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Abstract

This study investigates the short-term effects of public-sponsored job training (PJT) for the unemployed on their working status and income using a large-scale Japanese government survey and the propensity score matching technique. We find a significantly positive effect on the subsequent probability of working for both men and women; however, the point estimate for women is larger than for men. We also find a gendered difference in the effects on income and probability of being employed as a regular worker; that is, significantly positive effects for women but no significant effects for men, suggesting that PJT might be more effective for women. We confirm that the results are robust to a range of empirical specifications.

Keywords: public-sponsored job training, short-term effect, gendered difference, employment and income
JEL classification: J24, J18, C81

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1 Introduction

Provision of public-sponsored job training (PJT) for the unemployed is one form of active labor market policy that has been implemented in many countries and is a feature of the modern welfare state. However, while its effects have long been discussed and empirically researched, especially in the US and Europe, one of the empirical questions that remains is whether or not PJT participants actually benefit from these programs. While a number of studies have investigated this question using experimental or quasi-experimental designs,[1] the results are ambiguous, with some studies reporting positive effects and others finding negative or no significant effects.

In Japan, although there has been long-standing and widespread interest in public-sponsored job training (PJT) for the unemployed, due to data limitations, the topic has not been investigated to date from a quasi-experimental framework.[2] Furthermore, a meta-analysis of over 200 studies of active labor market programs by Card et al. [2018] includes a total of 857 estimates but none of Japan despite it being the third-largest economy in the world.[3] While Japan is known for having a very low unemployment rate (2.4% in 2018);[4], as with other countries worldwide, it has not escaped the COVID-19 shock, with jobs being lost in specific sectors such as accommodations, restaurants, transportation, and other service industries.[5] Therefore, as the world begins to envision what a post-Covid economy might look like, it is worthwhile examining the effectiveness of PJT in order to gauge its potential for enabling a smooth transition to a new job for the currently unemployed who have been devastated by its effects.

[1]For a comprehensive overview, see LaLonde [1995], Heckman et al. [1999], Card et al. [2010], and Card et al. [2018]. Also see Ibarrarán and Shady [2009] for reviews in Latin American countries supported by the Inter-American Development Bank.

[2]The only study to explore the effects of PJT in Japan is Kurosawa [2003], which conducts a before-after comparison of PJT participants using training participant data at a regional vocational school in Tokyo but not a quasi-experimental analysis.

[3]The Japanese share of the world GDP was 5.7% in 2018 after the US (23.9%) and China (16.1%) (OECD, Annual National Accounts Database).

[4]In 2018, it was the second lowest after the Czech Republic (OECD, Unemployment rate (indicator).)

[5]See, for example, Fukui and Kikuchi [2020] and Kikuchi et al. [2020].

Fortunately, data has recently become available that enables us to use a counterfactual treatment-control framework in Japan. Since 2007, the *Employment Status Survey* (ESS), which is a general survey conducted by the Statistics Bureau of Japan to assess the usual labor force status of Japanese at the survey point, has surveyed whether respondents had taken job training and whether that training was subsidized by the government. We used this information to construct treatment and control groups within a quasi-experimental research design in order to examine the short-term effects of PJT on labor market outcomes including income and the probabilities of working and of being employed as a regular worker. Using micro data from the large-sample ESS dataset and the propensity score matching (PSM) technique, we estimated the average treatment effect on the treated (ATT).

Since large-sample general survey datasets such as the US Current Population Survey (CPS) tend to collect little or no information on job training, they have not been widely used to investigate public-supported job training.[6] PJT studies thus tend to use one of three other options, each of which has advantages and disadvantages. These are: 1) a combination of experimental data and existing survey data that provides information on the comparison group,[7] 2) administrative datasets,[8] and 3) a fresh data source.[9] Unlike the CPS and other general surveys, Japan's ESS does collect extensive information on PJT and, moreover, as we cannot yet access Japanese administrative data or collect fresh data, it is currently the best available option for the study of PJT in Japan. Further, while response quality can be a concern with surveys, a feature of the ESS dataset is its large sample size and much richer set of baseline characteristics on both participants and non-participants than is usually available

[6] The England and Wales Youth Cohort Study (YCS) in the UK does survey PJT (O'Higgins [1994] and Whitfield and Bourlakis [1991]), but as the main aim of that study is to understand young people's activities related to education, training and work after compulsory education, it has more of a job training focus than most general surveys. Further, its sample size is about 20,000, which is much smaller than the ESS dataset used in this study.

[7] See LaLonde [1986], Dehejia and Wahba [1999], Dehejia and Wahba [2002], Smith and Todd [2005]. The latter study from the US uses experimental data from the National Supported Work (NSW) Demonstration supplemented with non-experimental data from the CPS and the Panel Study of Income Dynamics (PSID).

[8] This approach is common in studies of European countries, such as Biewen et al. [2014] and Gerfin and Lechner [2002].

[9] See Heckman et al. [1999] for a detailed discussion of the advantages and disadvantages of each.

from either administrative or fresh data sources.

While potential for bias is a concern with any non-experimental research, quasi-experimental research aims to address this by replicating the conditions of an experiment as much as is possible in the social sciences. Moreover, previous studies have shown that with careful design, much potential bias can be attenuated.[10] For example, Smith and Todd [2005] identify three important conditions in order for matching estimators to have low bias: (i) uniform data source for participants and nonparticipants (i.e., the same survey or the same type of administrative data or both), (ii) uniform labor market for participants and nonparticipants, and (iii) data containing a rich set of variables that affect both program participation and labor market outcomes. The Japanese dataset used in this study meets all these criteria to some extent. Criteria (i) and (iii) are strictly met, as the ESS surveys work histories and place of residence before PJT for both participants and non-participants using the same questionnaire. Card and Sullivan [1988] and Ham and LaLonde [1996] also note that design considerations such as controlling for work history before PJT participation is important. Further, While (ii) might not be strictly met, we can control for differences among local labor markets using residence information.

One contribution of the current study is that it is based on a more refined analysis sample than is typically available for PJT research. Because the ESS collects such robust data on socioeconomic variables, particularly about personal reasons why individuals quit their previous job that are not usually included in administrative data, it enabled us to exclude from the analysis those people who were not really looking for work. Administrative data, by contrast, is gathered to obtain specific information for tax or social security purposes, so any unrelated or tangential information is left out. For example, Japanese unemployment insurance (UI) data has information about whether an individual left their previous company because of company circumstances or personal reasons. However, we cannot determine what those personal reasons might be from UI data because companies are required to report

[10]See Heckman et al. [1997], and Heckman et al. [1998] for more.

only basic information about employee turnover to the regulatory agency. On the other hand, because the ESS is a household survey, we could obtain detailed information about the reasons for quitting the previous job that allowed us to fine-tune the construction of our analysis sample.

Another contribution of this study is that it is the first study of public-sponsored job training in Japan. As the existing literature is ambiguous on the effects of PJT, the results for Japan cannot be inferred from studies abroad, and so this research will help to inform Japanese government policy. This study is not only beneficial to Japan, however, as it also provides a different geographical perspective from which to examine the effectiveness of labor policies, specifically PJT, in a mature industrial economy.

Following Card et al. [2018], whose meta-analysis of over 200 studies of active labor market programs finds that PJT effects are likely to be different between men and women, we have also incorporated gender into our analysis to determine if there are gendered effects of PJT in Japan as well. The main findings of the study are as follows. There is a significantly positive short-term effect on the probability of working for both men and women after completing PJT. Additionally, while for men there is no effect on annual income or the probability of finding employment as a regular worker, these outcomes too are significantly positive for women, which suggests that PJT might be more effective for women at least in the short term. As for the long term effects, while we do not have an index of long-term outcomes, a regular worker in Japan is usually working on an indefinite (permanent) contract with additional benefits and seniority-based wages, so our short-term results suggest that PJT could also have a long term positive effect on the working conditions of women.

The structure of the paper is as follows: Sections 2 and 3 explain the econometric method and the data used in the study, while Section 4 explains the public-sponsored training system in Japan and Section 5 describes how the analysis samples were constructed. Sections 6 and 7 report the results of the main estimation analysis and a sensitivity check, and Section 8 concludes the paper.

2 Econometric Framework: PSM Estimation

In this study, we use the propensity score matching (PSM) estimation method. With Y_1 denoting the outcome conditional on participation in PJT and Y_0 the outcome conditional on non-participation, the impact of participating in training is $\Delta = Y_1 - Y_0$. As only Y_1 or Y_0 is observed for each individual, Δ is not observed for anyone. Therefore, assessing the impact of training requires making a counterfactual inference about the outcomes that would have been observed for PJT participants had they not participated.

Let $D = 1$ for the group of individuals who participated in PJT for whom Y_1 is observed and $D = 0$ for those who did not take PJT for whom Y_0 is observed. Let X denote a vector of observed individual characteristics used as control variables. We estimate the average treatment effect on the treated, conditional on X ($ATT(X)$):

$$\begin{aligned} ATT(X) = E(\Delta|X, D = 1) &= E(Y_1 - Y_0|X, D = 1) \\ &= E(Y_1|X, D = 1) - E(Y_0|X, D = 1). \end{aligned} \tag{1}$$

A necessary assumption to achieve a consistent matching estimator of the average treatment effect on the treated (ATT) is that outcomes are independent of participation in training, conditional on a set of observable characteristics. That is, there exists a set of observable conditioning variables Z (which may be a subset or a superset of X), in which case conditional mean independence suffices:

$$E(Y_0|Z, D = 1) = E(Y_0|Z, D = 0) = E(Y_0|Z). \tag{2}$$

Common support is also assumed in order to guarantee the possibility of a non-participant analogue for each participant, which requires that

$$Pr(D = 1|Z) < 1. \tag{3}$$

Under these assumptions, ATT (X) can be written as

$$
\begin{aligned}
ATT(X) &= E(Y_1 - Y_0|D=1) \\
&= E(Y_1|D=1) - E_{Z|D=1}[E_Y(Y_0|D=1,Z)] \\
&= E(Y_1|D=1) - E_{Z|D=1}[E_Y(Y_0|D=0,Z)],
\end{aligned}
\tag{4}
$$

where the first term can be estimated from the treatment group and the second term from the matched-on-Z comparison group, which is the estimand of interest. We also assume the stable unit treatment value assumption (SUTVA), which is that treatment of unit i affects only the outcome of unit i. Because the number of PJT participants is very small relative to the size of the labor market, as explained in Section 3, this assumption is reasonable.

As our data provides the mean outcome in the treated state $E(Y_1|X, D = 1)$ but not the counterfactual mean $E(Y_0|X, D = 1)$, we need to construct econometrically the adjusted outcomes of the nonparticipant proxy for the missing counterfactual in order to obtain a consistent estimator. For this, we use the nonparametric *propensity score matching* (PSM) technique which enables us to construct a match for each training participant using a kernel-weighted average over multiple nonparticipants. More specifically, we adopt *local linear matching*, a generalized version of kernel matching that has several advantages over more standard kernel estimation methods as noted by Fan [1992] and Fan [1993].[11] [12]

What is important for our PSM estimation is that we include only samples meeting the common support condition. Therefore, the estimated treatment effect is redefined as the treatment impact for training participants whose propensity scores exist within the common support region. The first stage entails a logit regression to estimate the propensity score and the second stage estimation uses the local linear matching technique explained above.[13]

[11] Smith and Todd [2005] also indicate a faster rate of convergence near boundary points and greater robustness to different data design densities as advantages.

[12] The epanechnikov kernel function is used.

[13] A cross-validation procedure is implemented to select the choice of the optimal bandwidth for the local linear estimation.

3 Data

In this study, we use micro data from the *Employment Status Survey* (ESS) conducted by the Statistics Bureau of Japan which aims to assess the *usual* labor force status of Japanese at the survey point, which is October 1st each survey year. Although the ESS extends back to 1956, it only began surveying participation in training in 2007, so our study pools data from the 2007, 2012, and 2017 survey years. The ESS is a household survey,[14] with all household members aged 15 or older required to respond to the questionnaire, providing a sample size of about a million individuals each survey year.

To examine the effects of Japanese public-sponsored training (PJT) for the unemployed, the best option currently available in Japan is survey data because experimental research with randomized control trials (RCT) has not yet been conducted on this topic, and the large-sample ESS provides the best survey data available. In addition to government surveys such as the ESS, numerous surveys are conducted by universities and public/private research institutes, but the sample sizes are much smaller at around 5,000. Because PJT participation in Japan is small relative to the size of the labor force (according to the Japanese Ministry of Health, Labour, and Welfare (MHLW), there were only 166,565 PJT participants in FY2012 within a labor force of about 60 million),[15], a large-sample survey like ESS is needed in order to secure a sufficient number of PJT participants in the analysis sample.

In addition to its size, another advantage of using the ESS is that it surveys detailed information about previous job experience such as employment format, tenure, industry, and occupation. This enables us to control for heterogeneity in previous work experience before training which some previous studies such as Heckman et al. [1999] have identified as important. Furthermore, as it surveys information about the personal reasons why individuals quit their previous job that is not usually covered in administrative data, this enables us to

[14] Approximately 470,000 households are selected randomly by a stratified two-stage sampling method each survey year.

[15] See Section 4 for details.

construct a more refined analysis sample by excluding people who are not really looking for a new job.

While randomized control trials represent the gold standard in experimental research design, RCT has not been used to investigate PJT in Japan. Moreover, the method presents ethical issues regarding human subjects, particularly in limiting access to publicly available human development resources, and so educational studies in particular typically use a quasi-experimental design to address these concerns. As for data sources, while administrative data or fresh data are commonly used in PJT studies because large-scale general surveys in many countries typically do not collect data focused on job training, this information is available in the ESS while these former types of datasets are not yet available in Japan.[16] While public training facilities in Japan do usually conduct follow-up surveys of their training participants after program completion, this yields information only about the treatment group but not the control group, so this data is less useful for quasi-experimental research. In contrast to other large-scale nationwide surveys, the ESS does survey whether a respondent participated in public-sponsored training, and this enabled us to create treatment and control groups within a quasi-experimental research design. Needless to say, it is important to perform an 'apples to apples' comparison, and so the manner in which the analysis sample is defined with respect to constructing a control group that is comparable to the treatment group is crucial. We explain how we accomplished this in more detail below.

Lastly, some readers may be familiar with the *Labor Force Survey* (LFS), another large-sample governmental survey of working status in Japan. However, as the LFS does not cover training, it cannot be used for this research, leaving the ESS as the best (and, indeed, only) large-sample Japanese government dataset that we can use to explore the effects of public-sponsored training for the unemployed.

[16] A survey to collect fresh data was conducted by a research group including the author from 2010-2011, commissioned by the Japanese PJT agency *Japan Organization for Employment of the Elderly, Persons, with Disabilities and Job Seekers* (JEED). We planned to use the RDD framework, with the forcing variable being the JEED score for selecting PJT participants. However, as it was shown that the forcing variable was manipulated by the agency, the project was abandoned.

4 Japanese Public-Sponsored Job Training System

Japan has a comprehensive public-sponsored job training system for disadvantaged people in the labor market provided by the Japanese Ministry of Health, Labour, and Welfare (MHLW) under the brand "*Hello, Training*" to cultivate a sense of familiarity. Although its broad coverage includes the unemployed, small business workers, graduates of only middle school or high school and the disabled, we focus here on training for the unemployed who left their previous job and are looking for new employment. This is provided through both in-facility and commissioned training,[17] which we collectively define as public-sponsored job training (PJT).[18] While both in-facility and commissioned training are managed by the national or relevant prefectural PJT agency, in-facility training is provided at dedicated government PJT agency locations[19] whereas commissioned training is conducted at private companies such as training or vocational schools commissioned to provide courses related to manufacturing, nursing care, cooking, and office/clerical work such as PC and IT skills and information processing.

From our ESS survey data, we can know whether the unemployed take PJT but we cannot isolate which type of training they take, so our PJT variable includes both in-facility and commissioned training. Although there are some minor differences between the two in terms of training providers (national or prefectural) and specific courses offered, both types of training have common eligibility criteria: 1) registration as a job-seeker at the local public employment service (PES) office,[20] which involves a counseling interview with a staff member;

[17]In Japanese, in-facility training is *shisetu-nai kunren* and commissioned training is *itaku kunren.*

[18]"*Hello, Training*" also provides training for the unemployed who are not eligible for UI benefits; that is, job seeker support training. However, those participants are likely to have greater difficulty in gaining employment than those in the in-facility and commissioned training because only those who have failed to find a job after graduation or who have not succeeded in their own business are eligible for it. As they are not comparable with in-facility and commissioned trainees, they have been excluded from our study.

[19]The national agency, the Japan Organization for Employment of the Elderly, Persons with Disabilities and Job Seekers (JEED), is a national governmental administrative agency with 61 "Polytechnic Centers" throughout Japan, with some of the more populated prefectures having more than one location. Meanwhile, there are 156 prefectural "Polytechnic School" PJT locations across Japan's 47 prefectures and also one municipal public training facility in Yokohama, which is one of the largest cities in Japan.

[20]Japan has 544 PES offices and, according to the MHLW, the estimated number of users per day

2) endorsement by a director of the PES office indicating that the applicant needs to take PJT to find a new job and has enough ability and motivation to take the program; and 3) successful completion of the entrance examination for the indicated PJT program, held either at the national or a prefectural PJT agency and consisting of a paper test, an interview, or both. While the MHLW PJT application brochure, aiming for simplicity, emphasizes that eligibility for PJT is *mainly* entitlement to unemployment insurance (UI) benefits, even those who are not entitled to UI benefits are permitted to take PJT if conditions 1)–3) are satisfied.[21] There is a difference in benefits during PJT participation between persons with and without UI benefits, however.

Once one is accepted into a training program, the cost is essentially free[22] to participate in a program typically lasting for 6 months[23] and extending from morning to evening each weekday. Management of participant attendance is rigorous, and trainees with excessive absences may lose their trainee qualification and be required to leave the program. In addition, importantly for this research, only those who have not already taken PJT within one year of the program start date may enroll. As this study examines the effects of PJT taken in the previous year, we therefore do not need to be concerned about a potential "multiple training participation issue" mentioned in other studies whereby the effects of different training programs taken simultaneously or in close succession might conflate the results.[24]

As for the total cost of providing public-supported training, according to the MHLW, the total amount budgeted for PJT nationally in FY2017 was around $970 million,[25] representing about 0.1% of the $9.26 trillion Japanese national budget. The number of PJT participants

was about 17,000 persons in FY2017 ($https://www.mhlw.go.jp/file/06-Seisakujouhou-11600000-Shokugyouanteikyoku/0000067861.pdf$).

[21]See https://www.mhlw.go.jp/content/11800000/000659814.pdf for the Japanese brochure.

[22]Ancillary costs for textbooks and materials are paid by participants.

[23]While the standard PJT program length is 6 months, there is some variation, with some programs lasting only three or four months or as long as one or two years.

[24]See Gerfin and Lechner [2002] for more detail.

[25]$1=108 JPY. Note that the budget was not exclusively for training the unemployed but also those who worked in small business and those who had graduated only from middle school or high school because these budget categories are not broken out separately. $https://www.mhlw.go.jp/file/05-Shingikai-11801000-Shokugyounouryokukaihatsukyoku-Soumuka/0000193548.pdf$.

in FY2007, FY2012, and FY2017, the three years under study, ranged between 112,000 and 152,000 which, averaged over the three years, represents only 5.7% of those unemployed at that time,[26] indicating that only a small minority of those unemployed take PJT.

Lastly, the subsequent employment rate *of PJT participants* reported by the MHLW was 85.2% for in-facility training and 73.2% for commissioned training in FY2017. While these numbers at first glance suggest that PJT in Japan is effective, a principled assessment requires us to examine whether the subsequent employment rate of PJT participants is higher than the rate that would have been observed had they not participated in PJT, and that is what we estimate in this study. Although we unfortunately cannot examine the effectiveness of each type of PJT training, we can examine the overall effect of PJT.

5 Analysis Framework

5.1 Public Training Variable, Analysis Sample, and Outcome

Our main variable, public-sponsored training for the unemployed (PJT), was constructed as follows: the ESS asks respondents whether they had taken a training program *during the year prior to the survey date* and, if so, to choose which type of training program they had taken[27] and indicate whether a public subsidy was provided. We constructed the PJT dummy variable to take 1 (0 otherwise) if the respondent took a training program supported by a public subsidy. We treat PJT participation as a binary event, as does much of the literature on program evaluation.[28] Note that because the survey date is October 1st in survey year t, "during the year prior to the survey date" refers to the period from October in year $t-1$ to September in year t. It should also be noted that the ESS asks only whether a respondent

[26] The number of PJT participants comes from MHLW administrative data and the number of unemployed from the *Labour Force Survey* of the Statistics Bureau of Japan. The average proportion of PJT participants among the unemployed was 5.6% for FY2007, 5.4% for FY2012, and 6.1% for FY2017.

[27] The options are as follows: 1) training at a public training facility, 2) training at a university/graduate school, 3) training at a vocational school, 4) a training session/seminar, 5) a workshop/study group, or 6) other training.

[28] See, for example, Ashenfelter [1978], Ashenfelter and Card [1985]

participated in training but not whether they successfully completed it, so we cannot identify whether training participants finished their programs or not.

Because constructing comparable treatment and control groups is essential to accurately identifying the effect of training in our quasi-experimental design, we paid close attention to the construction of our analysis sample. Figure 1 shows a timeline of the relationship between unemployment period, PJT participation, outcomes, and analysis samples. For clarity, we call October 1st in year t the *survey date* and October in $t-1$ the *previous October*.

Sample construction began with the pooled data of the ESS from 2007, 2012, and 2017 which yielded an initial sample size of 2,915,733. From this, we restricted the sample to those who had graduated from school and were between 25 and 49 years old on the survey date because we wanted to focus on people who have had a relatively long working life. Further, as 55 years of age is a major turning point for employees in Japan, after which the employment rate starts to fall[29] because some workers begin to retire earlier than the typical mandatory retirement age of 60,[30] we therefore restricted the sample further to people with at least 5 more years before turning 55 years old and also excluded those who were in school, which reduced the sample size to 945,717.

A second consideration is that we are looking only at PJT for the unemployed in this study. Although there is considerable overlap between eligibility for the PJT programs and UI benefits, there are some complicated exceptions for accessing both PJT and UI benefits. Consequently, we considered only the minimum UI requirements, limiting the sample to those who had held a previous job as an employee and thus excluding those who were self-employed, bringing the sample size to 528,200. Further, as we are examining the effects of PJT taken

[29] For example, for 2012, the middle year of our dataset, the employment rates reported by the *Labor Force Survey* for each five-year age range between 25 and 54 averages about 80%, but the rate for those aged 50–54 years is 81.3% and decreases to 75.4% for those aged 55–59.

[30] *The Elderly Employment Security Act* stipulates that companies in Japan that introduce a mandatory retirement age must set it at 60 years old or more. According to the 2012 MHLW *General Survey on Working Conditions*, 92.2% of Japanese companies introduced a mandatory retirement age system, and 82.7% of those were set at 60 years old.

in the previous year on labor outcomes at the survey date,[31] we next restricted the sample to those who had quit their previous job earlier than the previous October and who were still not working then, which further reduced the sample size to 117,633. Lastly, in order to focus on people likely to be highly motivated to look for a new job, we excluded those who quit their previous job because of mandatory retirement or old age/illness,[32] leaving a sample size of 107,885. This sample consists of people eligible for PJT who are not yet old enough to exit the labor market.

Next, to create a main analysis sample from this base sample, we wanted to exclude people not actively looking for new jobs, so we further limited the sample to those who had left their previous job after October in $t-2$. This means that they had been searching for a new job for *at most* one year in the October prior to the survey date, and for reasons *other than* family reasons such as marriage, child rearing, and nursing care. This restriction left us with a sample size of 2,855 men and 4,957 women.

The rationale for these two limitations above is that as the period of unemployment grows longer, people are more likely to lose their motivation to look for a new job, so we wanted to exclude the long-term unemployed from the analysis. Additionally, people who had quit their previous job due to marriage, child rearing or nursing care a year ago are less likely to be looking for a new job a year later, based on evidence from the ESS. The ESS asks respondents who are not working but who wish to work on the survey date (but not the previous October) whether they are looking for a new job or preparing to open a new business.[33] We found that the proportion of people "doing nothing for a new job/business" was 19.3% for men and 43.2% for women, but focusing only on people who quit their previous

[31] Outcomes include income, probability of working, and probability of being employed as a regular worker, as explained below.

[32] ESS requires a respondent to choose one of the following options as the reason for quitting the previous job: 1) downsizing, 2) bankruptcy of employer, 3) business downturn, 4) it was a temporary job, 5) low income, 6) bad working conditions, 7) was not suitable for me, 8) family moving/establishment moving, 9) mandatory retirement age, 10) termination of contract, 11) sick or elderly, 12) marriage, 13) child-rearing, 14) nursing, 15) confidential.

[33] The response options are 1) I am looking for a job, 2) I am preparing to open a new business, or 3) I am doing nothing for a new job/business.

job due to family reasons, the ratio of people doing nothing became 27.6% for men and 72.2% for women. Therefore, particularly among women, those who quit their job within the past year due to family reasons include a substantial number of people who are not now actively searching for a new job. Therefore, by excluding the long-term unemployed and those who left their previous job for family reasons, our main analysis sample AS1 can be considered to be composed mainly of those who are unemployed but who are highly motivated to be re-employed.

At this point, we want to ensure that our sample adequately captures the participants in public-sponsored training in Japan. Recall that according to the published data, the average rate of PJT participation among the unemployed for FY2007, FY2012, and FY2017 was 5.7% (See Section 4), while we find that the ratio of PJT participants in the main analysis sample is 7.5%. While the comparison is imperfect because the age distribution of our analysis sample is truncated, our analysis sample does appear to adequately capture PJT participants. Note that the number of PJT participants is usually very small, with even the large-sample ESS data pooled over three years having only 226 male and 361 female participants in the main analysis sample.

Lastly, we discuss the outcome variables of this study which are 1) the probability with which a PJT participant will later obtain work and, if they do obtain work, 2) whether or not they are employed as a regular worker, and 3) the natural logarithm of their annual income. Note that annual income could indicate expected income rather than actual income because the ESS asks respondents to provide an estimate of annual income based on their recent status if they have been in the new job for less than a year. Further, the probability of being employed as a regular worker could be a proxy for long term working conditions because regular employees in Japan usually have an indefinite (i.e. not contractually time-delimited) permanent position with higher income and benefits than other workers, which is explained in more detail below.

Table 1 shows the descriptive statistics of the outcomes by gender. The baseline, that is, the probability of PJT non-participants working, is 56.8% for men and 48.3% for women. Regarding the PJT participants, the probabilities of working are 73.0% for men and 72.6% for women, which are similar to the numbers released by the MHLW (73–86%) shown in Section 4. We thus see a 16.2 percentage point difference between male participants and non-participants, and a 24.3 percentage point difference between female participants and non-participants. In addition, while male PJT participants have a higher probability of working, all outcomes are higher for women PJT participants than for non-participants. In Section sec:result, we will see the estimation results of propensity score matching to confirm whether we can see similar results even after applying the PSM technique.

5.2 Characteristics of PJT Participants

Table 2 shows the characteristics of PJT participants and non-participants as well as their previous workplaces, and we see that PJT participants differ in some ways from non-participants in the analysis sample. The final academic background of male participants is less likely to be high school and is more likely to be technical school (*senmon gakko*).[34] In the previous job, they were less likely to be non-regular workers.

As for women, PJT participants are less likely to be married or to have children and they are also more likely to have graduated from university. In their previous job, they were more likely to have been employed as regular or contract workers and less likely to have worked as non-regular workers, with years of tenure in the position longer than for non-participants.

Because these differences in the characteristics of PJT participants and non-participants have the potential to influence our estimates of PJT outcomes, we have adopted the propensity score matching approach to construct an appropriate counterfactual sample for PJT participants. The results of the first stage examination of the propensity score are shown in Table A_1 in the Appendix.

[34]In Japan, primary and middle school is compulsory but high school education and above is not. Technical school is one of the school options in Japan after graduating high school, and it features a practical training-centered curriculum specializing in obtaining a profession, such as a hairdresser.

5.3 Balancing Test

In order to ensure that the treatment and control groups are comparable, a balancing test was conducted before performing the propensity score matching estimation. We followed the approach of Dehejia and Wahba [2002], Dehejia and Wahba [1999] and Smith and Todd [2005] by first dividing the observations into strata based on estimated propensity scores. Then, within each stratum, t-tests were conducted to test for mean differences in each control variable (that is, individual characteristics and work history) between the treatment and control group observations to confirm that there was no statistically significant difference in the means of the estimated propensity scores between them.

The null hypothesis is that the means of the control variables are the same for the treatment and control groups in each strata; that is, people in both groups have similar propensity scores. Though in a statistical sense it is not possible to test for covariate balance, a failure to reject the null hypothesis can be interpreted as supporting evidence for covariate balance, suggesting that endogeneity among unobservable characteristics is less likely. The results of the t-tests are that the null hypothesis was not rejected at a 5% level of statistical significance for men and 10% for women,[35] indicating that the distributions of the treatment and control groups are indeed comparable.

6 Results

Table 3 shows the results of the propensity score matching (PSM) estimation of the effects of public-sponsored job training (PJT) using the main analysis sample, which was further restricted to those observations that met the common support condition.[36] Individual characteristics, work history, the unemployment rate in the prefecture where participants lived

[35] Results are not shown but available from the author upon request.

[36] The common support condition was imposed by dropping the treatment observations whose propensity score was higher than the maximum or less than the minimum propensity score of the controls.

before PJT training, and survey year dummy variables were controlled for in all regressions.[37] As explained above, the first stage entailed a logit regression to estimate the propensity score and the second stage estimation used the local linear matching technique.

First, looking at the results for working probability, the effect of PJT for men is statistically significantly positive (Column (1)), indicating that PJT increased their probability of finding work within one year after training by 15.4 percentage points. As the baseline working probability is 56.8% (See Table 1), PJT would increase the working probability of men to 77.2%. Meanwhile, the result for women is also statistically significantly positive (Column (4)), but the point estimate for women is larger than that for men (17.4 percentage points), increasing the likelihood of finding work from 48.3% to 65.7%. PJT participation thus seems to be more effective for women in finding work in the short run. One possible explanation is that there could be a gendered difference in the reservation wage. As the reservation wage is typically higher for men than for women because of a higher opportunity cost,[38] the reservation wage of male PJT participants could also be higher than that of female participants. If this is true, then male participants may not begin to work soon after PJT because even if a job were available, they might wait in the hope of finding a better one.

Next, looking at the results for income (conditioned by working), we find no significant effect for men but a significantly positive effect for women (Columns (2) and (5)). In theory, as PJT participants acquire more skills, their annual income after PJT should be higher. One possible reason why we do not see this for men is that in the short run after PJT, only those men with a low reservation wage might be working while men with a high reservation wage may be continuing to search for a new job.

Another interpretation is that women might succeed in finding a new job in which they can utilize the new skills acquired from PJT sooner than men, or they take training programs related to sectors with high labor demand. As explained above, the income variable in this

[37] See Appendix 2 for a list of all control variables and their definitions. Table A_1 in the Appendix 3 shows the results of the first stage, using the logit model.

[38] For example, see Caliendo et al. [2017] for evidence of this, using German data.

study could indicate an expected income rather than an actual income, so men may initially be accepting lower-skilled jobs (which are recorded in the ESS) before they ultimately obtain a job that utilizes their newly developed skills. Taking this into consideration, looking at the results for the effect of PJT on the probability of being employed as a regular worker (Columns (3) and (6)), we see that there is no significant effect for men but a significantly positive effect for women. In Japan, there are two basic categories of employment: regular and non-regular,[39] with regular employees generally working full-time under a permanent (not time-delimited) employment contract and non-regular employees working either part-time or full-time on a fixed-term contract. One of the greatest distinctions between the two categories is wages, with the annual incomes of regular employees usually being much higher than those of non-regular employees even for those who work similar hours.[40] Because a regular employee expects a higher annual income than a non-regular worker, and because the distribution of the two categories is gendered (with more women being non-regular workers), this could be the cause of the observed differences in the results for annual income by gender, with the income of male participants lower but that of females higher after PJT.[41]

In addition, although we do not have an index of long-term outcomes in this study of short-term PJT effects, the status of regular worker might provide some insight into long-term effects, as a regular worker usually has a permanent contract and enjoys seniority-based wages. The finding that women have a significantly positive probability of finding a position as a regular worker with stable employment and regular salary increments in the future after PJT suggests that these training programs could have a long term positive effect on the working conditions of women.

[39] About 60% of Japanese workers are regular employees and about 40% are non-regular employees (*Labour Force Survey 2017*)

[40] For example, in 2017, the average annual income of male regular and non-regular employees was \$48,100 and \$18,960, respectively, and that of female regular and non-regular employees \$32,380 and \$12,280 (ESS 2017, \$1 = 100 JPY).

[41] Table A_2 in the Appendix shows the characteristics of the new jobs of PJT participants and non-participants after PJT, but there is no systematic difference between them that could explain the difference in the estimation results, other than employment categories.

7 Robustness Check

In this section, in order to ensure the robustness of our results, we first investigated to what extent the estimation results vary: 1) if we used OLS estimation instead of propensity score matching (PSM) and 2) if we did not control for work history. Second, we conducted several additional matching estimations: one-to-one matching, five-nearest neighbors matching, and kernel matching.[42]

Panels A and B of Table 4 show the effects of PJT by gender using OLS and PSM estimation procedures, respectively. For clarity of the comparison, Columns (1), (5), and (9) are presented again from Table 3, and Columns (3), (7), and (11) are the results of the OLS estimation using the same specifications. We see that the results of the OLS and the PSM estimations are almost the same for both men and women, both in the magnitude of the coefficients and the statistical significance. These results are not unexpected, showing that the analysis samples with and without common support condition restrictions (i.e. PSM and OLS, respectively) are similar, taking into account the nature of both estimation methods (Angrist [1998]). This also demonstrates that the PSM estimates are reliable, and suggests that the manner in which analysis samples are constructed is important.

Next, we checked whether the point estimates changed if we did not control for work history. Columns (2), (6), and (10) of both Panels A and B show the PSM results when the work history variables were excluded. The point estimates without work history become around 1–3 percentage points larger than those with work history, except for the probability of men working as a regular worker and men's annual income. This is consistent with previous studies such as Smith and Todd [2005] that show that effects might be overestimated if we do not control for work history.

Last, we conducted an additional robustness check using several different matching methods to adjust for pre-treatment observable differences between PJT participants and non-

[42] For the kernel matching, we used the epanechnikov kernel.

participants. Table 5 presents the results, and we see that Columns (1), (5), and (9) in each panel are the same as in Table 3, which reports our main results using the local linear matching. Although the magnitude of the estimates is slightly different, the results are all statistically significantly positive even when using other matching methods: one-to-one matching, five-nearest neighbors matching, and kernel matching, so we can conclude that our main estimation results are robust to alternative specifications.

8 Conclusion

This study investigates the short-term effects of public-sponsored job training for the unemployed (PJT) on three labor market outcomes: probability of working, annual income, and probability of being employed as a regular worker, using micro data from a large-scale Japanese government survey. This is the first study of this topic in Japan to use a treatment-control group quasi-experimental research methodology.

We found a significantly positive effect on the probability of working both for men and women, but different results were obtained regarding income and the probability of being employed as a regular worker. For men, there was no significant effect on either income or regular emplyment but for women, we found significantly positive effects for both, suggesting that PJT might be more effective for women than for men, at least in the short term.

While we have made every effort to satisfy the requirements of a quasi-experimental analysis, limitations of the study include a holistic approach to dealing with PJT because of a lack of access to more detailed PJT information such as when the training began, how long it took, which course was taken, and whether it was completed. In addition, although we used annual income as an outcome variable, this variable might be more accurately interpreted as estimated income rather than actual income due to the construction of the ESS survey. Despite these limitations, however, this study advances the investigation of PJT in Japan by adopting a quasi-experimental methodology.

Further, notwithstanding the limitations mentioned above, the results suggest that PJT might be an effective public policy. However, more fine-tuned research is needed of the effectiveness of each PJT course and program length among the array that are provided, as the literature suggests that returns could differ by PJT type and length.[43] Such an investigation might find that some courses have little to no effect while others have substantial positive effects or that a specific PJT program length might be effective for some topics but not for others. Additionally, the PJT programs that are most effective for men and women might be different. Future research investigating these questions in detail would help to inform a more targeted public policy.

Finally, when evaluating the effects of a policy, the long-term effects are often more important than the short-term effects. In practice, however, long-term policy evaluation is quite difficult due to the great challenges associated with tracking individuals over long intervals consisting of 10–20 years or more. While we do not have an easy solution to this problem, this study which focuses on the short-term effects of PJT can nonetheless provide some insight into possible long-term effects due to the nature of the labor force in Japan. In particular, our finding that women are more likely to be employed as a regular worker if they participate in PJT has important implications that may not be well understood outside of Japan. The "regular worker" category in Japan conveys status, employment stability and high and increasing income over time, so the observed positive short-term effects of PJT for women are likely to persist. However, of course, before any definitive conclusion is made, more precise and extensive research is needed, which could include the use of administrative data from the relevant PJT agencies.

[43] See Gerfin and Lechner [2002], Jacobson et al. [2005a] and Jacobson et al. [2005b]. Jacobson et al. [2005a] examine the effects of community college in Washington State in the US and show that the returns to training differ substantially by the length of the course. They also find that completion of courses in quantitative or more technically oriented vocational subjects also generate an earnings gain.

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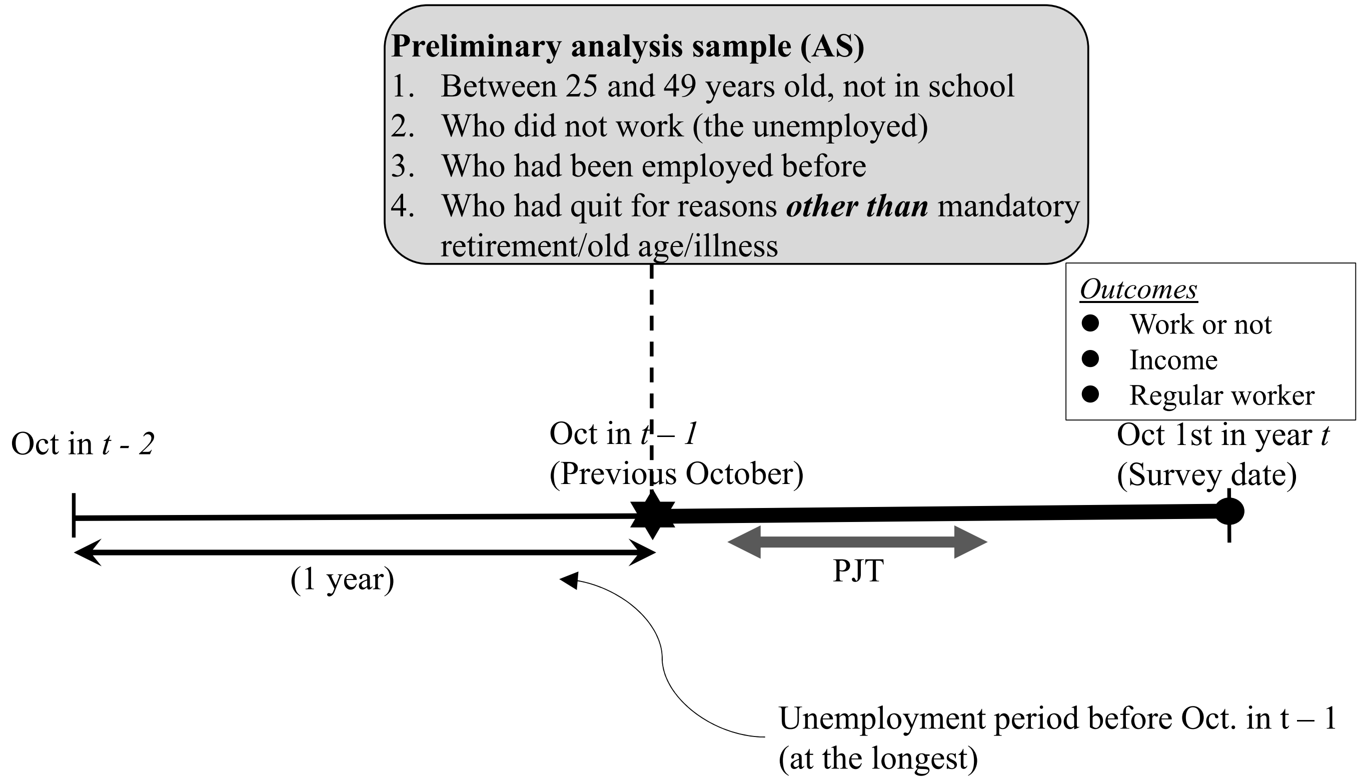

Figure 1: Construction of Analysis Sample

Note: "PJT" indicates public-sponsored job training.

Table 1: Descriptive Statistics of Outcomes

Panel A: Men	Participant	Non-participant		N
Probability of working	0.730 (0.445)	0.568 (0.496)	***	2,855
Ln (income)	5.265 (0.596)	5.322 (0.642)		1,619
Probability of working as a regular worker	0.573 (0.496)	0.554 (0.497)		1,619
Panel B: Women				
Probability of working	0.726 (0.447)	0.483 (0.500)	***	4,957
Ln (income)	5.028 (0.540)	4.775 (0.661)	***	2,468
Probability of working as a regular worker	0.382 (0.487)	0.232 (0.422)	***	2,468

Source: Statistics Bureau of Japan *Employment Status Survey* 2007, 2012, and 2017.
Notes: 1. The size of the participant samples for men and women are 226 and 361 for probability of working and 164 and 262 for ln (income) and probability of working as a regular worker. These statistics indicate the mean, with standard deviations in parentheses.
2. *** indicates results of t-test, and denotes $p<0.01$.

Table 2: Characteristics and Previous Workplace by PJT Participants and Non-participants

	Men					Women				
	Participant		Nonparticipant			Participant		Nonparticipant		
age	35.78	(6.97)	35.70	(7.25)		36.49	(6.86)	36.98	(7.12)	
Age category										
20s	0.23	(0.42)	0.26	(0.44)		0.22	(0.41)	0.20	(0.40)	
30s	0.45	(0.50)	0.41	(0.49)		0.39	(0.49)	0.42	(0.49)	
40s	0.32	(0.47)	0.33	(0.47)		0.40	(0.49)	0.39	(0.49)	
married (=1 if yes)	0.29	(0.45)	0.28	(0.45)		0.44	(0.50)	0.62	(0.49)	***
child (=1 if yes)	0.14	(0.35)	0.17	(0.38)		0.17	(0.37)	0.21	(0.41)	**
Academic background										
middle school	0.11	(0.31)	0.10	(0.29)		0.02	(0.15)	0.04	(0.20)	*
high school	0.37	(0.48)	0.47	(0.50)	***	0.41	(0.49)	0.45	(0.50)	
technical school	0.20	(0.40)	0.16	(0.36)	*	0.18	(0.39)	0.16	(0.36)	
2 year/technical college	0.03	(0.17)	0.02	(0.15)		0.11	(0.32)	0.13	(0.34)	
university	0.27	(0.45)	0.24	(0.43)		0.21	(0.41)	0.16	(0.37)	**
graduate school	0.02	(0.15)	0.02	(0.15)		0.06	(0.25)	0.06	(0.24)	
Employment status in the previous job										
regular worker	0.69	(0.46)	0.65	(0.48)		0.48	(0.50)	0.33	(0.47)	***
non-regular worker	0.13	(0.34)	0.18	(0.39)	**	0.28	(0.45)	0.48	(0.50)	***
temporary staff	0.06	(0.23)	0.05	(0.22)		0.09	(0.28)	0.08	(0.27)	
contract worker	0.11	(0.31)	0.09	(0.29)		0.11	(0.31)	0.07	(0.26)	**
commissioned worker	0.00	(0.07)	0.00	(0.07)		0.02	(0.14)	0.02	(0.13)	
other	0.01	(0.09)	0.02	(0.15)		0.02	(0.16)	0.02	(0.15)	
Industry in the previous job										
agriculture, forestry & fishery	0.00	(0.07)	0.01	(0.12)		0.01	(0.07)	0.01	(0.07)	
mining	0.00	(0.07)	0.00	(0.03)		0.00	(0.05)	0.00	(0.01)	**
construction	0.09	(0.29)	0.11	(0.31)		0.02	(0.16)	0.02	(0.16)	
manufacturing	0.26	(0.44)	0.26	(0.44)		0.19	(0.39)	0.16	(0.37)	
public utilities	0.00	(0.07)	0.00	0.00		0.00	0.00	0.00	0.00	
communication	0.05	(0.22)	0.03	(0.18)		0.04	(0.19)	0.03	(0.16)	
transportation	0.06	(0.23)	0.08	(0.28)		0.02	(0.13)	0.03	(0.16)	
sales	0.18	(0.39)	0.17	(0.38)		0.24	(0.43)	0.24	(0.43)	
finance insurance	0.02	(0.13)	0.01	(0.12)		0.07	(0.25)	0.06	(0.23)	
real estate	0.01	(0.09)	0.01	(0.12)		0.01	(0.12)	0.01	(0.10)	
food/accommodation	0.06	(0.24)	0.06	(0.24)		0.06	(0.24)	0.08	(0.27)	
medical/nursery	0.07	(0.26)	0.03	(0.18)	***	0.13	(0.34)	0.14	(0.35)	
education	0.05	(0.23)	0.06	(0.23)		0.09	(0.29)	0.08	(0.27)	
complex service	0.02	(0.13)	0.01	(0.10)		0.01	(0.07)	0.01	(0.11)	
misclassified service	0.09	(0.29)	0.10	(0.30)		0.07	(0.25)	0.08	(0.28)	
government	0.00	(0.07)	0.01	(0.12)		0.03	(0.18)	0.03	(0.17)	
unclassified	0.02	(0.15)	0.03	(0.16)		0.02	(0.15)	0.03	(0.17)	
Occupation in the previous job										
specialist	0.11	(0.31)	0.10	(0.30)		0.30	(0.46)	0.27	(0.44)	
administrative	0.00	(0.07)	0.00	(0.06)		0.00	0.00	0.00	0.00	
clerical	0.15	(0.36)	0.14	(0.35)		0.31	(0.46)	0.25	(0.43)	***
sales	0.16	(0.37)	0.12	(0.33)	*	0.13	(0.34)	0.17	(0.37)	*
service	0.09	(0.29)	0.08	(0.27)		0.09	(0.29)	0.11	(0.31)	
security	0.02	(0.13)	0.01	(0.11)		0.00	0.00	0.00	0.00	
agricultural	0.02	(0.15)	0.04	(0.20)		0.01	(0.07)	0.01	(0.07)	
transportation/communication	0.02	(0.15)	0.03	(0.18)		0.00	0.00	0.00	0.00	
production/construction	0.41	(0.49)	0.45	(0.50)		0.15	(0.36)	0.19	(0.39)	*
unclassified	0.01	(0.09)	0.02	(0.15)		0.01	(0.09)	0.02	(0.14)	
years of tenure in the previous job	6.94	(6.07)	6.40	(6.54)		5.79	(5.45)	4.69	(4.91)	***
months after leaving previous job	17.81	(3.06)	18.01	(3.40)		17.39	(2.78)	18.11	(3.27)	***
worked before previous job (=1 if yes)	0.68	(0.47)	0.70	(0.46)		0.77	(0.42)	0.80	(0.40)	
unemployment rate 1 year ago	4.03	(1.09)	3.96	(1.05)		4.02	(1.11)	3.91	(1.05)	*
Survey year										
2007	0.32	(0.47)	0.43	(0.50)	***	0.39	(0.49)	0.44	(0.50)	*
2012	0.47	(0.50)	0.37	(0.48)	***	0.44	(0.50)	0.34	(0.47)	***
2017	0.22	(0.41)	0.20	(0.40)		0.18	(0.38)	0.22	(0.42)	*
N	226		2,629			361		4,596		

Source: Statistics Bureau of Japan *Employment Status Survey* 2007, 2012, and 2017.
Notes: Standard deviations are in parentheses. Results of t-test are reported. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively. "PJT" indicates public-sponsored job training.

Table 3: Estimation Results of the Effects of Public-Sponsored Job Training (PSM estimation)

	Probability of working	Ln (income)	Probability of working as a regular worker
Panel A: Men			
	(1)	(2)	(3)
PJT	0.154***	-0.033	0.032
	(0.034)	(0.051)	(0.043)
N	2,854	1,617	1,617
Panel B: Women			
	(4)	(5)	(6)
PJT	0.174***	0.185***	0.107***
	(0.025)	(0.034)	(0.032)
N	4,957	2,468	2,468

Source: Statistics Bureau of Japan *Employment Status Survey* 2007, 2012, and 2017.
Notes: 1. *** denotes $p<0.01$. Bootstrapped standard errors are in parentheses (repetitions = 100).
2. Both individual characteristics and work history variables are controlled for in all estimations. Individual characteristics include age, marital status, having children, and academic background. Work history includes work style, industry, and occupation of the previous job; the number of months after quitting the previous job; years of tenure in the previous job; and prefectural unemployment rate a year ago. Survey year is also controlled for.
3. The only sample that meets the common support condition is used; therefore, the sample size is the same as or smaller than that in Table 1.
4. "PJT" indicates public-sponsored job training.
5. The cross-validation procedure is used for the choice of the bandwidth. The number of columns and the bandwidth are as follows: (1)–(3) 0.3 respectively, (4) 0.42, (5) 0.21, and (6) 0.6.

Table 4: Results of PSM and OLS

A. Men					B. Women			
	a. Probability of working				a. Probability of working			
	(1) PSM	(2) PSM	(3) OLS	(4) OLS	(1) PSM	(2) PSM	(3) OLS	(4) OLS
PJT	0.154***	0.165***	0.153***	0.166***	0.174***	0.192***	0.178***	0.199***
	(0.034)	(0.025)	(0.033)	(0.033)	(0.025)	(0.024)	(0.027)	(0.027)
Work history	Yes	No	Yes	No	Yes	No	Yes	No
N	2,854	2,854	2,855	2,855	4,957	4,957	4,957	4,957
	b. ln (income)				b. ln (income)			
	(5)	(6)	(7)	(8)	(5)	(6)	(7)	(8)
PJT	-0.033	-0.045	-0.038	-0.040	0.185***	0.209***	0.181***	0.212***
	(0.051)	(0.049)	(0.050)	(0.051)	(0.034)	(0.040)	(0.039)	(0.040)
Work history	Yes	No	Yes	No	Yes	No	Yes	No
N	1,617	1,618	1,618	1,618	2,468	2,468	2,468	2,468
	c. Probability of working as a regular worker				c. Probability of working as a regular worker			
	(9)	(10)	(11)	(12)	(9)	(10)	(11)	(12)
PJT	0.032	0.019	0.031	0.022	0.107***	0.129***	0.110***	0.132***
	(0.043)	(0.039)	(0.040)	(0.041)	(0.032)	(0.034)	(0.027)	(0.028)
Work history	Yes	No	Yes	No	Yes	No	Yes	No
N	1,617	1,618	1,617	1,617	2,468	2,468	2,468	2,468

Source: Statistics Bureau of Japan *Employment Status Survey* 2007, 2012, and 2017.
Notes: 1. *** denotes p<0.01. Bootstrapped standard errors are in parentheses in Columns (1) and (2) in each panel (repetitions = 100), and standard errors are in parentheses in Columns (3) and (4) in each panel. As the only sample which meets the common support condition is used, the sample size is different among Columns (1) – (4).
2. Individual characteristics include age, marital status, having children, and academic background. Work history includes work style, industry, and occupation of the previous job; the number of months after quitting the previous job; years of tenure in the previous job; and prefectural unemployment rate a year ago. All specifications are included individual characteristics and survey year.
3. Columns (1), (5) and (9) in each panel are the same as those in Table 3.
4. "PJT" indicates public-sponsored job training.

Table 5: Results of Robustness Check

A. Men					B. Women			
	a. Probability of working				a. Probability of working			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Local linear matching	One-to-one matching	Five-nearest neighbors matching	Kernel matching	Local linear matching	One-to-one matching	Five-nearest neighbors matching	Kernel matching
PJT	0.154***	0.120***	0.156***	0.166***	0.174***	0.169***	0.163***	0.166***
	(0.034)	(0.056)	(0.038)	(0.028)	(0.025)	(0.040)	(0.027)	(0.029)
N	2,854	2,854	2,854	2,854	4,957	4,957	4,957	4,957
	b. ln (income)				b. ln (income)			
	(5)	(6)	(7)	(8)	(5)	(6)	(7)	(8)
PJT	-0.033	-0.033	-0.061	-0.044	0.185***	0.297***	0.209***	0.241***
	(0.051)	(0.088)	(0.065)	(0.049)	(0.034)	(0.060)	(0.043)	(0.033)
N	1,617	1,617	1,617	1,617	2,468	2,468	2,468	2,468
	c. Probability of working as a regular worker				c. Probability of working as a regular worker			
	(9)	(10)	(11)	(12)	(9)	(10)	(11)	(12)
PJT	0.032	-0.012	0.023	0.022	0.107***	0.130***	0.133***	0.149***
	(0.043)	(0.073)	(0.052)	(0.039)	(0.032)	(0.045)	(0.036)	(0.028)
N	1,617	1,617	1,617	1,617	2,468	2,468	2,468	2,468

Source: Statistics Bureau of Japan *Employment Status Survey* 2007, 2012, and 2017.
Notes: 1. *** denotes p<0.01. Standard errors are in parentheses in Panel A, bootstrapped standard errors are in parentheses in Panel B (repetitions = 100), and the only sample which meets the common support condition is used.
2. Individual characteristics include age, marital status, having children, and academic background. Work history includes work style, industry, and occupation of the previous job; the number of months after quitting the previous job; years of tenure in the previous job; and prefectural unemployment rate a year ago. Survey year is also controlled for.
3. As only samples meeting the common support condition are included in the estimation.
4. Columns (1), (5), and (9) are the same as those in Table 3.
5. "PJT" indicates public-sponsored job training.

Appendix 1: Variables

1. **Individual characteristics**
   age, marital status, having children, and academic background: 1) primary school/middle school; 2) high school/former junior high school; 3) vocational school; 4) junior college/technical college; 5) university; and 6) graduate school.

2. **Work history**

   (a) **Work style in the previous job (Only the employed)**
   1) regular worker; 2) part-time worker; 3) part-time worker in "arubaito"; 4) temporary staff; 5) contract worker; 6) commissioned worker; and 7) others.

   (b) **Industry in the previous job**
   1) agriculture, forestry & fishery; 2) mining; 3) construction; 4) manufacturing; 5) public utilities; 6) communication; 7) transportation; 8) sales; 9) finance/insurance; 10) real estate; 11) food accommodation; 12) medical nursery; 13) education; 14) complex service; 15) misclassifieds service, 16) public service; and 17) unclassified.

   (c) **Occupation in the previous job**
   1) specialist; 2) administrative; 3) clerical; 4) sales; 5) service; 6) security; 7) agricultural; 8) transportation/communication; 9) production/construction; and 10) unclassified.

   (d) **Years of tenure in the previous job**

   (e) **The number of months after quitting the previous job until the year before the survey date**

   (f) **Prefectural unemployment rate the year before**

Appendix 2: Appendix Table

Table A_1: Results of First Stage (Logit Model)

	(1)	(2)	(3)	(4)
	Men	Men	Women	Women
age	-0.004	-0.002	0.009	-0.005
	(0.012)	(0.014)	(0.009)	(0.011)
married (=1 if yes)	0.113	0.173	-0.656***	-0.331**
	(0.202)	(0.231)	(0.123)	(0.153)
child (=1 if yes)	-0.291	-0.619**	0.155	0.219
	(0.251)	(0.279)	(0.169)	(0.205)
Academic background				
high school	-0.450*	-0.557*	0.443	0.142
	(0.250)	(0.316)	(0.377)	(0.449)
technical school	-0.045	0.072	0.618	0.396
	(0.280)	(0.341)	(0.393)	(0.465)
2 year/technical college	0.128	-0.038	0.450	0.295
	(0.466)	(0.569)	(0.410)	(0.488)
university	-0.144	-0.227	0.677*	0.529
	(0.275)	(0.341)	(0.395)	(0.468)
graduate school	-0.399	-0.574	0.184	0.015
	(0.530)	(0.689)	(0.435)	(0.524)
(ref: middle school)				
Employment category in the previous job				
non-regular worker	-0.296	-0.142	-0.609***	-0.183
	(0.226)	(0.285)	(0.153)	(0.180)
temporary staff	0.083	0.37	-0.241	-0.076
	(0.323)	(0.369)	(0.222)	(0.266)
contract worker	0.155	0.081	0.096	0.130
	(0.240)	(0.310)	(0.199)	(0.254)
commissioned worker	0.000	--	-0.051	-0.200
	(1.076)		(0.413)	(0.545)
other	-0.911	-0.427	-0.17	0.319
	(0.732)	(0.769)	(0.373)	(0.472)
(ref: regular worker)				
Industry in the previous job				
mining	3.205*	--	2.336	1.419
	(1.660)		(1.695)	(1.819)
construction	1.297	0.622	-0.175	-1.586
	(1.106)	(1.159)	(0.979)	(1.237)
manufacturing	1.458	0.790	0.329	-0.503
	(1.094)	(1.145)	(0.926)	(1.137)
public utilities	2.901*	--	--	--
	(1.576)			
communication	1.604	0.508	-0.076	-1.158
	(1.141)	(1.237)	(0.960)	(1.187)
transportation	1.234	0.854	-0.297	-1.159
	(1.104)	(1.165)	(0.972)	(1.239)
sales	1.384	1.06	0.129	-0.623
	(1.098)	(1.149)	(0.921)	(1.133)
finance insurance	1.416	0.986	0.099	-0.869
	(1.213)	(1.299)	(0.943)	(1.158)
real estate	0.792	0.666	0.202	-0.560
	(1.313)	(1.364)	(1.038)	(1.266)
food/accommodation	1.319	0.828	0.159	-0.592
	(1.136)	(1.195)	(0.950)	(1.163)
medical/nursery	2.023*	1.409	-0.120	-0.894
	(1.133)	(1.201)	(0.928)	(1.141)
education	1.167	0.728	-0.062	-0.725
	(1.129)	(1.193)	(0.930)	(1.145)
complex service	1.882	1.270	-1.037	-1.399
	(1.198)	(1.294)	(1.149)	(1.357)
misclassified service	1.359	0.549	-0.180	-1.119
	(1.093)	(1.143)	(0.937)	(1.152)
government	0.033	--	0.167	-1.45
	(1.471)		(0.965)	(1.242)
unclassified	2.128*	1.179	0.238	-0.717
	(1.259)	(1.369)	(1.030)	(1.282)
(ref: agriculter/fishery/forestry)				

Table A_1: (Cont.) Results of First Stage (Logit Model)

	(1) Men	(2) Men	(3) Women	(4) Women
Occupation in the previous job				
administrative	-0.101	--	--	--
	(1.079)			
clerical	0.158	-0.143	-0.056	0.03
	(0.305)	(0.369)	(0.163)	(0.193)
sales	0.281	-0.039	-0.453**	-0.567**
	(0.308)	(0.364)	(0.211)	(0.251)
service	0.041	-0.081	-0.327	-0.526*
	(0.375)	(0.436)	(0.257)	(0.301)
security	0.975	1.269	--	--
	(0.655)	(0.797)		
agricultural	-0.095	-0.464	0.276	--
	(0.586)	(0.667)	(0.922)	
transportation/communication	-0.315	-1.139	--	--
	(0.599)	(0.871)		
production/construction	-0.064	-0.127	-0.420**	-0.382
	(0.295)	(0.345)	(0.213)	(0.254)
unclassified	-1.663*	-0.803	-1.237	-0.846
	(0.986)	(1.101)	(0.761)	(0.862)
tenured years of previous job	0.012	0.014	0.026**	0.047***
	(0.013)	(0.016)	(0.012)	(0.014)
months after leaving previous job	-0.023	0.006	-0.072***	-0.040*
	(0.022)	(0.026)	(0.018)	(0.022)
unemployment rate 1 year ago	0.075	-0.004	0.027	-0.024
	(0.084)	(0.101)	(0.065)	(0.080)
(ref: specialist)				
Survey year				
2012	0.482***	0.276	0.487***	0.468**
	(0.182)	(0.216)	(0.163)	(0.196)
2017	0.478**	0.194	0.002	-0.053
	(0.235)	(0.281)	(0.201)	(0.234)
(ref: 2007)				
N	2,855	1,618	4,957	2,468
Pseud R2	0.036	0.035	0.058	0.040
LR chi2	56.82*	36.71	148.78***	66.81***

Source: Statistics Bureau of Japan *Employment Status Survey* 2007, 2012, and 2017.
Notes: Standard errors are in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively.

Table A_2: Work Place of New Job by PJT Participants and Non-participants

	Men					Women				
	Participants		Non-participants			Participants		Non-participants		
Firm size/public sector										
1-49	0.46	(0.50)	0.49	(0.50)		0.38	(0.49)	0.39	(0.49)	
50-99	0.12	(0.33)	0.11	(0.31)		0.14	(0.35)	0.11	(0.31)	*
100-999	0.29	(0.46)	0.24	(0.43)	*	0.22	(0.41)	0.23	(0.42)	
1000-	0.10	(0.30)	0.14	(0.34)		0.19	(0.39)	0.20	(0.40)	
public sector	0.03	(0.17)	0.03	(0.17)		0.08	(0.28)	0.08	(0.27)	
Industry										
agriculture, forestry & fishery	0.02	(0.15)	0.03	(0.17)		0.00	(0.05)	0.01	(0.09)	
mining	0.00	0.00	0.00	0.00		0.00	0.00	0.00	(0.02)	
construction	0.10	(0.30)	0.12	(0.32)		0.03	(0.17)	0.03	(0.17)	
manufacturing	0.27	(0.45)	0.24	(0.42)		0.12	(0.32)	0.13	(0.34)	
public utilities	0.01	(0.11)	0.00	(0.06)	**	0.01	(0.07)	0.00	(0.05)	
information/communication	0.03	(0.18)	0.03	(0.18)		0.03	(0.17)	0.02	(0.15)	
transportation	0.06	(0.23)	0.10	(0.30)	**	0.01	(0.11)	0.03	(0.17)	*
retail/wholesale	0.12	(0.32)	0.15	(0.36)		0.14	(0.35)	0.21	(0.40)	***
finace/insurance	0.01	(0.09)	0.01	(0.11)		0.04	(0.19)	0.04	(0.19)	
real estate	0.01	(0.09)	0.01	(0.12)		0.02	(0.14)	0.01	(0.10)	**
food/accommodation	0.05	(0.22)	0.05	(0.22)		0.03	(0.17)	0.07	(0.26)	***
medical/nursery	0.17	(0.38)	0.05	(0.22)	***	0.25	(0.43)	0.19	(0.39)	***
education	0.02	(0.13)	0.02	(0.14)		0.06	(0.23)	0.05	(0.21)	
complex service	0.00	0.00	0.00	(0.07)		0.01	(0.07)	0.01	(0.09)	
misclassified service	0.11	(0.31)	0.14	(0.35)		0.19	(0.40)	0.14	(0.35)	***
public	0.02	(0.13)	0.01	(0.12)		0.03	(0.17)	0.03	(0.17)	
unclassified	0.01	(0.11)	0.02	(0.15)		0.04	(0.21)	0.03	(0.18)	
Occupation										
specialist	0.10	(0.30)	0.08	(0.27)		0.10	(0.30)	0.11	(0.31)	
administrative	0.01	(0.09)	0.01	(0.08)		0.00	0.00	0.00	(0.04)	
clerical	0.13	(0.33)	0.10	(0.30)		0.51	(0.50)	0.35	(0.48)	***
sales	0.11	(0.31)	0.14	(0.35)		0.08	(0.27)	0.14	(0.35)	***
service	0.18	(0.38)	0.10	(0.30)	***	0.18	(0.38)	0.19	(0.40)	
security	0.00	(0.07)	0.02	(0.12)		0.00	0.00	0.00	(0.03)	
agricultural	0.02	(0.15)	0.03	(0.17)		0.00	0.00	0.01	(0.08)	
transportation/communication	0.06	(0.23)	0.09	(0.29)	*	0.01	(0.07)	0.00	(0.06)	
production/construction	0.38	(0.49)	0.43	(0.50)		0.11	(0.32)	0.18	(0.38)	***
unclassified	0.01	(0.09)	0.02	(0.13)		0.02	(0.13)	0.02	(0.14)	
N	235		3,760			383		4,683		

Source: Statistics Bureau of Japan *Employment Status Survey* 2007, 2012, and 2017.
Notes: Standard deviations are in parentheses. Results of t-test are reported. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively.