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Kazuma Sato*

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* Takushoku University, Faculty of Political Science and Economics, Associate Professor

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Many industrialized countries are facing an ageing population. This threatens the sustainability of the social security system. To overcome this issue, policymakers must consider measures to encourage older people to work. Job-related training is considered to be effective for this purpose because it can prevent the deterioration of human capital. However, studies that examine the relationship between training and employment, especially in Asia where ageing is advancing rapidly, are still scarce. To fill this gap, this study examines the effect of training on the employment of older workers using the Longitudinal Survey of Middle-aged and Elderly Persons, the largest panel data available on the elderly in Japan. The key findings can be summarized as follows. First, the probability of re-employment rises significantly one year and two years after training. Second, training is effective in the case of re-employment as regular worker. This effect is notable because most re-employed workers are employed as non-regular workers. These results indicate that training is a useful measure for keeping older workers in work.

JEL Code: J21, J26

Key Word: Older Worker, Training, Matching Method

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* Takushoku University

1 Introduction

Many industrialized countries are facing an ageing population. This threatens the sustainability of the social security system, such as pensions. To overcome this issue, policymakers must consider measures to encourage older people to work. Job-related training is considered to be valid for this purpose because it can prevent the deterioration of human capital. Picchio and van Ours (2013) investigated this issue and show that firm-provided training can enhance the employability of older workers. Kajitani (2006) also examined the effect of training on employment after compulsory retirement and shows that training can shorten the period of unemployment. However, studies that examine the relationship between training and employment for older workers are still scarce.[1] In particular, studies that use data for Asia, where ageing is advancing rapidly, are scarce. On the other hand, there are many studies concerning wages and productivity that show training has a positive effect on wages and productivity (Bartel 1994, 1995; Barret & O'Conell 2001; Booth & Bryan 2005; Conti 2005; Frazis & Loewenstein 2005; Dearden et al. 2006; Zwick 2006; Konings & Vanormelingen 2009; Almeida-Santos et al. 2010; Görlitz 2011). To fill this gap in the research, we examine the effect of training on the employment of older workers by using Japanese panel data.

As a general survey of working conditions conducted by the Ministry of Health, Labour and Welfare in 2014 shows, the compulsory retirement system is instituted in 93.8% of companies in Japan. Hence, older workers have to retire when they reach the prescribed age. Among Organisation for Economic Co-operation and Development countries, the elderly in Japan are particularly motivated to work, so there are many workers who desire re-employment. While some workers find a job soon after compulsory retirement, others become unemployed for a period of time before starting to look for a

[1] Although Ham and Lalonde (1996), Alba-Ramirez (1999), Lee and Lee (2005), and Choi and Kim (2012) also examined the effect of training on employment, they did not focus on older workers. Kluve (2010) surveyed the literature on the effect of training on the employment prospects of unemployed workers and clarified that training had a mild effect on employment, with impacts that changed by targeted age group.

job. We focus on the latter and verify whether training during the period of unemployment is able to enhance the probability of re-employment. Since compulsory retirement can be regarded as an exogenous job loss, it is possible to control for the heterogeneity of factors that have fallen into unemployment.

In estimating the effect of training, we must pay attention to the self-selection for participation in training. If more able workers carry out the training, the effect of training will be overestimated due to the selection. On the other hand, if less able workers tend to do the training, the effect of training will be underestimated. Therefore, taking into account the selection is key for estimating the causal effect of training. To overcome this issue, Heckman et al. (1997) employ a matching method. We also exploit a matching method, entropy balancing, which was developed recently by Hainmueller (2011, 2012). Entropy balancing is a matching method that creates a sample weight to control for the differences in covariates among workers who carry out training and workers who do not. The advantage of using entropy balancing is that it can control for the individual heterogeneity among workers more accurately than any other matching method. In the model of entropy balancing, we control not only for individual attributes, work-related variables before retirement, and current health but also for the intention to work, which jointly determines the participation of training and re-employment. This makes it possible to examine the causal effect of training.

The key findings can be summarized as follows. First, the probability of re-employment rises significantly one year and two years after training. Second, training is effective in the case of re-employment a regular worker. This effect is notable because most re-employed workers are employed as non-regular workers. These results indicate that training is a useful measure for keeping older workers in work.

The remainder of this paper is organized as follows. The next section describes the data, and Section 3 explains the empirical strategy. Section 4 discusses the estimation results, and Section 5 provides concluding remarks.

2 Data

2.1 Data description

The data used in this analysis is from the Longitudinal Survey of Middle-aged and Elderly Persons conducted by Ministry of Health, Labour and Welfare in Japan. This is the largest panel survey of elderly people in Japan. The survey was first implemented in 2005 with 33,815 male and female respondents aged 50–59 years. The survey is conducted annually, and we use the data for 2005–2009 because the questionnaire on training is available until 2009. The data investigates families, income, employment, well-being, and type of residence.

In this analysis, we limit the sample to men and women who were employed and experienced compulsory retirement. Of the 3,130 individuals that experienced compulsory retirement, 1,365 were re-employed immediately after retirement, and 1,765 were unemployed after retirement. We focus on the latter to clarify the effect of training on re-employment. After deleting the missing values of the explanatory variables, the total number of individual-year observations becomes 1,716. The average retirement age from the questionnaire is 60 years old, which is almost the same as in the 2014 general survey of working conditions of the Ministry of Health, Labour and Welfare.

Before entering the econometric specification, we briefly check the relationship between training and re-employment for older workers by using descriptive statistics. Training is defined as the development of skills for work or self-enlightenment during the last year of employment before retirement, and training conducted after retirement. The employment rate is defined as the percentage of employed workers. Figure 1 shows the employment rate up to three years after the training at period t. The figure clearly shows that the employment rate in each period is higher for those who received training. This result implies the potential of training to enhance the employability of older workers. However, it should be noted that as this casual observation does not take into account self-selection, the effect of training may be overestimated.

2.2 Transition of employment status, occupation, and firm size before and after compulsory retirement

How do employment status, occupation, and firm size change before and after compulsory retirement? Since these changes have a great influence on the working conditions of older workers, we briefly check the transitions. Table 1 shows the changes in employment status. The results indicate that while most of the workers who worked in regular employment before retirement changed to non-regular employment after re-employment, workers who worked in non-regular employment before retirement stayed in non-regular employment after re-employment. In particular, 92.31% of part-time workers before retirement worked in the same employment status after re-employment. These results indicate that regardless of employment status before retirement, many workers work as non-regular employees after re-employment.

Table 2 indicates the changes in occupation. The results show that the percentage of workers with the same occupation before and after re-employment is low, except for agriculture, fishery, forestry, and other work, implying that many workers experience a change in occupation. This implies the possibility that older workers cannot make effective use of their occupational experience gained before retirement.

Table 3 indicates the changes in firm size. It shows that in many cases, company size becomes smaller after re-employment, and there are few cases where the company size becomes larger.

3 Econometric model

3.1 Entropy balancing

Taking the self-selection bias into account is key to estimating the pure training effect on the re-employment of older workers. Propensity score matching and propensity score weighting are useful for reaching this goal. However, we employ entropy balancing because it has two advantages (Hainmueller & Xu 2013). First, entropy balancing is more effective for reducing the imbalances of individual heterogeneity than other matching methods. Second, it is easier with entropy balancing to do the balance check, which confirms whether imbalances in individual attributes between workers who carry out training and workers who do not still exist after matching. We briefly explain the method to estimate the average treatment effect on the treated (ATT) using entropy balancing.[2]

When estimating the effects of training on re-employment, the ATT is as follows.

$$\mathrm{ATT} = \mathrm{E}[Y_{1i} - Y_{0i} | D_i = 1] = \mathrm{E}[Y_{1i} | D_i = 1] - \mathrm{E}[Y_{0i} | D_i = 1] \tag{1}$$

In equation (1), Y_i indicates the re-employment dummy, where Y_1 indicates the value at the time when workers engaged in training, and Y_0 is the value when workers did not. D indicates the training dummy. D = 1 indicates workers who engaged in training (treatment group), and D = 0 indicates workers who did not engage in training (control group). In equation (1), $\mathrm{E}[Y_{0i} | D_i = 1]$ is the value of re-employment of workers who did not engage in training had they engaged in training. This value cannot be observed because it is counterfactual. To solve this issue, entropy balancing

[2] There are still few analyses that use entropy balancing; representative studies in economics are Marcus (2013) and Freier et al. (2015). Marcus (2013) uses entropy balancing to estimate the effect of job displacement on the mental health of spouses. Freier et al. (2015) use entropy balancing to estimate the effect of graduating from university with an honours degree on later income.

replaces $\mathrm{E}[Y_{0i}|D_i = 1]$ by using a weighted control group:

$$\mathrm{E}[Y_{0i}|\widehat{D_i = 1}] = \frac{\sum_{\{i|D=0\}} Y_{0i} w_i}{\sum_{\{i|D=0\}} w_i} \qquad (2)$$

In equation (2), w_i is the sample weight for the control group. This sample weight is calculated by the constraint equations, which satisfy an exact balance between the first and second moments of the individual attributes in the treatment and control groups. This is the most important feature of entropy balancing. By satisfying the first and second individual attribute moments, we can obtain similar means and variances for the individual attributes between the treatment and control groups. Thus, most differences in the individual attributes between the treatment and control groups are removed. In the analysis, the first and second moments are employed to equate the mean and variance among groups.

We conduct the estimation through two steps. First, the sample weight for the control group is estimated by entropy balancing. Second, the probit model is estimated with the sample weight. The mean differences and the probit model without the sample weight are also estimated to check the extent of the self-selection bias. In addition, we also estimate propensity score matching by applying kernel matching for the robustness check.

The dependent variable is the re-employment dummy. The re-employment dummy takes a value of 1 if unemployed workers in period t were employed in period t+1, and takes a value of 0 if unemployed workers in period t stayed unemployed in period t+1. The re-employment dummies at periods t+2 and t+3 are also used to confirm the persistence of the training effect. The variable that identifies the treatment and control groups takes a value of 1 if workers engaged in job-related training in period t, and takes a value 0 if workers did not. In the analysis, we treat the training after retirement.

The covariates have three categories. The first category is the individual attributes and variables related to work before retirement; the second category is a variable relating to employment willingness past the age of 60 years old; and the third category is a health variable. In the analysis, these variables are used step by step as covariates to verify how the effect of training on re-employment changes. Individual attributes include dummy variables for gender, education, age, the number of family members, home ownership, years, and earnings from public pensions, employment insurance, social security benefits, and private pensions. Work-related variables before retirement include job tenure, employment status, occupation, and firm size.

The variables concerning the employment intentions past 60 years of age are constructed from the question, “Do you want to carry out work and receive income after the age of 60?”[3] We created a dummy variable that equals 1 if respondents answered they wanted to work as long as possible for this question, and 0 otherwise. We also created a dummy variable that equals 1 if respondents answered they wanted to work until a certain age over 60, and 0 otherwise. Finally, we created a dummy variable equalling 1 if respondents answered that they did not want to work after 60 years old, and 0 otherwise. In the analysis, the last dummy variable is used as a reference group. As Kajitani (2006) points out, to control for these intentions is crucial because they jointly determine training and re-employment.

The health-related variables include dummy variables for good health and the number of serious diseases of the respondent. The dummy for good health indicates whether respondents have good subjective rated health or not. The dummy for serious diseases indicates the number of diseases the respondent suffers from, including diabetes, heart disease, stroke, hypertension, hyperlipidemia, and cancer.

[3] This question exists only in the survey for the first year, and we assume that the value does not change over the whole period.

3.2 Basic statistics before and after matching

Entropy balancing controls for the differences in individual attributes between the treatment and control groups. Basic statistics before and after matching, shown in Table 4, are used to check the extent of such control measures. The variables before matching show significant differences in the means for education, age, home ownership, earning from public pension, earning from employment insurance, occupation and firm size before compulsory retirement, and intention to work. These results show that while workers who engage in training tend to have higher educational attainment and have higher percentages for receiving employment insurance, working at professional and technical work, and intention to work as long as possible after retirement, they have a lower average age and lower percentages of home ownership, reception of employment insurance, and working in production and labour work. On the other hand, the basic statistics after matching indicate that the mean difference for all variables becomes 0.00, implying that differences in individual attributes disappear through entropy balancing.

4 Empirical results

Table 5 shows the results for the effect of training on the re-employment of older workers. Panel (A) shows the results for re-employment one year after training.[4] All coefficients of the mean differences, probit model, entropy balancing, and propensity score matching for panel (A) are positively significant. This indicates that training increases the probability of re-employment after one year. Although the size of the coefficients decreases when the individual attributes, employment

[4] The values of the probit model represent the marginal effects.

motivation, and health are controlled step by step, the variables are significant in any cases, so the training effect on employment is robust. Comparing the sizes of the coefficients of the probit model and entropy balancing, those for entropy balancing are larger. This indicates a negative bias of self-selection, implying that less able older workers tend to engage in training. Panel (B) shows the results for re-employment two years after training. Also for these results, even if individual attributes, intention to work, and health are controlled for, all coefficients are positively significant. These results indicate that training increases the probability of re-employment after two years. Panel (C) shows the results for re-employment three years after training. Unlike the previous results, most of the coefficients, except for the mean difference, probit, and propensity score matching, are not significant. This indicates that training does not have an effect on the probability of re-employment after three years.

To summarize the results so far, training significantly increases the probability of re-employment after one and two years. Training is promising for the employment of older workers. This result is consistent with Picchio and van Ours (2013) and Kajitani (2006). However, the result for the selection bias is different from previous studies. Picchio and van Ours (2013) point out the existence of a positive selection bias, while Kajitani (2006) points out there is no selection bias. On the other hand, our study shows the existence of a negative selection bias. This is because our study focuses on workers who become unemployed after compulsory retirement. While able workers become employed soon after retirement, less able workers become unemployed after retirement. Hence, it can be considered that the analysed samples consist of workers with relatively low abilities.[5]

Whether subjects are unemployed are re-employed with regular employment or non-regular employment has a big impact on income and working hours. Determining whether job-related training

[5] We check the differences in the work-related variables between workers who were re-employed immediately after retirement and workers who were not. Workers who were re-employed after retirement have a higher ratio of regular employment, and their occupations and company sizes did not change much at re-employment.

promotes employment in regular employment can provide useful policy information. Therefore, we examine the effect of training on employment status at the time of re-employment with a multinomial logit model. The dependent variable is 1 for regular employment, 2 for non-regular employment, and 3 for continuing unemployment at period t. All workers are unemployed in period t-1. We use the same explanatory variables as those in Table 5.

Table 6 shows the results of the effect of training on re-employment by employment status. All values in Table 6 are marginal effects. Panel (A) shows the results of re-employment one year after training. While all coefficients for regular workers in panel (A) are positively significant, those for non-regular workers are not significant. This result indicates that although training enhances the probability of re-employment by regular workers after one year, it does not affect the re-employment of non-regular workers.

Panel (B) shows the results for re-employment two years after training. Most of the coefficients in panel (B) are not statistically significant. This indicates that training has no effect on re-employment after two years. On the other hand, panel (C), which shows the results for re-employment three years after training, shows all coefficients for regular workers to be positively significant. This result indicates that training increases the probability of re-employment by regular workers after three years. Considering the coefficients for non-regular employment are not significant, training appears to be effective for the re-employment of regular workers.

5 Conclusion

The purpose of this study is to clarify the effect of job-related training on the re-employment of older workers. Compared with previous studies, there are two advantages to this study. First, we use the largest available panel data for older workers in Japan, which is ageing rapidly among Asian countries. As most studies in this field use data for the United States or Europe, this study contributes to the accumulation of empirical analysis for other regions. Second, we use entropy balancing to account for the self-selection bias of training. We control for the bias by including the intention to work past 60 years old in the covariates for entropy balancing. The key findings can be summarized as follows. First, the probability of re-employment rises significantly one year and two years after training. Second, training is effective in the case of re-employment a regular worker. This effect is notable because most re-employed workers are employed as non-regular workers. These results indicate that training is a useful measure for keeping older workers in work.

The findings show that active labour market policies can be effective for promoting the employment of older workers. Considering the trend of ageing in the future, it is essential to implement support measures to promote the development of capacity for the elderly. While support measures for young and middle-aged workers are being expanded in Japan, capacity development for the elderly is not sufficient, and future improvement is needed.

Finally, an outstanding issue should be noted. In this study, we analyzed the relationship between training and the employment of older workers in Japan. However, as the employment of elderly people will become an issue in other Asian countries experiencing ageing populations, it is necessary to carry out analysis using data for countries other than Japan. This will be a future research topic.

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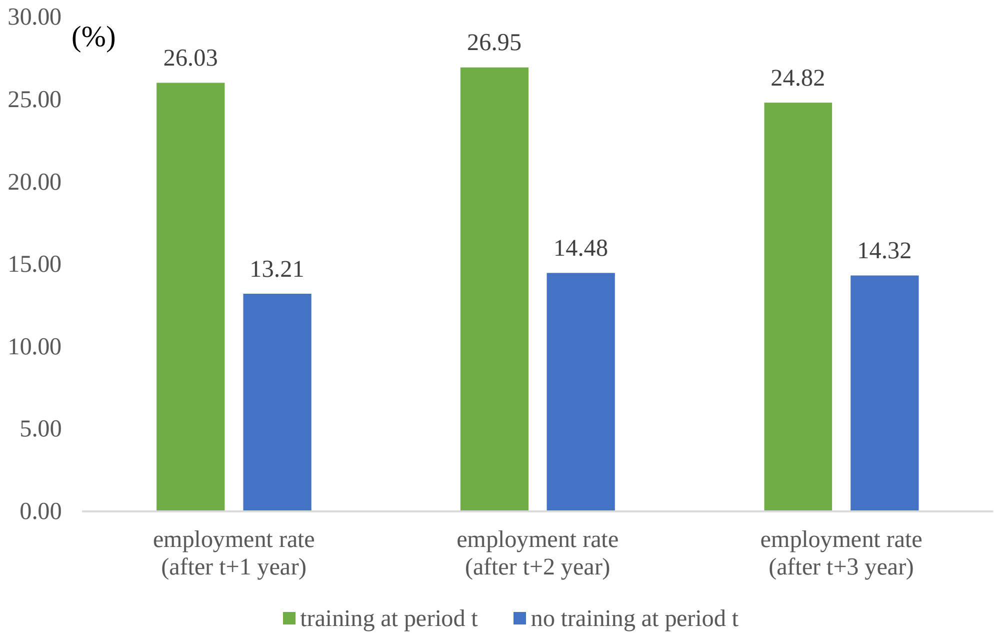
Figure 1. Employment rate after training



Source: Author’s calculations by using Longitudinal Survey of Middle-aged and Elderly Persons.

Table 1. Change in employment status before and after compulsory retirement

(%)

Employment status before retirement		Employment status after re-employment: Regular employee: Full-time employee - manager	Regular employee: Full-time employee - under manager	Non-regular employee: Part-time worker	Non-regular employee: Subcontracted worker	Non-regular employee: Contract employee /Specialized contract employee	Total
Regular employee	Full-time employee - manager	25.00	0.00	50.00	0.00	25.00	100
	Full-time employee - under manager	0.00	14.29	60.00	6.67	19.05	100
Non-regular employee	Part-time worker	0.00	7.69	92.31	0.00	0.00	100
	Subcontracted worker	0.00	0.00	0.00	100.00	0.00	100
	Contract employee / Specialized contract employee	0.00	0.00	71.43	0.00	28.57	100
Total		0.77	12.31	63.08	6.15	17.69	100

Source: Author’s calculations by using Longitudinal Survey of Middle-aged and Elderly Persons.

Table 2. Change in occupation before and after compulsory retirement

(%)

Occupation before retirement	Occupation after re-employment: Professional and technical work	Management	Office work	Sales	Services	Security	Agriculture,fishery, forestry	Transportation, communication	Production process, labor work	Other work	Total
Professional and technical work	46.43	14.29	0.00	0.00	7.14	0.00	3.57	0.00	21.43	7.14	100
Management	7.14	14.29	28.57	14.29	7.14	0.00	7.14	0.00	21.43	0.00	100
Office work	0.00	6.67	20.00	6.67	0.00	6.67	0.00	13.33	20.00	26.67	100
Sales	0.00	0.00	0.00	50.00	16.67	8.33	0.00	0.00	16.67	8.33	100
Services	9.09	9.09	0.00	9.09	36.36	0.00	0.00	9.09	9.09	18.18	100
Security	0.00	0.00	0.00	0.00	75.00	0.00	0.00	0.00	25.00	0.00	100
Agriculture,fishery, forestry	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100
Transportation,communication	16.67	16.67	0.00	0.00	16.67	0.00	0.00	33.33	0.00	16.67	100
Production process, labor work	6.67	0.00	0.00	0.00	33.33	6.67	6.67	3.33	30.00	13.33	100
Other work	0.00	12.50	0.00	0.00	25.00	0.00	0.00	0.00	0.00	62.50	100
Total	13.85	7.69	5.38	7.69	19.23	3.08	4.62	4.62	19.23	14.62	100

Source: Author’s calculations by using Longitudinal Survey of Middle-aged and Elderly Persons.

Table 3. Change in firm size before and after compulsory retirement

(%)

	Firm size after re-employment				
Firm size before retirement	Less than 99	100-999	1000 or more	Public worker	Total
Less than 99	84.44	11.11	2.22	2.22	100
100-999	53.66	39.02	2.44	4.88	100
1000 or more	45.71	22.86	22.86	8.57	100
Public worker	50.00	50.00	0.00	0.00	100
Total	62.40	24.80	8.00	4.80	100

Source: Author’s calculations by using Longitudinal Survey of Middle-aged and Elderly Persons.

Table 4. Basic statistics before and after matching

	before matching					after matching				
	treatment group (training=1)		control group (training=0)			treatment group (training=1)		control group (training=0)		
	mean	variance	mean	variance	mean difference	mean	variance	mean	variance	mean difference
individual attributes										
male	0.63	0.24	0.59	0.24	0.04	0.63	0.24	0.63	0.23	0.00
education: vocational college / junior college	0.15	0.13	0.09	0.08	0.06***	0.15	0.13	0.15	0.13	0.00
education: university/graduate school	0.21	0.17	0.14	0.12	0.06**	0.21	0.17	0.21	0.17	0.00
age	60.12	4.28	60.82	2.76	-0.70***	60.12	4.28	60.12	4.39	0.00
number of family members	1.78	1.07	1.88	1.67	-0.11	1.78	1.07	1.78	1.42	0.00
married	0.83	0.14	0.87	0.11	-0.04	0.83	0.14	0.83	0.14	0.00
having own home	0.88	0.11	0.93	0.06	-0.05***	0.88	0.11	0.88	0.11	0.00
earning from public pension	0.52	0.25	0.67	0.22	-0.15***	0.52	0.25	0.52	0.25	0.00
earning from employment insurance	0.15	0.13	0.10	0.09	0.05**	0.15	0.13	0.15	0.13	0.00
earning from social security benefit	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
earning from private pension	0.13	0.12	0.14	0.12	-0.01	0.13	0.12	0.13	0.12	0.00
work related variables before compulsory retirement										
job tenure	26.03	204.20	27.68	177.20	-1.65	26.03	204.20	26.03	188.60	0.00
regular worker	0.81	0.15	0.79	0.17	0.02	0.81	0.15	0.81	0.15	0.00
professional and technical work	0.31	0.22	0.18	0.15	0.13***	0.31	0.22	0.31	0.22	0.00
management	0.12	0.11	0.12	0.11	0.00	0.12	0.11	0.12	0.11	0.00
sales	0.08	0.08	0.06	0.05	0.03	0.08	0.08	0.08	0.08	0.00
services, security	0.11	0.10	0.09	0.08	0.03	0.11	0.10	0.11	0.10	0.00
transportation,communication	0.03	0.03	0.04	0.04	-0.01	0.03	0.03	0.03	0.03	0.00
production process, labor work	0.13	0.11	0.24	0.18	-0.11***	0.13	0.11	0.13	0.11	0.00
other work	0.05	0.05	0.05	0.04	0.01	0.05	0.05	0.05	0.05	0.00
firm size: 100-999	0.33	0.22	0.35	0.23	-0.02	0.33	0.22	0.33	0.22	0.00
firm size: 1000 or more	0.29	0.21	0.27	0.20	0.02	0.29	0.21	0.29	0.21	0.00
firm size: public worker	0.09	0.09	0.06	0.06	0.03*	0.09	0.09	0.09	0.09	0.00
intention to work over 60										
want to work as long as possible	0.42	0.25	0.27	0.20	0.15***	0.42	0.25	0.42	0.24	0.00
want to work even if over 60	0.28	0.20	0.31	0.21	-0.03	0.28	0.20	0.28	0.20	0.00
health related variables										
good health	0.45	0.25	0.39	0.24	0.06	0.45	0.25	0.45	0.25	0.00
number of serious disease	0.64	0.69	0.68	0.76	-0.05	0.64	0.69	0.64	0.69	0.00
sample size	201		1515			201		1515		

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Source: Author's calculations by using Longitudinal Survey of Middle-aged and Elderly Persons.

Table 5. Effect of training on re-employment

(A) 1 year after training	Mean difference	Probit	Entropy balancing	PSM	$N_{Treatment}$	$N_{Control}$
Individual attributes		0.064**	0.080**	0.089**	145	1,257
		(0.025)	(0.033)	(0.036)		
Individual attributes+intention to work	0.128***	0.050**	0.058*	0.072*	145	1,257
	(0.031)	(0.025)	(0.033)	(0.037)		
Individual attributes+intention to work+health variables		0.048*	0.055*	0.068*	145	1,257
		(0.025)	(0.033)	(0.036)		

(B) 2 year after training	Mean difference	Probit	Entropy balancing	PSM	$N_{Treatment}$	$N_{Control}$
Individual attributes		0.068**	0.078**	0.093**	141	1,217
		(0.027)	(0.032)	(0.038)		
Individual attributes+intention to work	0.125***	0.055**	0.061*	0.080**	141	1,217
	(0.032)	(0.026)	(0.032)	(0.040)		
Individual attributes+intention to work+health variables		0.051*	0.054*	0.074*	141	1,217
		(0.027)	(0.032)	(0.041)		

(B) 3 year after training	Mean difference	Probit	Entropy balancing	PSM	$N_{Treatment}$	$N_{Control}$
Individual attributes		0.047*	0.047	0.061*	136	1,171
		(0.028)	(0.033)	(0.037)		
Individual attributes+intention to work	0.105***	0.027	0.022	0.050	136	1,171
	(0.033)	(0.027)	(0.032)	(0.038)		
Individual attributes+intention to work+health variables		0.025	0.018	0.047	136	1,171
		(0.027)	(0.031)	(0.036)		

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The matching method of propensity score matching is kernel matching. The kernel type used is Gaussian, and the kernel bandwidth is 0.06.

Source: Author’s calculations by using Longitudinal Survey of Middle-aged and Elderly Persons.

Table 6. Effect of training on re-employment by employment status

(A) 1 year after training	Multinomial logit		Sample size
	Regular worker	Non-regular worker	
Individual attributes	0.019**	0.037	1402
	(0.008)	(0.026)	
Individual attributes+intention to work	0.019**	0.022	1402
	(0.008)	(0.026)	
Individual attributes+intention to work+health variables	0.018**	0.020	1402
	(0.007)	(0.026)	

(B) 2 year after training	Multinomial logit		Sample size
	Regular worker	Non-regular worker	
Individual attributes	0.013	0.051*	1358
	(0.008)	(0.027)	
Individual attributes+intention to work	0.013	0.038	1358
	(0.008)	(0.027)	
Individual attributes+intention to work+health variables	0.012	0.034	1358
	(0.008)	(0.027)	

(C) 3 year after training	Multinomial logit		Sample size
	Regular worker	Non-regular worker	
Individual attributes	0.019**	0.020	1307
	(0.008)	(0.028)	
Individual attributes+intention to work	0.018**	0.003	1307
	(0.008)	(0.028)	
Individual attributes+intention to work+health variables	0.018**	0.001	1307
	(0.008)	(0.028)	

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The estimated values represent the marginal effects.

Source: Author's calculations by using Longitudinal Survey of Middle-aged and Elderly Persons.