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SUSTAINABLE DEVELOPMENT OF SCIENCE: PRODUCTION OF SCIENCE VS. SCIENTISTS IN LIFE SCIENCE LABORATORIES

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Abstract

Academic institutions are responsible for scientific research, or production of scientific knowledge, and academic training, or production of scientists, but the two functions are not necessarily compatible and this can undermine the sustainability of the science system. Drawing on a sample of life science laboratories in Japan with 184 lab heads (i.e., professors) and their 1,126 PhD students, this study illustrates two conflicts that lab heads are facing and investigates how they could influence the shape of science. The result shows that offering intensive training, especially for cognitive skills, for PhD students improves students' publication productivity in the long term but decreases it in the short term. Since lab heads are not generally rewarded for students' publication after their graduation, this presents lab heads a dilemma between prioritizing their mentor role vs. principal-investigator (PI) role. This dilemma can be mitigated when lab heads keep employing ex-students as postdocs (i.e. inbreeding), collaborating with them, or gaining reputation through citations from them. However, these approaches can narrow students' research subjects and restrict their career paths, potentially compromising the diversity and sustainability of science. Hence, this presents lab heads another dilemma of exploiting students for direct returns vs. allowing students' exploration to maintain the diversity. Indeed, the result suggests that excessive constraint on students' research subjects is detrimental to their career prospect.

1. Introduction

The modern society is increasingly becoming knowledge-driven and major challenges our society faces today require solutions with scientific expertise, and accordingly, innovation and science policy literature emphasizes the role of the academic science (Dasgupta and David, 1994; Etzkowitz and Leydesdorff, 2000; Furman et al., 2002). A peculiarity of knowledge production in science is that it relies on scientists as a fundamental input, but that scientists are simultaneously an output of the science system (Bozeman et al., 2001; Hackett, 1990). Nevertheless, the aspect of scientists being an output, as opposed to an input, has insufficiently featured both scholarly and practically.

The production of scientists, or academic training, typically takes the forms of postgraduate education and postdoc experience. Academic training is a substantial investment costing junior trainees (e.g., PhD students) several years or possibly longer and senior scientists intensive supervision (Stephan, 2012). Nevertheless, the contemporary academic training practices have been criticized, for instance, for not satisfying societal needs (National Research Council, 1998a; Cyranoski et al., 2011), and yet effective solutions have been lacking. This is possibly because of the complex nature of academic training, namely that junior scientists are simultaneously the output of training and the input of scientific research. In addition, academic training might fall into a policy gap between (mass) education and scientific research, resulting in inconsistent policies and unintended consequences such as PhD overproduction. Noticeably, recent policies emphasize accountability, which is often translated into short-term and merit-based evaluation, and a relatively long-term payoff from academic training tends to be overlooked (Hackett, 1990).

In scholarly literature, there seems a similar gap between studies on knowledge production and those on higher education. Though academic career has been a popular subject (e.g., Allison and Long, 1990; Geuna, 2015; Stephan, 2012), early careers are relatively understudied. The scarcity of literature on academic training may be attributed to a limited access to the inside of academic laboratories where training takes place. A few ethnographies have attempted to open the black box of academic labs (Campbell, 2003; Delamont and Atkinson, 2001; Delamont et al., 1997 ; Salonius, 2008), but their implications are restricted to certain lab contexts. Some higher-education studies have inquired into professors' training performance (e.g., Marsh et al.,

2002) but have been mostly detached from the aspect of knowledge production.

An essential part of academic training takes the form of research projects to which students and junior scientists devote substantial time and effort. In most natural sciences and engineering, research projects are usually organized in a laboratory composed of a lab head and junior members. Although collaboration between multiple laboratories is indispensable, a laboratory is still the fundamental unit of decision-making in academic research except for "big science" projects (Carayol and Matt, 2006; Latour and Woolgar, 1979) and provides junior scientists with the base of training. In this context, lab heads have to fulfill dual roles of a principal investigator (PI) and a mentor; in other word, students are workers as well as mentees. As a PI, lab heads are supposed to maximize their research output while as a mentor having to develop future scientists. Although these two goals are compatible at the community level, they are not necessarily so at the individual level, especially with the modern short-term oriented policies where the mentor aspect is relatively neglected, and the sustainability of the science system might be undermined.

The objective of this study is to fill in the theoretical gap and to inform science policies as to sustainable production of scientific knowledge and that of scientists. In particular, this study is interested in two conflicts that lab heads are facing. In the short term, lab heads face a dilemma due to incompatible two roles of a mentor and a PI, having to decide whether to train their students as future scientists or exploit them as research workers. In the long term, lab heads have options of developing their students into their followers or into leaders in new fields, the former of which can reciprocate the lab heads directly but might compromise the dynamics and sustainability of science. Drawing on unique data of life science laboratories in Japan with 184 professors and their 1,126 PhD graduates, this study empirically illustrates these conflicts in academic training and investigates how they contribute to the shape of science.

The remainder of this paper is structured as follows. Section 2 summarizes the literature and the theoretical background. Section 3 explains the empirical setting. Section 4 presents the results and Section 5 discusses the implications and concludes.

2. Literature Review and Theoretical Background

2.1. Academic Training

While scientific knowledge production is one of the primary missions of academic institutions, education is another (Fox, 1992; Hackett, 1990). Formal teaching set aside, senior scientists are responsible for training students and other junior trainees as future scientists, or more broadly, intellectual workforce that sustains the innovation system. Obviously, developing scientists for the next generation is indispensable for the long-term progress of science.

In many disciplines, scientific research is conducted in a laboratory that consists of a lab head, who is usually a professor, and some junior members such as students and postdoctoral researchers (postdocs) under the lab head's supervision (e.g., Carayol and Matt, 2006; Latour and Woolgar, 1979; Owen-Smith, 2001). Lab heads, as PIs, are responsible for setting up research environment (e.g., funding, equipment, and recruitment) and coordinating a series of projects, while members carry out specific projects (Traweek, 1988). In addition, lab heads as mentors are supposed to train junior members, who will become independent scientists by acquiring research skills and possibly lab heads in the next generation (Delamont and Atkinson, 2001; Delamont et al., 1997; Knorr-Cetina, 1999; Owen-Smith, 2001). For lab heads, fulfilling these dual roles can be a challenge due to potentially incompatible goals of research and training.

The incompatibility may be attributed to different expertise needed for research and education in general. Anecdotes suggest that excellent PIs are not always excellent mentors. Sociology of education and higher-education literature has long debated this issue, and not a few studies have reported conflicts between research and teaching skills although a clear consensus is yet to be formed (e.g., Fox, 1992; Hattie and Marsh, 1996; Marsh and Hattie, 2002).

A more serious conflict seems attributable to the incentive system employed in the modern science (Hackett, 1990). Hackett (1990) refers to "producing research results versus educating students" as one of value tensions in science, arguing that the roles of a PI and a mentor are not compatible anymore. Apparently, lab heads' effort for training is made at the cost of that for research. Under the publish-or-perish culture, lab heads should be tempted to reduce efforts for the former to secure those for the latter (Dasgupta and David, 1994; Laband and Tollison, 2003). Although trained junior members may help lab heads' research, it might take too long a time for lab heads to patiently wait for. As is common to most forms of education, the payoff of training

spills over and lab heads may not be able to collect all the training cost. As later discussed, these issues might be addressed in the traditional science system, but the modern system tends to emphasize shorter-term merit and fail to adequately appreciate payoff from academic training. Thus, even excellent PIs (or perhaps exactly because of their excellence) end up producing mediocre scientists whose skills satisfy neither scientific nor societal needs. Indeed, literature often criticizes a mismatch between demands and supplies of PhDs and questions the effectiveness of postgraduate education systems (Cyranoski et al., 2011; Stephan, 2012).

Despite its critical role in science, academic training has been relatively understudied both theoretically and empirically. Theoretically, this might be because the subject is on the border between studies on higher education (e.g., higher education, sociology of education) and those on scientific knowledge production (e.g., economics of science, scientometrics). Academic career development has been a popular topic in sociology of science and science policy literature, but it is often restricted to postdoctoral careers (e.g., Allison and Long, 1990). Some studies are concerned with PhDs' placement (Burris, 2004; Long et al., 1979), but training itself is not of their primary interest. It is more recently that a holistic view of science system incorporating both knowledge production and academic training has been discussed (Bozeman and Corley, 2004; Bozeman et al., 2001; Laudel and Glaser, 2008).

Empirical ground has been also weak perhaps due to a poor access to the inside of academic laboratories. Some ethnographies attempt to address this issue, investigating in great detail how academic lab activities operate in certain laboratories (Campbell, 2003; Delamont and Atkinson, 2001; Delamont et al., 1997 ; Salonius, 2008), yet general picture is lacking. The recent use of curriculum vitae (CV) data and large surveys have expedited career research (Canibano and Bozeman, 2009; Geuna, 2015; Stephan, 2012), but they rarely identify detailed information such as mentor-mentee relationships. Some scientometric studies have measured such relationships but their focus tends to be attached to knowledge production rather than to training (Lariviere, 2012; Long and Mcginnis, 1985). To illustrate the details behind academic training, higher-education literature draws on surveys asking PhD students to evaluate their supervisors' performance and supervising styles (e.g., Marsh et al., 2002), but these studies overlook interaction between research and training.

The goal of this study is to fill in these gaps in literature by examining how academic training is incentivized and how it affects the shape of science, especially focusing on two forms of conflict that lab heads face, which are discussed in the following two sections.

2.2. Conflicting Roles of Mentor vs. Principal Investigator

Academic training provides a collective benefit for the scientific community in that trained scientists contribute to advancing science, or more generally to innovation system. Lab heads engaged in training may not directly gain from their own students but usually gain indirectly from someone else's students through a chain of mentor-mentee relationships (see [A] in Figure 1). Apparently, such an indirect reciprocity is prone to free riding; i.e., lab heads would be better off exploiting scientists trained by someone without training their own students. Altruistic norms may help exclude such free riders (Merton, 1973) -- scientists can monitor one another and informally punish those who are not serious about training --, but solely relying on altruism does not seem plausible especially when the science system emphasizes short-term merit (Shibayama, 2015).

The science system has provided more direct incentives for academic training. As above discussed, lab heads and their students usually tackle common research questions as a team called a laboratory. In this setting, lab heads can exploit the labor of students if they have successfully trained their students (see [B] in Figure 1). Although training may take time, postgraduate programs require several-year commitment of students, during which lab heads could collect sufficient returns from their training investment. Though depending on systems, if the wage of students is sufficiently low, lab heads may consider students as cheap labor (Cyranoski et al., 2011; Stephan, 2012). Some lab heads perceive young students as a source of serendipity and creativity though age-productivity association has been inconclusive (Stephan and Levin, 1992; Zuckerman, 1988). These explanations can justify the investment in academic training, but there might be a gap between what students as a mentee should learn and what lab heads as a PI want them to learn.

A general process of scientific research, particularly of experimental research in life sciences,

follows a few steps: 1) it starts from setting research questions and developing research plans; then, 2) the questions are tested by experiments, simulations, and other approaches, and the test results are analyzed and interpreted; 1) and 2) are repeated until 3) certain amount of results are accumulated and are articulated in an article to be published (Nightingale, 1998). I distinguish two sets of skills required in these steps following Bozeman et al. (2001): technical skills which are specific to the context and pertinent to the execution of research in Step 2; and cognitive skills which are independent of context such as reasoning skills, more relevant to Steps 1 and 3.[1] A stereotyped division of labor in academic laboratories is that students are engaged in Step 2 while lab heads are responsible for Steps 1 and perhaps 3. For example, a report on life scientists in the US states "[a] principal investigator builds a research group by defining the scientific questions to be addressed, specifying the methods to be used …. The research personnel in the group usually work on more specific tasks that pertain to the construction of research tools or the acquisition and analysis of data" (National Research Council, 1998b). Similarly, ethnographies of British academic laboratories find that the primary responsibility of students is to master technical skills through a research project while lab heads are responsible for arranging the project (Delamont and Atkinson, 2001; Delamont et al., 1997). These observations appear reasonable considering that Step 2 in empirical research is extremely labor-intensive and time-consuming while other two steps require greater intelligence and longer experience (Delamont and Atkinson, 2001; Knorr-Cetina, 1999). Nevertheless, with a survey of Japanese life science laboratories, Shibayama et al. (2015) find that division of labor between lab heads and students are rather nuanced, with some young members engaged in upstream tasks requiring cognitive skills while some lab heads engaged in labor-intensive tasks.

Undoubtedly, technical skills are indispensable for students not only to become a productive researcher but also to later become an effective lab head. Without understanding the knack of experimental techniques, PIs would have difficulty in instructing their students (Salonius, 2008; Shibayama et al., 2015). Training for technical skills can be an acceptable investment because it directly contributes to knowledge production and technical skills are easier to instruct. Nowadays, numerous experimental techniques are illustrated in textbooks and are even available as commercial kits, which have dramatically reduced training cost.

[1] This distinction of knowledge types is consistent with literature on creativity (e.g., Amabile, 1988) and so forth.

However, whether students should be trained for cognitive skills as well seems open to debate. From the PI's perspective, training for cognitive skills could be a high-risk investment because its return is realized only in the long term, possibly after students leave from their supervision. PIs who are to maximize research productivity should be better off having students concentrate on labor-intensive tasks rather than allowing them to learn cognitive skills. On the other hand, from the perspective of mentors, who should develop future lab heads, training only for technical skills is obviously insufficient because it is likely to end in producing technicians rather than scientists. Thus, lab heads need to find an acceptable balance between these conflicting roles in deciding how to train their students. The balance may be contingent to policy, technical, and organizational contexts. For example, as above discussed, recent policies tend to prioritize the PI's perspective over the mentor's and is likely to discourage cognitive skill training.

2.3. Training as Followers vs. Innovator

The aforementioned conflict occurs because the mentor-mentee relationship lasts only for a limited period. In other words, if the relationship is sufficiently long, training cognitive skills can turn profitable investment even for egoistic PIs (See [C] in Figure 1). For example, this can be done by delaying graduation (Stock et al., 2011). Inbreeding is another option, where lab heads continue to employ their ex-students after graduation. The feasibility of these options differs by science systems. For example, delayed graduation is quite common in the US (Stephan, 2012) but is less so in Japan. Inbreeding has been discouraged or even prohibited in many countries but is still common in Japan (Morichika and Shibayama, 2015).

Less direct forms of continuous relationship is plausible. Namely, when graduates remain working on either technically or semantically related research areas to their ex-lab heads, they can continue collaboration. If not collaborating, they could disseminate the ex-lab heads' line of research and improve their visibility, which might take the form of citation (see [D] in Figure 1). These benefits are important in that peer reputation is the fundamental reward for scientists (Merton, 1973). For these benefits to be realized, graduates need to remain in research areas close to their ex-lab head's. If graduates are likely to become their followers rather than innovators of a new field, lab heads can expect greater direct reciprocity and possibly find it

beneficial to train students for cognitive skills whereby to improve their long-term productivity.

Of course, the decision of graduates' career paths or research subjects is not entirely made by lab heads, but at least, lab heads can decide the level of training based on students' expected career/research prospect. In addition, lab heads can proactively influence graduates' decisions. For example, the employment of junior scientists can be influenced by their ex-supervisor's social network (Horta et al., 2011; Pezzoni et al., 2012). Lab heads can exert a considerable influence when the job market is dull, as is currently the case in most countries. An inbreeding contract can be an acceptable option even if graduates do not really like ex-supervisor's research subjects. Regarding the choice of research subjects, dissertation projects should form the basis of scientists' research paths for the rest of their careers. If assigned a dissertation project closely linked to the lab head's interest, students are likely to continue similar research after graduation. Overall, lab heads could somehow control graduates' career/research paths, based on which they could decide how to train them.

Although these options offer lab heads a rationale for providing a serious training, they are not without a flaw. From the graduates' perspective, staying under the same lab heads' supervision or in research areas similar to their dissertation project is not always advantageous. Doing so can send to the job market a message that they are not ready for independence and lower their employability. Furthermore, if lab heads attempt to keep many graduates as their own followers, competition becomes intense among the graduates, some of whom must lose the competition unless the field is growing sufficiently rapidly (Shibayama and Baba, 2015).

Also from the collective perspective of the scientific community, supervisors influencing their students' employment is often regarded as unfair (Horta et al., 2010; Pezzoni et al., 2012). More importantly, lab heads controlling graduates' research paths can reduce the community-level research diversity and the dynamics of knowledge production (Morichika and Shibayama, 2015). This can undermine the capacity of the community to adjust the realms of knowledge production according to changing scientific and societal needs, to overarch seemingly unrelated research areas, and so forth, and therefore, can compromise the sustainability of the science system.

3. Methods & Data

3.1. Context of Japanese postgraduate education system

To empirically illustrate the above-discussed conflicts, this study employs data of life science laboratories in Japan concerning PhD training and research activities of PhD graduates.[2] Before explaining the data, this section outlines the characteristics of the postgraduate education system in Japan.

The Japanese university system consists of three types of universities that offer four-year undergraduate programs. As of 2014, it has 86 national universities, 92 regional universities (of prefecture or city), and 603 private universities. Among the three categories, national universities are the main player of academic research, whereas most private universities are education-oriented. In 2014, approximately 12,000 PhD degrees were awarded, of which national, regional, and private universities account for 70%, 10%, and 20% respectively.[3] The three categories of universities fulfill similar proportions of responsibility in scientific research. For example, on the basis of national research funding, they received 65%, 18%, and 17% of the total budget in 2014.[4]

Most postgraduate education programs in Japan are composed of a two-year master program and a three-year PhD program.[5] Students usually decide whether to proceed to a PhD program in the middle of a master program (Kato et al., 2012). A relatively high proportion of bachelor graduates go on to the master level, but a smaller proportion further pursues PhD degrees. In 2014, 175,000 students earned STEM bachelor degrees, 26% of whom proceeded to the master level, and 47,000 students earned STEM master degrees, 9.1% of whom went on to the PhD level. The corresponding figures specifically in national universities are 51% and 11%.

In STEM fields, lab training usually starts in the undergraduate third or fourth year, and many students stay in the same lab after admitted to master programs. Further, when enrolling in a PhD

[2] This paper does not study postdoc experience as another form of academic training for a few reasons: the primary source of workforce in Japanese universities is still postgraduate students rather than postdocs; postdocs include various types of academics, which can confound the analysis; and postdocs are extremely difficult to identify.
[3] The statistics about students are obtained from School Basic Survey.
[4] Source: https://www.jsps.go.jp/j-grantsinaid/27_kdata/kohyo/h26_01.html
[5] A few universities offer 5-year integrated PhD programs. PhD programs in some fields take four years, such as in Medicine, Veterinary sciences, and Pharmacy.

program, many students remain under the supervision of the same lab head in the same affiliation. In 2014, 62% of new PhDs and 83% of new master students in STEM fields were from the same university.

The attrition rate is fairly low and the majority of students graduate with limited delay in STEM fields. In Science and Engineering, 90% of masters enrolled in 2011 graduated in two years and 95% within three years (one year plus); 50% of PhDs enrolled in 2008 graduated in three years, 79% within four years (one year plus), and 91% within six years (three years plus).

In STEM fields, a PhD degree is virtually a requirement for professional academic careers, as in many other countries. It is typical to experience some years of postdoc period after graduation before employment as a faculty member. For example, 44% of Science PhD graduates in 2002-2006 became postdocs while only 6.2% obtained faculty positions immediately after graduation (Misu et al., 2010). Most Japanese universities do not have a tenure-track system. Inbreeding is still common though discouraged by recent policies (Morichika and Shibayama, 2015). For example, 45% of Science PhD graduates in 2002-2006 who pursued academic careers were employed by the same universities (Misu et al., 2010).

Financial support for PhD students is rather limited. Misu et al. (2010) find that the majority of PhD graduates in 2002-2006 were self-financed and that lab heads were rarely responsible for financially supporting students.[6]

3.2. Sample and Data

The sample of this study consists of 184 lab heads in Japanese university laboratories and 1,126 of their PhD graduates who earned degrees during 2000-2010 under the lab heads' supervision. I collected the data with a questionnaire survey conducted in May-July 2010 and from several databases of CVs, dissertations, and publications. To begin, I interviewed 30 Japanese life scientists concerning the context of lab activities, which was used to design the survey

[6] Misu et al. (2010) sent a survey to administrators of all universities. Although they obtained responses from all universities, the administrators failed to figure out the financial source for 40% of students.

instrument. The survey inquired into a variety of questions but this study uses only relevant parts of it, such as PhD training policies and training effort.

The sampling frame of the survey was prepared with the following criteria. First, I chose scientists in the positions of full professorship as of 2010.[7] Second, I chose scientists who had received a national research grant in the field of life sciences at least once in the previous three years (2007-2009), which implies that they were active researchers.[8] Third, I focused on 20 universities that publicly and electronically provide dissertation databases in which the names of supervisors are listed.[9] Drawing on the list of grant awardees and other public information, I prepared a sampling frame of 504 professors in 20 universities. I mailed the survey and collected 228 responses (response rate = 45%) after two waves of requests.[10]

For the 228 respondents, I further collected their CV information to identify their past affiliations in case they were mobile.[11] Seven professors were dropped because their past affiliations do not offer dissertation databases. For the rest of 221 respondents, I identified their PhD students who graduated in 2000-2010. I did not include graduates after 2010 because their post-graduation career and productivity cannot be analyzed, and I excluded graduates before 2000 because the connection to the survey information becomes unclear. Removing professors who produced no PhD during the period, I have the final sample of 184 professors. They have 26 years of academic career on average. Only six respondents are female.

I identified PhD graduates of the 184 professors using the dissertation database of each university. Some universities offer dissertation databases in which the supervisor of each PhD graduate can be specified as a search condition.[12] In this case, I used the names of the respondents, research fields, and graduation years as search criteria. In other universities, I first retrieved all PhD

[7] Japanese universities have a three-level promotion system with full professors at the top, followed by associate professors, and then, by assistants or lecturers. Unlike American universities, junior faculty members are usually under the supervision of senior professors, and even associate professors are sometimes so.

[8] We prepared our sampling list using the government's database of Grants-in-Aid for Scientific Research (GiA) (https://kaken.nii.ac.jp/en/). This sampling strategy is based on the assumption that academics who received no grant for three years are not researchers. Although doing research without receiving this particular grant is possible, previous research shows that it is not common (Shibayama, 2011), as GiA is the primary funding source for Japanese academics and widely awarded (http://www.jsps.go.jp/j-grantsinaid/index.html).

[9] See Supplementary Document.

[10] To examine non-response bias, we randomly selected 50 non-respondents and found no significant difference between the response and non-response groups in publication productivity, organizational rank, or gender ($p > 0.1$).

[11] Source: Researchmap (http://researchmap.jp/)

[12] An example is the University of Tokyo (http://gazo.dl.itc.u-tokyo.ac.jp/gakui/).

graduates in relevant research fields and graduation years, and then, identified those whose supervisors were among the respondents. I find 1,126 PhD graduates supervised by the 184 professors during the decade (on average 0.90 PhD per year per professor).

For these professors and PhDs, I collected their publication information from Web of Science (WoS). As search criteria, I used their names, affiliations, research areas, and publication years. Since PhD programs (including master programs) in Japan usually take five years, we searched each PhD's articles published as early as five years before graduation and up to 2015. After downloading all publication data, I removed false matches on the basis of authors' full names, affiliations, and so forth. Finally, 27,000 publications for the professors (148 per professor) and 12,000 publications for the PhDs (11 per PhD) are identified.

For regression analyses, I constructed two datasets: 1) unbalanced panel data tracing each PhD's career and 2) PhD-level cross-sectional data. The descriptive statistics and correlation matrix of variables of each dataset are given in Appendix 1.

3.3. Measures

3.3.1. Cognitive skill training

To measure cognitive skill training, I inquired into what research tasks PhD students are engaged in. I defined six research tasks: 1) choosing a subject, 2) formulating a hypothesis, 3) planning experiment, 4) doing experiment, 5) analyzing data, and 6) writing papers. I assumed that tasks 1), 2), 3), and 6) mainly require cognitive skills and 4) and 5) technical skills. For each of the six tasks, I asked the extent of engagement of PhD students as well as professors (the respondents) and other junior members, respectively. The response takes a three-point scale: 0: no role, 0.5: minor role, and 1: main role.[13] I take the average of the four measures of PhD's engagement in tasks 1), 2), 3), and 6) (cognitive skill training).[14] The Cronbach's alpha is 0.83, suggesting a reasonable reliability. A limitation of this measure is that it overlooks variations in training

[13] A "main role" can be played by more than one rank group. Each rank group may involve more than one scientist, when this survey instrument cannot measure different degrees of engagement of each scientist.
[14] Since task 6) may be qualitatively different from other three tasks, I also computed another variable averaging tasks 1)-3) and obtained basically the same results.

efforts between times and between students, which warrants a cautious interpretation.

3.3.2. PhD's publication productivity

First, the number of each PhD's publications is counted in each year and its natural logarithm is computed (#pub). In addition, to incorporate a qualitative aspect of productivity, I also sum up the journal impact factors (JIF) of PhD's publications in each year and computed the natural logarithm (total JIF).[15] For the cross-sectional data, I further sum up these measures for certain time periods (e.g., before graduation and after graduation).

3.3.3. Publication relationships between PhDs and lab heads

I identified all citation relationships between PhDs' and lab heads' publications as well as their coauthorships. For the cross-sectional data, for each PhD, the percentage of publications coauthored with their ex-lab heads (%coLH) and the percentage of publications that cite their ex-lab heads (%citeLH) are computed for certain time periods (e.g., after graduation). I also computed the lab-level mean of these two variables (avg %coLH and avg %citeLH). Further, to measure the proximity of research subjects between students and lab heads, I drew on the references cited by students' publications and by their lab head's publications and computed the ratio of common references to students' references (%shared references), following Morichika and Shibayama (2015).[16]

3.3.4. PhD's career

[15] The qualitative aspect of publication productivity is often measured by citation count. Since citation count cannot be used for recent publications, this study uses JIF as a proxy of quality. I confirmed that citation count and JIF are highly correlated.

[16] I first listed all references cited by each student's publications before graduation and those cited by his/her lab head's publications in the same period. From lab head's publications, I excluded articles coauthored with the focal student. Then, I identified the references cited by both the student and the lab head and computed its ratio to all references cited by the student.

PhDs' careers after graduation are investigated with career databases and public information. For panel data, an ordinal variable is coded 0 when a PhD is still in the PhD program, 1 if under employment as a postdoc, 2 if employed as a junior faculty member, and 3 if employed as a senior faculty member (organizational rank). In addition, if a PhD is employed in the same university that awarded a PhD degree, a dummy variable is coded one and otherwise zero (inbred). For cross-sectional data, a dummy variable is coded one if a PhD is employed in academia after graduation and zero otherwise (stayed in academia). Another dummy variable is coded one if a PhD is employed as any faculty member (but not as postdoc) within 10 years after graduation and zero otherwise (became faculty).[17] Further, if a PhD is at least once employed by his/her degree-awarding university, a dummy variable is coded one (inbred). The graduation year of PhDs is controlled for (graduation year).

3.3.5. PhD's other attributes

As a proxy of students' ability, I use the university ranking based on undergraduate entrance exams (univ ranking).[18] Since the mobility of Japanese students is rather low, I assume that the average ability of PhD students can be proxied by that of undergraduate students in the same university. To measure the extent of internal competition, I use the number of PhDs who graduated from the same laboratory in the same year (#graduates in the same year).

3.3.6. Lab head's attributes

To control for lab head's publication productivity, I compute the yearly average of publication count in 2000-2010 for each lab head and take its natural logarithm (*LH's #pub*). Similarly, the natural logarithm of the yearly average of total JIF is computed (*LH's total JIF*). Lab head's seniority is measured by the year of their graduation (*LH's graduation year*).

[17] Graduates after 2005 are dropped from the analyses that use this measure. For clarification, if a PhD became a postdoc but was not employed as a faculty member, stayed in academia = 1 and became faculty = 0.

[18] The ranking is published by private cram schools. They grade their students on the basis of practice exams. After entrance exams are given by each university, the cram schools survey who passed and who failed among their students, and then, rank each university on the basis of the lowest student grade.

3.3.7. Research fields

The field of a PhD degree is controlled for (field dummies).[19] In addition, I surveyed the research orientation of each lab head by asking "which describes your research goal, basic (aiming at advancement of theory and knowledge) or applied (aiming at solving problems in the real society)?" with a five-point scale, 1) mostly basic, 2) more basic than applied, 3) both to a similar extent, 4) more applied than basic, and 5) mostly applied. Of our respondents, 55% chose 1), implying that their research goal was completely basic. For these lab heads, a dummy variable is coded one, and others are regarded as engaging in applied research with the variable coded zero (basic research).

4. Results

4.1. Description of cognitive skill training

First, to illustrate the general picture of lab training, Figure 2A summarizes the responses to the questionnaire on lab head's and students' engagement in six research tasks. As expected, lab heads play the major role in upstream tasks and writing while PhD students are mainly responsible for labor-intensive tasks. Nevertheless, not a few PhDs are engaged in tasks requiring cognitive skills. Figure 2B shows the distribution of the measure of cognitive skill training. The measure greater than 0.5 (approximately half of the sample) means that PhDs are given a main or minor role on average, while the measure less than 0.5 means that PhDs are given minor or no role. In contrast, the engagement in experiment and analysis, or technical skill training, is fairly common; PhDs play the main role in the two tasks in about 90% of the laboratories.

Although I assume that student's engagement in a certain task implies that lab heads aim to train for the skills required for the task, lab heads might have abandoned the mentor role and students had to fulfill every task on their own. Although directly testing this possibility is not feasible with the available data, I examine the correlation between cognitive skill training and lab heads'

[19] The degree fields include Agriculture, Engineering, Medicine, Pharmaceutical, Philosophy, and Science.

training policies based on the survey data (Appendix 2). The analysis shows that the measure of cognitive skill training is significantly positively correlated with lab heads' policy to assign a scientifically important project to PhD students. This implies lab heads' seriousness in training when they allocate upstream tasks to PhD students. Further, task allocation may differ by the type of research projects; in particular, team-based projects might result in clear division of labor and PhD students may be forced to concentrate on labor-intensive tasks. However, the result does not show a significant correlation with lab heads' policies to assign a team project or to assign an individual project.

I also run regressions to examine the association between cognitive skill training and several lab head's attributes and find three factors significantly associated (Appendix 3). First, lab head's graduation year is curvilinearly correlated. I expected that young lab heads have become egoistic under a strong competitive pressure, and indeed, the result suggests that the youngest lab heads are slightly less willing to train students than middle-aged lab heads. However, the result also shows that the oldest lab heads are by far the least willing to train students.[20] This is possibly because recent unpopularity of academic careers does not allow lab heads to behave as they used to in the traditional feudalistic culture.[21] Second, university ranking is positively correlated; i.e., lab heads are more willing to train students in higher-ranked universities. This is perhaps because lab heads are motivated to train students who have higher ability and are likely to become productive scientists. Finally, the number of PhD students is negatively correlated, possibly because lab heads cannot spare sufficient training effort for too many students (Salonius, 2008; Shibayama and Baba, 2015).

4.2. Training and PhD's publication productivity

This section examines the assumption that cognitive skill training meets the PhD's interest but contradicts PI's. Namely, I test whether cognitive skill training decreases PhD's publication productivity in the short term but increases it in the long term. For this analysis, I use the

[20] The prediction of cognitive skill training is 0.30 for lab heads graduated in 1970, 0.57 for those graduated in 1995, and 0.63 for those graduated in 1987.

[21] PhD enrolment has been declining since 2004 in Japan probably because of increasing competition and job insecurity.

PhD-level panel data (Appendix 1A). The result is presented in Table 1. The dependent variables are the PhD's publication count in each year (Models 1-4) and the total JIF in each year (Models 5-8). The estimation is made with generalized least squares (GLS) with the random-effects of lab heads.[22]

The models include two focal independent variables. The number of years since graduation shows significantly positive coefficients, suggesting that PhD's publication productivity grows over time, but cognitive skill training does not show a significant direct effect (Models 1 and 5). Models 2 and 6, incorporating the interaction term between these two variables, show significantly positive coefficients. Thus, the PhD's productivity growth differs according to the level of cognitive skill training that PhDs received during PhD programs. This interaction effect is graphically shown in Figure 3. It suggests that PhD's productivity during the PhD program (i.e., #years since graduation < 0) is lower with cognitive skill training (blue lines) than without training (red lines). However, after a few years from graduation, the productivity of those who received cognitive skill training surpasses the productivity of those who did not.

This result can be spurious in that PhD's productivity growth differs by PhD's innate ability regardless of training, and that lab heads determined the level of training according to PhD's ability. To address this issue, Models 3 and 7 additionally introduce the interaction term with univ ranking, a proxy of students' ability, yet the interaction with cognitive skill training remains significant. Further, to account for the individual difference in ability, Models 4 and 8 add PhD's publication productivity before graduation and predict the productivity after graduation. Although pre-graduation productivity shows a significant correlation, the interaction with cognitive skill training remains significant.

Overall, these results suggest that cognitive skill training is costly in the short term but is beneficial in the long term for PhDs. Supposing that lab heads are not rewarded for ex-students' publication, the long-term payoff from cognitive skill training does not incentivize lab heads to offer training at the cost of short-term productivity. Therefore, as anticipated, this creates a dilemma for lab heads who are supposed to fulfill PI's and mentor's roles simultaneously.

[22] Breusch and Pagan test indicated no random effects of PhDs. I also ran regressions with random-effects model with maximum likelihood estimator and obtained similar results. For Models 1-4, I also ran negative binomial regressions without taking the logarithm of publication count, finding qualitatively similar results.

The models include several control variables. Lab head's publication productivity is correlated obviously. Lab head's graduation year, as a measure of lab head's generation, is found insignificant. The number of graduates in the same year is controlled as a measure of internal competition, but no significant effect is found. PhDs' graduation year is found weakly associated with total JIF (Models 5-7), suggesting that recent graduates tend to publish in somewhat higher-IF journals. Organizational rank shows positive coefficients. Inbred also shows positive coefficients, suggesting that inbred academics are more productive than non-inbred academics.

4.3. Reciprocity through publication

This section examines mentor-mentee relationships through publications after PhDs' graduation. Figure 4 traces the frequency of PhDs' publications coauthored by their ex-lab heads (%coLH) and those citing their ex-lab heads (%citeLH). The figure shows decreasing trends for both types of publications, suggesting that graduates are shifting their research subjects away from their PhD supervisors. Nevertheless, after 10 years from graduation, 15% and 19% of graduates' publications have coauthorships with and citations to their PhD supervisors. The whole sample (blue curve) is split into inbred and non-inbred graduates (red and green, respectively), which indicates that coauthorships with and citations to PhD supervisors are more common for inbred graduates.

To predict the frequency of these publications, this section uses the PhD-level cross-sectional data (Appendix 1B). Table 2A shows the regression results. The dependent variables are the ratio of publications coauthored with ex-lab heads (Models 1 and 2) and the ratio of publications citing ex-lab heads (Models 3 and 4). Estimation is made with GLS with the random-effects of lab heads. The models include the same set of control variables as in Table 1.

Models 1 and 3 indicate positive coefficients of inbred because inbred graduates continue working on their ex-lab head's line of research, and thus, are likely to cite and coauthor with them. To remove the effect of inbreeding, Models 2 and 4 exclude inbred graduates from the sample. Then, cognitive skill training turns positively associated with coauthorships with and citations to ex-lab heads.

A possible interpretation is that graduates who received serious training have greater commitment to their supervisors and favor continuously working with them. Conversely, another interpretation is that lab heads are willing to offer training if they expect students to reciprocate them after graduation. To further examine these possibilities, I run regressions controlling for the proximity of students' research subject to their lab head's before graduation (Table 2B). The regression models include the interaction term between cognitive skill training and %shared references, finding a significant coefficient. That is, positive association between cognitive skill training and coauthorship/citation after graduation is found only if students were engaged in subjects close to their lab head's before graduation but no significant association otherwise. Because the dissertation subject is a good predictor of students' future research path, this result is consistent with the interpretation that lab heads decide the level of training with expected reciprocity in mind.

Further, I investigate the contextual contingency.[23] In particular, I am interested in two variables, basic research (Table 2C) and lab head*'s graduation year* (Table 2D), to examine the potential impact of recent policy trends. For one, recent policies emphasize practical application of academic science, which has actually shifted the composition of academic research toward applied research (Nagaoka et al., 2009). Recent policies also emphasize merit-based evaluation and impose stronger competitive pressure particularly on younger scientists (Geuna and Martin, 2003). The regression models attempt to examine whether these contexts affect the above results.

Table 2C, introducing research orientations of lab heads (and accordingly of their students) in terms of being basic vs. applied, finds a significantly negative coefficient for its interaction term with cognitive skill training (Models 2 and 4). Coauthorships and citations are positively associated with cognitive skill training in applied research but are rather negatively associated in basic research. A possible interpretation is that lab heads in applied labs expect greater direct returns than those in basic labs possibly because applied research is narrowly specialized and lab heads cannot gain from students' research done in different areas; on the other hand, lab heads in basic research might expect a greater extent of spillover from students' research even in different areas.

[23] In addition to the prediction of the ratios of coauthorships and citations, I also examined the contextual contingency of the prediction of PhD's publication productivity but found no noticeable results.

Table 2D incorporates lab heads' generation effect. Models 2 and 5 show positive interaction effects, suggesting that cognitive skill training is positively associated with coauthorship/citation for younger lab heads but insignificantly for older lab heads. Possibly, younger lab heads, under stronger competition, might become more egoistic, and train students only if direct reciprocity is expected. As recent policies could affect also students, Models 3 and 6 additionally control for the interaction effect with PhD's graduation year, finding that it is insignificant while the lab head's generation effect remains significant.

4.4. Reciprocity and career prospect

A potential downside of close relationships between lab heads and their students after graduation is that it can cause excessive competition in narrow research areas and that it can reduce the dynamics of knowledge production. Although the latter point is difficult to directly test in the current empirical setting, this section attempts to examine the former. Table 3 predicts the career outcome of PhDs using the PhD-level cross-sectional data (Appendix 1B). The dependent variables are dummies of staying in academia (Models 1-2), being inbred (Model 3), and being employed as a faculty member within 10 years from graduation (Models 4-6). Since all dependent variables are dichotomous, estimation is made by logit regressions with the random-effects of lab heads. The focal independent variables are the ratios of publications coauthored with and citing lab heads;[24] the PhD-level measures (%coLH and %citeLH) are averaged over all graduates from the same lab head to gauge the lab-level tendency to reciprocate lab heads in the long term.

Models 1 and 4 show positive coefficients for PhD's publication before graduation, suggesting that employment decision is made on a merit basis to some extent. Model 1 indicates a negative coefficient for PhD's graduation year, probably because academic career has become more competitive these years or because academic career has become less popular and many graduates choose not to pursue it. Cognitive skill training is positively associated with the probabilities of staying in academia (Model 1) and of being inbred (Model 3). This suggests either that training improves PhDs' skills and accordingly their employability, or that lab heads are willing to train

[24] Since both measures gave similar results, I report the result with %citeLH.

students only if students are likely to stay in academia or to be inbred. Since the result in Section 4.2 suggests that cognitive skill training reduces short-term productivity, I also examine the overall effect of cognitive training on the employability by dropping the PhD's publication before graduation (Models 2 and 5). Model 2 remains to show a significantly positive coefficient of cognitive skill training, suggesting that PhDs are more likely to be employed with cognitive skill training even though they are disadvantaged in terms of short-term productivity.

On condition that PhDs stayed in academia after graduation, Models 4-6 predict the probability of their employment as a faculty member within 10 years. Inbred shows strongly positive coefficients, perhaps because inbreeding contracts are rather permanent than temporary. Univ ranking shows negative coefficients after PhD's publication productivity is controlled for, possibly because the employment competition is stronger in higher-ranked universities. Students' citing lab heads at the individual level (%citeLH) does not show a significant effect, but the lab-level average (avg %citeLH) does show a significantly negative effect (Model 3). Thus, individually reciprocating ex-lab heads does not affect graduates' employability, but if many graduates follow their ex-lab heads, it decreases their employability. This effect should depend on the prospect of the lab head's line of research in that competition among graduates would be mitigated if the lab head's research is growing to a sufficient extent. To test this possibility, Model 6 adds the interaction term with lab head's publication productivity and finds a positive interaction effect, supporting the argument.

5. Discussion & Conclusions

In the modern knowledge-based economy, the role of academic science has become indispensable. For sustainable development of science, the academic sector must not only produce scientific knowledge but also develop scientists for the knowledge production in the next generation (Hackett, 1990). Nevertheless, scholarly research on academic training has been limited and actual policies on academic training have been criticized for various reasons (National Research Council, 1998a; Cyranoski et al., 2011). The goal of this study is to fill in the gap and contribute to the design of relevant policies. In particular, this study investigates how lab heads, who are responsible both for knowledge production as a PI and for training junior

scientists as a mentor, are incentivized. Drawing on a sample of life science professors and their PhD graduates, this study obtains the following results.

This study distinguishes cognitive and technical skills and finds that about half the lab heads in the sample assigned PhD students tasks requiring cognitive skills such as research planning while other half did not. In fact, many of my interviewees recognized the existence of two types of laboratories: one where students are treated like factory workers to produce research results, and the other where students are trained as future scientists. This study empirically tests if the factory-like labs actually gain productivity compared to training-oriented labs, and the result indeed shows that training for cognitive skills is negatively associated with students' publication productivity in the short term, and therefore, causes a loss for their lab heads. The result also suggests that cognitive skill training increases students' productivity in the long term after graduation. Therefore, cognitive skill training is collectively beneficial for the scientific community but does not directly benefit lab heads. This places lab heads in a dilemma situation, having them choose whether to prioritize short-term research productivity or to train students at the cost of research productivity. This finding is consistent with the argument of the incompatibility between research and education (Hackett, 1990).

A potential solution to this incompatibility is to extend mentor-mentee relationships. For example, literally extending PhD periods and employing one's own graduates (i.e., inbreeding) can be straightforward means to this end, though neither is considered appropriate in recent policies (Stephan, 2012). Continuous relationships can be maintained in indirect manners when graduates collaborate with ex-lab heads or follow ex-lab head's line of research. Indeed, the data show that even 10 years after graduation about 20% of PhDs' publications are coauthored with and cite their ex-lab heads. Regression analyses indicate that both forms of publications are positively associated with cognitive skill training, especially so if students' dissertation subjects are similar to their lab head's other lines of research. Results also suggest a positive association between inbreeding and cognitive skill training. Although the empirical setting of this study does not reveal causality directions, a possible interpretation is that lab heads provide cognitive skill training particularly when they expect direct reciprocity such as labor supply through inbreeding, collaboration, and reputation gain through citations.

Although these results suggest that the incompatibility of research and education can be mitigated, it might impose certain cost on the community. Lab head's exerting too much influence over graduates' careers or research areas is considered undesirable (Pezzoni et al., 2012). Restricting graduates' research paths might undermine the dynamics of knowledge production or cause excessive competition in narrow research areas. In fact, this study suggests that employment as a faculty member is deterred when many graduates from the same lab follow their lab head. Consistently, some of my interviewees referred to the inefficiency of supervising too many students under a single lab head due to internal competition.

Finally, this study investigates if the aforementioned results differ by contexts, particularly by research orientation and lab head's generation. First, the association between cognitive skill training and reciprocal publications (with coauthorships and citations) is found to be positive in applied research but rather negative in basic research. This might be attributed to the broad applicability of basic research output (Calvert, 2004; Stokes, 1997). That is, the fruit of basic research allows wider scientific application than that of applied research, and thus, lab heads in basic labs are willing to train students even if they are likely to change subjects (possibly even encourage to do so) while lab heads in applied labs prefer to secure direct returns. Second, the result shows stronger association between cognitive skill training and reciprocal publications for younger lab heads. Younger lab heads under stronger competition might be tempted to secure direct returns for their training efforts. Since recent policies tend to emphasize applied research and competitive evaluation (Geuna and Martin, 2003), these results imply that direct mentor-mentee relationships can be further facilitated. If this scenario is true, current policies can compromise the capacity of science community to adjust to changing scientific and societal needs and lead to the opposite consequence of what the policies intended to produce.

These results must be interpreted with reservations of some limitations. Among others, this study draws basically on a cross-sectional data, and thus, causality behind the observations cannot be clearly known. I believe that the presented interpretations are plausible but alternative explanations are possible. The measure of training needs cautious interpretation, in that it was measured only once without distinguishing multiple students supervised by each respondent. In reality, however, lab heads might change their supervising styles over time and use different styles for different students. This study ignores non-academic careers of PhD graduates, which

can affect lab heads' decisions. The sample of this study restricts the generalizability of the findings; in particular, postgraduate education systems differ by country and lab heads might be under different incentive structures.

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Figure 1 Reciprocity in Academic Training

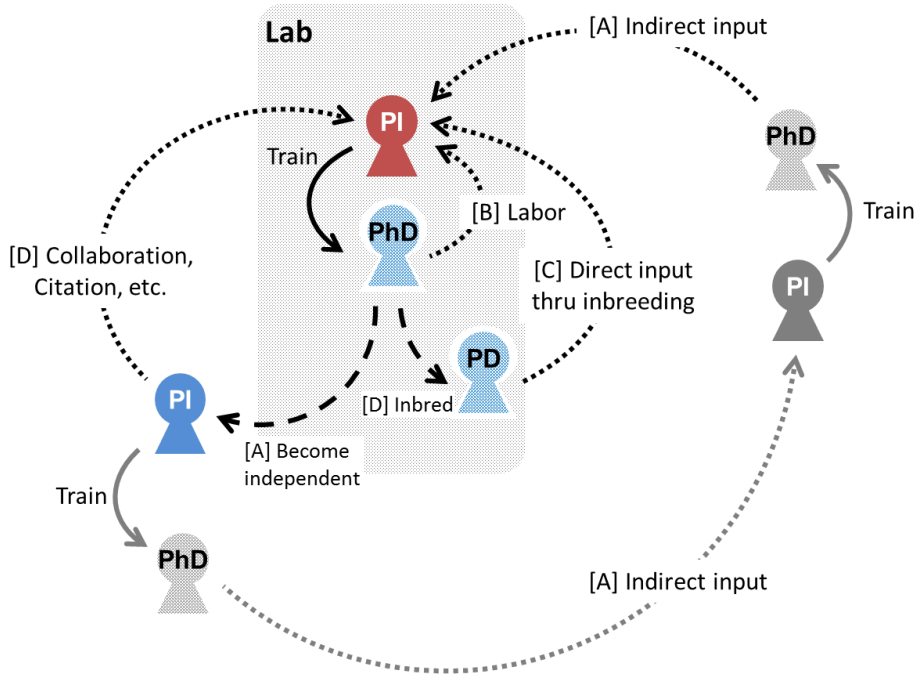
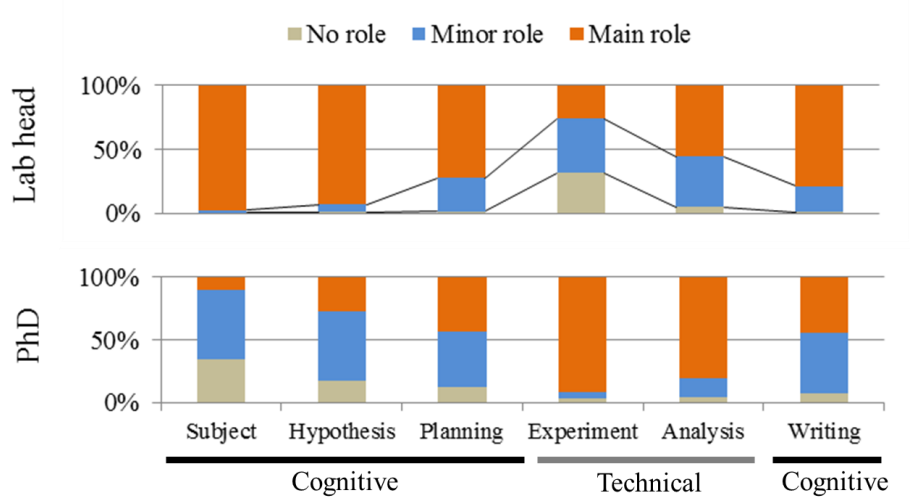
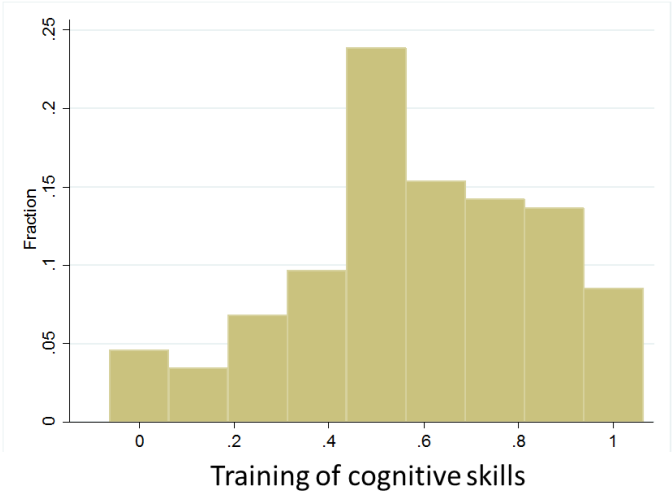


Figure 2 Cognitive skill training

(A) Roles of lab heads and PhDs in each research task



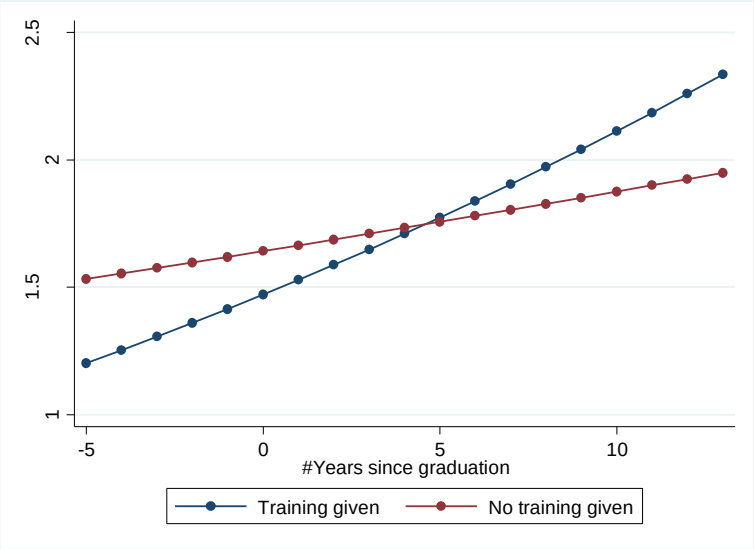
(B) Distribution of cognitive skill training



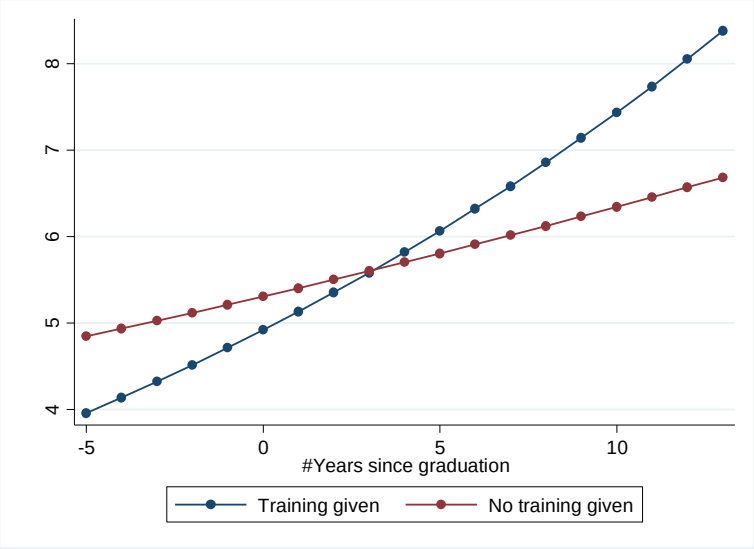
Note: This measure is computed by averaging PhD's engagement in four tasks requiring cognitive skills. For each task, the main role, minor role, and no role are given scores of 1, 0.5, and 0, respectively.

Figure 3 Prediction of PhD's production

(A) Prediction of #Pub



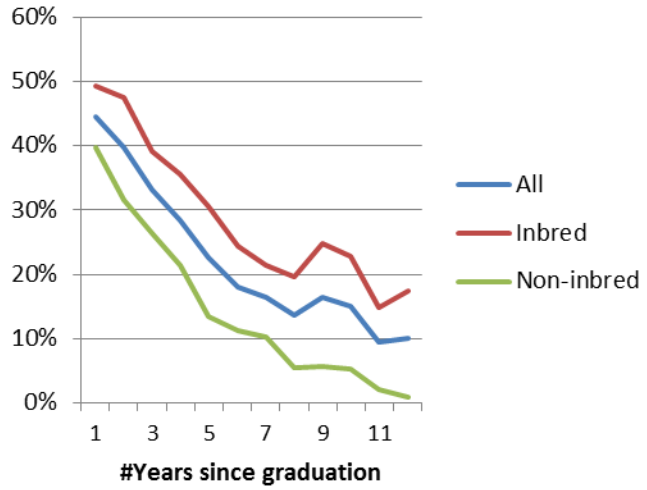
(B) Prediction of total JIF



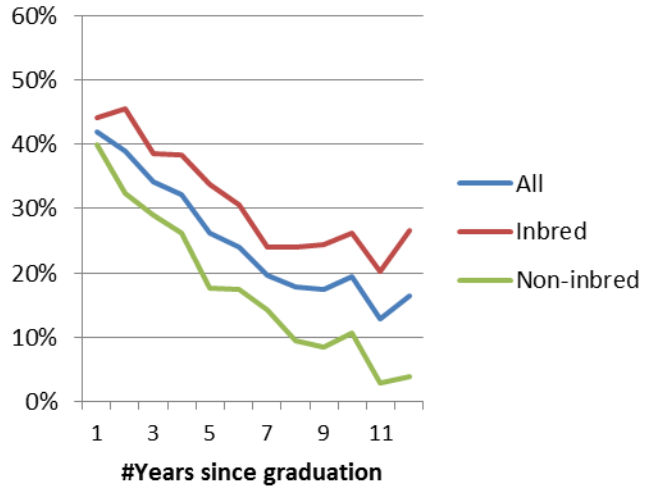
Note: Figures (A) and (B) are based on Models 2 and 6 in Table 1 respectively. Prediction is made with the mean values of all independent variables except for #years since graduation and cognitive skill training. The predicted values for cognitive skill training = 1 (training given) and cognitive skill training = 0 (No training given) are plotted vs. #years since graduation.

Figure 4 Reciprocal Publication

(A) %Publications coauthored with ex-lab heads (%coLH)



(B) %Publications citing ex-lab heads (%citeLH)



Note: PhD graduates who left academia are excluded from computation.

Table 1 Prediction of PhD's publication productivity

	#Pub								Total JIF							
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
LH's #pub	.035 **	(.011)	.035 **	(.011)	.035 **	(.011)	.020	(.013)								
LH's total JIF									.128 ***	(.016)	.128 ***	(.016)	.127 ***	(.016)	.114 ***	(.018)
LH's graduation year	.001	(.001)	.001	(.001)	.001	(.001)	.000	(.002)	.002	(.003)	.002	(.003)	.002	(.003)	.002	(.003)
#Graduates in the same year	.001	(.005)	.001	(.005)	.001	(.005)	.000	(.006)	-.009	(.010)	-.009	(.010)	-.009	(.010)	-.015	(.011)
Graduation year	.003	(.003)	.003	(.003)	.003	(.003)	.000	(.003)	.009 †	(.005)	.009 †	(.005)	.009 †	(.005)	-.001	(.006)
Organizational rank	.054 ***	(.008)	.054 ***	(.008)	.054 ***	(.008)	.058 ***	(.009)	.104 ***	(.016)	.104 ***	(.016)	.104 ***	(.016)	.114 ***	(.018)
Inbred	.027 †	(.015)	.029 †	(.015)	.029 †	(.015)	.009	(.018)	.060 †	(.031)	.061 *	(.031)	.061 *	(.031)	.043	(.034)
#Years since graduation (A)	.017 ***	(.001)	.008 ***	(.003)	-.004	(.011)	.014 **	(.005)	.027 ***	(.002)	.015 **	(.005)	-.001	(.021)	.036 ***	(.009)
Cognitive skill training (B)	-.029	(.026)	-.067 *	(.028)	-.065 *	(.028)	-.013	(.039)	-.012	(.053)	-.064	(.056)	-.061	(.056)	-.044	(.072)
(A) x (B)			.015 ***	(.004)	.013 **	(.004)	.011 *	(.006)			.020 **	(.007)	.019 *	(.008)	.023 *	(.010)
Univ ranking (C)	.002	(.001)	.002	(.001)	.001	(.001)	.001	(.001)	.008 **	(.002)	.008 **	(.002)	.007 **	(.002)	.006 *	(.003)
(A) x (C)					.000	(.000)							.000	(.000)		
#Pub (before grad) (D)							.174 ***	(.017)								
(A) x (D)							-.007 **	(.002)								
Total JIF (before grad) (E)															.233 ***	(.020)
(A) x (E)															-.015 ***	(.003)
Field dummies	YES		YES		YES		YES		YES		YES		YES		YES	
Chi squared test	389.307 ***		402.778 ***		404.068 ***		307.499 ***		383.664 ***		390.982 ***		391.577 ***		353.000 ***	
Log likelihood	-2.40E+03		-2.40E+03		-2.40E+03		-2.00E+03		-6.20E+03		-6.20E+03		-6.20E+03		-4.70E+03	
N	6064		6064		6064		4548		6064		6064		6064		4548	

Note: Generalized Least Square regressions with random-effects of lab heads. Unstandardized coefficients and standard errors (parentheses). Two-tailed test. † p<0.10; * p<0.05; ** p<0.01;*** p<0.001. For Models 4 and 8, pre-graduation periods (#years since graduation < 0) are dropped from the analyses.

Table 2 Prediction of PhD's Reciprocal Publication

(A) Base model

	%coLH (after grad)				%citeLH (after grad)			
	(All)		(Non-inbred)		(All)		(Non-inbred)	
	Model 1		Model 2		Model 3		Model 4	
LH's #pub	.009 *	(.004)	.005	(.004)	.013 **	(.004)	.009 †	(.005)
LH's graduation year	-.005	(.004)	-.007	(.005)	-.005	(.004)	-.008	(.005)
#Graduates in the same year	-.017	(.012)	-.017	(.017)	-.025 *	(.012)	-.029	(.018)
Graduation year	.009	(.006)	.008	(.008)	.011 *	(.005)	.009	(.008)
Univ ranking	-.006 †	(.004)	-.003	(.004)	-.007 †	(.004)	-.005	(.005)
Organization rank	-.013	(.022)	.014	(.031)	.001	(.021)	.025	(.031)
Inbred	.190 ***	(.029)			.142 ***	(.028)		
Cognitive skill training	.067	(.044)	.082 †	(.047)	.069	(.045)	.104 *	(.052)
Field dummies	YES		YES		YES		YES	
Chi squared test	78.600 ***		27.251 **		61.089 ***		19.968 †	
N	563		248		563		248	

(B) Interaction with research proximity

	%coLH (after grad)				%citeLH (after grad)			
	Model 1		Model 2		Model 3		Model 4	
Cognitive skill training (A)	.076 †	(.042)	-.002	(.055)	.094 *	(.045)	.036	(.057)
%Shared references (before grad) (B)	.576 ***	(.116)	.093	(.243)	.764 ***	(.113)	.414 †	(.238)
(A) x (B)			.419 *	(.186)			.307 †	(.184)

(C) Interaction with basic research

	%coLH (after grad)				%citeLH (after grad)			
	Model 1		Model 2		Model 3		Model 4	
Cognitive skill training (A)	.014	(.032)	.102 *	(.045)	.026	(.037)	.170 ***	(.051)
Basic research (B)	-.002	(.039)	.219 *	(.090)	.028	(.046)	.390 ***	(.103)
(A) x (B)			-.182 **	(.067)			-.298 ***	(.076)

(D) Interaction with lab head's generation

	%coLH (after grad)						%citeLH (after grad)					
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Cognitive skill training (A)	.082 †	(.047)	-34.834 *	(15.533)	-62.517 *	(30.748)	.104 *	(.052)	-50.376 **	(16.506)	-66.112 *	(31.588)
LH's graduation year (B)	-.007	(.005)	-.025 **	(.009)	-.022 *	(.010)	-.008	(.005)	-.034 ***	(.010)	-.033 **	(.010)
Graduation year (C)	.008	(.008)	.008	(.008)	-.011	(.020)	.009	(.008)	.009	(.008)	-.002	(.021)
(A) x (B)			.018 *	(.008)	.015 †	(.008)			.025 **	(.008)	.024 **	(.009)
(A) x (C)					.016	(.016)					.009	(.016)

Note: Generalized Least Square regressions with random-effects of lab heads. Unstandardized coefficients and standard errors (parentheses). Two-tailed test. † p<0.10; * p<0.05; ** p<0.01;*** p<0.001. Since research conducted before graduation may be published after graduation, I repeated the same analyses with different time windows to compute the dependent variables. The basic model structure in (B)-(D) is the same as Models 2 and 4 in (A). For parsimony, only focal independent variables are presented.

Table 3 Prediction of post-graduation career

	Stayed in academia				Inbred		Became faculty					
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
LH's #pub (A)	-.132	(.147)	-.113	(.144)	-.245 *	(.118)	-.299	(.345)	-.323	(.336)	-.856	(.533)
LH's graduation year	-.003	(.017)	.005	(.016)	.011	(.014)	.007	(.038)	.015	(.037)	.011	(.037)
#Graduates in the same year	.017	(.053)	.025	(.052)	-.006	(.048)	.110	(.154)	.200	(.153)	.114	(.152)
Graduation year	-.063 *	(.026)	-.060 *	(.025)	-.030	(.025)	.063	(.100)	.051	(.097)	.061	(.098)
#Pub (before grad)	.163 ***	(.027)			.135 ***	(.023)	.223 **	(.075)			.216 **	(.071)
Univ ranking	.015	(.015)	.018	(.014)	.020 †	(.012)	-.069 †	(.036)	-.057 †	(.034)	-.077 *	(.036)
Inbred							.900 **	(.344)	.990 **	(.334)	.858 *	(.335)
Cognitive skill training	.769 *	(.306)	.562 †	(.297)	.438 †	(.251)	-.155	(.622)	-.138	(.612)	-.294	(.593)
%citeLH	-.115	(.202)	.144	(.196)	.099	(.208)	.484	(.491)	1.048 *	(.466)	.471	(.490)
Avg %citeLH (B)	.391	(.393)	.320	(.386)	.147	(.355)	-1.909 *	(.901)	-1.845 *	(.905)	-6.509 *	(2.688)
(A) x (B)											2.043 †	(1.117)
Field dummies	YES		YES		YES		YES		YES		YES	
Chi squared test	56.908 ***		21.734 †		70.273 ***		28.824 *		28.824 *		28.345 **	
N	1084		1084		1084		260		260		260	

Note: Logit regressions with random-effects of lab heads. Unstandardized coefficients and standard errors (parentheses). Two-tailed test. † p<0.10; * p<0.05; ** p<0.01;*** p<0.001. Models 4-6 exclude PhDs who did not start academic careers and those who graduated after 2005.

Appendix 1 Descriptive statistics and correlation matrix

(A) PhD-level panel data

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	#Pub	1.00	0.39	0.69	2.64													
2	Total JIF	1.91	0.75	0.00	4.42	0.71												
3	LH's #pub	2.16	0.70	0.00	3.49	0.11	0.15											
4	LH's total JIF	3.21	0.96	0.00	5.06	0.09	0.20	0.91										
5	#Pub (before grad)	1.55	0.64	0.00	2.77	0.26	0.17	0.15	0.12									
6	Total JIF (before grad)	2.57	0.99	0.00	4.39	0.21	0.28	0.16	0.21	0.87								
7	LH's graduation year	1982	5.43	1967	1997	-0.02	-0.01	-0.05	0.01	-0.01	-0.01							
8	#Graduates in the same year	2.35	1.56	1.00	9.00	0.05	0.07	0.36	0.37	0.10	0.12	0.06						
9	Graduation year	2005	3.00	1999	2010	-0.11	-0.09	-0.14	-0.10	0.04	0.06	0.27	-0.04					
10	Univ ranking	60.90	6.13	42.50	67.50	0.05	0.12	0.31	0.31	0.04	0.09	-0.12	0.06	-0.07				
11	Organizational rank	1.51	0.98	0.00	3.00	0.19	0.19	0.02	0.01	0.14	0.13	-0.06	-0.03	-0.28	0.03			
12	Inbred	0.46	0.50	0.00	1.00	0.11	0.13	0.01	0.03	0.17	0.18	-0.02	-0.02	-0.08	0.05	0.44		
13	#Years since graduation	2.80	4.37	-5.00	15.00	0.21	0.18	0.04	0.03	-0.17	-0.17	-0.09	0.01	-0.38	0.05	0.25	0.09	
14	Cognitive skill training	0.57	0.28	0.00	1.00	0.02	0.06	0.00	0.05	-0.07	-0.01	0.21	-0.03	0.00	0.26	0.10	0.06	0.03

Note: N = 6,285.

(B) PhD-level cross-sectional data

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	%coLH (after grad)	0.37	0.42	0.00	1.00														
2	%citeLH (after grad)	0.36	0.41	0.00	1.00	0.86													
3	LH's #pub	2.12	0.66	0.00	3.49	0.04	0.08												
4	#Pub (before grad)	1.48	0.85	0.00	3.93	0.07	0.11	0.08											
5	LH's graduation year	1982	5.35	1967	1997	-0.03	-0.03	-0.08	0.03										
6	#Graduates in the same year	2.30	1.58	1.00	9.00	-0.13	-0.12	0.33	0.04	0.10									
7	Graduation year	2006	2.97	1999	2010	0.11	0.11	-0.15	-0.04	0.27	-0.03								
8	Univ ranking	60.58	6.22	42.50	67.50	-0.06	-0.04	0.27	0.05	-0.15	0.05	-0.08							
9	Organizational rank	1.06	1.00	0.00	3.00	-0.16	-0.13	0.00	0.33	-0.01	-0.01	-0.16	0.03						
10	Inbred	0.33	0.47	0.00	1.00	0.03	0.02	-0.02	0.19	0.02	0.01	-0.04	0.05	0.53					
11	Basic research	0.57	0.50	0.00	1.00	-0.04	-0.01	-0.13	-0.07	-0.05	-0.13	-0.09	0.21	0.07	0.05				
12	%Shared references	0.15	0.20	0.00	0.92	0.51	0.56	0.12	0.10	-0.14	-0.11	0.06	-0.04	0.02	0.03	0.05			
13	%citeLH (before grad)	0.38	0.44	0.00	1.00	0.54	0.62	0.08	0.11	-0.10	-0.14	0.13	-0.04	0.05	0.01	0.02	0.79		
14	Avg %citeLH (before grad)	0.38	0.28	0.00	1.00	0.42	0.48	0.12	0.02	-0.16	-0.20	0.01	-0.06	0.02	-0.03	0.02	0.54	0.63	
15	Cognitive skill training	0.57	0.27	0.00	1.00	0.02	0.02	-0.04	-0.04	0.21	-0.05	0.02	0.24	0.07	0.06	0.15	-0.02	0.00	0.00

Note: N = 1,126.

Appendix 2 Correlation between cognitive skill training and training policies

Questionnaire item	Mean (s.d.)		Correlation coefficient (p-value)	
To encourage learning accurate techniques	4.34	(0.81)	-0.069	(0.368)
To assign an individual project	4.03	(0.98)	-0.018	(0.812)
To assign a team project	2.87	(1.13)	-0.035	(0.648)
To assign a safe project that should be completed in the designated period	3.46	(0.95)	-0.055	(0.466)
To assign a scientifically important project	4.26	(0.77)	0.172	(0.022)*
To monitor students frequently	4.04	(0.79)	-0.028	(0.712)

Note: Pearson's correlation coefficients. For each questionnaire item, we asked "to what extent does your training policy for PhD students agree with the statement?" with five-point scale (1:disagree – 5:agree).

Appendix 3 Prediction of cognitive skill training (lab head-level cross-section)

	Cognitive skill training			
	Model 1		Model 2	
LH's #pub	.030	(.049)	.048	(.049)
LH's graduation year	.009 *	(.004)	4.040 *	(2.010)
(LH's graduation year)^2			-.001 *	(.001)
University rank	.009 *	(.004)	.009 *	(.004)
#PhD	-.062 †	(.037)	-.064 †	(.036)
Budget	.020	(.016)	.024	(.016)
LH foreign experience	-.004	(.014)	-.005	(.013)
LH inbred	.014	(.065)	.007	(.064)
Median (#Coauthor)	-.012	(.011)	-.013	(.011)
Basic research	.019	(.042)	.029	(.042)
F test	2.465 *		2.666 **	
Adjusted R-squared	.076		.094	
N	161		161	

Note: Ordinary Least Squares regressions. Unstandardized coefficients and standard errors (parentheses). Two-tailed test. † p<0.10; * p<0.05; ** p<0.01;*** p<0.001. The independent variables unique to this regression are as follows. The yearly average number of PhD graduates in 2000-2010 is controlled for (#PhD). Research budget in the year of 2010 was surveyed with a 7-point scale: 1 = less than 5 million JPY (roughly $1 = 100 JPY), 2 = 5-10, 3 = 10-25, 4 = 25-50, 5 = 50-75, 6 = 75-100, and 7 = greater than 100 (budget). Lab head's international mobility was surveyed with a 6-point scale: 1 = none, 2 = less than half a year, 3 = one year, 4 = 2 years, 5 = 3 years, and 6 = 4 years or more (LH foreign experience). If a lab head is inbred, a dummy variable is coded one and zero otherwise (LH inbred). The average project size is measured by the median number of authors in lab heads' publications in 2000-2010 (median(#coauthor)).