Life-cycle Productivity of Industrial Inventors: Education and Other Determinants

Onishi Koichiro
Faculty of Intellectual Property, Osaka Institute of Technology
5-16-1, Ohmiya, Asahi-Ku, Osaka, 535-8585, Japan
Phone:+81-6-6954-4887, Fax: +81-6-6954-4164
E-mail: onishi@ip.oit.ac.jp

Nagaoka Sadao
Institute of Innovation Research, Hitotsubashi University and RIETI
2-1 Naka, Kunitachi, Tokyo, 186-8601, Japan

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Abstract

This paper examines the life-cycle inventive productivity of Japanese industrial inventors. Using a panel of 1,731 inventors, we explore two issues. First, we examine whether and how inventors with advanced doctorate degrees (PhDs) perform better than their non-PhD counterparts. Second, we examine whether inventors who earned their doctorate degrees on the basis of a dissertation only (PhD-DO) are similarly productive. We found that inventors with traditional PhDs are significantly more productive than inventors with lower education levels, even controlling for their delayed start. We further found that inventors with PhDs-DO have also high productivity, and they work longer as inventors.

Keywords: Inventor, life-cycle inventive productivity, productivity profile, education, patent

JEL Classifications: O31, O34, I21

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]. In this vein, scientists and engineers with advanced doctoral degrees (PhDs) would help a firm increase its absorptive power for exploiting recent scientific advances (see Cohen and Levinthal, 1989 for the importance of absorptive power). In addition, hiring a PhD can directly transfer a new technological expertise from universities to industries (Stephan, 2011)[2]. Recognizing these implications, many countries have expanded their respective higher education systems and have thus increased the supply of PhD scientists and engineers. As a reflection of these efforts, the Organization for Economic Co-operation and Development (OECD, 2010) reported that enrolment in doctoral programs increased

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[1] Agihon et al. (2009) emphasized that highly skilled workers who acquire higher level education are the engine of economic growth for the countries which have already reached the technological frontier. On the other hand, basic education is found to have a positive effect on economic growth more globally (Kruger and Lindahl, 2001).

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

annually by 4% between 1998 and 2006 among OECD countries.

In Japan, individuals with PhDs still represent a small minority (just over 10%) of inventors. In contrast, nearly half of American inventors possess a PhD (Walsh and Nagaoka, 2009). Moreover, only half of the Japanese inventors with PhDs have obtained their degrees by completing traditional doctoral course work. The other half have obtained their PhDs only by submitting dissertations which are largely based on their firm-related research ('PhD (dissertation only'); hereafter 'PhD-DO')[3].

Despite recognizing the importance of strengthening the technological basis of their firms, many Japanese managers are reluctant to hire PhDs. Some of them point out that PhDs tend to be narrow-minded and inflexible. In addition, acquiring a PhD requires several years of schooling. As such, PhD inventors are typically delayed in beginning their professional careers. In Japan, inventors begin and leave their careers as inventors at younger ages than their American counterparts[4], thus making the attendance of a

[3] PhD-DO is a unique Japanese PhD accreditation system. People wishing to acquire a PhD-DO don't need to take any PhD course works. They only submit their dissertations to a university, and if these dissertations show excellent academic achievements, they are awarded PhD degree.

[4] Almost 80% of Japanese inventors have their first patent application before the age of 30, but less than 30% of the US inventors do so (see Walsh and Nagaoka 2009).

traditional PhD program costlier in Japan.

These observations raise several pressing questions. First, given the delayed start to their careers, how do corporate inventors with PhDs perform in relation to their non-PhD counterparts? In particular, can a higher annual productivity compensate for a delayed start to an inventing career? While it will not be surprising to know that the PhD inventors have higher life cycle inventive productivity than the others, the sources of such higher productivity have not been well understood. As Jones (2008) indicated, if overcoming the 'burden of knowledge' has become a critical component of a successful career, inventors must spend more time or money to acquire state-of-the-art technology and training to invent new products. Attending a PhD program may be one important channel for doing this. If so, a PhD's delayed start of his/her professional career may not necessarily result in the delayed start of their inventive career. Moreover, we need to control for types of places at which inventors work and the types of projects in which they are engaged in assessing the productivity of a PhD inventor, since they significantly affect the resources and opportunities for inventions.

Secondly, are PhD-DO inventors similarly productive as inventors who obtained their PhDs through traditional coursework? If they are, the system of awarding PhDs-DO may be an efficient complement to a formal education program. Since PhDs-DO write their dissertations on the basis of their industrial research, unemployment is hardly an issue for them. This can be an important advantage of such system since many traditional PhD holders face difficult job markets in many countries[5]. Because a PhD-DO system is unique to Japan, the assessment of how such pure certification system based on industrial research may help corporate inventors reveal and/or develop scientific human capital will provide important lessons for policy makers in other countries.

To explore these issues, we investigate the relationship between invention productivity and inventor education level using a life-cycle perspective. Specifically, we assess whether an inventor who acquired his PhD through a traditional doctoral program (i.e. one that grants a PhD for the completion of numerous requirements, including coursework) can compensate for a late start to his professional career by generating a greater number or higher quality inventions and/or by quickly starting their

[5] See Cyranoski et al. (2011).

invention activities and maintaining them later into their professional careers. We also compare how PhD-DO inventors compare with traditional PhD inventors in order to understand how a certification based PhD granting system differs from a traditional PhD granting system. In these analyses, we control for the type of workplace in which the inventor works as well as the type of R&D project that he pursues. Since a PhD inventor may look to be productive not because he has higher human capital but because he is given more time and resources for inventions or he is given a task (in particular, basic research) more prone for generating inventions, it is very important to control workplace and the type of R&D. We also control for the abilities of the inventor by constructing an indicator variable for the quality of the university from which he/she graduated as well as by using a panel estimation. This new variable (a T-score hereafter) is a standardized score gauging the difficulty of the attended university's entry examination. Further, we employ a Hausman-Taylor estimation in panel data analysis to control for unobserved inventor ability or other unidentified individual characteristics. To the best of our knowledge, there has been very little research focusing on life-cycle inventive productivity for industrial workers and those studies that do exist do not control for the ability of inventors nor the workplace and the type of R&D. As such, this study provides a more structural and accurate view of the association between education level and invention productivity than has been produced in the past.

We find that traditional PhDs have significantly higher annual productivity than the inventors with other education levels in terms of both patent and forward citation counts, and that they can easily compensate for their delayed start to their business-related activities. We find that this is the case even after controlling for workplace, research stage and inventor ability. One source of higher life cycle productivity of traditional PhDs is the short period of time between the first work year and the first invention year. PhDs-DOs also have high patent productivity (which increases more rapidly with greater levels of experience), which are lower but do not significantly differ from traditional PhDs. They often work in independent laboratories and are involved in basic research as frequently as traditional PhDs. In addition, PhDs-DO leave their inventive activity significantly later than the other inventors, controlling for the types of project the inventor is working on, the number of co-inventors or the inventor's ability.

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 used for this study. Section 5 presents the estimation results. Section 6 concludes the paper.

2. LITERATURE REVIEW

Empirical studies on corporate inventors are limited. One of the pioneering works in this domain was conducted by Narin and Breitzman (1995), which confirmed the finding by Lotka (1926) that scientists' respective productivities are highly skewed. Four recent studies based on large scale datasets which are salient to the current research are summarized in Table 1. Each of these studies used individual patent application or grant data which was matched with firms. Only one study (Kim, Lee and Marschke, 2004) used panel data (inventors organized by application/grant years), as this study does. Mariani and Romanelli (2007) uncovered a significant relationship between education level and patent development. They found that inventors with PhDs generate 21% more patents (on average) than inventors with only a high school degree, but that there is no significant difference in the level of citations per patent. Kim, Lee and Marschke (2004) also found that an inventor with a PhD has a significantly greater number of patent applications. In contrast, Hoisl (2007) found that over his/her life-cycle, a PhD inventor does not generate more patent applications than a non-PhD when the productivity measure takes into account the loss of invention period above the age of 25. Finally, with respect to quality, Schettino, Sterlacchini and Venturini (2008) discovered that patent quality increases by 17% with a higher level of education (PhD relative to non-university degree).

(Table 1)

One reason for the observed variations in the relationship between education level and invention activity relates to the accounting for delayed commencement of one's invention career resulting from pursuing a PhD. To account for this delay, it is imperative to measure life-cycle patent applications and to assess how cumulative applications differ as a result of variance in educational level. Among the studies in Table 1, only Hoisl (2007) has undertaken such an endeavor. By contrast, the other studies may overestimate the effect of higher education on life-cycle invention productivity. As the ‘burden of knowledge’ has become more prominent, the issue of delayed invention careers has become serious (Jones 2008). An increased burden of knowledge has required a longer period of time for a new PhD to absorb past knowledge. To accommodate for this ‘lost time’ in academia, some PhDs may offset the late entry into inventive work by departing that work later as well. Thus, the adoption of a life-cycle perspective allows for the analysis of invention productivity that may be affected by late entry and exit into the invention workforce.

A second reason for observed variations in how education affects invention productivity is a varying degree of control over omitted variables which are highly interrelated with education or ability. For example, none of the studies listed in Table 1 control for inventor ability. Hoisl (2007), however, controls for inventor knowledge sources, but that variable is likely correlated with level of education and ability. In fact, according to her study, this is one of the few sources of advantage to a PhD inventor.

Extant research has controlled for neither the type of the workplace (e.g. independent laboratory, manufacturing division laboratory, software development divisions) in which inventors operate, nor the stage of the research being conducted (e.g. basic research, applied research, development, technical services, or other). Despite the failure of past research to include them as control variables, workplace and project type are likely to significantly affect invention productivity. A laboratory dedicated to research is more likely to provide assets conducive to invention and patenting. In addition, basic research is likely to generate more patents than development,. An inventor with a PhD is more likely to be employed in a laboratory and in the basic stage of research. To redress these gaps in the literature, we take workplace and the research stage into account as controls while conducting our analyses.

There are many empirical studies on the research productivity of scientists. Although they work in different settings, some of the findings from these studies may be useful for understanding the productivity of corporate inventors. One of the basic findings from this research is that the research productivity distribution of scientists is highly skewed, with a relatively small number of scientists accounting for a significant portion of the publications. One influential explanation for this skewedness is the cumulative advantage resulting from the 'Matthew effect' or preferential attachments (see Merton, 1968, Allison and Stewart, 1974).

Another finding from this literature may be relevant for invention productivity research relates to human capital theory. As human capital theory postulates, a scientist's productivity will initially rise but then decline with age and experience. Diamond (1984) investigated the relationship between age and the number of research publications among mathematicians, and found an inverted U-shape relationship over the life-cycle. Levin and Stephan (1991) also found a similar association among physicists (except particle physicists) and earth scientists. Oster and Hamermesh (1998) and Baser and Pema (2004) showed that publications increase with age and experience at the early stages of one's life-cycle but sharply decline during these stage among economists. Recently, Turner and Mairesse (2005) investigated the relationship between age and publications in French physicians and found an inverted U-shape function during their academic life-cycle[6]. We employ a similar econometric model which accommodates the inverted U-shape relationship over the life-cycle. However, for corporate inventors, the decline of productivity with age may be caused by the changes of an inventor's primary tasks within a firm from invention to management. Given this, we cannot adopt human capital theory for interpreting the results.

An alternative to estimating the patent production function is to follow the tradition of Becker (1965) and Mincer (1974) and use wage as a performance measure. Some recent surveys on the relationship between education and wage suggest that Master's degree (MA) and PhD holders respectively earn 10% to 30% higher wages than those with undergraduate degrees alone (Card 1999, Deere and Vesovic 2006). In a Japanese case, Morikawa (2012) found that workers who have MAs or higher earn approximately 20% higher wage premiums than those workers who have Bachelor's degrees or lower[7]. However, corporate inventors are not directly

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[6] 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).

[7] To our knowledge, Toivanen and Vaananen (2012) is an unique study to investigate the relationship between inventors' education level and their reward. However, they don't refer to their results in more detail in their paper.

rewarded with wages for their creations. Instead, employee inventors receive generally fixed salaries and transfer ownership of their inventions to the companies for whom they work. In addition, there are significant financially intangible benefits to inventive work, which makes a wage amount an undervalued variable representing the inventive performance. As a result, wage may not be very informative to this end.

3. DATA DESCRIPTION

3.1. *Data*

We focus the industrial inventors who responded to the RIETI Inventor Survey in 2007, which surveyed Japanese patent inventors selected by quasi-random sampling[8]. The questions that comprise this survey cover not only the inventive process and the use of patents but also inventor characteristics. Questions related to birth year, gender, the first employed year, highest education, and year of graduation were all included in the

[8] Around 70% of the focal patents are selected from triadic patents, which are skewed toward high quality patents. The rest are selected from non-triadic patents, which is close to a pure random sampling of the population. This indicates that the survey oversamples the respondent inventors having high ability. For a more detailed description of the sampling method, see Nagaoka and Tsukada (2007).

survey, to which 5,278 inventors responded. We gathered all patents which included respondent inventor names to obtain the life-cycle inventive profile of these inventors (which was comprised of responses to questions related to personal characteristics). We used the Institute of Intellectual Property (IIP) patent database for Japanese patent bibliographic data which cover patent applications from 1964 to 2009.

We then identified which patents are truly invented by the respondents[9]. To avoid treating different inventors with the same name as the same person, we used only the patent applications whose inventor's name appears only for one company. This matching strategy likely produces a valid panel data of corporate inventors because the probability of different persons who have the same name appear only in one particular company (and nowhere else) is quite low in Japan[10]. While this procedure caused us to

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[9] Since inventor mobility is larger for smaller firms, our sample is somewhat biased towards large companies. 91% of our inventors come from companies that employ more than 500 employees.

[10] Japanese names have a lot of variety in both family name and first name (typically three or four different Chinese characters are used for a name). For example, the most frequently used name is Minoru Tanaka in the overall Japanese telephone directory database for 2001, and the frequency with which this name appeared is only 2,620 out of 30,552,849 records. As a result, the probability of such name appearing for an inventor is only less than 1/10,000. Since the distribution of the frequency of names is highly skewed, almost all names have much lower probability of appearance. To identify

lose all those inventors who moved from one company to another, we could focus on inventors who stayed in the same company until retirement, a practice that is quite typical in Japan.

After these screening procedures, we were left with 1,978 inventors and their corresponding patents. From here, we further screened our sample by removing those respondents whose age at which he created his first invention age was younger than the age when the inventor was employed first time.

3.2. *Explanations of output indicators*

We used an inventor's number of applications as an indicator of his/her innovative output. However, almost all patent applications are contributed to by multiple inventors, and a whole patent count which attributes each patent to each inventor regardless of the number of inventors tends to inflate the innovative output of an inventor who invents primarily as a team. This is especially the case when forward citation counts are used as output measures, since using a whole patent count approach results in

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whether an inventor belongs to one company or not, we used the patent applicant database provided by Onishi et al. (2012).

double or more counting of the same forward citations made. To cope with this problem, we use fractional counts as one patent divided by the number of inventors[11].

In addition, we counted the number of forward citations which each patent received from other patents, so as to develop data related to quality-adjusted outputs. The number of forward citations a patent receives is correlated with that patent's quality (Hall, Jaffe and Trajtenberg, 2005; Haroff, Scherer and Vopel, 2003). To ensure consistency of our indicator over time, we used only the citation count by patent examiner. Finally, to cope with truncations of forward citations, we counted the number of forward citations which each patent received within five years following its application.

As shown in Figure 1, the life-cycle number of patents per an inventor (fractional counts) nearly follows a log-normal distribution. That is, it has a highly skewed distribution whereby most inventors have a relatively small number of patent applications. Narin and Breitzman (1995) noted that this was particularly salient for industrial inventors in a few firms. On average,

[11] We show the results based on whole counts in appendix table 1 for a robustness check.

each inventor had 9.1 patents. Similarly, the number of citations an inventor receives also nearly follows a log-normal distribution (see Figure 2). Inventors received, on average, 16.8 forward citations for the cumulative total of all his patent applications.

(Figure 1 and 2)

4. ESTIMATION MODELS AND METHODOLOGY

4.1. *Cross section estimation based on cumulative outputs*

We first use cross sectional data, with the cumulative patent counts and forward citations received by these patents (within the first 5 years from patent applications) as dependent variables. The estimation equation is:

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

Here the dependent variables are the natural log of the number of patent applications or the number of forward citations received by inventor i. The dependent variables were then 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 explanations for these control variables below). Equation (1) does not include the length of an inventor's active span, so the coefficient for an explanatory variable (such as an education dummy) reflects both its effect on annual productivity and the length of inventive time span. We control for cohort years (our sample's main cohorts cover birth years from 1946 to 1975), technology areas, and firms.

To measure annual productivity, we used the following equation:

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

We use two measures for inventive span in the denominator . The first is from the year in which the inventor was first employed to the last year in which he was employed[12]. The second is from eighteen years old to the last year in which he invented. The former measures inventors' productivity in terms of their actual employment spans. The latter is an indicator of life-cycle productivity, taking into account the opportunity cost of attending

[12] 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.

schools to obtain a BA degree or higher.

Educational level: To measure education level, we use the following dummy variables: (a) the BA degree dummy, (b) the MA degree dummy, (c) the traditional PhD degree dummy, and the PhD-DO dummy. The appropriate dummy variable is assigned according to participants' responses to questions regarding their highest degree at the time of their first invention as well as the registry of PhDs[13]. The reference group for these dummy variables is two year college degree or lower. With these variables, we investigate how different levels of education contribute to inventive productivity after controlling for workplace characteristics, inventor motivations, technological areas, and inventor ability. One of our primary focuses is the comparison between the traditional PhDs and PhDs-DO with respect to their inventive productivity. If the two types of PhDs perform comparably as corporate inventors, it would suggest that the screening or certification function of a university is very important, or perhaps dominant, in enhancing inventive productivity.. If traditional PhD performs

[13] 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.

significantly better than PhDs-DO with respect to inventive productivity, it would imply that additional graduate education does provide significant added value to inventive productivity[14].

To test these relationships, we must control for several potential confounding influences. These variables are the characteristics of workplace, firm characteristics, personal motivations and profiles, and technology. It is to the explication of these control variables to which we now turn.

Workplace: We introduce the variables related to workplace to indicate which type of a unit the inventor belonged to when they invented the patent of interest. The types of unit are categorized as 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 time an inventor can devote to his invention and how many complementary assets he has at his disposal for his inventive work. A PhD

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[14] Another possibility is lower standard for PhDs-DO in certification. However, there seems to exist no consensus view on the level of standard for PhD-DO vs. that for traditional PhD.

inventor may look to be productive not because he has higher human capital but because he is given more time and resources for inventions. This variable controls for such a confounding effect.

Research stage: The research stage at which respondents performed their work was also included as a control variable. The questionnaire asked the inventor to identify whether he was engaged in basic research, applied research, development, technical service or others (multiple choices are allowed). A PhD inventor may look to be productive simply he is engaged more in basic research. This variable controls for such a confounding effect.

Firm fixed effects and firm patent applications: We controlled for firm characteristics with the firm dummies or firm fixed effects. These variables control for the firm's complementary assets, the internal knowledge stock, and 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 firm's propensity for developing patent applications over time.

Motivation: The questionnaire also asked the inventors about the importance of their motivations for invention. Some of these motivations included scientific contributions, challenge, contribution to firm performance, career advancement, improved working conditions, and pecuniary motivation. This was assessed with five-point Likert scale items ranging from very important to absolutely not important. If their answer was very important or important, this variable was coded as 1. Otherwise, it was coded as 0.

Gender: We use gender of the inventor as an independent variable. If the inventor is male, gender was coded as 1; otherwise, it was coded as 0.

Technological dummies and cohort dummies: To control for the technological areas in which the inventor worked, we included technological area dummies, which were determined by the most frequent IPC class of the patent applications by each inventor[15]. Finally, to control for a cohort effect on patent productivity, we included cohort dummy variables in our estimation

[15] We constructed dummy variables in accordance with IPC sub-class. As a result, the number of technological dummies was 258.

equation.

T-score (a measure of inventor ability): To control for the effect of independent inventor abilities, we used T-score calculated using the entrance exams from university which the inventor attended[16]. Unfortunately, our sample was reduced when we included this variable because T-score was available only for the inventors with degree higher than a BA. We obtained this data from Kawai-jyuku, which is one of the largest preparatory schools in Japan[17].

Table 2 shows the mean scores for major variables by educational level. There are significant mean differences between levels of education with regard to all of four variables related to patent output. Both types of PhD-holding inventors largely belong to independent laboratory (84% for

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

[17] We deduct 5 points from T-scores for private universities because T-scores for private universities tend to be higher, since they impose fewer number of exam subjects on examinees than t national universities

inventors with traditional PhDs and 95% for inventors with PhD-DO). Their projects often cover basic research (46% for inventors with traditional PhDs and 48% for inventors with PhD-DO), relative to those inventors with other education levels. In these two respects, the two types of PhD-inventing inventors are very similar. On the other hand, the average length of the inventive span is around 7 years longer for inventors with PhD-DO than for those with traditional PhDs (25 years vs. 18 years). We will investigate why PhDs-DO have so long inventive span after controlling for cohort effects in the paper. While cumulative patent outputs are similar between the two types of PhD-holding inventors, the annual productivity of the inventors with traditional PhDs is significantly higher than those with PhD-DO[18]. Furthermore, PhD-DO holders graduated from the universities with the highest T-score, indicating that these inventors have significantly higher inventive ability.

[18] While means of the annual productivity of PhD-DO holders are same as those of BA holders, differences between the two groups are much larger after including technological dummies in the estimation results. This reason is that PhD-DO holders in the sample are often in the chemical or medical science area which produces less number of patent applications relative to IT or electronics area.

(Table 2)

4.2. *Panel estimation*

Next, to investigate the determinants of life-cycle inventive profile within a firm, we develop a panel estimation model. This also allows us to control for time-invariant unobserved heterogeneity among inventors. Though a fixed-effect model is the most suitable for this procedure, it does not allow us to estimate the effect of time-invariant variables such as education level. To cope with this problem, we employ a Hausman-Taylor random effect model (Hausman and Taylor, 1981). Through this model, we can identify the effect of the variables which are potentially correlated with unobserved individual characteristics by using exogenous variables as instruments after fixed effects are estimated. That is, instrumental variables are composed of the exogenous time-variant and time-invariant variables in the equation. We estimate inventor's life-cycle productivity profile with Equation (3):

$$\ln\left(patent_{it}\ or\ citation_{it}\right) = \sum_{s=2}^{5} education\ dummy_{is} + \gamma_1 experience_{it} +$$

$$\gamma_2 experience_{it}^2 + \beta_k X_{ki} + t + \mu_i + \varepsilon_{it} \tag{3}$$

Here the dependent variables are the natural logarithm of fractional patent and forward citation counts for inventor i in year t[19]. In this equation, we assume that level of education and experience are independent. However, it is unlikely that an inventor with only high school diploma has the same experience trajectory as inventors with PhD degrees. Thus, our second specification is defined by Equation (4):

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

In this equation, we permit differentiation of inventive productivity profiles between educational levels by experiences. We treat level of education, experience, and its square as endogenous variables in Equations (3) and (4). While our control variables are essentially the same as listed in

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

Equation (2), the number of patent applications by each firm in year t becomes a time-variant variable in Equations (3) and (4).

4.3. *Estimation of exit from inventive activity*

Finally, to know determinants of inventive span, we analyze how education level are associated with an inventor's exit from his/her inventive activity. To do so, we employ a Cox Proportional Hazard model to estimate the likelihood of exit from inventive activity, taking into account the truncations. We prepare the duration data starting with the year in which the focal patent was applied. In addition, we define the year in which an inventor applied for a patent finally as the exit year. Following this, 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 a patent. This indicates that the peaks of the distribution occur after 2005. Many inventors are truncated simply because their inventive activity has not yet been reflected into the patent data. We decided to use the last year before 2004 as the actual exit year. In our view, this criterion is a conservative one

(Figure 3)

We specify the hazard function h(t) following Equation (5):

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

Here, h_0 is the baseline hazard, and $h(t)$ is the exit rate at time t when the inventor stops his/her inventive activity. All covariates in the exponents 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. Further, we treat the inventor's age and the age square as time-variant covariates. Since Japanese companies traditionally implement seniority systems, age may be an important factor for exit. Other time-variant covariates include the average number of co-inventors with whom the inventor invented during his/her career, 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 individual respondents. Table 3 reports the regression results from Equations (1) and (2)[20]. The first year of inventive activity is defined as the first year of employment in these estimations. Columns 1 to 4 of Table 3 are the results without including the variables for workplaces and research stages; Columns 5 to 8 are the results with these variables included.

(Table 3)

All coefficients associated with the level of education variables are significantly positive for the number of patent applications and forward citations. Further, the coefficients increase with the level of education in all estimations. These results indicate that a higher level of education is

[20] The results of these estimations based on whole counts of patent outputs are quite similar, and reported in the Appendix.

significantly associated with the production of more patents and forward citation counts. Specifically, the respective cumulative life-cycle patent applications and forward citations of inventors with traditional PhDs are 80% and 70% higher than those inventors with BAs, according to columns 5 and 6[21]. Relative to MAs, the annual productivity of inventors with traditional PhDs is higher by 72% and 63% respectively. These differences are statistically significant[22].

If we compare the inventors with traditional PhDs to those with PhDs-DO, the cumulative life-cycle productivity of the former is higher than those of the latter in terms of patent applications (39% higher) and forward citations (35% higher; Columns 5 and 6) though these differences are statistically insignificant[23]. The annual productivity of traditional PhDs is also higher than PhDs-DO by around 42% for patent applications and 38%

[21] The 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 test this possibility, we estimated the interaction between cohort and education level. As a result, we learned that the coefficient for traditional PhDs is still larger than the inventors with lower education levels even among younger inventors.

[22] An F test for differences in coefficients between traditional 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.

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

for forward citations, according to Columns 7 and 8. However, these differences are also insignificant[24].

With respect to research stage, the coefficients associated with 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 favour of basic research suggests that an inventor working in basic research tends to have a longer professional life as an inventor than those that engage in research at other levels. Conversely, the technical service dummy variable is significantly negative for forward citations indicating a reduction in annual productivity by 25%.

The independent laboratory variable is also significantly positive for all output variables. Similar to basic research, inventors who work in independent research laboratories 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

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

productivity). Thus, working in an independent research laboratory significantly increases an inventor's research productivity.

As shown in Table 2, both types of PhDs work significantly more on basic research and in independent laboratories. In addition, the coefficients associated with education level in column 1 to 4 are larger than those in Column 5 to 8 of Table 3 (around 20% higher in the case of a traditional PhD). This suggests that without controlling for research stage and workplace, we will significantly overestimate the effect of education on patent outputs.

With respect to individual characteristics, males produce significantly more patents in terms of fractional counts. A preference for challenge is significantly positive for patent outputs in Columns 1 to 4.

Table 4 presents the estimations associated with Equation (2). The first year of inventive activity is set at eighteen years old to account for the delay due to time spent pursuing a higher level of education. The coefficient associated with the traditional PhD variable decreased most, nearing the level of PhDs-DO. This indicates that the delay in starting inventive work due to the pursuit of higher education is significant but also that this delay is completely overcome as the inventive output of traditional PhDs still exceeds that of PhDs-DO.

(Table 4)

The effect of education level may also be overestimated since they do not control for the inventor's inherent ability. An inventor with higher ability is more likely to pursue higher education to refine his craft. To address this possibility, we estimate Equations (1) and (2) by adding a T-score variable associated with inventor ability as a control. In this estimation, we lose the respondents with an education level associated with a two-year college or less from our sample. Columns 1 to 4 in Table 5 are the results of this estimation with the T-score control included and Columns 5 to 8 are the estimations without the T-score variable. The coefficients associated with the T-score variable 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 between PhDs and MAs do not significantly change after including a T-score variable, while those of MAs relative to those of BAs decline and become insignificant. This indicates that there is no significant difference in inventor ability between MAs and PhDs so that the productivity difference can be significantly attributed to PhD education, while this difference may exist between BAs and MAs. While the coefficients of traditional PhD inventors remain significant and positive in all columns, the coefficients associated with PhDs-DO are insignificant except in column 1. However, the difference between the coefficients of the two types of PhDs does not significantly change. These results indicate that controlling for the ability of inventors does not significantly influence the difference between different graduate degrees, suggesting that such difference in the level of graduate educations matters in inventor productivity.

(Table 5)

5.2. *Estimation results based on panel data*

Before estimating the Hausman-Taylor random-effect model, we regressed Equations (3) and (4) using the fixed-effect model (fixed effect given for each inventor), in order to get consistent estimates of the slope coefficients with respect to experiences. The results are shown in Columns 1 to 4 of Table 6. The coefficients for experience are significantly positive while the coefficients for the square terms are significantly negative for both outputs in Column 1 and 2. Further, these results are robust after allowing for interactions between the education level and experience in Columns 3 and 4, although the interaction terms associated with the square of experience are not significant at the highest education levels. This result produces a simple inverted U-shape relationship between experience and patent productivity, especially pronounced at the lower education level. The initial slopes with experience do not vary significantly across education levels, according to the estimation results. BA and PhD-DO have the largest coefficients.

Using these estimation results, the experience-related yearly profile of patent and citation counts by education level are shown in Figures 4 and 5. The slope for PhDs-DO is steeper than those for the other education levels[25]. This indicates a strong within-firm learning curve for those who seek for a

[25] While we estimate Equation (4) with an additional time variant dummy variable which is 1 if inventor obtains PhD-DO degree and is 0 otherwise, this variable is not significant in any specifications.

PhD while working and/or their increased deployment to tasks favorable for inventions.

(Table 6)

(Figure 4 and 5)

Table 7 shows that the results of Equation (4) using a Hausman-Taylor random-effect model. As mentioned above, this method can estimate time-invariant variables after controlling for unobserved heterogeneity among inventors. In Table 7, Column 1 for patent outputs and Column 2 for citation outputs are estimated, allowing for the interaction effects between the education level and experience. With respect to the fixed effects of education levels, the coefficients for both types of PhDs are significantly positive for forward citations and the highest, but only that for traditional PhDs is significantly positive for patent application counts. The fixed-effect coefficient of traditional PhDs remains higher than that of PhDs-DO. Using the estimation results, the experience-related yearly profile of patent and citation on counts by education level are shown in Figures 6 and 7. Traditional PhDs produce more patents and forward citations than PhDs-DO. This indicates that while a rapidly increases his productivity as he gains experience, the productivity of a traditional PhD remains significantly higher during the average inventive span.

(Table 7)

(Figure 6 and 7)

To investigate the influence of receiving a PhD-DO during their inventive career, we estimate Equation (4) by differentiating the PhD-DO dummy variable into two time periods: before and after receiving the PhD-DO degree. In Table 7, Columns 3 and 4 illustrate the results. While both PhD-DO dummies are significant and positive for both types of patent output, there are no significant differences between the two. This indicates that the award of a PhD-DO degree, in and of itself, does not significantly affect the resources available for the inventor.

The above results indicate that traditional PhD holders have significantly higher research productivity than inventors with other education levels. However, they also have a potential loss of inventive productivity in their younger years because of longer time spent obtaining higher educations. This begs the question: how quickly can their high productivity compensate the lost productivity in their younger period? To answer this question, we calculate when traditional PhD inventors can recover their potential inventive loss due to delayed start-up by exploiting the learning time according to the estimation results. In this estimation, we assume that all inventors start their inventive activity immediately after graduating. That is, BA inventors begin their inventive activity at age 23, MA inventors begin at age 25, and traditional PhD inventors begin at age 28. We additionally assume that PhD-DO inventors have MA degrees and begin of their inventive activity at age 25. This assumption significantly overestimates the potential inventive loss of traditional PhD inventors because the difference between the first job year and first invention year declines significantly with education level (see Table 8)[26]. That is, an

[26] We do not calculate 'less than two year college' because it is composed of two groups for which standard graduate years are different.

inventor with a BA degree starts invention in 5 years since its first job year, while an inventor with a PhD degree starts invention in 2 years.

(Table 8)

Table 9 presents the estimated average time it takes an inventor with a traditional PhD to surpass the cumulative inventive output of an inventor with the other education levels, by using the results in Columns 1 and 2 of Table 7. Cumulative invention productivity of traditional PhD inventors surpasses that of PhD-DO inventors in approximately 4.6 years for patents and 5.3 years for forward citations. This time frame is somewhat shorter among BA and MA inventors. These results indicate that traditional PhD inventors recover their potential invention loss due to their late start fairly quickly (within at least 5.3 years, on average), even if we assume that they are late by the full length of their additional educational period.

(Table 9)

5.3. *Estimation results of exit analysis*

Table 10 shows the results of estimating the hazard model for exit from inventive activity. Column 1 in Table 10 presents the the results estimated without research stage and workplace as controls. Column 2, by contrast, includes these control variables. Results suggest that rate of exit decreases with education level. The coefficients associated with both types of PhDs are significant and negative for exit in Column 1 and 2. Further, PhDs-DO have a lower exit rate than traditional PhDs. Specifically, when compared to baseline, the exit rate for traditional PhD inventors and for PhD-DO inventors is 62% and 69% lower respectively. Moreover, the rate for exit for PhDs-DO is significantly negative even after controlling for inventor ability (see Column 3). This indicates that if an inventor obtains a PhD-DO degree, he/she tends to remain in their career as an inventor for a longer period of time. As such, the awarding of a PhD-DO may serve as a signal in a firm that such individual deserves a longer career as an inventor.

(Table 10)

The age coefficients in Table 10 show that the exit rate is low for younger respondents, as expected. Moreover, the exit rate drastically increases with age. This indicates that while young inventors remain in research workplaces, they exit from their careers as inventors as they become more senior. Interestingly the exit rate for inventors who engages in basic research is significantly low. Conversely, the exit rate for inventors who perform technical services is significantly high. The coefficient associated with the number of inventors on a given patent is strongly significant and positive. This result is reasonable because it suggests that the probability that an inventor in a big team is a core inventor is lower.

5.4. Discussions of the robustness of our findings

We would like to discuss two sources which can potentially affect the significance of our findings. The first source is our use of fractional counting, instead of whole counting. A fractional count significantly discounts the output of a co-invention, even though a fractional counts makes sense when forward citation counts is used, as pointed out earlier. Table 1 in the Appendix provides the estimation results for life-cycle cumulative patent counts based on whole counts. The results are essentially the same as those based on fractional counting. The inventors with traditional PhDs are most productive, followed closely by inventors with PhD-DO. The gap between the two types of PhD is a bit larger in the case of whole counts, which suggests that a traditional PhD inventor works more in a team.

The second potential source is a sampling bias due to our oversampling of higher quality inventions. Such bias tends to cause a downward bias of the estimated coefficients of educational levels with respect to invention performance, since we tend to pick up the inventors with exceptionally good invention performance for those with lower educational records. Thus, our estimates of the effects of higher education are conservative estimates.

6. CONCLUSION

This paper has analyzed the life-cycle inventive productivity of Japanese industrial inventors, using panel data of 1,731 inventors matched with firm data. We focused on two issues. First, we examined whether and how doctoral educations contribute to inventive performance, despite of their delayed start. Second, we explored whether inventors with PhDs obtained solely by completing a dissertation (PhDs-DO) are similarly productive as inventors who earn PhDs through more traditional coursework. For these analyses, we controlled for the types of places at which inventors work, the types of projects in which they are engaged, inventors' motivations, firm size, cohort effects, technology fields and inventor's abilities. We used the number of patent applications and the total forward citations the applications received within five years of their submission as performance measures. Given this, we found the following:

1. The life-cycle productivity of traditional 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. The most important reason for this is a high level of annual productivity of PhD inventors. Additional source of high life-cycle productivity of traditional PhD inventors is a short interval between the time an inventor starts his/her job and the time he/she begins inventing.

2. The life-cycle productivity of a PhD-DO inventor is lower than that of a traditional PhD inventor, but this difference is not statistically significant. Our survey data suggests that a PhD-DO inventor works in independent laboratories and engages in basic research as frequently as traditional PhD inventors. The panel data estimates suggest that PhDs-DO have a steeper 'learning' curve and remain inventors for longer periods of time, although there is no clear award effect. These results suggest that a system that provides PhDs-DO to corporate inventors may serve as an important screening and signaling device for encouraging high-ability inventors with no PhD education to acquire scientific human capital and to move into a position more suitable for inventions.

3. The Hausman-Taylor estimations suggest that higher productivity estimates for traditional PhD inventors are robust to an additional control on the possible correlation between unobserved heterogeneity of inventor ability and the educational level. Thus, a PhD program functions as an effective channel for helping an inventor acquire scientific human capital increasing his inventive productivity.

4. Inventor productivity is significantly higher when the inventors belong to the units dedicated to research, they are involved in basic research, and they belong to a large firm with a large number of patent applications. In addition, PhD inventors are more likely to work in those units, for such projects and in a larger firm. Thus, productivity estimates without considering these resource and task factors tend to significantly overestimate the influence of higher education on patent productivity.

Our research shows that a traditional PhD inventor has higher inventive productivity and can compensate easily for a delayed start to his inventive career. This holds even if we control for the fact that such an inventor is more likely to be assigned to a workplace, a project which generates more patents, and their individual set of abilities. This suggests that it would be worthwhile for a firm to recognize PhDs as important sources of innovation. We can also note that PhD inventors are more likely to generate internal knowledge spillover within a company through his absorption of external scientific knowledge.

However, this raises a new question. Why are many PhDs unable to find research jobs in the private sector despite their high inventive productivity. There are various potential reasons for this. One possible reason relates to an inherent selection bias in our study. The PhDs in our sample have already been employed. Therefore, our sample consists of the inventors whose specialization and capability are matched to the demands of their employer or are suitable for inventive activity in private sector. If specialization is more important for PhDs, the mismatch between demand and supply may be more pronounced for PhDs.

A second potential reason is that there is asymmetric information between PhDs and companies in the job market. As mentioned above, the number of PhDs employed by companies is still quite low in Japan. As a result, companies have not been able to effectively gauge their potential inventive productivity and to develop the career plans exploiting fully the potential of PhD inventors.

A third potential explanation for the lack of widespread PhD employment relates to the expectations for multi-tasking by corporate researchers in Japan. Inventive productivity is only one characteristic that a new PhD hire must have. For example, they are expected to effectively engage in technology transfer to the manufacturing sector. They may also be expected to take on management roles within the company. These multi-task expectations for inventors in Japan suggest that even traditional PhD holders cannot continue their inventive activity in their late 40s, so that they may not be able to realize fully the outputs of their human capital Unfortunately, we do not have sufficient data to test these views, although we plan to do so in the future.

Our evidence also shows that a system of PhD-DO is a useful complement for traditional PhD. PhD-DO inventors are productive and remain active for relatively long periods of time. Our evidence suggests that a PhD-DO inventor realizes his inventive potential over time and will gain the skills needed to take on more inventive jobs as he develops. As such, a system for PhDs-DO seems to provide an incentive for a corporate inventor to deepen his scientific understanding of the invention process under the support of the firm. While the PhD-DO educational track is being phased out in Japan, it will prove useful to retain the positive aspects of this system in the new design of graduate education.

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REFERENCES

AGIHON, P., BOUSTAN, L., HOXBY, C. and VANDENBUSSCHE, J. (2009), "The Causal Impact of Education on Economic Growth: Evidence from U.S." (Working Paper, Harvard University)

ALLISON, P. D. and STEWART, J. A. (1974), "Productivity Differences among Scientists: Evidence for Accumulative Advantage", *American Sociological Review*, **39**, 596–606.

BASER, O. and PEMA, E. (2004), "Publications over the Academic Life-cycle: Evidence for Academic Economists", *Economics Bulletin*, **1**, 1–8.

BECKER, G. S. (1964), "*Human Capital*" (New York: Columbia University Press).

CARD, D. (1999), "The Causal Effect of Education on Earnings", in Ashenfelter, O. and D. Card (eds) *Handbook of Labor Economics 3* (Amsterdam, Netherlands: Elsevier).

COHEN, W. M. and LEVINTHAL, D. A. (1989), "Innovation and Learning: The Two Faces of R&D", *The Economic Journal*, **99**, 569–596.

CYRANOSKI, D, GILBERT, N., LEDFORD, H., NAYAR, A. and YAHIA, M.,

2011. “The PhD Factory”, *Nature*, **472**, 276–279.

DIAMOND, A. M. (1986), “The Life-Cycle Research Productivity of Mathematicians and Scientists”, *Journal of Gerontology*, **41**, 520–525.

DONALD, D. R. and VESOVIC, J. (2006), “Educational Wage Premiums and the U.S. Income Distribution: A Survey”, in Hanushek, E. A. and Welch, F. (eds) *Handbook of the Economics of Education 1* (Amsterdam, Netherlands: Elsevier).

FOX, J. T. and SMEETS, V. (In press), “Does Input Quality Drive Measured Differences in Firm Productivity?”, *International Economic Review*.

HAUSMAN, J. A. and TAYLOR, W. E. (1981), “Panel Data and Unobservable Individual Effects”, *Econometrica*, **49**, 1377–1398.

HALL, B. H., JAFFE, A.B. and TRATJENBERG, M. (2005), “Market Value and Patent Citations”, *RAND Journal of Economics*, **36**, 16–38.

HALL, B.H., MAIRESSE, J. and TURNER, L. (2007), “Identifying Age, Cohort, And Period Effects In Scientific Research Productivity: Discussion And Illustration Using Simulated And Actual Data On French Physicists”, *Economics of Innovation and New Technology*, **16**, 159–177.

HARHOFF, D., SCHERER, F. M. and VOPEL, K. (2003), “Citations, Family Size, Opposition and the Value of Patent Rights”, *Research Policy*, **32**, 1343–1363.

HOISL, K. (2007), “Tracing Mobile Inventors - The Causality between Inventor Mobility and Inventor Productivity”, *Research Policy*, **36**, 619–636.

HOISL, K. (2007), “A Closer Look at Inventive Output - The Role of Age and Career Paths”, Munich School of Management Discussion Paper No. 2007-12.

JONES, B. F. (2009), “The Burden of Knowledge and the 'Death of the Renaissance Man': Is Innovation Getting Harder?”, *Review of Economic Studies*, **76**, 283–317.

KIM, J., LEE, S. J. and MARSCHKE, G. (2004), “Research Scientist Productivity and Firm Size: Evidence from Panel Data on Inventors”, (Working Paper, SUNY Albany)

KRUEGER, A. B. and LINDAHL, M. (2001), “Education for Growth: Why and for Whom?”, *Journal of Economic Literature*, **39**, 1101–1136.

LEVIN, S. and STEPHAN, P. (1991), “Research Productivity over the Life

Cycle: Evidence for Academic Scientists", *American Economic Review*, **81**, 114–132.

LOTKA, A. J. (1926), "The Frequency Distribution of Scientific Productivity", *Journal of the Washington Academy of Science*, **16**, 317–323.

MERTON, R. K. (1968), "The Matthew Effect in Science", *Science*, **159**, 56–63.

MORIKAWA, M. (2012), "Postgraduate Education and Human Capital Productivity in Japan", RIETI Discussion Paper 12-E-009.

MINCER, J. (1974), "*Schooling, Experience, and Earnings*" (New York, Colombia University Press)

MARIANI, M. and ROMANELLI, M. (2007), "'Stacking' and 'Picking' Inventions: The Patenting Behavior of European Inventors", *Research Policy*, **36**, 1128–1142.

NAGAOKA, S. and TSUKADA, N. (2007) "Innovation Process in Japan: Findings from the RIETI Inventors Survey (in Japanese)", RIETI Discussion Paper 07-J-046.

NARIN, F. and BREITZMAN, A. (1995), "Inventive Productivity", *Research Policy*, **24** (4), 507–519.

OECD. (2010), "*OECD Science, Technology and Industry Outlook 2010*", (OECD Publishing, http://dx.doi.org/10.1787/sti_outlook-2010-en)

ONISHI, K., NISHIMURA, Y., TSUKADA, N., YAMAUCHI, I., SHINBO, T., KANI, M. and NAKAMURA, K. (2012), "Standardization and Accuracy of the Japanese Patent Applicant Names", IIPR Discussion Paper No. 2012-001.

OSTER, S. M. and HAMERMESH, D. S. (1998), "Aging and Productivity among Economists", *Review of Economics and Statistics*, **80**, 154–156.

SCHETTINO, F., STERLACCHINI, A. and VENTURINI, F. (2008), "Inventive Productivity and Patent Quality: Evidence from Italian Inventors", MPRA Paper 7765.

SERNEELS, P. (2008), "Human Capital Revisited: the Role of Experience and Education When Controlling for Performance and Cognitive Skills", *Labour Economics*, **15**, 1143–1161.

STEPHAN, P. (2011), "*How Economics Shapes Science*", (Cambridge, MA: Harvard University Press).

TOIVANEN, Otto and VAANANEN, L. (2012) "Return to Inventors", *Review of Economics and Statistics*, **94**, 1173–1190.

TURNER, L. and MAIRESSE, J. (2005), "Individual Productivity Differences in Public Research: How Important are Non-individual Determinants? An Econometric Study of French Physicists' Publications and Citations. (1986–1997)", (Working Paper, http://piketty.pse.ens.fr/files/Turner2005.pdf).

WALSH, P. J. and NAGAOKA, S. (2009), "Who Invents?: Evidence from the Japan-US Inventor Survey", RIETI Discussion Paper 09-E-034.

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. 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 3. Life-cycle cumulative patent outputs and average productivity with cohort dummies

	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 manufacturing division					0.488**	0.548**	0.422**	0.483**
					(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 4. Life-cycle average productivity with cohort dummies (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 5. Life-cycle cumulative patent outputs and average productivity with cohort dummies and 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 6. 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 7. 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***	0.237***	0.206***	0.237***
	(0.005)	(0.008)	(0.005)	(0.008)
male	0.317**	0.382*	0.324***	0.390***
	(0.131)	(0.211)	(0.091)	(0.148)
basic research	0.01	-0.022	0.008	-0.024
	(0.058)	(0.094)	(0.040)	(0.065)
applied research	0.05	0.078	0.051*	0.079*
	(0.040)	(0.064)	(0.027)	(0.045)
development	0.008	0.012	0.009	0.013
	(0.045)	(0.072)	(0.031)	(0.050)
technical service	-0.042	-0.05	-0.043	-0.052
	(0.056)	(0.090)	(0.038)	(0.063)
other division	0.029	0.034	0.031	0.038
	(0.105)	(0.169)	(0.072)	(0.118)
software development division	0.01	0.003	0.01	0.005
	(0.107)	(0.172)	(0.073)	(0.120)
laboratory attached to manufacturing division	0.064	0.073	0.065	0.076
	(0.081)	(0.131)	(0.056)	(0.091)
independent laboratory	0.106	0.122	0.107*	0.124
	(0.084)	(0.135)	(0.057)	(0.094)
BA degree	0.276	0.42	0.269	0.409
	(0.329)	(0.529)	(0.229)	(0.371)
MA degree	0.324	0.547	0.311	0.532
	(0.291)	(0.466)	(0.204)	(0.330)
PhD degree	1.332**	2.433**	1.352***	2.446***
	(0.621)	(1.000)	(0.430)	(0.699)
PhD degree(dissertation only)	0.889	1.588*		
	(0.579)	(0.937)		
PhD degree(dissertation only) before			0.895**	1.584**
			(0.396)	(0.647)
PhD degree(dissertation only) after			0.901**	1.552**
			(0.400)	(0.652)
Two years college or less *experience	0.031*	0.052**	0.031***	0.052***
	(0.016)	(0.026)	(0.012)	(0.019)
BA degree*experience	0.042***	0.066**	0.042***	0.066***
	(0.016)	(0.026)	(0.011)	(0.018)
MA degree*experience	0.038**	0.058**	0.038***	0.058***
	(0.016)	(0.026)	(0.011)	(0.018)
PhD degree*experience	0.039**	0.039	0.039***	0.039*
	(0.019)	(0.029)	(0.015)	(0.023)
PhD degree(dissertation only)*experience	0.048***	0.066**	0.047***	0.068***
	(0.018)	(0.028)	(0.014)	(0.021)
Two years college or less *experience^2	-0.027**	-0.044***	-0.027**	-0.044***
	(0.011)	(0.015)	(0.011)	(0.015)
BA degree*experience^2	-0.083***	-0.110***	-0.083***	-0.110***
	(0.008)	(0.011)	(0.008)	(0.011)
MA degree*experience^2	-0.057***	-0.073***	-0.057***	-0.073***
	(0.008)	(0.011)	(0.008)	(0.011)
PhD degree*experience^2	-0.078*	-0.024	-0.078*	-0.024
	(0.045)	(0.064)	(0.046)	(0.064)
PhD degree(dissertation only)*experience^2	-0.081***	-0.082**	-0.081***	-0.083**
	(0.030)	(0.042)	(0.030)	(0.042)
_cons	-0.117	-0.52	-0.862	-1.39
	(0.738)	(1.174)	(0.900)	(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 8. 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	29.74	8.58
	(4.77)	(7.48)	(7.28)
BA degree	23.99	29.01	5.02
	(3.00)	(5.49)	(5.15)
MA degree	25.24	28.15	2.91
	(2.54)	(3.51)	(3.92)
PhD degree	28.39	30.45	2.05
	(2.90)	(3.83)	(2.79)
PhD degree(Dissertation only)	26.07	29.98	3.91
	(3.12)	(4.48)	(3.78)

Standard deviations are in parentheses.

Table 9. Time required to compensate for the invention loss due to late start of inventive activity by a traditional PhD.

	patent	forward citation
BA degree	4.43	4.61
MA degree	3.43	3.51
PhD degree(dissertation only)	4.59	5.25

Column 1 is calculated by using column 1 in Table 8, and column 2 is calculated by using column 2 in Table 2.

Table 10. 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

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

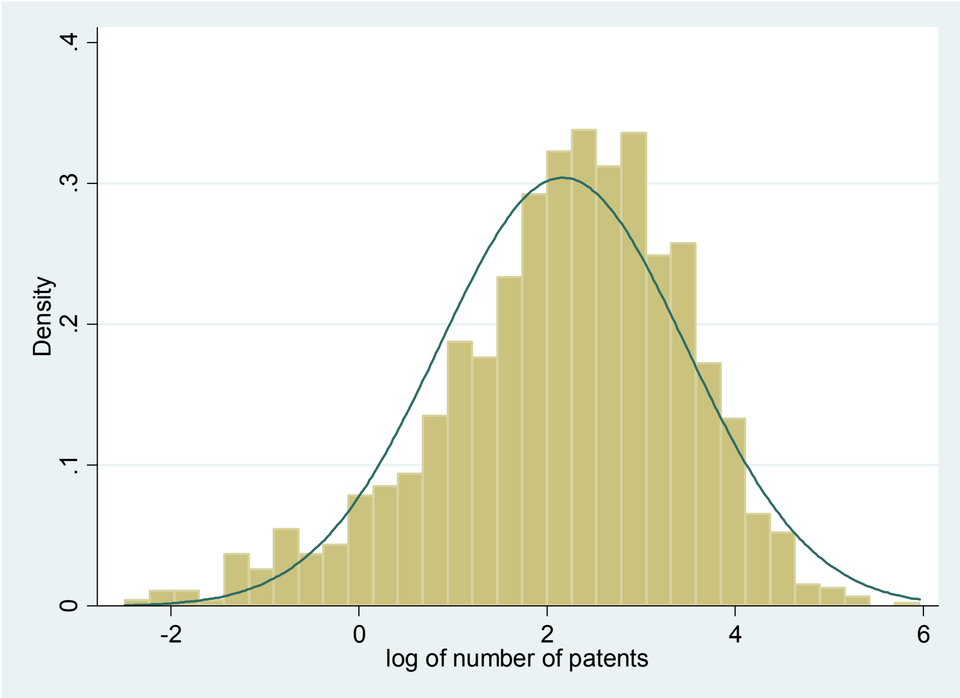


Figure 2. Distribution of the logarithm of the number of forward citations (life-cycle productivity)

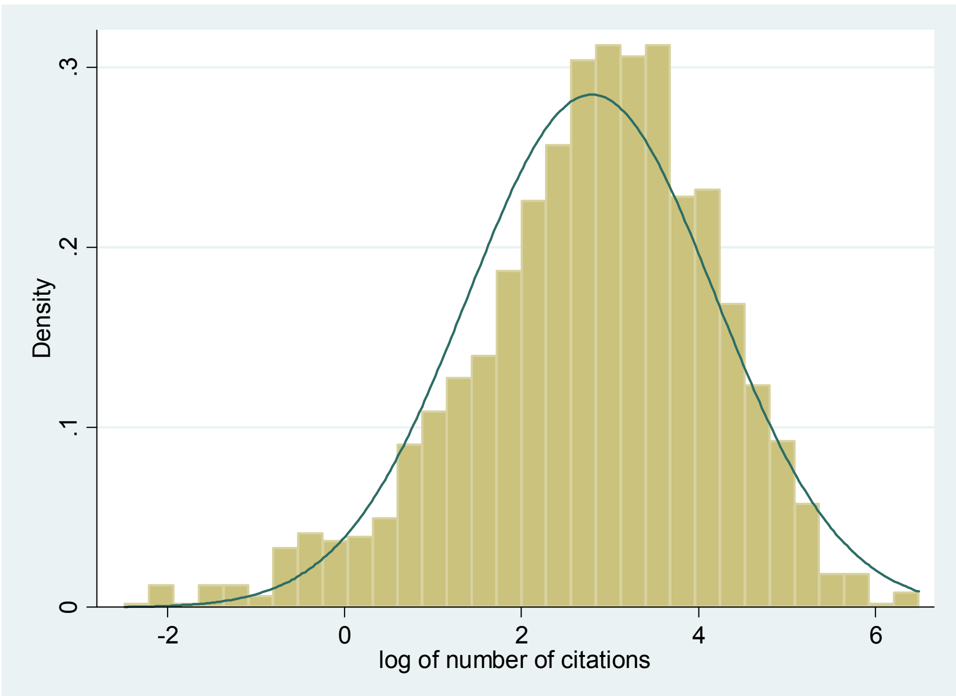


Figure 3. Timing of 'Exit' inventive activity by cohort groups

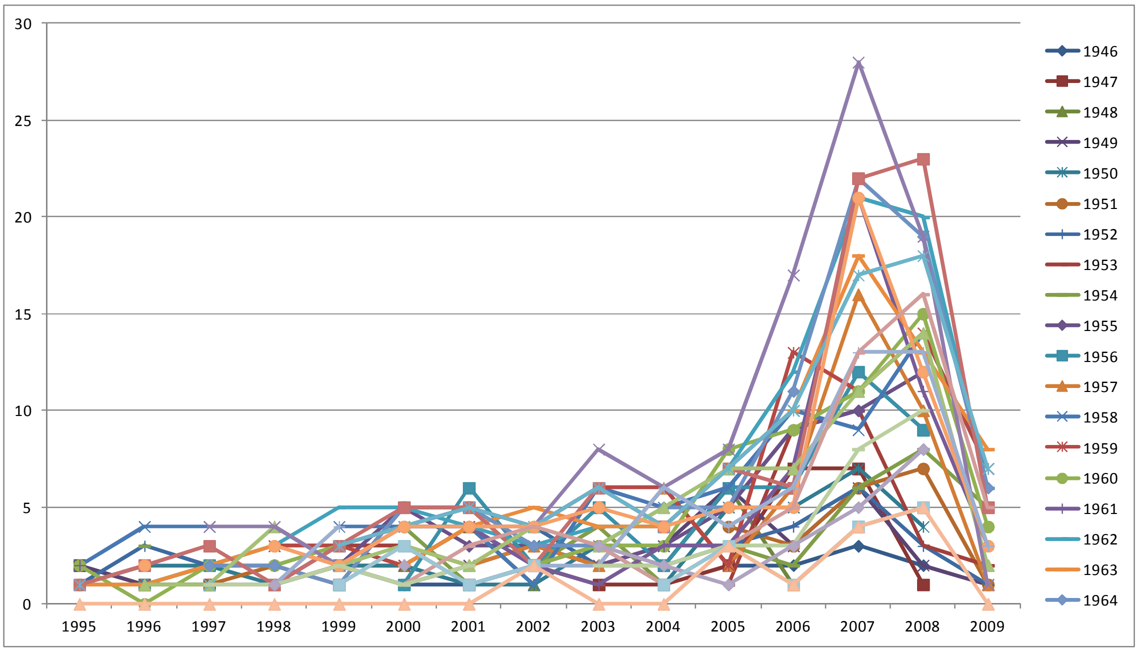


Figure 4. Experience effect on the number of patents (FE model)

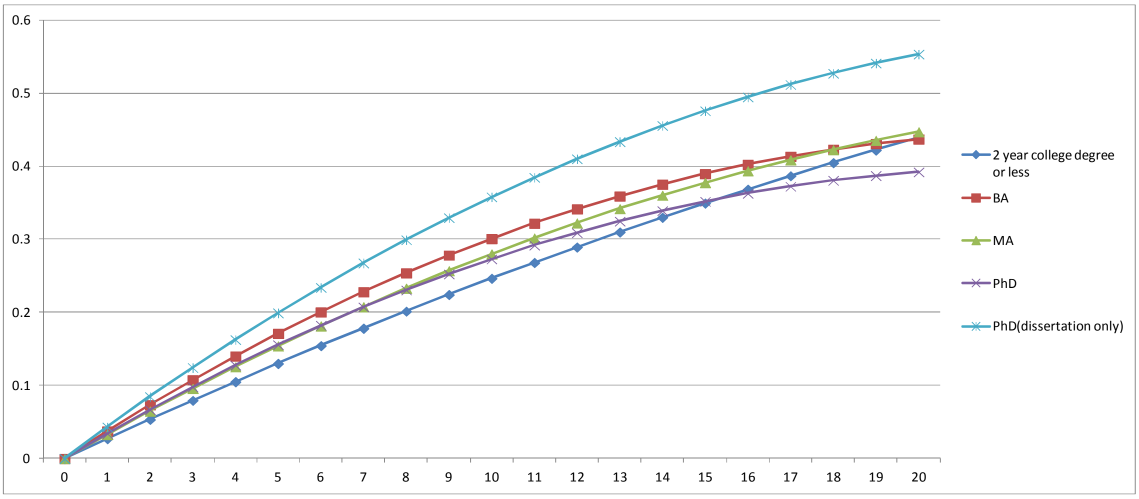


Figure 5. Experience effect on the number of forward citations (FE model)

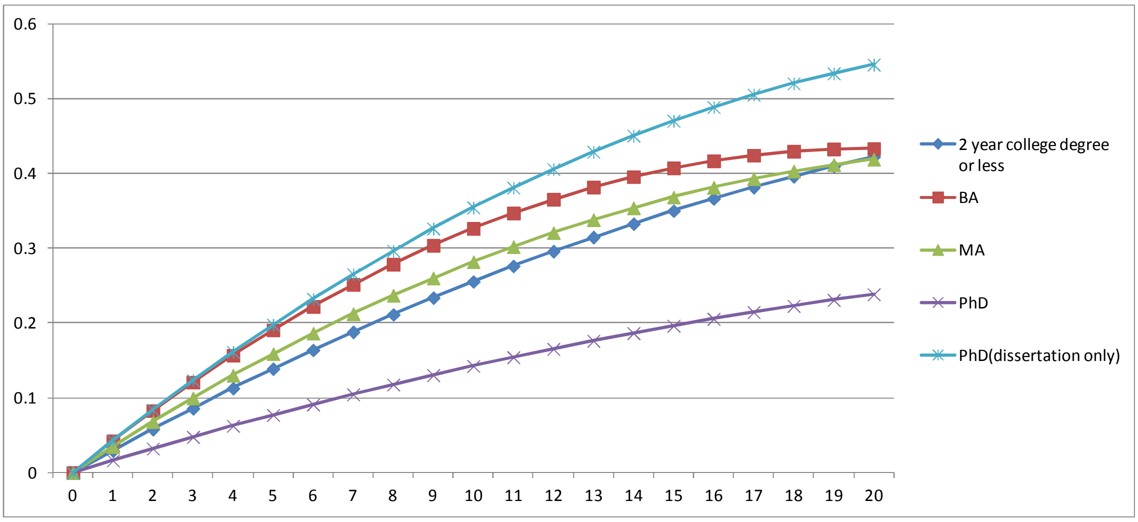


Figure 6. Experience effect on the number of patents (Hausman-Taylor RE model)

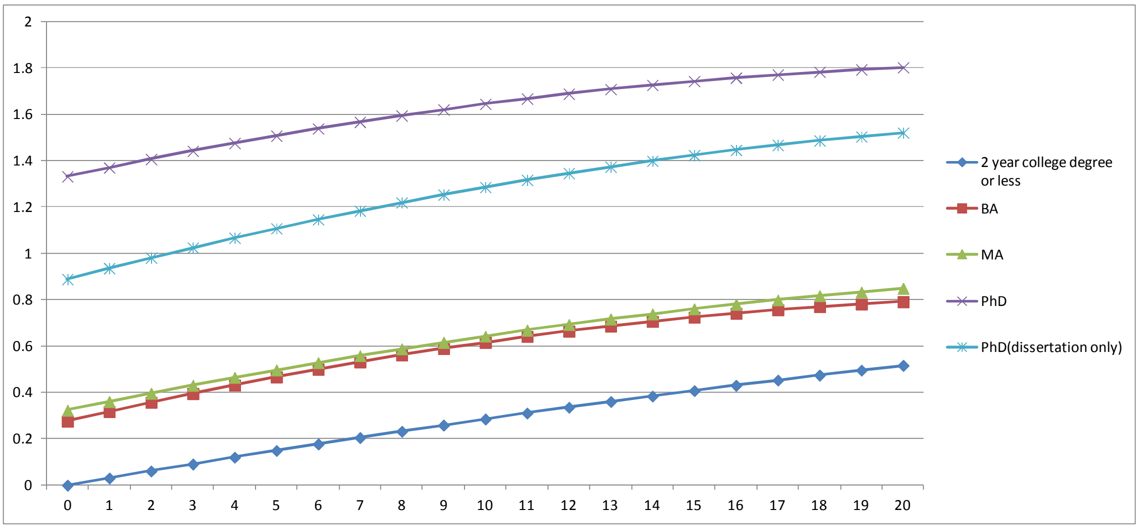
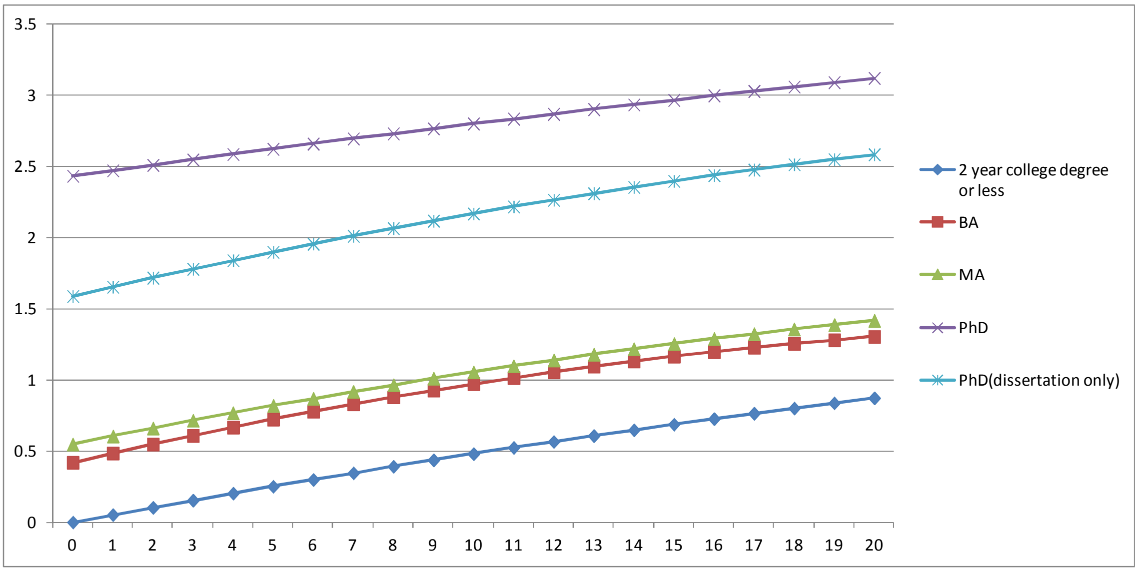


Figure 7. Experience effect on the number of forward citations (Hausman-Taylor RE model)



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