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Effects of State-Sponsored Human Capital Investment on the Selection of Training Type*

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Abstract

Since the 1990s, firms in Japan have reduced their human capital investment in the workplace to minimize costs. Moreover, in response to the increase in the number of non-regular employees and turnover rates, workers need to have greater incentive to make the self-motivated investment in themselves for their self-protection. In this study, we first estimate the effects of workers' self-motivated investment in themselves on wage rates. Next, we explore who is likely to participate in which training type and accordingly estimate the effects of the self-motivated investment on wage rates by training type. Our estimates controlling for individual-level fixed-effects indicate that the return is significantly positive and particularly high for practical training related to workers' current jobs, and regular workers tend to self-select these higher-returns programs, while non-regular workers are more likely to enroll in lower-returns programs, such as schooling. This trend in investment in oneself could potentially increase the wage inequality between regular and non-regular workers through the self-selection of training types. Our estimates reveal that receiving the training and education benefit raises the likelihood for workers to participate in a high-return training program regardless of whether they are non-regular or regular workers. This suggests that government benefits on self-investment change workers' self-selection of training type and serve to promote practical trainings that lead to high returns.

Keywords: Training and education benefits, Wage rates, Human capital, Self-investment
JEL Classification: J33, J38, J24, H20

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1. Introduction

It is well known that Japanese companies used to offer education and training to their employees intently against a backdrop of the implicit long-term employment that had long been customary in Japan. The country's low job turnover, labor unions organized by companies, and seniority-based wage systems enabled companies to have a long-term perspective and engage in human capital investment to improve their employees' skills. However, from the 1990s onward, a prolonged economic slump and intensifying competition has led to a decline in the amount of money that Japanese companies spend on the development or education and training of internal human capital.

Many papers have pointed out such a decrease in human capital investment. For instance, according to Miyagawa, Takizawa, and Tonogi (2016), the total amount of investment in human capital at all private companies in 2012 was about 20% of the total amount invested in 1991. In addition, Hara (2007) demonstrates that compared with the early 1970s, off-the-job training (Off-JT) opportunities in Japanese companies decreased in the early 2000s.

Furthermore, according to Toda and Higuchi (2005), the probability of participation by female part-time workers in a training course significantly dropped in the late 1990s. Moreover, as non-regular work increases, the job turnover rates rise. The number of those who seem to be outside the scope of human capital investment by firms has increased, and they may have greater needs and incentive to invest in skill development themselves. However, it is not always easy for workers to find the time or money to improve their abilities themselves. In response to the sharp drop in human capital investment by companies, in 1998 the Japanese government set up a training and education benefit (TEB) system to provide financial aid to individuals who invest in improving their skills. The system provides cash benefits to workers who have paid for, participated in, and completed programs designated by the Ministry of Health, Labor, and Welfare. While many developed countries have expanded or maintained their apprenticeship systems that support individuals through private sectors, Japan chose to increase its direct subsidies to individuals for skill improvement.

In this study, we employ unique individual panel data to estimate the effect of participation in trainings on wage rates controlling for fixed effects, and we explore individuals' selection of training types. Our estimates indicate that voluntary vocational education and training, particularly practical training related to employees' current jobs, significantly increases wage rates. Further, while regular workers tend to self-select higher-returns programs, non-regular ones select lower-returns programs, such as schooling. We also estimate the causal impact of receiving the TEB on participation in each training type by performing an instrumental variable (IV) estimation. The results reveal that receiving the TEB enhances the probability of participating in higher returns programs, irrespective of workers' current position. These findings suggest that the TEB mitigates economic bipolarization caused by the self-selection problem concerning training choices.

There are a few studies that have examined the impact of the state-sponsored human capital investment on wages. Finegold and Soskice (1988) explore training policies in the United Kingdom and find that they deliver little wage returns for participants. Using cross-section survey data, Abe et al. (2005) demonstrate that human capital investments subsidized by the Japanese government have a limited impact on wages. Holmes (2017) explains that state-run or -funded training programs are only imperfect substitutes for employer-provided trainings, unless there is a guarantee that the skills will be applied in employees' jobs.

This paper is the first one to explore the impact of the TEB on the self-selection of training type using individual panel data. Our data include rich information on the contents of training in which each worker participated, which enables us to examine "who chooses what kind of training" in detail.

The remainder of this paper is organized as follows. Section 2 describes the TEB system in Japan. Section 3 presents the empirical model, and Section 4 offers a brief description of the data. Section 5 shows the empirical results. Section 6 concludes the paper.

2. TEB System in Japan

The TEB system developed by the Japanese government began in 1998. To receive the benefit, workers need to pay for, participate in, and complete programs designated by the Ministry of Health, Labor, and Welfare. The programs are courses that lead to career improvements in the following areas: office work, business, and sales; the study of foreign languages; the use of computers and information processing techniques; services (for specialists and businesses, or individuals and households); healthcare and sanitation, such as caregivers and nurses; social welfare; education; production techniques; construction and public works; agriculture, forestry, and the fisheries industry; and specialized fields offered by colleges and graduate schools. Since these courses are funded by unemployment insurance premiums, the recipients of the benefits must pay an unemployment insurance premium for a sufficient number of years in their current workplace or must have a sufficient history of past enrollment to be eligible for the TEB.

During 1998–2014, the period we analyze, the system experienced three large revisions to the eligibility requirement, refund rate, and maximum amount of benefits in response to fiscal tightness in unemployment insurance and misuse of the benefits, as shown in Table 1.

Table 1: Changes in the TEB System

Period	10/1998–12/2000	1/2001–4/2003	5/2003–9/2007	10/2007–9/2014
Eligibility requirements	People insured for 5 years or more	People insured for 5 years or more	People insured for 3 years or more	People insured for 3 years or more[1]
Benefit percentage (refund rate)	80% of training cost	80% of training cost	Insured 3–5 years: 20% of training cost Insured 5 years or more: 40% of training cost	20% of training cost
Maximum amount	200,000 yen	300,000 yen	Insured 3–5 years: 100,000 yen Insured 5 years or more: 200,000 yen	100,000 yen

Note: Table 1 summarizes the reforms on the TEB system up to the 2014 reform.

A minor change was undergone in 2001. The maximum amount of benefits was increased from 200,000 yen to 300,000 yen. In 2003, there was a significant decrease in the maximum amount of benefits and refund rate. Before 2003, recipients could receive 80% of their training cost, but after 2003, the refund rate became 20% for those insured 3-5 years and 40% for those insured 5 years or more. Since 2003, the number of users of education and training declined drastically.[2]

In the revision in 2007, the maximum amount of benefits and refund rate were reduced further.[3]

[1] However, benefits can be received after 1 year or more for the first time only.
[2] In the 2003 reform, the eligibility requirement was expanded from those insured for 5 years or more to those insured for 3 years or more.
[3] After 2014, major revisions were made to not only benefit amounts and eligibility requirements, but also to the structure of the system, creating two tiers of benefits according to the content of the education program: general training and education benefits, and practical specialized training and education benefits. This study conducts an analysis using data from the period before the revisions in 2014.

3. Empirical Model

3.1 Fixed-Effects DID

First, to examine the returns to training in the context of wage rates, we estimate the following:

$$\ln(RealWageRate_{it}) = \alpha + \beta After_{it} \cdot Treatment_i + \gamma X_{it}$$
$$+(individual\ fixed\ effects)_i + (time\ fixed\ effects)_t + u_{it}, \qquad (1a)$$

where $Treatment_i$ is a dummy variable that takes the value 1 if the worker participates in a training at least once during the sample period. $After_{it}$ takes the value 1 if individual i is trained in the year t and afterward, and 0 otherwise. We exclude the treatment dummy from the right-hand side variable because $Treatment_i$ is time-invariant, and thus, dropped from the estimation as a fixed effect. The estimated coefficient of $After_t \times Treatment_i,$ which is the interaction term for the $After_t$ and $Treatment_i$, is of key interest. X_{it} includes time-variant control variables, such as the potential years of experience and the square of experience; tenure and its square; number of children; marital status. Additionally, area, industry, firm size, occupation, and job position dummies are also included in X_{it} for some specifications. Note that all unobserved time-invariant individual characteristics are captured by individual fixed effects. Failing to control for such effects could result in a serious bias. Individuals who have higher self-motivation or innate talents are more likely to receive training than others, and thus, earn a higher wage.

The common trend assumption should be satisfied when we conduct the DID estimation. The treatment group that participated in trainings and the control group may not exhibit different trends in wages. To address this problem, we employ specifications that allow time trends to be different between the treatment and control groups following Li *et al.* (2016).

$$\ln(RealWageRate_{it}) = \alpha + \beta After_{it} \cdot Treatment_i + \gamma X_{it}$$
$$+(individual\ fixed\ effects)_i + \theta_1 Trend_t + \theta_2 Trend_t \cdot Treatment_i + \theta_3 Trend_t^2$$
$$+ \theta_4 Trend_t^2 \cdot Treatment_i + u'_{it}. \qquad (1b)$$

In Equation (1b) that includes a treatment-specific time trend and its square, the estimates are not biased, even if the common trend assumption is violated.

3.2 Multinomial Regression

Next, we employ a multinomial regression to estimate what types of people more likely to participate in each program. The training programs are divided into the following six categories on the basis of their content: (1) attended vocational, advanced vocational, or trade school; (2) attended public vocational training; (3) attended a university (degree program) or graduate school (including adult education); (4) took a correspondence course (including university courses), attended university or other public lectures, or learned from a television or radio course and books; (5) attended lectures or seminars; and (6) participated in a company's voluntary study groups. The reference group is those who did not participate in a training program for each year. These categories of the training programs are regressed on years of education, male dummy, potential experience years and its square, tenure and its square, number of children, marital status, regular worker dummy, and the time trend and its square.

Furthermore, we aggregate the six categories into the following two types of training: Type I (schooling), which includes training categories (1), (2), and (3); and Type II (practical training related to current job), comprising categories (4), (5), and (6). Next, we re-estimate returns from trainings for both the training categories.

3.3 DFL Decomposition

In addition to the estimations above, we apply DFL decomposition to visually confirm the effects of participation in the two types of trainings on the overall distribution of wage rates (DiNardo et al. 1996, DiNardo and Lemieux 1997). An advantage of this method is that it visually decomposes changes in the distribution into structural and compositional effects. We compare the training distribution before and after training, by category.

For example, the pre-training distribution for the real wage rate among those who participated in Type-I training during the sample period is expressed as:

$$F_{Type\ I} = \int f_{Type\ I,Before}(y|X)h(X|Type = I, Before)dX, \qquad (2)$$

where $f_{Type\ I,Before}(y|X, Before)$ is a determination mechanism of y (real wage rate) before the training that maps workers' and firms' attributes (X) to the distribution of y. Density $h(X|Type = I, Before)$ denotes the attributes of workers and firms that participated in Type-I training before the training. In contrast, the post-training distribution for those who participated in Type-I training is:

$$F_{Type\ I} = \int f_{Type\ I,After}(y|X)h(X|Type = I, After)dX, \qquad (3)$$

Next, the post-training distribution for those who participated in Type-I training if the determination mechanism of y (real wage rate) was identical to that of Type-II training is:

$$F_{Type\ II}^{Type\ I} = \int f_{Type\ II,After}(y|X)h(X|Type = I, After)dX. \qquad (4)$$

This can be considered a counterfactual distribution, which would have been realized if workers who participated in Type-I training participated in Type-II training instead. In other words, the counterfactual distribution has the same workers and firms' attributes as the real distribution of X for those who experienced Type-I training but are similar to those of β (coefficients of X) for the Type-II training. We estimated the counterfactual distribution using DiNardo et al.'s (1996) method for reweighting term ω:

$$\begin{aligned} F_{Type\ II}^{Type\ I} &= \int f_{Type\ II,After}(y|X)h(X|Type = I, After)dX \\ &= \int \omega f_{Type\ II,After}(y|X)h(X|Type = II, After)dX. \qquad (5) \end{aligned}$$

Note that since we are using panel data, $h(X|Type = I, Before) \approx h(X|Type = I, After)$ holds.[4] Thus, regardless of the timing of evaluating the attributes, let us define that the density $h(X|Type = i)$ denote the attributes of workers and firms that participated in Type- i $(i = I, II)$ training. Then, the former equations (2)–(4) can be rewritten as:

$$F_{Type\ I} = \int f_{Type\ I,Before}(y|X)h(X|Type = I)dX, \qquad (2)'$$

$$F_{Type\ I} = \int f_{Type\ I,After}(y|X)h(X|Type = I)dX, \qquad (3)'$$

$$\begin{aligned} F_{Type\ II}^{Type\ I} &= \int f_{Type\ II,After}(y|X)h(X|Type = I)dX \\ &= \int \omega f_{Type\ II,After}(y|X)h(X|Type = II)dX. \qquad (4)' \end{aligned}$$

[4] The equation holds only when we use balanced panel data, while the "nearly equal" condition, i.e., $h(X|Type = I, Before) \approx h(X|Type = I, After)$, can be satisfied even when we use unbalanced panel data. Here, we use unbalanced panel data, but the main results do not change when we use balanced data.

Then, the calculation for reweighting term ω using DiNardo et al.'s (1996) method is:

$$\omega = \frac{h(X|Type = I)}{h(X|Type = II)} = \frac{P(X)P(Type = I|X)/P(Type = I)}{P(X)P(Type = II|X)/P(Type = II)}$$
$$= \frac{P(Type = I|X)P(Type = II)}{P(Type = II|X)P(Type = I)}, \qquad (6)$$

where density $h(X|Type = i)$ is the p.d.f. of attributes in training Type i $(i = I, II)$. The second equation is derived from Bayes' rule. In the actual regression for ω, $P(Type = i|X)$ can be calculated using propensity scores obtained from the probit model in which $P(Type = i)$ $(i = I, II)$ is regressed on X, that is, years of education, male dummy, potential experience years and its square, tenure and its square, the number of children, marital status, and the dummies for year, area, industry, firm size, occupation, and job position. $P(Type = i)$ is calculated as the proportion of those who participated in Type i $(i = I, II)$ training in the pooled data.

3.4 Fixed-Effects Instrumental Variable Estimation

Finally, we explore the effect of receiving a state subsidy (i.e., TEB) on an individual's choice of training program. Since the decision of whether to receive a state subsidy is endogenous, we use TEB eligibility as the IV. The first-stage regression for the IV estimation is:

$$TEB_{it} = \alpha + \beta(Eligible\ for\ TEB)_{it} + \gamma X_{it}$$
$$+(individual\ fixed\ effects)_i + (time\ fixed\ effects)_t + v_{it}. \qquad (7)$$

To satisfy the instrument relevance condition, we first assess whether TEB eligibility significantly affects the decision to receive TEB. Variable $Eligible\ for\ TEB_{it}$ is a dummy variable that takes the value 1 if the worker was eligible for TEB. The same person could change his/her eligibility status when either he/she changed jobs or the recipient's qualification of TEB was changed by the system reform. After confirming sufficient partial correlation between $Eligible\ for\ TEB_{it}$ and TEB_{it}, we progress to the second-stage regression of the IV estimation. In the second stage, we regress a dummy variable for each type of training on TEB, which is instrumented by $Eligible\ for\ TEB_{it}$. Note that tenure and regular worker dummy variables will be controlled for in the second stage regressions, and thus the TEB eligibility is unlikely to be correlated with any factors remaining in the error term. This implies the exogeneity of the IV will be satisfied under this specification.

$$Participation\ in\ Type\ I\ Training_{it} = \alpha_I + \beta_I TEB_{it} + \gamma_I X_{it}$$
$$+(individual\ fixed\ effects)_i + (time\ fixed\ effects)_t + e_{it}. \quad (8)$$

$$Participation\ in\ Type\ II\ Training_{it} = \alpha_{II} + \beta_{II} TEB_{it} + \gamma_{II} X_{it}$$
$$+(individual\ fixed\ effects)_i + (time\ fixed\ effects)_t + \varepsilon_{it}. \quad (9)$$

By employing the IV estimation, we can exclude the inverse causality, that is, a case in which workers first determine the program in which they would participate, and this decision affects whether they receive TEB. In addition, we can overcome the simultaneous bias using the IV estimation. Thus, the coefficient on TEB allows us to capture the causal impact of receiving TEB on participating in each training type. In addition to this, by estimating these equations and comparing the magnitude of β_I and β_{II}, we can find the training type in which TEB encourages workers to participate. For example, if $\beta_I < \beta_{II}$, receiving TEB stimulates workers to participate in Type-II over Type-I training.

4. Data

We employ Japanese panel data from the Keio Household Panel Survey (KHPS), which is conducted annually by Keio University. It includes observations randomly chosen from almost all regions and industries in Japan. A key feature of the KHPS is that it is the first nationwide follow-up survey for individuals (4,000 households and 7,000 people) of all ages and both sexes and captures information on education, employment, income, expenses, health, and family structure. The survey is designed to enable comparisons with major international panel surveys, such as the Panel Study of Income Dynamics (PSID) and the European Community Household Panel (ECHP) survey. The KHPS data were first collected in 2004; we use sample data for 2004–2015 for male and female employees in the 20–80-year-old age group[5].

Furthermore, people who had experienced education or training prior to 2004 are dropped from the sample to prevent the coefficients from being impacted by the lagged effects of past training. Thus, the sample we use is restricted to those who had never

[5] The year *t* survey gathers information during year *t* -1 for some questions, and thus we included the sample year up to 2015 to recover information in 2014. We exclude those who are unemployed and self-employed from our analysis.

experienced education or training and those who experienced education or training within the sample period.

Table 2. Descriptive Statistics (2004–2015)

	(1) All Sample	(2)	(3) Training=1	(4) Training=0
		[Type-I Training] Schooling	[Type-II Training] Practical Training Related to Current Job	
Real Wage Rate (Yen)	1915.174	1375.837	2496.567	1853.041
	(3055.803)	(1108.263)	(5657.779)	(2600.728)
Training Cost (Ten Thousand Yen per Month)	0.190	8.018	1.085	0.000
	(1.722)	(11.913)	(3.098)	(0.000)
Time Spent on Training (Hours per Month)	2.130	67.500	14.050	0.000
	(11.581)	(65.414)	(19.036)	(0.000)
Age	49.225	39.416	47.229	49.537
	(11.483)	(13.350)	(10.774)	(11.486)
Education Years	13.067	13.982	14.197	12.930
	(2.186)	(2.159)	(2.151)	(2.150)
Tenure	17.188	11.319	17.477	17.204
	(11.673)	(9.945)	(10.397)	(11.812)
Number of Children	1.360	1.027	1.396	1.358
	(0.920)	(1.065)	(0.903)	(0.920)
TEB	0.007	0.133	0.027	0.000
Male	0.637	0.558	0.673	0.633
Married	0.862	0.566	0.850	0.866
Regular Workers	0.537	0.425	0.701	0.519
Observations	15134	113	1545	13476

Note: Standard deviations are in parentheses. Type-I training includes those who (1) attended vocational, advanced vocational, or trade school; (2) attended public vocational training; (3) attended a university (degree program) or graduate school (including adult education), while Type-II training includes those who (4) took a correspondence course (including university courses), attended university or other public lectures, or learned from a television or radio course and books; (5) attended lectures or seminars; and (6) participated in a company's voluntary study groups.

Table 2 presents the summary statistics for the key variables in our regression analysis. On average, the treatment group that participated in Type-II training reports a higher wage rate than those who opted for Type-I training. Those in Type-II training were more likely to be regular workers. Further, the time investment is lower for Type-II training than Type-I training. The training cost paid by workers is also significantly lower for Type-II training, suggesting that part of the expense is paid by firms, or simply, the training costs are low. Since Type-II training includes seminars and lectures that do not require considerable time and cost investment, Type-II training can be characterized as relatively inexpensive practical training compared with Type-I training. In addition, because the fraction of regular workers is relatively high for those who participated in Type-II training, it is highly likely that the content of Type-II training is closely related to their current job and the costs are partially incurred by the firms. Thus, it is possible that the trend of firms' underinvestment in human capital at their workplace is replaced by workers' voluntary training outside a company to compensate for the insufficient training provided by the firms.

5. Empirical Results

5.1 Fixed-Effects DID

Table 3 reports the impact of investing in oneself on ln (real wage rate). Columns (1)–(3) report the results without controlling for time fixed effects, and Columns (4)–(6) present the results for Equation ($1a$) that controls for year dummies. To allow for differences in trends between the treatment and control groups, Columns (7)–(9) consider a treatment-specific time trend and its square, as shown in Equation (1b). All estimations control for individual fixed effects.

As expected, the estimated coefficients on $Treatment \cdot After$ are significantly positive in all specifications. As shown in Table 3 (Columns (7)–(9)), the coefficients for both the interaction terms, $Trend \cdot Treatment$ and $Trend^2 \cdot Treatment$, are insignificant, which means the trend in the treatment group does not significantly differ from that in the control group. In response to the common trend between the treatment and control groups, the estimated coefficients on $Treatment \cdot After$ in Columns (4)–(6), which control for year dummies, are similar to those in Columns (7)–(9), which allow for differences in the trend between the treatment and control groups. These results indicate the robustness of our estimates and confirm that training boosts hourly wages by about 7%, even after controlling for individual fixed effects.

Table 3. Impact of Training on ln (Real Wage Rate)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	No Time Fixed Effects Controlled			Year Dummies Controlled			Time Trend and Its Square Controlled Differences in Trend are Allowed		
Treatment·After	0.050*	0.052*	0.051*	0.073***	0.076***	0.074***	0.069**	0.068**	0.068**
	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.035)	(0.035)	(0.035)
Experience	0.020	0.020	0.018	-0.042	-0.046	-0.044	-	-	-
	(0.014)	(0.013)	(0.012)	(0.036)	(0.038)	(0.042)			
Experience^2/100	-0.052***	-0.050***	-0.042***	-0.055***	-0.051***	-0.046***	-0.052***	-0.049***	-0.043***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Tenure	0.027**	0.026**	0.023**	0.029***	0.028***	0.025***	0.027**	0.026**	0.023**
	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)
Tenure^2/100	-0.032***	-0.033***	-0.028**	-0.039***	-0.041***	-0.036***	-0.040***	-0.040***	-0.036***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Number of Children	0.001	0.003	0.004	-0.020	-0.019	-0.018	-0.012	-0.011	-0.010
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Married	-0.002	-0.004	-0.001	-0.008	-0.010	-0.006	-0.011	-0.015	-0.011
	(0.061)	(0.061)	(0.061)	(0.058)	(0.058)	(0.057)	(0.061)	(0.060)	(0.060)
Trend	-	-	-	-	-	-	-0.043**	-0.045***	-0.045***
							(0.017)	(0.016)	(0.015)
Trend·Treatment	-	-	-	-	-	-	0.013	0.011	0.008
							(0.020)	(0.020)	(0.020)
Trend^2	-	-	-	-	-	-	0.005***	0.005***	0.005***
							(0.001)	(0.001)	(0.001)
Trend^2·Treatment	-	-	-	-	-	-	-0.001	-0.0004	-0.0002
							(0.001)	(0.001)	(0.001)
Year	No	No	No	Yes	Yes	Yes	No	No	No
Area	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm Size	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Occupation	No	No	Yes	No	No	Yes	No	No	Yes
Position	No	No	Yes	No	No	Yes	No	No	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.483	0.485	0.488	0.518	0.520	0.522	0.486	0.489	0.491
N	15134	15134	15134	15134	15134	15134	15134	15134	15134

Note: Standard errors clustered at the individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Multinomial Regression and Fixed-Effects DID by Training Type

Table 4 presents the determinants of participation in each type of training. In the multinomial regression, the base outcome is "did not participate in training." As explained in Section 3.2, the six categories of trainings are categorized into two broad types—Type I (schooling) and Type II (practical training related to workers' current jobs). However, in addition to training contents, workers' attributes also significantly differ between Type-I and Type-II trainings. For example, according to Table 4, regular workers are considerably more likely to participate in the Type-II trainings, i.e., (Column 4) correspondence course (including university courses); university or other public lectures; a television or radio course and books; (Column 5) various lectures or seminars; and (Column 6) a company's voluntary study group.[6]

Furthermore, the coefficients for the time trend term are all significantly positive for trainings categorized into Type-II training. This might capture the current trend that workers have become more likely to participate independently in trainings outside of their firm, given the accelerating underinvestment in human capital.

Next, we aggregate the six categories in Table 4 into Type-I (schooling) and Type-II (practical training related to workers' current jobs) training. We then re-estimate the returns from each training type in Table 5. Comparing the coefficients on $Treatment \cdot After$, we find that the estimates for Type-I training are all insignificant, while those for Type-II training are significantly positive, even at the 1% significance level. In addition, the magnitude of the returns from each of the training type is much higher for Type-II than Type-I training.

We determine that high returns in Type-II training cannot be explained by workers' and firms' attributes because the estimated coefficients are positive and significant (Columns (3) and (6) in Table 5), even after controlling for occupation and position as well as individual fixed effects.

[6] Although for Column 5 (Various lectures or seminars), the coefficient of regular worker dummy variable is not significant, the magnitude of the coefficient is much larger than the Type I trainings, i.e., Columns 1, 2, and 3.

Table 4. Multinomial Logistic Regression (Determinants of Training Type)

	(1)	(2)	(3)	(4)	(5)	(6)
Type of Training	Vocational school or Trade school	Public vocational training	University or Graduate school	Correspondence course; University or public lecture; TV or radio course and books	Various lectures or seminars	Company voluntary study group
Years of Education	0.052	0.0003	0.405*	0.274***	0.276***	0.152***
	(0.070)	(0.121)	(0.229)	(0.043)	(0.037)	(0.038)
Male	-0.266	0.267	0.141	-0.021	-0.171	-0.614***
	(0.439)	(0.413)	(0.502)	(0.180)	(0.190)	(0.154)
Experience	-0.115**	-0.061	-0.387***	-0.021	0.022	-0.029
	(0.051)	(0.079)	(0.100)	(0.035)	(0.028)	(0.029)
Experience^2/100	0.111	0.059	0.457***	-0.009	-0.044	0.032
	(0.102)	(0.124)	(0.161)	(0.061)	(0.048)	(0.049)
Tenure	-0.012	-0.005	0.214	0.055*	0.036	0.030
	(0.053)	(0.079)	(0.160)	(0.031)	(0.023)	(0.025)
Tenure^2/100	0.040	-0.040	-0.827	-0.140*	-0.052	-0.061
	(0.099)	(0.192)	(1.156)	(0.073)	(0.051)	(0.055)
Number of Children	0.135	0.223	-2.094***	-0.059	0.114*	0.054
	(0.198)	(0.220)	(0.751)	(0.071)	(0.067)	(0.067)
Married	-0.596	-0.454	-1.033	-0.223	-0.050	0.122
	(0.466)	(0.614)	(0.991)	(0.250)	(0.207)	(0.226)
Regular Worker	0.033	-1.870***	-1.812***	0.515***	0.078	1.147***
	(0.323)	(0.556)	(0.647)	(0.194)	(0.172)	(0.161)
Trend	0.021	0.144**	0.295	0.068***	0.041***	0.043***
	(0.047)	(0.071)	(0.185)	(0.019)	(0.014)	(0.015)
Pseudo-R^2				0.077		
N				15134		

Note: Standard errors clustered at the individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is those who did not participate in any training in each year.

This suggests that the practical training related to workers' current jobs is likely to contribute to an increase in real wages. In sum, regular workers tend to select practical training that is likely to lead to an increase in wage rates, while non-regular workers tend to participate in training for which this is not the case.

Table 5. Impact of Training on ln (Real Wage Rate) by Training Type

Type of Training	(1)	(2) [Type-I Training] Schooling	(3)	(4)	(5) [Type-II Training] Practical Training Related to Current Job	(6)
Treatment·After	-0.006	0.014	0.018	0.060**	0.081***	0.078***
	(0.068)	(0.067)	(0.067)	(0.028)	(0.029)	(0.029)
Experience	0.022*	-0.043	-0.041	0.019	-0.045	-0.043
	(0.014)	(0.040)	(0.043)	(0.014)	(0.039)	(0.042)
$Experience^2/100$	-0.054***	-0.056***	-0.049***	-0.051***	-0.053***	-0.046***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Tenure	0.027**	0.028***	0.025***	0.027**	0.028***	0.025***
	(0.012)	(0.010)	(0.009)	(0.012)	(0.010)	(0.009)
$Tenure^2/100$	-0.032***	-0.039***	-0.035***	-0.032***	-0.041***	-0.036***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Number of Children	0.001	-0.018	-0.017	0.001	-0.019	-0.018
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Married	-0.001	-0.009	-0.005	-0.001	-0.008	-0.004
	(0.061)	(0.058)	(0.057)	(0.061)	(0.057)	(0.057)
Year	No	Yes	Yes	No	Yes	Yes
Area	No	Yes	Yes	No	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes
Firm Size	No	Yes	Yes	No	Yes	Yes
Occupation	No	No	Yes	No	No	Yes
Position	No	No	Yes	No	No	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.483	0.519	0.521	0.483	0.519	0.522
N	15134	15134	15134	15134	15134	15134

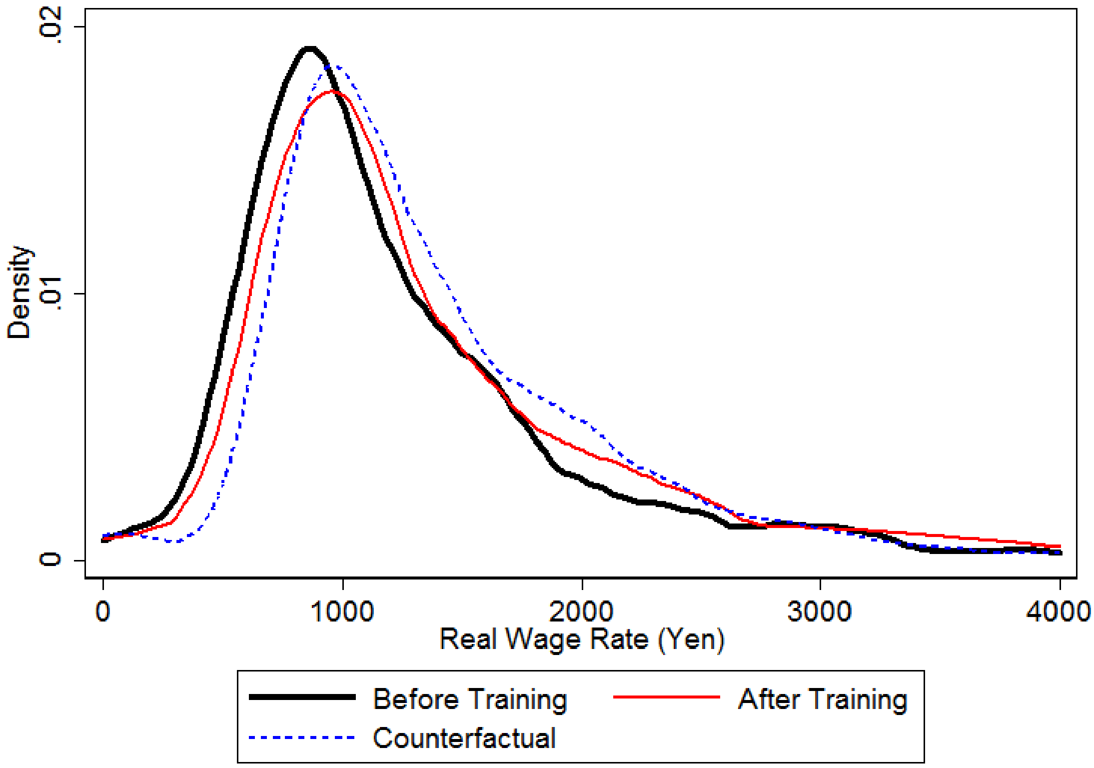
Note: Standard errors clustered at the individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. A treatment dummy (whether a worker participated in trainings at least once) is defined separately for Type-I and Type-II trainings.

One potential explanation for why non-regular workers select programs that lead to low returns is the problem of asymmetric information. Non-regular workers may not know what skills are needed for their own jobs or that practical training is more likely to lead to high returns. Another explanation is that the practical training related to workers' current jobs is more firm-specific than general training, while non-regular workers tend to invest general skills that can be used in any job and office.

5.3 DFL Decomposition

Figure 1 presents the results for the DFL decompositions of ln (real wage rate) based on those who participated in Type-I training. The bold line denotes the actual distribution before Type-I training, while the thinner solid line represents the actual distribution after Type-I training. The dashed line represents a counterfactual distribution that represents a possible post-training distribution if the same workers had participated in Type-II rather than Type-I training.

Figure 1. Real Wage Rate Distribution for Type-I Training Participants

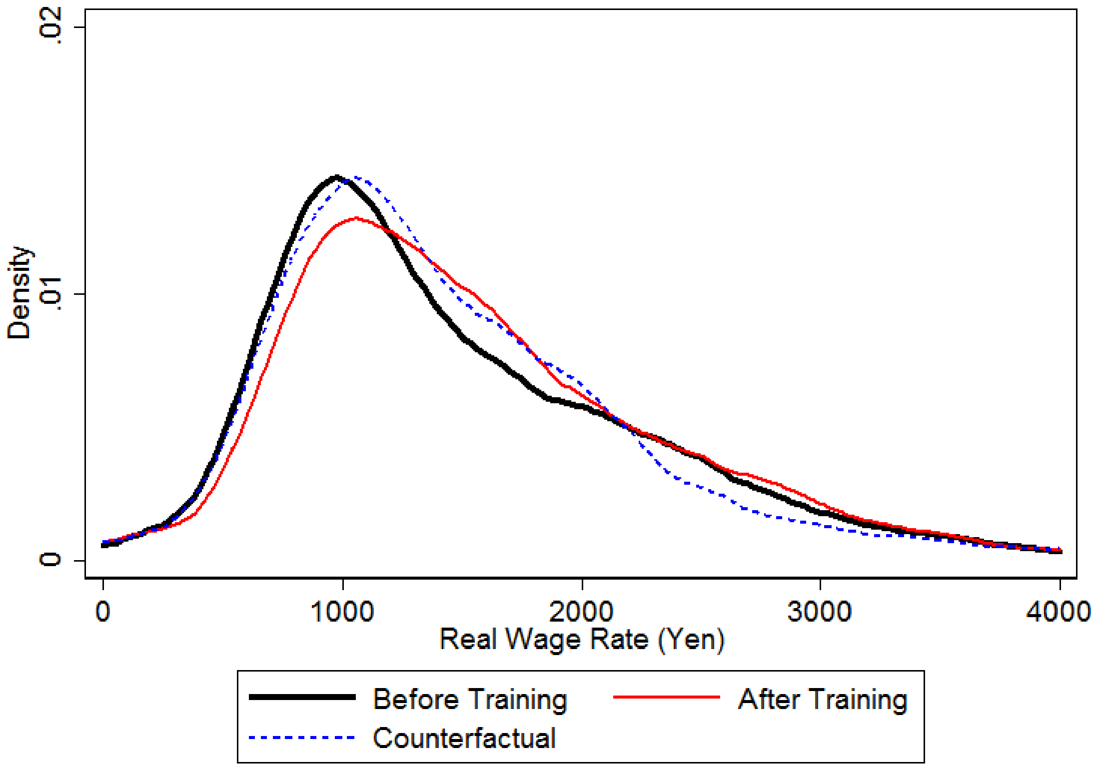


Note: The bold and solid lines represent the real wage rate distributions before and after Type-I training. The counterfactual distribution denotes the possible distribution post-training if workers had participated in Type-II instead of Type-I training.

Following Type-I training participation, the distribution shifted slightly to the right, which indicates a small increase in the real wage rate. As confirmed in Table 5, the returns from Type-I training are too small to make the estimates significantly positive. Next, the counterfactual distribution is positioned on the right-hand side of the “after” distribution, which confirms that Type-I training participants would have earned higher wage rates if they had participated in Type-II training instead. This is consistent with the results in

Table 5, that is, returns from training are higher for Type-II rather than Type-I training.

Figure 2. Real Wage Rate Distribution for Type-II Training Participants



Note: The bold and solid lines denote the real wage rate distributions before and after Type-II training. The counterfactual distribution represents the possible distribution post-training if workers had participated in Type-I instead of Type-II training.

As shown in Figure 2, we conduct a similar DFL decomposition for those who participated in Type-II training. Compared to Figure 1, the real wage distribution shifted significantly more to the right after the Type-II training, indicating higher returns from Type-II than Type-I training. In addition, the counterfactual distribution is positioned on the left-hand side of the "after" distribution, confirming that those who participated in Type-II training would have earned lower wage rates if they had participated in Type-I training instead. This supports the evidence presented in the previous sub-sections thus far: that is, even after controlling for workers' and firms' attributes or unobserved characteristics, such as their ability and motivation, the returns are higher for Type-II training, which comprises practical courses related to workers' current jobs.

5.4 Fixed-Effects Instrumental Variable Estimation

Table 6 reports the first-stage regression in which a dummy variable for receiving TEB is regressed on the eligibility for TEB and other control variables. As expected, being eligible for TEB has a significantly positive effect on receiving TEB, and the correlation between the two variables is sufficiently strong to implement the second-stage IV regression. In other words, TEB eligibility satisfies the instrument relevance condition and is a good candidate of the IV for the receiving TEB dummy variable.

Table 6. First-Stage Regression: Effect of TEB Eligibility on Receiving TEB

Dependent Variable: TEB	(1)	(2)	(3)
Eligible for TEB	0.072***	0.072***	0.072***
	(0.010)	(0.010)	(0.010)
Experience	-0.0001	0.001	0.0004
	(0.001)	(0.001)	(0.001)
$\text{Experience}^2/100$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Tenure	0.0001	-0.00001	-0.00001
	(0.0005)	(0.0005)	(0.0005)
$\text{Tenure}^2/100$	-0.001	-0.0004	-0.0005
	(0.001)	(0.001)	(0.001)
Number of Children	-0.00004	-0.00002	-0.0001
	(0.001)	(0.002)	(0.001)
Married	-0.002	-0.002	-0.002
	(0.005)	(0.005)	(0.005)
Regular Worker	-0.003	-0.002	-0.003
	(0.004)	(0.004)	(0.004)
Year	No	Yes	Yes
Area	No	Yes	Yes
Industry	No	Yes	Yes
Firm Size	No	Yes	Yes
Occupation	No	No	Yes
Individual Fixed Effects	Yes	Yes	Yes
R-squared	0.273	0.276	0.278
N	15134	15134	15134
F Test (H_0: Coef. of IV=0)			
F Statistic	48.222	48.230	48.306
P Value	0.000	0.000	0.000

Note: Standard errors clustered at the individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7 reports the results for the second-stage IV regression. Since receiving TEB is an endogenous decision, we adopt TEB eligibility as an IV for the receiving TEB dummy variable. As explained in Section 3, by employing the IV method, we can overcome the simultaneous bias: for example, we can exclude inverse causality, that is, a case in which workers first determine the program in which they would participate and then decide whether they receive TEB. Thus, the coefficient on TEB allows us to capture the causal impact of receiving TEB on participating in each training type.

Moreover, because tenure and regular worker dummy variables are controlled for, TEB eligibility is unlikely to be correlated with any factors remaining in the error term, which ensures the exogeneity of the IV.

Table 7. Second-Stage Regression: Local Average Treatment Effect of Receiving TEB on Participation by Training Type

Type of Training	(1)	(2) [Type-I Training] Schooling	(3)	(4)	(5) [Type-II Training] Practical Training Related to Current Job	(6)
TEB (Instrumented)	0.184***	0.183***	0.181***	0.516***	0.392**	0.396**
	(0.058)	(0.059)	(0.059)	(0.165)	(0.161)	(0.160)
Experience	-0.003***	-0.003***	-0.003***	0.0004	0.0002	-0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2/100	0.003***	0.003***	0.003***	-0.003	-0.003	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Tenure	0.0003	0.0003	0.0003	0.005***	0.002*	0.002*
	(0.0002)	(0.0002)	(0.0002)	(0.001)	(0.001)	(0.001)
Tenure^2/100	-0.0004	-0.0004	-0.0004	-0.008***	-0.002	-0.003
	(0.0004)	(0.0004)	(0.0004)	(0.002)	(0.002)	(0.002)
Number of Children	-0.0001	-0.0003	-0.0003	0.001	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Married	-0.010***	-0.009***	-0.009***	-0.011	-0.007	-0.009
	(0.003)	(0.003)	(0.003)	(0.013)	(0.013)	(0.012)
Regular Worker	-0.008***	-0.010***	-0.010***	0.041***	0.044***	0.039***
	(0.002)	(0.002)	(0.003)	(0.008)	(0.008)	(0.008)
Year	No	Yes	Yes	No	Yes	Yes
Area	No	Yes	Yes	No	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes
Firm Size	No	Yes	Yes	No	Yes	Yes
Occupation	No	No	Yes	No	No	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	15134	15134	15134	15134	15134	15134

Note: Standard errors clustered at the individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. TEB eligibility is used as the IV for TEB. The reported coefficients are not marginal effects because we are interested only in the relative magnitude of coefficients between the two types of trainings. IV estimates that consider individual fixed effects are reported.

The coefficients of TEB are all significantly positive. However, the magnitude of the coefficients varies considerably for the training types. Table 7 shows that the effects of receiving TEB on participation in Type-II training are greater than those for Type-I training. In other words, it appears that receiving the TEB induces workers to participate in Type-II rather than Type-I training.

Note that we controlled for workers' attributes of job position, industry, occupation, area, and firm size, our estimates suggest that receiving TEB stimulates workers to participate in Type-II instead of Type-I training, irrespective of workers' current position. Put differently, even non-regular workers can be motivated by TEB to participate in Type-II training.

Why can the TEB encourage workers to participate in high-returns training, irrespective of the workers' current position? As shown in Table 2, Type-I training requires considerable time and cost investments, while Type-II training requires relatively short time and cost investment. It is easier for people to participate in Type-II training when they obtain the TEB than Type-I training. The price elasticity of Type-II training is high, i.e., if the price of training were reduced by the TEB, this would lead to the expansion of demand of Type-II training rather than that of Type-I training. In contrast, it is not easy to decide to participate in Type-I training without sufficient time and cost investment, even though they can obtain the TEB. This may lead to the relatively low price-elasticity of Type-I training. Consequently, this suggests that the presence of the TEB naturally induced people to participate in practical programs that tend to increase wage rates.

Because we have controlled for workers' attributes of their job position, industry, occupation, area, firm size, and individual fixed effects in Table 7, we can discuss the price elasticity of each training type, holding factors that determine the income level of each worker fixed. If we did not control for these attributes, a part of our estimates could capture the difference in employment status (regular/non-regular workers). However, because we have controlled for these attributes, we can demonstrate that the different coefficients between Type-I and Type-II training are due to the difference in price elasticity between the two types of trainings.

6. Conclusion

A prolonged economic slump and intensifying competition have led Japanese companies to shrink their investment in human capital in the workplace. On one hand, with rising job turnover and increases in non-regular work as well, firms have come to lose their incentive to invest in their employees. On the other hand, workers have no choice but to try to improve their careers on their own because companies cannot be counted on to make generous investments in human capital. To support workers' self-investment in their skills, the government-sponsored benefits program called the TEB was introduced in

Japan.

In this study, we estimate the effects of workers' self-motivated investment in themselves on wage rates. We also explore the self-selection in training types by workers' type, and the effect of the TEB on the self-selection.

First, our fixed-effects estimates using the KHPS indicate that the return of investment in skills is positive, particularly high for practical training related to workers' current jobs. Furthermore, regular workers tend to self-select practical training that is likely to lead to an increase in wage rates in the near future. In contrast, non-regular workers tend to choose training with a low return (or at least which takes time to yield returns, such as schooling). If this trend is caused by asymmetry in information about training returns between non-regular and regular workers, it is important for non-regular workers to be aware of the high returns that Type-II training yields

Second, our IV estimates revealed that receiving the TEB raise the likelihood for workers to participate in high-return, practical training regardless of whether they are non-regular or regular workers. This suggests that government benefits change workers' self-selection of training type and serve to promote practical trainings that lead to high returns.

References

Abe, M., M. Kurosawa, and A. Toda. 2005. Effects of Education and Training Benefit and Public Qualification (in Japanese). *Economic Analysis of Labour Market Design*. ed. Y. Higuchi, T. Kodama, and M. Abe (Tokyo: Toyo Keizai Shinposha).

DiNardo, J. E., N. M. Fortin, T. Lemieux. 1996. Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach. *Econometrica* 64(5), 1001-1044.

DiNardo, J. E., T. Lemieux. 1997. Diverging Male Wage Inequality in the United States and Canada, 1981–1988: Do Institutions Explain the Difference? *Industrial and Labor Relations Review*, 50(4), 629–651.

Finegold D. and D. Soskice. 1988. The Failure of Training in Britain: Analysis and Prescription. *Oxford Review of Economic Policy*, 4(3): 21-53.

Hara, H. 2007. Capacity Development in Japanese Enterprises (in Japanese). *Japanese Journal of Labour Studies*. 563: 84-100.

Holmes, C. 2017. The Individual Benefits of Investing in Skills. *Oxford Handbook on the Skills and Training*, ed. J. Buchanan, D. Finegold, K. Mayhew, and C. Warhurst (New

York: Oxford University Press).

Li, P., Y. Lu, and J. Wang. 2016. Does Flattening Government Improve Economic Performance? Evidence from China. *Journal of Development Economics*, 123, 18-37.

Miyagawa, T., M. Takizawa, and K. Tonogi. 2016. Declining Rate of Return on Capital and the Role of Intangibles in Japan, RIETI Discussion Paper Series, 16-E-051.

Toda, A. and Y. Higuchi. 2005. Training within Enterprises and Change of its Role. *Economic Analysis of Labour Market Design*. ed. Y. Higuchi, T. Kodama, and M. Abe (Tokyo: Toyo Keizai Shinposha).