ESSAYS ON ECONOMICS OF INNOVATION AND KNOWLEDGE PRODUCTION

BY

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Abstract

As articulated in economic growth theory, the accumulation of knowledge and human capital in higher education can be the essential sources of long-term economic growth. This PhD thesis carried out the following three empirical analyses on factors affecting these knowledge production and human capital accumulation. Focusing on the role carried out by universities in knowledge and human capital growth, Chapter 1 empirically analyzed the effects that university governance have on research activities by university researchers. Chapter 2 empirically analyzed the effects that post-graduate education has on human capital accumulation in research activities by PhD student. These analyses were treated as accumulations in intellectual human capital and mechanisms for cultivation. Moreover, Chapter 3 analyzed the effect of public and government research and development investment strongly linked to academic-industrial collaboration on businesses producing patents.

Chapter 1 estimates the causal effects of university governance on their research activity through the analysis of the transformation of Japanese national universities into “national university corporation”, a juridical public body separated from central government. The Corporatization (or Partial Privatization) of the Japanese national universities since 2004 is characterized as exogenous source of promoting additive competitive environments within national universities, improving accountability, and expanding a range of some aspects of autonomous function of national universities. Some detailed estimation results were attained through DID estimations using private universities as the control group that had not affected by the corporatization of national universities bringing about a significantly positive impact for engineering and economics publication activity in national universities. Moreover, analyses of these fields of study that divided universities into less research-intensive universities and more research-intensive universities found that the more research-intensive universities had significantly robust positive effects, whereas significant effects couldn't be seen in the less research-intensive universities. The analyses largely indicated that the transformation into independent institutions resulted in the advancement of domestic competition and resources being concentrated on universities with superior research capabilities in line with the drastic decrease in subsidies for operations. Furthermore, the analyses suggest that the effect coincided

with intensified efforts to acquire competitive-type research funding also induced by the reform. These results suggests the possibility that competitive research resources (perhaps more efficiently) have become concentrated towards universities that are achieving superior research results, and indicates a positive effect for research-intensive universities and no significant effect for less research-intensive universities. However, research output in medical science by national universities has shown a pronounced decrease. This result is consistent with the expectation that corporatization, which encourages income-generating activity, results in a decrease in the research output of university hospitals. This finding reflects the special characteristics of university hospitals that render them the main producers of research output and the greatest national university revenue earners from the provision of clinical services.

The objective of Chapter 2, co-authored with Ryo Nakajima (Keio University), is to quantitatively elucidate the effectiveness of research guidance given by supervisors to student advisees, value-added, by focusing on post-graduate education as the provider of innovation in cultivating human capital. Here, a problem arises where the matching of the supervisor and student pair is endogenously determined making it difficult to deal with the resulting self-selection effect. Therefore, this research analyzed issues with matching by expanding on the value-added model technique used by Rivkin, Hanusheck and Kain (2005), and constructing data on supervisor and student pairs that exogenously broke down as a result of supervisor turnover during guidance based on data on supervisors and students from the Department of Physics at the University of Tokyo. We find that a one-standard-deviation increase in professor quality results in a 0.54 standard deviation increase in a doctoral student's research achievement growth, increasing the number of first-authored papers that are published in top journals by 0.64 at the doctoral level.

The purpose of Chapter 3, co-authored with Taro Akiyama (Yokohama National University), Tatsumi Ishizuka (Yokohama National University) and Ryuichi Tamura (Hitotsubashi University), is to analyze the influence of the Japanese government R&D investment on private sector patenting in the field of fuel cell. Specifically, using the data set on fuel cell-related patents between 1999 and 2011, we analyzed the patent productivity of companies following a partnership with NEDO (New Energy and Industrial Technology Development Organization.) The results of the estimation showed that, when analyzing without using the panel data structure, there was a significant positive influence on the number of patent applications; however, it was also revealed that there was no significant positive influence on the quality indexes such as the number of times those patents were cited. Furthermore, when analyzing while taking advantage of the characteristics of panel data, no significant influence was found in either of the two cases.

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Statement of Conjoint Work

I confirm that Chapter 2 was jointly co-authored with Professor Ryo Nakajima and Chapter 3 was jointly co-authored with Professors Taro Akiyama, Tatsumi Ishizuka and Ryuichi Tamura and, all authors equally contributed to these work at every stage of the projects.

Contents

Chapter1

The Impact of University Reform on Research Performance: Evidence from the Partial Privatization (Corporatization) of Japanese National Universities

1 Introduction

In this chapter, I estimate the effect of university governance (reform) on research performance by overcoming the problem of endogeneity of university governance. Specifically, I focus on a type of university governance reform that introduced both additional autonomy and a competitive environment.

Economic intuition lead a hypothesis that autonomy and competition, in combination, improve university's research output. The production function of a university is almost impossible to understand for an external audience such as government policy-makers. Therefore, a more effective form of governance might be a model with considerable university autonomy and institutional competition for resources and prizes rather than centralized government control. Autonomy without competition is ineffective because universities may not be accountable for their activity. A competitive environment without autonomy is ineffective because universities are not free to respond to competitive pressure with productive programs. Following this logic, Aghion, Dewatripont, Hoxby, Mas-Colell, and Sapir (2010) attempt to empirically show the importance of these two factors. However, the authors' findings are incomplete mainly because of the endogeneity of the autonomous and competitive status of universities.

This paper uses the partial privatization of Japanese national universities since 2004, "the greatest changes in higher education policy since the WWII (Yamamoto (2004),p154)" in Japan, to identify the causal effects of university governance reform. The advantages of focusing on this specific event are, first, that this reform is considered to have exogenously introduced additional autonomy and competition to national universities (see Section 2.2 for details). Second, while many countries set nationwide standards for university systems, Japanese private universities can be viewed as a control group unaffected by such systematic reform that provides within-country variations in governance change. Consequently, this situation is adequate for a natural experiment that tests shifting autonomy and competition status to investigate causal consequences of university reform.

The fixed effect specifications including difference-in-differences estimators suggest that with respect to engineering and economics, which are selected as counterparts of Aghion et al. (2010)'s results, positive effects of partial privatization are observed. To reveal the underlying mechanism, I document that among relatively more research-intensive universities, the effect was positive and gradually evolved. Among relatively less research-intensive universities, the effect was negative and gradually advanced. This implies evolution towards resource concentration in top research universities via intensified competition, and the allocation of resources resulted in an overall positive impact on national universities' research performance. I find that partial privatization intensified the competitive-type fund acquisition efforts, underscoring the existence of such a competitive mechanism, and that the evolution of the impact almost perfectly follows that of research outcome. Interestingly, the number of engineering publications increased after the reforms, particularly among higher ranked journals, without change in the average quality per article.

In contrast, I find robust negative effects for medical science. This is consistent with the often voiced claim, including government reports, that partial privatization, which encourages revenue-generating activity, results in a decrease in research output of university hospitals. First, this is likely because of the specificity of this institutional change that causes national universities to own their existing assets as a consequence of increasing university autonomy. However, at the same time, the universities are obligated to repay their own debts for university hospital management. Second, another explanation is that when a university acquires more autonomy, the university shifts focus towards more income-generating activities, provision of clinical services in this case, to maintain or enlarge its budget at the expense of research activity. Therefore, the role of hospital management was magnified after the reforms. In fact, I find that the partial privatization increased the hospital revenue of national university hospitals.

In addition to expanding Aghion et al. (2010)'s work, this study contributes to a recent strand of literature that investigates the relation between university governance or managerial factors and performance. McCormack et al. (2014) showed some association between the higher management index and superior performance for both research and teaching in the UK without claiming causality. Quentin (2014) also tried to capture the determinants of research production at top US universities, but the results also suffer from an endogenous problem[1]. The prominent features of my study compared to these studies are that the results provide a causal relationship between university governance with research outcome and thereby provide direct policy-relevant implications of university reform.

Understanding the role of university governance (reform) on the research activities may be particularly important for science policy-makers in a knowledge-based society where universities are the most prevailing producers of knowledge. Although the channel by which universities contribute to knowledge spillover is not fully elucidated, many studies have highlighted the importance of university as the center of knowledge disseminater and localized source of innovation and economic performance from the earlier study of Jaffe (1989) to the recent study of Kantor and Whalley (2014). Also, although previous literature has consistently shown that government research grants have a significant impact on subsequent publications and citations of universities[2] (Adams and Griliches (1998); Payne and Siow (2003);

[1] Quentin (2014) regressed university ranking with various explanatory variables. The analysis imposed strong assumptions that the share of the revenue spent on research activities, the number of hired professors, the average salary of the professors, the proportion of students in hard sciences, and total revenue are not endogenous explanatory variables after controlling for the endogeneity of total revenue by instrumental variables: the number of students enrolled in the institution, the share of undergraduates, and a dummy equal to one if the institution has a medical degree. All of these variables, including the instruments, should be treated as endogenous variable.

[2] Analyzing units at the university level has one advantage over the analysis of individual researchers when investigating the impact of research grants. Arora et al. (1998) and Jacob and Lefgren (2011) found that the receipt of a government grant has, at most, a small effect on the research output of individual researchers. In response to these studies, Rosenbloom et al. (2014) suggested that some type of downward bias may produce these results. One possibility is that the effect of grant is a positive spillover to the control group who are not the targets of the support. For instance, public research funding affects researchers through the direct costs

Rosenbloom et al. (2014)), the university performance, including how well the university performs when in receipt of a research grant, depends on how the institution is governed or managed.

Section 2 suggests developing Aghion et al. (2010)'s empirical work and provides a detailed explanation of the partial privatization of the national universities to advance their argument. Section 2 also explains the expected effects of partial privatization on national university hospitals. Section 3 presents the data construction process and identification strategies. Section 4 shows the main results, attempts to reveal the underlying mechanism, and examines various types of robustness checks. Section 5 discusses my findings.

2 Background

2.1 Aghion et al. (2010)'s empirical work on university governance and research performance

The first empirical evidence of the importance of autonomy and competition among universities for research performance originated in Aghion et al. (2010). The authors are motivated by the fact that the performance of European universities as a whole trails the US by a wide margin (Aghion et al. (2007)), and several European countries are considering reforms that would change their university systems to resemble those of the US, which are given more autonomy and face greater competition.

The authors create an autonomy and competition index of universities using both the survey and administrative data. First, the authors present the positive correlation between the autonomous and competitive index of universities concerning their university ranking[3]. Second, using the number of publications in the fields of engineering, art science, hard science, and patent counts as dependent variables separately, the authors indicate the greater impact

of an individual researcher and through indirect costs (facilities and administration). Hence, the receipt of a grant spills over into the university as a whole. Therefore, the effect of funding on university research output as a whole is significant.

[3]Aghion et al. (2010) measured the autonomy and competition index based on the following nine components: (1) no government approval of university budget; (2) freedom to select students; (3) freedom to differentiate wages; (4) control over professor appointments; (5) low endogamy; (6) proprietary buildings; (7) freedom to set curriculum; (8) a low share of public funding, and (9) a large share of research grants.

of increases in government funding on university research output if a university's autonomy and competition index is high. With derivations for these results, the authors call for university reform that strengthens the function of autonomy and competition among European universities.

The study is illuminating as a first step, however, there are two empirical difficulties in fully and robustly supporting the study's policy recommendation. First, the autonomy and competition index of universities is an endogenous variable, therefore, the results do not capture causal effects. Second, although the authors strongly insist on the need to reform universities to achieve more autonomy and competitiveness, the authors do not analyse the actual situation, for instance, university reform where these components actually vary. Consequently, the estimation results are incomplete and provide insufficient policy implications to support such governance reform.

To identify the effects of (reform on) governance or managerial factors on university performance, therefore, an event that exogenously shifts those factors is required.

2.2 Partial privatization of the national universities in Japan

This subsection provides an overview of the partial privatization of national universities in Japan that will be used to identify the effect of increasing university autonomy and competition.

In 2004, all national universities were partially privatized (corporatized) under the National University Corporation Law and acquired the status of a national university corporation, a juridical public body separated from the central government. Prior to this reform, although academic freedom and partial autonomy were guaranteed, the organization structure, finance, and operation of national universities were directly controlled by the Ministry of Education, Culture, Sports, Science and Technology (MEXT), a public administrative organization. The government (and MEXT) also took initiative in this reform with three reforming points:

> identifying the missions and goals of universities, defining the responsibility and granting autonomy in management through the adoption of business management tools, and introducing a competitive mechanism among universities in addition to respecting more student needs and the business world (Yamamoto (2011) and the

"New Vision for National University Corporations").

After the reform, national universities were granted greater autonomy in their operations (Center for National University Finance and Management (2004); Oba (2007); Yamamoto (2011)). This administrative reform included four essential features. First, a more autonomous administrative management system was centered around the president of each national university. Second, the management system intensified the degree of discretion in the financial management system. Until today, the largest part of the budget of each national university was allotted as a lump sum by MEXT, called "operating support funds." Before the reform, the operating support funds had a regulatory framework that involved bureaucratic restrictions on how much to invest where, and extending the budget to the next fiscal year was not allowed. After the reform, these two restrictions were abolished. Third, term employment and performance-based payment became available. Fourth, national universities began to own their own assets, such as buildings and debt. Consequently, presidents (and the boards of directors) of national universities assumed more autonomous control of each university based on block grant budgets and their own revenue obtained from tuition, entrance fees, competitive funds, hospital revenues, and other sources of income-generating activity.

National universities are required to set their own targets in the form of a medium-term plan, which is approved by the Minister of MEXT. Universities are accountable for enhancing the quality of teaching, research, and operations to meet social expectations. University performance is now reported to the public through an annual report that is reviewed by the Evaluation Committee. Moreover, MEXT has continued to exert substantial power over the overall national university system to date despite the delegation of authority in university operations. Accordingly, it is more appropriate to call this reform a type of "partial" privatization, as discussed in Gupta (2005). The author focuses on partial privatization of state-owned firms where the stock market monitors and rewards managerial performance and the government remains the controlling owner.[4].

[4]From another perspective, Yamamoto (2011) summarizes this particular government-national university relational change as follows:

> The relation between national universities and government was transformed from the hierarchical or simple principal-agent model (Holmstrom (1979)) within the ministry and replaced by an arrangement of a multiple principal and agent relationship (Bernheim and Whinston (1986)).

In addition to managerial structure changes, the operational support funds, which are over-represented in the budgets of national universities to date (about half of their budget), are obligatorily decreasing by 1% annually. The main culprit of this annual reduction is often assumed to be the government, which is accused of attempting to curtail government expenditure from fiscal consolidation efforts, and this seems to be true to some extent. However, the main reason is that increasing managerial efficiency in the allocation and utilization of resources has become mandatory for national universities (Center for National University Finance and Management (2004)). Therefore, many universities have promoted managerial efficiency reforms.

More importantly, this substantial reduction in budget has provided incentive for competitive fund acquisition efforts and income-generating activities, thereby creating a more competitive environment for national universities. Faculty members are increasingly encouraged to acquire external research grants, such as Grants-in-Aid for Scientific Research (Kaken hi) and other types of competitive funds to compensate for the loss in operational support funds. Accounting standards based on corporate accounting principles were introduced in conjunction with the structural changes, thus making it difficult to use the information on the balance sheet before 2004 for simple comparison, but Table 1, which is quoted from Urata (2010), shows that the ratio of operational support funds in 2008 to that of 2005 is approximately 0.956, and the operational fund remained the largest portion of revenue during that period. In contrast, the ratio of competitive-type funds in 2008 to that of 2005 is above 1.1 for any type of competitive fund. These frequently mentioned incentives and data suggest that partial privatization intensified competition, particularly among Japanese national universities.

It is critical for my identification strategy that the 2004 reform represented a forced exogenous event incited by external pressure (particularly among researchers) on national universities (Amano (2008)). Combined with large reductions in governmental budget support, expected disruption of institutional transition, and additional clerical duties mainly because of the increased accountability for university operations, the debates among researchers in national universities focused on whether the new governance and management system would hinder their research activity. Also, some claimed that the reforms were promoted as part of an administrative and fiscal consolidation government attempt to detach national universities from MEXT. Therefore, national universities were consistently skeptical of the consequences

Table 1: Main Sources of Revenue for National University Corporations (million Yen)

		2005	2008	2008/2005
Operating Support Fund		1138866	1088668	0.956
Competitive-type Funds (total)		364313	469537	1.289
	Consignment Study	122303	172262	1.408
	Commissioned Development	11453	18388	1.606
	Donation	67654	82597	1.221
	Grants-in-Aid for Scientific Research	132647	147071	1.109
	COE	25392	39180	1.543
	Other Fund	4864	10039	2.064
Own Revenue (total)		1000990	1086565	1.085
	Tuition	300591	293492	0.976
	Entrance Fee	56653	55713	0.983
	Hospital Revenue	643747	737360	1.145
Other Sources of Revenue		82958	136933	1.651
Total		2587127	2781703	1.075

Note: This table is quoted from Urata (2010). COE (Center of Excellence) is large-scale research funding from the Japanese government.

of the reforms and did not take initiative when it was enforced[5].

I briefly summarize the evaluation of partial privatization conducted by the Center for National University Finance and Management, an independent administrative corporation that was established to promote the education and research activity of national universities. To evaluate the perceived changes of the 2004 reform, the corporation conducted a series of interviews with all of the national university presidents in 2004, 2006, and 2009. In 2009, 84% of the presidents considered that the reforms had a positive impact on the individuation of each university; 80% reported positive impacts on administrative improvement; 76% reported positive impacts on autonomy enhancement; 70.6 % reported positive impacts on the expansion of social contribution activity, and 66.6% reported positive impacts on the enhancement

[5] In Amano (2008), a very detailed description of the unique consequences that support the exogeneity of this event for national universities is expressed by the author, who had extensive involvement in this reform as a researcher in the Center for National University Finance and Management.

of competitiveness[6].

In conclusion, the partial privatization of national universities changed exogenously some of the autonomous and competitive components. This situation is thus suitable to test the hypothesis that greater university autonomy and competitive environment produces greater output.

To extend Aghion et al. (2010)'s analysis, it is critical to note that the autonomous and competitive components that are intensified or induced by the partial privatization also satisfy five-ninths of the autonomy and competition criteria that the authors used to construct the autonomy and competition index for each university. These include, for instance, no government approval of university budget, proprietary buildings, freedom to differentiate wages, a low share of public funding, and a large share of research grant funding. The partial privatization of the national universities weakened the role of government in approving university budgets, enabled universities to own buildings as proprietary assets, allowed them to differentiate wages, decreased the share of public funding, and increased the share of competitive-type research grants in conjunction with other governance changes described above.

2.3 The effect of partial privatization on national university hospitals

Aghion et al. (2010)'s hypothesis expects the partial privatization of national universities to increase research output. However, a survey conducted by the government (MEXT (2010)) and many researchers in university hospitals indicates that the reform led to a decrease in the research output of the medical science field in national university hospitals.

University hospitals have three different missions: education, research, and providing clinical services. However, after reform, the third mission, acquiring hospital revenue, was encouraged. This was probably because of the fourth structural change outlined in the previous section, that is, national universities started to own their assets but also their debt, which they were not previously obligated to repay. The debt, which is associated with the man-

[6]The main focus is whether partial privatization changed the governance style; however, there is controversy concerning the effect on research activity. In the 2009 interviews, 50.4% of faculty heads of each national university responded that the partial privatization's effect was negative, and only 23.2% reported a positive effect.

agement of university hospitals amounted to one trillion yen and induced university hospitals to engage in acquiring additional hospital revenue. Another explanation is that when a university acquires more autonomy, the university shifts and focuses more on income-generating activities to maintain or enlarge its budget: hospital revenue represents the greatest source of revenue for universities with a hospital[7]. Consequently, university hospitals are considered to have increased clinical services, and the increased workload crowded out research-generating efforts.

I collect data on university hospital revenue from balance sheet of each national university, and the data show that the mean of the ratio of national university hospital revenue in 2009 to that of 2005 is approximately 1.275. Because of data limitations, I do not have the full counterpart information on private universities (approximately half of the full sample of private university hospitals in my analysis), but the ratio of hospital revenue of private university hospitals in 2009 to that of 2005 is approximately 1.093, indicating that acquired hospital revenue was approximately 16.7% higher in national university hospitals. The estimated impact of the partial privatization on university hospital revenue is also shown in section 4.5.

A survey conducted among national university hospitals (see MEXT (2010)) in 2005 reports that 48.9% of faculties experienced reductions in time spent on research activity, and this percentage increased by 77.8% in 2008. A survey in 2005 reports that 48% of faculties in university hospitals experienced an increase in time spent on clinical services, and this percentage increased by 66.7% in 2008. A survey in 2005 reports that 11.1% of faculties in university hospitals experienced a reduction in time spent on education, and this percentage increased by 24.4% in 2008.

These contexts and data imply that partial privatization, which encourages revenue-generating activity, leads to a decrease in research output of university hospitals. However, another theory may imply mitigation of the likelihood of this deleterious effect. For example, clinical research activities may be direct by-products of usual clinical services, and scientific articles and the provision of clinical services may routinely convert related pieces of knowledge. For instance, Azoulay et al. (2009) concluded that "the often voiced concern that patenting in academe has a nefarious effect on public research output is misplaced". The following results

[7] Table 1 shows that the revenue from university hospitals constitutes a large portion of university revenue.

of this paper provide some insights into this theory.

3 Data and Identification

3.1 Data

I create a list of Japanese national and private universities[8] from the Grants-in-Aid for Scientific Research (KAKEN) database, which records all research projects that received Grants-in-Aid for Scientific Research (Kaken-hi). Grants-in-Aid for Scientific Research is the largest and most representative competitive research fund in Japan. The KAKEN database includes affiliation data; therefore, I can identify universities that received the grant. I restrict my sample to universities that appear in this affiliation data because the database indicates the universities engaging in research activity. Next, from this university set, I excluded universities that did not publish during the period 2000 to 2003 to select the universities more actively involved in research[9].

Data on research output is based on articles contained in the web database "ISI Web of Science." The database is provided by Thomson Scientific and includes all papers from a large number of research journals. From this database, I compute annual paper publication counts for each university. I count equally all papers for which a university is listed in the affiliation data.

I use the Journal Citation Reports (JCR), published by Thomson Scientific, to measure the quality of the articles published. JCR reports the impact factor (IF) of each journal contained in the Web of Science. The impact factor is an index of the frequency of average journal article citations in particular periods, and JCR reports impact factors annually. I select only the journals with IF information for the period 2000 to 2009. I then take the average IF for each journal during the period 2000 to 2009 and create "average IF". I weight each article published by the universities in my sample by the corresponding journal's average IF and then sum these weights for all the published output in a given year.

To compare my results with the results of Aghion et al. (2010), I create output for en-

[8]In Japan, there are basically three types of universities, national, private, and public. I omit public universities because these universities are incorporated during my sample period, but the timing was intentionally decided by public universities.

[9]The results remain robust if I include universities that did not publish.

gineering, economics (I arbitrarily choose economics as the counterpart of art science), and hard science[10]. I also compute the output for medical science (clinical medicine and immunology), but I limit the universities to those with university hospitals because they are the main producers of medical science research[11].

3.2 Identification

To detect the impact of partial privatization on national university research outcomes, I use difference-in-difference estimators in a linear model. The first specification of this fixed-effect model is:

$$ResearchOutcome_{it} = \beta(national_i \times post2004_t) + \lambda_t + \theta_i + \varepsilon_{it} \tag{1}$$

where i indicates university; t indicates year; $ResearchOutcome_{it}$ is the output variable computed in Section 3.1; $national_i \times post2004_t$ is a dummy variable that takes the value of one if the university i is national and the observation at year t is after 2004 and zero otherwise; λ_t is the year dummy capturing effects common to Japanese universities; θ_i represents all time-invariant university-specific characteristics for university i, and ε_{it} represents university-specific temporal shocks[12].

I assume that in the absence of partial privatization, national universities and private universities follow similar research trends. Consequently, β detects whether or not the reform impacted the research outcome of the national university. I check the plausibility of this assumption in the robustness check. Moreover, to control for potential heteroskedasticity and serial correlation, standard errors are clustered at the university level (Bertrand et al. (2004)).

Given the long-term nature of institutional transition and the annual reductions in the university system operational budget in this specific event, there is a chance that the effect on research could be gradual. To provide a more detailed description of the evolution of the

[10] Hard science is the sum of research output from the following fields; biology, physics, and chemistry.

[11] I obtain the same results if I include universities that have no hospital.

[12] I also try the following specification:

$$ResearchOutcome_{it} = \beta(national_i \times post2004_t) + \mathbf{X}_{it}\beta + \lambda_t + \theta_i + \varepsilon_{it} \tag{2}$$

where $\mathbf{X}_{it}$ incorporate a full suite of regional dummy times year dummy, age (of a university), square of age as well as interaction of these variables, but the main results remain robust regardless of the different specifications.

impact, I also estimate the second specification of the fixed-effect model:

$$ResearchOutcome_{it} = \sum_{t=2004}^{2009} \beta_t(national_i \times \lambda_t) + \lambda_t + \theta_i + \varepsilon_{it} \tag{3}$$

where $national_i$ is a dummy variable that takes the value of one if university i is a national university and zero otherwise. Each coefficient β_t captures the effect in a specific year after 2004.

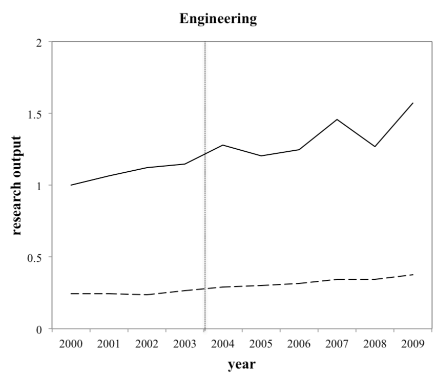
These estimation strategies are adequate, first, because all national universities were partially privatized uniformly in 2004 without selection, as stated in Subsection 2.2. Second, these specifications can eliminate the common macro shock in the research trend in both national and private universities by common year effects. For instance, in the field of medical science, all university hospitals in Japan experienced a system change in 2004 (*New Postgraduate Medical Education Program*) that reduced the number of medical students with whom university hospitals collaborated by obligating the students to work as clinicians for two years (Iizuka and Watanabe (2015)). This might have negatively affected the research activity of university hospitals because it decreased the labor force. There is a danger, therefore, that an econometrician may capture the effect instead of the partial privatization. However, my approach avoids such potential threats to the identification by capturing the common macro shock via year effects. Third, these fixed effect strategies can eliminate unobservable university-specific components and alleviate the heterogeneity of each university, such as scale and differences in fundamentals between national and private universities.

4 Data Analysis

4.1 Main results

Figure 1 show the annual total research output for three research areas of Japanese national and private universities from 2000 to 2009, standardized at the initial total output of national universities.

There are three notable factors with respect to the analysis. First, although the levels of all research fields are significantly different between national and private universities in each figure, this factor does not become a serious threat to my analysis. Since I assume the fixed-effect specification, the differences in levels disappear. Second, the plots in Engineering, Economics, and Medical science suggest that the trends in research outputs in national and private universities evolved similarly before 2003. These points will be quantitatively checked in the robustness section again. Third, for national universities comparatively different behaviors are evident after 2004 in the fields of engineering, economics and medical science. After 2004, research output for engineering and economics increased for national universities. In contrast, research output for medical science decreased for national universities after 2004. For private universities, the trend in research output for engineering and medical science seems stable during the study period. The trend in economics for private universities shows an increase during the study period, but the increase seems to be slightly lower than that of national universities after 2004. The patterns of the series in Engineering and Economics suggest, therefore, consistency with the hypothesis that partial privatization has a positive impact. However, the pattern of the series for medical science is consistent with the prediction of a negative impact of partial privatization.



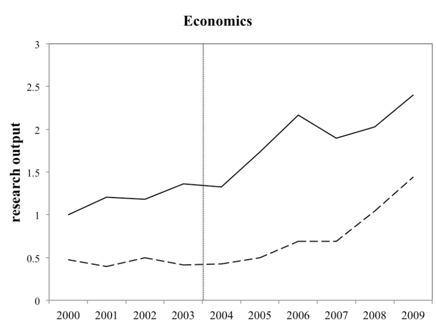


Table 2 reports descriptive statistics for my sample of universities in Japan. Compared to private universities, national universities tend to produce greater research output for all

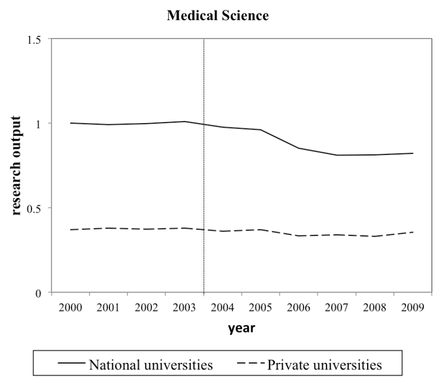


Figure 1: Trend of Total Research Output in National and Private Universities (standardized at the inital total output of national universities)

research fields. This result indicates that the national universities in Japan are more research intensive than private universities. For estimation, I conduct robustness checks to balance the data by sub-grouping universities with their research achievements.

Table 2: Descriptive Statistics

	Engineering			Economics			Clinical Medicine & Immunology		
	All	National	Private	All	National	Private	All	National	Private
Publication (Raw count)	11.52	31.64	3.35	1.46	3.16	.65	143.64	195.17	89.46
	(32.21)	(53.54)	(7.99)	(4.01)	(6.41)	(1.50)	(127.54)	(149.71)	(64.05)
Publication (Impact factor weighted)	9.87	27.54	2.69	.70	1.55	.29	445.42	626.14	255.43
	(29.44)	(49.50)	(6.89)	(1.97)	(3.14)	(.75)	(478.18)	(581.24)	(209.28)
Established year	1956.56	1949.54	1959.42	1952.08	1944.23	1955.80	1950.93	1944.93	1956.93
	(18.87)	(17.90)	(18.55)	(19.65)	(18.38)	(19.21)	(18.63)	(18.85)	(16.54)
COE (rate)	.061	.13	.03	.07	.15	.03	.27	.44	.10
	(.24)	(.34)	(.18)	(.25)	(.36)	(.17)	(.45)	(.50)	(.30)
Hospital (rate)	.30	.54	.20	.27	.66	.09	1.0	1.0	1.0
	(.46)	(.50)	(.40)	(.45)	(.48)	(.29)			
Number of universities	263	76	187	146	47	99	80	40	40

Note: Standard errors are in parentheses. COE (Center of Excellence) is large-scale research funding from the Japanese government.

To quantify the differences observed in Figure 1 to Figure 3 for the research output of national and private universities after 2004, I estimate difference-in-difference models that control for the effects of unobservable university-specific characteristics. Table 3 reports the baseline estimates for my basic specifications in equation (1) with standard errors clustered at the university level. The first and second columns report the results for the fields of engineering and economics. These two coefficients of the interaction $national_i \times post2004_t$ indicate that, after 2004, the research output was significantly higher for national universities that experienced partial privatization[13].

In the third column of Table 3, I use the medical science field as output. In contrast to the other results, the impact in university hospital is significantly negative, indicating that the special features of this field, discussed in Subsection 2.3, led to such a result.

Table 3: The Effect of Partial Privatization on National University (Difference-in-differences)

	Engineering	Economics	Medical science
National × post 2004	5.150***	0.840**	-66.83***
	(1.812)	(0.351)	(18.02)
Observations	2,030	910	800
R-squared	0.08	0.098	0.235
Number of Univ	203	91	80
Outcome Mean of National University (2000-2003)	24.14	2.01	672.25
Effect in %	21.3%	41.8%	-9.9%

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

Table 4 provides the results of equation (2), that is, annual evolution of the effects after the partial privatization of the national universities with different degrees of exposure to institutional change. This is the second baseline result. These columns report the estimated coefficients on the interactions between a national university dummy and time dummies for

[13]The value of β does not necessarily identify the magnitude itself of the results especially for engineering, because the robustness check below show that my main result in this field may indicate the upper bound of the effect.

the years 2004 to 2009 for each research field with clustered standard errors at the university level. The first and second columns of Table 4 show that the effect of institutional change in engineering and economics appeared positive and significant during the study period 2004 to 2009. The coefficients for engineering increased monotonically during the period 2005 to 2009 with a dip in 2008. For the clinical science field, the third column indicates that the effect is significantly negative during the study period and supports the notion that the effects evolved monotonically.

Table 4: The Dynamic Effect of Partial Privatization on National University

	Engineering	Economics	Medical science
National × year 2004	4.272**	0.203	-5.699
	(1.713)	(0.235)	(15.48)
National × year 2005	2.312*	0.726**	-23.63
	(1.291)	(0.354)	(14.81)
National × year 2006	3.143**	1.142**	-70.54***
	(1.385)	(0.548)	(26.08)
National × year 2007	7.762***	0.969**	-101.9***
	(2.523)	(0.375)	(25.99)
National × year 2008	3.268	0.811*	-93.81***
	(2.255)	(0.432)	(25)
National × year 2009	10.14***	1.190*	-105.4***
	(3.043)	(0.627)	(22.45)
Observations	2,030	910	800
R-squared	0.1	0.11	0.272
Number of Univ	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

For the most part, the results in the first and second columns of Table 3 and Table 4 support Aghion et al.'s (2010) hypothesis, which suggests that universities with more autonomy and competitiveness produce more output. I select engineering and economics as counterparts for the authors' empirical findings. The authors' results lack the causality of the above hypothesis; however, my results indicate the causal effect and reflect direct implications of the university reform: introducing autonomy and competitive status to the universities leads to more research output for the engineering and economics fields.

In contrast, for the field of medicine science, I present significant negative effects. This is consistent with the expectation that partial privatization that encourages revenue-generating activity results in a decrease in the research output of university hospitals.

4.2 Heterogenous effects

Now that I have documented the substantial effect that partial privatization has on research performance, I attempt to anatomize this effect by investigating its underlying mechanism. Specifically, I look at the heterogenous effect of partial privatization depending on the research intensiveness of each national university.

I voluntary divide universities into two groups according to whether each university is in the top 50th percentile or the bottom 50th percentile of the distribution of the summation of research output for the period 2000 to 2003 for each university. The variables *top* 50 *percentile* and *bottom* 50 *percentile* in Table 5 and Table 6 are dummy variables indicating whether each university falls in the top 50 percentile tier or bottom 50 percentile tier of the distribution of the research intensity.

For the field of engineering and economics, the results in Table 5 report that the effect was positive among relatively more research-intensive universities, and the effect was negative among relatively less research-intensive universities. The corresponding fields in Table 6 indicate that among more research-intensive universities, the positive effect gradually evolved as time elapsed. Among less research-intensive universities, the negative effect gradually evolved as time elapsed. This is evidence of evolution towards resource concentration in top research universities through intensified competition; resource allocation has increasingly become performance and competition-based. The resources involved, for instance, are competitive-type research acquisition efforts and employment of new productive faculty members. This expansion of inequality, seemingly because of intensified competition, resulted in an overall increase in the research performance of national universities.

However, in medical science, national universities experienced a reduction in research outcome regardless of the research intensiveness suggesting the dominance of other channels, such as a reduction in the time spent on overall research activity because of the increased workload of clinical services, as documented in subsection 2.3.

Table 5: The Heterogenous Effects of Partial Privatization on National Universities

	Engineering	Economics	Medical Science
National × post 2004 × top 50th percentile	6.267***	0.982**	-86.45***
	(2.099)	(0.393)	(24.55)
National × post 2004 × bottom 50th percentile	-1.044***	-0.155**	-28.98**
	(0.307)	(0.0714)	(11.2)
Observations	2,030	910	800
R-squared	0.091	0.108	0.25
Number of Univ	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

4.3 Competitive-type fund acquisition efforts

In the previous subsection, with respect to engineering and economics, I documented evidence that the baseline overall positive average treatment effects for the treated (ATT) might be partially a result of intensified competition among national universities. To confirm this observation, I investigate the effect of partial privatization on acquisition efforts of competitive-type research grants, that is, Grants-in-Aid for Scientific Research. Specifically, I use the acquisition number of Grants-in-Aid for Scientific Research as an explanatory variable and repeat the previous regression exercises. Although Grants-in-Aid for Scientific Research (Kaken-hi) represents only one-third of the entire competitive-type grant, as seen in Table 1, I selected it because no other comparable inputs are available for both national and private universities in Japan.

The columns in Table 7 show that partial privatization has a positive impact on the acquisition of competitive-type funds, indicating the promotion of competitive research activity among national universities.

Table 6: The Dynamic Heterogenous Effects of Partial Privatization on National Universities

	Engineering	Economics	Medical Science
National × year 2004 × top 50th percentile	5.143**	0.233	-8.357
	(1.994)	(0.267)	(19.96)
National × year 2005 × top 50th percentile	2.874*	0.820**	-24.52
	(1.504)	(0.401)	(20.35)
National × year 2006 × top 50th percentile	3.871**	1.334**	-98.30***
	(1.606)	(0.618)	(36.58)
National × year 2007 × top 50th percentile	9.390***	1.117***	-135.3***
	(2.924)	(0.42)	(35.19)
National × year 2008 × top 50th percentile	4.055	0.967**	-121.4***
	(2.639)	(0.485)	(34.65)
National × year 2009 × top 50th percentile	12.27***	1.423**	-130.9***
	(3.516)	(0.702)	(29.51)
National × year 2004 × bottom 50th percentile	-0.555*	-0.00526	-0.573
	(0.329)	(0.0586)	(15.65)
National × year 2005 × bottom 50th percentile	-0.801***	0.067	-21.92*
	(0.304)	(0.0811)	(12.57)
National × year 2006 × bottom 50th percentile	-0.892**	-0.202**	-17
	(0.369)	(0.0857)	(14.21)
National × year 2007 × bottom 50th percentile	-1.270***	-0.0658	-37.47**
	(0.379)	(0.0799)	(16.2)
National × year 2008 × bottom 50th percentile	-1.100**	-0.282**	-40.67***
	(0.472)	(0.123)	(13.68)
National × year 2009 × bottom 50th percentile	-1.648***	-0.442**	-56.23***
	(0.486)	(0.177)	(16.56)
Observations	2,030	910	800
R-squared	0.117	0.124	0.303
Number of Univ	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

For engineering, column 1 in Table 8 decomposes the positive ATT into positive impact among research-intensive universities and negative impact among less research-intensive universities. This pattern is reflected in the first column of Table 9, which exhibits the evolution of the heterogenous impact of this institutional transition.

In economics, column 2 in Table 8 decomposes the positive ATT into positive impact among research-intensive universities and, although not significant, a negative coefficient among less research-intensive universities. This pattern is reflected in the second column of Table 9, which also exhibits the evolution of the heterogenous impact of this institutional transition.

Importantly, the results in column 1 (engineering) and 2 (economics) of Table 9 almost perfectly delineate the same positive increasing pattern among *top 50th percentile* universities and the same negative decreasing pattern among the *bottom 50th percentile* universities in column 1 and column 2 of Table 6. Therefore, the expansion of inequality in research performance after the reform coincided with, and were partially attributable to, intensified competition to acquire competitive-type research funding. Additionally, the resulting resource allocation inequality has an overall positive impact on national universities' research performance. These findings are consistent with the competitive mechanism suggested in Aghion et al. (2010).

Table 7: The Effects of Partial Privatization on Competitive-type Grant Acquisition (Difference-in-differences)

	Engineering	Economics	Medical Science
National × post 2004	5.766***	3.804**	34.71***
	(1.923)	(1.565)	(5.396)
Observations	2,030	910	800
R-squared	0.114	0.231	0.34
Number of Univ	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

Table 8: The Heterogenous Effects of Partial Privatization on Competitive-type Grant Acquisition

	Engineering	Economics	Medical Science
National × post 2004 × top 50th percentile	7.058***	4.547***	9.862***
	(2.216)	(1.718)	(3.069)
National × post 2004 × bottom 50th percentile	-1.401**	-1.397	20.07***
	(0.646)	(1.18)	(4.382)
Observations	2,030	910	800
R-squared	0.129	0.249	0.426
Number of Univ	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

4.4 Research quality

I analyze how the partial privatization shifted the research activity of researchers in national universities.

I perform another base specification (2) by creating the outcome for which the level of each journal is in a higher or lower tier. Table 10 shows the results. The first and third column of Table 10 show the results for engineering and economics when I use journals with an average impact factor (IF) above the 70 percentile tier of the entire journal quality distribution for creating output. Almost all of the results are the same as the result that uses the full set of journals. However, in the second column of Table 10, if I use journals with an average IF below the 30 percentile tier for creating output, the results become less significant for all of the periods.

Table 11 uses the average quality per article. That is, the IF-weighted output divided by the corresponding number of research papers in a specific year, as output, and repeated specification (2). The results show less significant effect in engineering. For engineering, combined with the results in Table 10, the results suggest a pattern whereby the publishing activity shifted, particularly to higher ranked journals after partial privatization without

Table 9: The Dynamic Heterogenous Effects of Partial Privatization on Competitive-type Grant Acquisition

	Engineering	Economics	Medical Science
National × year 2004 × top 50th percentile	3.904**	3.029***	7.730**
	(1.586)	(1.045)	(3.156)
National × year 2005 × top 50th percentile	6.266***	3.027**	21.02***
	(2.034)	(1.478)	(4.427)
National × year 2006 × top 50th percentile	6.327***	5.018***	32.10***
	(2.405)	(1.853)	(6.591)
National × year 2007 × top 50th percentile	8.932***	5.667**	49.07***
	(2.707)	(2.186)	(9.296)
National × year 2008 × top 50th percentile	7.640***	5.737***	42.92***
	(2.853)	(2.127)	(8.356)
National × year 2009 × top 50th percentile	9.282***	4.804*	58.41***
	(3.029)	(2.466)	(10.96)
National × year 2004 × bottom 50th percentile	-0.764	-1.319**	27.86***
	(0.532)	(0.512)	(6.098)
National × year 2005 × bottom 50th percentile	-0.621	-1.607*	36.26***
	(0.783)	(0.951)	(8.218)
National × year 2006 × bottom 50th percentile	-1.014	0.812	37.15***
	(0.723)	(2.012)	(8.471)
National × year 2007 × bottom 50th percentile	-1.351	-0.217	34.81***
	(0.819)	(1.541)	(8.428)
National × year 2008 × bottom 50th percentile	-2.018**	-2.611*	32.23***
	(0.88)	(1.46)	(8.937)
National × year 2009 × bottom 50th percentile	-2.641***	-3.438***	34.09***
	(0.817)	(1.265)	(9.606)
Observations	2,030	910	800
R-squared	0.138	0.261	0.418
Number of Univ	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

Table 10: The Dynamic Effect of Partial Privatization on Research Output Using High or Low Impact Factor Journals Only

	Engineering		Economics		Medical science	
Journal quality	over 70th percentile	under 30th percentile	over 70th percentile	under 30th percentile	over 70th percentile	under 30th percentile
National × year 2004	4.581***	0.0814	0.061	-0.0164	-3.91	-1.421
	(1.743)	(0.118)	(0.228)	(0.0435)	(14.38)	(1.016)
National × year 2005	2.440*	0.00914	0.263	0.126	-19.81	-3.377***
	(1.246)	(0.123)	(0.254)	(0.116)	(14.12)	(1.198)
National × year 2006	2.347**	0.355**	0.527*	0.205	-64.40**	-4.621***
	(1.172)	(0.18)	(0.3)	(0.143)	(25.03)	(1.262)
National × year 2007	7.911***	-0.106	0.489**	0.186*	-92.94***	-3.281**
	(2.482)	(0.17)	(0.231)	(0.11)	(25.5)	(1.273)
National × year 2008	3.262	0.0286	0.246	0.229**	-81.80***	-4.189***
	(2.167)	(0.183)	(0.268)	(0.101)	(24.37)	(1.33)
National × year 2009	10.66***	-0.271	0.755**	0.212	-86.63***	-3.720**
	(2.946)	(0.176)	(0.375)	(0.146)	(21.83)	(1.51)
Observations	2,030	2,030	910	910	800	800
R-squared	0.111	0.033	0.058	0.075	0.258	0.089
Number of id	203	203	91	91	80	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

changing the average quality per paper.

Columns 5 and 6 of Table 10 show the results for medical science, and these two columns indicate the same decreasing pattern as the baseline results regardless of journal level. Combined with the zero effect on average quality per paper in the third column of Table 11, this indicates that the partial privatization of national universities induced a quantitative overall reduction in the research activity of university hospitals.

Table 11: The Dynamic Effects of Partial Privatization on Average Quality Per Paper

	Engineering	Economics	Medical Science
National × year 2004	0.0647	0.0493	-0.0386
	(0.0558)	(0.0521)	(0.11)
National × year 2005	0.0333	0.0939*	-0.0921
	(0.0445)	(0.0541)	(0.0919)
National × year 2006	0.0347	0.058	0.0624
	(0.0617)	(0.0534)	(0.082)
National × year 2007	0.086	0.199***	-0.085
	(0.057)	(0.0626)	(0.0788)
National × year 2008	0.052	-0.0102	0.0558
	(0.061)	(0.0628)	(0.0896)
National × year 2009	0.101*	-0.0153	0.0605
	(0.0567)	(0.0696)	(0.0849)
Observations	2,030	910	800
R-squared	0.01	0.029	0.101
Number of Univ	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

4.5 University Hospital Revenue

One interpretation of the negative effect in medical science is that an increase in the time spent on providing clinical services may have crowded out the research activity of national university hospitals. Hence, if it is true, it might have increased the national university hospitals' revenue. To see this, I investigate the impact of partial privatization on university hospital revenue.

Because we cannot use data on balance sheet before 2004, as I mentioned in subsection 2.2, we set 2006 as the alternative enforcement year and set 2005 as the pre-treatment year. Under such setting, I repeat the difference-in-differences estimation using the data on hospital revenue during 2005 - 2009. Table 12 presents the result. The result shows that the partial privatization significantly increased the log of hospital revenue among national university hospitals. This appears to emphasize the mechanism, described in subsection 2.3, that induced the robust negative effect on the research outcome in national university hospitals.

Table 12: The Effects of Partial Privatization on hospital revenue

	Hospital revenue (log)
National × post 2006	0.142***
	(0.0282)
Observations	295
R-squared	0.688
Number of Univ	59

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

4.6 Robustness check

In this subsection, I assess the validity of the results of the previous sections using a number of methods.

Regional Effects

To control for the effect specific to each region in Japan, I also show the cases where the full set of prefecture level dummy of university i interacted with year dummies (that is, $Prefecture_i \times \lambda_t$) are included in the baseline two specifications. Table 13 shows that the main qualitative results stay the same even with this addition.

Henceforth, almost all of the robustness checks below are reported with or without regional effects.

Placebo Test

The difference-in-difference specification in equation (1) depends upon the assumption of a parallel trend in the absence of partial privatization. Although this assumption is not directly testable, it is straightforward to assess the plausibility of the assumption by conducting a placebo test. Under the parallel trend assumption during the periods $t = \{t_{-1}, t_0, t_1\}$ where $t_{-1} < t_0 < t_1$, t_0 indicates a pre-treatment period, t_{-1} indicates a period before t_0, and t_1 indicates a post-treatment period,

$$E[Y(t_0) - Y(t_{-1})|National = 1] - E[Y(t_0) - Y(t_{-1})|National = 0] = 0 \tag{4}$$

also holds. If I apply the same specification as equation (1) for period $t = t_{-1}$ and $t = t_0$, placebo treatment effect β_0 can also be identified, and the expected magnitude is relatively closer to zero. To implement this test, I reproduce the estimation of Table 3 with pre-2004 data only. I divide the pre-2004 data into two approximately equal periods depending on whether the observation is before or after 2002. Then I proceed as in Table 3 using a post-2002 dummy in place of the post-2004 dummy. This divide is arbitrary, but the following results remain unchanged if I use a post-2001 dummy in place of the post-2002 dummy.

Table 14 shows the results of placebo tests. The first column report the placebo effect for engineering. The coefficient β_0 is insignificant and approximately 0.46 of the magnitude presented in Table 3 suggesting the hypothesis that, at least prior to 2004, trends in research output were similar[14]. The main concern with this check is whether the magnitude of this coefficient is reasonably smaller than the corresponding coefficient in Table 3. The same coefficient with regional effects in the fourth column is insiginificant and approximately 0.32 of the magnitude presented in Table 13. Both of the coefficients β_0 for economics and medical science in the second and third columns of Table 14 are approximately zero (approximately 0.27 of the baseline coefficient in economics and 0.05 of the baseline coefficient in medical science) and statistically insignificant, strongly indicating the validity of a parallel trend assumption, at least before 2004.

However, the parallel trend assumption seems to be violated for hard science. The first column in Table 15 reports the same setup as base equation (1), where the parameter of interest is the coefficient of $national_i \times post2004_t$ for the field of hard science. The coefficient is significantly positive. However, its falsification coefficient in the second column is significantly larger than the coefficient of $national_i \times post - 2004_t$. Consequently, I cannot compare my results for hard science with those of Aghion et al. (2010), and the estimation result remains

[14] We do not have the critical threshold of the ratio on $|\beta_0/\beta|$ that rejects the plausibility of the parallel trend assumption. The largest ratio is 50.73% when Abadie and Dermisi (2008) concluded that the parallel trend assumption is plausibly satisfied.

Table 13: Regional Effects (Difference-in-Difference & Dynamic Effect)

	Engineering		Economics		Medical science	
	DID	Dynamic Effect	DID	Dynamic Effect	DID	Dynamic Effect
National × post 2004	7.794***		1.748***		-145.1**	
	(2.751)		(0.615)		(59.71)	
National × year 2004		6.902**		0.323		-4.291
		(2.933)		(0.448)		(31.22)
National × year 2005		4.073**		1.408**		-45.12
		(1.955)		(0.65)		(48.63)
National × year 2006		4.986***		2.285**		-194.2*
		(1.917)		(1.025)		(98.26)
National × year 2007		10.80***		1.910***		-219.3**
		(4.026)		(0.631)		(88.46)
National × year 2008		4.936		1.806**		-206.6**
		(3.618)		(0.787)		(95.3)
National × year 2009		15.07***		2.753***		-200.8***
		(4.388)		(1.003)		(64.21)
Prefecture dummy × year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,030	2,030	910	910	800	800
R-squared	0.25	0.276	0.332	0.369	0.524	0.595
Number of Univ	203	203	91	91	80	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

Table 14: Placebo Test

	Engineering	Economics	Medical science	Engineering	Economics	Medical scienc
National × post 2002 (β_0)	2.348	0.224	3.245	2.507	0.414	16.16
	(1.439)	(0.283)	(10.06)	(1.651)	(0.64)	(22.23)
Prefecture dummy × year dummy				Yes	Yes	Yes
Observations	812	364	320	812	364	320
R-squared	0.027	0.011	0.003	0.284	0.179	0.442
Number of Univ	203	91	80	203	91	80
baseline DID coefficient (β)	5.150***	0.840**	-66.83***	7.794***	1.748***	-145.1**
	(1.812)	(0.351)	(18.02)	(2.751)	(0.615)	(59.71)
$\lvert\beta_0/\beta\rvert$	0.46	0.27	0.05	0.32	0.24	0.11

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

Table 15: Placebo Test (Hard Science)

	Baseline	Placebo	Baseline	Placebo
National × post 2004	56.06***		84.39***	
	(16.83)		(22.32)	
National × post 2002		113.1***		169.6***
		(33.39)		(55.71)
Prefecture dummy × year dummy			Yes	Yes
Observations	2,130	852	2,130	852
R-squared	0.102	0.169	0.169	0.247
Number of Univ	213	213	213	213

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

inconclusive in my analysis[15].

Permutation Inference

Moreover, I perform permutation inference to check the significance of the benchmark results of the coefficients in Table 3. Approximated parametric distributions, such as the normal, the t-distribution, and the F-distribution do not model for data exactly and, therefore, "the exact inference is the randomization inference derived from the randomization distribution of statistical quantities" (Rosenbaum (2002)). To obtain such a randomization distribution as a reference, I randomly re-label the treatment status without replacement and re-estimate the coefficients of Table 3 for each permutation for each field. I repeat the exercise 10,000 times. Figure 2 shows the empirical densities of the estimated coefficients on the effect of partial privatization. The benchmark estimates from Table 3, represented by vertical lines, lie at the edge of the range of coefficients estimated in this re-sampling exercise. Under the null hypothesis of no treatment effect, this inferential procedure shows a low probability of obtaining results similar to those in Table 3 and, thus, exactly and significantly rejects the null hypothesis. This inference is exact regardless of the sample size and the covariance structure of the regression errors, ε_{it}.

Sub-Grouping

I perform two types of sub-grouping that balance the research level of national and private universities. Section 4.1 shows that national universities in Japan tend to be more research intensive than private universities. To reduce heterogeneity in the research activity, I took the summation of research output of the period 2000 to 2003 for each university and then excluded lower ranked universities from my sample and repeated the fixed-effect regressions. Table 16 shows the results of this sub-grouping. The first column of each research field includes only universities that produce greater output than the median of the entire distribution. The coefficient estimates for a sample of higher producers in Table 16 are similar to those previously reported in Table 4 for the entire sample.

[15] Same patterns are obtained regardless of the field selection; that is, physics only, chemistry only, life science only, and any combination of these three fields.

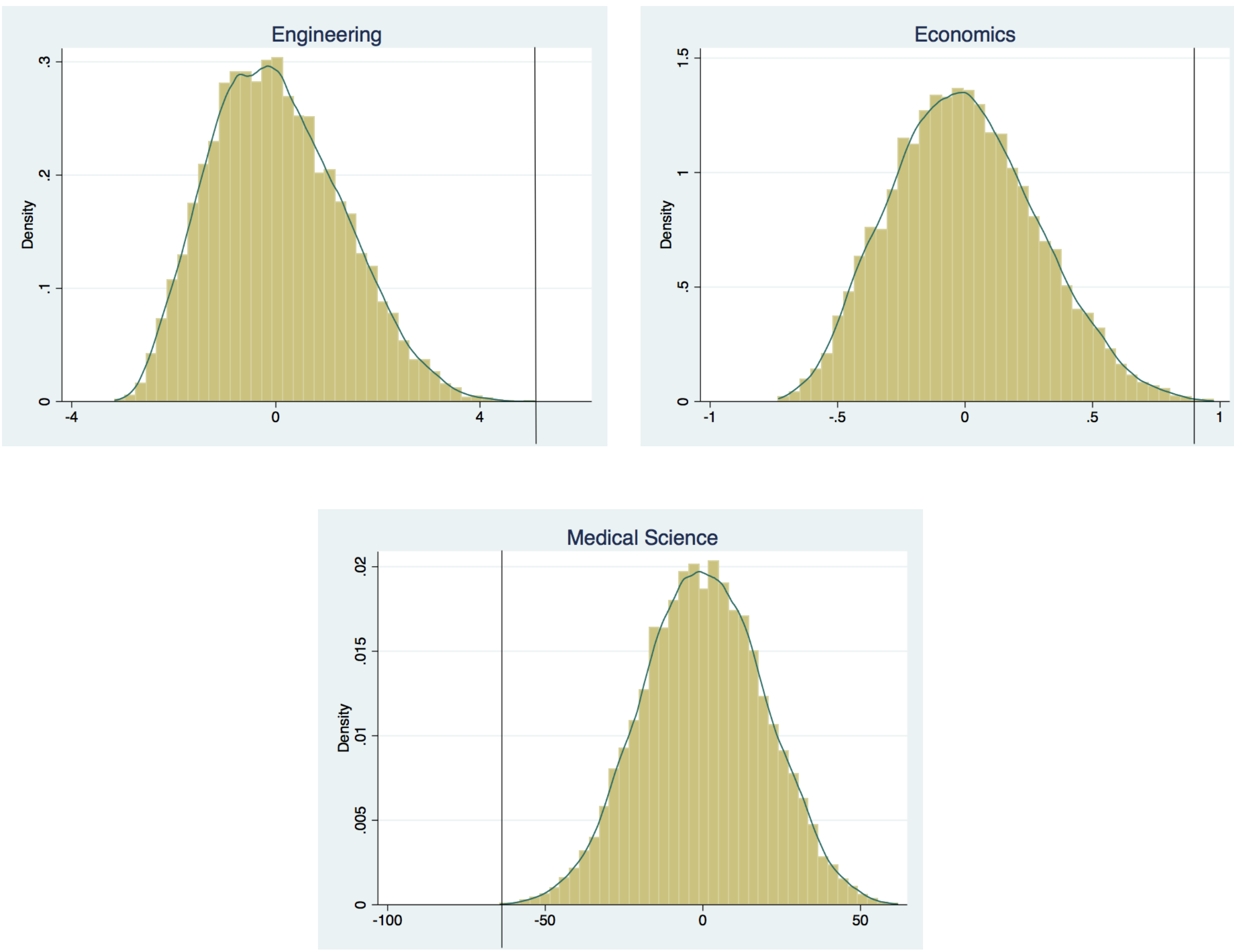


Figure 2: Permutation Distribution

Note: Vertical lines represent the benchmark estimates from Table 3 for each research field.

Table 16: The Dynamic Effect of Partial Privatization on Research-intensive Universities

	Engineering		Economics		Medical science		Engineering		Economics		Medical science	
Research intensity of university	over median	COE	over median	COE	over median	COE	over median	COE	over median	COE	over median	COE
National × year 2004	4.851**	21.11**	0.335	-0.427	15.91	-21.11	12.67**	44.13**	0.577	-0.224	12.63	32.57
	(2.326)	(9.671)	(0.405)	(1.086)	(28.77)	(53.9)	(5.617)	(17.94)	(0.71)	(1.493)	(43.85)	(111.5)
National × year 2005	2.214	9.917	1.075*	1.9	4.357	8.549	6.848*	18.05	2.522**	3.03	21.48	56.35
	(1.788)	(6.866)	(0.591)	(1.505)	(24.98)	(39.17)	(3.51)	(12.09)	(1.05)	(3.147)	(88.74)	(102.3)
National × year 2006	2.849	5.15	1.691*	2.113	-52.18	-89.88	8.776**	8.837	3.866**	5.921	-341.2*	-166.2
	(1.922)	(6.302)	(0.892)	(2.109)	(41.02)	(61.01)	(3.493)	(11.74)	(1.62)	(3.905)	(195.9)	(203)
National × year 2007	8.206**	24.88*	1.418**	3.204**	-94.85**	-130.8**	17.89**	66.36***	2.827***	4.939***	-329.6*	-172.7
	(3.297)	(11.96)	(0.615)	(1.243)	(41.43)	(60.09)	(8.095)	(19.7)	(1)	(1.166)	(193.2)	(196.5)
National × year 2008	2.374	0.818	1.161	1.787	-72.95*	-98.18	8.378	35.74	3.038***	3.754*	-256.3	-127.1
	(3.074)	(12.73)	(0.71)	(1.647)	(38.16)	(58.67)	(7.908)	(43.72)	(1.121)	(2.008)	(234.1)	(226.1)
National × year 2009	10.48***	26.55*	1.675	2.177	-104.5**	-153.8*	23.83***	69.54***	4.350***	1.941	-303.8**	-214.5
	(3.974)	(14.26)	(1.023)	(2.22)	(39.18)	(79.89)	(8.555)	(15.87)	(1.375)	(1.481)	(130.7)	(181.6)
Prefecture dummy × year dummy							Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,010	160	450	100	400	220	1,010	160	450	100	400	220
R-squared	0.133	0.416	0.162	0.445	0.338	0.367	0.385	0.815	0.513	0.836	0.749	0.814
Number of Univ	101	16	45	10	40	22	101	16	45	10	40	22

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. COE (Center of Excellence) is large-scale research funding from the Japanese government. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

In the second column of each research field in Table 16, I report estimates for a subgroup of universities that obtained Center of Excellence (COE) funding, which is large-scale research funding from the Japanese government[16]. COE funding can be an indicator that the university is close to the research frontier. Ida and Fukuzawa (2013) analyzed the 21st Century Center of Excellence program, and this large-scale funding led to an increase in the research output for the recipients. Therefore, a differential trend exists for the recipients of the 21st Century Center of Excellence program, and this is another indicator of higher achievement. Because controlling for selection into the COE program is difficult, I limit the sample to the universities that obtained $21st$ COE or GCOE funding. Restricting the sample to COE-fund recipients only reduces the sample size to 160 observations (16 universities times 10 years) in engineering, 100 observations (10 universities times 10 years) in economics, and 220 observations (22 universities times 10 years) in medical science. The results in the second columns of each field indicate that the baseline patterns suggestively hold despite substantial increases in the standard errors of most estimated coefficients caused in part by a reduced sample size, with one exception in the last column for the result of medical science with regional effects.

Ex-ante Anticipation or Preparation for the Partial Privatization

Although the partial privatization itself was an exogenous phenomenon for national universities, another concern is that it was anticipated, and some of the essential structural changes were partially prepared before 2004 (Amano (2008)). In addition, the effect for engineering appeared immediately after 2004 (see Table 4). This poses another threat to the identification that the policy reform was anticipated, and researchers in national universities were already prepared or effected.

To address this issue, I set 2003 as an alternative falsification enforcement year (a one-year lead) and reproduce the estimation of Table 4 under this specification. The results in Table 17 show that the falsification coefficient is insignificant in 2003 for each field. Therefore, the results emphasize the notion that the effect appeared after 2004[17].

[16]There are two COE programs; 21st Century Center of Excellence implemented in 2002 to 2004 and the Global Center of Excellence implemented in 2007 to 2009.

[17]The same pattern holds if I use acquisition effort of Kaken-hi as a dependent variable in this specification.

Table 17: The Effect of Falsification Enforcement Year: 2003

	Engineering	Economics	Medical Science	Engineering	Economics	Medical Science
National × falsification enforcement year 2003	1.711	0.359	5.244	1.581	0.583	-2.713
	(1.423)	(0.31)	(12.2)	(1.857)	(0.646)	(31.54)
National × year 2004	4.700**	0.293	-4.388	7.297**	0.469	-4.97
	(1.927)	(0.25)	(16.97)	(3.252)	(0.473)	(33.94)
National × year 2005	2.740*	0.815**	-22.32	4.468**	1.553**	-45.8
	(1.501)	(0.364)	(15.82)	(2.185)	(0.675)	(48.61)
National × year 2006	3.571**	1.231**	-69.23**	5.382**	2.431**	-194.9*
	(1.621)	(0.557)	(27.45)	(2.183)	(1.061)	(103)
National × year 2007	8.190***	1.059***	-100.6***	11.19***	2.056***	-220.0**
	(2.714)	(0.4)	(27.46)	(4.221)	(0.722)	(94.28)
National × year 2008	3.696	0.901**	-92.50***	5.331	1.952**	-207.2**
	(2.455)	(0.451)	(26.49)	(3.722)	(0.856)	(101.2)
National × year 2009	10.57***	1.280*	-104.1***	15.46***	2.898***	-201.5***
	(3.24)	(0.656)	(23.96)	(4.577)	(1.082)	(69.62)
Prefecture dummy × year dummy				Yes	Yes	Yes
Observations	2,030	910	800	2,030	910	800
R-squared	0.101	0.112	0.272	0.277	0.372	0.595
Number of Univ	203	91	80	203	91	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Other control variables, which are not reported in this table, incorporate a full suite of year dummy.

Contamination of other trends

More generally, Figure 3 depicts the trends of coefficients on the base specification (2) augmented with the full leads and lags with regional effects (Table 18) to see any other differential research trend between treatment and control groups that existed before the treatment. This is another test on parallel trend assumption.

For engineering, the three coefficients on the enforcement leads are closer to zero than the coefficients after the year of enforcement, showing evidence in favor of the positive impact of partial privatization. The trend of the lags shows that the effect increases rapidly after the first year of the treatment and follows a zigzag increasing path.

For economics, the coefficients on the leads are reasonably smaller than the coefficients on the lags, showing little evidence of anticipatory or differential process within national universities. The lags trend shows that the impact increases rapidly after 2005 and then remains relatively constant after 2007.

In medical science, the coefficients on the leads are very close to zero, showing no evidence of an anticipatory or differential process within universities about to partially privatize. The coefficients decrease rapidly one year after the enforcement until three years after the enforcement.

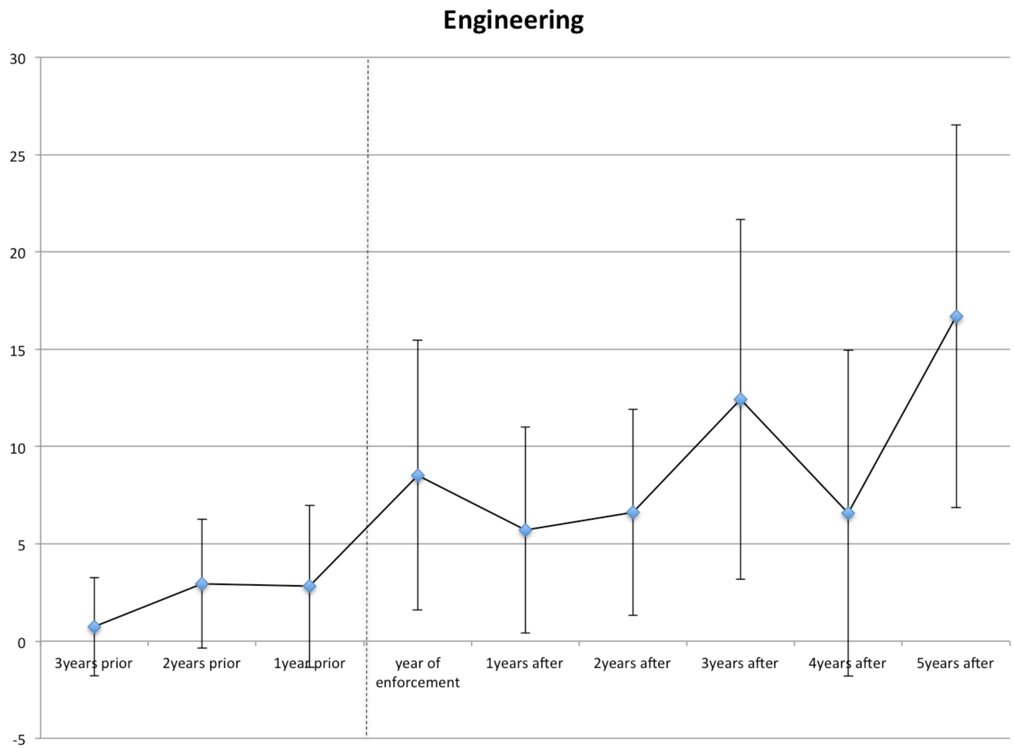
Outlier

To further address the concern that my results may be affected by some outlying observations, I focus on a sub-sample that excludes the observations at the top and bottom 1% of the corresponding outcome variables, which operation excludes, for instance, University of Tokyo. Although the results are not reported here, the regression results show the robustness of my earlier findings.

Table 18: Full Leads and Lags

	Engineering		Economics		Medical science	
	Full leads & lags	Baseline	Full leads & lags	Baseline	Full leads & lags	Baseline
National × year 2001	0.749		0.681		3.776	
	(1.289)		(0.455)		(75.02)	
National × year 2002	2.950*		0.525		28.17	
	(1.686)		(0.72)		(31.42)	
National × year 2003	2.813		0.985		7.934	
	(2.12)		(0.925)		(50.83)	
National × year 2004	8.530**	6.902**	0.871	0.323	5.677	-4.291
	(3.543)	(2.933)	(0.637)	(0.448)	(52.76)	(31.22)
National × year 2005	5.701**	4.073**	1.955**	1.408**	-35.15	-45.12
	(2.698)	(1.955)	(0.873)	(0.65)	(52.27)	(48.63)
National × year 2006	6.615**	4.986***	2.833**	2.285**	-184.3	-194.2*
	(2.699)	(1.917)	(1.252)	(1.025)	(124.2)	(98.26)
National × year 2007	12.42***	10.80***	2.458**	1.910***	-209.3*	-219.3**
	(4.715)	(4.026)	(0.995)	(0.631)	(113.3)	(88.46)
National × year 2008	6.564	4.936	2.354**	1.806**	-196.6	-206.6**
	(4.271)	(3.618)	(1.084)	(0.787)	(120.7)	(95.3)
National × year 2009	16.70***	15.07***	3.300**	2.753***	-190.8**	-200.8***
	(5.016)	(4.388)	(1.337)	(1.003)	(89)	(64.21)
Prefecture dummy × year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,030	2,030	910	910	800	800
R-squared	0.278	0.276	0.374	0.369	0.596	0.595
Number of Univ	203	203	91	91	80	80

Note: Standard errors clustered at the university level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Second, forth and sixth coolumns are the same as the corresponding columns of Table 13 respectively.

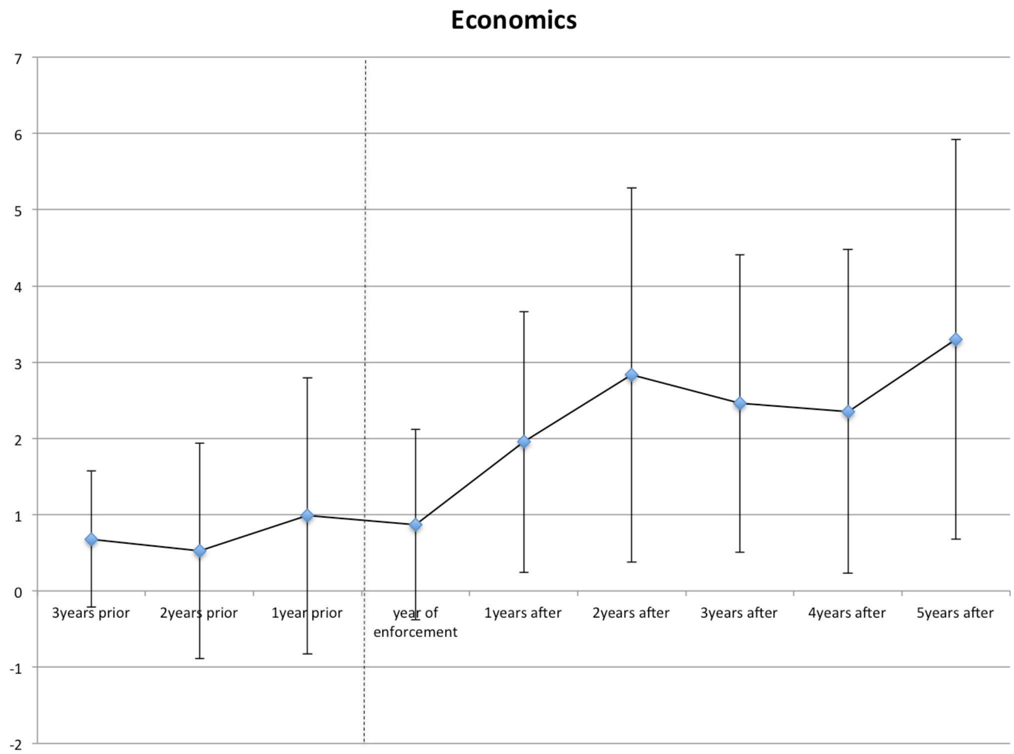


5 Discussion

Net effect on social welfare?

I find robust negative effects of partial privatization for research outcome of medical science for national university hospitals. Because of the lack of individual data to indicate resource allocations during the same period for both national and private universities, I cannot strongly insist on this conclusion, but one interpretation of the negative effect is that an increase in the time spent on providing clinical services may have crowded out the research activity of national university hospitals.

However, the total effect on welfare is ambiguous: if provision of clinical services has been strongly promoted, this would improve social welfare. Accordingly, it is difficult to evaluate the net effect on welfare. This poses two questions. First, is there any policy to effectively solve this conflict and augment these two activities? Second, if this is not possible, which is more welfare improving, advancing medical science to create lasting and non-excludable intellectual products or providing more clinical services?



Lessons for other countries.

Although these results are not readily applicable in other situations, the results provide some implications for university reform in other countries.

As shown in Table 19, and as the discussion in Subsection 2.2, the partial privatization lowered the share of core government funds from approximately 44% in 2005 to 39% in 2008, raised the share of competitive-type funds from approximately 14% in 2005 to 17% in 2008, enabled national universities to own the buildings as their own assets, gave freedom to differentiate wages, and, at the same time, weakened the role of government in approving university budgets and so on. These first five changes compose five out of nine components of autonomy and competitive criteria Aghion et al. (2010) used to construct the autonomy and competition index.

The estimation results imply, in some research disciplines, that this type of governance reform might be particularly effective for countries with universities with a high share of public funding, a low share of competitive-type funding, a low share of owning their own buildings, weak discretion in setting wages, and that require government approval for budgets simply because there is room to change each component. For instance, according the survey

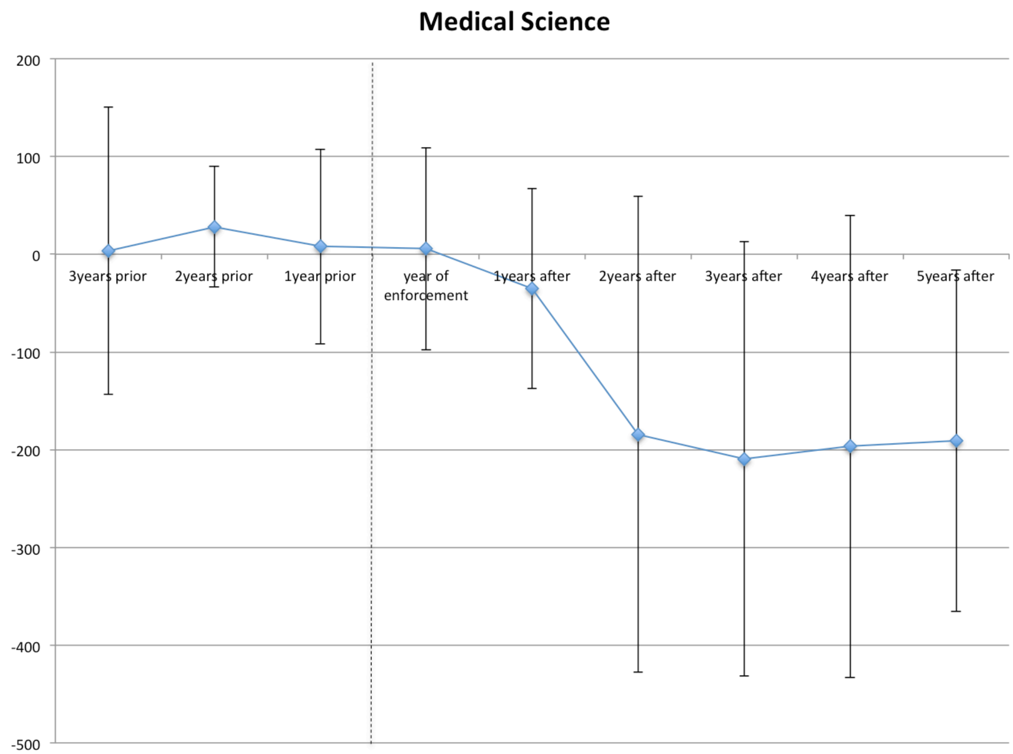


Figure 3: Estimated Impact of Partial Privatization on Research Performance for the Years Before, During, and After the Enforcement, 2001 to 2009 (Table 18)

Note: Vertical bands represent ± 1.96 times the standard error of each point estimate.

result of Aghion et al. (2010) (See p.55 for details and for other countries) these countries include France — where the share of public funding is 71%, the share of competitive funding is 9.3%, the share of universities that own their own buildings is 0%, the share of universities in which all faculty with same seniority and rank must have same pays is 50%, and the share of universities that are required to obtain government approval for their budgets is 100% — Belgium, and Spain. If a university has a university hospital, reductions in medical science output may occur, but the net effect on welfare is unclear if it actually induces increases in provision of clinical services, as already mentioned.

In contrast, the same policy might have little effect on universities such as those in the UK — where the share of public funding is 34%, the share of competitive funding is 21%, the share of universities that own their own buildings is 94%, the share of universities in which all faculty with same seniority and rank must have same pays is 0%, and the share of universities that require government approval for their budget is 13% — and Sweden. These countries are considered to have unusually autonomous and unusually productive universities.

Table 19: The Share of Some Components of Autonomy and Competitive Criteria

University type	National university						
Country	Japan		France	Belgium	Spain	UK	Sweden
Year (row one and two)	2005	2008					
Year (row three to five)	before 2004						
Share of the budget from core government funds	44%	39%	71%	65%	62%	34%	60%
Share of the budget from research grants for which the university must compete	14%	17%	9%	12%	10%	21%	34%
Share of universities in which budget must be approved by the state	100%	100%, but the role of government is weakened	100%	63%	50%	13%	20%
Share of universities that own their own buildings	0%	100%	0%	100%	100%	94%	20%
Share of universities in which all faculty with same seniority and rank must have the same pay	bureaucratic restrictions	the restriction is weakened	50%	0%	50%	0%	0%

Note: This table is an excerpt from Aghion et al.'s (2010) survey and based on Urata (2010).

6 Conclusion

I find that governance reform of universities that increases autonomy and competitive status caused increases in research output for engineering and economics. I also document evidence that the positive effect might be due to intensitfied competition, including competitive-type fund acquisition efforts. These results concur with the hypothesis that a more autonomous and competitive university produces more output. However, this reform caused a decrease in research output for medical science. This result indicates, suggestively, a trade-off between the progress of clinical academic science and the provision of clinical services that may occur when universities are encouraged to engage in revenue-generating activity. By offering a direct causal implication of university reform these results extend Aghion et al. (2010)'s results, which report (1) the positive correlation between the autonomous and competitive index of universities with their ranking and (2) the larger impacts of increases in government funding on university output for more competitive and autonomous universities.

These results are also significant as the first quantitative evaluation of the partial privatization (corporatization) of Japanese national universities.

Given the significant role of universities as a source of technological innovation for economic growth, the demand for a more productive form of university governance exists at any time in any country. Because this analysis represents a preliminary step towards assessing the effect of university governance on research performance, further research is warranted.

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Chapter2

Evaluating Professor Value-added: Evidence from Professor and Student Matching in Physics

1 Introduction

1.1 Overview

How is knowledge created? Economists have had a particular and long-standing interest in knowledge production. Indeed, the new economic growth theory literature regards the way in which knowledge is created and accumulated as crucial for a nation to grow (Romer, 1990; Lucas, 1988; Grossman and Helpman, 1991).

Recently, there has been an increase in the number of empirical studies on knowledge creation in the field of science and technology. They have investigated how an individual's knowledge creation is affected by knowledge created by others, with a particular emphasis on knowledge spillovers between individuals within and across institutions. The evidence obtained thus far, however, has been mixed. Some studies (e.g., Azoulay, Zivin and Wang, 2010; Moser, Voena and Waldinger, 2014; Borjas and Doran, 2014) provide evidence in favor of positive knowledge spillovers, while others (Waldinger, 2012; Borjas and Doran, 2012) do not.

Surprisingly little attention has been devoted to knowledge *reproduction* processes across generations. As is often argued, scientific and technological knowledge is tacit (Polanyi, 1958, 1966). It is not easily translated and thus needs to be intentionally articulated, codified and diffused. Therefore, knowledge has long been reproduced through a deliberate process of education and learning whereby those with knowledge take voluntary action to pass it on to those who do not. Thus, to investigate the creation and diffusion of scientific and technological knowledge, it seems natural to distinguish *vertical* knowledge flow (i.e., the knowledge flow from an individual with high expertise to one with low expertise) from *horizontal* knowledge flow (i.e., the knowledge flow among individuals with the same level of expertise). If the two lines of knowledge flow differ in the efficiency of the transmission of know-how, the mixed results obtained by prior studies on the extent of spillovers might be explained with regard to such differences.

This paper focuses on the knowledge reproduction process whereby knowledge is conveyed through vertical relationships, including master-apprentice, teacher-student and senior-junior-collaborator relationships. We specifically focus on the *advisor-advisee* relationship in post-graduate education to examine its effectiveness in expanding scientific frontiers. Under the hypothesis that a professor's "quality" has a consequential impact on the growth of a student's research achievement, we estimate the professor's (advisor's) *value added* as the contribution to student's (advisee's) progress on research outcomes.

Empirically estimating a graduate school professor's value added is complicated by the endogenous selection process involving students, professors and schools. We anticipate that students of promise will apply and be admitted to highly ranked schools. Moreover, professors with good academic standing are likely to have faculty positions at prestigious schools. These types of selective recruitment will lead to nonrandom sorting of students and professors across graduate programs. Furthermore, the existence and extent of sorting can be reinforced by the advisor-advisee matching process *within* a school, whereby students will choose and be chosen by faculty members.[1] Therefore, the mere association of research productivity, measured by, say, publication records, between a professor and a student does not necessarily imply a causal relationship whereby the professor's advising and mentoring could enhance the research capabilities of his or her students.

To disentangle the influence of professors on students from the sorting and matching effects, we use an identification strategy that exploits professor *turnover* from events such as retirement, relocation, or death. We borrow this idea from Rivkin, Hanushek and Kain (2005, henceforth, RHK), who estimate a lower bound of the teacher quality effect, which can be

[1] These choices give rise to "assortative matching" between students and professors within a school with respect to research ability.

either observed or unobserved, on student achievement gains by exploiting teacher turnover.

This paper estimates within-school professor value added at a world-leading postgraduate program in physics in Japan using unique panel data on matched advisor-advisee pairs. Japanese graduate schools provide an ideal setting for applying RHK's strategy of turnover-based value-added estimation. When an advisor exits a Japanese graduate school due to turnover, the advisees usually remain in the same program and continue their research projects under the supervision of new advisor. Therefore, the advisees who experience advisor turnover are influenced by two advisers of different quality. Thus, the student's research achievement growth, under the varied influences of different advisors, would be more volatile than that of advisees who did not suffer advisor turnover. To measure the magnitude of advisor impact on advisee research performance, we exploit the degree to which the student's research achievement growth differs across cohorts.

Certainly, factors other than advisor quality might affect an advisee's research performance. This paper employs a semi-parametric education production function, which is widely used in the economics of education literature, that attributes the student's achievement gains to various fixed effects. Repeated observations of an individual student's research outcomes, which are measured by publication records, in master's and doctoral degree programs enable us to eliminate student fixed effects by taking the difference of the research outcomes of a given student from one degree program to another.

This paper employs a quasi-experimental design. We base our analysis on a *lab*, defined by a cohort of students who were assigned to the same advisor. We assign labs to a treatment group, in which the advisor was replaced due to turnover, and a control group, in which the advisor was not replaced. We use cohort-to-cohort variation in the average gain in student research achievement to measure the effect of the advisor quality on advisee research achievement gains. We demonstrate that the squared double-difference in student research achievement gains between the degree programs (i.e., master's and doctoral programs) and between cohorts is larger for the treatment group than for the control group and is driven primarily by the change in advisor quality following turnover.

For a treatment and control study to be valid, some degree of randomness in the treatment assignment is necessary, which is equivalent to random advisor replacement in our empirical context. To address the lack of sufficient randomness in the actual school environment, we employ propensity score matching, which selects a subset of the control group that has a similar likelihood of the treatment being offered to that for individuals in the treatment group. We compute the propensity score as the estimated likelihood of advisor turnover occurring and match the sample of control group labs with the treatment group labs based on the estimated propensity score. We implement regression analysis based on the matched sample to obtain an unbiased estimate of the lower bound of the variance in advisor effectiveness on advisee research achievement gains.

We estimate a professor's value added to student research achievement growth in the department of physics, University of Tokyo (henceforth, UTokyo), which is a prestigious research and educational institution in physics. The estimation results provide strong evidence for the existence of professor value added, which is consistent with the expectation that knowledge and ideas are transmitted vertically from advisor to advisee. Indeed, the results consistently demonstrate that the difference in the quality of a student's advisor makes a notable difference in the student's research outcome growth at the doctoral level. Specifically, our estimates indicate that a one-standard-deviation increase in advisor quality will increase an doctoral advisee's research achievement by 0.54 standard deviations. We also find that a one-standard-deviation increase in advisor quality entails an increase in the number of articles published by a doctorate student in top journals as a first author by 0.64. The findings of this paper are robust to different definitions of student research outcomes and are also insensitive to many different model specifications. The results are also robust to a falsification exercise that examines whether the timing of the increased variability in the double-differenced student research achievement gain agrees with that of advisor turnover, as predicted by the empirical model.

We also investigate alternative mechanisms for knowledge transmission other than that based on learning through the advisor-advisee relationship. The data indicate that advisor turnover does not have a significant unidirectional, positive or negative, impact on an advisee's research achievement gain, *per se*, as is consistent with the mechanism that our value-added model postulates, and is thus not fully explained by the other mechanisms such as that emphasizing the recombination role of various extant pieces of knowledge in new knowledge creation (e.g., Weitzman, 1998). Further analysis reveals that the effect of knowledge transmission from advisor to student *within* a lab tends to outweigh that from non-advisor to student *across* labs.

The remainder of the paper proceeds as follows. A brief literature review is provided in the remainder of this section. Section 2 describes the institutional background of postgraduate physics education in Japan. Section 3 presents the empirical model and describes a regression-based approach to estimate the lower bound of professor value added. Section 4 explains the data set used for the analysis. Section 5 discusses some empirical issues concerning value-added estimation. Section 6 presents the estimation results and provides robustness checks. Section 7 concludes.

1.2 Related Literature

This paper contributes to the literature by measuring the effectiveness of professors in promoting students' research productivity growth at a postgraduate institution. The most closely related work to this paper is Waldinger (2010), who estimates the causal effect of prominent professors on the research outcomes of Ph.D. students in mathematics at German universities during the Nazi era. Although we share his view that "university quality is believed to be one of the key drivers for a successful professional career of university graduates "(Waldinger, 2010, p.787), we highlight the importance of direct interactions between advisor and advisee as a medium whereby knowledge is memorized, transferred and accumulated. Indeed, anecdotal evidence (e.g., Zuckerman, 1977) suggests the importance of vertical social ties in scientific enterprises at academic institutions. However, to the best of our knowledge, no systematic quantitative study, especially one that carefully controls for endogenous matching between master (teacher, advisor or senior collaborator) and apprentice (student, advisee or junior collaborator), has been conducted to date.

Our findings validate the view of earlier studies (e.g., Azoulay et al., 2010; Moser et al., 2014; Borjas and Doran, 2014) that vertical social interactions among scientists are enduring and consequential for scientific and technological knowledge to be created and diffused. For example, a recent study by Moser et al. (2014), who estimate the effect of German Jewish émigrés on U.S. innovation, suggests that knowledge externalities occurred and were amplified through educational and collaborative ties in scientist networks such that U.S. junior scientists were trained by and collaborated with prominent Jewish senior scientists who emigrated. Borjas and Doran (2014) study the impact of the influx of Soviet mathematicians into the United States after the collapse of the Soviet Union and conclude that positive knowledge spillovers are generated through the relationships among collaborating mathematicians who regularly interact when at least one of them is an outstanding knowledge producer.

This study is also related to a voluminous education economics literature that evaluates teacher value added (e.g., Hanushek and Rivkin, 2006, 2010). We base our empirical analysis on the value-added model approach that is widely employed in the literature. Specifically, as mentioned above, we adopt a semi-parametric value-added model and employ the turnover estimator proposed by RHK. However, we depart from the previous literature on teacher value added in that we focus on value added at a level higher than secondary education. Although numerous studies estimate value added at the primary and secondary education levels (e.g., Hanushek and Rivkin, 2012, for a recent review), few studies (e.g., Hoffmann and Oreopoulos, 2009; Carrell and West, 2010) estimate a professor's value added in the context of post-secondary institutions. While these studies on professor value added attempt to estimate the effectiveness of professors in improving students' grade gains at the *undergraduate* level, we turn to professors' value added to students' research achievement gains at the *postgraduate* level and thus evaluate the effectiveness of professors in terms of their "quality" in advising or mentoring graduate students' research projects.

To the best of our knowledge, no studies assess the impact of professor quality on graduate student research productivity growth by shedding light on the value-added contribution. A partial exception is the study by Hilmer and Hilmer (2009), who find a positive effect of an advisor's research prominence on advisees' early career publication success in U.S. economics Ph.D. programs. While they are successful in disentangling the effect of advisor quality from that of program quality on Ph.D. students' publication outcomes, they do not address endogenous advisor-advisee matching between professors and students within and across institutions. Thus, it seems questionable to interpret their finding of a positive correlation between the research productivity of advisors and advisees as causal.

2 Institutional Background

2.1 Postgraduate Physics Education in Japan

Postgraduate education in Japan, including in physics, has a two-tiered structure, that is, a two-year master's degree program followed by a doctoral program that typically lasts three or four years.[2] Leading Japanese research universities typically offer both master's and doctoral courses. In most cases, students enrolled in a doctoral degree program graduate with a master's degree from the same school. However, they are institutionally separated. Thus, a master's student seeking to pursue a doctorate must take an entrance examination, which is largely based on a master's thesis, to be admitted to a doctoral course even if it is offered by the same institution. In a sense, the master's degree program implicitly serves as a screening device for doctoral programs in Japan.

Three features are notable for graduate education in physics for master's programs in Japan. First, Japanese physics master's students are closely linked to their faculty advisors immediately after enrollment in a program. Indeed, applicants to a master's degree program must declare their desired field of specialization and submit a short list of faculty advisors from whom mentorship is sought upon admission. Only those who are approved for support by designated advisors are admitted to a graduate school.[3]

Second, physics education in Japan at the master's level is best characterized by research-based apprentice training, which is often contrasted by coursework-based training in the U.S. (Abe and Watanabe, 2012). Although Japanese master's students in physics are required to take some "coursework" credits toward their degrees, they can earn most of their credits through learning-by-doing style research "seminars" taught by a faculty advisor.[4]

Finally, for Japanese physics graduate students, a thesis is required to complete the master's program. It is expected to be original, as a doctoral thesis should be, although they are evaluated according to different criteria of scholarly maturity. Students are encouraged to begin original research in their chosen fields at an early stage of the master's degree program under the instruction and guidance of a faculty advisor. Because the master's thesis is a critical factor for admittance to doctoral programs, Japanese students and professors attach great importance to a master's thesis as a pathway to doctoral study.

In contrast, the doctoral programs in physics at Japanese universities are more similar to

[2]The basic structure has remained unchanged since World War II, although the organizational structure of universities has been reformed (see Ushiogi, 1993; Ogawa, 2002)

[3]This contrasts with U.S. graduate students, who are matched with their supervisors through the rotation of faculty labs after they complete their coursework and become Ph.D. candidates (see Gumport, 1993).

[4]For example, for the master's degree program in physics at UTokyo, students must take at least thirty credits of coursework at the master's degree level. However, lab-based research "seminars" offered by thesis advisors constitute two thirds of their total credits.

their counterparts in Western countries than are the master's programs. Specifically, Japanese doctoral students and American Ph.D candidates are considered comparable in that there is no coursework requirement. Japanese students at the doctoral level, similar to Ph.D. candidates in the U.S., begin the research for their doctoral dissertations under the supervision of their research advisors and continue the research topic they pursued in their master's thesis in their doctoral dissertation. In general terms, Japanese physics students are required to write several articles published in refereed journals as a prerequisite for a doctoral degree. These publications are usually included in a doctoral thesis.

2.2 Physics Labs in Japanese Universities

Interaction between a graduate student and a faculty advisor is lab-oriented in Japanese physics graduate programs. Upon enrollment in the master's program, Japanese physics students are assigned individually to a lab, and the lab's leader (or sometimes sub-leader) becomes their thesis research advisor. Students acquire the knowledge necessary to conduct their research through frequent interaction with their advisors in a lab setting. The content of this lab-based teaching and learning includes basic research skills, such as how to read scientific articles, how to select research topics, how to present results at seminars and conferences, and how to write publishable papers, as well as the culture of physics such as the style of work, mode of thought, and a taste for "good" physics (Abe and Watanabe, 2012).

While apprenticeship-style education is also employed in Western countries,[5] it is particularly personalized in Japan. It is typical to refer to a lab using the lab leader's family name.[6] Indeed, a research lab is often referred to as an "*ie*", which means a household in Japanese: the leader (a faculty member who is a full or associate professor) is the father, the sub-leader (associate professor or research associate) is the mother, the doctoral course students (and postdocs if any) are the older brother or sisters, and the master's students are the younger siblings. In Japanese universities, the everyday activities of graduate students are organized around a lab (Kawashima and Maruyama, 1993).

Although Japanese physics labs are often likened to a household, they are generally democratic, not feudal, in tone. The "laboratory democracy" in Japanese physics communities

[5]See Gumport (1993) for the U.S.; Becher (1993) for the UK; and Gellert (1993) for Germany.

[6]For instance, if the last name of a lab leader is *Nakajima*, the lab is usually called the *Nakajima Lab* in Japanese universities.

can be traced back to the end of World War II, the period when there were immediate and insistent calls for the creation of a new "scientific Japan" under the control of the allied occupation (Low, 2005).[7] To place this in perspective, it is broadly understood that Japanese physics labs are less prescriptive and less hierarchical than their U.S. counterparts.[8] For example, Sharon Traweek, an anthropologist who studied various research groups of elementary particle physicists in Japan and the U.S., reports that decision-making in Japanese physics labs was based on the consensus of the members. There is no strict division of labor among lab members, even between faculty members and graduate students, in Japanese physics labs. Traweek (1988) offers a first-hand account of the democratic nature of labs in Japan by asking group leaders of a lab for the source of new ideas for experimental design or data analysis. Traweek (1988) writes, (p.147) " [lab leaders] generally credited the graduate students ... they said the group then responds to their ideas, perhaps modifying or amplifying them".

Hence, although it is not uncommon for the research topics of master's and doctoral theses to be suggested by advisors as a part of a large, ongoing project in a given lab, Japanese physics graduate students are, generally, given some autonomy to pursue their own research based on their original ideas.

3 Empirical Model

In this section, we introduce a simple value-added model that associates growth in student research achievement with the "quality" of the professor supervising the student. Then, we present a regression-based approach to estimate a lower bound of the variance in professor quality, which can be interpreted as the extent to which any professor differences matter in

[7] Low (2005) also notes that professor Shouichi Sakata at the physics department of Nagoya Imperial University, an influential physicist at that time, played an important role in developing the new democratic lab system in the Japanese physics community. Sakata, who was under the philosophical influence of Marxism, introduced a charter for the physics department at Nagoya in 1946. The charter holds that democracy should serve as the guiding principle in department affairs; all faculty members and students should be treated equally concerning physics research (Department of Physics, Nagoya University, 2015). The idealism of Sakata's "laboratory democracy" then spread. Soon after the Nagoya Charter was announced, several physics departments at other universities introduced similar systems. See Tanabashi (2012) for details on Sakata's laboratory democracy.

[8] Regarding the difference in lab cultures between Japan and America, it can be insightful to contrast the description of Kawashima and Maruyama (1993) with that of Gumport (1993).

determining student research outcome growth.

3.1 Value-added Specification

Following the standard value-added modeling approach (e.g., Hanushek and Rivkin, 2010), we employ a semi-parametric specification of a professor's contribution to a student's achievement growth.

Consider graduate student i who entered the master's program of a graduate school in year c. Below, we treat year c as the student's cohort. We denote the research outcome growth of a graduate student in the master's degree program by $g = m$ and in the doctoral degree program by $g = d$. The growth is measured by the *gains* in research output from the previous degree program to the current degree program.[9] Let $\Delta outcome^{c}_{iag}$ be the research outcome growth of student i under the supervision of professor $a \in \mathscr{A}$ in degree program $g \in \{m, d\}$ in cohort $c \in \mathscr{C}$. We assume that it is given by the following function:

$$\Delta outcome^{c}_{iag} = \gamma_i + \theta_{ag} + \nu^{c}_{iag}, \tag{1}$$

where γ_i is student i's individual fixed effect, θ_{ag} is professor a's quality that influences the student research outcome growth in degree program g, and ν^{c}_{iag} is an idiosyncratic random shock.

The specification highlights the components that affect a student's research outcome growth. The model is very simple given its additive structure. First, note that other effects, such as school fixed effects and research field fixed effects, are not included in the value-added model. We opt not to include these fixed effects because they are subtracted out of the estimation model in the process of "differencing", as presented below. Second, professor quality, θ_{ag}, and student quality, γ_i, will be correlated. Specifically, because of endogenous matching between professor (advisor) and student (advisee), we expect that θ_{ag} and γ_i are positively correlated. Finally, as in the standard specification of the value-added model, the idiosyncratic shock, ν^{c}_{iag}, is assumed to be uncorrelated with the student fixed effect, γ_i, or the advisor fixed effect, θ_{ag}.

[9] We assume that the research output of students at the bachelor level is zero. We compute a publication-based research proficiency score, which is explained in detail in Section 4, for students in the sample when they are undergraduate students and find that it is negligible.

We assume that matching between student and professor is many-to-one, that is, multiple students are assigned to one advisor. Let us define a *lab* as a group of students (advisees) in the same cohort who were assigned to the same professor (advisor). Specifically, we use $\ell(a,c)$ to denote a lab in which students are in cohort c and assigned to professor a as an advisor. Let L be the number of all labs in a school, and let students in lab $\ell(a,c)$ be indexed by $i = 1, \cdots, I^{\ell(a,c)}$, where $I^{\ell(a,c)}$ is the number of students in lab $\ell(a,c)$. We use $\mathscr{I}^{\ell(a,c)} \equiv \{1, \cdots, I^{\ell(a,c)}\}$ to denote the set of students in the lab.

We take the average of Equation (1) over all students in the same lab $\ell(a,c)$. Because the students in the same lab have the same advisor quality, we have the following equation for the lab-level average of the student research outcome growth:

$$\overline{\Delta outcome}_{ag}^{\ell(a,c)} = \bar{\gamma}^{\ell(a,c)} + \theta_{ag} + \bar{\nu}_{ag}^{\ell(a,c)}, \tag{2}$$

where the overbar notation indicates the group average.

Note that the *superscript* a denotes the *initial* advisor to whom the students in lab $\ell(a,c)$ were assigned, while the *subscript* a denotes the advisor who supervised the students in degree program g. Thus, the advisors represented by the superscript and subscript could be different. For example, suppose that a turnover incident causes the students in lab $\ell(a,c)$ to switch their research advisor from professor a in the master's degree program to professor b in the doctoral degree program. Here, the average student research outcome gain at the doctoral level, which is the left-hand side of Equation (2), is given by $\overline{\Delta outcome}_{bd}^{\ell(a,c)}$, where the index a in the superscript differs from the index b in the subscript.

We use the event of professor turnover (e.g., retirement, relocation and decease) to identify the variance in professor quality. We implicitly assume that, when a professor exits a graduate program due to turnover, the students in the lab whom he or she initially supervised are re-assigned to a new advisor and continue their research projects in the same program.[10] In what follows, we therefore assume that an event of professor turnover on the faculty side leads to an event of advisor *switch* on the student side. In other words, we treat these two events, advisor turnover and advisor switch, identically. When advisor turnover occurs in a lab, two faculty members, whose quality levels are generally different, advised students in the lab.[11]

[10] A joint transfer of faculty and students is quite rare in Japanese universities, and hence, even if a faculty member changes affiliation, the students usually remain in the same program.

[11] Based on the observed pattern of advisor replacement in UTokyo's physics graduate program, when

It should be noted that the professor, say b, who was assigned to the students in the lab of a professor, say a, after the latter exited due to turnover was not necessary drawn at random from a pool of professors available at the school at that time. Indeed, the newly assigned professor might select the students that he or she is willing to take over. We thus allow the student fixed effect, γ_i, to be correlated with the quality of the re-assigned professor, θ_{bd}, in the same way as we assume it to be correlated with the quality of the original advisor, θ_{ad}.

3.2 A Lower-bound Estimation of the Variance in Advisor Quality

We are interested in decomposing the total variation in student outcome gains into the variation that can be attributed to professor quality, θ_{ag}. First, take the difference of Equation (2) between the master's degree and doctoral degree programs. Doing so eliminates the student fixed effect, γ_i, because it is constant across degree programs for a given student. If advisor turnover did not occur in lab $\ell(a,c)$, it is given by the following between-degree difference equation:

$$\overline{\Delta outcome}_{ad}^{\ell(a,c)} - \overline{\Delta outcome}_{am}^{\ell(a,c)} = (\theta_{ad} - \theta_{am}) + (\bar{\nu}_{ad}^{\ell(a,c)} - \bar{\nu}_{am}^{\ell(a,c)}). \tag{3}$$

In contrast, assume that there was advisor turnover in lab $\ell(a,c)$. As the students switched their advisors from advisor a in the master's program to advisor b in the doctoral program, the between-degree difference equation, corresponding to Equation (3), is given by:

$$\overline{\Delta outcome}_{bd}^{\ell(a,c)} - \overline{\Delta outcome}_{am}^{\ell(a,c)} = (\theta_{bd} - \theta_{am}) + (\bar{\nu}_{bd}^{\ell(a,c)} - \bar{\nu}_{am}^{\ell(a,c)}). \tag{4}$$

Comparing Equations (3) and (4) shows that advisor turnover influences the development of student research achievement in different ways. There is a clear difference in student research outcome growth, which appears on the left-hand side of each equation, that responds differently to a change in advisors due to the difference in degree-level advisor effects, $(\theta_{ad} - \theta_{am})$ and $(\theta_{bd} - \theta_{am})$, which are generally not equal. This plays a key role in the identification of the effect of advisor quality on student research outcome growth at each degree level.

The point is illustrated by Figure1, which depicts three labs with different cohorts, c_0, c_1 and c_2, whose initial advisor is professor a. In the figure, each lab is portrayed by a connected

advisor turnover occurred, the students were usually either assigned to a junior faculty member or the sub-leader of the same lab or they were moved to a different lab in closely related research fields within the same institution and were supervised by the faculty member who managed that lab.

line segment, which represents the two-year master's degree program (the first half of the segment) and the three-year doctoral degree program (the last half of the segment).[12] Here, advisor turnover did not occur in labs $l(a, c_0)$ or $l(a, c_1)$ before cohort c_2, and hence, the students in these labs were supervised by the same professor, a, throughout both the master's and doctoral programs. However, in lab $l(a, c_2)$, professor a exited the school due to turnover, and professor b took charge of the doctoral students.

Note that, on average, the research outcome gains of lab $l(a, c_0)$ and $l(a, c_1)$ students are the same, which is given by $(\theta_{ad} - \theta_{am})$, whereas, following advisor turnover, the average student research outcome gain of lab $l(a, c_2)$, which is given by $(\theta_{bd} - \theta_{am})$, could be better or worse than those of the previous cohorts, depending on whether the supervising quality of the newly assigned professor, b, is higher than that of the departing professor, a. In either case, irrespective of whether the achievement growth is positive or negative, an instance of turnover triggers a change in professor quality at the doctoral level and could thus result in a disparity in the between-degree research achievement gains between cohorts. We will use the induced divergence in research outcome growth as evidence of an advisor's impact on an advisee.

Insert Figure 1

To improve the identification, we use the *double-differencing* approach as proposed by RHK to estimate a lower bound of the variance in unknown teacher quality. We take the difference of Equations (3) and (4) with respect to cohort year. Let c' denote the cohort before c, and let τ be the years between c and c'. For professor a, consider two labs, $\ell(a, c)$ and $\ell(a, c')$. Let $W^{\ell(a,c,c')}$ denote a dummy variable indicating a change in advisor due to turnover: it takes value one if professor a is replaced in lab $\ell(a, c)$ due to turnover and zero otherwise. Without loss of generality, we assume that supervisor replacement is from professor a to professor b such that, if there were advisor turnover, the students would have been supervised by two different professors, a and b, in the master's and doctoral degree programs, respectively. Then,

[12]For the ease of exposition, the labs' cohorts are not overlapped in the figure, although this is not necessarily the case in the actual sample.

we have the following double-differenced (DD) average student research outcome growth:

$$
\begin{aligned}
& DD\overline{\Delta outcome}^{\ell(a,c,c')} \\
= & \begin{cases} [\overline{\Delta outcome}_{bd}^{\ell(a,c)} - \overline{\Delta outcome}_{am}^{\ell(a,c)}] - [\overline{\Delta outcome}_{ad}^{\ell(a,c')} - \overline{\Delta outcome}_{pm}^{\ell(a,c')}] & \text{if } W^{\ell(a,c,c')} = 1 \\ [\overline{\Delta outcome}_{ad}^{\ell(a,c)} - \overline{\Delta outcome}_{am}^{\ell(a,c)}] - [\overline{\Delta outcome}_{pd}^{\ell(a,c')} - \overline{\Delta outcome}_{pm}^{\ell(a,c')}] & \text{if } W^{\ell(a,c,c')} = 0 \end{cases} \\
= & \begin{cases} (\theta_{bd} - \theta_{ad}) + error\ term & \text{if } W^{\ell(a,c,c')} = 1 \\ error\ term & \text{if } W^{\ell(a,c,c')} = 0, \end{cases}
\end{aligned} \tag{5}
$$

where the *error term* is a catchall random noise term that combines the average idiosyncratic errors.

Equation (5) shows that all of the fixed effects, except for doctoral-level advisor quality, are eliminated after the double difference is taken with respect to degree programs and cohorts. The double-differenced measure is more variable,on average, for the pair of labs with and without a change in advisor ($W^{\ell(a,c,c')} = 1$) than that for the pair of labs without such a change ($W^{\ell(a,c,c')} = 0$). The gap is attributable to a discrete change in doctoral-level advisor quality from θ_{ad} to θ_{bd} due to advisor turnover. Note that advisors' quality levels can be correlated with the lab averages of student fixed effects, $\bar{\gamma}^{\ell(a,c)}$ and $\bar{\gamma}^{\ell(a,c')}$, and they can also be correlated with one another, that is, $\text{Corr}(\theta_{ad}, \theta_{bd}) \neq 0$. In what follows, we ascribe the sample variation in the double-differenced measure as a series of variance and covariance components of advisor quality and idiosyncratic shocks.

The Assumption on Advisor Quality

We make the following assumptions concerning the distribution of advisor quality.

> assumption 1.1: The expectation and variance of advisor quality are given by $\text{E}(\theta_{ag}) = \mu_g$ and $\text{Var}(\theta_{ag}) = \sigma_g^2$, for any $a \in \mathscr{A}$, $g \in \{m, d\}$, and $c, c' \in \mathscr{C}$.
>
> assumption 1.2: The correlation of advisor quality across professors, $a \neq b \in \mathcal{A}$, is given by $\text{Corr}(\theta_{ag}, \theta_{bg}) = \rho_g$, for any $a, b \in \mathscr{A}$, $a \neq b$, $g \in \{m, d\}$ and $c, c' \in \mathscr{C}$.

These assumptions state the stationarity of the advisor quality distribution, which characterizes the notion that the professors' advising quality levels are drawn from a common distribution for each degree type. It requires that the grade-program-specific mean and variance do not vary across cohorts and that the correlation with any given advisor is constant.

Specifically, we interpret μ_g and σ_g^2 as the long-run mean and variance of the stationary distribution of advisor quality in degree program g within a school. The stationarity assumption simplifies the estimation of professor value added because it reduces the number of parameters to be considered. In the empirical section of the paper that follows, we estimate a lower bound of the variance in the advisor effect, σ_d^2, which is a measure of a professor's effectiveness in improving a student's research achievement growth at the doctoral level.

The Assumption on the Random Shock

The following assumptions impose restrictions on the moments of the idiosyncratic shock after *demeaning* by each cohort. Let $\bar{\nu}_g$ be the average of the random shock ν_{iag}^c, the average of which is taken over all cohorts in each degree program, g, such that the *demeaned* random shock is given by $\tilde{\nu}_{iag}^c = \nu_{iag}^c - \bar{\nu}_g$.

assumption 2.1: The conditional expectation and variance of the demeaned random shock, $\tilde{\nu}_c$, for student $i \in \mathscr{I}^{\ell(a,c)}$ are $\mathrm{E}(\tilde{\nu}_{iag}^c | W^{\ell(a,c,c')}) = 0$ and $\mathrm{Var}(\tilde{\nu}_{iag}^c | W^{\ell(a,c,c')}) = \phi_g^2$, respectively, for any $a \in \mathscr{A}$, $g \in \{m, d\}$, and $c, c' \in \mathscr{C}$.

assumption 2.2: The covariance of the demeaned random shocks *between* degree programs *within* the same student, $i \in \mathscr{I}^{\ell(a,c)}$, is given by $\mathrm{Cov}(\tilde{\nu}_{iam}^c, \tilde{\nu}_{iad}^c | W^{\ell(a,c,c')}) = \phi_{md}$ for any $a \in \mathscr{A}$, and $c, c' \in \mathscr{C}$.

assumption 2.3: The covariance of the demeaned random shocks between different students $i \in \mathscr{I}^{\ell(a,c)}$ and $j \in \mathscr{I}^{\ell(a,c)}$ who are advised by the *same* professor in degree program g is given by $\mathrm{Cov}(\tilde{\nu}_{iag}^c, \tilde{\nu}_{jag}^c | W^{\ell(a,c,c')}) = \mathrm{Cov}(\tilde{\nu}_{iag}^c, \tilde{\nu}_{jag}^{c'} | W^{\ell(a,c,c')}) = \psi_g$, for any $a \in \mathscr{A}$, $g \in \{m, d\}$, and $c, c' \in \mathscr{C}$.

assumption 2.4: The covariance of the demeaned random shocks between different students $i \in \mathscr{I}^{\ell(a,c)}$ and $j \in \mathscr{I}^{\ell(a',c')}$ who are advised by *different* professors in degree program g is zero, that is,

$$\mathrm{Cov}(\tilde{\nu}_{iag}^c, \tilde{\nu}_{ja'g}^c | W^{\ell(a,c,c')}) = \mathrm{Cov}(\tilde{\nu}_{iag}^c, \tilde{\nu}_{ja'g}^{c'} | W^{\ell(a,c,c')}) = 0,$$

for any $a, a' \in \mathscr{A}$, $a \neq a'$, $g \in \{m, d\}$, and $c, c' \in \mathscr{C}$.

assumption 2.5: The covariance of the demeaned random shocks *between* different students $i \in \mathscr{I}^{\ell(a,c)}$ and $j \in \mathscr{I}^{\ell(a',c')}$ *between* degree programs is zero, that is,

$$\mathrm{Cov}(\tilde{\nu}^{c}_{iam}, \tilde{\nu}^{c'}_{ja'd} | W^{\ell(a,c,c')}) = \mathrm{Cov}(\tilde{\nu}^{c}_{iad}, \tilde{\nu}^{c'}_{ja'm} | W^{\ell(a,c,c')}) = 0$$

for any $a, a' \in \mathscr{A}$, and $c, c' \in \mathscr{C}$.

The random shocks demeaned by cohort are assumed to be independent of turnover incidents (assumption 2.1). They can be serially correlated between degree programs within a student (assumption 2.2) and between students in each degree program if they are supervised by the same advisor (assumption 2.3). However, they are neither cross- nor serially correlated (assumptions 2.4 and 2.5). Note that, even if the demeaned random shock, $\tilde{\nu}^{c}_{iag}$, is uncorrelated with others under assumptions 2.4 and 2.5, the original random shock, ν^{c}_{iag}, is allowed to be correlated through the common mean factor, $\bar{\nu}_g$.

The Regression Model

Finally, given the assumptions presented above, we square both sides of Equation (5) and take the expectation conditional on the occurrence of turnover. We have the following result:[13]

$$\mathrm{E}\left[\left(DD\overline{\Delta outcome}^{\ell(a,c,c')}\right)^2 | W^{\ell(a,c,c')}\right] = \alpha\left(\frac{1}{I^{\ell(a,c)}} + \frac{1}{I^{l(a,c')}}\right) + \left\{2\sigma_d^2(1-\rho_d)\right\} W^{\ell(a,c,c')}, \quad (6)$$

where we define $\alpha = \{\phi_d^2 + \phi_m^2 + 4(\psi_d + \psi_m) - 2\phi_{dm}\}$.

Equation (6) provides a basis for estimating the variance in advisor quality at the doctoral level. Using the cohort examples, c_0, c_1, and c_2, that are depicted by Figure1 for illustration, the squared difference measure of student research outcome growth, which is the right-hand side of Equation (6), is greater for $\ell(a, c_1, c_2)$ than that for $\ell(a, c_0, c_1)$ by $2\sigma_d^2(1-\rho_d)$. We can therefore ascribe the large sample variation of the right-hand side of Equation (6), if any, to the variance in doctoral-level advisor quality, σ_d^2, unless the correlation coefficient, ρ_d, is equal to one.

We now present a regression model to obtain a lower-bound estimate of the variance of σ_d^2. Consider the following:

$$\left(DD\overline{\Delta outcome}_n\right)^2 = \alpha X_n + \beta W_n + \varepsilon_n, \quad (7)$$

[13] See Appendix A for the derivation.

where $n = 1, \cdots, N$ is the index of observations. Here, the unit of observation is each element of (a, c, c') for any advisor $a \in \mathscr{A}$ and cohort c, c' such that $0 < c - c' \leq \tau$, where τ is the period over which the difference is taken.[14]. Note that, analogous to Equation (6), the covariate $X_n = 2(1/I^{\ell(a,c)} + 1/I^{l(a,c')})$ is introduced into the regression. The random term ε_n is interpreted as the prediction error between the expected and observed values of the divergence measures, that is:

$$\varepsilon_n \equiv \mathrm{E}\left[\left(DD\overline{\Delta outcome_n}\right)^2 \middle| W_n\right] - \left(DD\overline{\Delta outcome_n}\right)^2.$$

Assume for a moment that the advisor switch indicator, W_n, is independent of the prediction error, ε_n. If the value of ρ_d were known perfectly, the OLS estimate $\hat{\beta}$ in Equation (7) would provide a consistent estimate of σ_d^2 through the following equation:

$$\hat{\beta} = \left\{2\hat{\sigma}_d^2(1 - \rho_d)\right\}. \tag{8}$$

As the correlation is imperfect ($\rho_d < 1$), a lower-bound estimate of σ_d^2 is given by the last term of the following equation:

$$\hat{\sigma}_d^2 = \frac{\hat{\beta}}{2(1 - \rho_d)} \geq \frac{\hat{\beta}}{4}. \tag{9}$$

In other words, a lower-bound estimate of the within-school variance of faculty quality at the doctoral level is equal to the estimated coefficient, $\hat{\beta}$, of the regression model (7) divided by four.

4 Data

We assemble data sets of professors and students in a graduate program in physics in Japan. Among the numerous Japanese research universities that offer both master's and doctoral programs in the field of physics, we focus on the graduate program at UTokyo, which is the oldest institution of its kind in the country and has enjoyed high prestige in the global academic community.[15]

[14] To obtain the double-differenced average of the research outcome gain, which is the left-hand side of Equation (7), we take the difference between all cohorts within a period of τ years. As $\binom{\tau+1}{2} = \frac{\tau!}{(\tau-2)!2!}$ samples are created for each lab, the total sample size of the regression is given by $N = \frac{\tau! L}{(\tau-2)!2!}$, where L is the total number of labs.

[15] According to several world university rankings, UTokyo has been in the top 10 in the discipline of physics. The alumni include five Nobel laureates in physics as of 2015.

The graduate program in physics at UTokyo consists of the department of physics as its core and other physics-related research institutes on campus.[16] The average number of graduates in recent years is 105.6 for the master's program and 58.4 for the doctoral program[17]. At present, there are more than 130 full-time faculty members. Many subfields of physics are covered by laboratories in UTokyo's physics graduate programs, such as nuclear physics, particle physics, condensed matter physics, and biophysics.

4.1 Data on Advisor and Advisee Pairs

To extract the information on matched advisor-advisee pairs, we use the master's and doctoral thesis catalogs for graduate students in UTokyo's physics program.[18] For each thesis entry in the catalog, the available information includes the degree date, the title of the thesis, the name of the student, and the name of the faculty advisor who supervised the student.

We compile the thesis data for the students who obtained their doctoral degrees in the cohorts between 1970 and 2004 (35 years). Among all of the graduate students who were listed in both the master's and doctoral thesis catalogs, we restrict our attention to those who earned doctorates within six years of enrollment. In addition, we restrict the analysis to those who were supervised by faculty members with the ranks of full and associate professors in the physics department or on-campus physics-related research institutions.

4.2 Data on Advisor Turnover and Switch

We obtain information on faculty turnover from the University Personnel Directory Book ("*Zenkoku Daigaku Shokuin Roku*") published by *Koujyun Sha*, which includes information on the full name, rank, department, school, specialized fields and year of birth of all staff members at every Japanese university, public or private, in a given year. By compiling the roster of faculty members at UTokyo, we can obtain their turnover information.

We identify turnover as a case in which a faculty member left UTokyo. We classify the reasons for turnover into the following three categories: (1) retirement if the instance of

[16] The institutes are the Institute of Cosmic Ray Research, (ICRR), the Institute of Solid State Physics (ISSP), and the International Center for Elementary Particle Physics (ICEPP).

[17] These are the average figures over the period from 2010 to 2014.

[18] The catalogs are available on the department's website at `http://www.phys.s.u-tokyo.ac.jp/TOSHO/ronbun.html`.

turnover occurred at the mandatory retirement age predetermined by UTokyo;[19] (2) move if turnover occurred before the retirement age and the faculty name began to reappear on other universities' roasters beginning in the year after the turnover instance; and (3) decease/quit otherwise.[20]

Figure 2 presents the graphs that plot the number of turnover incidents in each year of the sample period, broken down by the reasons.[21]

Insert Figure 2

The matched advisor-advisee data reveal that approximately 14.4 percent of graduate students switched advisors between the master's program and the doctoral program. Instances of professor turnover are responsible for some, although not all, of the students' observed changes in advisors. As mentioned previously, in Japanese universities, a joint transfer of faculty member and student is quite rare. If a faculty member exits a graduate program, another other faculty member – usually a sub-leader of the same lab or, sometimes, a faculty member from a different lab in the same institution whose research area is closely related to the professor who exited – becomes the new advisor of the students who are left behind. In either case, the student remains in the same program.[22]

We identify an advisor switch due to turnover if a student's master's thesis advisor exited

[19] Before fiscal year 2000, the mandatory retirement age at UTokyo was 60. After the 2001 fiscal year, it was increased by one year every three years until it reached 65. As of 2004, which is the end of the sample period, the retirement age was 61.

[20] However, note that the reasons for faculty turnover are not perfectly distinguishable. Indeed, the majority of faculty members categorized as "retire" did not actually retire from academic life and were reemployed at other universities or research institutions. This is possible because of the gap in retirement ages between universities: UTokyo set its faculty retirement age at 60 during the most of the sample period, while other Japanese universities, public and private, adopted retirement ages that were several years older.

[21] There is a considerable number of incidents in 1997, when the Institute for Nuclear Study (INS) at UTokyo, which was one of the on-campus research institutes affiliated with the physics department, was closed and merged with the High Energy Accelerator Research Organization (also known as the KEK (Kō Enerugī Kasokuki Kenkyū Kikō.), and some of the faculty members at the INS chose to leave UTokyo for the KEK.

[22] It is often noted that Japanese graduate students are loyal not to their advisors but to their labs. Cultural norms dictate that each member of a lab is expected to keep its resources intact and pass them on to the next generation (see, e.g., Traweek p.148), which is congruent with the analogy of *ie* (the household) to labs in Japanese universities, as described in the previous section.

UTokyo before the student earned a doctoral degree. Such cases account for 53.2 percent of all advisor switches in the sample. We exclude students who switched advisors on their own initiative from the sample observations, as such student-side advisor switches are likely to be caused by a mismatch between advisor and advisee and could be correlated with student research outcomes. Ultimately, the resulting sample contains 801 students and 158 advisors, and this sample is used to estimate professor value added in what follows.

4.3 Data on Student Research Achievement

To measure a graduate student's research achievement, we use the number of journal articles that he or she published. To obtain this information, we employ the Thomson Reuters Web of Science (WoS) archive. We collect physics articles with author names that match the name of the graduate student under consideration. We further restrict our attention to those articles published around the period when the target student was enrolled.

The articles selected by author name matching may contain false positives: these articles could have an author who coincidentally has the same name as the graduate student in the sample but is in fact a different person. To minimize such identification errors, we add a further restriction; that is, for an article to be identified as written by the student in question, we impose a restriction that the words in the article title should overlap to some extent with those in the title of the master's or doctoral thesis. [23]

Based on a student's publication records, we define the *research proficiency score* as the number of publication counts during *a given year*. Here, we employ two quality adjustment methods. First, we limit the publications to those published in twelve high-quality peer-reviewed journals, including three high-reputation general-interest science journals and nine highly ranked physics journals.[24] Second, we consider a student's share of credit for an article if there are multiple authors. In physics, as in other scientific disciplines, papers are usually written by a group of authors whose contributions are not necessarily equal. We follow a standard bibliometric method (e.g., Liu and Fang, 2012; Waltman, 2012) based on the byline

[23] See Appendix B for details on the score of word overlap in titles.

[24] *Nature*, *Science* and *Proceedings of the National Academy of Sciences of the United States of America (PNAS)* are included as the general-interest science journals, and *Physical Reviews A, B, C, D, and E*; *Physical Reviews Letters*; and *Physics Letters A and B* are included as the top physics journals. We received advice from physicists regarding the selection of the top journals.

hierarchy rule to quantify an coauthor's share of credit for an article with multiple authors.[25]

Figure 3 plots the average research proficiency score for our sample graduate students in each year. Note that, in the figure, we begin the graduate school year index at one in the year when a student entered the master's program and increase it throughout the duration of the graduate program. For the sake of expedience, the graduate school year is also defined for the postdoctoral period after the student obtained a doctorate degree. In the figure, it corresponds to the period after the 6th year.

Insert Figure 3

The figure illustrates the time pattern of how physics graduate students at UTokyo develop their research outcomes: the achievement curve rises and reaches its peak in the years near the completion of the doctoral degree (D1 and P1). Then, the research outcomes begin to decline during the postdoctoral periods (P1-P5). We suspect that this reflects two types of lag structure: the first relates to a publication lag, that is, the time lag from the submission to publication of articles in journals. The second concerns a gestation lag, that is, the time lag between project inception and completion.

5 Empirical Issues

In this section, as a starting point for our empirical analysis, we describe the empirical issues involved in estimating a lower bound of professor quality based on the regression model in Equation (7). We first address how to construct the squared difference measure of the student outcome growth variable, which is used as the dependent variable in the regression model. We next discuss the non-randomness of professor turnover, which could cause an endogeneity

[25]What follows illustrates how the coauthor's credit share is constructed. Suppose that the names of the authors are ordered alphabetically. Then, the contribution weight is fractional: each author receives equal credit. Suppose this alphabetical approach is not used. Then, each author receives a share of credit that decreases in the authorship ranking. Following Liu and Fang (2012), the credit formula is given by $n^{-1/k}r^{-(1-1/k)}$ for the r-th author of a paper with n authors. The integral constant, k, controls the declining rate of credit allocated in proportion to that of the first author. According to the suggestion of Liu and Fang (2012), we set $k = 3$ for our analysis. Waltman (2012) notes that authorship could unintentionally be alphabetical, especially when the number of authors is small, despite the authors' intention to list their names based on a non-alphabetical criterion. Therefore, we account for the probabilities of both such incidental and intentional alphabetical authorship and use the expected value as the final research outcome measure.

problem and thus threaten the validity of the estimates. We then propose a method to address this endogeneity concern.

5.1 Student Research Outcome Variable

As presented in Section 3.2, the regression model is based on the double-differenced student research outcome measure, which requires systematic difference — the first-stage difference is taken with respect to the degree program g, and then, the second stage is taken regarding cohort c.

Two issues arise: (i) the choice of years over which the student research outcomes are aggregated at the program level [26] and (ii) the choice of interval years between the pair of cohorts that are differenced.

Regarding the first issue, which publications should we count as research outcomes of the master's program and which as those of the doctoral program?

Figure 4 presents the student average research proficiency scores that are decomposed into those related to the master's thesis and those related to the doctoral thesis.[27] The findings indicate that the proficiency score associated with the master's thesis peaks in the second year of the doctoral program (D2) and decreases thereafter, while the score related to the doctoral thesis continues to increase. We thus opt to aggregate the research proficiency scores over the period from the first year of the master's program (M1) to the second year of the doctoral program (D2) to compute the research outcome at the master's level. However, for the research outcome at the doctoral level, we assemble the research proficiency scores from the first year of the doctoral program (D1) up to the fourth year of the postdoctoral period (P4). We choose a rather long aggregation period at the doctoral level in light of the lag between the time of article publication and the time the degree is awarded, as seen in Figure 3.

Insert Figure 4

[26]Because the value-added model focuses on the student research achievement gain while in school, the magnitude might be minute and unnoticeable if it is measured by the annual gain. We thus select the unit of measure as each *degree program* period.

[27]As explained in Section 4.3, to implement the decomposition, we classify student articles as those related to the master's thesis and those related to the doctoral thesis by considering the overlap of the title of the article and that of the thesis.

In sum, our benchmark student research outcomes are aggregated over the period from M1 to D2 and the period from D1 to P4 for the master's degree and doctoral degree programs, respectively. Table 1 presents the descriptive statistics. Figure 5 presents the box plots of the research outcome distributions at the master's and doctoral levels.

Insert Table 1

We turn to the second issue concerning the interval in years between cohorts. In Section 3.2, τ denotes the number of years between two cohorts, c and c', such that $c - c' \leq \tau$ when determining the double-difference student research outcome growth. Note that there is no theoretical rule for which year should be used as τ. On the one hand, the longer the interval is, the more efficient the estimator because it yields more samples for the regression analysis.[28] On the other hand, the shorter interval is, the better because it requires a weaker assumption on the covariance stationarity of the distribution of the demeaned random shocks (assumption 2.3).[29] In light of balance, we adopt the adjacent cohort period of $\tau = 3, 4$ and 5 years as the benchmark when implementing the regression.

Insert Figure 5

5.2 Non-Random Turnover

Thus far, we have assumed that professor turnover is independent of various factors in the value-added model and thus does not affect student research performance except through the change in advisor quality. However, the assumption might be untenable. Arguably, a professor's decision of whether to retire, move, or remain at a graduate program might be endogenous to the student's performance.

Consequently, the regression model in Equation (7) might suffer from the standard endogenous variable problem, as the catch-all error term, ε_n, which influences student research outcome growth, will be confounded by the advisor switch dummy variable, W_n, through the heterogeneity of advisors, who systematically differ between those with and without turnover.

[28] As presented in footnote 14, the total sample size is given by $N = \frac{\tau! L}{(\tau-2)!2!}$, which is an increasing function of the adjacent period, τ, ceteris paribus.

[29] To be more precise, assumption 2.3 states that the covariance of the demeaned error terms is constant between any two students, i and j, in different cohorts, c and c'. This assumption might be reasonable only for adjacent cohorts.

In this case, we might not be able to obtain an unbiased estimate of β from the regression and thus be unable to obtain a reliable estimate of the lower bound of advisor quality.

Table 2 reports the descriptive statistics for some characteristics of advisors and compares those of advisors when turnover occurred and the corresponding advisor characteristics when it did not.[30] We find that, for some characteristics, the differences in means between the two groups, professors with turnover in column (1) and those without in column (2), are statistically significant at the 5 percent level. We also find that the absolute values of the standardized differences, reported in column (3), are large for some characteristics.[31] Therefore, this suggests that the sample is not balanced, that is, there are systematic differences between the groups with and without professor turnover on some characteristics.

Insert Table 2

To make the sample balanced and comparable, we employ a propensity score matching method. The basic idea is to match a turnover case with a case of no turnover that has approximately the same conditional likelihood, typically called the propensity score, that an incident of advisor turnover would have occurred. After constructing a new balanced sample based on the propensity score matching procedure, we estimate the regression model in Equation (7) using the balanced sample, as if advisor changes due to turnover occurred at random.

Note that, to account for the endogeneity of the advisor switch dummy variable in the regression model, we only control for advisor characteristics. It is potentially justifiable not to balance the sample on student characteristics because we exclude all cases in which a change in advisor occurs for a student's own reasons, as described in Section 4.2. The sample restriction can eliminate the possibility that student factors are confounded with the occurrence of an advisor switch, and therefore, it is deemed to occur exclusively for reasons on the faculty side. Hence, we control for the professor's characteristics in the propensity score analysis.

[30]The research proficiency scores of professors are computed in the same way as those of students. The score is, in essence, the number of publications in top general and physics journals, with the coauthor's credit share being adjusted. The data source is the WoS.

[31]The standardized difference considers the size of the difference in means of a conditioning variable, scaled by the square root of the variances of the treatment and control groups in the original sample. According to the suggestion of Rosenbaum and Rubin (1985), an absolute value of the standardized difference greater than 0.2 should be considered "large".

Following standard practice in the literature, we estimate the propensity scores using a logit model. We include all of the characteristics presented in Table 2 when estimating the propensity scores. We determine a baseline specification of the model by a stepwise likelihood-test-based procedure, suggested by Imbens (2014) and Imbens and Rubin (2015).[32] The results of the logit estimation of the propensity score can be found in Appendix C.3. Given the estimated propensity scores, we match a case with $W_n = 1$ (a lab with an advisor switch) to one with $W_n = 0$ (a lab without an advisor switch) that share approximately identical estimated propensity scores. We employ a one-to-one nearest-neighbor matching method.

To assess the quality of the propensity score matching, we present Figure 6 that depicts the absolute values in the standardized differences of the variables for the original and matched samples. The imbalance between the treatment and control cases is attenuated on many professor characteristics. For example, professor's age differs between the treatment and control labs by more than the average standard deviation (the absolute standard deviation is 1.129) before matching, whereas the difference is considerably reduced (the absolute standard deviation is 0.006) after matching.

Insert Figure 6

Figure 7 presents the distributions of the estimated propensity scores for the treatment labs (left) and control labs (right) in each case of the adjacent period, $\tau = 3, 4$, and 5. The top and bottom groups in the graphs correspond to those before and after matching, respectively. Before matching, the shapes of distributions differ considerably between the treatment and control groups. Nevertheless, the propensity score distributions have some degree of overlap. Moreover, after matching, the dissimilarity of the distributions between the treatment and control groups is considerably reduced.

Insert Figure 7

One might worry that the spread of the common support of the propensity score distribu-

[32]Specifically, in the first step, we begin with a set of basic covariates and add an additional linear term based on a likelihood ratio test for the null hypothesis that the coefficient of the added variable is equal to zero. In the second step, we proceed to the choice of the quadratic and cross-product terms and apply the same type of likelihood test as that used in the first step. We follow the suggestion of Imbens and Rubin (2015) that the threshold values for the likelihood ratio test should be $C_L = 1.0$ and $C_Q = 2.71$ for the linear and quadratic terms, respectively.

tions should not be across the full range [0 1] and hence that the observations of the treatment group, especially those with high propensity scores, are matched forcibly with those of the control group, the propensity scores of which are not sufficiently close. To address the problem caused by the limited common support of the propensity score distribution, we employ a systematic approach proposed by Crump et al. (2009) and discard all observations with estimated propensity scores outside the range of [0.1 0.9].

6 Estimation Results

6.1 Benchmark Results

This section presents the estimation results for professors' value added to the students' research achievement gains. We estimate the econometric model (7) using the propensity score matching method that we described in the previous section. The main estimate of interest is the lower bound of the variance in advisor quality at the doctoral level, which is given by one-fourth of the coefficient of the advisor switch indicator variable in the regression model.

Table 3 presents the baseline results. We report the regression estimates in rows (1) and (2). Columns (1), (2) and (3) are used to report the estimation results for the three cases of adjacent periods between cohorts, $\tau = 3$, 4 and 5 years, respectively. As the estimated propensity scores are used for the true values, we compute resampling-based standard errors to correct for the additional sampling variability arising from estimation.[33] All estimates of βs are positive and statistically significant from zero at the 10 percent level except for one case.

Insert Table 3

Row (3) of Table 3 presents the estimated lower bound of advisor quality variance at the doctoral level. As the variance must be non-negative, we perform one-sided tests on the lower-bound estimates such that $\sigma_d^2 = 0$ against the alternative $\sigma_d^2 > 0$. The results indicate that the null hypothesis is rejected at least at the 5 percent level for all cases, indicating

[33] Abadie and Imbens (2008) demonstrate that the bootstrap method generates biased estimates of the standard errors for a nearest-neighbor matching estimator and suggest the subsampling method developed by Politis and Romano (1994). We therefore use the subsampling method whereby we draw fewer observations than the same size at each iteration without replacement.

that a professor's quality has a measurable effect on the research performance growth of the student to whom he or she is assigned.

For the results that we have presented thus far, we base the student research outcome on the research proficiency scores that are adjusted for the share of credit of each author. Alternatively, we can quantify the research outcome of a student *without* credit share adjustment. To this end, we count the number of *first-authored* articles that the student published as a lead author in the selected top general and field journals in physics. While the alternative research outcome measure might be crude and subject to a certain amount of noise — it might underrate the research achievement of a student because it ignores the articles for which he or she is not a lead author, or it might overrate the student's attainment because it accords him or her all of the credit, even for multi-authored articles, irrespective of how many coauthors are involved — it nonetheless serves as a simple and easily interpreted yardstick.

The estimation results using the alternative research outcome measure are presented in columns (4) to (6) of Table 3. The regression estimates are larger than previous results that adjusted the author's credit share. This is unsurprising because the first-author-based measure is greater than the original measure to the extent that the credit share is not weighted.[34] The estimated values of the lower bound of σ_d^2, reported in row (3), are correspondingly larger than those previously reported. Reassuringly, the null hypothesis that the variance in advisor quality is zero cannot be rejected at least at the 5 percent level. We therefore obtain qualitatively similar evidence on the professor's value added as previously.

The results presented above indicate the effectiveness of professors in improving doctoral students' research productivity growth. Indeed, better advisor quality causally affects advisees' research achievement gains in graduate school. If we use 0.0489 as the most conservative estimate of the lower bound of the advisor quality variance among those reported in columns (1) to (3) of Table 3, we find that a one-standard-deviation increase in professor quality raises the average student research achievement gain at the doctoral level by at least 0.221, which corresponds to approximately 0.54 standard deviations of the total doctoral program research outcome distribution.

If we base the estimation results on the first-author-based research outcome measure reported in columns (4) to (6) of Table 3, we find that, if professor quality increases by one

[34] The mean and standard deviation of the first-author-based research outcome at the doctoral level are 0.39 and 0.96.

standard deviation, the average student publishes 0.64 more first-authored articles in top journals at the doctoral level.[35] We are thus able to conclude that professor's value added to graduate student research outcomes is substantial.

Our estimates of value added provide an interesting comparison with the professor value-added estimates at the undergraduate level reported by previous studies. For example, Hoffmann and Oreopoulos (2009) estimate professor value added to student's achievement gains, measured by undergraduate course grades in a large Canadian university. They report that a one-standard-deviation increase in professor quality yields an approximately 0.05 standard deviation increase in a student's grade. Carrell and West (2010) obtain a similar value-added estimate for professors at the U.S. Air Force Academy who teach introductory courses at the undergraduate level. They report that the standard deviation of value added is approximately 0.05. Therefore, our estimates of professor-value added at the postgraduate level are substantially larger than those standard-deviation estimates at the undergraduate level.

The observed difference in the estimates might not be too surprising considering several factors that make our study distinct from other studies. First, the professor quality that we measure is different. We evaluate the dimension of professor quality that promotes a student's *research* capability, whereas those previous studies assess the aspect of quality that enhances a student's *academic* capability. Second, closely related to the first point, the student outcome is different. We focus on the research achievement gains of postgraduate students, while previous studies investigate the academic achievement gains of undergraduate students. Finally, the estimation method is different. Our estimation method, following that of RHK, is based on professor turnover and provides a lower bound of professor quality. By contrast, the approach employed by Hoffmann and Oreopoulos (2009) is based on the covariance estimation procedure proposed by Page and Solon (2003) and is interpreted as an upper bound of professor quality. The estimation method used in Carrell and West (2010) is a random effect estimation of unobserved professor quality, relying on the fact that the courses are randomly assigned to students and, therefore, that no issue of self-selection arises. We hope further studies will add evidence on the difference in professor value added between undergraduate and postgraduate education.

[35]When computing the standard deviation increase, we use 0.410 as the estimated value of the lower bound of advisor quality variance.

6.2 Robustness Tests

This section provides various robustness checks for the benchmark results. First, we implement a falsification test that investigates whether a false instance of an advisor switch predicts an increase in the volatility of student research outcomes between programs and cohorts. Second, we perform specification checks to examine whether the benchmark results are robust to alternative definitions of the student research outcome. Third, we discuss the possibility that the lower bound of the estimate of the advisor quality variance might be overestimated.

Falsification Test

In our estimation framework, the variance in advisor quality is identified by an increase in the squared difference of the student research outcome gain at the time of advisor turnover. We thus implement a falsification exercise that examines whether the timing agrees with what is predicted by the empirical model.

To do so, we construct a *false* advisor switch dummy variable, $\tilde{W}_n$, that takes value one for the lab in one cohort before the actual incident and zero otherwise. Specifically, given lab $\ell(a, c)$, where advisor turnover occurred, the variable $\tilde{W}_n$ is one in the *latest* cohort, c', in which advisor a supervised at least one student before cohort c. We estimate a regression similar to regression model (7) using the dummy variable $\tilde{W}_n$ as the regressor instead of using the true advisor switch dummy variable, W_n, with $\tilde{\beta}$ being the coefficient of the variable $\tilde{W}$.

We present the results in Table 4, where we adopt the same definition of the student research outcome measures as the baseline case, and replicate the regression results except that we use the false advisor switch dummy variable. Columns (1) to (3) show the results for the credit-share-based research outcome measure, and columns (4) to (6) show those for the first-authored-paper-based research outcome measure. The false advisor switch dummy variable is sometimes negative and has no systematic impact on the the squared difference of the student research outcome gain. Indeed, in all cases except one, the false advisor switch dummy variable is not statistically significant, suggesting that the results survive the falsification test. As there is no clear sign that the previous results can be explained by a spurious trend, we might be able to conclude that the timing of increased volatility in the student research outcome gains is consistent with that of advisor turnover.

Insert Table 4

Specification Checks

One might wonder whether our estimates are sensitive to specific assumptions on the definition of the student research outcome. To verify the robustness of the estimates to these assumptions, we consider alternative configurations in terms of the period over which the research proficiency scores are aggregated for each degree program. Specifically, in addition to the benchmark case (M1-D2 for the master's program and D1-P4 for the doctoral program), we examine alternative cases that change the aggregation period at the master's and doctoral levels.

Table 5 summarizes the set of lower-bound estimates of advisor quality under various definitions of student research outcomes. We employ the same specification and the same propensity-score-based estimation method as in the baseline case. For the purpose of comparison, the first row reports the corresponding estimate from the baseline case. We examine several different aggregation periods for both the baseline and alternative research outcome measures. All of the results are qualitatively similar to the previously reported findings. The null hypothesis that the variance in doctoral-level advisor quality is zero is rejected at the 10 percent level in all cases.

Insert Table 5

We also provide additional robustness tests regarding whether the results are driven by a specific value of the threshold that is used to compute students' research proficiency scores. As explained above, we consider research articles that are actually published by a target student if the author's name matches the student's name and, in addition, the degree of word overlap in the titles between the article and the student's thesis exceeds some predetermined threshold value. While the default value is set to minimize both type 1 and type 2 errors, we employ both over-matching and under-matching criteria in the robustness exercise. The results presented in Table C.2 in Appendix C.4 show that, while some estimates are not statistically significant in the cases in which the adjacent cohort period is five and the over-matching criterion is used, they tend to be positive and statistically significant. Despite the insignificant estimates, our conclusion regarding an advisor's effectiveness in improving an advisee's research productivity growth appears to be supported on the grounds that the value-added estimates are lower-bound estimates.

We turn to issues concerning the quality of research publications when computing student research achievement. In the benchmark case, we select twelve top journals (three general-interest science and nine physics journals). To examine the sensitivity of our estimates to the particular choice of top journals, we replicate the baseline analysis by narrowing the coverage to nine journals (two general-interest science and seven field journals) instead of twelve journals.[36]

Table 6 presents the estimation results. Although the estimates as a whole become smaller than those for the case of broader journal coverage, they are qualitatively unchanged, indicating that the findings from the regression model are not merely artifacts of the specific choice of top journals.[37]

Insert Table 6

In summary, considering all of the estimation results presented above, we can conclude that the specification of the student research outcome measure has little or no systematic effect on the estimation of professor value added.

Factors That Might Lead to Upward Bias

As we are interested in estimating a lower bound of the variance in advisor quality, downward bias would not be problematic, as is the case for the original turnover estimator that RHK propose. There is, however, a set of potential sources of upward bias.

The first possibility is that the assumption on the time-invariance of advisor quality, given by assumption 1.1, might be violated. Suppose, contrary to the assumption, that it varies across cohorts *within* a professor. In particular, if it fluctuates as the end of a professor's research career approaches, the squared difference measure, the dependent variable in regression model (7), becomes more volatile in the last cohorts before a professor's turnover. In this case, the regression coefficient of the advisor switch dummy variable might overstate

[36] The three of the original twelve journals excluded here are *PNAS* in the general-interest science journal category and *Physics Letters A and B* in the field journal category. This is based on suggestions that we received from several physics researchers.

[37] Table C.3 in Appendix C.4 summarizes the estimation results for the lower-bound estimates of advisor quality at the doctoral level for the case in which the student research outcome is based on the top nine journals and aggregation years are allowed to vary. The results demonstrate that the null hypothesis that the variance in doctoral-level advisor quality is zero is rejected at the 10 percent level for the majority of the cases, although we hasten to add that it cannot be rejected for some cases. Nevertheless, all of the estimates of the variance are positive.

the lower bound of advisor quality variance, as the increase in the dependent variable, which is indeed caused by within-advisor quality change, is mistakenly attributed to a systematic and discrete change in advisor quality due to turnover, despite that it should not be.

To shed some light on this concern, we augment the regression model in Equation (7) by including a set of dummy variables that capture the possible change in advisor quality variance in the period near turnover. Specifically, the dummy variable $D_k^{(a,c,c')}$ takes value one if cohort c is within k years before professor a exited and zero otherwise, for $k = 1, 2$, and 3.

The estimation results from the augmented specification are presented in Table 7, with δ_k being the coefficient of the dummy variable $D_k^{(a,c,c')}$. As reported in rows (3) to (5), for both the baseline and alternative research outcome measures, none of the coefficients concerning the added dummy variables are statistically significant. Moreover, row (6) indicates that the estimated coefficient of the advisor switch dummy variable is not substantially affected by the inclusion of the cohort-specific dummy variables. Furthermore, encouragingly, the null hypothesis that advisor quality in the doctoral program has no effect on student research outcome growth is rejected at least at the 10 percent level in all cases.[38] On the basis of this evidence, we obtain the same conclusion regarding professor value added even if we allow for the possibility of time-varying advisor quality.

Insert Table 7

Another possibility that might introduce upward bias into the lower bound of the variance in advisor quality concerns the allocation of the research *credit share* between advisor and advisee. Note that our empirical study relies on the assumption that the student made an original and substantial contribution to his or her thesis research projects and that the articles with titles that are closely associated with the master's thesis or doctoral dissertation can be used as an unbiased yardstick to gauge the student's in-school research achievement. The assumption appears somewhat reasonable for physics departments in Japanese universities, where, as described in Section 2.2, graduate students are typically accorded a fair amount of autonomy when choosing a research topic and approach.

Nevertheless, the assumption might not be tenable. One could imagine that students are

[38] Table C.4 in appendix C.4 presents the estimation results for the lower bound of advisor quality variance when we change the aggregation period for the student research outcomes. The estimates are qualitatively similar to those reported in Table 7.

merely given a part of a larger research project, or subtopic, that the advisor has pursued, and thus, their contribution to the project in collaboration with their advisors is marginal.[39] If this is true, our turnover estimator for the lower bound of the variance in advisor quality might suffer from systematic upward bias, as we would then mistakenly ascribe the advisor's research contribution to the student's research achievement.

Because the actual collaboration process is not observed for joint research activities, it is impossible for us to allocate the true share of credit to each member of an advisor-advisee pair that engaged in a joint research project. We therefore consider an extreme case in which the student's contribution is *zero* whenever he or she collaborated with a research advisor to highlight the sensitivity of the previous estimation results to the assumption on the allocation of research credit.

Table 8 presents the estimation results for the cases of the baseline and alternative student research outcome measures, assuming that the research proficiency score of student publication is equal to zero if it is coauthored with the advisor.[40] Looking across the columns of the table, the size of the estimated coefficients and the lower bound of advisor quality variance tend to be lower. Nonetheless, the one-sided test of the null hypothesis that doctoral-level advisor quality has no effect on an advisee's research achievement growth is rejected at the 10 percent level. Because we consider a severe restriction on the allocation of the credit share to the side of advisees, which is overly severe for the advisees in terms of their research contributions, the reported evidence of positive professor value added reassuringly supports the conclusion that professors enhance their students' research achievement gains by advising and mentoring their research projects at the postgraduate level.

Insert Table 8

[39]The view that attributes substantially greater credit for knowledge contribution to an accomplished senior researcher than to a less-known junior researcher is referred to as the "Matthew effect," a term coined by sociologist Robert K. Merton.

[40]In Table C.5 in appendix C.4, we report the estimation results of the lower bound of the advisor's quality variance when the aggregation period for the student research outcome is allowed to differ. These estimates are reassuringly statistically significant at the 10 percent level in more than half of the cases. Note that, in particular, if the research outcomes are measured by the number of the first-authored papers, then all estimates are statistically significant.

6.3 Additional Evidence for Professors' Influence on Students

Other Mechanisms

The estimation results have shown that advisor turnover generates significant variations in an advisee's research achievement gains at UTokyo's department of physics. According to a standard value-added model, we ascribe the increased diversity of student research achievement gains to the discrete change in advisor quality at the time of turnover. Admittedly, however, there may remain other mechanisms that create such a pattern.

One possibility is that professor turnover always has a *positive* effect on students' research capacity and thus increases the variability in student achievement gains between cohorts with and without turnover. The positive advisor turnover effect could be caused by a mechanism that reflects a well-known understanding that innovation (and thus economic growth) is due to the recombination of existing ideas (e.g., Weitzman, 1998). It follows from this view that, as new innovation is likely to arise from recombining old knowledge elements, students who are supervised by different professors would have access to a wider variety of knowledge and ideas and can thus enhance their research capabilities.

Another mechanism is the one that yields a *negative* effect of professor turnover on students' research achievement gains. As is often noted in the education literature (e.g., Wisker and Robinson, 2013), if an advisor is lost due to turnover, an advisee who becomes an "orphan" occasionally perceives this as a traumatic event and suffers from psychological problems that might occasionally result in under-development of academic achievement. If this understanding is correct, advisor turnover would retard the advisee's research progress, irrespective of how high the quality of the newly assigned advisor is, and thus generate a noticeable gap in student research outcome gains between cohorts with and without turnover.

Recall that, according to the mechanism captured by the value-added model, the advisee's research outcome growth can be positive or negative after turnover – indeed, as explained in Section 3.1, the direction of growth depends decisively on the relative levels of advisor quality that were switched when turnover occurred and will thus not be predicted *a priori* unless the information on the exact quality levels is available. In sum, because under all of the mechanisms presented above, advisor turnover can generate divergence in advisee research achievement gains, the baseline regression specification given in Equation (7) would misattribute the effects of turnover that are essentially attributable to different mechanisms.

In the analysis that follows, we investigate which mechanism is more likely by estimating a regression similar to the regression model in Equation (7), except with the dependent variable being *in levels*, $\left(DD\overline{\Delta outcome_n}\right)$, not *in squares* $\left(DD\overline{\Delta outcome_n}\right)^2$. To identify the mechanism in place, we focus on the sign of the turnover effect on the advisor's research achievement gain. As explained, if the first alternative mechanism (i.e., a student's research derives from the recombination of advisors' ideas) dominates the others, the coefficient of the advisor switch indicator dummy variable will be positive in the regression model with the double-differenced student achievement measure in levels as the dependent variable. However, if the second mechanism (i.e., a student's research progress is hampered by a traumatic experience triggered by advisor turnover) dominates, that coefficient will be negative.

Table 9 presents the regression results for which all estimated coefficients of the advisor switch indicator are shown to be positive but are not statistically significant in all cases. We can interpret the results as indicating that, contrary to the predictions of the alternative mechanisms, advisor turnover can have a positive or negative impact on an advisee's research productivity growth. As the individual impacts cancel one another out, the aggregate effect, as reflected by the integration, is not significantly different from the null in levels. It thus appears to confirm that the mechanism that the value-added model postulates should be a main driver of the empirical findings obtained thus far and to endorse the conclusion that professor quality plays a distinct role in enhancing a student's research capacity in the doctoral program.

Insert Table 9

Indirect Influence

Our analysis thus far has concentrated on the advisor-advisee relationship within a lab and intended to measure the effectiveness of knowledge transmission through a direct interaction channel within a lab. However, knowledge might be transmitted beyond lab-oriented master-apprenticeship-style contact. There might also exist an indirect transmission route across labs. For instance, students will learn, formally or informally, research skills and expertise in their discipline from faculty members who are not their supervisors through coursework, lectures or collaboration opportunities.

To measure such an indirect effect from non-advisor faculty members on students across labs within the same institution, consider the following augmented model of student research outcome gains:

$$\overline{\Delta outcome}_{eg}^{\ell(e,c)} = \bar{\gamma}^{\ell(e,c)} + \theta_{eg} + \sum_{f \in \mathscr{A}} \pi_{ef}\theta_{fg} + \bar{\nu}_{eg}^{\ell(e,c)}, \tag{10}$$

where we consider lab $\ell(e,c)$ of professor $e \in \mathscr{A}$ in cohort $c \in \mathscr{C}$. We modify the baseline specification in Equation (2) by incorporating an "indirect" effect of professor f on the average research outcome gain in program g for students in lab $\ell(e,c)$ who are supervised directly by professor e, where $e \neq f \in \mathscr{A}$. The magnitude of the indirect influence from non-advisor faculty member f is captured by the parameter π_{ef}, which can vary across professors, depending on the type of relationship the students in lab $\ell(e,c)$ have with professor f.

In what follows, for the purpose of simplicity, we restrict the scope of indirect influence to that between professors and students within the *same* research field (or subfields). We, particularly, assume that $\pi_{ef} = \pi$ if the research field or subfield of professor f is the same as or closely related to that of the direct advisor, e, and $\pi_{ef} = 0$ otherwise.

Analogous to Equation (6), we compute the conditional expectation of the squared double-differenced average student research outcome growth and construct a regression model based on the comparison of the conditional expectations between labs with and without a "treatment" assignment. To achieve this aim, let us use $V^{\ell(e,c,c')}$ to denote an assignment indicator of an "indirect" turnover incident. Specifically, define $V^{\ell(e,c,c')} = 1$ if a professor whose research subfield is the same as that of professor e is replaced due to turnover in cohort c and $V^{\ell(e,c,c')} = 0$ otherwise. In other words, the binary indicator variable $V^{\ell(e,c,c')}$ represents an instance of turnover in which a professor from the same research field has an indirect impact on the average student research outcome growth from lab $\ell(e,c')$ to lab $\ell(e,c)$.

We obtain the following result under the same assumptions as above on the distributions of advisor quality and the idiosyncratic error terms:

$$\begin{aligned} &\mathrm{E}\left[\left(DD\overline{\Delta outcome}^{\ell(e,c,c')}\right)^2 | W^{\ell(e,c,c')} = 0, V^{\ell(e,c,c')}\right] \\ &= \alpha\left(\frac{1}{I^{\ell(e,c)}} + \frac{1}{I^{l(e,c')}}\right) + \pi^2\left\{2\sigma_d^2(1-\rho_d)\right\} V^{\ell(e,c,c')}, \end{aligned} \tag{11}$$

where α is the same as that given in Equation (6).

This, in turn, leads to the following regression model using the subsamples that consist of labs in which advisor turnover did *not* occur ($W^{\ell(e,c,c')} = 0$):

$$\left(DD\overline{\Delta outcome}_m\right)^2 = \alpha_{ind}X_m + \beta_{ind}V_m + \varepsilon_m, \tag{12}$$

where $m = 1, \cdots, M$ is the index of observations[41].

Comparing Equations (11) and (12) leads to the parameter relationship that $\beta_{ind} = \pi^2\{2\sigma_d^2(1-\rho_d)\}$. Let us use $\hat{\beta}_{dir}$ to denote an estimate of the coefficient of W_n from the baseline regression model given by Equation (7), and let $\hat{\beta}_{ind}$ be an estimate of the coefficient of V_m from Equation (12) presented above. We therefore obtain $\hat{\pi} = \sqrt{\hat{\beta}_{ind}/\hat{\beta}_{dir}}$, which can be used as a measure of indirect knowledge transfer from a non-advisor professor in the same research field.

An empirical challenge is to identify a group of professors whose research subjects were close enough to that of the professor experiencing turnover. As the type of data necessary to judge the similarity between research subjects is absent or rarely present, we adopt a simple and heuristic method for identifying the same research subject groups, which exploits the information revealed by the actual turnover events. It is conceivable that, when an instance of professor turnover occurred, the students in the lab of the professor who exited were highly likely to be re-assigned to a professor whose research area was closely related to that of the original professor. In the empirical analysis that follows, we therefore assume that the original professor who exited and the re-assigned professor were working in the same research area.

The situation is illustrated in Figure 8, which parallels that illustrated in Figure 1. In the former figure, there are three cohorts, c_0, c_1 and c_2. As we have assumed previously, an instance of turnover involving professor a occurred in cohort c_2, and the students in lab $\ell(a, c_2)$ switched their research advisor from professor a to professor b in the doctoral program. Then, professor b, whose research area is the same as that of professor a, took over the students in lab $\ell(a, c_2)$, whereas he had supervised two labs, $\ell(b, c_0)$ and $\ell(b, c_1)$, before the incident occurred, and oversaw another lab, $\ell(b, c_2)$, at the time of the incident. We assume that professor a's turnover affects the doctoral research productivity of the students in lab $\ell(b, c_2)$ because the indirect influence from the professor, θ_{ad}, ceases to exist after turnover.[42] In this case, to identify the magnitude of the indirect impact, we essentially compare the gap in student

[41] Here, the unit of observation is each element of (e, c, c') such that $W^{\ell(e,c,c')} = 0$ for any advisor $e \in \mathscr{A}$ and cohorts c, c' such that $0 < c - c' \leq \tau$.

[42] In the estimation that follows, we choose the lab of professor b that was influenced "indirectly" by professor a's turnover if the turnover occurred while the students in the lab were in the doctoral program (i.e., from the first doctoral year to the final year of the doctoral program). We require this because the indirect influence from professor a at the doctoral degree level, not the master's degree level, needs to be changed.

research outcome growth between labs $\ell(b, c_2)$ and $\ell(b, c_1)$ (treatment group with $V^{\ell(b,c_2,c_1)} = 1$) with the same gap between labs $\ell(b, c_1)$ and $\ell(b, c_0)$ (control group with $V^{\ell(b,c_1,c_0)} = 0$).

Table 10 presents the regression estimates. We adopt the default setting for the student research outcome and use the same estimation method as before.[43] As shown, the estimates are ambiguous for β_{ind}. One of the estimates is negative, and in the case in which the estimates are positive, they are not statistically significant at the 10 percent level in any specification except one. The estimates of the squared indirect influence parameter, π^2, are reported in row (3).[44] Again, the signs of the estimates differ. The maximum estimate is 0.269, while the value where $\hat{\beta}_{ind}$ is statistically significant is as low as approximately 0.1, as reported in column (6). This result implies that the indirect knowledge transfer effect from non-advisor faculty is $\hat{\pi} = 0.33$, suggesting that it is, at most, less than one-third of the direct effect from the advisor.

On balance, therefore, there appears to be little or no indirect influence from non-advisor faculty members across labs on doctoral student research productivity growth.

Insert Table 10

7 Conclusion

In this paper, we investigated the extent to which professors can affect the development of the research performance of the graduate students whom they supervise. By using detailed data on professors and students at UTokyo's department of physics, we estimated a lower bound of the professor value added to student research achievement growth while in school. The estimation results consistently show that postgraduate research education based on an advisor-advisee relationship is quite effective — professors have a substantial impact on the students' achievement gains in terms of the number of publications in top journals in physics. This corroborates the view of earlier studies (e.g., Azoulay et al., 2010; Moser et al., 2014; Borjas and Doran, 2014) that research interactions among scientists in vertically aligned

[43]The research outcomes in the master's degree and doctoral degree programs are aggregated over the period from M1 to D2 and the period from D1 to P4, respectively. Furthermore, the set of "top journals" here consists of twelve journals.

[44]We compute $\hat{\pi}^2$ as the quotient of the estimate $\hat{\beta}_{ind}$ over the estimate $\hat{\beta}_{dir}$ that appear in the corresponding number of columns in Table 3 and Table 10, respectively.

relationships, including senior-and-junior-collaborator, teacher-student, and adviser-advisee relationships, matter for the creation and diffusion of scientific ideas and knowledge.

Our findings also suggest that the accumulation of prominent scientists in a comparatively small number of universities is explained, at least partially, by the results of successful education at the postgraduate level. For example, in Japan, five out of ten Nobel Prize winners in physics completed their doctoral degrees at UTokyo, and four earned their doctorate degrees at Nagoya University. Given our results on the effectiveness of professors in enhancing students' research capability growth, we can speculate that the relatively high concentration of physics Nobel laureates in these two universities in Japan might be caused not only by the processes of students' self-selection or schools' selective recruitment but also by the beneficial reproduction of elite physicists, which was enabled by a deliberate process of teaching and learning in a lab. While previous studies (e.g., Waldinger, 2010) suggest that high-quality universities can facilitate human capital accumulation among graduate students, our paper specifically adds that this outcome is based on advisor-advisee-based education.

We need to highlight some limitations of this paper. First, our analysis of the professor's value added is essentially short run. Although the estimation results reveal that research advisors can influence the research development of their students, the impact might be limited to the short span of time while the student is in graduate school or several years after the completion of graduate school. It is left to future research to examine whether a professor's supervision during a graduate program has a long-term impact on student research performance during their postgraduation careers.

Second, the analysis in the paper is limited to a small, albeit prominent, group of physicists. Thus, our conclusion regarding a professor's value added might not be generalizable to groups of other scientists from different disciplines or other graduate schools. We hope that the findings of this paper regarding the efficacy of professors in promoting student progress in research performance will be helpful to stimulate further research in related areas including the economics of higher education and the economics of science and technology.

Tables

Table 1: Descriptive Statistics for the Student Research Outcomes in Levels and in Differences

	Research Outcome at the Master's Level	Research Outcome at the Doctoral Level	Research Outcome Gain at the Doctoral Level
	$outcome^c_{iam}$	$outcome^c_{iad}$	$\Delta outcome^c_{iad}$
Mean	0.0677	0.2202	0.1481
S.D.	0.2184	0.5075	0.4068
Min	0.0000	0.0000	-0.4738
Max	2.3175	4.7303	4.7303
Sample Size	1019	1019	1019

Note:
1) The research outcome at each degree level is computed based on the research proficiency scores. The aggregation years are M1-D2 for the master's level and D1-P4 for the doctoral level, respectively.
2) The research outcome gain at the doctoral level is given by the difference of the research outcome from the doctoral level to the master's level. Since the research outcome at the bachelor's level is normalized as zero, the research outcome gain at the master's level is equal to the research oucome at the master's level.

Table 2: Descriptive Statistics of Advisors: Comparison between Advisors When Turnover Occurred and When It Did Not

Variable	Description	With Turnover	Without Turnover	t-stat		Absolute Standardized Difference
Age	Professor Age	53.72 (6.37)	47.06 (5.77)	-9.00	***	1.10
Num_Stud	Number of Students	1.16 (0.41)	1.27 (0.52)	1.63		0.22
*Outcome*5	Profeessor's Research Outcome (5 years average)	0.18 (0.29)	0.21 (0.40)	0.50		0.07
Rank_Assoc	Associate Professor Dummy	0.21 (0.41)	0.44 (0.50)	3.73	***	0.51
Rank_Prof	Full Professor Dummy	0.79 (0.41)	0.53 (0.50)	-4.27	***	0.59
Dept_Phys	Department of Physics Dummy	0.72 (0.45)	0.75 (0.43)	0.62		0.08
Inst_Solid	Institute of Solid State Dummy	0.72 (0.41)	0.22 (0.41)	0.27		0.03
Inst_Other	Other Institutes Dummy	0.34 (0.48)	0.29 (0.45)	-0.85		0.11
*Period_*70*s*	70's Dummy	0.15 (0.36)	0.21 (0.41)	1.19		0.16
*Period_*80*s*	80's Dummy	0.16 (0.37)	0.26 (0.44)	1.71	*	0.23
*Period_*90*s*	90's Dummy	0.57 (0.50)	0.35 (0.48)	-3.72	***	0.46
*Period_*00*s*	00's Dummy	0.12	0.19	1.46		0.20

Note:
1) $***\ p < .01$, $**\ p < .05$, $*\ p < .10$
2) The standardized difference is given by the size of the difference in means of a conditioning variable, scaled by the square root of the variances in the original samples (Ronsenbaum and Rubin 1985)

Table 3: Baseline Estimation Results: The Effect of Advisor Turnover on Student Research Outcome Growth at the Doctoral Level

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
(1) α	0.0667 ***	0.0742 ***	0.0960 ***	0.0570	0.1267 **	0.4025 ***
	(0.0237)	(0.0225)	(0.0134)	(0.0682)	(0.0545)	(0.0720)
(2) β	0.3371 *	0.2663 **	0.1956 **	2.3091 *	2.1322 **	1.6401 **
	(0.1746)	(0.1204)	(0.0985)	(1.3249)	(0.9220)	(0.8251)
(3) Lower bound of σ_d^2	0.0843 **	0.0666 **	0.0489 **	0.5773 **	0.5331 **	0.4100 **
	[0.0268]	[0.0135]	[0.0236]	[0.0407]	[0.0104]	[0.0234]
Sample Size	104	186	271	104	186	271

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The standard errors are in parentheses, and p-values are in square brackets

3) The standard errors are computed by the subsampling method of Politis and Romano (1994)

Table 4: Falsification Test Results

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
(1) α	0.1827 ***	0.1902 ***	0.1736 ***	0.2819 ***	0.6911 ***	0.8996 ***
	(0.0418)	(0.0409)	(0.0443)	(0.0458)	(0.1828)	(0.2287)
(2) $\tilde{\beta}$	0.2979	0.2039	0.0814	0.6315 **	-0.0969	-0.7784
	(0.2123)	(0.1725)	(0.1270)	(0.2616)	(0.3965)	(0.4350)
Sample Size	422	763	603	422	763	603

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The standard errors are in parentheses, and p-values are in square brackets

3) The standard errors are computed by the subsampling method of Politis and Romano (1994)

Table 5: The Estimates of the Lower Bound of Advisor Quality Variance for Various Aggregation Periods

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
M1-D2/D1-P4†‡	0.0843 **	0.0666 **	0.0489 **	0.5773 **	0.5331 **	0.4100 **
	[0.0268]	[0.0135]	[0.0236]	[0.0407]	[0.0104]	[0.0234]
M1-D2/D1-P3†	0.0689 **	0.0498 **	0.0257 *	0.4578 **	0.4099 ***	0.2793 **
	[0.0232]	[0.0181]	[0.0973]	[0.0310]	[0.0080]	[0.0338]
M1-D1/D1-P4†	0.1460 **	0.1243 **	0.0910 **	0.9274 **	0.8522 **	0.7525 **
	[0.0488]	[0.0210]	[0.0389]	[0.0450]	[0.0133]	[0.0145]
M1-D1/D1-P3†	0.1215 **	0.0966 **	0.0572 *	0.7711 **	0.6911 **	0.5745 **
	[0.0485]	[0.0271]	[0.0913]	[0.0384]	[0.0119]	[0.0175]

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The p-values are in square brackets

†)(master's level aggregation period) / (doctoral level aggregation period)

‡) The baseline case.

Table 6: Estimation Results: When Only 9 Top Journals Are Included in Student Research Outcomes

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
(1) α	0.0151 ***	0.0154 ***	0.0648 ***	0.0491 *	0.0533 ***	0.3727 ***
	(0.0061)	(0.0040)	(0.0096)	(0.0348)	(0.0185)	(0.0628)
(2) β	0.1797 ***	0.1451 ***	0.0843 **	0.7449 ***	0.6364 ***	0.0963
	(0.0551)	(0.0320)	(0.0349)	(0.2798)	(0.1851)	(0.1942)
(3) Lower bound of σ_d^2	0.0449 ***	0.0363 ***	0.0211 ***	0.1862 ***	0.1591 ***	0.0241
	[0.0005]	[0.0000]	[0.0079]	[0.0039]	[0.0003]	[0.3100]
Sample Size	104	186	271	104	186	271

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The standard errors are in parentheses, and p-values are in square brackets

3) The standard errors are computed by the subsampling method of Politis and Romano (1994)

Table 7: Estimation Results: When a Change in Advisor Quality Variance Is Allowed during the Period Near Turnover

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
(1) α	0.0717 ***	0.0604 ***	0.0982 ***	0.0622	0.1395 **	0.4297 ***
	(0.0234)	(0.0156)	(0.0144)	(0.0674)	(0.0614)	(0.0752)
(2) β	0.3391 *	0.2431 *	0.2145 **	2.3320	2.1209 **	1.7108 *
	(0.1839)	(0.1294)	(0.1065)	(1.4204)	(0.9704)	(0.8976)
(3) δ_1	—	-0.1207	-0.0085	—	-0.2789	-0.5772
		(0.032)	(0.022)		(0.123)	(0.181)
(4) δ_2	-0.1512	0.4291	-0.2504	-0.4563	-0.1015	-1.4842
	(0.2259)	(0.296)	(0.152)	(1.5777)	(0.938)	(1.093)
(5) δ_3	-0.1195	—	—	-0.1036	—	—
	(0.0431)			(0.0843)		
(6) Lower bound of σ_d^2	0.0848 **	0.0608 **	0.0536 **	0.5830 *	0.5302 **	0.4277 **
	[0.0326]	[0.0301]	[0.0220]	[0.0503]	[0.0144]	[0.0283]
Sample Size	104	186	271	104	186	271

Note:
1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$
2) The standard errors are in parentheses, and p-values are in square brackets
3) The standard errors are computed by the subsampling method of Politis and Romano (1994)
4) The coefficient of the dummy variable $D_k^{(a,c,c')}$ is given by δ_k for $k = 1, 2$ and 3. The dummy variable $D_k^{(a,c,c')}$ is omitted from the regression if there is no cohort with the dummy variable being one in the matched sample.

Table 8: Estimation Results: The Student Proficiency Score is Set to Zero If the Student Coauthored with the Advisor

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
(1) α	0.0544 ***	0.0670 ***	0.0439 ***	0.0215	0.0713 *	0.0528 **
	(0.0230)	(0.0225)	(0.0091)	(0.0448)	(0.0419)	(0.0250)
(2) β	0.2057	0.1665	0.2374 **	1.3776	1.3374 **	1.3690 **
	(0.1727)	(0.1187)	(0.1022)	(0.9758)	(0.6807)	(0.5814)
(3) Lower bound of σ_d^2	0.0514	0.0416 *	0.0593 **	0.3444 *	0.3343 **	0.3422 ***
	[0.1168]	[0.0803]	[0.0101]	[0.0790]	[0.0247]	[0.0093]
Sample Size	104	186	271	104	186	271

Note:

1) $*** \ p < .01, \ ** \ p < .05, \ * \ p < .10$

2) The standard errors are in parentheses, and p-values are in square brackets

3) The standard errors are computed by the subsampling method of Politis and Romano (1994)

Table 9: Estimation Results: the Double-Difference Measure in Levels Is Used as the Dependent Variable

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]$				First-authored-paper Based $[DD\overline{\Delta outcome}]$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$		$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)		(4)	(5)	(6)
(1) α	-0.0462	-0.0186	0.0362	***	-0.0655	-0.0693	0.0963
	(0.0237)	(0.0225)	(0.0134)		(0.0961)	(0.0856)	(0.0893)
(2) β	0.1439	0.1480	0.0310		0.2655	0.3968	0.2276
	(0.1746)	(0.1204)	(0.0985)		(2.1883)	(1.5374)	(1.3783)
Sample Size	104	186	271		104	186	271

Note:

1) $*** \ p < .01, \ ** \ p < .05, \ * \ p < .10$

2) The standard errors are in parentheses, and p-values are in square brackets

3) The standard errors are computed by the subsampling method of Politis and Romano (1994)

Table 10: Estimation Results: Effect of Non-Advisor Turnover on Student Research Outcome Growth at the Doctoral Level

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
(1) α_{ind}	0.0434 ***	0.0356 ***	0.0335 ***	0.0988 ***	0.0863 ***	0.0755 ***
	(0.0175)	(0.0056)	(0.0060)	(0.0358)	(0.0094)	(0.0136)
(2) β_{ind}	-0.0230	0.0274	0.0527	0.0764	0.1007	0.1768 *
	(0.0374)	(0.0320)	(0.0336)	(0.1192)	(0.0924)	(0.0924)
(3) $\pi^2 = \beta_{ind}/\beta_{dir}$	-0.0682	0.1030	0.2694	0.0331	0.0472	0.1078
Sample Size	145	282	288	145	282	288

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The standard errors are in parentheses, and p-values are in square brackets

3) The standard errors are computed by the subsampling method of Politis and Romano (1994)

Figures

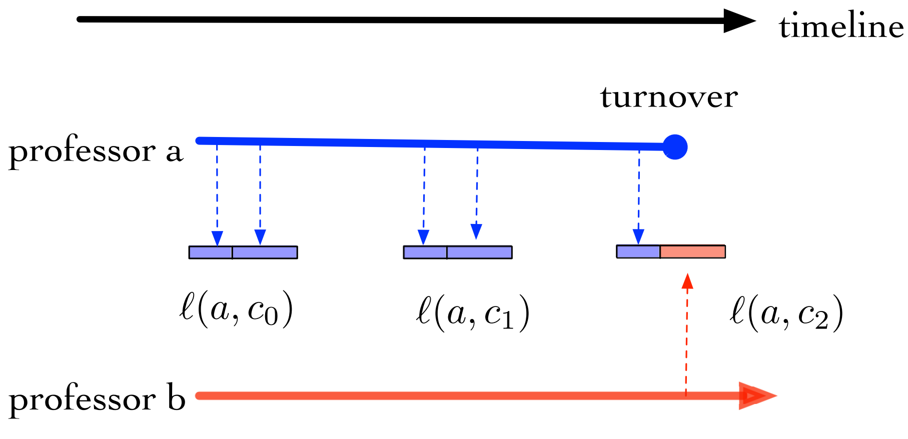

Figure 1: Example of Labs with and without Turnover

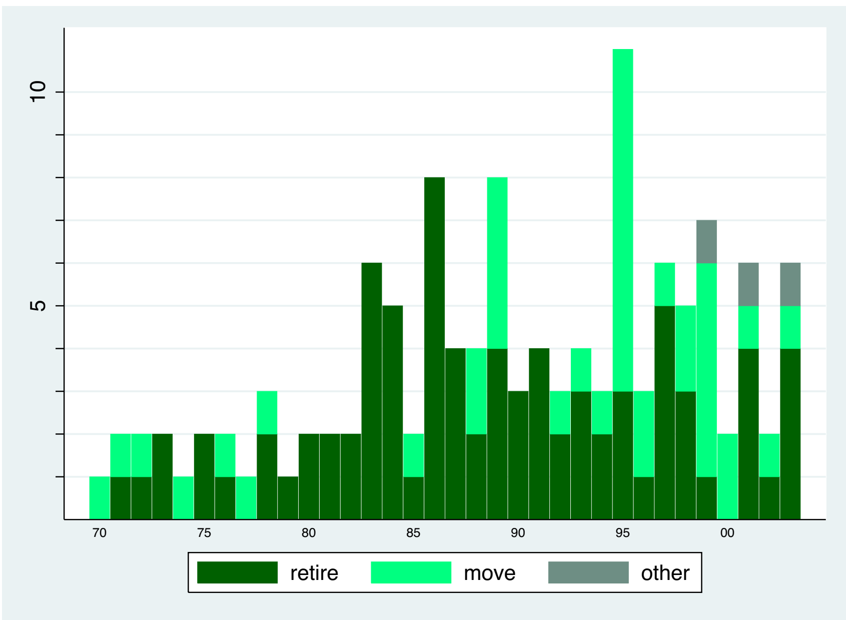

Figure 2: Number of Turnover Incidents in Each Year (1970-2004)

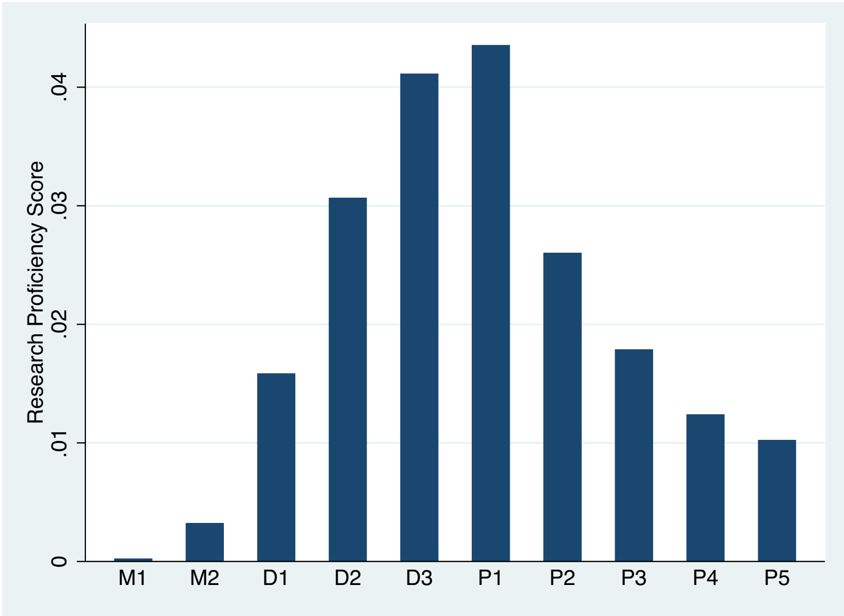

Figure 3: Average Student Research Proficiency Scores

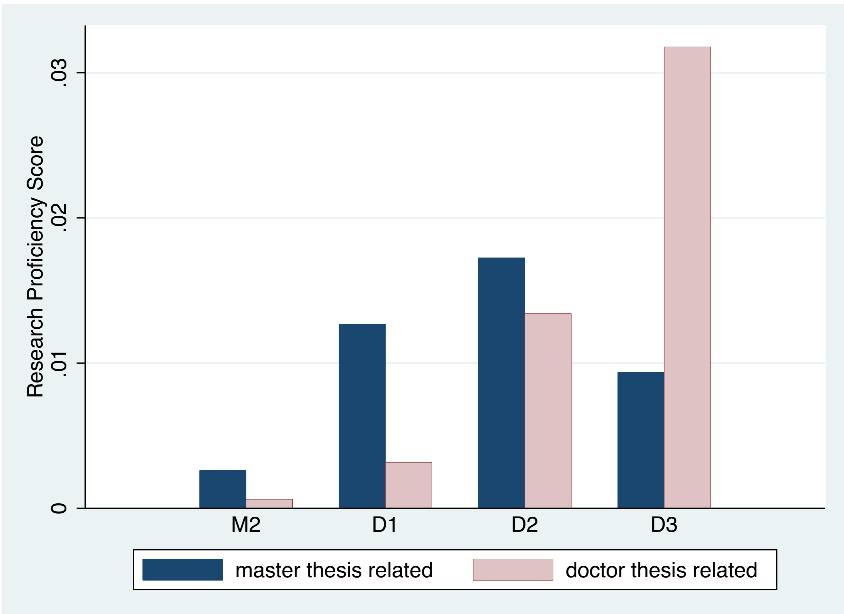

Figure 4: Decomposition of the Student Research Proficiency Scores: Those Related to Master's and Doctoral Theses

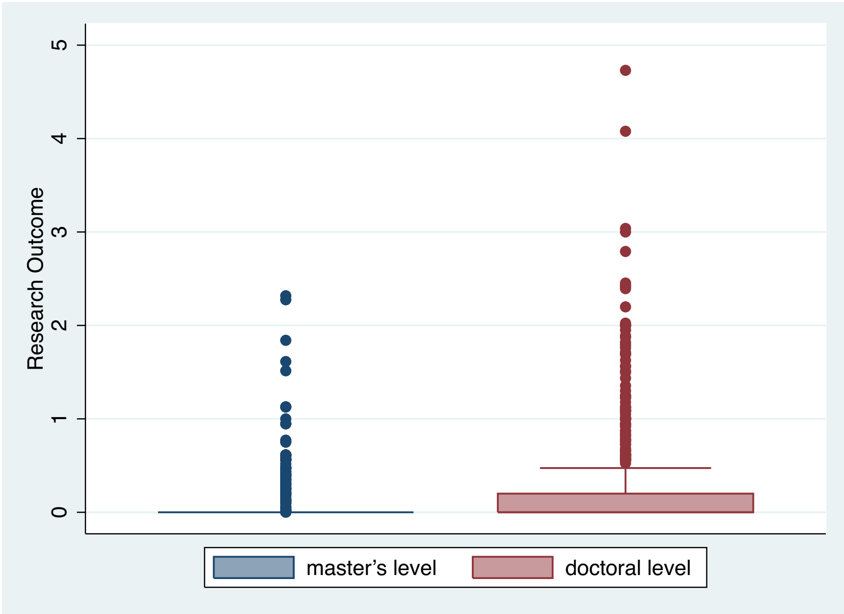

Figure 5: Box Plots of the Student Research Outcome Distributions in the Master's and Doctoral Programs

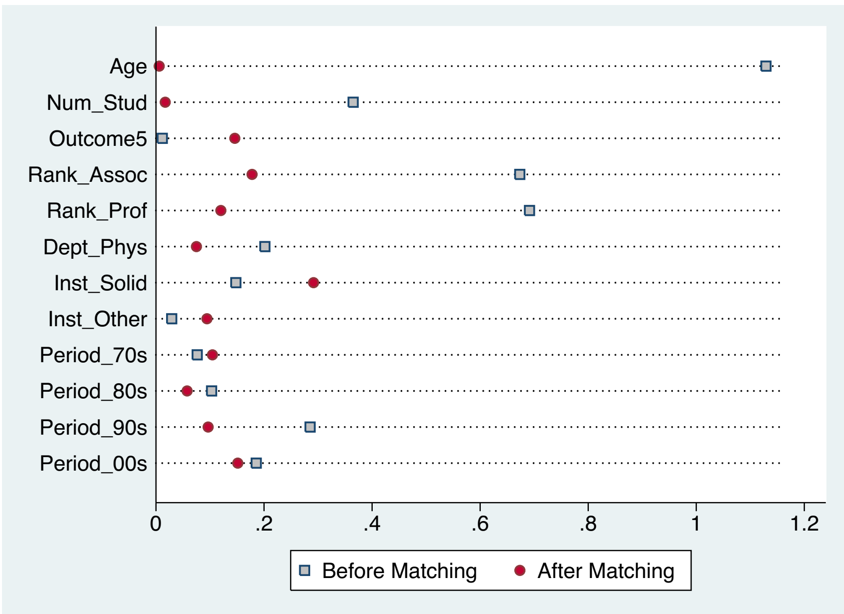

Figure 6: Comparison of the Absolute Values of the Standardized Differences between Treatment and Control Groups

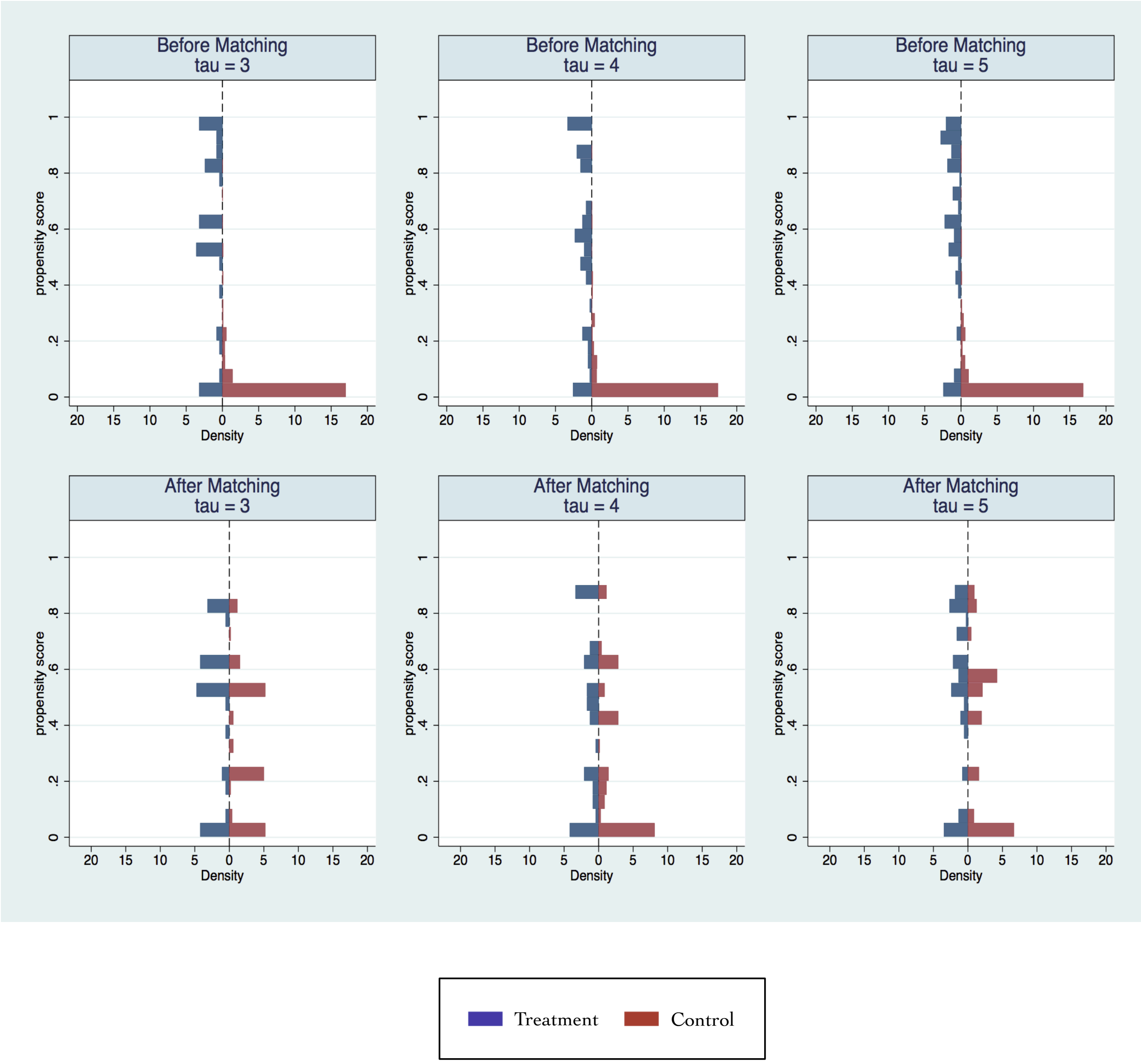

Figure 7: Distribution of the Propensity Score for the Treatment and Control Groups: Before and After Matching

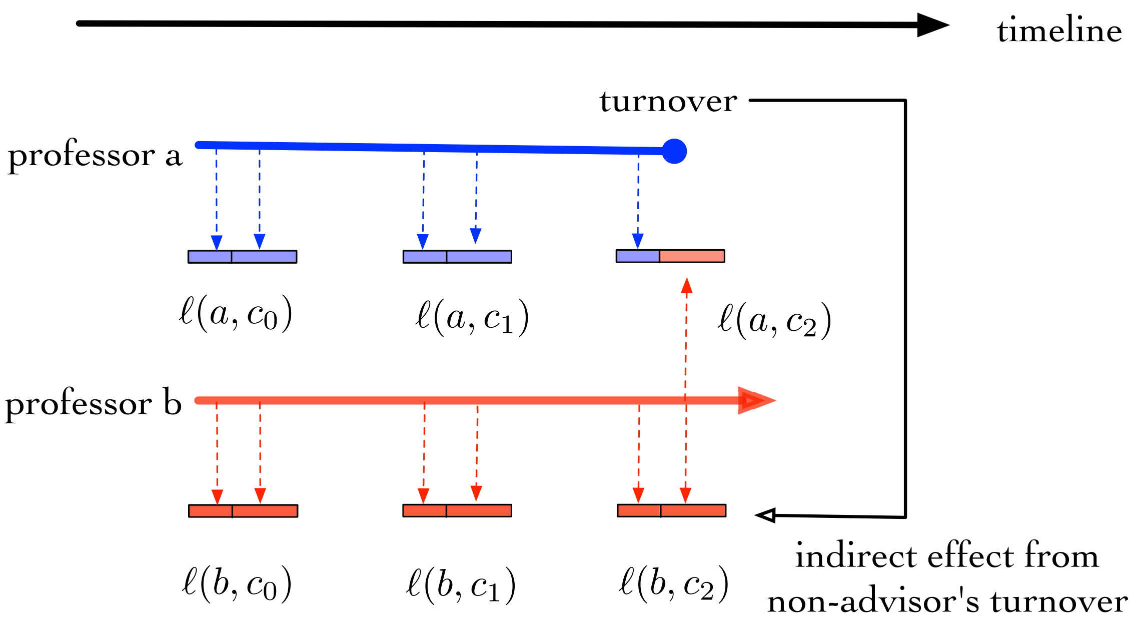

Figure 8: Example of Labs with and without Turnover for Advisors and Non-Advisors

Appendix

A Derivation of Equation (6)

We compute the conditional expectation of the squared left-hand side of Equation (5). Under the assumption that the random shock, ν^c_{iag}, is orthogonal to advisor quality, θ_g, for any student $i \in \mathscr{I}^{\ell(a,c)}$, professor $a \in \mathcal{A}$, cohort $c \in \mathcal{C}$ and program $g \in \{m, d\}$, the conditional expectation is given as follows:

$$
\begin{aligned}
&\mathrm{E}\left[\left(DD\overline{\Delta Outcome}^{\ell(a,c,c')}\right)^2 \middle| W^{\ell(a,c,c')}\right] \\
&= \mathrm{E}\left[(\theta_{bd} - \theta_{ad})^2 \middle| W^{\ell(a,c,c')} = 1\right] \cdot W^{\ell(a,c,c')} \\
&+ \mathrm{E}\left[\left\{\left(\bar{\nu}^{\ell(a,c)}_{bd} - \bar{\nu}^{\ell(a,c)}_{am}\right) - \left(\bar{\nu}^{\ell(a,c')}_{ad} - \bar{\nu}^{\ell(a,c')}_{am}\right)\right\}^2 \middle| W^{\ell(a,c,c')} = 1\right] \cdot W^{\ell(a,c,c')} \\
&+ \mathrm{E}\left[\left\{\left(\bar{\nu}^{\ell(a,c)}_{ad} - \bar{\nu}^{\ell(a,c)}_{am}\right) - \left(\bar{\nu}^{\ell(a,c')}_{ad} - \bar{\nu}^{\ell(a,c')}_{am}\right)\right\}^2 \middle| W^{\ell(a,c,c')} = 0\right] \cdot (1 - W^{\ell(a,c,c')}). \quad \text{(A.1)}
\end{aligned}
$$

Under assumption 1.1-1.2, we can compute the first part of Equation (A.1) as follows:

$$
\mathrm{E}\left[(\theta_{bd} - \theta_{ad})^2 \middle| W^{\ell(a,c,c')} = 1\right] = 2\sigma^2_d(1 - \rho_d). \tag{A.2}
$$

We turn to the second part of Equation(A.1), which is related to the conditional expectation of when turnover occurred, $W^{\ell(a,c,c')} = 1$. We have the following equality concerning the value within the expectation operator:

$$
\begin{aligned}
&\left\{\left(\bar{\nu}^{\ell(a,c)}_{bd} - \bar{\nu}^{\ell(a,c)}_{am}\right) - \left(\bar{\nu}^{\ell(a,c')}_{ad} - \bar{\nu}^{\ell(a,c')}_{am}\right)\right\}^2 \\
&= \left\{\left(\bar{\tilde{\nu}}^{\ell(a,c)}_{bd} - \bar{\tilde{\nu}}^{\ell(a,c)}_{am}\right) - \left(\bar{\tilde{\nu}}^{\ell(a,c')}_{ad} - \bar{\tilde{\nu}}^{\ell(a,c')}_{am}\right)\right\}^2 \\
&= \left\{\left(\bar{\tilde{\nu}}^{\ell(a,c)}_{bd}\right)^2 + \left(\bar{\tilde{\nu}}^{\ell(a,c)}_{am}\right)^2 - 2\left(\bar{\tilde{\nu}}^{\ell(a,c)}_{bd}\right)\left(\bar{\tilde{\nu}}^{\ell(a,c)}_{am}\right)\right\} + \left\{\left(\bar{\tilde{\nu}}^{\ell(a,c')}_{ad}\right)^2 + \left(\bar{\tilde{\nu}}^{\ell(a,c')}_{am}\right)^2 - 2\left(\bar{\tilde{\nu}}^{\ell(a,c')}_{ad}\right)\left(\bar{\tilde{\nu}}^{\ell(a,c')}_{am}\right)\right\} \\
&-2\left\{\left(\bar{\tilde{\nu}}^{\ell(a,c)}_{bd}\right)\left(\bar{\tilde{\nu}}^{\ell(a,c')}_{ad}\right) - \left(\bar{\tilde{\nu}}^{\ell(a,c)}_{bd}\right)\left(\bar{\tilde{\nu}}^{\ell(a,c')}_{am}\right) - \left(\bar{\tilde{\nu}}^{\ell(a,c)}_{am}\right)\left(\bar{\tilde{\nu}}^{\ell(a,c')}_{ad}\right) + \left(\bar{\tilde{\nu}}^{\ell(a,c)}_{am}\right)\left(\bar{\tilde{\nu}}^{\ell(a,c')}_{am}\right)\right\}, \quad \text{(A.3)}
\end{aligned}
$$

where $\bar{\tilde{\nu}}^{\ell(a,c)}_{ag}$ is the lab $\ell(a, c)$ average of $\tilde{\nu}^c_{iag}$, and hence, we use $\bar{\nu}^{\ell(a,c)}_{ag} = \bar{\tilde{\nu}}^{\ell(a,c)}_{ag} + \bar{\nu}_g$ in the computation above. We take the conditional expectation of each piece of the last term of Equation (A.3) under assumptions 2.1 - 2.5.

1. Consider the squared term of the average demeaned error, $\bar{\tilde{\nu}}^{\ell(a,t)}_{pg}$, where professor $p \in$

$\{a,b\}$, program $g \in \{d,m\}$ and cohort $t \in \{c,c'\}$. We have the following equation:

$$\begin{aligned}\left(\bar{\tilde{\nu}}_{pg}^{\ell(a,t)}\right)^2 &= \left[\frac{1}{N^{\ell(a,t)}}\sum_{i\in I^{\ell(a,t)}}\left(\tilde{\nu}_{pig}^{t}\right)\right]^2 \\ &= \left(\frac{1}{N^{\ell(a,t)}}\right)^2\left\{\sum_{i\in I^{\ell(a,t)}}\left(\tilde{\nu}_{pig}^{t}\right)^2 + 2\sum_{j\in I^{\ell(a,t)}}\sum_{k\neq j\in I^{\ell(a,t)}}\left(\tilde{\nu}_{jpg}^{t}\right)\left(\tilde{\nu}_{jpg}^{t}\right)\right\}.\end{aligned}$$

Assumptions 2.1 and 2.3 lead to the following conditional expectation:

$$\mathrm{E}\left[\left(\bar{\tilde{\nu}}_{pg}^{\ell(a,t)}\right)^2 \middle| W^{\ell(p,c)} = 1\right] = \frac{\phi_g^2 + 2\psi_g}{N^{\ell(a,t)}}. \tag{A.4}$$

2. Consider the cross-term of the average demeaned errors, $\bar{\tilde{\nu}}_{pd}^{\ell(a,t)}$ and $\bar{\tilde{\nu}}_{am}^{\ell(a,t)}$, between master's and doctoral programs *within* lab $\ell(a,t)$ for cohort $t \in \{c,c'\}$, where professor $p = b$ if the professor switched from a to b due to turnover and $p = a$ if not. Then, we have:

$$\begin{aligned}\left(\bar{\tilde{\nu}}_{pd}^{\ell(a,t)}\right)\left(\bar{\tilde{\nu}}_{am}^{\ell(a,t)}\right) &= \left[\frac{1}{N^{\ell(a,t)}}\sum_{i\in I^{\ell(a,t)}}\left(\tilde{\nu}_{ipd}^{t}\right)\right]\cdot\left[\frac{1}{N^{\ell(a,t)}}\sum_{i\in I^{\ell(a,t)}}\left(\tilde{\nu}_{iam}^{t}\right)\right] \\ &= \left(\frac{1}{N^{\ell(a,t)}}\right)^2\left\{\sum_{i\in I^{\ell(a,t)}}\left(\tilde{\nu}_{ipd}^{t}\right)\left(\tilde{\nu}_{iam}^{t}\right) + \sum_{j\in I^{\ell(a,t)}}\sum_{k\neq j\in I^{\ell(a,t)}}\left(\tilde{\nu}_{jpg}^{t}\right)\left(\tilde{\nu}_{kam}^{t}\right)\right\}.\end{aligned}$$

Given Assumption 2.2 , the conditional expectation is given by:

$$\mathrm{E}\left[\left(\bar{\tilde{\nu}}_{pd}^{\ell(a,t)}\right)\left(\bar{\tilde{\nu}}_{pm}^{\ell(a,t)}\right) \middle| W^{\ell(p,c)} = 1\right] = \frac{\phi_{md}}{N^{\ell(a,t)}}. \tag{A.5}$$

3. Consider the cross-term of the average demeaned errors between $\bar{\tilde{\nu}}_{pg}^{\ell(a,c)}$ and $\bar{\tilde{\nu}}_{p'g'}^{\ell(a,c')}$ *across* cohorts c and c', where professors $p \in \{a,b\}$ and $p' \in \{a,b\}$ and grad programs $g \in \{d,m\}$ and $g' \in \{d,m\}$. It is equal to:

$$\begin{aligned}\left(\bar{\tilde{\nu}}_{pg}^{\ell(a,c)}\right)\left(\bar{\tilde{\nu}}_{p'g'}^{\ell(a,c')}\right) &= \left[\frac{1}{N^{\ell(a,c)}}\sum_{i\in I^{\ell(a,c)}}\left(\tilde{\nu}_{ipg}^{c}\right)\right]\cdot\left[\frac{1}{N^{\ell(a,c')}}\sum_{j\in I^{\ell(a,c')}}\left(\tilde{\nu}_{jp'g'}^{c'}\right)\right] \\ &= \left(\frac{1}{N^{\ell(a,c)}}\right)\left(\frac{1}{N^{\ell(a,c')}}\right)\left\{\sum_{i\in I^{\ell(a,c)}}\sum_{j\neq i\in I^{\ell(a,c')}}\left(\tilde{\nu}_{ipg}^{c}\right)\left(\tilde{\nu}_{jp'g'}^{c'}\right)\right\}.\end{aligned}$$

The conditional expectation is zero under Assumption 2.4-2.5. That is:

$$\mathrm{E}\left[\left(\bar{\tilde{\nu}}_{pg}^{\ell(a,c)}\right)\left(\bar{\tilde{\nu}}_{p'g'}^{\ell(a,c')}\right) \middle| W^{\ell(a,c,c')} = 1\right] = 0. \tag{A.6}$$

Using results (A.4), (A.5), and (A.6) presented above, the conditional expectation of Equation (A.3), regardless of whether an advisor switch occurred, is equal to:

$$
\begin{aligned}
&\mathrm{E}\left[\left\{\left(\bar{\nu}_{bd}^{\ell(a,c)}-\bar{\nu}_{am}^{\ell(a,c)}\right)-\left(\bar{\nu}_{ad}^{\ell(a,c')}-\bar{\nu}_{am}^{\ell(a,c')}\right)\right\}^2\middle| W^{\ell(a,c,c')}=1\right] \\
&=\left(\frac{1}{N^{\ell(a,c)}}+\frac{1}{N^{\ell(a,c')}}\right)\left\{\phi_d^2+\phi_m^2+4\big(\psi_d+\psi_m\big)-2\phi_{md}\right\}. \qquad \text{(A.7)}
\end{aligned}
$$

Similar computation reveals that the third part of Equation (A.1), for the case in which turnover did not occur, $W^{\ell(a,c,c')}=0$, is the right-hand side of Equation (A.7).

Based on Equations (A.2) and (A.7), we therefore have the following result:

$$
\mathrm{E}\left[\left(DD\overline{\Delta Outcome}^{\ell(a,c,c')}\right)^2\middle| W^{\ell(a,c,c')}\right]=\alpha\left(\frac{1}{N^{\ell(a,c)}}+\frac{1}{N^{\ell(a,c')}}\right)+\beta\cdot W^{\ell(a,c,c')},
$$

where $\alpha=\phi_d^2+\phi_m^2+4\big(\psi_d+\psi_m\big)-2\phi_{md}$ and $\beta=2\sigma_d^2(1-\rho_d)$.

B Identification of Students' Publications

B.1 A Score of Word Overlap in Titles

As described in Section 4, our measure of a graduate student's research achievement is based on the number of articles that he or she published in selected physics journals.

To identify the articles that were authored by each student in the sample, we compile physics papers from the Thomson Reuters WoS archive that satisfy the following three conditions: (1) the author names match the name of the student; (2) the publication dates are in the period from the year in which the student was enrolled in graduate school to four years after he or she received a doctoral degree; and (3) the words in the title overlap to some extent with those in the title of the student's master or doctorate thesis.

The first and second conditions can be easily verified because the authors' names and publication dates of articles are available from the WoS database, whereas the student names and the degree date of each student are found in the the master's and doctoral thesis catalogs of UTokyo's physics department.

To enforce the third condition, we define a score that assesses the degree of overlap in the words in titles. Let $\tilde{R}_i$ be the set of all physics articles that are associated with student $i\in\mathscr{I}$ after the first and second conditions presented above are satisfied. Note that, although all articles in the set $\tilde{R}_i$ include authors whose names are the same as student i, the student may or may not actually be the author of these articles. Such misidentification arises because of false positives in author name matching.

We use $t(r_{ij})$ to denote the *title* of article $r_{ij} \in \tilde{R}_i$ and use t_i to denote the title of student i's thesis (either master's or doctoral, depending on the context). Each title of an article or a thesis consists of *words*. For each article $r_{ij} \in \tilde{R}_i$, we compute the following score of word overlap in titles:

$$m_{ij} = \frac{\sum_{w \in \{t_i \cap t(r_{ij})\}} \phi(w)}{\max\left\{ \sum_{w \in t_i} \phi(w),\ \sum_{w \in t(r_{ij})} \phi(w) \right\}}, \tag{A.8}$$

where $\phi(w)$ is a weighting of word w that measures the rareness of the word.

Indeed, the frequency of words used in article titles varies substantially, some being common and others rare. Clearly, such information is potentially useful in deciding whether an article sharing the author name with a thesis is actually authored by the person who wrote the thesis. If the words included in both the titles of an article and thesis are relatively rare, there is a higher likelihood that the authors are the same, whereas the converse is true if the words are relatively common.

To utilize the intuition, $\phi(w)$ assigns high weight to relatively rare words and low weight to relatively common words. Following a similar approach to that proposed by Tang and Walsh (2010), we determine the weight, $\phi(w)$, based on the relative frequency of word w, which is computed by dividing its count frequency by the total counts of all technical terms that appear in all titles of the master's and doctoral theses of UTokyo's students. Specifically, we sort all words used in titles into five categories or quintiles based on their relative frequencies. For word w_k that is in the k-th quintile, the weight is given by $\phi(w_k) = (6 - k)^{-2/3}$ for $k = 1, 2, 3, 4, 5$.

One remaining issue concerns words referring to the same concept in physics that are rendered differently. For instance, words such as "energy", "energies", "energetics", and "energetic" are considered to represent the same notion. We address this issue by "standardizing" the words. Specifically, we undertake the following actions. First, we transform all non-letter, non-Greek characters and symbols into spaces. Second, we convert all words into lower case. Third, we reduce inflected (or derived) words to their word stem using a stemming algorithm.[45] For instance, the stemming algorithm reduces the words "energy", "energies",

[45] Specifically, we use Porter's stemming algorithm, which is the most commonly used algorithm for word

"energetics", and "energetic" to the unique root word, "energi". Fourth, we eliminate all of the non-informative "stopwords", that is, very high-frequency words such as *the*, *to*, *of*, and *study*. For example, consider an article with the title "*ENERGY-LEVEL STATISTICS OF METALLIC FINE PARTICLES.*" In this case, the title is decomposed into the set of standardized root words as "energi", "level", "statist", "metal", "fine" and "particl".

We use the title word overlap score, given by Equation (A.8), when we identify that article $r_{ij} \in \tilde{R}_i$ is authored by student i, depending on whether the score, m_{ij}, exceeds the predetermined threshold, $\bar{m}$. Let $\hat{R}_i$ be the set of articles associated with student i by the word-overlapping-score method presented above such that $\hat{R}_i \subseteq \tilde{R}_i$.

B.2 An Optimal Threshold

How can we determine the threshold, $\bar{m}$, for the title word overlap score when matching articles and theses? Two types of matching errors are possible. We refer the first as a type 1 error, which occurs if we under-match articles, i.e., if we miss articles that are indeed authored by a student by regarding them as being written by another author. However, the second error, referred to as a type 2 error, arises when we include articles that are not authored by a target student. A type 1 error is likely to occur when we impose a threshold value, $\bar{m}$, that is too high, whereas a type 2 error will be more likely when we impose a low threshold, $\bar{m}$, and end up with spurious matches that actually belong to different authors.

One fundamental problem regarding the problem of identifying students' publications is that the true set, R_i, is unknown for student $i \in \mathscr{I}$, and therefore, the degrees of type 1 and type 2 errors cannot be assessed.

However, we might be able to obtain a reasonably accurate approximation set of published articles for certain students, especially for those who became academic researchers and published their CVs on the web. Let $\bar{\mathscr{I}} \subseteq \mathscr{I}$ be the set of such students/researchers. We acquired the CVs of 40 such researchers by a random web search and parsed the research publication information to create the benchmark set of articles. Our expectation is that the benchmark article set, $\bar{R}_i$, will contain reliable and comprehensive information on the true set, R_i, at least for student/researcher $i \in \bar{\mathscr{I}}$. Nevertheless, the set $\bar{R}_i$ might include some articles that are not directly related to their thesis projects. In this regard, the benchmark

stemming in English.

set should be close to but somewhat larger than the true set.

We use the benchmark article set to evaluate the performance of the matching procedure based on the word overlap score in titles. Specifically, to gauge the performance at each threshold value, we use two goodness-of-fit indices, $GOFI2a$ and $GOFI2b$, proposed by Trajtenberg et al. (2006). Let $\bar{R}_i$ be the benchmark set of student $i \in \bar{\mathscr{I}}$ and $\hat{R}_i(m)$ the corresponding set estimated by the matching procedure based on the word overlap score in titles, with m being the threshold value.

Those measures are defined as:

$$\begin{aligned} GOFI2a(m) &\equiv \text{Average}\left[\tfrac{|\bar{R}_i \cap \hat{R}_i(m)|}{|\bar{R}_i|}\right] \\ GOFI2b(m) &\equiv \text{Average}\left[\tfrac{|\bar{R}_i \cap \hat{R}_i(m)|}{|\hat{R}_i(m)|}\right], \end{aligned}$$

where the average is taken over all persons in the selected set $\bar{\mathscr{I}}$. In essence, if our matching procedure tends to under-match or over-match, $GOFI2a(m)$ or $GOFI2b(m)$ decrease, respectively. Therefore, we should seek to increase these indices to avoid type 1 and type 2 errors to the greatest extent possible, but a trade-off exists between the two goals.

Figure 9 presents those two indices for various values of m in increments of 0.05. $GOFI2b(m)$, which is presented as a solid blue line, increases in the range of a smaller threshold value, m, and reaches nearly 0.65 when $m = 0.25$ with no improvement being observed if $m > 0.25$. This leads to the implication that type 2 error will no longer be reduced dramatically if we set $m > 0.25$. Turning to $GOFI2a(m)$, which is presented as a dashed red line, it decreases consistently as the threshold value, m, rises, implying that type 1 error will be alleviated as the value of m decreases.

Accordingly, we consider the optimal threshold to be $\bar{m} = 0.25$, as this is the value that balances the two goodness-of-fit measures — $GOFI2a(m)$ is maximized (thus, type 1 error is minimized) on the *condition* that $GOFI2b(m)$ remains at a high level (thus, an increase in type 2 error is reduced as much as possible).

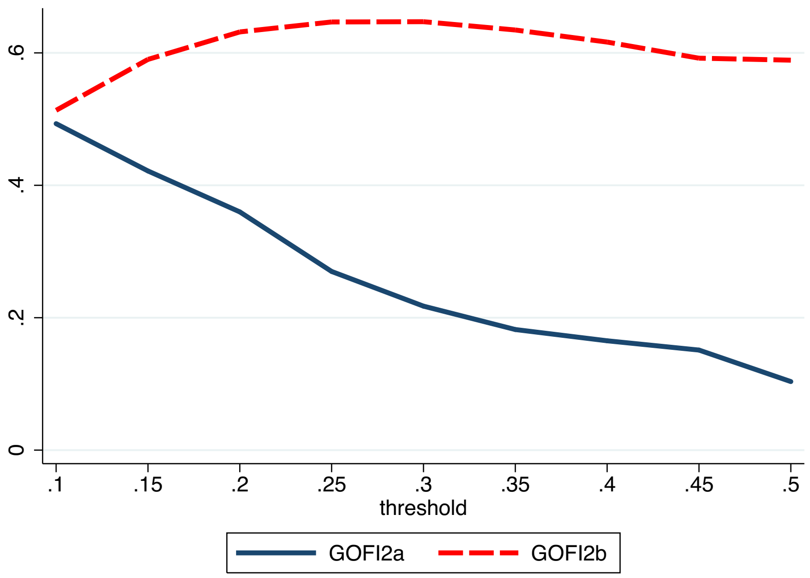

Figure 9: Comparison of Two Goodness-of-Fit Indices over Various Thresholds for the Word Overlap Score in Titles

C.3 Supplementary Materials for Section 5.2

Table C.1 : Estimation Results of Propensity Score

Adjacent Period	$\tau = 3$		$\tau = 4$		$\tau = 5$	
Age	-5.823	***	-6.494	***	-6.784	***
	[9.70]		[9.39]		[6.55]	
Num_Stud	21.900		-0.701	*	-0.212	
	[0.02]		[1.86]		[0.46]	
Rank_Assoc	0.832		1.109		-0.552	
	[0.76]		[1.00]		[0.26]	
Inst_Other	-0.208		-0.462		-0.308	
	[0.46]		[0.99]		[0.46]	
Period_90s	1.014	**	1.777	***	1.101	
	[1.99]		[4.11]		[1.49]	
Period_00s	-1.724	***	-1.375	**	-1.782	*
	[2.67]		[2.44]		[1.92]	
Age^2	0.063	***	0.072	***	0.073	***
	[10.11]		[9.58]		[6.84]	
Num_Stud^2	-7.263					
	[0.02]					
Age × *Period_80s*	1.465	**			1.157	
	[2.47]				[1.56]	
Num_Stude × *Period_80s*	-80.110	**			-63.27	
	[2.43]				[1.53]	
Outcome5 × *Inst_Other*	-1.816	*	-2.325	**	-3.059	**
	[1.76]		[2.06]		[1.99]	
Rank_Assoc × *Inst_Solid*			2.346	*	2.941	*
			[1.90]		[1.83]	
Inst_Solid × *Period_00s*	3.487	***	3.168	**		
	[3.02]		[2.29]			
Inst_Other × *Period_80s*	-3.700	***			-2.757	*
	[2.95]				[1.83]	
Constant	111.7		138.900	***	148.800	***
	[0.16]		[8.98]		[6.05]	
Sample Size	1446		1202		925	

Note:

1) The dependent variable is advisor switch indicator W

2) $***\ p < .01$, $**\ p < .05$, $*\ p < .10$

3) The p-values are in square brackets

C.4 Supplementary Materials for Section 6.2: Robustness Checks

Table C.2 : The Estimates of the Lower Bound of Advisor Quality Variance for Various Aggregation Periods with Over-Matching and Under-Matching Criteria for the Degree of Technical Term Overlap in Titles

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
Threshold 0.20 (overmatch)						
M1-D2/D1-P4†‡	0.0953 **	0.0790 **	0.0576 **	0.7246 **	0.6833 **	0.5492 **
	[0.0407]	[0.0184]	[0.0341]	[0.0460]	[0.0115]	[0.0213]
M1-D2/D1-P3†	0.0621 **	0.0425 **	0.0205	0.4672 **	0.4179 ***	0.2641 **
	[0.0323]	[0.0341]	[0.1505]	[0.0280]	[0.0071]	[0.0438]
M1-D1/D1-P4†	0.1659 *	0.1466 **	0.1214 **	1.1114 **	1.0467 **	2.2262 ***
	[0.0580]	[0.0231]	[0.0247]	[0.0490]	[0.0134]	[0.0085]
M1-D1/D1-P3†	0.1159 *	0.0913 **	0.0639 *	0.7805 **	0.7055 **	0.6066 **
	[0.0565]	[0.0349]	[0.0665]	[0.0364]	[0.0105]	[0.0127]
Threshold 0.30 (undermatch)						
M1-D2/D1-P4†‡	0.0509 *	0.0378 **	0.0191	0.3490 **	0.3135 ***	0.1795 *
	[0.0712]	[0.0476]	[0.1037]	[0.0222]	[0.0042]	[0.0548]
M1-D2/D1-P3†	0.0401 *	0.0282 *	0.0023	0.2662 **	0.2282 ***	0.0884
	[0.0719]	[0.0609]	[0.4395]	[0.0110]	[0.0019]	[0.1246]
M1-D1/D1-P4†	0.1123 *	0.0988 **	0.0683 *	0.6166 **	0.5541 ***	0.4385 **
	[0.0599]	[0.0237]	[0.0541]	[0.0345]	[0.0094]	[0.0220]
M1-D1/D1-P3†	0.0923 *	0.0783 **	0.0360	0.4971 **	1.0168 ***	0.3002 **
	[0.0582]	[0.0261]	[0.1507]	[0.0265]	[0.0094]	[0.0331]

Note:

1) $***\ p < .01$, $**\ p < .05$, $*\ p < .10$

2) The p-values are in square brackets

†)(master's level aggregation period) / (doctoral level aggregation period)

‡) The baseline cases.

Table C.3 : The Estimates of the Lower Bound of Advisor Quality Variance for Various Aggregation Periods: When Only 9 Top Journals Are Included in Student Research Outcomes

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
M1-D2/D1-P4†‡	0.0449 ***	0.0363 ***	0.0211 ***	0.0127 ***	0.1862 ***	0.1591
	[0.0005]	[0.0000]	[0.0079]	[0.3911]	[0.0039]	[0.0003]
M1-D2/D1-P3†	0.0377 ***	0.0262 ***	0.0070	0.0065 ***	0.1403 ***	0.1117 **
	[0.0027]	[0.0000]	[0.2448]	[0.4584]	[0.0010]	[0.0000]
M1-D1/D1-P4†	0.0829 ***	0.0675 ***	0.0355 **	0.1520 **	0.4216	0.3441 **
	[0.0080]	[0.0017]	[0.0431]	[0.0739]	[0.7579]	[0.0038]
M1-D1/D1-P3†	0.0680 ***	0.0495 ***	0.0115	0.0923 ***	0.3389 ***	0.2588 *
	[0.0085]	[0.0026]	[0.2533]	[0.1124]	[0.0084]	[0.0025]

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The p-values are in square brackets

†)(master's level aggregation period) / (doctoral level aggregation period)

‡) The baseline case.

Table C.4 : The Estimates of the Lower Bound of Advisor Quality Variance for Various Aggregation Periods: When Change in Advisor Quality Variance Is Allowed in the Period Near Turnover

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
M1-D2/D1-P4†‡	0.0449 ***	0.0363 ***	0.0211 ***	0.0127 ***	0.1862 ***	0.1591
	[0.0005]	[0.0000]	[0.0079]	[0.3911]	[0.0039]	[0.0003]
M1-D2/D1-P3†	0.0377 ***	0.0262 ***	0.0070	0.0065 ***	0.1403 ***	0.1117 **
	[0.0027]	[0.0000]	[0.2448]	[0.4584]	[0.0010]	[0.0000]
M1-D1/D1-P4†	0.0829 ***	0.0675 ***	0.0355 **	0.1520 **	0.4216	0.3441 **
	[0.0080]	[0.0017]	[0.0431]	[0.0739]	[0.7579]	[0.0038]
M1-D1/D1-P3†	0.0680 ***	0.0495 ***	0.0115	0.0923 ***	0.3389 ***	0.2588 *
	[0.0085]	[0.0026]	[0.2533]	[0.1124]	[0.0084]	[0.0025]

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The p-values are in square brackets

†)(master's level aggregation period) / (doctoral level aggregation period)

‡) The baseline case.

Table C.5 : The Estimates of the Lower Bound of Advisor Quality Variance for Various Aggregation Periods: The Student Proficiency Score is Set to Zero if the Student Is Coauthor with the Advisor

Dependent	Credit Share Weighted $[DD\overline{\Delta outcome}]^2$			First-authored-paper Based $[DD\overline{\Delta outcome}]^2$		
Adjacent Period	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 3$	$\tau = 4$	$\tau = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
M1-D2/D1-P4†‡	0.0514	0.0416 *	0.0593 **	0.3444 *	0.3343 **	0.3422 ***
	[0.1168]	[0.0803]	[0.0101]	[0.0790]	[0.0247]	[0.0093]
M1-D2/D1-P3†	0.0359	0.0246	0.0496 **	0.2433 *	0.2301 **	0.2351 ***
	[0.1393]	[0.1413]	[0.0072]	[0.0645]	[0.0264]	[0.0097]
M1-D1/D1-P4†	0.0589	0.0422 *	0.0558 **	0.3712 *	0.3389 **	0.3547 ***
	[0.0878]	[0.0823]	[0.0155]	[0.0645]	[0.0236]	[0.0075]
M1-D1/D1-P3†	0.0434 *	0.0252	0.0461 **	0.2700 *	0.2347 **	0.2475 ***
	[0.0985]	[0.1445]	[0.0126]	[0.0580]	[0.0251]	[0.0073]

Note:

1) $***\ p < .01,\ **\ p < .05,\ *\ p < .10$

2) The p-values are in square brackets

†)(master's level aggregation period) / (doctoral level aggregation period)

‡) The baseline case.

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Chapter3

The Influence of Public R&D Investments on Private Sector Patenting in Fuel Cells

1 Introduction

Public R&D investment policies by government play an important role in today's world where issues we face, including the stability and efficiency of our energy supply, global warming, and environmental issues, are long-term in nature. Fuel cell technologies and hydrogen technologies (technologies that enable production, transportation, storage and supply of hydrogen) examined by the present analysis are the core technologies instrumental in constructing a hydrogen-powered society that will help us reduce energy consumption and environmental impact, diversify energy sources, and create new industries. As some issues including global warming are becoming increasingly perilous, these policies are crucial now more than ever. Huang et al. (2015) points out that, to maintain a global technical leadership role, many nations have been pouring an enormous amount of resources into the fuel cell industry particularly while encouraging the collaborative relationship between the academia and the industry. For instance, the European Union established the European Hydrogen and Fuel Cell Technology Platform (HFP) in 2004 to promote focused and continuous collaboration between the academia and the industry (Neef (2009)). Meanwhile, *Fuel cell collaboration in the United States. A report to the Danish partnership for hydrogen and fuel cells.* (2013) reported that consistent and frequent collaboration between universities and the industry was aided by the support provided by the Unities States government to state agencies and industry groups. In China, virtually all fuel cell projects are supported by government financial aids and involve top-tier universities of the respective regions. (*Fuel cells and hydrogen in China* (2012)).

In Japan, the importance of policies for the commercial development of fuel cells has been recognized to be crucial in the report by the Society for Fuel Cell Commercialization Strategy, Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry (2001), the policy speech by then Prime Minister Koizumi (February, 2002) as well as the report by the Deputy Prime Minister ' s project team (May, 2002). Various policy programs based on these proposals and principles have since been implemented. Many issues to be overcome in the commercialization of fuel-cell cars and stationary fuel cell were also chosen as key themes for technological development chiefly through NEDO (New Energy and Industrial Technology Development Organization) and public research institutes.

NEDO ' s missions include supporting the expanding use of energy- and environment-related technologies by promoting their development; however, as NEDO does not have its own R&D facility, actual technological development is conducted by outside agencies and industries contracted through public tender. A company contracted by NEDO will then work in collaboration with various industry, government, and academic organizations through its association with the project. It can be surmised that, aside from the public financial aid, companies working with NEDO may benefit from these various collaborative relationships and experience a spillover of the valuable knowledge, which may subsequently be beneficial to their research activities.

The present research analyzes the influence of the experience with NEDO has on the patent productivity and value. The issue, when estimating this effect, is that one cannot observe the potential outcome had the company not received any assistance from NEDO. As this makes it difficult to estimate the effectiveness of NEDO ' s policies, the matching method was used for analysis. Specifically, the matching estimation method used in Abadie and Imbens (2006) and Imbens (2014) and, in view of the panel data, the difference-in-difference matching method were used. The results of our estimation showed that, when analyzing without taking advantage of the characteristics of the panel data, there is a noticeable positive influence on the number of patents; however, all the other analyses showed that no significant influence was shown by any indexes.

2 Data

NEDO-associated patent information was extracted through data search using the entire texts of fuel cell-related patents. As NEDO is mentioned in the text if the patent is associated with a NEDO program, if at least one company associated with NEDO is included in the patent, the said patent was considered to be "associated" with NEDO, for which a dummy variable was created for treatment.

Company information obtained through Tokyo Keizai Inc. was used as covariates of the company size and economic activities. To take into consideration the accounting information of the companies, the ordinary income and total asset for each fiscal year was introduced. Also, the total number of employees for each fiscal year was included as the proxy variable for the size of the companies. Assuming that the R&D expenditure of the previous fiscal year would have a positive influence on this fiscal year's patent applications, "R&D share", the ratio of R&D expenditure to the total expenditure, was also included in the model. Furthermore, the "inventor ratio", the number of inventors that applied for fuel cell patents for each fiscal year divided by the total number of employees for each fiscal year, was introduced. Note that we were not able to obtain these variables consistently all throughout the target time period but were able to obtain usable data for three time periods only, namely 2001, 2005, and 2010. For other years, interpolated or extrapolated values based on data were used.

The present research considered the following two indexes in order to control the degree of network between units.

- "Degree centrality": A measure that shows how many co-applicants an applicant has had when submitting a joint application. The higher the value, the more co-applicants there are for the organization, which in turn indicates that a co-applicant network is expanding among more organizations.

- "Constraint" developed by Burt (2004): This index measures the importance of nodes within the network from the point of view of cross-linking information. Submitting a joint application with a node group that had already submitted a joint application in the past would then reduce this value. Conversely, if a joint application were to be submitted with a node group that had never submitted a joint application, the constraint for this node would increase as this node group is considered to have played a role in information sharing.

As for the degree centrality (the number of direct ties), it can be surmised that, the more organizations there are participating in a joint research project working towards a certain deadline to produce a joint application, a wider range of information may be gathered and accumulated within the said company. If this was the type of information that the said company lacked prior to the project, it is highly possible that this newly acquired knowledge can be used to generate innovation. It may therefore be expected that this variable can have a positive influence on the outcome. The constraint variable is an index that indicates the level of success the R&D network -established during the previous period- had in cross-linking information. When there are groups of companies within which many join applications are generated while few were generated among these groups, the constraint value of a company linking these groups of companies by generating joint applications with them would be low. If an R&D network evolves in the direction where various types of knowledge can be merged together through joint applications, one can expect the influence of this variable to be negative.

3 Estimation Method

The issue, when performing estimation in the present study on companies impacted by NEDO, is that one cannot observe the potential outcome had the company not received any assistance from NEDO. As this makes it difficult to estimate the effectiveness of NEDO's policies, the matching method was used for analysis. Using observable attributes of companies, we matched companies that were impacted by NEDO's policies with those that were not affected by NEDO. These companies that were not associated with NEDO then served as the model for the potential outcome for the companies that were impacted by NEDO had they not experienced any "NEDO effect" in order to estimate the effect of its policies.

Specifically, the following matching method described in Imbens and Rubin (2015) and Abadie and Imbens (2006) was used. The output is represented by Y_i and the company attribute is represented by X_i while $W_i = 1$ if the company was impacted by NEDO's policies, and $W_i = 0$, if not. Matching was performed using the Mahalanobis' Distance for observable variables and attributes between companies that were impacted by NEDO's policies and those that were not. In other words, $\ell(i)$ is defined as:

$$\ell(i) = \arg\min_{j:W_j \neq W_i} ||X_i - X_j||.$$

and for the samples that matched based on the above,

$$\hat{Y}_i(0) = \begin{cases} Y_i^{obs} & \text{if } W_i = 0, \\ Y_{\ell(i)}^{obs} & \text{if } W_i = 1, \end{cases} \qquad \hat{Y}_i(1) = \begin{cases} Y_{\ell(i)}^{obs} & \text{if } W_i = 0, \\ Y_i^{obs} & \text{if } W_i = 1, \end{cases}$$

thus creating the potential output when the company experienced (or not) the effect of the policies. This would create N_t pairs of groups. The simplest matching estimation of the average treatment effect on treated groups can be calculated by:

$$\hat{\tau}_{simplematch} = \frac{1}{N_t} \sum_{i:W_i=1} \left(\hat{Y}_i(1) - \hat{Y}_i(0)\right)$$

The explanatory variable here is calculated by:

$$\hat{X}_i(0) = \begin{cases} X_i^{obs} & \text{if } W_i = 0, \\ X_{\ell(i)}^{obs} & \text{if } W_i = 1, \end{cases} \qquad \hat{X}_i(1) = \begin{cases} X_{\ell(i)}^{obs} & \text{if } W_i = 0, \\ X_i^{obs} & \text{if } W_i = 1. \end{cases}$$

Abaddie and Imbens (2006, 2012) indicated that, if variables used for matching contained multiple continuous variables, a bias might be created in the nearest-neighbor matching estimation by the gap between $\hat{X}_i(0)$ and $\hat{X}_i(1)$ in the above formula setting. As the present analysis does contain multiple continuous variables, as indicated in Abadie and Imbens (2012) the following linear regression is used to correct the bias.

$$\hat{Y}_i(0) = \alpha_c + \beta_c' \hat{X}_i(0) + \varepsilon_{ci} \qquad \hat{Y}_i(1) = \alpha_t + \beta_t' \hat{X}_i(1) + \varepsilon_{ti}$$

When performing the above calculation, the potential output is adjusted as follows:

$$\hat{Y}_i^{adj}(0) = \begin{cases} Y_i^{obs} & \text{if } W_i = 0, \\ \hat{Y}_i(0) + \hat{\beta}_c'\big(\hat{X}_i(1) - \hat{X}_i(0)\big) & \text{if } W_i = 1, \end{cases}$$

Furthermore, if adjusted as such,

$$\hat{Y}_i^{adj}(1) = \begin{cases} \hat{Y}_i(1) + \hat{\beta}_t'\big(\hat{X}_i(0) - \hat{X}_i(1)\big) & \text{if } W_i = 0, \\ Y_i^{obs} & \text{if } W_i = 1, \end{cases}$$

the average treatment effect on the treated (ATT) on the bias-corrected treated groups is estimated by:

$$\hat{\tau}_{match} = \frac{1}{N_t} \sum_{i:W_i=1} \left(\hat{Y}_i^{adj}(1) - \hat{Y}_i^{adj}(0) \right)$$

The present analysis also estimates the average treatment effect on the treated (ATT) on the treated groups by propensity score matching.

4 Estimation Results

We considered the years following the start of a company's association with NEDO through research to be the period "impacted by NEDO," for which $W_i = 1$ is applied. For matching companies impacted by the subsequent year's NEDO policies with those who were not, the following data were used: each company's inventor ratio based on the total number of employees during the previous fiscal year, R&D share, logarithmic total number of employees, logarithmic ordinary income, logarithmic total net asset, dummy variable for joint applications with universities, two variables associated with the network and cross term between these two variables and the logarithmic total number of employees, and industry classification dummy variable. Companies that had prior association with NEDO before the said year and had already begun research are also considered to be a treated group based on the definition of W_i. Among the data between 1999 and 2010, those from 1999 were only used for matching purposes while samples after matching were from 2000 - 2010. As a result, the sample size of treated groups is 277.

The estimation of the average treatment effect using the nearest-neighbor matching method after bias correction is shown in Table 1. A significant positive influence on the number of patent applications can be seen, as the number is approximately 53% more than the group that has not been affected by NEDO; however, the influence on the quality measured by the total number of citations and the number of citations by examiners is not significant and, therefore, unclear.

Furthermore, using the propensity score matching, based on a logit model, W_i is estimated as a dependent variable as shown in Table 2. According to Table 2, being associated with NEDO has had a significant positive influence on the company size and the number of joint applications with universities compared with the previous fiscal year; however, the ordinary income was affected negatively. The result of the estimation seems to remain mostly unchanged even when including JSIC ' s dummies.

Table 3 shows the matching results based on the propensity score, which show a positive influence and are virtually identical to Table 1.

The present analysis is conducted using panel data, which allowed for eliminating unobservable company heterogeneities as fixed effects enabling the use of the difference-in-difference method. Hence, as the next step, based on the traditional analysis of science and technological changes as well as the Poisson fixed effect model developed by Hausman et al. (1984) an estimate was calculated using the conditional quasi-maximum likelihood model. The standard deviation given by this estimate is robust against the voluntary serial correlation pattern and, therefore, the criticism by Bertrand et al. (2004) of DD estimates is unlikely to apply. The present analysis used cluster robust standard deviation on the company level.

As a result of the estimation, it was revealed that, unlike the analysis that did not make use of the characteristics of panel data, no significant effect was observed on the number of patents. Similarly, no significant effect was observed on the number of citations.

5 Conclusion and Discussion

As a result of the present analysis, it was revealed that associating with NEDO had basically no effect on the number of patent applications of the company nor did it have any effect on their quality. One possible interpretation of this result is that companies have been said to shy away from identifying their important patents as being the result the NEDO program, which may have been reflected in the result of the analysis. This stems from the fact that, although the applicant company can claim the priority licensing right of its patent, the NEDO program allows other companies to make use of it if the applicant company does not, possibly leading companies to submit applications for important patents as being the result of " non-NEDO " projects. The second possible interpretation is that the Program has not affected the quality of patents since the companies may have already prepared the " results " (albeit not high-quality) when they submitted their applications to the NEDO project. They then may have submitted their patent applications before the end of the Project as required for the post audit. The third and last possible interpretation is that NEDO may not be as effective on the private-sector corporate level and more appropriate to be used to impact the public sector, for instance, for generating (international) standards.

Table 1: ATT of NEDO (Bias Corrected Matching Estimator)

	(1)	(2)	(3)
	(log)Number of patent application	Total citation	examiner citation
ATT	0.527***	-1.693	-0.857
	(0.123)	(1.233)	(0.848)
N	929	929	929

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 2: The Determinants into NEDO(logit)

	(1)	(2)
NEDO		
inventor ratio	-46.26	-3.939
	(29.74)	(37.06)
total number of employees (log)	0.503***	0.576**
	(0.193)	(0.225)
ordinary income (log)	-0.373***	-0.420***
	(0.0876)	(0.102)
total asset (log)	0.135	0.0942
	(0.101)	(0.11)
joint applications with universities	0.834***	0.741***
	(0.195)	(0.235)
R&D share	0.601	0.222
	(0.639)	(0.829)
degree centrality	0.525***	0.463***
	(0.0839)	(0.0848)
constraint	2.734	1.354
	(2.803)	(2.648)
total number of employees (log)× degree centrality	-0.0490***	-0.0419***
	(0.00798)	(0.00775)
total number of employees (log)× constraint	-0.444	-0.246
	(0.324)	(0.3)
sicdummy		YES
Observations	929	929

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 3: ATT of NEDO (p-score matching)

	(1)	(2)	(3)
	(log)Number of patent application	Total citation	examiner citation
ATT	0.490***	-0.399	-0.0875
	(0.151)	(0.639)	(0.424)
N	929	929	929

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: Conditional Quasi-maximum likelihood estimates based on the fixed effect Poisson model (Matching DID)

	(1)	(2)	(3)
	(log)Number of patent application	Total citation	examiner citation
NEDO × Post	0.101	-0.315	-0.223
	(0.0675)	(0.603)	(0.16)
log of employer	0.433***	0.42	0.525***
	(0.0623)	(0.522)	(0.197)
inventor ratio	75.50***	-0.125	18.19
	(11.18)	(29.57)	(39.22)
log of ordinary income	0.0416	-0.0165	-0.0689
	(0.0298)	(0.44)	(0.0794)
log of total asset	-0.0784	0.0123	0.134
	(0.0646)	(0.193)	(0.176)
R&D share	-0.0496	-1.527	-1.461**
	(0.223)	(1.403)	(0.678)
Network statistics	Yes	Yes	Yes
Observations	444	444	444
N	105	105	105

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

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