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An Analysis Using the Japanese National Innovation Survey

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PhD holders and Innovation in Firms:
An Analysis Using the Japanese National Innovation Survey

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Abstract

This paper investigates the relationships between PhD holders and innovation in firms. We examine the effects of the existence or absence of PhD holders on the success of product and process innovations in firms, using micro data from the Fourth Round of the Japanese National Innovation Survey conducted by the National Institute of Science and Technology Policy. Our results indicate that firms with PhD holders are more likely to succeed in both product and process innovations in comparison to firms without PhD holders. The magnitudes of these effects are 11 percentage points and 7-8 percentage points higher, respectively. However, we also find that the effects of PhD holders differ depending on firm size. More specifically, the existence of PhD holders has no positive effects on process innovation in small-sized firms.

1. Introduction

The Japanese government in the 1990s sought to produce more workforce with professional skills and knowledge. Education ministry expanded graduate schools and implemented so-called the "10,000 Postdocs Plan" for increasing the number of PhD holders.[1] This resulted in a substantial increase in new PhD holders, including in the humanities and social sciences, from 10,633 in 1999 to 17,396 in 2015 (Fig. 1).[2] However, many PhD holders failed to obtain a job after completing their doctoral program (Fig. 2).[3] That is not worth the time and money which they had spent on their carrier. One of the reasons behind this is the shortage of tenure-track positions, as well as the firm's passive attitude toward employing PhD holders.[4] Some scholars therefore have argued that Japanese universities have produced too many PhD holders (e.g., Cyranoski et al., 2011).

To succeed in innovation, firms need to acquire new knowledge and then accumulate it into the company's knowledge base (Gebauer et al., 2012; Zahra and George, 2002). One of the major channels used is newly hiring researchers, as they transfer knowledge previously developed and accumulated outside the firm (Almeida and Kogut, 1999; Hoti et al., 2006; Mansfield, 1985). Recruiting PhD holders could also be considered a channel of transferring knowledge in this manner. Not only does this transfer the up-to-date knowledge created and accumulated in universities to industry (Zellener, 2003), but recruiting PhD holders can also be expected to bring tacit knowledge that contributes to inventions and their commercialization (Agrawal, 2006). PhD holders can also help to build relationships between firms and universities, which can lead in turn to joint research projects (Cruz-Castro and Sanz-Menéndez, 2005).[5] They can thus strengthen the ability of firms to create and absorb knowledge, thereby promoting innovation.

This paper investigates the relationship between PhD holders and innovation in firms. More specifically, we analyze the impact of PhD holders on product or process innovation, using the Fourth Round of the Japanese National Innovation Survey. This General Statistical Survey was conducted by the National Institute of Science and Technology Policy in 2015, which includes approximately 12,000 Japanese firms with 10 or more regular persons employed.

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[1] See Iwasaki (2009) for further discussion on the government policy relating to PhD holders and the postdoc problem.

[2] The number of PhD holders began to fall in 2007 and fell to 15,045 in 2014.

[3] According to the Ministry of Education, Culture, Sports, Science and Technology (2017), 24.8% of those who completed or withdrawn from their PhD program in March 2017 were unable to find a job.

[4] According to the National Institute of Science and Technology Policy (2015), 58.6% of PhD holders found employment in universities or public research institutes, compared with 26.2% who went on to work in the private sector. Statistics Bureau (2018) also reported that of the 23,538 new researchers recruited by firms in the 2016 fiscal year, only 904 of them were PhD holders.

[5] See Thune (2009) for a review of how recruiting PhD holders builds relationships between universities and industry.

Our results show that firms with PhD holders are more likely to succeed in both product and process innovation compared with other firms. Specifically, the rates of product innovation are 11 points higher in firms with PhD holders, and the rates of process innovation are 7–8 points higher. This suggests that in addition to developing new products and services, PhD holders also contribute toward introducing production processes and logistics to make the production of existing products and services more efficient. However, the effect of PhD holders differs depending on the firm size. In particular, employing PhD holders has no statistically significant effects on process innovation for small-sized firms.

The remainder of this paper is structured as follows. The next section provides an overview of existing research, and Section 3 explains the data and model used for our analysis. Section 4 presents our findings, and Section 5 examines the robustness of the results. Finally, Section 6 provides the conclusion.

2. Existing research

Knowledge is a firm's most important resource in terms of competitiveness, but the ability to create and absorb new knowledge depends on the firm's human capital: the collective knowledge, skills, and capacity of its workers that contribute to production activities (Lepak and Snell, 1999; Levinthal and March, 1993; March, 1991). A doctoral degree is the highest level of academic attainment, and the involved educational investment makes the human capital of PhD holders higher than that of other employees. PhD holders are therefore the optimal employees for creating and absorbing new knowledge (Auriol, 2010).

The mobility of PhD holders and other researchers allows firms to acquire external knowledge. Researcher mobility exerts the effect of transferring knowledge accumulated in universities and public research institutes (Salter and Martin, 2001), thus enabling the destination firm to acquire the expertise and problem-solving skills possessed by the researcher. The knowledge and skills contributing to the commercialization of inventions have a particularly high correlation with firms' innovation levels. Consequently, several studies have shown a tendency among academic inventors affiliated with universities or public research institutes in particular—researchers possessing such knowledge and skills—to migrate to industry (Zucker et al., 2002; Crespi et al., 2007; Fritsch and Krabel, 2012). Kaiser et al. (2015) examined the effect of researcher mobility on R&D and patents in industry. They analyzed a sample of Danish firms and found that researcher mobility leads to an increase in patenting activity. Herrera et al. (2010) analyzed a sample of Spanish firms and, similarly, found that researcher mobility increases R&D intensity and patent propensity.

Several studies on firms recruiting PhD holders have investigated individual PhD holders and analyzed the relationship between their personal characteristics and career choices (Agarwal and

Ohyama, 2013; Mangematin, 2000; Roach and Sauermann, 2010; Sauermann and Roach 2014, Stern, 2004).[6] To summarize the findings, PhD holders with a preference for pecuniary remuneration tend to choose a career in industry, whereas PhD holders with more of an appetite for nonpecuniary remuneration place greater value on being interested in and contributing to scientific research, and tend to choose an academic career in spite of the relatively low earnings.[7] Conti and Visentin (2015) investigated the relationship between cohort size and the subsequent career path of PhD holders. They found that a larger cohort size rendered it more difficult for PhD holders to advance to firms with higher levels of R&D intensity or universities conducting a higher level of research.

Other studies on the recruitment of PhD holders have focused on firms rather than individual PhD holders.[8] For example, Garcia-Quevedo et al. (2012) pointed out that firm size and age, R&D activities, and research collaboration between firms and universities have a positive influence on the propensity to hire PhD holders in Spanish firms.[9] Herrera et al. (2010) and Garcia-Quevedo et al. (2012) have found that firms in the high-tech industry tend to recruit more PhD holders because of the greater demand for creating and absorbing cutting-edge knowledge in this sector.

Numerous studies evaluating the performance of PhD holders and other researchers employed in firms have focused on the number of their patents or citations (e.g., Onishi and Nagaoka, 2012; Singh and Agrawal, 2011; Subramanian et al., 2013). Onishi and Nagaoka (2012) analyzed data that combined industrial inventors in Japan with company information. They found that researchers who graduated from a university with a doctorate ("course doctorate") had a higher number of patent applications and citations than did those whose PhD was awarded based on research conducted outside university ("dissertation doctorate" [10]) or those with a master's degree. However, studies focusing on patents as a measure of innovative output have failed to identify innovation that does not lead to a patent application, thus have producing a one-dimensional picture of the role of researchers in a firm's strategy and innovation process. Herrera and Nieto (2015) recognized this and positioned activities relating to inventions and the creation and absorption of new knowledge as playing upstream roles in the innovation process, and activities such as product manufacturing and marketing as playing downstream roles in the

[6] Other studies have analyzed PhD holder employment and associated geographical factors. For example, Sumell et al. (2009) showed that cities with a flourishing R&D scene and high-quality research infrastructure tend to attract more PhD holders.

[7] Stern (2004) referred to this appetite for academia as a "taste for science."

[8] Eckhardt and Shane (2011) demonstrated a correlation between firms employing researchers and a high growth rate.

[9] Since PhD holders contribute toward building relationships between industry and universities, recruiting PhD holders is believed to overcome the difficulty of identifying a suitable project partner in the innovation process (Hess and Rothaermel, 2011).

[10] This is a feature of the Japanese system.

innovation process. They found that the knowledge and skills of PhD holders exert an upstream as well as a downstream effect, with firms conducting downstream activities also tending to recruit more PhD holders.[11]

These previous studies have shown that recruiting PhD holders can be expected to improve a firm's R&D capacity, the result of which has been observed, primarily, as an increase in patents. However, identifying the actual effect of PhD holders on firms' innovation levels is not easy; based on our research, several points in this regard remain unclear. The fourth round of the Japanese National Innovation Survey, which was conducted by the National Institute of Science and Technology Policy in 2015, aimed to assess the innovation activities and trends of Japanese firms. Because the survey involved asking firms whether they employed PhD holders, this enabled analyzing the relationship between firms employing PhD holders and innovation levels. This paper presents the unique features of this survey by analyzing how PhD holders influence the levels of product innovation and process innovation, and by demonstrating the effects on innovation that are not limited to patent numbers.

3. Data and model

3.1 Data

The data used in this study were obtained from the fourth round of the Japanese National Innovation Survey, which was conducted by the National Institute of Science and Technology Policy in 2015.[12] The survey extracted a random sample of firms from a population of 380,224 companies with 10 or more regular employees.[13] The sample comprised 24,825 firms, and the survey had a response rate of 50%. For our study, from the valid responses, we excluded instances in which missing values and contradictory responses had been corrected for. We then analyzed the remaining 12,094 firms. The fourth round of the Japanese National Innovation Survey concerned activities conducted during the 3-year period spanning FY 2012 to FY 2104, and comprised cross-sectional data collected simultaneously.

The fourth round of the Japanese National Innovation Survey used a questionnaire conforming to definitions established in the international Oslo Manual (3rd edition) guidelines for collecting and interpreting the innovation data. Product innovation was measured by an affirmative response to one of the following two questions pertaining to FY 2012–FY 2014: "Did you launch a new or substantially improved product?" or "Did you launch a new or

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[11] Kampelmann et al. (2018) looked beyond patents as a measure of innovative output and created a data set relating to firms and workers in Belgium. They found that PhD holders have a positive effect on labor productivity.

[12] The survey data were used with permission acquired through a secondary use application based on Article 32 of the Statistics Act (Act no. 53 of 2007).

[13] For further details on the methodology, see the National Institute of Science and Technology Policy (2016).

substantially improved service?” Process innovation was measured by an affirmative response to one of the following three questions pertaining to the same period: “Did you launch a new or substantially improved production process for products and services?”; “Did you launch a new or substantially improved logistics, shipment, or distribution method for intermediate inputs (raw materials, parts, etc.), products, or services?”; or “Did you launch a new or substantially improved maintenance system or purchasing, accounting, computer, or other process to support production processes or shipment methods?”

The data relating to PhD holders are as of the end of FY 2104. Firms that responded in the affirmative on the survey to the question of whether their postgraduates employed as regular employees included PhD holders were deemed to be firms employing PhD holders for our study. Because the question asked about postgraduates, this limited “PhD holders” to those who had graduated from a university program with a “course doctorate”; the figures therefore do not include those awarded a doctorate by completing a dissertation outside university—“dissertation doctorates”—or other researchers with equivalent or higher academic standing. In addition, the question did not distinguish between disciplines and was not limited to PhD holders employed in R&D departments. Therefore, firms employing someone with a PhD in the humanities or social sciences or employing a PhD holder in an administrative department are considered “firms employing PhD holders” for our study.

Table 1 shows the rates of product and process innovation depending on whether firms employ PhD holders. The product innovation rate across the whole sample for firms employing PhD holders is 39.6%, compared with 14.4% for firms not employing PhD holders. This constitutes a difference of 25.2%, which is statistically significant. The process innovation rate for firms employing PhD holders was 35.5%, compared with 17.9% for firms not employing PhD holders. This constitutes a difference of 17.6%, which is also statistically significant.[14] The findings show that firms employing PhD holders have higher rates of product and process innovation compared with other firms, and this trend holds for all firm sizes.

3.2 Model and variables

This section investigates the impact of differences in firm characteristics, such as company size or sector, on the finding that firms employing PhD holders have higher rates of product and process innovation compared with other firms. We controlled for these characteristics to verify the impact of employing PhD holders on levels of product and process innovation. Specifically, we estimated the following probit model for product innovation:

[14] The Wilcoxon signed rank test of the mean difference for product innovation and process innovation also yielded the same results.

$$
\begin{aligned}
Pr(PRODUCT\_INV = 1) = f(\alpha &+ \beta_1 PHD + \beta_2 SHARE\_MASTER \\
&+ \beta_3 FIRM\_SIZE + \beta_4 R\&D\_INT \\
&+ \beta_5 FOREIGN\_MAR \\
&+ \gamma\ REGION + \delta\ INDUSTRY + \epsilon)
\end{aligned} \tag{1}
$$

Product innovation (*PRODUCT_INV*) is defined by a dummy variable, with 1 indicating product innovation and 0 indicating no innovation. Process innovation (*PROCESS_INV*) is defined in the same manner. PhD holders (*PHD*) constitute an independent variable, where a firm employing PhD holders is 1, and a firm not employing PhD holders is 0. The company characteristics influencing innovation include the proportion of employees with a master's degree (*SHARE_MASTER*), firm size (*FIRM_SIZE*), R&D intensity (*R&D_INT*), foreign market presence (*FOREIGN_MAR*), region dummy (*REGION*), and industry dummy (*INDUSTRY*). *FIRM_SIZE* is expressed as the natural logarithm of sales (for FY 2014), *SHARE_MASTER* is the proportion of employees with a master's degree, and *R&D_INT* is the proportion of sales associated with R&D expenses. *REGION* is based on prefecture, and *INDUSTRY* is based on the broad categories established in the Japan Standard Industrial Classification (13th revised edition). The summary statistics relating to these variables are shown in Table 2, and the correlation coefficients are shown in Table 3.

4. Results

Table 4 lists the estimated values for Formula (1) concerning the entire sample. The dependent variables are product innovation in (i) and (ii), and process innovation in (iii) and (iv).

The estimated values in (i) show a significantly positive correlation between *PHD* and *PRODUCT_INV*. This result does not change in (ii), where *SHARE_MASTER* is not accounted for. The marginal effect for *PHD* in (i) is 0.108, showing that the product innovation rate for firms employing PhD holders is 11 points higher than that for other firms. Table 1 shows a 25-point difference for the product innovation rate between firms with and without PhD holders, but this difference shrinks when we account for the impact of company characteristics on product innovation.[15]

The estimated values in (iii) and (iv) in Table 4 show a significantly positive correlation between *PHD* and *PROCESS_INV*. This result does not change even when *SHARE_MASTER* is not accounted for. The marginal effect of *PHD* in (iii) is 0.081, showing that the process innovation rate for firms employing PhD holders is 8 points higher than that for other firms. In

[15] Some results were omitted from this paper. Nevertheless, when we estimated the probit model using sales based on product innovation instead of *PRODUCT_INV* as the dependent variable, *PHD* was still found to have a positive effect on product innovation.

the same way as that for product innovation, Table 1 shows an 18-point difference for the process innovation rate between firms with and without PhD holders, with this difference shrinking when we account for the impact of company characteristics.

Reviewing the results for company characteristics indicates that *FIRM_SIZE*, *R&D_INT*, and *FOREIGN_MAR* all have a positive effect on product innovation and process innovation. These results show that larger firms with higher R&D intensity rates that supply products and services to foreign markets have higher rates of product and process innovation. *SHARE_MASTER*, by contrast, has no statistically significant effect on product innovation, but it has a negative effect on process innovation. Since PhD holders will also have completed a master's program, this trend could be because *PHD* already includes the effect of completing a master's program. However, Table 4 shows that even accounting for *SHARE_MASTER* does not change the effect of *PHD*. This suggests that employing PhD holders exerts an effect, regardless of the number of employees with master's degrees.

Table 5 presents the estimated values for Formula (1) by firm size. The results for the sample of smaller firms in (i) and (ii) show that although *PHD* has a significantly positive effect on *PRODUCT_INV*, it has no statistically significant effect on *PROCESS_INV*. The results for the medium-sized firms in (iii) and (iv) show that *PHD* has a significantly positive effect on both *PRODUCT_INV* and *PROCESS_INV*. The results for the larger firms show a significantly positive effect for *PHD* on *PROCESS_INV*, and although the effect is also statistically significant effect for *PRODUCT_INV*, the level of significance is low. The marginal effect on *PRODUCT_INV* is 10 points for smaller firms and 14 points for medium-sized firms, where the marginal effect for the medium-sized firms is stronger than that for the whole sample. The marginal effect on *PROCESS_INV* is 12 points for medium-sized firms and 14 points for larger firms, with both effects being stronger than that for the whole sample. In summary, the results in Table 5 suggest that the effect on the product and process innovation of a company employing PhD holders differs depending on firm size.

5. Verifying robustness

Since baseline characteristics differ for firms employing PhD holders compared with other firms, it is possible that this may have confounded the results in Table 4 and Table 5. That is, if other factors influence both variables, then a correlation could be observed even though there is no causal relationship between PhD holders and product and process innovation. We can avoid the effects of this confounding factor by preventing the independent variable from becoming an endogenous variable. However, as with most economic phenomena, the results can be observed only after treatment, and untreated data cannot be observed. Many economics studies, therefore, have used statistical processes to extract a control group with the same baseline characteristics as the treatment group, thus making a counterfactual assumption. The main method for doing so is propensity score matching, which is the method employed in this paper. To verify the effect of firms employing PhD holders on product and process innovation, we adjusted for the difference in baseline characteristics between firms employing PhD holders and other firms.

We used *PHD* as the dependent variable in the logistic regression model to calculate the propensity score, and we inserted *FIRM_SIZE* and its square—*R&D_INT*—and *INDUSTRY* as the baseline characteristics. The estimated values are listed in Table 6. Interpolating the data for each firm based on these parameters enabled calculating the respective propensity scores. Since the propensity score is the probability of a given firm employing PhD holders, it is presented as a value between 0 and 1.

For our study, we used nearest neighbor matching as the propensity score matching method. This involves taking as the control group the firms with the closest propensity score to that of the treatment group (firms with PhD holders), and it has been the most frequently used method in previous studies. For our study, we established a caliper size of 0.03 as the upper limit for the propensity scores. This resulted in excluding 45 firms with a propensity score that exceeded this limit from the matched sample. To adjust for the baseline characteristics based on the propensity score, there must be sufficient overlap between the propensity scores for the treatment and control groups. The box plot in Figure 3 shows the propensity score distribution for firms with and without PhD holders. As indicated, there is no overlap in the prematched propensity scores for the two groups, but there is considerable overlap in the propensity score distribution after matching. After matching, to test for bias in the baseline characteristics that were used for calculating the propensity scores, we calculated the standardized mean difference and variance for the baseline characteristics that were derived both before and after matching. The results are shown in Table 7. Compared with that before matching, the standardized mean difference is closer to 0 and the variance is closer to 1. This shows that there is no bias in the baseline characteristics of the treatment and control group after matching.

We used the matched sample to calculate the causal effect in the form of the average treatment effects on the treated (ATET). ATET is generally expressed as in Formula (2):

$$ATET = E[Y_1 - Y_0 | T = 1] \tag{2}$$

Table 8 shows the estimated ATET for firms employing PhD holders. The positive ATET of *PHD* is significant for both *PRODUCT_INV* and *PROCESS_INV*. These effects of 0.120 and 0.085 respectively show that the rates of product innovation are on average 12 points higher for firms employing PhD holders compared with other firms with similar baseline characteristics, and that the rates of process innovation are 9 points higher. We can therefore assume that the effect of employing PhD holders on the product and process innovation of a company is not the result of a confounding factor.

6. Conclusion

We used individual data from the fourth round of the Japanese National Innovation Survey to analyze the effect of PhD holders on levels of product and process innovation. The fourth round of the Japanese National Innovation Survey was conducted by the National Institute of Science and Technology Policy in 2015 as a general statistical survey of a sample of approximately 12,000 Japanese firms with 10 or more regular employees. We measured product and process innovation on the basis of firms introducing new products and services, new production processes, or new shipping methods in the 3 years spanning FY 2012 to FY 2014.

Our findings show that employing PhD holders had a positive effect on product and process innovation. Specifically, the rates of product innovation were 11 points higher in firms employing PhD holders compared with other firms, and the rates of process innovation were 7–8 points higher. However, the effect of employing PhD holders differed depending on the size of the firm. In smaller firms, employing PhD holders was found to have no significant effect on process innovation.

Previous studies have shown that innovation requires processes for externally acquiring new knowledge, which then must be accumulated internally. Recruiting PhD holders is a crucial means of transferring knowledge in this manner, and PhD holders can be expected to transfer the cutting-edge knowledge created and accumulated in universities to industry. In addition to promoting research collaboration with universities, it is suggested that the impact of the highly specialized skills and problem-solving capacity of PhD holders is not limited to R&D but also spills over into innovation processes. Our findings are consistent with those of previous studies, suggesting that PhD holders promote firms' levels of innovation. However, this effect is not necessarily equal for all sizes of a firm. In particular, larger firms employing PhD holders did not necessarily have higher rates of product innovation compared with other larger firms. We were unable to identify the reason for this in our study. Because larger firms have a higher ratio of PhD holders than do small- and medium-sized firms, just accounting for the number of PhD holders in the employees is not sufficient for measuring the effect on innovation. However, as Haneda and Ito (2018) showed in analyzing individual data from the second round of the Japanese National Innovation Survey (conducted in 2009), product and process innovation rates are influenced by how a firm is organized and how its human capital is managed, which could mean that ineffective policies in this regard prevent larger firms from fully exploiting the potential of PhD holders.

Since our analysis is based on cross-sectional data, we were unable to fully verify the causal relationship between employing PhD holders and innovation; moreover, an inverse causal relationship—whereby many innovative firms employ PhD holders—is also feasible. Furthermore, our findings do not adequately explain the mechanisms by which employing PhD holders influences innovation rates. Further research is necessary to address these limitations.

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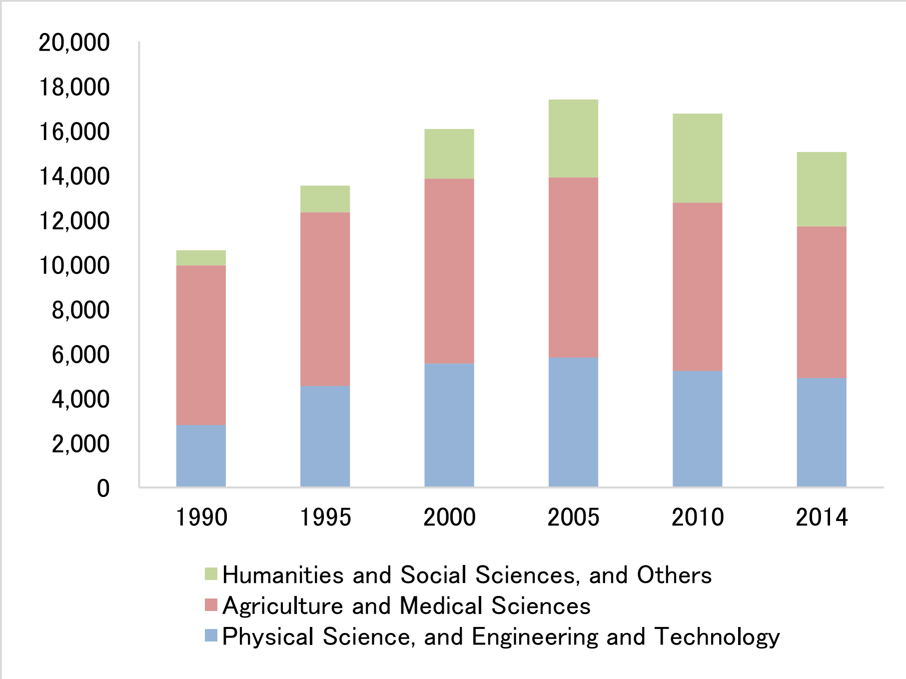
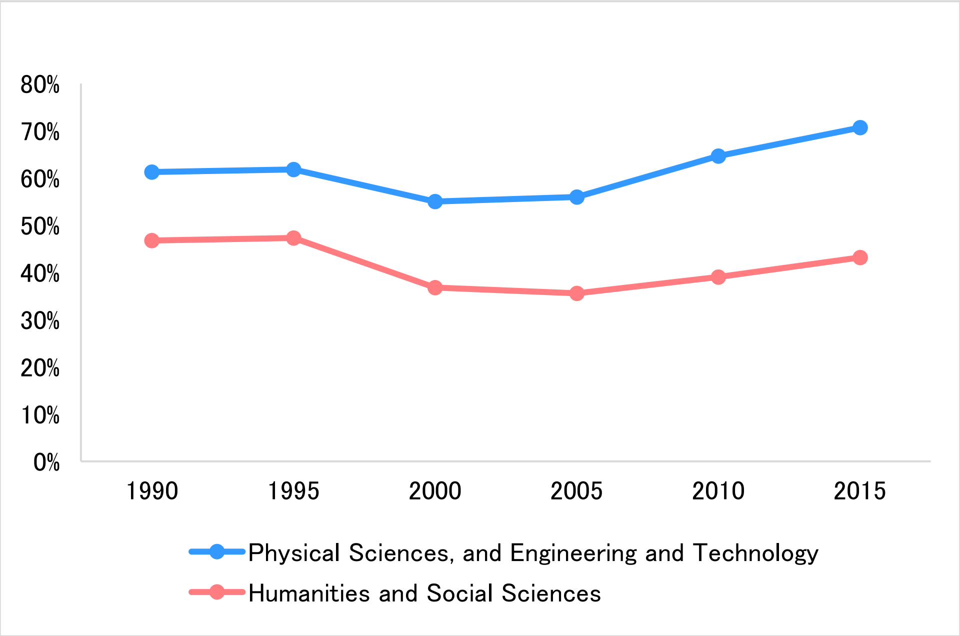
Figure 1: The Number of New PhDs, 1990-2014 (Unit: Person)



Source: National Institute of Science and Technology Policy (2017) and Ministry of Education, Culture, Sports, Science and Technology (2017).

Notes: Figures indicate the number of those who get a doctorate degree, including a degree by dissertation, in each year.

Figure 2: Employment Rate of New PhDs, 1990-2015 (Unit: %)



Source: National Institute of Science and Technology Policy (2017).
Notes: Employment rate refers to the proportion of those who have found employment (including a fixed term positions) among those who have completed or withdrawn from a doctorate program.

Table 1: Innovations and PhD Holders

	Type of innovation	PhD holders: Yes	PhD holders: None	Difference (*t*-value)
Full sample	Product	39.6%	14.4%	12.529***
	Process	35.5%	17.9%	8.906***
		(608 firms)	(11,486 firms)	
Small-sized	Product	31.2%	13.4%	5.403***
	Process	24.8%	17.1%	2.503**
		(202 firms)	(7,756 firms)	
Medium-sized	Product	39.1%	15.1%	7.118***
	Process	38.6%	19.5%	5.684***
		(220 firms)	(2,796 firms)	
Large-sized	Product	49.5%	20.8%	7.341***
	Process	43.5%	20.7%	5.900***
		(186 firms)	(934 firms)	

Notes: **, *** indicates that statistical significance at 0.05 and 0.01 levels, respectively. Small-sized firms are those with 10 or more and 49 or less regular persons employed. Medium-sized firms are those with 50 or more and 249 or less regular persons employed. Large-sized firms are those with 250 or more regular persons employed. *t* is test statistic for the null hypothesis that whether there is no difference between two groups means. In the test, it is assumed that the two groups have different variance.

Table 2. Summary Statistics

Variable	Measure	Mean	S.D.	Min.	Med.	Max.
PRODUCT_ INV	Binary	0.157	0.364	0	0	1
PROCESS_INV	Binary	0.188	0.391	0	0	1
PHD	Binary	0.050	0.219	0	0	1
SHARE_MASTER	Continuous	0.012	0.054	0	0	1
FIRM_SIZE	Continuous (Log)	6.500	1.728	0	6.273	16.046
R&D_INT	Continuous	0.011	0.348	0	0	29.667
FOREIGN_MAR	Binary	0.127	0.333	0	0	1

Notes: The number of observations is 12,904. S.D. is standard deviation. Figures for industry dummies and regional dummies are omitted in this table.

Table 3. Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	*PRODUCT_ INV*	1						
(2)	*PROCESS_INV*	0.404	1					
(3)	*PHD*	0.152	0.098	1				
(4)	*SHARE_MASTER*	0.092	0.032	0.395	1			
(5)	*FIRM_SIZE*	0.136	0.108	0.224	0.112	1		
(6)	*R&D_INT*	0.060	0.049	0.052	0.059	-0.049	1	
(7)	*FOREIGN_MAR*	0.211	0.150	0.200	0.147	0.205	0.031	1

Notes: The number of observations is 12,904. Figures for industry dummies and regional dummies are omitted in this table.

Table 4. Estimated Results I: Probit Model

	(i)	(ii)	(iii)	(iv)
	PRODUCT_ INV	*PRODUCT_ INV*	*PROCESS_INV*	*PROCESS_INV*
	dF/dx	*dF/dx*	*dF/dx*	*dF/dx*
PHD	0.108***	0.114***	0.081***	0.067***
	(0.020)	(0.019)	(0.020)	(0.019)
SHARE_MASTER	0.052		-0.161**	
	(0.060)		(0.076)	
FIRM_SIZE	0.022***	0.022***	0.026***	0.025***
	(0.002)	(0.002)	(0.002)	(0.002)
R&D_INT	0.322***	0.326***	0.498***	0.471***
	(0.038)	(0.038)	(0.069)	(0.067)
FOREIGN_MAR	0.143***	0.144***	0.089***	0.087***
	(0.013)	(0.013)	(0.012)	(0.012)
Regional dummies	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES
Observations	12,094	12,094	12,094	12,094
Log likelihood	-4,752	-4,752	-5,457	-5,459
χ^2	1,008***	1,007***	783***	779***

Notes: Marginal effects are reported. The figures in the bracket are standard errors. **, *** indicate that statistical significance at 0.05 and 0.01 levels, respectively.

Table 5. Estimated Results II: Probit Model, by Firm Size

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	Small-sized	Small-sized	Medium-sized	Medium-sized	Large-sized	Large-sized
	PRODUCT_ INV	*PROCESS_INV*	*PRODUCT_ INV*	*PROCESS_INV*	*PRODUCT_ INV*	*PROCESS_INV*
	dF/dx	*dF/dx*	*dF/dx*	*dF/dx*	*dF/dx*	*dF/dx*
PHD	0.098***	0.020	0.138***	0.116***	0.088*	0.137***
	(0.033)	(0.031)	(0.034)	(0.036)	(0.048)	(0.048)
SHARE_MASTER	-0.009	-0.109	0.022	-0.126	0.481	-0.373
	(0.078)	(0.094)	(0.113)	(0.148)	(0.297)	(0.285)
FIRM_SIZE	0.579***	0.309***	0.127**	0.669***	3.403***	1.270**
	(0.072)	(0.067)	(0.052)	(0.192)	(0.774)	(0.564)
R&D_INT	0.156***	0.086***	0.140***	0.120***	0.153***	0.097**
	(0.016)	(0.016)	(0.024)	(0.025)	(0.040)	(0.038)
FOREIGN_MAR	0.098***	0.020	0.138***	0.116***	0.088*	0.137***
	(0.033)	(0.031)	(0.034)	(0.036)	(0.048)	(0.048)
Regional dummies	YES	YES	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES	YES	YES
Observations	7,958	7,958	3,016	3,016	1,120	1,120
Log likelihood	-2,937	-3,255	-1,277	-1,407	-519	-556
χ^2	530***	810***	283***	274***	235***	133***

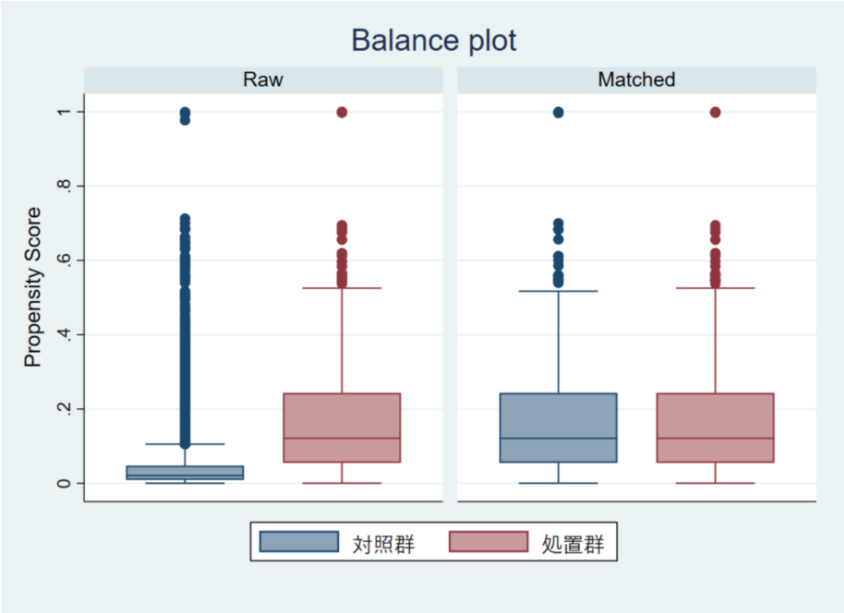
Notes: Marginal effects are reported. The figures in the bracket are standard errors. *, **, and *** indicate that statistical significance at 0.1, 0.05, and 0.01 levels, respectively.

Table 6. Estimated Results III: Propensity Score (logit model)

	coef	*dF/dx*
FIRM_SIZE	1.009***	0.022***
	(0.141)	(0.003)
FIRM_SIZE^2	-0.024***	-0.001***
	(0.008)	(0.000)
R&D_INT	11.749***	0.258***v
	(1.626)	(0.038)
Constant term	-9.886***	
	(0.654)	
Industry dummies	YES	YES
Observations	7,958	7,958
Log likelihood	-2,937	-3,255
χ^2	530***	810***

Notes: The figures in the bracket are standard errors. *** indicates that statistical significance at 0.01 level.

Figure 3. Distribution of Propensity Score



Notes: Propensity scores are matched with the nearest neighbour matching. The width of caliper is set at 0.03 and those observed subjects which go over this are removed from the sample.

Table 7. Balancing Test for Baseline Characteristics

		Standardized difference	Variance ratio
FIRM_SIZE	Before matching	0.883	1.695
	After matching	3.957×10^{-4}	0.986
FIRM_SIZE^2	Before matching	0.846	2.544
	After matching	-0.001	0.966
R&D_INT	Before matching	0.307	11.019
	After matching	0.048	0.943

Notes: The pre-matching observation value is 12,049. The post-matching observed value is 1,164. Figures for industry dummies are omitted.

Table 8. Estimated Results IV: Average Treatment Effects on Treated (ATET)

	(i)	(ii)
	PRODUCT_ INV	*PROCESS_INV*
	ATET	ATET
PHD	0.120***	0.085***
	(0.028)	(0.028)

Notes: The number of observation is 1,164. The number of treated groups (firms with PhD holders) is 582. The figures in the bracket are standard errors in Adabie-Imbens. *** indicates that statistical significance at the 0.01 level.