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How does Graduate Education Affect Inventive Performance? Evidence from undergraduates' choices during recessions[†]

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Abstract: This paper investigates the effects of graduate education on inventive performance, as well as the underlying mechanisms, using inventor life-cycle data to focus on the factors affecting the capability of an inventor to absorb and combine diverse external knowledge. In order to control for endogeneity in the choice of graduate education, we use as an instrument the unemployment rate of college graduates in the year preceding the graduation of the focal inventor, as well as in the academic field in which the inventor is specialized. Our first-stage estimation results show that a college student who graduates under adverse labor market conditions chooses much more frequently to pursue a graduate degree. This instrument is also likely to satisfy the exclusion restriction, since our dependent variables are long-run inventor activities. We find that graduate education induced by this instrument significantly enhances inventive performance, as measured by the level and scope of forward citations and the number of patent applications. It also significantly enhances the scope of knowledge exploited for inventive processes, both in the use of scientific knowledge as well as in the scope of knowledge cited in the prior patent literature.

Keywords: Invention, Graduate education, Knowledge exploitation, Patent, Recession
JEL Classifications: O31, O34, I21

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1. Introduction

Human resources are often seen as the central pillar of the creation of inventions and, therefore, of knowledge-based economic growth. On the theoretical front, endogenous growth theory identifies the number of highly educated persons in a society as a key determinant of the growth rate (as pioneered by Romer 1990). Many countries, including emerging as well as developed countries, have expanded graduate education programs (master's and PhD courses) based on this view (OECD 2016, p.146). Despite the widespread belief in graduate education's role in enhancing inventive performance, there is surprisingly little empirical support for this conjecture[1]. Furthermore, existing studies have not focused on how graduate education programs affect inventors' skills and their innovation processes.

To fill these gaps, we analyze the effects of graduate education not only on inventive productivity, but also on the scope of knowledge sources that inventors use in their inventive processes. We expect that obtaining higher education enhances their inventive performance. We also expect that graduate education improves their inventive process by enabling them to learn how to absorb and combine knowledge from more diverse sources. The ability to absorb scientific advances seems to be of particular importance as a determinant of the innovative capability of a firm (Cohen and Levinthal 1990; March 1991). Further, since innovation is often based on recombinations of existing knowledge (Schumpeter 1934; Weitzman 1998), one can expect that the inventive performance of the better educated will be higher than those with less education, if the former can combine existing knowledge more effectively. On the other hand, successful technologies and ideas have often been noted to arise without being influenced by existing science or knowledge (Price 1965).

To confirm these expectations, we focus on detailed Japanese inventor information derived from the RIETI Inventor Survey. We gathered all the available life-cycle patent applications these inventors had applied for the Japan Patent Office in order to capture the histories of their inventive activities. The two databases are then matched using inventor's name, address and other details. We obtain the data on individuals' final educational degrees and their demographic information mainly from the RIETI Inventor Survey. Further, we measure the scope of knowledge that inventors utilize and their inventive performance using patent applications and their citation data, which are commonly recognized as useful indicators. One advantage of using Japanese patent data is that typical Japanese companies have a much higher patenting propensity than their US counterparts (Cohen et al. 2002); also, the JPO publishes all patent applications, like the EPO, but in contrast with the USPTO. Therefore, we can more easily trace the profiles of inventors' inventive activities than is possible with other patent data sources[2].

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[1] One notable exception is Toivanen and Väänänen (2016), but they focus on undergraduates rather than graduates or PhDs.

[2] A comparison of similar studies that gather inventors' overall life-cycle patents shows that the number of patents per inventor in our sample is 39.1, which is much higher than 14.7 in Hoisl (2007) using EPO patent data and 1.2–1.4 in Toivanen and Väänänen (2012), using data on US patent applications made by Finnish inventors. The number of patents per inventor depends on the time window on which a study focuses. For example, Toivanen and Väänänen (2012) used 1988–1996, which is half the length of our study period, covering 1991–2007. Consequently, the mean of patenting in our study is more than 40 times larger than that of their study.

Obtaining causal evidence on such educational effects is challenging, because the choice of level of education by an individual is endogenous to the unobserved characteristics of each such person. We expect that individuals with high ability will generally choose higher levels of education, due to the higher returns they anticipate from this investment. To control for this endogeneity, we propose to use as an instrument the unemployment rate of college graduates in the year preceding the graduation of the focal inventor, as well as within the academic field in which the inventor is specialized[3]. Choosing to go to graduate school seems to be an important choice for college graduates who face a negative labor market situation at the time of graduation, since they can occupy their time with graduate school until the labor market recovers. Prior studies found that labor market conditions affect enrolment for graduate school and PhD courses in the US (Bedard and Herman 2006; Johnson 2013; Shu et al. 2012). Further, Kondo (2007) finds a negative correlation between labor market conditions and the propensity to go to college of high school students in Japan. Thus, we can expect that labor market conditions for college graduates significantly influence the probability that college graduates go to graduate schools. This instrument, based on the labor market conditions at the time of college graduation, is also likely to satisfy the exclusion restriction for the long-run inventive activities studied, since we use a common window (1992 to 2007) for assessing the long-run inventive outputs of all inventors, using cohort dummies[4]. Our study provides several validations of this exclusion restriction.

In the estimation, we find that higher unemployment rates at that age and in that field significantly increased the inventor’s choice of seeking a graduate degree. Further, this finding satisfies robustness checks[5]. After controlling for the endogeneity of the choice for graduate school education, we find that graduate education significantly enhanced invention performance, measured by the level and the scope of forward citations (referred to as the “generality” of a patent) and the number of patent applications. It also significantly enhanced the scope of knowledge exploited for inventions, comprising the use of scientific knowledge as well as the scope of the technical knowledge disclosed in prior patent documents (“originality”). These results indicate that a government policy supporting students who wish to acquire higher degrees will have a substantial impact on national innovative capability. Interestingly, our study suggests that a recession has a positive impact on future innovative performance through encouraging students to enter graduate school. The results also suggest that employing graduates with higher degrees will strengthen the capability of a firm to absorb broader

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[3] This idea is borrowed from labor economics literature (Heckman, Lochner and Todd 2006; Neumark 2002). Heckman et al. (2006) proposed the local unemployment rate as an attractive instrument for years of education in a wage equation, since this variable affects the opportunity cost for further education, but not the long-term income performance.

[4] While a temporary demand-side shock to the college graduate labor market would affect the educational choice of a college graduate, this study assesses inventors’ performances based on their patent applications made from 1992 to 2007, a common window for all inventors under our study. Thus, most of the focal inventors face a common external environment in terms of market demand and technological opportunity. As a result, such temporary demand-side shocks will significantly affect the long-run performance of an inventor, relative to that of an inventor with only an undergraduate degree, only through the choice of going to a graduate school.

[5] We find similar results using local labor market conditions as an instrument as a robustness check. Our preferred instrument is the unemployment rate for the corresponding academic subject level, because the college graduate labor market is essentially national. At the same time, however, we do find that local labor market conditions also affect undergraduate students’ choices.

knowledge, as well as enhancing its inventive productivity.

The rest of the paper is organized as follows. The next section provides a brief review of the literature on the relationship between education and inventive activities. Section 3 describes the data and section 4 provides estimation methods. Section 5 presents the results, while section 6 discusses the results and explains the conclusions.

2. Brief review of prior literature

Attaining graduate education seems to enhance the understanding of inventors of the knowledge stock available and improve their ability to explore ideas and new knowledge, including greater familiarity with the research tools available to address frontier research questions. As Jones (2009) indicated, if the “burden of knowledge” has become a critical barrier against successful innovation, inventors must spend more time or money to acquire state-of-the-art technology and training to absorb different technological knowledge. Attending a master’s or PhD program may be one important channel for achieving this. Stephan (2011) comprehensively discussed how PhDs working in industry contribute to economic growth, quoting the former president of the National Academy of Sciences saying that “the real agents of technology transfer from university laboratory were the students who took jobs in the local biotech industry.” Thus, one can expect that corporate researchers with PhDs contribute to bring fresh knowledge from scientific communities to industry (Cockburn and Henderson 1998). In this view, graduate education will increase inventive performance by accumulating existing knowledge and enhancing absorptive ability with respect to scientific knowledge.

Only a few studies explore the relationship between attaining advanced education and subsequent research output. Mariani and Romanelli (2007) and Kim, Lee and Marschke (2004) find that inventors with PhD degrees make significantly greater numbers of patent applications, compared with those with high school degrees. However, Hoisl (2007) shows that PhD inventors do not generate more patent applications than non-PhDs, in terms of the life-cycle productivity of inventors. With respect to quality, Schettino, Sterlacchini and Venturini (2008) report that patent quality increases with the level of education. In contrast, Mariani and Romanelli (2007) find that there is no significant difference in the level of citations per patent across education levels. Further, Shu et al. (2012) find that the labor market conditions at graduation of MIT students affect their subsequent patent output; and conclude that this positive correlation comes from their intensive accumulation of human capital after graduation, such as attending graduate school, although they do not directly assess the effects of graduate education. Finally, Onishi and Nagaoka (2012) use life-cycle data of Japanese inventors and find that inventors who attained graduate degrees have higher productivity in terms of patent quantity and quality. Unfortunately, since the above studies do not address the endogeneity of educational choice, the positive correlation between graduate degree and higher patent productivity might have come from inventors’ innate ability or from omitted variables affecting both attaining a PhD degree and patent outputs.

Recently, Toivanen and Väänänen (2016) use Finnish inventor level data to analyze whether increased opportunities for engineering university education through establishing technical universities have enhanced the propensity to patent in Finland. They use the geographical distance to university engineering education and its policy-induced reduction over time as the instruments driving educational choice and controlling for its endogeneity. The results show significant causal effects of university education on patent numbers and quality. Surprisingly, their study also shows a negative selection bias: that is, those who have a high innate propensity for invention have a lower propensity to study at a technical university. However, importantly, it remains to be investigated whether such findings can be extended to graduate education, to establish whether obtaining graduate degrees by college graduates is a more crucial issue for inventive activities than obtaining college degrees by high school graduates, as well as assessing how graduate education enhances inventive performance.

As for the effects of education on knowledge consolidation, Gruber, Harhoff and Hoisl (2013) empirically show that inventors with a scientific education tend to generate inventions that recombine knowledge across technological domains more than inventors with an engineering education. Further, they also find that inventors with higher educational attainment (especially PhDs) have higher ability and skill to recombine different technologies, irrespective of the field of education. Giuri and Mariani (2013) show that PhD holders gain more knowledge from geographically far distant places than do less educated inventors. Unfortunately, these studies fail to rule out the possibility that such correlations are driven by the endogenous choices of students with higher innate ability to choose to obtain higher levels of education. Our study fills this gap by considering the causality between advanced education and the utilization of knowledge sources.

3. Data

To examine the effect of educational attainment on inventive performance, we captured detailed individual information and developed an invention life-cycle profile database for more than 2,300 Japanese inventors. The data on inventor-level information (level of education, field of study, employment year, and gender) came from the RIETI Inventor Survey. This survey sent questionnaires to quasi-randomly selected patent inventors requesting their demographic information as well as details of their inventive processes[6]. The patents selected for the survey were applied for in the period 1995–2002. The effective response rate of the survey is 30.9% and 5,278 inventors responded. We also gathered the entire stock of patent applications of these inventors in their life-cycle up to 2014 and matched the survey responses to this patent database, based on the inventor's name, address, and patent applicant information. We obtained the patent data from the IIP patent database, which covers

[6] Around 70% of the focal patents are selected from triadic patents (granted in the US and applied for both in Japan and at the European Patent Office), which accounted for less than 10% of the patent applications in Japan. 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).

all patent applications made to the Japan Patent Office since 1964[7]. To identify the patents invented by the focal inventors in the survey—that is, to treat a unique person by avoiding persons with the same name—we focus on inventors whose name are rare, judged by using the telephone directory[8]. We define a name as rare if it is listed only once in the telephone directory. Further, we used only those patent applications whose inventor's name appears for only one company. This procedure makes disambiguation very tight, because the probability of different persons with same name appearing more than once in a particular company is then quite low, given that such a name appears nowhere else. To confirm our procedure, we manually checked whether all patents gathered are matched to genuine inventors based on the survey and patent information.

We exclude inventors who graduated with two years of college or less from our sample, because we cannot specify their academic subject in the survey. We also exclude inventors who qualified for their PhD degree only through their PhD dissertation, because they need neither to enter PhD programs nor to obtain any formal education from graduate school. Further, some samples were dropped in the process where the survey was matched to the unemployment rate data of college students, which is commonly available from 1970. In order to match the unemployment rate of graduates across the inventors' subjects, we had to drop a few inventors whose subjects could not be matched to a database for academic subjects. We also dropped some inventors who were born after 1970, because they have not had much time to obtain higher degrees. After this process, our final sample is 2,308, among which bachelor's degree holders account for 47%, master's degree holders for 44%, and PhD holders for 9% (see Table A1).

To measure the patent output performance and the knowledge sources involved in the related inventive activities, we use two patent citation datasets. One is prior patent documents cited by inventors (not by patent examiners) in their patent documents. The other is non-patent literature cited by them in the documents. These two datasets are all collected by a text-mining procedure from text databases of patent documents. We obtain these noteworthy data from Alife-Lab[9]. Unfortunately, since the text database is only available from patents that were disclosed after around 1991, we have to limit the patent outputs collected to those years since 1992. Further, we place an upper bound on the year of application to 2007 in order to solve the truncation problem involved with the use of forward citations; this procedure means we can use a five-year citing period for all patent applications in counting the frequencies of forward citations. That is, our time interval for aggregating inventors' overall patent outputs for the following econometric analysis is the period from 1992 to 2007, which forms a common window for all inventors under our study. Thus, most of the focal inventors face a common external environment in terms of market demand and technological opportunities[10]. Finally,

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[7] The IIP patent database is provided by the Institute of Intellectual Property (IIP). This database includes bibliographic information on patents applied for at the Japan Patent Office. The database was first described by Goto and Motohashi (2007) and has been updated almost yearly by the IIP. The version we use in the study includes patent applications up to 2014.
[8] We use the 2002 edition of the database provided by Nippon Telegraph and Telephone Corporation (NTT).
[9] This database is available at: www.alife-lab.co.jp/patdb/construction.html.
[10] A large majority (around 80%) of the inventors entered the labor market before the window period. Even if we use a

since the length of experience varies according to the cohort year, we control for cohort year effects by cohort dummies.

We obtain data on the unemployment rate of new graduate students from the School Basic Survey (SBS), which provides official statistics compiled by the ministry of education, culture, sports, science and technology. The survey gathers information annually on new graduate students from all universities in Japan, including the number of students who obtain jobs by their graduation date and the overall number of graduates[11]. The SBS defines unemployed college graduates as those who are neither employed nor self-employed and do not go to graduate school when they graduate from college. Using the survey results, we calculate the unemployment rate of college students in a given year and in the relevant academic subject field for each focal inventor. The denominator is all graduates minus those students who had jobs before graduation.

4. Empirical strategy

4.1 Basic specification

To examine the effect of higher education on patent performance, we estimate the following regression model:

$$PAT_i \ \ or \ \ Knowlege \ \ source_i = \alpha_0 + \alpha_1 Education \ \ attainments_i + \delta' Z_i + \varepsilon_i \qquad (1)$$

We regress patent output and knowledge source indicators of inventor *i* on our education variable and other control variables. To measure inventive outputs, we employ three indicators: forward citation weighted patent counts, the number of patent applications, and their generality. The number of forward citations received is a standard inventive quality indicator for inventive outputs (Hall, Jaffe and Trajtenberg 2005; Haroff, Scherer and Vopel 1999). To cope with a truncation problem in that more recent patents are systematically less cited, because the number of potential patents that may cite prior patents decreases due to the fact that they have not yet been applied for or published, we count citations within five years from the application. In addition, we introduce cohort dummies for inventors, as explained later. We calculate the logarithm of the total number of patent applications made between 1992 and 2007, weighted by the number of forward citations to capture inventive productivity. This provides a measure of each inventor's life-cycle productivity that synthesizes both the quality and quantity of inventive performance. In contrast, the logarithm of the number of patent applications we use reflects inventive performance in term of quantity[12].

subsample that excludes those inventors who entered the market after 1992, the basic results of our econometric analysis do not change (details available on request).

[11] The response rate of the survey is 100%. These data cover all college graduates in Japan.

[12] Using a fixed window for all inventors may result in underestimating these two performance measures for those inventors with graduate degrees, because they tend to work longer as inventors. In fact, the average length of the inventive career (the duration from the first year of invention to the last observed year of invention) for our sample inventors is 17.7 years for inventors with bachelor's degrees, 18.1 years for those with master's degrees, and 18.3 years

The generality variable we use is the variable obtained by squaring the share of forward citations made by patents across diversified technological areas in the total number of forward citations, then summing the resulting numbers (i.e., obtaining the Herfindahl index) and finally subtracting this sum from one, first introduced by Trajtenberg, Jaffe and Henderson (1997). We use the International Patent Classification (IPC) subclass classification to capture technological areas. This variable becomes low if the citations for the patent come from narrow technological areas. A higher generality score shows that a patent had a broader impact on subsequent inventive activities.

We define the following three variables to capture the scope of knowledge source indicators: the ratio of patents citing non-patent literature, the originality, and the self-citation rate. We first calculate the ratio of the number of patents citing non-patent literature to the number of patents. A significant number of inventors cite non-patent literature in their patent documents to clarify their inventions. This literature almost entirely comprises scientific journals (Narin, Hamilton and Olivastro 1997; Meyer 2000; Tamada et al. 2006). If highly educated inventors have more capability to absorb scientific knowledge for their inventive activities, they will cite more scientific literature in their patents than others. One of the important roles of higher education is to develop the capability of the students to understand scientific advances, and the cutting edge of such knowledge is generally embodied in the scientific literature. We argue that non-patent literature cited in a patent is one appropriate indicator to measure the outcome of higher education attainments[13].

The originality is calculated by the same procedure as for the generality indicator, but using backward citations. This index is low if a patent mostly cites patent literature in the same technological area and is high in cases where a patent cites prior patent literature across many technological areas. This variable is often used to measure the extent of recombination of knowledge across different technology domains. If highly educated inventors obtain knowledge from broader technological areas, educational attainment will be positively associated with this variable.

We use the external citations per patent to capture utilization by the focal inventor of the relevant knowledge held by external inventors during the inventive process. Allen (1984) emphasized that researchers often gain information by communicating with external researchers. This variable captures these absorptions of external knowledge. We calculate it as the number of citations made to patents of other companies relative to all citations. Thus, if inventors cite more external patents in their patents, this indicator becomes high and vice versa.

We use two education attainment variables in equation (1). One is to count formal education years above college for each degree; a master's course is two years and a PhD course is five years. The baseline is a bachelor's degree. We further use a master's degree or higher dummy, which has the value one if the inventor attends master's or PhD programs, otherwise zero. This variable captures the

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for those with PhDs, if we do not impose the window (1992 to 2007). As is shown in Table A1, these values decline to 13.7 years, 13.5, years, and 12.7 years respectively once we impose the window. However, the effects are not so large, although a bias from this source works against us finding the positive effects of graduate education on inventive performance.

[13] However, since this measure varies by technological area, we will control for major technology areas.

average effect of advanced degrees.

We use the following covariates to control for spurious correlations between inventive performance and level of education. First, we use cohort dummies based on the first year of employment, to control for experience effects on inventive performance as well as truncation effects of forward citations. This also controls for variations in general economic conditions for inventive activities across cohorts of inventors. Further, we use a female dummy that is set to one if an inventor is female, otherwise zero. Finally, we also use six major technological area dummies, based on the focal patents in the survey in the estimations, to control for the effects of the variations of technological opportunities on incentives for higher education, as well as on the propensity to cite scientific literature. The importance of scientific knowledge as a source of invention is different across technological areas; for example, scientific journals are more important in life sciences than in mechanical areas, and the probability of an inventor acquiring graduate degrees is also higher in the former area.

4.2 Identification

Since students with high innate ability are more likely to gain from higher education, they are more likely to pursue graduate education. If this is the case, the positive association between education and inventive productivity may not come from education, but from ability. This endogenous choice problem will distort the OLS estimator for equation (1). To obtain a consistent estimator, the instrumental variable approach is appropriate. As we have discussed above, we use the unemployment rate of college graduates in academic subject *j* in year *t* as an instrument, as shown in the following first stage equation:

$$Education\ \ attainments_i = \gamma_0 + \gamma_1 Unemployment\ \ rate\ \ of\ \ the\ \ college\ \ graduates_{jt} \\ +\delta' Z_i + \epsilon_{ijt} \qquad (2)$$

We use 33 academic subjects as j[14], belonging to four major academic subjects (engineering, natural science, health science and agriculture) and others[15]. The students' decision year as *t* is given by the year when the focal inventor is 21 years old. We assume that college students decide to go to graduate school or enter the labor market at the age of 21 years, when typical college students have one year before their college graduations. In other words, we assume that the students forecast the next year's labor market based on the current market situation. This seem a very reasonable assumption in Japan, because the majority of students enter the university at 18 years of age and graduate when they are 22 years old[16]. Further, since entrance examinations for graduate schools take place in the first half of the

[14] The list of subjects and the sample are presented in Table A2; 98.8% of inventors are from four major academic subjects in the sample.

[15] The unemployment rate for each academic subject is an aggregated rate for all universities (the SBS does not provide data at university level). This is suitable as an instrument that is supposed to measure overall labor market conditions.

[16] For example, more than 94% students who enrolled at universities in 1980 (the middle generation of our sample) graduated high school in 1980 or 1979, and 86% of them graduated four years later, according to the SBS. That is,

graduation year, they need to choose before the last year of graduation. Thus, our assumption seems reasonable under the Japanese education system.

The instrument for education attainment must satisfy the two conditions that it is correlated with education, while being uncorrelated with the error terms of the second-stage equation for inventive performance and knowledge combination. Intuitively, the labor market conditions of an inventor in the decision year affect the student's choice on whether to enter the labor market or to go to a graduate school; and previous studies empirically confirm this relationship (Bedard and Herman 2006; Johnson 2013; Kondo 2007; Shu et al. 2012). In addition, we have designed the dataset and its specification so that we can assume that the labor market situation that students encountered at 21 years of age affects future inventive activities only through the students' education choice (exclusion restriction). First, it is important to note that the unemployment rates used as instruments are for college graduates who are one year older than those in our sample; since the Japanese education system does not have any grade-skipping programs, the instrument is not affected by our sample inventors' behavior.

One potential threat to this assumption is that the unemployment rate of college graduates from a given academic subject may be correlated with the students' ability in studying this subject or with future technological opportunities generated from scientific advances in that academic area. For an example, an academic subject experiencing rapid scientific progress may attract capable students or may provide education that would enable the exploitation of greater technological opportunities in the future. While college students are more likely to pursue graduate degrees in such academic subjects, unemployment may also be high due to the lag between scientific advances and industrial investment. In this case, a high unemployment rate may be correlated with high future inventive activities through inventor ability or future technological opportunities. To control for such correlations between labor market conditions and inventor ability across academic subjects, we normalized the unemployment variable using the average μ_j and standard deviation σ_j for unemployment rate in each subject j as follows:

$$Normilized\ unemployment\ rate\ of\ the\ graduates_{jt} = \frac{Unemployment\ rate\ of\ the\ graduates_{jt} - \mu_j}{\sigma_j} \quad (3)$$

The instrument for education for each academic subject thus has a standardized variation across years after controlling for the average level of unemployment rate of each academic field. In addition to normalization, we introduce a trend for each academic subject and also substitute the instruments based on academic subjects by those based on regional variations in our robustness analysis (section 5.3).

almost all high school students go to college immediately after graduation, and most of them graduate college in four years.

The second potential source of correlations between the labor market situation that students encounter before graduation and future inventive activities is that companies might hire graduates of higher ability in a recession, or students with higher ability may be more able to find new inventor jobs under the bad economy, if hiring is limited. If the inventors who graduated during the recession were positively selected above the others, they would be more productive even if they did not attend graduate school; this will bring an upward bias in the IV estimation. On the other hand, if hiring practice for researchers is stable across business cycles, or if there exists significant ex-post mobility of workers across jobs, the number and the ability of the inventors who have college degrees could be independent on the labor market situation at their graduation. Focusing on this issue, Shu et al. (2012) use data on MIT students to show that the unemployment rate at graduation does not affect whether a graduate ultimately becomes an inventor or not; and this rate affects future inventive outputs only through human capital accumulation.

To assess this possibility in Japan, we regressed the number of inventors aggregated for each cohort of college graduates on the unemployment rate in the year preceding graduation. The estimations additionally include the time trend and its square to control for the variation of population size in each cohort. We also include academic field dummies to control for inherent differences in the numbers of inventors across fields. The results are presented in Table A3. We do not find any significant correlation between the two variables[17]. This also verifies that recession in the year preceding graduation does not affect students' long-run probability of ultimately becoming an inventor in Japan, consistent with the results of Shu et al. (2012). Furthermore, to assess the average quality of inventors with only a bachelor's degree across economic conditions in Japan[18], we estimated a reduced form regression for the invention performance of inventors with bachelor's degrees in the sample. If college graduates with higher capability tend to become inventors during recessions, the unemployment rate of college students should be positively associated with the absorption of broader knowledge sources and patent productivity. We do not find such correlations, as will be reported in Table 9 in section 5.3.

Finally, it is important to note that the estimator of our IV method is best interpreted as the local average treatment effect (LATE) rather than the average treatment effect (ATE), as suggested by Imbens and Angrist (1994), because the impact of the unemployment rate of college graduates on attainment of advanced education is likely to be heterogeneous across them. That is, our estimator for graduate education presents the average effect for the compliers who reacted to the labor market condition, and otherwise, they had chosen to enter the labor market.

Tables 1 and 2 show the summary statistics and the correlation matrix between major variables, respectively.

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[17] We use all respondents of the RIETI inventor survey, rather than the estimation sample, to count the number of inventors in each year and field.

[18] This concern is important in Japan too, since existing studies find that recession has long-term effects on the careers of such graduates in Japan (Kondo 2007; Genda, Kondo and Ohta 2010).

5. Results

5.1 Inventive performance

Table 3 reports the results of OLS and IV estimations for inventive outputs across educational attainments, controlling for the cohort dummies (the employment year dummies) and six major technological area dummies. We use two education level indicators (one for graduate education years and another for master's degree or higher), and three dependent variables (the number of patents weighted by the number of forward citations, the number of patent applications, and the generality indicator) to capture the potential impacts of variations in education attainment on inventive performance. In the OLS estimation, the two education variables are all strongly significant and positive for these three dependent variables in columns (1), (3), (5), (7), (9), and (11).

As we explained above, these estimated coefficients will be biased by the inventors' own choices with respect to their level of education, although we can still use these results as benchmarks for assessing the selection bias in the OLS regression. Our instrument for education attainment will overcome the endogenous selection problem of education. Table 4 shows the results of the first stage of the instrumental variable estimation. The dependent variables are the two education indicators. The normalized unemployment rate of college graduates is positively correlated with higher education attainment in columns (1) and (2), indicating that when students perceive that many senior students cannot find jobs by their graduation, they tend to choose graduate education programs. These results strongly support our prediction that college graduates avoid entering the job market during a recession. One major concern in IV methods is a weak instrument problem. In order to confirm whether the weak instrument problem is serious or not, we also show the F statistics testing for weak instruments. The F statistics are 40.9 for education year and 33.2 for master's degree or higher dummy, showing that the weak instrument problem is not serious in the estimations. Overall, we do not have to be concerned about weak instruments.

The results for the second stages of the scope of knowledge sources are shown in columns (2), (4), (6), (8), (10), and (12) of Table 3. The first stages of the estimation are equivalent to the results of Table 4. The coefficients for the education year and master's degree or higher dummy are all positive and strongly significant for forward citation weighted patent counts and the number of patent applications in columns (2), (4), (6), and (8). This indicates that highly educated inventors have higher patent productivity in terms of both simple patent counts and quality-adjusted patent counts, even after controlling for endogeneity issues. Further, education variables are also significantly positive for generality in columns (10) and (12), indicating that inventors with higher education degrees affect broader technological domains through knowledge spillover than do inventors with lower educational attainments.

Interestingly, the comparison between OLS and IV estimations in Table 3 shows that the coefficients for education year and master's degree and higher dummies in the IV estimations are slightly higher than those in the OLS estimations. This is similar to a finding in a study regarding the choice of going to college in Finland reported by Toivanen and Väänänen (2016), who focused on the differences between inventors with high school or less education and those with university degrees, although the negative selection in our estimations is much smaller than in their results and perhaps more plausible[19]. They interpret a negative selection bias in OLS estimations as indicating that "those who have a high innate propensity for invention have a lower propensity to study at a technical university." Our explanation of such negative selection for graduate education by corporate inventors with ability is as follows. We ordinarily expect positive selection (students with higher innate capability will choose graduate education), since such students can gain more from graduate education. However, this scenario may only hold for undergraduate students who wish to pursue academic careers. Our sample does not cover these students. The best undergraduate students who intend to pursue industrial research careers may wish to find jobs in private firms immediately after college graduation. Japanese companies mainly recruited college graduates even as corporate researchers until 1990s. Large private companies in Japan often provide more excellent environments for researchers in terms of budgets and apparatus than do universities. They also often encourage excellent young corporate researchers to obtain PhDs based on work done in the firms[20]. In this situation, students with better capability may have found good industrial research jobs upon college graduation, while less capable students may have tended to choose to go to graduate school, bringing a negative selection bias in the OLS regression for corporate researchers.

Interestingly, students who chose to go to graduate school during recessions are likely to have somewhat weaker intrinsic motivation for science than others. Table A4 shows the results using the strength of their scientific motivation for their focal patents as the dependent variable in the IV estimation. Since the RIETI Inventor Survey provides information about their motives for initiating research projects, in the form of a five-point Likert scale for *Scientific motivation* behind the focal patent, we constructed a dummy variable such that if inventor chose "very highly motivated" or "highly motivated," the variable is set to one, otherwise to zero. The education variables are positive and highly significant for this dummy variable in the OLS estimations. In contrast, these variables are no longer significant in the IV estimations. This shows that the inventors who went to graduate school due to recession have lower scientific motivation than the others. These results provide support for the findings of Roach and Sauermann (2010) that PhD holders with a weak taste for science tend to choose careers in industry. This suggests that students with high innate ability, but a lower taste for science, went to graduate school during the recession.

5.2 Scope of knowledge sources and the first-stage estimations

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[19] Toivanen and Väänänen (2016) find an increase of between two and three times for the university degree dummy in IV estimations compared with the results of OLS estimations.
[20] Onishi and Nagaoka (2012) find that PhD holders who obtained their degree only by dissertation have similar patent productivity to formal PhDs over the inventors' life-cycle perspective in Japan.

Next, we examine the effect of education attainment on the scope of knowledge sources exploited in inventive activities. Table 5 reports the results for three knowledge exploitation indicators (the ratio of patents citing non-patent literature, the originality indicator, and the non-self-citation rate), using both OLS and IV estimations. The two education variables are all positive and highly significant for patents citing non-patent literature ratio in columns (1)–(4). This shows that inventors with higher degrees exploit the scientific literature significantly more for its inventive qualities, thanks in causal terms to higher education. Further, the education variables are also significantly positive for originality (more diverse combinations of knowledge embodied in patent literature) in columns (5)–(8), showing that highly educated inventors exploit knowledge from broader technological domains than do less educated ones. In contrast, while the non-self-citation rate is positively associated with all education attainments in OLS estimation, this variable become insignificant in IV estimation. We do not find that inventors with higher degrees adopt outside knowledge more than inside knowledge. Taken together, inventors with more than bachelor's degrees are more likely to combine scientific and technological knowledge from broader sources in their inventive processes, even after controlling for the selection bias.

We also find that the coefficients for education in IV are much higher than those in OLS estimations, showing that over the entire business cycle, inventors attaining advanced education due to weak labor market conditions exploit broader external knowledge (more scientific knowledge and broader technological knowledge) in their inventive processes than do average inventors who go to graduate school or PhD programs.

5.3 Robustness check

To assess the robustness of our findings, we conducted a number of robustness checks. One looks at the effects of variations of trends across academic subjects. The rate of unemployment for college students could be affected by long-term technological or industry trends, rather than temporary business shocks. Technologically stagnant academic fields or academic sectors catering for declining industries attract less capable students, while college graduates from such sectors tend to have high unemployment. Thus, variations in such trends can drive both the variations in unemployment rate of college graduates and the inventive performance of inventors across academic subjects, irrespective of the level of graduate education. This results in spurious correlations between IVs and the error terms in equation (1). To cope with this concern, we added time trends for each subject to equation (1) with IVs in Table 6. The results are very similar to those in Tables 3 and 5. Interestingly, the non-self-citation rate turns to be significant and positive in columns (11) and (12) in Table 6.

Further, we also use the active job opening ratio at the *regional level* as an instrument. The job opening ratios in the regions are obtained from the report of the Employment Service Agency[21]. Our data are obtained from 47 regions in Japan. We normalize these by subtracting the average job

[21] Our sample becomes small since we do not find old data on job opening ratios at regional level.

opening ratio in each region from the variable and dividing the values by their standard deviation. This process controls for time-invariant heterogeneity across regions. In the first stages, the local job opening ratios are all significant and negative for education variables, as reported in Table 7. A recession at the local level affects undergraduates' educational choices. Further, F statistics against weak instruments are high in two estimations (education year: 27.4, and master's degree and higher: 32.6). Table 8 shows the results in the second stages. The results remain similar to those in Tables 3 and 5. These results confirm that a recession affects graduates' choices for educational attainment, and their education level also affects their future invention productivity and their knowledge sources.

Finally, the unemployment rate of college graduates may be directly associated with patent outputs, because only students with high innate ability can obtain jobs as inventors during a recession, and this may create an upward bias for the coefficients of education variables in IV estimations. To examine whether superior students selectively become inventors in a bad economy, we estimate a reduced form of equations (1) and (2), using only the sample of inventors with bachelor's degrees. If better undergraduates become inventors during a recession, the unemployment rate of college graduates will become significant and positive in such estimations. As shown in Table 9, the coefficients for the unemployment rate are small and insignificant. This shows that unemployment rate is not directly associated with patent outputs and knowledge utilization of these inventors with bachelor's degrees as final degrees. That is, the average quality of college graduates in recessions is not different to that in other periods.

6. Conclusion

This paper investigated the effects of graduate education on the absorption of a diverse range of knowledge sources and on inventive performance, using inventor life-cycle data. To control for the endogeneity of educational attainments, we use the unemployment rate of college graduates in the year prior to that of graduation in their academic subjects as an instrument. Our estimation results show that a higher unemployment rate at that time and in a given academic field significantly increases the probability of inventors choosing to graduate school, including PhD programs. In particular, university students tend to go to graduate education during a recession. We find that the inventive productivities of inventors with higher graduate education induced by this instrument are higher than those with less education, in terms of both simple and quality-adjusted patent counts; and highly educated inventors also tend to affect sequential inventions in broader technological areas. We further find that these inventors cite a wider range of scientific literature and more diverse fields of prior patents. These findings are robust to the replacement of instruments based on variations among academic fields by those based on regional variations.

These results suggest that a policy encouraging students to go to a graduate school in science and engineering seems to play a significant role as an innovation policy. It genuinely enhances invention performance; it also enhances the absorptive capability of a firm for handling scientific knowledge and broader technical information. In fact, the positive association between higher educational attainment and higher productivity and knowledge exploitation understates the genuine contribution of advanced degrees, given the negative selection effects. This evidence supports the recent trend of expanding higher education programs in many countries. This trend will accelerate economic growth in the long run.

Interestingly, our results show that the recession gives students an opportunity to accumulate new knowledge. Our results depend on the decisions of students to put off entering the labor market during times of recession, in order to wait for better labor market conditions. The results indicate that inventors who chose graduate school even for such reasons become high performers on average in the inventive process. Given such an educational effect on inventive outcomes and negative selection, a recession contributes to future innovative activities through more choices by capable students for higher education. While Shu et al. (2012) have empirically shown the possibility of this recession effect, using unique data, our results improve our understanding of the process in terms of both causality and detailed knowledge production mechanisms, using an economy-wide sample. The findings of our study indicate that graduate education will enhance inventive productivity more effectively than will internal company training systems such as on-the-job training, partly because highly educated inventors have higher absorptive ability to obtain broader knowledge. This also offers new evidence to guide firm innovation strategy. Our results suggest that hiring researchers with advanced graduate degrees leads to strengthening the corporate ability to absorb broader scientific and technical knowledge. This will contribute to enhancing absorptive capacity to maintain a competitive advantage at firm level.

References

Allen, J.T. (1984) *Managing the Flow of Technology*, The MIT Press: Cambridge.

Bedard, K. and D.A. Herman (2008) "Who Goes to Graduate/Professional school? The Importance of Economic Fluctuations, Undergraduate Field, and Ability," *Economics of Education Review* 27(5):197-210.

Cockburn, I. and R. Henderson (1998) "Absorptive Capacity, Coauthoring Behavior, and the Organization of Research in Drug Discovery," *Journal of Industrial Economics* 46(2): 157-82.

Cohen, W.M., A. Goto, A. Nagata, R. Nelson and J.P. Walsh (2002) "R&D Spillovers, Patents and the Incentives to Innovate in Japan and the United States," *Research Policy* 31(8-9): 1349-1367.

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

Genda, Y., A. Kondo and S. Ohta (2010) "Long-term Effects of a Recession at Labor Market Entry in Japan and the United States," *Journal of Human Resources* 45(1):157-196.

Giuri, P. and M. Mariani (2013) "When Distance Disappears: Inventors, Education, and the Locus of Knowledge Spillovers," *Review of Economics and Statistics* 95(2): 449-463.

Goto, A. and K. Motohashi (2007) "Construction of a Japanese Patent Database and a First Look at Japanese Patenting Activities," *Research Policy* 36(9): 1431-1442.

Gruber, M., D. Harhoff and K. Hoisl (2013) "Knowledge Recombination across Technological Boundaries: Scientists versus Engineers," *Management Science* 59(4): 837-851.

Hall, B.H., A.B. Jaffe and M. Tratjenberg (2005) "Market Value and Patent Citations," *RAND Journal of Economics* 36: 16-38.

Harhoff, D., F. Narin, F.M. Scherer and K. Vopel (1999) "Citation Frequency and the Value of Patented Inventions," *Review of Economics and Statistics* 81: 511-515.

Heckman, J.J., L.J. Lochner and P.E. Todd (2006) "Earnings Functions, Rate of Returns and Treatment Effects: The Mincer Equation and Beyond," E.A. Hanushek and F. Welch eds. *Handbook of the Economics of Education*, Volume 1, North Holland, pp.307-458.

Hoisl, K. (2007) "Tracing Mobile Inventors: The Causality between Inventor Mobility and Inventor Productivity," *Research Policy* 36: 619-636.

Imbens, G. and J. Angrist (1994) "Identification and Estimation of Local Average Treatment Effects," *Econometrica* 62(2): 467-75.

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.

Johnson, M.T. (2013) "The Impact of Business Cycle Fluctuations on Graduate School Enrollment," *Economics of Education Review* 34: 122-134.

Kim, J., S.J. Lee and G. Marschke (2004) "Research Scientist Productivity and Firm Size: Evidence from Panel Data on Inventors," Working Paper, SUNY Albany.

Kondo, A. (2007) "Does the First Job Really Matter? State Dependency in Employment Status in Japan," *Journal of Japanese and International Economics* 21: 379-402.

March, J.G. (1991) “Exploration and Exploitation in Organizational Learning,” *Organizational Science* 2(1): 71-87.

Mariani, M. and M. Romannelli, M. (2007), “Stacking’ and ‘Picking’ Inventions: The Patenting Behavior of European Inventors,” *Research Policy* 36: 1128–1142.

Meyer, M. (2000) “Does Science Push Technology? Patents Citing Scientific Literature,” *Research Policy* 29(3): 409-434.

Nagaoka, S. and N. Tsukada (2007) “Innovation Process in Japan: Findings From the RIETI Inventors Survey,” RIETI Discussion Paper 07-J-046.

Narin, F., K.S. Hamilton and D. Olivastro (1997) “The Increasing Linkage Between U.S. Technology and Public Science,” *Research Policy* 26(3): 317-330.

Neumark, D. (2002) “Youth Labor Markets in the United States: Shopping Around vs. Staying Put,” *Review of Economics and Statistics* 84(3): 462-482.

OECD (2016) *OECD Science, Technology and Innovation Outlook 2016*, OECD Publishing: Paris.

Onishi, K. and S. Nagaoka (2012) “Life-cycle Productivity of Industrial Inventors: Education and Other Determinants,” RIETI Discussion Paper 12-E-059.

Price, D.J. de Solla (1965) “Is Technology Independent of Science?” *Technology and Culture* 6(4): 553-568.

Romer, P.M. (1990) “Endogenous Technological Change,” *Journal of Political Economy* 98(5): 71-102.

Roach, M. and H. Sauermann (2010) “A Taste for Science? PhD Scientists’ Academic Orientation and Self-selection into Research Careers in Industry,” *Research Policy* 39(3): 422-434.

Schettino, F., A. Sterlacchini and F. Venturini (2008) “Inventive Productivity and Patent Quality: Evidence from Italian Inventors,” MPRA Paper 7765.

Schumpeter, J.A. (1977) *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest and the Business Cycle*, translated from the German by Y. Shionoya, S. Touhata and I. Nakayama, Iwanami: Tokyo.

Shu, P., D. Acemoglu, S. Stern, R. Romano and L. Snover (2012) “The Long-term Impact of Business Cycles on Innovation: Evidence from the Massachusetts Institute of Technology,” MIT working paper.

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

Tamada, S., S. Naito, K. Genba, F. Kodama, J. Suzuki and A. Goto (2006) “Science Linkage and UIC,” in A. Goto and T. Tamada eds. *Japan’s National Innovation System: Rebuilding and Engine of Growth*, University of Tokyo Press: Tokyo.

Toivanen, O. and L. Väänänen (2012) “Return to Inventors,” *Review of Economics and Statistics* 94: 1173-1190.

Toivanen, O. and L. Väänänen (2016) “Education and Invention,” *Review of Economics and Statistics* 98(2): 382-396.

Trajtenberg, M., R. Henderson and A. Jaffe (1997) “University Versus Corporate Patents: A Window

on the Basicness of Invention," *Economics of Innovation and New Technology* 5(1): 19-50.
Weitzman L.M. (1998) "Recombinant Growth," *Quarterly Journal of Economics* 133(2): 33-360.

Table 1 Summary statistics

	Mean	Std. Dev.	Min	Max
Forward citation weighted patent counts	64.7	96.0	1	2006
The number of patent applications	39.3	46.0	1	606
Generality	0.1	0.1	0	0.4
Patents citing non-patent literature ratio	0.1	0.2	0	1
Originality	0.1	0.1	0	0.5
Non-self-citation rate	1.2	1.9	0	37.6
Education years	1.3	1.5	0	5
Master's degree or higher	0.5	0.5	0	1
Female	0.02	0.1	0	1
Normalized unemployment rate of college graduates	-0.5	0.5	-1.8	2.5
Normalized local job open ratios	0.4	1.0	-1.5	3.0
Science motivation	0.6	0.5	0	1

Table 2 The correlation matrix

	a.	b.	c.	d.	e.	f.	g.	h.	i.	j.	k.	l.
a. Forward citation weighted patent counts	1.00											
b. The number of patent applications	0.83	1.00										
c. Generality	0.46	0.41	1.00									
d. Patents citing non-patent literature ratio	0.14	0.05	0.17	1.00								
e. Originality	0.44	0.33	0.56	0.33	1.00							
f. Non-self-citation rate	0.40	0.16	0.26	0.33	0.60	1.00						
g. Education years	0.09	0.07	0.16	0.44	0.21	0.16	1.00					
h. Master's degree or higher	0.12	0.08	0.16	0.37	0.23	0.19	0.85	1.00				
i. Female	-0.01	-0.02	0.02	0.05	0.02	0.04	-0.01	-0.02	1.00			
j. Normalized unemployment rate of college graduates	0.08	0.08	0.03	0.08	0.06	0.03	0.09	0.04	-0.07	1.00		
k. Normalized local job opening ratios	-0.06	-0.09	-0.04	-0.01	-0.04	-0.01	-0.01	0.01	0.09	-0.47	1.00	
l. Science motivation	0.05	0.05	0.11	0.14	0.10	0.05	0.13	0.09	-0.01	0.03	-0.03	1.0

Table 3 The OLS and IV estimations for the inventive performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Forward citation weighted patent counts				The number of patent applications				Generality			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Education years	1.320**	1.571**			1.031**	1.339***			0.006***	0.006**		
	(0.387)	(0.616)			(0.331)	(0.468)			(0.001)	(0.003)		
Master's degree or higher			4.050**	5.496**			3.135**	4.683***			0.016***	0.022**
			(1.117)	(2.335)			(0.952)	(1.709)			(0.004)	(0.010)
Female	0.224	0.270	0.442	0.608	-0.184	-0.128	-0.018	0.160	0.011	0.011*	0.011*	0.012**
	(2.011)	(1.739)	(1.908)	(1.544)	(1.467)	(1.279)	(1.399)	(1.164)	(0.006)	(0.006)	(0.005)	(0.006)
Constant	13.467***	5.266***	13.026***	5.129**	11.063***	4.505***	10.740***	4.388***	0.058***	0.014**	0.059***	0.013**
	(0.731)	(1.982)	(0.806)	(2.012)	(0.622)	(1.587)	(0.684)	(1.605)	(0.002)	(0.006)	(0.003)	(0.006)
Cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technological area dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.062		0.063		0.058		0.059		0.066		0.058	
F statistics		40.94		33.18		40.94		33.18		40.94		33.18
Observations	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308

Standard errors are clustered by 6 technological areas in parentheses. First stages of each estimation are in Table 4.

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

Table 4 The result of first-stage estimations

	(1)	(2)
	Education years	MD or higher
Normalized unemployment rate of college graduates	0.507*** (0.079)	0.145*** (0.025)
Female	-0.137 (0.124)	-0.101 (0.095)
Constant	0.829** (0.326)	0.262** (0.119)
Cohort dummies	Yes	Yes
Technological area dummies	Yes	Yes
F statistics	40.94	33.18
Observations	2308	2308

Standard errors are clustered by 6 technological areas in parentheses.

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

Table 5 The OLS and IV estimations for the scope of knowledge sources

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Patents citing non-patent literature ratio				Originality				Non-self-citation rate			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Education years	0.057***	0.103***			0.009***	0.017***			0.146**	0.253		
	(0.005)	(0.032)			(0.002)	(0.004)			(0.048)	(0.154)		
Master's degree or higher			0.134***	0.362***			0.028***	0.060***			0.595**	0.884
			(0.018)	(0.131)			(0.007)	(0.018)			(0.174)	(0.645)
Female	0.079*	0.087***	0.083**	0.109***	0.005	0.007	0.007	0.010	0.347	0.367	0.389	0.422
	(0.031)	(0.031)	(0.026)	(0.036)	(0.012)	(0.011)	(0.011)	(0.009)	(0.537)	(0.456)	(0.504)	(0.396)
Constant	0.145***	0.280**	0.156***	0.271**	0.076***	0.022	0.072***	0.021	1.785***	1.120***	1.629***	1.098***
	(0.008)	(0.125)	(0.013)	(0.125)	(0.004)	(0.013)	(0.005)	(0.014)	(0.109)	(0.046)	(0.133)	(0.068)
Cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technological area dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R	0.271		0.222		0.128		0.132		0.070		0.080	
F statistics		40.94		33.18		40.94		33.18		33.18		0.222
Observations	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308

Standard errors are clustered by 6 technological areas in parentheses. First stages of each estimation are in Table 4.

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

Table 6 The IV estimations with time trends across academic subjects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Forward citation weighted patent counts		The number of patent applications		Generality		Patents citing non-patent literature ratio		Originality		Non-self-citation rate	
Education years	2.812*** (0.450)		1.034** (0.328)		0.011*** (0.004)		0.115*** (0.027)		0.026*** (0.005)		0.465** (0.187)	
Master's degree or higher		3.873** (1.116)		7.138*** (1.154)		0.015*** (0.004)		0.361*** (0.100)		0.081*** (0.021)		1.455** (0.699)
Female	0.086 (1.964)	0.066 (2.165)	-0.432 (1.684)	0.503 (1.546)	0.007 (0.007)	0.007 (0.007)	0.070** (0.035)	0.103** (0.045)	0.001 (0.010)	0.008 (0.012)	0.131 (0.334)	0.262 (0.304)
Constant	4.710*** (1.272)	12.152*** (0.767)	10.240*** (0.577)	4.134*** (1.272)	0.010*** (0.002)	0.051*** (0.004)	0.267* (0.137)	0.268** (0.129)	0.013*** (0.004)	0.013** (0.006)	0.908*** (0.251)	0.909*** (0.220)
Cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technological area dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Academic subject time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F statistics	41.61	30.93	41.61	30.93	41.61	30.93	41.61	30.93	41.61	30.93	41.61	30.93
Observations	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308	2308

Standard errors are clustered by 6 technological areas in parentheses.

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

Table 7 The result of first-stage estimations using local job opening ratios as an instrument

	(1)	(2)
	Education years	MD or higher
Normalized local job opening ratios	-0.264*** (0.050)	-0.092*** (0.016)
Female	-0.163 (0.132)	-0.093 (0.095)
Constant	0.710*** (0.010)	0.273*** (0.005)
Cohort dummies	Yes	Yes
Technological area dummies	Yes	Yes
F statistics	27.39	32.58
Observations	2011	2011

Standard errors are clustered by 6 technological areas in parentheses.

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

Table 8 The IV estimations with local job opening ratios as an instrument

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Forward citation weighted patent counts		The number of patent applications		Generality		Patents citing non-patent literature ratio		Originality		Non-self-citation rate	
Education years	1.854** (0.926)		1.693** (0.811)		0.010*** (0.004)		0.106*** (0.020)		0.017*** (0.006)		0.192 (0.240)	
Master's degree or higher		5.326* (2.718)		4.865** (2.414)		0.030*** (0.010)		0.305*** (0.064)		0.048*** (0.018)		0.553 (0.679)
Female	0.221 (1.828)	0.416 (1.708)	-0.085 (1.300)	0.092 (1.217)	0.011* (0.006)	0.012** (0.006)	0.091*** (0.034)	0.102*** (0.034)	0.006 (0.012)	0.008 (0.011)	0.378 (0.556)	0.398 (0.560)
Constant	2.460*** (0.623)	2.321*** (0.709)	1.783*** (0.545)	1.656*** (0.632)	0.014*** (0.003)	0.014*** (0.003)	0.094*** (0.014)	0.086*** (0.018)	0.038*** (0.004)	0.037*** (0.005)	0.946*** (0.183)	0.932*** (0.197)
Cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technological area dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F statistics	27.39	32.58	27.39	32.58	27.39	32.58	27.39	32.58	27.39	32.58	27.39	32.58
Observations	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011

Standard errors are clustered by 6 technological areas in parentheses. First stages of each estimation are in Table 7.

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

Table 9 The OLS results for reduced form estimations with inventors with bachelor's degrees

	(1)	(2)	(3)	(4)	(5)	(6)
	Forward citation weighted patent counts	The number of patent applications	Generality	Patents citing non-patent literature ratio	Originality	Non-self-citation rate
Normalized unemployment rate of college graduates	0.059 (0.655)	0.090 (0.531)	0.000 (0.005)	0.015 (0.016)	0.003 (0.004)	-0.018 (0.127)
Female	-0.380 (3.242)	-1.013 (2.498)	0.005 (0.010)	0.077 (0.070)	0.014 (0.026)	1.048 (1.043)
Constant	16.307*** (0.302)	13.179*** (0.248)	0.071*** (0.003)	0.286*** (0.009)	0.107*** (0.002)	2.441*** (0.072)
Cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Technological area dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.06	0.06	0.02	0.13	0.11	0.05
Observations	998	998	998	998	998	998

Standard errors are clustered by 6 technological areas in parentheses. The estimation sample is limited for BA holders.

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

Table A1 Summary statistics by education

	N	Avereage Patenting terms	Forward citation weighted patent counts	The number of patent applications	Generality	Patents citing non-patent literature ratio	Originality	Non-self-citation rate
Bachelor's degree	1,093	13.70 (2.38)	51.18 (69.66)	34.64 (44.09)	0.04 (0.05)	0.07 (0.13)	0.03 (0.05)	0.79 (1.01)
Master's degree	1,016	13.49 (2.44)	75.84 (117.05)	42.67 (47.31)	0.06 (0.05)	0.19 (0.23)	0.06 (0.08)	1.55 (2.43)
PhD degree	199	12.74 (2.85)	82.02 (92.11)	47.49 (47.51)	0.08 (0.06)	0.42 (0.30)	0.08 (0.08)	1.52 (1.93)

Standard deviation is in parentheses.

Table A2 Academic subjects

Major academic subject	Academic subject	N
Engineering	Mechanical Engineering	463
	Applied Physics	77
	Applied Chemistry	399
	Metallurgical engineering	80
	Management engineering	10
	Nuclear Engineering	11
	Craftsmanship	1
	Aviation engineering	10
	Mining studies	1
	Textile engineering	23
	Vessel engineering	11
	Telecommunications Engineering	539
	Civil engineering / construction engineering	16
	Other engineering	238
Science	Physics	99
	Biology	15
	Mathematics	12
	Chemistry	130
	Other science	34
Health science	Pharmacy	21
	Dentistry	2
	Medicine	10
	Other health science	2
Agriculture	Agriculture	1
	Agrochemical chemistry	37
	Agricultural engineering	7
	Forest Industry	22
	Fisheries Science	5
	Veterinary medicine / Animal husbandry	5
Others	Other natural science	15
	Commerce / Economics	2
	Law / Political Science	4
	Other Social science	6

Table A3 The OLS results for determination of the number of sampled inventors

	The number of inventors
Normalized unemployment rate of college graduates	-0.66 (0.451)
Time trend	150.20*** (28.689)
Time trend^2	-0.04*** (0.007)
Academic field dummies	Yes
Adj.R^2	0.84
Observations	452

Robust standard errors are in parentheses. The number of inventors is that they were 21 years old in year t and in academic subject j.

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

Table A4 The results for scientific motivation in the OLS and IV estimations

	(1)	(2)	(3)	(4)
	Scientific motivation dummy			
	OLS	IV	OLS	IV
Education years	0.038*** (0.002)	0.022 (0.038)		
Master's degree or higher			0.066*** (0.011)	0.077 (0.135)
Female	-0.029 (0.114)	-0.032 (0.104)	-0.028 (0.112)	-0.027 (0.100)
Cohort dummies	Yes	Yes	Yes	Yes
Graduation year dummies	Yes	Yes	Yes	Yes
Adj.R^2	0.021		0.013	
F statistics		49.89		38.57
Observations	2283	2283	2283	2283

Standard errors are clustered by 6 technological areas in parentheses.

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