variables for the mean share of priorities within the different age groups. The share of priorities between 1977 and 1981 forms the reference group. Results of Model 2 (Table 4) confirm this finding for the whole sample (Model (a)) as well as for the three sub-samples (Models (b)-(d)). In particular, the number of citations increases over time. The coefficients are highly significant at the 1% level. Model 2(a) provides results similar to those of Model 1(a). In particular, the relationship between age and inventive output is inverted u-shaped. However, the turning point of productivity is already reached at the age of 30 to 34 years. Afterwards, productivity again decreases but more rapidly compared to Model 1.

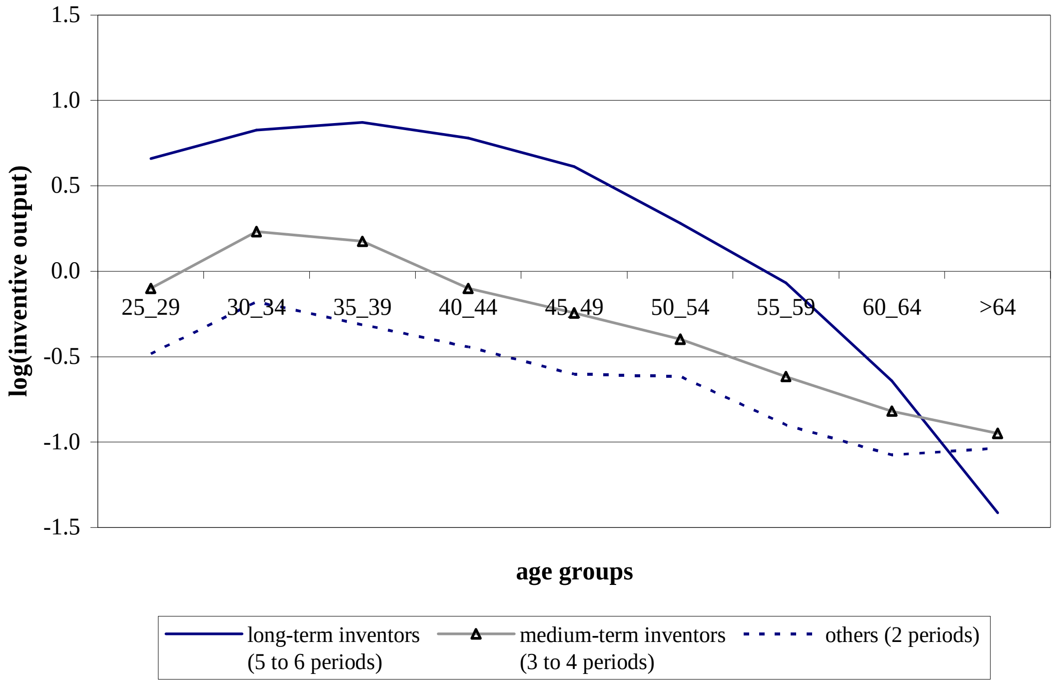

Figure 4: Productivity differences by age groups (additional control for the priority years of the patents); subdivided into three groups by number of periods observed (N_{5_6} = 929, N_{3_4} = 3,538, N_2 = 1,990).

Figure 4, in turn, displays the output-age relationship for the three sub-samples. It becomes apparent that *long-term inventors* (5 to 6 periods) are most productive and *others* (2 periods) again turn out to be least productive. However, the shape of the upper curve (*long-term inventors*) has changed slightly. In particular, *long-term inventors* no longer show a turning point at the age of 45 to 49 but at the age of 35 to 39. Afterwards, inventive output decreases monotonically. This change arises due to the correction of the time trend. In particularly, comparing Figure 3 and Figure 4 reveals that including control variables for the priority years and determinants of inventive output leads to a downward correction of the inventors' output at advanced age. Nevertheless, hypothesis H.1, an inverted u-shaped relationship between age and performance of the inventor, is confirmed for long-term inventors. Furthermore, the three sub-samples show that also hypothesis H.2 that the performance curve is highly dependent on the inventors' career paths is confirmed by the data, as well.

Finally, Table 4 shows that the control variables exhibit the expected signs. In particular, the number of claims affects the number of citations positively. The number of citations also increases with the size of the inventor team. This is not surprising, since inventor team size is a proxy for firm size. Inventors working with larger firms have more resources at their disposal to create inventive output. Surprisingly, claims and firm size only affect the output of *medium-term inventors* and *others* but do not affect the output of the *long-term inventors*. Industry dummies, on the contrary, do only exhibit a significant effect on inventive output with respect to the *long-term inventors*. A possible explanation for this finding may again be the different career paths of the inventors. On the one hand, inventors who decide to stay in R&D seem to produce output, regardless whether they work in large companies or in rather small firms. On the other hand, inventors who stop inventing at a certain point in time may profit from the organization of R&D in large firms, e.g., due to the fact that R&D managers are mentioned on patents because of seniority or their position within the firm.

6 Conclusion

The purpose of this paper was to analyze the age-performance relationship of inventors more closely, in particular, to trace inventive output over time. To do so, a panel regression model was estimated. Overall, results of the panel estimation provide clear evidence that the age of an inventor considerably influences his output. In particular, data show that the average inventive output decreases with the age of an inventor. However, results also suggest that one has to distinguish between *long-term inventors* and inventors who dropped out of R&D for certain reasons (*medium-term inventors*, *others*) to avoid biased results. Whereas *long-term inventors* remain visible in terms of patents over the whole period under consideration, *medium-term inventors* are no longer visible after they left R&D. Comparing the mean inventive output of both groups over time shows that not distinguishing between different career paths of inventors would lead to an underestimation of the performance of inventors who stopped inventing earlier. Furthermore, there is considerable evidence that failing to control for an increasing number of citations over time would also lead to biased results.

Finally, a limitation of this analysis should be mentioned: the problem of using patent data to measure inventive output. Griliches (1990) pointed out that “not all inventions are patentable, and not all inventions are patented”. This is one of the disadvantages of patent data used as output measures. Cohen et al. (2000) confirm that patent protection is accounted as a more effective appropriability mechanism for product innovations compared to process innovations. “Process innovations are less subject to public scrutiny and thus can be kept secret more readily” (Cohen et al. 2000). This constraint must be taken into account when interpreting the results.

Although this analysis improves on the current literature by including different data sources to depict the creative power of inventors as precise as possible, it does not raise the claim of providing a perfect picture of the inventive life cycle. In particular, since strong assumptions had to be made with respect to the interpretation of the three sub-samples. However, it is intended to provide a small step towards a better understanding of inventors’ ingenuity. Furthermore, this paper should sensitize further research to limitations that have to be taken into account when deriving implications for inventive output from patent data.

Overall, future research is needed to shed more light onto the inventors’ life cycle, for instance, onto reasons for leaving R&D. It is also necessary, to analyze career systems for R&D personnel more closely. In case, firms do not provide a dual ladder career system for management and R&D, a move into a management position is the only way for a productive inventor to get promoted. It will be interesting to analyze whether transferring productive inventors into management positions causes damage to the innovative potential of the firm or whether able inventors who agree to move to a management position do an even better job as a manager.

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