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Life-cycle Productivity of Industrial Inventors: Education and other determinants

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**Life-cycle Productivity of Industrial Inventors:
Education and other determinants**[♦]

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Abstract

This paper analyzes the life-cycle inventive productivity of Japanese industrial inventors, based on panel data of 1,731 inventors matched with firm data. We focus on two issues: whether inventors with PhD degrees perform better, even taking into account the late start in their business careers, and if those with PhD degrees based only on dissertation (PhDs (DO)), for which a university performs only a certification function, are similarly as productive as the regular PhD holders. Our main findings are the following. Inventors with regular PhD degrees have significantly higher annual productivity than those with other education levels in terms of both patent and forward citation counts, and they can easily compensate for the late start in their business careers. This is the case even after controlling for workplace, research stage, and inventor ability. PhDs (DO) also have high patent productivity (rising more rapidly with experience), although their level is lower than that of regular PhD holders. They work in independent laboratories and in projects involving basic research as frequently as do the regular PhD holders. Furthermore, the exits of PhDs (DO) from inventions are significantly late even when controlling for project type and inventor ability, so that they work longer as inventors.

Keywords: Inventor, Life-cycle inventive productivity, Productivity profile, Education, Patent
JEL Classifications: O31, O34, I21

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1. Introduction

It is widely recognized that higher education is essential for strengthening the innovative capacity of domestic industry, especially for those countries at the technology frontier[1]. PhD trained scientists and engineers would help a firm to enhance absorptive power of industry for exploiting recent scientific advances (see Cohen and Levinthal 1989 for the importance of absorptive power). In addition, hiring a PhD may serve as a direct path of technology transfer from universities to industries (Stephan 2011)[2]. Recognizing these, many countries have expanded higher education systems and have increased the supply of highly skilled scientists and engineers. The enrollment of doctoral programs have been rapidly increasing among OECD countries (OECD 2010), including Japan, by 40 per cent from 1998 to 2008.

In Japan, PhD inventors are still a small minority (only a little more than 10% of the inventors), compared to the US where almost half of the inventor are PhDs, according to the RIETI Inventor Survey implemented in 2007 focusing on triadic patents. Moreover, as explained later in more detail, only half of the PhD inventors in Japan have obtained their degrees through attending the formal doctoral course work. To put it in another way, half of them have obtained their PhDs only by submitting their dissertations, based on their research within their firms ("PhD (dissertation only)" or merely "PhD (DO)" hereafter). At the same time, there are many regular PhD holders who cannot be employed after attaining a PhD degree[3]. Many Japanese firms seem to be reluctant to hire PhDs. They often point out that they are narrow-focused and not flexible, while recognizing the importance of building the technological basis of their firms. In addition, since it takes at least additional three years for completing PhDs from the time of the award of a master degree (or at least five years from the award of the bachelor degree), PhD inventors are late in starting business careers. In Japan, inventors start invention careers early[4] and also exit early into managerial jobs, so that the average inventor age is significantly lower than that of the US. This career pattern as well as the availability

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1 Agihon et al. (2009) emphasizes that highly skilled workers who acquired higher level education are the engine of economic growth for the countries which have already reached technological frontier, and empirically validated this view, exploiting US state level data on economic growth and patenting. Some studies, however, find that only basic education has a positive effect on the economic growth from a global perspective (Kruger and Lindahl 2001).

2 Chapter 4 of Stephan (2011) discusses comprehensively how PhDs working in industry contribute economic growth. It quotes the statement of former President of the National Academy of Sciences that "the real agents of technology transfer from university laboratory were the students who took jobs in the local biotech industry."

3 See Cyranoski et al. (2011).

4 Almost 80% of the Japanese inventors have first patent application years below 30, but only lees than 30% of the US inventors (see Walsh and Nagaoka 2009).

of PhD (DO) may make attending a formal PhD program more costly in Japan.

These observations suggest the following questions. Do corporate inventors with PhDs perform better in life-cycle framework, that is, even taking into account their late start in business careers? That is, can their presumably higher annual productivity compensate the loss of starting early in a firm? Secondly, are the inventors with PhDs (DO) similarly productive as regular PhD inventors? If they are, the system of awarding PhDs (DO) may be evaluated as an efficient complement to a formal education program. In such system a university essentially specializes in the certification function for scientific contribution of an industrial engineer. Since these PhDs write their dissertations based on their industrial research, their unemployment cannot be an issue. PhDs (DO) is quite unique in Japan and its assessment may have important implications for the other countries.

In order to inquire these issues, we will assess how the invention productivity varies by educations of the inventors from a life-cycle perspective. In particular, we will assess whether a regular PhD inventor can compensate his late start by generating more number of inventions or higher quality inventions and/or by jumpstarting their invention activities and maintaining invention activities late in their work careers. We also compare how PhD (DO) inventors compare with regular PhD inventors in order to understand how a PhD grant system focusing on certification works. In such assessments we control for the type of workplace where the inventor works as well as the type of the R&D project where he pursues. Furthermore, we control for inventor ability by using an indicator variable (T-score) of the quality of the university from which he/she graduated, which is a standardized score of the difficulty of university entrant examination. Furthermore, we employ Hausman-Taylor estimation in panel data analysis, to control for unobserved inventor ability or the other characteristics. To the best of our knowledge, there are no much studies which investigate life-cycle inventive productivity for industrial workers (see section 2 for literature review) and, moreover, they do not control for the ability of inventors.

Our main findings are the following. Regular PhDs have significantly higher annual productivity than inventors with other education level in terms of both patent and forward citation counts, and they can easily compensate for their late start of business activity. This is the case even after controlling for workplace, research stage and inventor ability. One source of higher annual productivity of regular PhDs is short intervals between the first job year and the first invention year. PhDs (DO) have also high patent productivity (more rapidly rising with experience), the overall level of which are not significantly lower than those of regular PhDs. They work in an independent laboratory and in the project involving basic research as frequently as regular PhDs. In addition, PhD (DO) holders exit from inventive activity significantly late even if we control for project type and inventor ability.

The rest of the paper is organized as follows. Section 2 reviews relevant literature. Section 3 explains the data construction and patent application activities of Japanese industrial inventors. Section 4 explains the estimation models and methodology. Section 5 presents the estimation results and section 6 concludes.

2. Literature review

Empirical studies on corporate inventors are limited. One of the pioneering works is Narin, and Breitzman (1995), which confirmed the finding by Lotka (1926) that scientist's productivity is highly skewed. The four recent studies based on a large scale data which are also most relevant prior works for our research are listed in the following Table 1. All these studies use individual patent application or grant data, matched with firms. Only one study (Kim, Lee and Marschke 2004) uses panel data (inventors by application/grant years), as ours. All of these studies estimate the coefficients of PhDs or those of higher leanings. Mariani and Romanelli (2007) find a fairly significant coefficient of a PhD inventor. Such inventor generates on average 21% more patents than an inventor with a high school degree, while there is no significant difference in the level of citations per patent. Kim, Lee and Marschke (2004) also find that a PhD inventor has significantly more number of patent applications. Furthermore, Hoisl (2007) find that a PhD inventor has no more number of patent applications over its life-cycle, when the productivity measure takes into account the loss of invention period above age 25. Schettino, Sterlacchini and Venturini (2008) find that patent quality increase by 17% with higher level of education (university of PhD relative to non-university degree). Note that these studies differ in choosing the base for a comparison (high school vs. on-PhD), which prevents direct comparison.

(Table 1)

One substantive reason of the variations of the effect between these findings is whether a study takes into account the delay in starting inventions caused by an inventor attending higher educational institutions. Taking into account such delay requires us to measure life-cycle patent applications and to assess how cumulative applications by inventors differ by educational levels, controlling for cohorts or age.

Only Hoisl (2007) does that among the studies in Table 1. Thus, the other studies may overestimate the effect of higher education on life-cycle productivity. The problem of the delay in starting inventions may have become more serious with the increase of "the burden of knowledge" (Jones 2008). Due to the increasing burden of knowledge, increasingly longer period might have been required for a new PhD to absorb past accumulated knowledge, but at the same time, the negative effect of late entry into inventive work may be compensated by late exit. Thus, adopting a life-cycle perspective is very important and we will explicitly analyze the delay of starting invention works by an inventor attending a PhD program, as well as how the exit decision from inventive work is influenced by educational levels.

The second substantive reason is different level of controls over omitted variables which have correlations with education or ability. No studies in Table 1 controls for the inventor ability. Hoisl (2007) controls for inventor knowledge sources, which is likely to be correlated with level of education and ability (an inventor with PhD has better access to external knowledge disclosed in literature). In fact, according to her study, this is one of the few sources of the advantage of a PhD inventor. In addition, she also controls for mobility which has a significantly positive coefficient for inventive productivity and a PhD inventor is more likely to move.

The existing studies do not control for the type of the workplace: an independent laboratory, laboratory attached to a manufacturing division, manufacturing division, and software development division. The existing studies do not control for the stage of the research: basic research, applied research, development, technical service and the other. However, the workplace and the project type are likely to affect significantly the productivity. The laboratory dedicated to research is more likely to provide assets conducive to inventions and patenting. In additions, basic research is likely to generate more patents than development, while a PhD inventor is more likely to be employed in such stage of research. We take into account the characteristic of workplace and the research stage.

There are many empirical literatures on research productivity of scientists. Although some of the basic findings from these literatures would be relevant to corporate inventors, it is important to note that they work in the environment quite different from that for university scientists. One of the basic findings from the research on scientists' productivity is that the research productivity is highly skewed, with a relatively small number of scientists accounting for a significant share of the publications. One important source for such skewedness is cumulative advantage due to "Matthew effect" or preferential attachments (see Merton 1968, Allison and Stewart 1974).

Second, as human capital theory predicts, the scientist's productivity initially rises but then declines with age/experience. Diamond (1984) investigates relationship between age and the number of research publication among mathematician, and find inverted U-shape relation over the life-cycle. Levin and Stephan (1991) also find that inverted U-shape over the life-cycle are observed among Physics and Earth Science except particle physics. Oster and Hamermesh (1998) and Baser and Pema (2004) find that publications increase with age or experience at the early stage but sharply decline with them among economists. Recently, Turner and Mairesse (2005) investigate the relationship age and publications in French physician and find inverted U-shape is observed in their academic life-cycle[5]. We employ a similar econometric model which accommodates inverted U-shape relation over the life-cycle. However, in the context of corporate inventors, the decline of productivity with age may be caused by the changes of the main tasks of an inventor within a firm from invention to management, so that we cannot adopt the human capital theory for interpreting the results.

An alternative to estimating patent production function is to use wage as performance measures, following the tradition of Becker (1965) and Mincer (1974) traditions. Some recent surveys on the relationship between education and wage suggest that MA degree and PhD degrees holders earn more 10% to 30% higher wage than undergraduate (Card 1999, and Deere and Vesovic 2006). In Japanese case, Morikawa (2012) find the workers who have MA holders or more get approximately 20% higher wage premium than the worker who have BA or less. However, corporate inventors are not directly rewarded through wages for their inventive outputs. Employee inventors receive more or less fixed salaries while transferring the ownership to the companies. In addition, there are significant intrinsic benefits to the inventive work, which makes wage undervalue the inventive performance. Thus, wage may not be very informative on invention performance.

3. Data description

3.1 Data

We focus the industrial inventors who responded to the RIETI Inventor Survey in 2007, which surveyed the Japanese patent inventors selected by quasi-random sampling[6]. The questionnaire of this survey covered not only inventive process and the

[5] It is important to note, however, that identifying the age effect requires strong prior assumptions on cohort and year effects, as clarified by Hall, Mairesse and Turner (2007).

[6] A large part of the focal patents are selected in triadic patents, which somewhat skewed for high quality patents, and this indicate that respondent inventors also are skewed for potentially high ability. For sampling method in more detail, please see Nagaoka and Tsukada (2007).

use of the patents but also the inventor profiles: year of birth, gender, the first employed year, highest education and the graduate year. The number of inventors who effectively responded this survey is 5,278. We gathered all patents which include respondent inventor names in the inventors name list, in order to obtain the life-cycle inventive profile of these inventors. We use IIP patent database, for Japanese patent bibliographic data, as offered by Institute of Intellectual Property, which cover patent applications from 1964 to 2009.

We have then identified which patents are truly invented by the respondents. Our name matching method is basically manual inspect, as follow[7]. First, we collected the patents whose inventors' name appears in our inventors' data and we collected 386,828 patents with matched names by this procedure. In order to avoid treating the different inventor as the same person, we use only the patent applications whose inventor belongs only to one particular company (His name appears only under one particular company name and under no others over his life time). This is a very exact name matching strategy because the probability which the different persons who have the same name appears only in the same particular company (and nowhere else) is quite low[8]. While this procedure makes us to lose all inventors who moved from one company to another, this introduces no serious bias for us to evaluate the effects of educations on life cycle invention performance. Rather it is suitable to our analysis because we focus on the inventors which stayed in the same company until his retirement, which has been also quite typical in Japan[9]. This has additional advantage for defining the experience of an inventor clearly and to treat the impact of firm characteristics largely by fixed effects.

We have 1,978 inventors and their corresponding patents after this screening. We further screened by the condition (the sample size was reduced to 96.3 % of the above sample) the first invention age is no younger than the age when the inventor was employed first time. We can offer some evidence that our matching worked reasonably

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[7] Generally, name matching of inventors is a serious obstacle for undertaking a research based on life cycle invention performance. Fortunately, Japanese names have a lot of variety both in family name and in the first name, compared to the other Asian countries. For example, the most frequently used name is Minoru Tanaka in the overall Japanese telephone directory database in 2001 (This directory covers 40 million names which amounts to about 1/3 of overall Japanese population. In addition, the telephone directory covers a worker and a man more intensively.), and his frequency is only 2,620 in 30,552,849 people. Even though, the distribution of the frequency of name is highly skewed, almost all names have low probability for covering different persons under the same name. This is an advantage for Japanese researchers to do name-matching.

[8] To identify whether an inventor belong to one company or not, we use patent applicant database provided by Onishi et al. (2012).

[9] Since inventor mobility is larger in smaller firms, our sample is somewhat biased to large companies. Our sample of inventors is skewed to the inventors belonging to a large company (91% of our inventors have more than 500 employees).

well. We collected the first application years by the additional survey and 480 inventors responded in our selected samples. 86% of them are roughly consistent with the patenting record (3 years before or after the stated application year). Some gap is not surprising because patent application procedure is not inventors' task but that of an IP office or a patent attorney, and this survey is a retrospective survey which may pick up some errors.

3.2 Explanations of output indicators

We use the number of application as an indicator of each person's innovative output. However, almost all patent applications involve multiple inventors, and a whole patent count which attributes each patent to each inventor regardless of the number of inventors inflates a team oriented output. In order to cope with this problem, we use fractional counts as one patent divided by the number of inventors as our main indicator[10].

In addition, we construct the number of forward citations which each patent received from the other patents, so as to build the data on quality-adjusted outputs. The number of forward citations is correlated with patent quality (For example Haroff, Scherer and Vopel 2003, Hall, Jaffe and Trajtenberg. 2005). In Japan, there was no need for an applicant to report the prior art only until 2000, so that we use only the citation count by examiner, so as to ensure consistency of our indicator over time. Lastly, to cope with the truncations of forward citations, we count the number of forward citations which the patent received within five years after the applications.

As shown in Figure 1, the life-cycle number of patents per an inventor (fractional counts) follows almost a log-normal distribution. That is, it has a highly skewed distribution where most inventors have a relatively small number of patent applications, as pointed out by Narin and Breitzman (1995) for industrial inventors in a few firms. The average is 9.1 patents. Similarly, the number of citations received from the date of applications also follows an almost a log-normal distribution (in Figure 2). The average for an inventor is 16.8 times in total for all his patent applications.

(Figure 1 and 2)

4. Estimation models and methodology

4.1 Cross section estimation based on cumulative outputs

[10] We show the results based on whole counts in appendix tables.

We first use cross sectional data, with the cumulative counts of the patents and their forward citations (within the first 5 years) for each inventor as dependent variables. The estimation equation is as follow:

$$\ln(patent_i \ or \ citation_i) = \sum_{s=2}^{5} education \ dummy_{is} + \beta_k X_{ki} + \varepsilon_i \qquad (1)$$

Here the dependent variables are the natural logarithm of the number of patent applications or the number of forward citations received by inventor i, and these two variables are constructed by whole or fractural counts. The dependent variables are transformed into natural logarithmic forms because the distributions of these variables follow approximately log-normal distributions. *Education dummies* indicate each inventor's level of education. X is a vector of control variables (see the following explanations). To control for inventor ability, we introduce a T-score of a university from which the inventor graduated. It is a normalized score measuring the difficulty of university entrance examination. Equation (1) does not introduce the length of an inventor's active span, so that the coefficient of an explanatory variable (such as an education dummy) reflects both its effect on annual productivity as well as that on the length of inventive time span. We control for cohort years (our sample's main cohorts cover from 1946 to 1975 birth years), technology areas and firms (see the following explanations in more detail).

In order to measure annual productivity, we utilize the following equation:

$$patent_i \ or \ citation_i \big/ inventive \ span_i = \sum_{s=2}^{5} education \ dummy_{is} + \beta_k X_{ki} + \varepsilon_i \qquad (2)$$

We use the following two measures of the denominator (inventive span); the first one is from the year in which the inventor got employed to the last year when he invented in our dataset[11], the other is from eighteen years old to the last year when he invented. The former measures inventors' productivity in terms of their actual employment spans. The latter is a life-cycle productivity, taking into account the opportunity cost of attending to the schools for BA degrees or more.

Educational level: This is our key variables which are composed of the BA degree dummy, the MA degree dummy, regular PhD degree dummy and PhD degree with dissertation only dummy, which is assigned according to the questionnaire which asked

[11] Last year of inventive span is truncated by the patent data limitation. In order to control for this, we use cohort dummy as independent variables as explained bellow.

the highest degree at the time of the invention[12]. The reference group is high school diploma or two year college degree. We will investigate how different levels of educations as measured by these variables contribute to inventive productivity after controlling for the characteristics of workplace, inventor motivations, technological areas and inventor ability. One of our main focuses is the comparison between regular PhD and PhD (DO) degree. If two types of PhDs perform similarly as corporate inventors, it would suggest that university education does not significantly matter, except for its screening role. If PhD (DO) performs significantly worse than regular PhD, it would imply that additional graduate education effectively compensate for late of beginning of invention by an inventor with a regular PhD[13].

Next, we explain control variables, and these variables consist of the characteristics of workplace, firm characteristics, personal motivations and profiles, and technology.

Workplace: We use workplace variables to indicate which type of a unit in the firm the inventor belonged to when they invented the focal patent, which are categorized as follow; independent laboratory, laboratory attached to manufacturing division, software development division, manufacturing division, and other division. We use manufacturing unit as the reference group. These variables give us important information on how much an inventor can devote his time on invention and how much complementary assets he has for his inventive work. We assume (somewhat boldly) that an inventor does not significantly change the type of workplace over his career.

Research stage: The research stage of the project subject to our survey are also employed as control variables. The questionnaire asked the inventor to identify the research stages, which are categorized as basic research, applied research, development, technical service and others (multiple choices are allowed). We assume (somewhat boldly) that an inventor does not significantly change the stage of his research project over his career.

Firm fixed effects and firm patent applications: We control for the firm characteristics extensively by firm dummies or firm fixed effects, which cover the complementary

[12] To identify these two types of PhDs, we used Doctoral Dissertation Bibliographic Database which is provided by National Diet Library and National Institute of Informatics.

[13] Another potential interpretation is low standard for PhD (DO). However, there seems to exist no unanimous view on the level of standard for PhD (DO) vs. that for regular PhD.

assets, the internal knowledge stock etc. In addition, we introduce the natural logarithm of the number of patent applications by the firm each year. This variable controls for firm size change as well as the changes of patent application propensity over time.

Motivation: The questionnaire asked the inventors about the importance of their motivations for invention; taste of scientific contributions, challenges, contribution to firm performance, career step, better working conditions, and pecuniary motivation. This was assessed by five points Likert scale (very important, important, indifferent, not important, absolutely not important). If their answer is very important or important, this variable is one, and otherwise zero.

Gender: We use gender of inventor as independent variables, and if the inventor is male, it is given one and otherwise zero.

Technological dummies and cohort dummies: to control for time-invariant characteristic of technological areas, we include technological area dummies, which is determined by the most frequent IPC class of the patent applications by each inventor[14]. Lastly, to control for cohort effect on patent productivity, including truncation effects of our data set, we include cohort dummies in our estimation equation.

T-score: We use T-score of a university as an indicator variable of inventor ability[15]. Unfortunately, our sample is reduced when we use this variable because T-score is available only for the inventors with higher than university degree. We obtained this data offered by Kawai-jyuku which is one of the largest preparatory school in Japan[16].

Table 2 provides the descriptive statistics of these variables. The length of average inventive span based on the first employed year as the initial year is 20 years, and this is quite long period, compared to the data used in previous similar analysis. 98 per cent of our sample is male, and 70 per cent of inventors belonged to independent research laboratory and worked for development.

[14] We construct dummy variables in accordance with IPC sub-class. As the results, the number of technological dummies is 258.

[15] This variable may be partly education quality indicator for university education because high T-score university is also high research university. Therefore, the effect of level of education on patent outputs may be underestimated with T-score variable.

[16] We deduct 5 points from T-scores with private universities because T-scores with private university which imposes fewer exam subjects on examinees tend to higher than their originals compared to national university

(Table 2)

Table 3 shows the means of major variables by educational level. There are significant mean differences between levels of educations with regard to all of four patent outputs. Both types of PhD holding inventors largely belong to independent laboratory (84% for inventors with regular PhDs and 95% for inventors with PhD (OD)). Their projects often cover basic research (46% for inventors with regular PhDs and 48% for inventors with PhD(OD)), compared to other education level. In these two respects two PhDs are very similar. On the other hand, the average length of the inventive span is around 7 years longer for inventors with PhD(OD)) than for those with regular PhDs (25 years vs. 18 year). Since the difference of birth years is only 2 years, longer inventive span of the inventors with PhD (DO) is due to later exits of the inventors with PhD (DO) from inventions. While cumulative patent outputs are similar between the two types of PhD holding inventors, the annual productivity of the inventors with regular PhDs is significantly higher than those with PhD(OD)[17]. Furthermore, PhD (DO) holders graduated from the universities with the highest T-score, indicating that that these inventors have high potential ability.

(Table3)

4.2 Panel estimation

Next, to investigate the determinants of life-cycle inventive profile within a firm, we estimate a panel estimation model. This also has a merit of allowing us to control for unobserved heterogeneity (such as ability) among inventors. Even though fixed effect model is suited for this, this model does not allow us to estimate the effect of time-invariant education level. In order to cope with this problem, we employ Hausman-Tayler random effect model (Hausman and Talyer 1981). We can identify the effect of the variables which are potentially correlated with unobserved individual effect by using exogenous variable as instruments after fixed effect estimation. That is, instrumental variables are composed of the exogenous time-variant and time-invariant variables in the equation, but which are not correlated with unobserved individual

[17] While means of the annual productivity of PhD(DO) holders are same as those of BA holders, differentiation of both inventors are much larger after controlling technological dummies in the estimation results as bellow mentioned. This reason is that PhD(DO) holders in the sample often belong to chemical or medical science area which are fewer patent applications compared to IT or electronics area.

effect. We estimate inventor's life-cycle productivity profile as follows:

$$\ln(patent_{it}\ or\ citation_{it}) = \sum_{s=2}^{5} education\ dummy_{is} + \gamma_1 experience_{it} + \gamma_2 experience_{it}^2 + \beta_k X_{ki} + t + \mu_i + \varepsilon_{it}] \quad (3)$$

Here the dependent variables are the natural logarithm of fractional patent and forward citation counts for inventor i in year t where t represent year dummies[18]. In this equation, we assume that level of education and experience are independent. However, it may be unlikely that an inventor with only high school diploma has the same experience curve as the workers with PhD degrees. Thus, our second specification is as follow:

$$\ln(patent_{it}\ or\ citation_{it}) = \sum_{s=2}^{5} education\ dummy_{is} + \sum_{s=1}^{5} \alpha_s education\ dummy_{si} * experience_{its} + \sum_{s=1}^{5} \gamma_s education\ dummy_{is} * experience_{its}^2 \quad + \beta_k X_{ki} + \beta_l X_{lit} + t + \mu_i + \varepsilon_{it} \quad (4)$$

In this equation, we can differentiate inventive productivity profiles between each educational level by experiences. We treat level of education, experience and its square as endogenous variables in Equation (3) and (4). While our control variables are basically the same as Equation (2), the number of patent applications by each firm in year t becomes time variant variable in Equation (3) and (4).

4.3 Estimation of exit of inventive activity

Finally, we will analyze how the personal and workplace characteristic as well as levels of education are associates with an exit of an inventor from inventive activity. We employ Cox Proportional Hazard model to estimate the hazard of exit from inventive activity, to take into account the truncations. We prepare the duration data starting with the year which the focal patent was applied for, since there can be no observations of exit before that year. We need to distinguish the exit and right side truncation of patent data. Figure 3 gives the distribution of the last year when an inventor applied for the patent. This indicates that the peaks of the distribution occur after 2005, and a lot of inventors are truncated simply because their inventive activities have not yet been reflected into the patent data (publication of patent applications and incorporation into database). We decide to use the last year before 2004 as the actual exit year. In our view this criteria is a conservative one.

[18] In order to cope with zero count of patents, we add one in all dependent variables.

(Figure 3)

We specify the hazard function h(t) as follow:

$$h(t) = h_0 exp(\sum_{s=2}^{5} education\ dummy_{si} + \gamma_1 age_{it} + \gamma_2 age_{it}^2 + \beta_k X_{ki} + \beta_l X_{lit} + \mu_i + \varepsilon_{it} \qquad (5)$$

Here, $h(t)$ is the exit rate at time t when the inventors stopped their inventive activity, and h_0 is the baseline hazard. All of covariates in exponential parts are shift parameters of the hazard rate. We include education level, workplace, research stage, motivation, gender, technological dummies and cohort dummies as time invariant covariates. Furthermore, we also treat inventor's age and the age square as time variant covariates. Since Japanese companies traditionally have implemented seniority system, age might be important factor of exit. The other time variant covariates are the average number of co-inventors with whom the inventor invented in his inventive span, the number of patent applications by each firm in year t and year dummies.

5. Estimation results

5.1 Estimation results of cross sectional analysis

First we explain the major estimation results based on cross section cumulative life-cycle outputs. Here the observations are individuals. Table 4 reports the regression results from Equation (1) and (2), based on fractional counts[19]. The first year of inventive activity is defined as the first employment year in these estimations. Columns 1 to 4 of Table 4 are the results without including the variables for workplaces and research stages, and columns 5 to 8 are the results with all these variables.

(Table 4)

All coefficients of the levels of educations are significantly positive for the number of patent applications and the forward citations, and the coefficients increases with the level of education in all estimations. These results indicate that higher level of education is indeed significantly associated with more patent and forward citation counts. In particular, cumulative life-cycle patent applications and forward citations

[19] The results of these estimations bases on whole counts of patent outputs are quite similar, as reported in Appendix Table 1.

productivity of inventors with regular PhD is 80% and 70% higher than those inventors with master degrees, according to columns 5 and 6[20]. The annual productivity of inventors with regular PhD is also higher by 72% and 63 % respectively. In addition, these differences are statistically significant in all equation[21].

If we compare the inventors with regular PhDs and those with PhDs (DO), the cumulative life-cycle productivity of the former group is 39% and 35% higher than those of the latter in terms of patent applications and forward citations respectively (column 5 and 6) though these differences are statistically insignificant[22]. The annual productivity of the former group are also higher than PhD (DO) inventors by around 42% for patent applications and 38% for forward citations, according to column 7 and 8 though these differences are not significant again[23]. The fact that the difference in cumulative outputs in favor of inventors with PhDs is smaller than that in annual outputs indicates that the active inventive span is longer for inventors with PhD (DO).

As for research stage, the coefficients of basic research are significantly positive for patent outputs. Inventors who engage in basic research have 35% more patents and 28% more citations in terms of cumulative output and 31% more patents and 23% more forward citations in terms of annual productivity. The difference between cumulative output and annual productivity in favor of basic research suggests that an inventor working in basic research tends to have a longer active life as an inventor (we will confirm this more directly in the following estimation focusing on exit). Conversely, technical service dummy is significantly negative for forward citations (a reduction by 25% for annual productivity).

The independent laboratory variable is also significantly positive for all output variables. Similarly to basic research, inventors who work in independent research laboratory have higher patent productivity in terms of both patent counts and citation counts (90% and 71% respectively for life-cycle productivity and 100% and 66% respectively for annual productivity). Thus, working in an independent research laboratory significantly enhances research productivity.

As shown in Table 3, both types of PhDs significantly more work on the research

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[20] These results on education dummies are affected by the composition of cohorts in the sample since the effects of the delay of inventive activity due to attending additional school years are stronger for young inventors. To check this possibility, we estimated the interaction terms between cohort and education level. As a result, we obtained that the coefficient of regular PhD is still larger than the inventors with lower education levels even among younger inventors. The reason seems to be that inventive span is around ten years even for the youngest inventors who were born in 1971-1975.

[21] F test for differences in coefficients between regular PhD and MA are 7.4 and 4.7 in columns 5 and 6, and 7.2 and 4.2 in columns 7 and 8.

[22] F test for differences in coefficients between two PhDs are 0.9 and 0.6, respectively.

[23] F test for differences in coefficients between two PhDs are 1.3 and 0.8, respectively.

project involving basic research and in an independent laboratory. Thus, as shown in the comparison between columns 1 to 4 and columns 5 to 8, the coefficients of level of educations in column 1 to 4 are larger than that of them in column 5 to 8 of Table 4 (around 20% higher in the case of a regular PhD). This suggests that we will significantly overestimate the effect of education on patent outputs, without controlling for the characteristics of research stages and workplaces, since a PhD (or PhD (DO)) inventor works more in the place favorable for doing research and in the type of project generating more inventions.

Concerning individual characteristics, the male variable is significantly positive for patent quantity in term of fractional counts (but not in whole counts). This gender variable reflects unobservable effects such as childcare, maternity leaves, which are associated with overestimate of male variable. Taste for challenging is significantly positive for patent outputs in column 1 to 4. This may indicate that an inventor with such taste is more likely to engage in a project at research frontier. A reputation variable also is significantly positive for patent outputs. This may indicate that inventors who want to get a positive reputation prefer explicit outputs such as patent application.

Table 5 presents the result of estimating Equation (2) with the beginning year of inventive activity set at eighteen years old in order to count the delay due to higher level of educations as opportunity costs in years. The coefficient of regular PhD decreased most, so that they are much close to the level as that of PhD (DO). This indicates that the delay of starting inventive work due to attending higher education is significant but also shows a relatively high productivity of an inventor with a PhD (DO). This result is consistent with Jones (1998).

(Table 5)

The effect of education level may be also overestimated in the above estimations since they do not control for inventor's ability. An inventor with higher ability is more likely to choose higher education. In order to address this possibility, we estimate Equation (1) and (2) with adding a T-score variable as a control variable of inventor ability. In this estimation we lose inventors with less than two year college from our sample. Columns 1 to 4 in Table 6 are the results with a T-score variable and columns 5 to 8 are those without T-score variable. The coefficients of T-score are significant and positive for patent outputs. This confirms the importance of inventor ability on patent productivity.

The comparison between two groups of the estimates suggests that the difference of the coefficients of PhD and MA do not significantly change after including a T-score variable, even though the size of the coefficients (with BA as the base) declines. These results indicate that there is no significant inventor ability difference between MA and PhD, while there are such difference between BA and MA. While the coefficients of regular PhD remain significant and positive in all columns, the coefficients of PhD (DO) are no longer significant except in column 5. However, the difference of the coefficients between the two types of PhDs does not significantly change (slightly larger, with T-score variable). These results indicate that controlling for the ability of inventors does not significantly affect the difference between graduate degrees, while it reduces the difference between the BA degree and graduate degrees.

(Table 6)

5.2 Estimation results based on panel data

Before estimating Hausman-Taylor random effect model, we regressed Equation (3) and (4) with using Fixed effect model, and the results are shown in column 1 to 4 of Table 7. The coefficients of experience are significantly positive while the coefficients of square terms are significantly negative for both outputs in column 1 and 2. Furthermore, these results have remained, after allowing for interactions between the level of education and experience in column 3 and 4 while the interaction terms with the square of experience are not significant at highest education levels. This result presents that a simple inverted U-shape relationship between experience and patent productivity is observed in each education level, especially in lower education level.

Using the estimation results, the experience yearly profile of patent and citation counts by level of educations are shown in Figure 4 and 5. The slope of the PhD (DO) is steeper than the other education levels[24]. This indicates a strong within-firm learning curve for those who seek for a PhD while working and/or their increasing deployment to the jobs dedicated to inventions.

(Table 7)

(Figure 4 and 5)

Table 8 shows that the results of Equation (4) with using Hausman-Taylor random

[24] While we estimate Equation (4) with additional time variant dummy variable which is one if inventor obtains PhD (DO) degree and otherwise zero, this variable is not significant in any specifications.

effect model. As mentioned above, this method can estimate the time-invariant variables after controlling for unobserved heterogeneity among inventors. Column 1 for patent outputs and column 2 for citation output of Table 8 are estimated, with allowing for the interaction effects between the level of educations and experience, using Equation (4). As for the level of educations, both types of PhDs are significantly positive for forward citations in column 2 while only regular PhD is significantly positive for patent application in column 1. The fixed effect coefficient of regular PhD remains higher than that of PhD (DO). Using the estimation results, the experience yearly profile of patent and citation counts by level of educations are shown in Figure 6 and 7. The outputs in terms of both patents and forward citations are higher for a regular PhD compared to a PhD (DO). This indicates that while a PhD (DO) increases its productivity rapidly with its experience, the productivity of a regular PhD remains higher than the PhD (DO) during its inventive span.

(Table 8)

(Figure 6 and 7)

In order to investigate the impact of receiving PhD (DO) in their inventive career within a company, we estimate Equation (4) with separating PhD (DO) dummy at the time of before and after receiving year of PhD (DO) degree. Column 3 and 4 in Table 8 show the results. While both PhD (DO) dummies are positively significant for both patent outputs, there are no significant differences between two. This indicates that the award of a PhD (DO) degree itself does not significantly affect the resources available for the inventor or its position. It is already anticipated by the firm.

The above results indicate that regular PhD holders have significantly higher research productivity than the other education levels. However, they also have the potential loss of inventions in their younger period because of longer education terms. How quickly can their high productivity compensate their potential loss in younger period? To answer this question, we calculate when regular PhD inventors can recover their potential inventive loss due to late startup, exploiting the learning time according to the estimation results. We assume all inventors start their inventive activity immediately after graduating in standard education time. That is, BA inventors begin their inventive activity in age 23, MA inventors begin it in age 25 and regular PhD inventors begin it in age 28. We additionally assume PhD (DO) inventors have MA degree and beginning of their inventive activity is in age 25. This assumption overestimates potential inventive loss of regular PhD inventors because the difference between first job year and first invention year declines with education level (Table 9)[25].

(Table 9)

Table 10 shows the average time to surpass total inventions of each education level using the results in column 1 and 2 of Table 8. Cumulative invention of PhD inventors surpass that of PhD (DO) inventors in approximately 4.6 and 5.3 years respectively, and this time is somewhat shorter among BA and MA inventors. These results indicate that PhD inventors recover their potential invention loss by at least 5.3 years on average.

(Table 10)

5.3 Estimation results of exit analysis

Table 11 shows the results of estimating the hazard model on exit from inventive activity. Column 1 in Table 11 is estimated without research stages and workplaces variables, and column (2) is estimated with full sample. Hazard rate of exit decreases with higher level of education. The coefficients of both types of PhDs are negative and significant for exit in column 2, and PhD (DO) has a lower hazard rate than regular PhD. This indicates that the hazard rate of exit is 62% and 69% lower for regular PhD and PhD (DO), compared to baseline, respectively. Moreover, hazard rate for PhD (DO) is significantly negative even after controlling inventor ability in column 3 of Table 11. This shows that if an inventor gets a PhD (DO) degree, he/she tends to stay longer as an inventor. An award of PhD (DO) may help as a signaling/screening device, although it may also capture residual inventor ability.

(Table 11)

The age coefficients of Table 11 show that the hazard rate (exit rate) is low in younger stage, as expected. Moreover, the hazard rate increases drastically with age. This indicates that while young inventors remain in research workplaces, they exit from inventive works as they become more senior. Concerning the research stage, the hazard of basic research is significantly low. Conversely, hazard of technical service for exiting is significantly high. The coefficient of number of inventors is strongly significant and

[25] We don't calculate "less than two year college" because it is composed of two groups which standard graduate years are difference.

positive for exiting. This result is somewhat interesting because an inventor in a big team is more likely to exit from their inventive activities.

6. Conclusion

This paper has analyzed life-cycle inventive productivity of Japanese industrial inventors, based on the panel data of 1,731 inventors matched with firm data. We focused on two issues: whether PhDs contribute to inventive performance, even taking into account their late start in business careers, and whether the inventors with PhDs based only on dissertation (PhDs (DO), for which a university performs only a certification function) similarly productive as regular PhD inventors. We control for the types of work places, the types of project (research stage), inventor motivations, firm fixed effects, cohort effects, technology fields and inventor ability. We use the number of patent applications and the total forward citations received within 5 years from the applied by these patents as performance measures. Major findings are the following

1. The life-cycle productivity of PhD inventors in terms of both patent and citation counts is significantly higher than those with less education even if they are late in joining the firm, reflecting their high annual productivity. One source of high annual productivity of PhD inventors is a short interval between the first job year and the first invention year. The panel data estimates suggest that they also stay longer as inventors.
2. The life-cycle productivity of a PhD (DO) inventor is lower than that of a regular PhD inventor although the difference is not statistically significant. Our survey data suggests that a PhD (DO) inventor works in an independent laboratory and in the project involving basic research as frequently as a regular PhD does. The panel data estimates suggest that PhD (DO) have a steeper "learning" curve and stay longer as inventors, although there is no clear award effect. These results suggest that a system of providing a PhD (DO) might have served as a kind of screening and signaling device for encouraging high ability inventors to develop their careers as inventors. .
3. The Hausman-Taylor estimations suggest that higher productivity of regular PhD inventors are robust to the possible correlation between unobserved heterogeneity of inventor ability and the educational choice.
4. Inventor productivity is significantly higher when the inventors belong to the units dedicated to research, the project involves a basic research and they inventors belong to a large firm with large patent applications. Thus, productivity estimates without

considering these factors tend to significantly overestimate the productivity effect of higher education.

Let us turn to the implications and remaining research agenda. Our research shows that a regular PhD inventor is productive so that his late start in a business firm can be easily compensated, even if we control for the fact that such inventor is more likely to be assigned to a workplace, a project which generates patents more and their potential abilities. This suggests that it would be worthwhile for a firm to recognize PhDs as important human capital for the firm. We can also note that such inventors are more likely to generate internal knowledge spillover within a company through absorbing the external scientific knowledge.

However, this causes a new question why many PhDs are not able to find research jobs in private sector despite of their high inventive productivity. There are various candidate reasons for this. One possible reason is a selection bias of our study, that is, PhDs have already got employed by companies in our sample, therefore our PhD sample are the inventors who are matched to demand of company or are suitable to inventive activity in private sector. This indicates that life-cycle productivity in our sample is higher than average among PhDs. However, since this bias also lends itself well to other education levels, there needs to be additional explanation to why only PhD holders are highly selected.

A second potential reason is that there is an asymmetric information between PhDs and companies in first job market. In Japan, the number of PhDs employed by companies is quite low above mentioned. Therefore, since many companies have never hired them, they not only don't know their productivity but also don't have system to deal with them. This problem is maybe serious in Japan.

A third one is that inventive activity is not a unique task for corporate researchers. Since they have various objectives, invention is only one task for them to do. For example, they may accomplish their high productivity at the cost of linkage to manufacturing section or leadership of research management. In this case, companies are reluctant to hire PhD holders even if they have high inventive productivity. Furthermore, many Japanese companies expected not only research ability but also management skill for researchers and didn't prepare multiple career steps such as continuing to inventive activity. This is consistent our results, that even regular PhD holders cannot explicitly continue to their inventive activity. In this case, companies don't employ research intensive people such as regular PhD holders.

Unfortunately, we do not have sufficient data to test these points is persuasive, and this is one of our future tasks.

Our evidence also shows that a system of a PhD (DO) might have been a successful system. Such PhD inventor is productive and stays longer as an inventor. Our evidence suggests that a PhD (DO) inventor reveals his capability over time and will be able to take more important inventive jobs over time. A PhD (DO) may play an important role for such internal screening such transition (although we cannot detect a strong break at the time of the grant of a PhD). A system of a PhD (DO) seems to provide an incentive for an inventor to deepen his scientific understanding of the invention process under the support of the firm. While the system of granting PhD (DO) is in the direction of being phased out (especially due to the consideration of international recognition of a Japanese degree), it would be important to absorb the positive aspects of such system in the new graduate education system, especially a strong complementarily between the industrial research and academic research for PhD (DO).

There are a number of research agenda. First, it would important to look into the reasons why a PhD enhances research productivity. One potential source is effective utilization of external scientific knowledge. Another could be a large team which such inventor tends to participate, which works as a channel of internal knowledge flow. Our measure may be partly biased due to the positive correlation between an omitted individual fixed effect (ability) and educational choice, although our T-Score variable and H-T estimation tried to control for. Second it would be important to further unpack why the PhD (DO) inventor has high productivity, including the endogeneity of such choice.

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Table 1 Existing studies

Authors	Output measures, and comparison base	Effects of PhD in terms of elasticity		Major Controls			Sample
		Quantity	Citation	Inventor	Firm	The others	
Hoisl (2007)[1)]	(Cumulative number of patent applications) /(age-25) , PhD vs. high school or vocational training	insignificant	NA	Age, mobility, knowledge sources	Firm size		2409 German inventors, EPO patents (1977-2002)
Mariani and Romanelli (2007)	EPO patent application or grants in 1988-1998, PhD vs. high school	0.27	insignificant	Age	Firm size and number of patents	Co-inventors	793 inventors from Germany, Italy, The Netherlands and the UK, EPO patents (1988-1998)
Kim, Lee and Marschke (2004)[2)]	Grants per year, PhD vs. nonPhD degree	0.07**	NA	Age, patent stocks	(1)Firm size, capital intensity, etc. (2)Fixed effects	Co-inventors	US inventors, US patents (?)
Schettino, Sterlacchini and Venturini (2008)	EPO patent applications (1991-2005), University or PhD relative to non-university degree	-0.13	0.17	Age, knowledgesource	Firm size and number of patents	Co-inventors	743 Italian inventors,EPO partents(1991-2005)

Assuming an average level of the importance of literature as information source for the invention.

Since their specification has the cumulative number of patents as an explanatory variable, the long-run effect of a PhD is larger than this coefficient.

Table 2. Descriptive statistics

Variable name	Obs.	Mean	Std. Dev.	Min	Max
ln(patent)	1731	2.17	1.31	-2.48	5.96
ln(citation)	1731	2.80	1.40	-2.48	6.49
ln(patent/span)	1731	-0.74	1.18	-5.41	2.53
ln(citation/span)	1731	-0.11	1.29	-5.41	3.39
inventive span	1731	20.05	7.85	2.00	54.00
birth year	1731	1961.37	7.01	1946	1975
ln(firm patents)	1731	119.60	55.08	1.39	303.48
motivation: science	1731	0.58	0.49	0.00	1.00
motivation: challenge	1731	0.89	0.32	0.00	1.00
motivation: career	1731	0.29	0.46	0.00	1.00
motivation: reputation	1731	0.18	0.39	0.00	1.00
motivation: benefit	1731	0.18	0.38	0.00	1.00
motivation: money	1731	0.23	0.42	0.00	1.00
male	1731	0.98	0.14	0.00	1.00
basic research	1731	0.18	0.38	0.00	1.00
applied research	1731	0.34	0.47	0.00	1.00
development	1731	0.71	0.46	0.00	1.00
technical service	1731	0.10	0.30	0.00	1.00
other division	1731	0.06	0.24	0.00	1.00
software development division	1731	0.04	0.19	0.00	1.00
laboratory attached to manufacturing division	1731	0.15	0.35	0.00	1.00
independent laboratory	1731	0.70	0.46	0.00	1.00
2 year college degree or less	1731	0.13	0.33	0.00	1.00
BA degree	1731	0.46	0.50	0.00	1.00
MA degree	1731	0.35	0.48	0.00	1.00
PhD degree	1731	0.03	0.18	0.00	1.00
PhD degree(DO)	1731	0.03	0.18	0.00	1.00
T-score	1409	52.38	9.67	25.00	72.50

Patent output indicators are fractional counts.
First year of "inventive span" is the year in which inventors enrolled their companes.

Table 3. Mean statistics by level of educations

	2 year college degree or less	BA	MA	PhD	PhD(DO)
ln(patent)***	1.73	2.15	2.30	2.52	2.47
	(1.41)	(1.32)	(1.24)	(1.16)	(1.31)
ln(citation)***	2.29	2.76	2.97	3.16	3.06
	(1.53)	(1.38)	(1.33)	(1.27)	(1.44)
ln(patent/span)***	-1.35	-0.78	-0.50	-0.32	-0.73
	(1.29)	(1.17)	(1.07)	(1.04)	(1.24)
ln(citation/span)***	-0.79	-0.16	0.16	0.33	-0.14
	(1.44)	(1.25)	(1.17)	(1.19)	(1.41)
inventive span***	23.71	20.35	17.99	18.48	25.25
	(9.14)	(7.61)	(7.15)	(6.56)	(5.98)
birth year***	1960.12	1960.95	1963.04	1960.41	1955.29
	(8.01)	(6.83)	(6.50)	(6.96)	(5.40)
log(firm patents)**	128.14	117.46	120.03	102.30	129.41
	(66.19)	(55.79)	(50.17)	(37.12)	(57.22)
male	0.97	0.98	0.99	0.96	0.98
	(0.16)	(0.15)	(0.12)	(0.19)	(0.13)
basic research***	0.13	0.11	0.23	0.46	0.48
	(0.34)	(0.31)	(0.42)	(0.50)	(0.50)
applied research***	0.28	0.27	0.42	0.54	0.57
	(0.45)	(0.45)	(0.49)	(0.50)	(0.50)
development***	0.67	0.78	0.67	0.46	0.39
	(0.47)	(0.41)	(0.47)	(0.50)	(0.49)
technical service***	0.20	0.11	0.08	0.05	0.04
	(0.40)	(0.31)	(0.26)	(0.23)	(0.19)
other division***	0.09	0.08	0.03	0.04	0.00
	(0.28)	(0.27)	(0.17)	(0.19)	(-)
software development division**	0.05	0.05	0.02	0.02	0.00
	(0.23)	(0.21)	(0.15)	(0.13)	(-)
laboratory attached to manufacturing division	0.17	0.16	0.14	0.11	0.05
	(0.38)	(0.36)	(0.34)	(0.31)	(0.23)
independent laboratory***	0.54	0.66	0.77	0.84	0.95
	(0.50)	(0.47)	(0.42)	(0.37)	(0.23)
T-score***	-	49.02	55.51	57.74	61.02
		(9.63)	(8.34)	(7.89)	(5.49)

Inventive span is based on the first employed year as the initial year.
Standard deviations are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 4. Life-cycle cumulative patent outputs and average productivity

	ln(patent)	ln(citation)	ln(patent/span)	ln(citation/span)	ln(patent)	ln(citation)	ln(patent/span)	ln(citation/span)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(firm patents)	0.012***	0.010***	0.005**	0.003	0.012***	0.010***	0.005**	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
motivation: sciense	0.015	0.034	0.011	0.030	-0.039	-0.013	-0.028	-0.002
	(0.088)	(0.096)	(0.077)	(0.086)	(0.087)	(0.095)	(0.077)	(0.086)
motivation: challenge	0.220*	0.246*	0.223**	0.248**	0.168	0.183	0.178	0.192
	(0.129)	(0.138)	(0.112)	(0.123)	(0.126)	(0.135)	(0.111)	(0.122)
motivation: performance	-0.065	-0.042	-0.081	-0.058	-0.051	-0.029	-0.067	-0.044
	(0.080)	(0.085)	(0.071)	(0.077)	(0.079)	(0.085)	(0.070)	(0.078)
motivation: career	-0.161	-0.185*	-0.142	-0.166*	-0.134	-0.162	-0.119	-0.146
	(0.100)	(0.110)	(0.089)	(0.100)	(0.098)	(0.109)	(0.088)	(0.100)
motivation: reputation	0.222*	0.212*	0.210**	0.200*	0.207*	0.184	0.195**	0.171
	(0.114)	(0.124)	(0.098)	(0.111)	(0.111)	(0.122)	(0.097)	(0.109)
motivation: benefit	0.026	0.01	-0.012	-0.028	-0.027	-0.042	-0.052	-0.067
	(0.107)	(0.118)	(0.098)	(0.110)	(0.105)	(0.118)	(0.097)	(0.110)
motivation: money	0.095	0.151	0.103	0.159	0.087	0.142	0.097	0.152
	(0.101)	(0.109)	(0.089)	(0.099)	(0.096)	(0.105)	(0.085)	(0.095)
male	0.477*	0.351	0.402*	0.277	0.603***	0.466	0.495**	0.358
	(0.252)	(0.304)	(0.225)	(0.270)	(0.233)	(0.295)	(0.210)	(0.262)
basic research					0.303***	0.267**	0.243***	0.207*
					(0.103)	(0.115)	(0.093)	(0.106)
applied research					0.098	0.109	0.065	0.076
					(0.085)	(0.093)	(0.076)	(0.085)
development					0.095	0.055	0.069	0.028
					(0.095)	(0.104)	(0.086)	(0.096)
technical service					-0.164	-0.235	-0.176	-0.247*
					(0.137)	(0.151)	(0.125)	(0.140)
other division					0.082	0.185	0.043	0.146
					(0.245)	(0.276)	(0.221)	(0.254)
software development division					0.052	0.237	0.115	0.3
					(0.255)	(0.279)	(0.226)	(0.252)
laboratory attached to					0.488**	0.548**	0.422**	0.483**
manufacturing division					(0.201)	(0.221)	(0.184)	(0.203)
independent laboratory					0.641***	0.722***	0.538***	0.620***
					(0.191)	(0.210)	(0.173)	(0.192)
BA degree	0.437***	0.391**	0.468***	0.422***	0.386***	0.336**	0.426***	0.376***
	(0.149)	(0.161)	(0.135)	(0.148)	(0.142)	(0.154)	(0.130)	(0.142)
MA degree	0.739***	0.761***	0.739***	0.761***	0.635***	0.652***	0.653***	0.670***
	(0.168)	(0.176)	(0.149)	(0.158)	(0.161)	(0.170)	(0.144)	(0.155)
PhD degree	1.413***	1.386***	1.361***	1.333***	1.223***	1.182***	1.198***	1.157***
	(0.275)	(0.298)	(0.250)	(0.280)	(0.276)	(0.302)	(0.253)	(0.286)
PhD degree(dissertation only)	1.167***	1.161***	1.073***	1.067***	0.897***	0.883***	0.847***	0.833***
	(0.224)	(0.247)	(0.202)	(0.230)	(0.224)	(0.248)	(0.202)	(0.231)
_cons	-1.902**	-1.38	-5.106***	-4.584***	-1.975***	-1.595**	-4.131***	-3.751***
	(0.894)	(1.008)	(0.843)	(0.958)	(0.563)	(0.649)	(0.507)	(0.602)
Adj. R square	0.445	0.43	0.45	0.437	0.477	0.456	0.476	0.458
Observation	1736	1736	1736	1736	1731	1731	1731	1731

Patent output indicators are fractional counts.
Estimation method is OLS.
The beginning of inventive span is the first year inventor worked.
Firm dummies, technological dummies and cohort dummies are included in all equations.
Robust standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 5. Life-cycle average productivity (based on the standardized first year of 18 years old)

	ln(patent/span)	ln(citation/span)
	(1)	(2)
ln(firm patents)	0.009***	0.008**
	(0.004)	(0.004)
motivation: sciense	-0.039	-0.012
	(0.082)	(0.090)
motivation: challenge	0.169	0.185
	(0.115)	(0.126)
motivation: performance	(0.035)	(0.014)
	(0.075)	(0.081)
motivation: career	-0.147	-0.172*
	(0.091)	(0.102)
motivation: reputation	0.196*	0.173
	(0.101)	(0.112)
motivation: benefit	-0.046	-0.062
	(0.100)	(0.113)
motivation: money	0.067	0.125
	(0.090)	(0.100)
male	0.547**	0.407
	(0.217)	(0.274)
basic research	0.258***	0.222**
	(0.098)	(0.109)
applied research	0.078	0.09
	(0.082)	(0.089)
development	0.088	0.047
	(0.091)	(0.100)
technical service	-0.137	-0.212
	(0.131)	(0.145)
other division	0.143	0.237
	(0.229)	(0.260)
software development division	0.152	0.331
	(0.239)	(0.260)
laboratory attached to manufacturing division	0.521***	0.573***
	(0.188)	(0.206)
independent laboratory	0.655***	0.728***
	(0.178)	(0.196)
BA degree	0.178	0.155
	(0.129)	(0.141)
MA degree	0.276**	0.335**
	(0.137)	(0.144)
PhD degree	0.583**	0.613**
	(0.239)	(0.263)
PhD degree(dissertation only)	0.449**	0.482**
	(0.208)	(0.233)
_cons	-4.438***	-4.052***
	(0.544)	(0.628)
Adj. R square	0.454	0.441
Observation	1731	1731

Patent output indicators are fractional counts.
Estimation method is OLS.
The beginning of inventive span is the first year inventor worked.
Firm dummies, technological dummies and cohort dummies are included in all equations.
Robust standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 6. Life-cycle cumulative patent outputs and average productivity with T-score

	ln(patent)	ln(citation)	ln(patent/span)	ln(citation/span)	ln(patent)	ln(citation)	ln(patent/span)	ln(citation/span)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(firm patents)	0.014***	0.012***	0.007**	0.005*	0.013***	0.012***	0.006**	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
motivation: sciense	-0.073	-0.103	-0.05	-0.081	-0.062	-0.092	-0.042	-0.072
	(0.105)	(0.112)	(0.091)	(0.099)	(0.106)	(0.113)	(0.092)	(0.100)
motivation: challenge	0.177	0.19	0.153	0.166	0.197	0.21	0.169	0.182
	(0.145)	(0.154)	(0.127)	(0.140)	(0.146)	(0.155)	(0.128)	(0.140)
motivation: performance	-0.038	-0.015	-0.055	-0.032	-0.048	-0.024	-0.062	-0.039
	(0.088)	(0.096)	(0.077)	(0.086)	(0.088)	(0.096)	(0.077)	(0.086)
motivation: career	-0.148	-0.193	-0.146	-0.191	-0.178	-0.223*	-0.17	-0.215*
	(0.116)	(0.130)	(0.103)	(0.118)	(0.119)	(0.133)	(0.105)	(0.120)
motivation: reputation	0.252**	0.235*	0.246**	0.229*	0.259**	0.241*	0.251**	0.234*
	(0.123)	(0.137)	(0.108)	(0.123)	(0.124)	(0.138)	(0.109)	(0.124)
motivation: benefit	0.024	0.032	-0.011	-0.004	0.032	0.039	-0.005	0.002
	(0.121)	(0.137)	(0.112)	(0.129)	(0.122)	(0.138)	(0.112)	(0.129)
motivation: money	0.111	0.165	0.108	0.162	0.102	0.156	0.101	0.155
	(0.108)	(0.117)	(0.094)	(0.105)	(0.109)	(0.118)	(0.095)	(0.105)
male	0.531*	0.289	0.441*	0.2	0.530*	0.288	0.440*	0.199
	(0.311)	(0.378)	(0.261)	(0.323)	(0.321)	(0.390)	(0.267)	(0.331)
basic research	0.273**	0.252*	0.219**	0.198*	0.276**	0.255**	0.222**	0.201*
	(0.113)	(0.128)	(0.102)	(0.117)	(0.114)	(0.128)	(0.102)	(0.117)
applied research	0.129	0.15	0.089	0.11	0.13	0.152	0.09	0.111
	(0.091)	(0.100)	(0.081)	(0.091)	(0.092)	(0.102)	(0.082)	(0.092)
development	0.11	0.09	0.079	0.059	0.093	0.073	0.066	0.046
	(0.109)	(0.121)	(0.099)	(0.111)	(0.109)	(0.120)	(0.098)	(0.111)
technical service	-0.103	-0.156	-0.125	-0.178	-0.116	-0.169	-0.135	-0.188
	(0.173)	(0.186)	(0.154)	(0.168)	(0.171)	(0.184)	(0.152)	(0.167)
other division	-0.022	0.149	-0.03	0.14	-0.028	0.142	-0.036	0.135
	(0.292)	(0.319)	(0.264)	(0.291)	(0.292)	(0.316)	(0.263)	(0.289)
software development division	0.039	0.216	0.123	0.3	0.009	0.186	0.099	0.276
	(0.307)	(0.334)	(0.266)	(0.296)	(0.311)	(0.335)	(0.269)	(0.296)
laboratory attached to manufacturing division	0.415*	0.456*	0.389*	0.430*	0.425*	0.466*	0.397*	0.437*
	(0.239)	(0.256)	(0.214)	(0.231)	(0.241)	(0.257)	(0.216)	(0.232)
independent laboratory	0.520**	0.637***	0.471**	0.588***	0.546**	0.663***	0.491**	0.608***
	(0.227)	(0.245)	(0.205)	(0.223)	(0.231)	(0.247)	(0.208)	(0.225)
T-score	0.014**	0.014**	0.011**	0.011*				
	(0.006)	(0.007)	(0.005)	(0.006)				
MA degree	0.142	0.220*	0.132	0.210**	0.186*	0.264**	0.166*	0.245**
	(0.105)	(0.116)	(0.092)	(0.103)	(0.105)	(0.115)	(0.091)	(0.103)
PhD degree	0.806***	0.791**	0.746***	0.731**	0.848***	0.833***	0.778***	0.764***
	(0.268)	(0.308)	(0.244)	(0.292)	(0.268)	(0.306)	(0.245)	(0.290)
PhD degree (dissertation only)	0.365*	0.398	0.311	0.344	0.434**	0.467*	0.366*	0.399*
	(0.216)	(0.253)	(0.199)	(0.236)	(0.218)	(0.253)	(0.201)	(0.238)
_cons	-0.891	-0.428	-3.612***	-3.148**	-0.316	0.149	-3.158***	-2.693**
	(1.141)	(1.295)	(1.084)	(1.242)	(1.135)	(1.270)	(1.074)	(1.216)
Adj. R square	0.474	0.447	0.467	0.442	0.467	0.442	0.462	0.438
Observation	1409	1409	1409	1409	1409	1409	1409	1409

Patent output indicators are fractional counts.
The beginning of inventive span is the first year inventor worked.
Firm dummies, technological dummies and cohort dummies are included in all equations.
Robust standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 7. Life-cycle patent outputs: panel analysis (FE model)

	ln(patent) (1)	ln(citation) (2)	ln(patent) (3)	ln(citation) (4)
ln(firm patents)	0.204***	0.235***	0.206***	0.237***
	(0.009)	(0.013)	(0.010)	(0.013)
Two years college or less *experience			0.027***	0.030***
			(0.004)	(0.006)
BA degree*experience			0.038***	0.044***
			(0.003)	(0.004)
MA degree*experience			0.034***	0.035***
			(0.005)	(0.006)
PhD degree*experience			0.035**	0.017
			(0.017)	(0.023)
PhD degree(dissertation only)*experience			0.044***	0.044***
			(0.012)	(0.016)
Two years college or less *experience^2			-0.027**	-0.044**
			(0.013)	(0.019)
BA degree*experience^2			-0.082***	-0.110***
			(0.013)	(0.017)
MA degree*experience^2			-0.056***	-0.072***
			(0.022)	(0.026)
PhD degree*experience^2			-0.077	-0.023
			(0.081)	(0.110)
PhD degree(dissertation only)*experience^2			-0.081*	-0.082
			(0.046)	(0.060)
experience	0.034***	0.037***		
	(0.003)	(0.003)		
experience^2	-0.058***	-0.077***		
	(0.009)	(0.012)		
_cons	-0.820***	-0.988***	-0.826***	-0.989***
	(0.054)	(0.070)	(0.055)	(0.071)
Observation	30433	30433	30433	30433

Patent output indicators are fractional counts.
Estimation method is Fixed effect model.
Robust standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 8. Life-cycle patent outputs: panel analysis (Hausman-Taylor RE model)

	ln(patent) (1)	ln(citation) (2)	ln(patent) (3)	ln(citation) (4)
ln(firm patents)	0.206*** (0.005)	0.237*** (0.008)	0.206*** (0.005)	0.237*** (0.008)
male	0.317** (0.131)	0.382* (0.211)	0.324*** (0.091)	0.390*** (0.148)
basic research	0.01 (0.058)	-0.022 (0.094)	0.008 (0.040)	-0.024 (0.065)
applied research	0.05 (0.040)	0.078 (0.064)	0.051* (0.027)	0.079* (0.045)
development	0.008 (0.045)	0.012 (0.072)	0.009 (0.031)	0.013 (0.050)
technical service	-0.042 (0.056)	-0.05 (0.090)	-0.043 (0.038)	-0.052 (0.063)
other division	0.029 (0.105)	0.034 (0.169)	0.031 (0.072)	0.038 (0.118)
software development division	0.01 (0.107)	0.003 (0.172)	0.01 (0.073)	0.005 (0.120)
laboratory attached to manufacturing division	0.064 (0.081)	0.073 (0.131)	0.065 (0.056)	0.076 (0.091)
independent laboratory	0.106 (0.084)	0.122 (0.135)	0.107* (0.057)	0.124 (0.094)
BA degree	0.276 (0.329)	0.42 (0.529)	0.269 (0.229)	0.409 (0.371)
MA degree	0.324 (0.291)	0.547 (0.466)	0.311 (0.204)	0.532 (0.330)
PhD degree	1.332** (0.621)	2.433** (1.000)	1.352*** (0.430)	2.446*** (0.699)
PhD degree(dissertation only)	0.889 (0.579)	1.588* (0.937)		
PhD degree(dissertation only) before			0.895** (0.396)	1.584** (0.647)
PhD degree(dissertation only) after			0.901** (0.400)	1.552** (0.652)
Two years college or less *experience	0.031* (0.016)	0.052** (0.026)	0.031*** (0.012)	0.052*** (0.019)
BA degree*experience	0.042*** (0.016)	0.066** (0.026)	0.042*** (0.011)	0.066*** (0.018)
MA degree*experience	0.038** (0.016)	0.058** (0.026)	0.038*** (0.011)	0.058*** (0.018)
PhD degree*experience	0.039** (0.019)	0.039 (0.029)	0.039*** (0.015)	0.039* (0.023)
PhD degree(dissertation only)*experience	0.048*** (0.018)	0.066** (0.028)	0.047*** (0.014)	0.068*** (0.021)
Two years college or less *experience^2	-0.027** (0.011)	-0.044*** (0.015)	-0.027** (0.011)	-0.044*** (0.015)
BA degree*experience^2	-0.083*** (0.008)	-0.110*** (0.011)	-0.083*** (0.008)	-0.110*** (0.011)
MA degree*experience^2	-0.057*** (0.008)	-0.073*** (0.011)	-0.057*** (0.008)	-0.073*** (0.011)
PhD degree*experience^2	-0.078* (0.045)	-0.024 (0.064)	-0.078* (0.046)	-0.024 (0.064)
PhD degree(dissertation only)*experience^2	-0.081*** (0.030)	-0.082** (0.042)	-0.081*** (0.030)	-0.083** (0.042)
_cons	-0.117 (0.738)	-0.52 (1.174)	-0.862 (0.900)	-1.39 (1.437)
Observation	30433	30433	30433	30433

Patent output indicators are fractional counts.

Estimation method is Hausman-Taylor random effect model

Motivation dummies, Firm dummies, technological dummies and cohort dummies are included in all equations.

Robust standard errors are in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Table 9. Average age of first job and first patent invention

	first job year (A)	first invention year (B)	(B) - (A)
less than two year college	21.16 (4.77)	29.74 (7.48)	8.58 (7.28)
BA degree	23.99 (3.00)	29.01 (5.49)	5.02 (5.15)
MA degree	25.24 (2.54)	28.15 (3.51)	2.91 (3.92)
PhD degree	28.39 (2.90)	30.45 (3.83)	2.05 (2.79)
PhD degree(Dissertation only)	26.07 (3.12)	29.98 (4.48)	3.91 (3.78)

Standard deviations are in parentheses.

Table 10. Time required to compensate for the invention loss due to late start of inventive activity by a regular PhD.

	column 1 in Table 8	column 2 in Table 8
	patent	forward citation
BA degree	4.43	4.61
MA degree	3.43	3.51
PhD degree(dissertation only)	4.59	5.25

Table 11. The estimation of Cox Proportional Hazard Model

	(1)	(2)	(3)
ln(firm patents)	-0.108**	-0.115***	-0.128**
	(0.044)	(0.044)	(0.054)
motivation: sciense	-0.338**	(0.238)	(0.209)
	(0.155)	(0.155)	(0.184)
motivation: challenge	(0.264)	(0.224)	(0.318)
	(0.209)	(0.203)	(0.253)
motivation: performance	0.03	-0.002	0.106
	(0.143)	(0.145)	(0.163)
motivation: career	0.116	0.115	0.007
	(0.154)	(0.154)	(0.180)
motivation: reputation	0.124	0.115	0.201
	(0.196)	(0.198)	(0.228)
motivation: benefit	-0.025	0.065	-0.017
	(0.194)	(0.191)	(0.213)
motivation: money	0.083	0.095	0.115
	(0.160)	(0.158)	(0.174)
male	0.136	0.005	0.414
	(0.472)	(0.478)	(0.680)
ln(number of inventors)	1.351***	1.394***	1.388***
	(0.059)	(0.059)	(0.066)
basic research		-0.626***	-0.641**
		(0.219)	(0.252)
applied research		-0.243	-0.188
		(0.166)	(0.188)
development		0.014	0.103
		(0.181)	(0.213)
technical service		0.452**	0.630**
		(0.214)	(0.268)
other division		0.535	0.154
		(0.371)	(0.513)
software development divisior		0.828**	0.489
		(0.381)	(0.494)
laboratory attached to manufacturing division		0.281	0.046
		(0.324)	(0.444)
independent laboratory		0.094	-0.142
		(0.309)	(0.409)
T-score			-0.01
			(0.009)
BA degree	-0.256	-0.227	
	(0.208)	(0.205)	
MA degree	-0.417*	-0.289	-0.086
	(0.217)	(0.213)	(0.193)
PhD degree	-1.226**	-0.958*	-0.523
	(0.506)	(0.512)	(0.505)
PhD degree(dissertation only)	-1.435***	-1.172**	-0.873*
	(0.484)	(0.494)	(0.528)
age	-0.242***	-0.215**	-0.289***
	(0.089)	(0.092)	(0.106)
age2	0.003***	0.003**	0.004***
	(0.001)	(0.001)	(0.001)
Log likelihood	-3343.527	-3325.804	-2540.043
Observation	10447	10420	8512

Estimation method is Cox Proportional Hazard model.

Standard error are clustered by firms are in parentheses.

Technological dummies and cohort dummies are included in all equations.

Robust standard errors are in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Appendix Table 1. Life-cycle cumulative patent outputs and average productivity (whole counts)

	ln(patent)	ln(citation)	ln(patent/span)	ln(citation/span)	ln(patent)	ln(citation)	ln(patent/span)	ln(citation/span)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(firm patents)	0.011*** (0.003)	0.009*** (0.003)	0.004** (0.002)	0.003 (0.002)	0.011*** (0.002)	0.009*** (0.003)	0.004** (0.002)	0.002 (0.002)
motivation: sciense	0.024 (0.084)	0.069 (0.095)	0.02 (0.073)	0.065 (0.085)	-0.03 (0.082)	0.02 (0.093)	-0.02 (0.072)	0.03 (0.084)
motivation: challenge	0.194 (0.129)	0.219 (0.141)	0.196* (0.111)	0.221* (0.126)	0.132 (0.124)	0.142 (0.137)	0.141 (0.109)	0.151 (0.124)
motivation: performance	-0.002 (0.076)	0.012 (0.084)	-0.018 (0.067)	-0.004 (0.076)	0.014 (0.074)	0.026 (0.083)	-0.002 (0.066)	0.01 (0.076)
motivation: career	-0.144 (0.097)	-0.168 (0.108)	-0.125 (0.086)	-0.149 (0.099)	-0.119 (0.095)	-0.143 (0.108)	-0.103 (0.085)	-0.128 (0.099)
motivation: reputation	0.181* (0.109)	0.164 (0.122)	0.169* (0.093)	0.152 (0.108)	0.157 (0.106)	0.124 (0.120)	0.144 (0.092)	0.111 (0.107)
motivation: benefit	0.039 (0.104)	0.037 (0.117)	0.001 (0.095)	-0.001 (0.109)	-0.019 (0.103)	-0.023 (0.118)	-0.044 (0.095)	-0.048 (0.110)
motivation: money	0.087 (0.097)	0.141 (0.108)	0.096 (0.084)	0.149 (0.097)	0.077 (0.092)	0.13 (0.104)	0.087 (0.080)	0.139 (0.094)
male	0.215 (0.248)	0.096 (0.321)	0.14 (0.208)	0.021 (0.283)	0.352 (0.235)	0.226 (0.310)	0.244 (0.196)	0.118 (0.272)
basic research					0.315*** (0.101)	0.291** (0.115)	0.255*** (0.092)	0.231** (0.106)
applied research					0.13 (0.081)	0.165* (0.091)	0.097 (0.072)	0.133 (0.082)
development					0.056 (0.091)	0.035 (0.103)	0.029 (0.083)	0.009 (0.094)
technical service					-0.224* (0.125)	-0.301** (0.143)	-0.236** (0.112)	-0.313** (0.131)
other division					0.081 (0.239)	0.19 (0.275)	0.043 (0.217)	0.151 (0.254)
software development division					0.037 (0.246)	0.24 (0.277)	0.1 (0.213)	0.303 (0.246)
laboratory attached to manufacturing division					0.434** (0.194)	0.495** (0.223)	0.368** (0.178)	0.429** (0.205)
independent laboratory					0.651*** (0.187)	0.735*** (0.212)	0.548*** (0.169)	0.632*** (0.195)
BA degree	0.399*** (0.144)	0.368** (0.159)	0.430*** (0.130)	0.399*** (0.146)	0.346** (0.136)	0.311** (0.153)	0.385*** (0.124)	0.350** (0.141)
MA degree	0.743*** (0.159)	0.779*** (0.172)	0.743*** (0.141)	0.779*** (0.156)	0.624*** (0.152)	0.652*** (0.167)	0.642*** (0.136)	0.670*** (0.152)
PhD degree	1.490*** (0.258)	1.452*** (0.284)	1.438*** (0.235)	1.399*** (0.269)	1.271*** (0.260)	1.217*** (0.292)	1.246*** (0.240)	1.191*** (0.278)
PhD degree(dissertation only)	1.233*** (0.213)	1.226*** (0.239)	1.138*** (0.194)	1.132*** (0.224)	0.923*** (0.211)	0.905*** (0.240)	0.873*** (0.192)	0.856*** (0.226)
_cons	-1.189 (0.779)	0.358 (0.909)	-4.393*** (0.734)	-2.846*** (0.866)	-1.184** (0.549)	0.267 (0.631)	-3.341*** (0.502)	-1.889*** (0.592)
Adj. R square	1736	1736	1736	1736	1731	1731	1731	1731
Observation	0.389	0.373	0.401	0.39	0.432	0.41	0.438	0.421

Patent output indicators are whole counts.
Estimation method is OLS.
The beginning of inventive span is the first year inventor worked.
Firm dummies, technological dummies and cohort dummies are included in all equations.
Robust standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Figure 1. Distribution of the logarithm of the number of patents (life-cycle productivity)

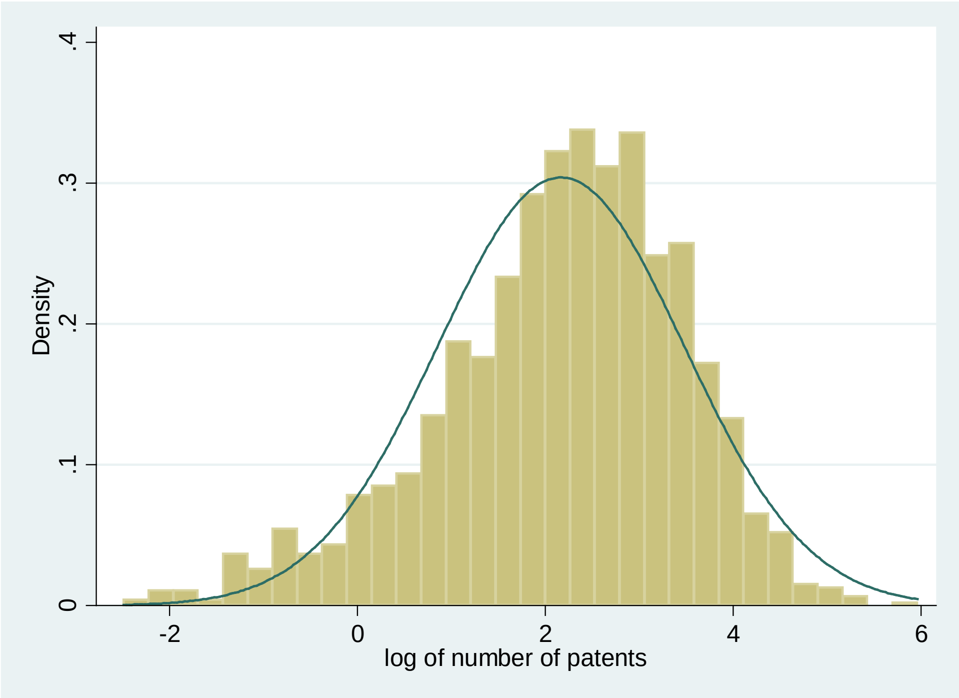

Figure 2. Distribution of the logarithm of the number of forward citations (life-cycle productivity)

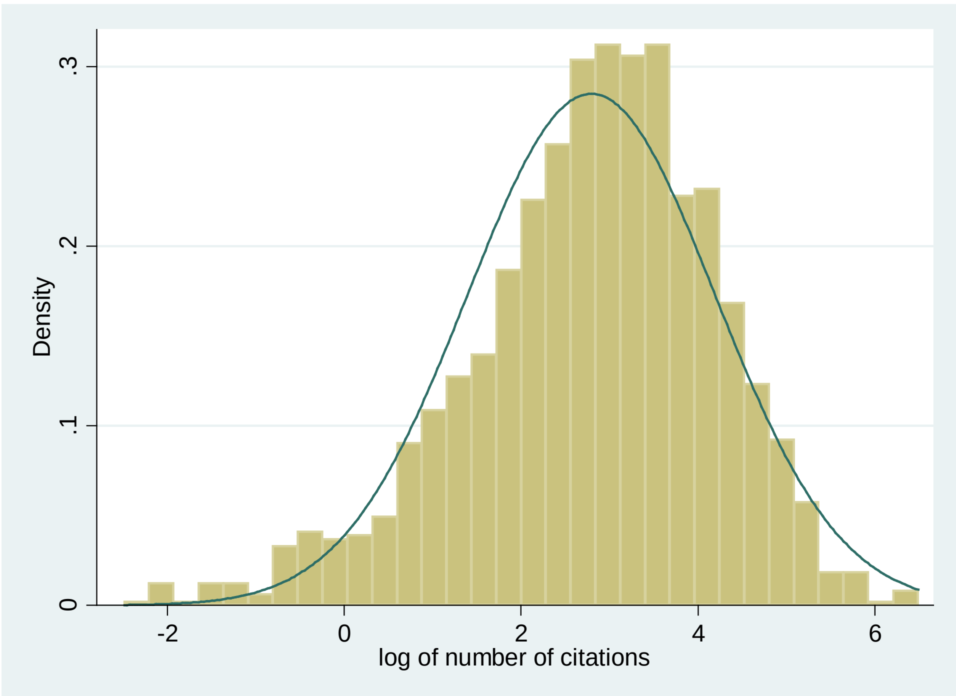

Figure 3. Timing of "Exit" inventive activity by cohort groups

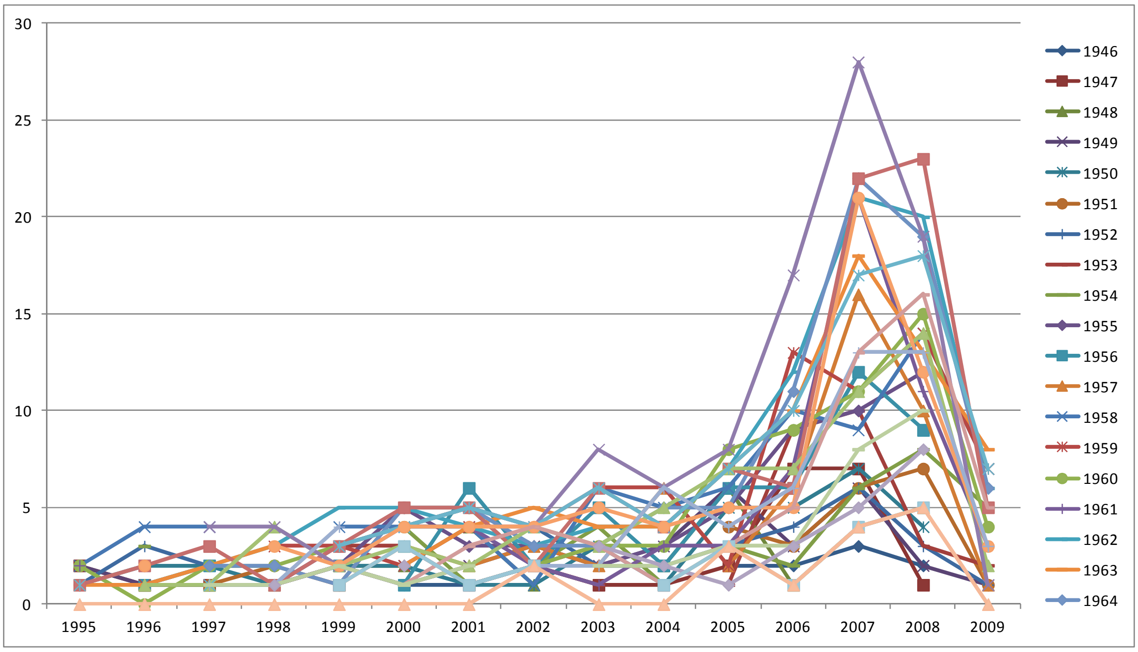

Figure 4. Experience effect on the number of patents (FE model)

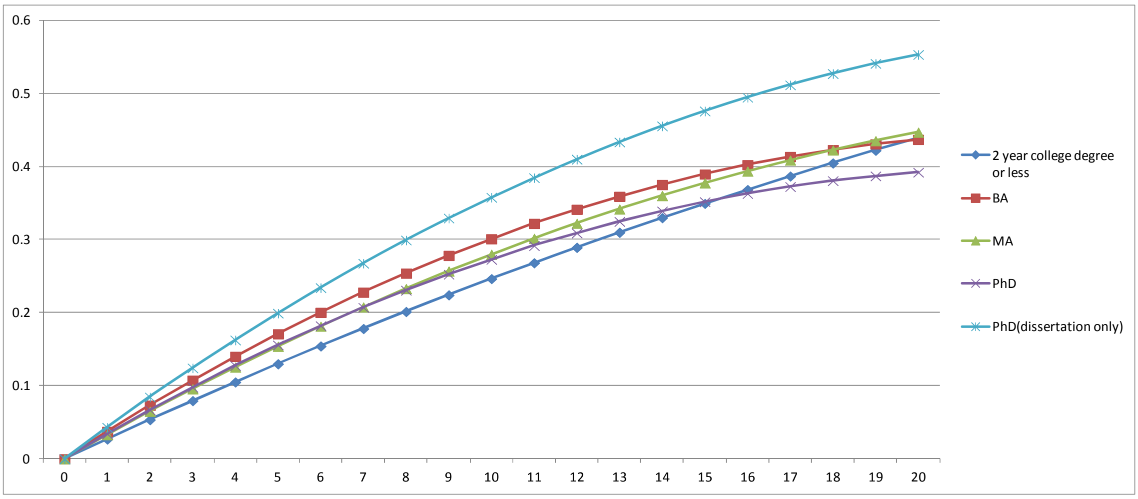

Figure 5. Experience effect on the number of forward citations (FE model)

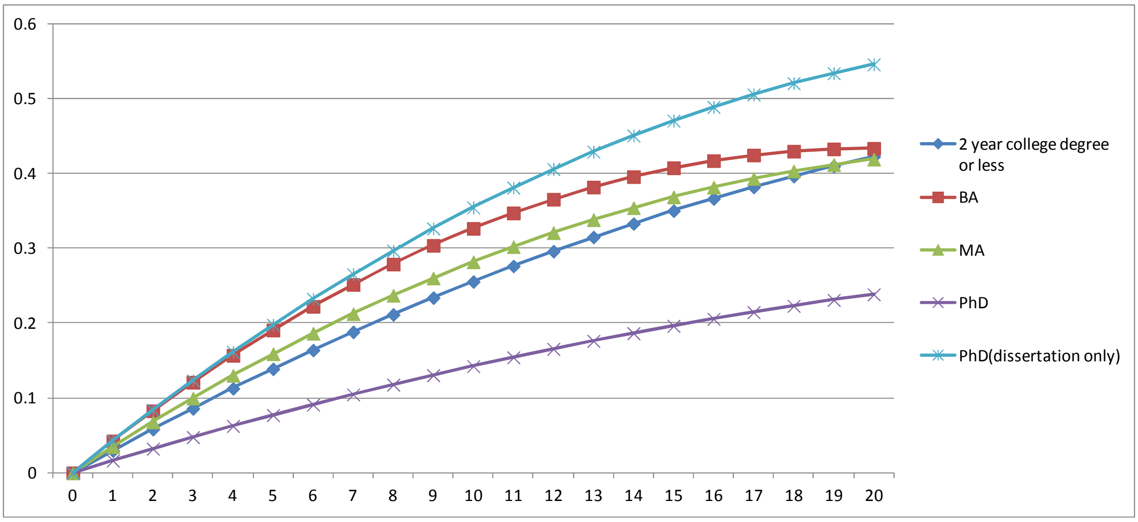

Figure 6. Experience effect on the number of patents (Hausman-Taylor RE model)

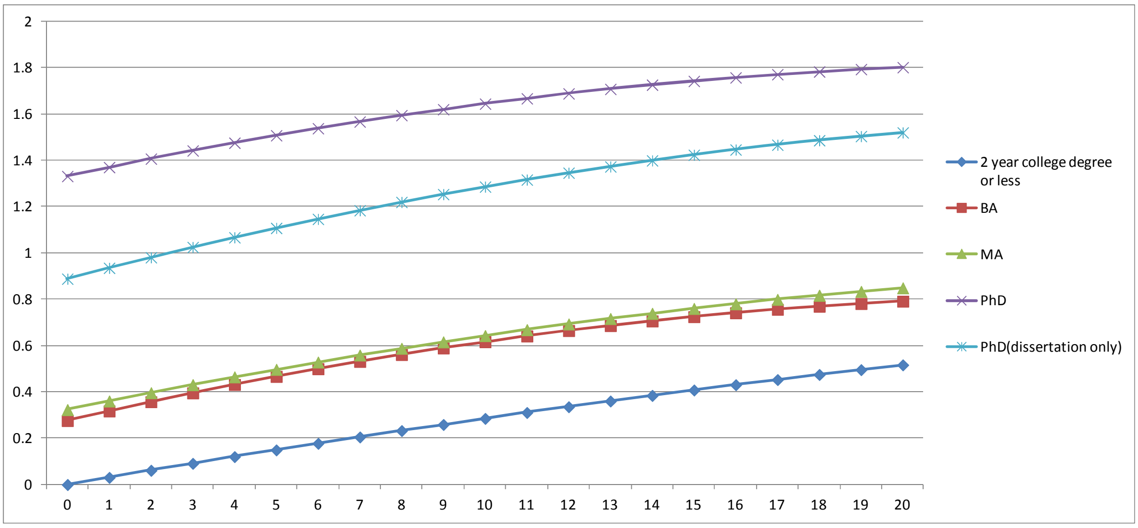

Figure 7. Experience effect on the number of forward citations (Hausman-Taylor RE model)