Labor-Market Attachment and Training Participation[1]

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Abstract

This paper examines how expected attachment to the labor market and expected tenure at a specific firm affect training participation. The results, based on cross-sectional data from Japan, indicate that expected attachment to the labor market affects participation in both employer- and worker-initiated training, while expected tenure at a specific firm mainly explains participation in employer-initiated training. These two attachment indices explain almost half of the gender gap in training participation. Employers in a less competitive labor market are more likely to offer employer-initiated training to their workers.

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1. Introduction

Job training and skill development play a central role in the formation of job skills and subsequent wage growth (e.g., Kurosawa, 2001; Kawaguchi, 2006). Although the share of women and nonregular employees in the workforce has steadily increased in Japan, their job-training opportunities remain substantially limited when compared to those of male and regular employees (Hara, Kurosawa, and Yamamoto (2009) and Kosugi and Kimura (2009)).

The lower rate of training participation among female and nonregular workers is often attributed to their shorter expected periods of labor-force participation or job tenure with a specific firm. Indeed, theory suggests that these expected lengths are important determinants for the quantity of human-capital investment, because the strength of labor-market attachment and expected job tenure determine the length of time that agents can reap returns to their human-capital investment. In particular, when human capital is firm-specific for technological reasons or labor-market friction, the costs involved in human-capital investment will be paid by firms or shared between firms and employees (Hashimoto 1980, Stevens 1994, Chang and Wang 1996, Acemoglu and Pischke 1998, 1999). Under these circumstances, to secure their investment, firms are likely to invest more in employees whom they expect to stay at the firm for a longer time.

These predictions of human-capital theory are well known, but empirical tests of these predictions are scarce. One notable exception that directly tests these predictions is Royalty (1996), who used panel data from the *National Longitudinal Survey of Youth 1979* (NLSY79) of the United States to estimate job-to-job and job-to-nonemployment turnover probabilities and showed that the estimated probabilities well explain the probability of receiving training. Lowenstein and Spletzer (1997) offered indirect evidence consistent with theoretical predictions. They claimed that both employers and employees have an incentive to delay the timing of formal on-the-job training, because they postpone it until they learn the quality of the current employer-employee match. Once both sides learn that the match is good and expect the relationship to last for a long period, both sides start to invest in human capital. Lowenstein and Spletzer indeed found that on-the-job training tends to take place after a few years of job tenure, even after conditioning on the years of completed job tenure to control for the quality of job match, based on the NLSY79. Brunello and Gambarotto (2007) empirically investigated the relation between labor-market competition and employer-provided training and found that employer-provided training in the United Kingdom occurs less frequently in economically denser areas and argued that poaching and turnover effects of agglomeration discourage employers from providing training.

This paper proposes an alternative test of the theoretical prediction relying on a single cross-sectional data set of the *Employment Status Survey 2007* under a stationarity assumption. We first calculate an "attachment index" for each worker, that is, how long each worker is expected to stay in the labor market until retirement, by adding up the average hours worked until the standard retirement age for each of the worker's attributes. In addition, we similarly calculate each worker's expected "remaining tenure," that is, how many more years each worker is expected to continue to work at the current firm, based on workers' observable characteristics. Greater attachment to the labor market as a whole implies a longer payoff period for investment in general human capital, and this should increase job training initiated by both employers and workers. At the same time, longer remaining tenure implies a longer payoff period for firm-specific human-capital investment, and this should increase employer-initiated training. We then examine to what extent differences in indices in general labor-market attachment and in specific-firm attachment explain differences in the participation rate of employer- and worker-initiated trainings by sex, education, and regular/nonregular employment status. The relation between the expected length of job tenure and employer-initiated job training is predicted to be stronger in labor markets with more significant labor-market friction, because firms can exploit higher rents from human-capital investment. We construct proxy variables for labor-market friction and examine how the relation between expected tenure and employer-initiated training differs by the degree of labor-market friction.

The main findings of our analysis are as follows. First, job-training probabilities for female, less educated, and nonregular workers are smaller than for the respective reference groups when we hold workers' age, size of employer, tenure, industry, and occupation constant. The difference is particularly large for employer-initiated training. In contrast, with regard to worker-initiated training, there is almost no difference by sex, and differences by workers' age and size of employer are also small. Second, whereas the predicted future-employment period overall affects participation in both employer- and worker-initiated trainings, the predicted future employment period at a particular firm mainly affects participation in employer-initiated training. Third, expected labor-market attachment and expected remaining tenure explain more than half of the difference between men and women in the probability of participating in employer-initiated training. In contrast, these proxy variables explain very little of the difference in training probabilities between regular and nonregular workers. These results suggest that a considerable part of the difference in job-training participation between men and women is the result of differences in the length of the payoff period of investment, while differences in job-training participation between regular and nonregular workers arise largely because of the difference in skill requirements between the two groups. Fourth, firms in more competitive local labor markets are less likely to offer employer-initiated training to their workers, presumably in face of higher poaching risk.

The remainder of this study is organized as follows. Section 2 outlines the data and presents the heterogeneous training-participation rate across workers' attributes. Section 3 estimates training-participation equations to describe the determinants of the training participation. Section 4 constructs measures of labor-market attachment and expected length of job tenure by workers' characteristics and examines the extent to which these measures can explain patterns of training participation by workers' characteristics. Section 5 explores the implication of local labor-market friction on training participation. Section 6 provides conclusions.

2. Data and Descriptive Analysis

The source of our data is microdata from the 2007 *Employment Status Survey*, which is a household survey of Japan that records job employer-initiated and worker-initiated training. Distinguishing between whether training was conducted at the employer's initiative or that of the worker himself, it provides a breakdown of such training into the following categories: (a) training at the workplace (this category applies only to employer-provided training); (b) attending college or graduate-school courses; (c) attending courses at a special training school or other vocational school; (d) attending courses at a public occupational skills development facility; (e) attending short courses or seminars; (f) participating in study-group meetings or workshops; (g) taking distance-learning courses; (h) self-learning (this category applies only to self-development), and (i) other. In this study, we refer to training initiated by the employer as "employer-initiated training" and training initiated by the worker as "worker-initiated training."

We limit our sample to employed persons aged 15-59 and exclude those enrolled in education. Moreover, we exclude company executives, the self-employed (with or without employees), family workers, and those doing piecework at home, because their work status is somewhat different in nature from the concept of an "employee" that we focus on here. Furthermore, we exclude observations for individuals when we think there are recording errors.[3] Table 1 reports descriptive statistics of the analysis sample.

Table 2 shows the training-participation rate by workers' attributes for employed persons. The job-training-participation rate for women is about 7 percentage points lower than that for men, and this difference is mainly caused by differences in participation in employer-initiated training. The training-participation rate for nonregular employees is lower than that for regular employees, with the difference being more pronounced for employer-initiated training. Both the employer-initiated training-participation rate and the worker-initiated training-participation rate increase with the level of education. The training-participation rate overall is highest for those in their 20s and early 30s, and then it gradually declines with age. The employer-initiated training-participation rate is highest, at 39.5 percent, for those in their early 20s and then declines, but it remains stable at over 30 percent for those in their 30s to early 50s, reflecting the fact that employed workers continuously receive employer-initiated training. On the other hand, worker-initiated training peaks at around 25 percent for those in their late 20s, then remains stable at around 20 percent for those in their 30s and 40s, and then declines again for those in their 50s.

By industry, the highest participation rate is found in the education and learning-support sector; moreover, employer-initiated training is particularly widespread in finance and insurance, as well as electricity, gas, heat supply, and water, while worker-initiated training is especially common in medical, health care, and welfare, as well as information and communications. By occupation, the overall ratio is high for specialist and technical occupations, as well as administrative and managerial occupations, with employer-initiated training especially widespread in administrative and managerial occupations and worker-initiated training especially common in specialist and technical occupations. By size of employer, the larger the employer, the higher is the training-participation rate. Although this applies to both types of training, the pattern is particularly pronounced for employer-initiated training. The highest participation rates, though, are found for those working at government offices.

Finally, contrary to our expectation that investment in job training would concentrate on those with a shorter tenure, we find that the participation rate increases with workers' job tenure, with a peak of about

[3]For example, cases in which the years of tenure are greater than 45, the age at which the present job was taken up is less than 15, etc.

50 percent for those with a tenure of 25-29 years. This conceivably reflects increased training for career development within firms, such as in management-training programs, as the different patterns for employer-initiated training and worker-initiated training indicate, with the latter being relatively stable at around 20 percent and showing comparatively little variation across tenure groups. Overall, patterns of training-participation rates for the different aggregate categories by sex, age group, education, or employment status confirm once again that training-participation rates of women and nonregular workers are low.

3. Estimation of the training-participation equation

Next, we examine the probability that workers will engage in any employer- or worker-initiated training by the attributes, such as sex, age, education, and employment status, as well as such workplace attributes as industry, occupation, and employer size, affect training probabilities.

Dependent variables of our probit estimation are whether a person received employer-initiated training and whether a person engaged in worker-initiated training. As explanatory variables, we include a female dummy, employment-status dummies, education dummies, and dummies for five-year age brackets, employer size, and tenure. Estimation results are presented in Table 3, with column (2) showing the results when the dummies control for industry (major classification, 16 industries), column (3) showing those when the dummies control for occupation (major classification, 10 occupations), and column (4) showing those when both sets of dummies are included.

Starting by looking at the female dummy, in contrast with Table 2, here we find that the probability of receiving employer-initiated training is actually higher for women, and this difference is statistically significant. For worker-initiated training, the coefficient is even larger and indicates that the probability of this kind of training is 3.5 percentage points higher for women than for men. For employer-initiated training, however, the coefficient becomes negative when the industry and occupation dummies are included. In particular, controlling for industry has a large impact on the coefficient. This indicates that women tend to work in industries where the probability of receiving training is high. In contrast, when it comes to worker-initiated training, there are almost no differences between men and women once industry and occupation are controlled for.

Turning to employment status, we find that the participation probabilities for nonregular workers are lower than those for regular workers, and the difference is larger for employer-initiated training than for worker-initiated training. For example, the probability of receiving employer-initiated training is roughly 20 percentage points lower for part-time and casual workers and dispatched workers than for regular employees. For contract employees, the gap vis-à-vis regular employees is roughly half the size of that of part-time and casual workers.

Next, looking at the role of education, we find that even when we hold other factors constant, the training probabilities of the highly educated are very high, with regard to both employer- and worker-initiated training. This is a phenomenon already well documented in previous research on Japan, the United States, the UK, Germany, and other countries (Kurosawa (2001), Kawaguchi (2006), Altonji and Spletzer (1991), Green (1993), Pischke (2001)). As highlighted by Altonji and Spletzer (1991), this can be interpreted as evidence that those with greater learning abilities acquire more years of education and are more likely to participate in job training. When industry and occupation dummies are included, however, that difference becomes considerably smaller. This means that more highly educated workers are more likely to work in industries and occupations where the training probability is high. Moreover, differences by educational attainment are larger for worker-initiated than employer-initiated training. As for the role of age, although the probability of employer-initiated training decreases with age from the late 20s onward, for worker-initiated training, no significant differences can be observed until the early 40s.

Turning to the role of employer size, the results indicate that the larger the employer, the higher is the probability of training participation. The probability of receiving employer-initiated training is about 30 percentage points higher for workers at firms with more than 1,000 employees or at government offices than for workers at firms with fewer than 10 employees. With regard to worker-initiated training, however, differences by employer size are quite small. Next, looking at tenure, the probability of employer-initiated training increases with tenure and reaches a peak in the neighborhood of 30-39 years. This is a finding that differs from our theoretical expectation and implies that workers receive continuous employer-initiated training as part of a process of career development with length of service. This pattern can also be found in the estimation that includes the occupation dummies and hence a dummy for administrative and managerial occupations suggests that this employer-initiated training for career development continues to takes place across occupations.[4] In contrast, the longer workers' tenure, the less likely they are to engage in worker-initiated training.

[4] Pischke (2001) arrives at a similar finding regarding this kind of continuous training, showing that in Germany training remains high for workers into their 40s.

Summarizing these findings, we can say that among those who are employed, the probabilities of training participation for women, less-educated workers, and nonregular workers are still lower when controlling for age, employer size, tenure, industry, and occupation. The differences are particularly large when it comes to employer-initiated training. For worker-initiated training, however, there is almost no difference between the sexes, while differences by age or size of employer are also small. Taken together, these results suggest that the probability of receiving employer-initiated training is noticeably smaller for women, those at small firms, and nonregular employees, though it seems that women and those employed at small firms compensate for this by pursuing worker-initiated training. In contrast, the difference between the less educated and the better educated is even greater for worker-initiated training than for employer-initiated training.

4. Relations among labor-market attachment, remaining tenure, and job training

4.1 Theoretical framework and empirical methodology

Human-capital models claim that the amount of investment in general human capital at a particular point in time is determined by the marginal rate of return on investment and marginal cost. The marginal rate of return on investment is determined by the length of the payoff period, the future price of human capital, and workers' learning ability. In contrast, marginal cost of investment is determined by the direct cost of investment and the opportunity cost of training, that is, the current wage rate.

When human capital is firm-specific as a result of technological factors or market friction, there is a divergence between workers' outside option (the wage rate in the labor market) and their marginal productivity, because they cannot sell those skills to other firms. Depending on the firm's bargaining power, the firm reaps part of this divergence as rent and the discounted present value of that rent determines the amount of human-capital investment financed by the firm. The discounted present value of that rent depends on workers' remaining employment period and is closely related to the difficulty with which workers can switch jobs (i.e., the degree of market friction), the future value of goods made with firm-specific human capital, and workers' learning ability.

The purpose here is to examine to what extent we can explain differences in training probabilities across workers' attributes found in the preceding section with differences in workers' remaining employment period. Differences in training probabilities between men and women and across workers with different employment statuses are often explained with differences in expected employment periods in the labor market and/or lengths of employment at a specific firm. Royalty (1996), as mentioned above, using the NLSY panel dataset of the United States, examined the effect of turnover probabilities on receiving job training. Specifically, she estimated turnover probabilities, that is, the probability of staying in the current job, job-to-job turnover, and job-to-nonemployment turnover, and then compared the estimated[5] training probabilities when job-turnover probabilities are included and when they are not. Royalty found that the probability of receiving employer-initiated training is higher for men, but when turnover probabilities are included, the difference in the probability between men and women declined by 25 percent.[6] She also showed that the probability of receiving employer-initiated training for the highly educated is no longer significantly higher when turnover probabilities are taken into account.

The approach we take in this study is to examine whether differences in the length of future employment and differences in predicted years of tenure with a specific firm can explain training probabilities. Specifically, we examine whether differences in the length of future employment (expected labor-market attachment) affect the probabilities of both employer- and worker-initiated training. At the same time, we examine the effect of the remaining employment period at the same firm (expected remaining tenure) on the probability mainly of employer-initiated training. In addition, we examine to what extent taking these factors into account changes the gap in training probabilities of female and nonregular workers vis-à-vis their reference groups.

4.1.1 The attachment index (AI)

The more workers are attached to the labor market, the higher is their incentive to participate in training and raise their job skills, holding other variables constant. The degrees of labor-market attachment are presumably different by workers' characteristics such as age, sex, or educational background. To gauge this labor-market attachment, we calculated the total amount of time each worker can be expected to spend in the labor market under the assumption that the worker behaves as the average person within the demographic group to which he/she belongs.

Specifically, the attachment index is calculated as:

[5] Setting those receiving no training as the reference group, she conducted multinomial probit regressions between training conducted by the employer and off-the-job training (vocational training school, business school, courses, etc.).

[6] i.e., the coefficient for the male dummy declined from 0.011 to 0.008.

$$\mathrm{AI(age, sex, education)} = \sum_{\mathrm{t=age}}^{59} \overline{\mathrm{hours}_{\mathrm{t}}}\mathrm{(sex, education)} \Big/ 2000$$

where $\overline{\mathrm{hours}_{\mathrm{t}}}\mathrm{(sex, education)}$ is the average hours worked[7] by workers of t years old, defined by workers' sex and educational backgrounds. The summed hours worked until 59 years old, general retirement age is divided by 2000, which is the typical number of annual hours worked by a full-time worker. This AI index attempts to capture the total strength of labor-market attachment before retirement age; thus the sample now includes those out of the labor force and employed persons who are in education, company executives, the self-employed (with or without employees), family workers, and those doing piecework at home. The sample of 15-59 year olds (sample A) is divided into 442 groups according to their attributes (age, sex, education). Next, we divide the sample of employed persons used in the estimation in Section 3 (sample B) into groups according to the same attributes (age, sex, education) (415 groups). We then apply the AI of a particular group in sample A to each of the same 415 groups in sample B.

This index is an indicator showing how many full-time years a worker of a given sex and with a given education will work in the period that remains from his or her age until age 59. It should be noted that we implicitly assume a stationary economic environment, because we take the average employment patterns in the *Employment Status Survey* for the observations and assume that the cross-sectional observations represent observations of the employment patterns for individuals over time. This is a strong assumption, but it is a standard one made, for example, in estimations of Mincerian wage equations using cross-sectional data.

4.1.2 Remaining tenure (RT)

In the case that a skill acquired through job training is not perfectly valued in the market, firms will have an incentive to invest in workers, because workers will not change their job even if the firm does not offer a wage increase commensurate with the increase in skill, thus allowing the firm to reap the return to investment. Consequently, how long a worker with given attributes is expected to continue working for the present employer is likely to be an important determinant of employer-initiated training. Therefore, as our second measure, we calculate the expected remaining tenure (RT) for each attribute, which gauges how

[7]We apply zero in the case of those not employed.

long a worker with given attributes can be expected to continue working for the present employer.

To calculate the expected remaining tenure period of a worker with certain demographic characteristics, we calculate the following index:

$$\mathrm{RT}(\mathrm{sex}, \mathrm{education}, \mathrm{employment\ status}, \mathrm{industry}, \mathrm{size\ of\ employer}, \mathrm{directly\ hired\ from\ schools})$$
$$= \overline{\overline{\mathrm{tenure}}}(\mathrm{sex}, \quad \mathrm{education}, \quad \mathrm{employment\ status}, \quad \mathrm{industry}, \quad \mathrm{size\ of\ employer}, \quad \mathrm{directly\ hired\ from\ schools}) - \mathrm{tenure}$$

based on the sample of employed persons from Sections 2 and 3 (labeled sample B). There are 6,151 groups according to workers' attributes (sex, education, employment status, industry, size of employer, and directly hired from schools [whether workers entered a firm directly upon graduation]).[8] The variable $\overline{\overline{\mathrm{tenure}}}$ is the median years of job tenure for each demographic group. Because the number of observations may be very small for some groups, we employ the median to avoid any distortion from outliers. We subtract the actual years of tenure from the median value of years of tenure for each group and set this as remaining tenure (RT). If the value thus obtained is negative, we set RT to zero. Moreover, we create a dummy that takes a value of 1 if the value obtained is negative to represent strong attachment to a firm that is unascertainable from workers' observable attributes.

The variable "directly hired from schools" indicates whether the worker took up the current employment right after his/her school graduation. The reason that we distinguish whether workers took up their current employment directly upon graduation is that, in the Japanese labor market, there is a strong tendency for fresh graduate recruits to follow a career path through promotion within the firm, while mid-career recruits represent a much more fluid working force and can be expected to subsequently follow a career through job changes. Here, we mechanically regard as having started their present job as fresh graduate recruits those for whom the age at which they took up the job (current age minus years of tenure) was 15-16 years in the case of junior-high-school graduates; 18-19 years in the case of high-school graduates; 20-21 years in the case of graduates of vocational schools, junior colleges, or technical colleges; and 22-25 in the case of graduates of colleges and graduate schools.

Figure 1 shows the distribution, average, and median for the RT of 30-year-old male regular employees who graduated from college or graduate school, with the upper panel for fresh graduate recruits and the

[8]We do not consider occupation as a workers' attribute because workers' occupation can change with age, such as when they move into administrative and managerial occupations.

lower panel for mid-career recruits. Whereas the RT of graduate recruits is around 12 years, that for mid-career recruits, even though they otherwise have the same attributes in terms of sex, education, and employment status, is strikingly lower at around 2 years. Based on this result, we expect that those recruited upon graduation are in jobs in which they will continue to work for a long time and the probability that they will receive employer-initiated training is consequently high.

4.2 AI, RT, and training probabilities

We now attempt to explain the difference in training-participation probabilities across demographic groups by the difference in the expected length of labor-market attachment or tenure at a specific firm. In particular, we examine whether the lower rate of training participation by female and nonregular workers can be explained by the shorter length of expected length of labor-market attachment or tenure at a specific firm. Table 4 tabulates the means and standard deviation of the Attachment Index (AI) and Remaining Tenure (RT) by demographic characteristics and employment status. Here Table 4 focuses only on statistics of the RT with 0 and over. The figures indicate that female workers tend to have both lower average AI and RT. All types of nonregular workers have a shorter expected length of RT than regular workers.

We start by looking at the effects of AI and RT on the probabilities of training participation by types of trainings. To identify the relations, the following probit models are estimated:

$$\mathrm{Pr}(\mathrm{Training_i} = 1 | \mathrm{AI_i}, \mathrm{RT_i}) = \Phi\left(\beta_0 + \mathrm{AI_i}\beta_1 + \mathrm{RT_i}\beta_2\right),$$

where “$\mathrm{Training}_i$” is a dummy variable indicating whether person i received employer- or worker-initiated training, and AI_i and RT_i are sets of dummy variables that correspond to the years of AI or RT of person i.

Results are presented in Figures 2 and 3, which on the horizontal axis show the values of the dummy variables and on the vertical axis indicate the size of the marginal effect estimated from the probit estimation. As can be seen, for AI, the higher the index (i.e., the greater the predicted future labor-market attachment), the higher is the training probability. There are no great differences in the shapes of the curves for employer- and worker-initiated training. For RT, we also find that the higher the value, the higher is the training probability, but there is a considerable difference in the shapes of the curves for the two types of training. That is, whereas the probability of employer-initiated training displays a steep increase, the probability of worker-initiated moves sideways until 8 years of RT, and after that it rises relatively slowly. This result shows that whereas a greater length of future employment, as represented by

AI, is associated with an increase in job training at the initiative of both workers and firms, a greater length of predicted employment at a specific firm, represented by RT, is associated mainly with an increase in job training at the firms' initiative. These results are consistent with human-capital theory, under the assumption that firms do not fully compensate workers for their skill upgrading induced by training participation because of skill specificity or labor-market friction, and thus firms have an incentive to invest in workers to reap the return to investment.

The preceding results show that the length of the expected payoff period for investment in human capital affects participation in job training. Now, we attempt to quantify how much these two indices can explain the difference in the probability of training participation between male and female workers or between regular and nonregular workers found in Section 3. If short expected-investment payoff periods explain why the job-training probabilities of female and nonregular workers are low, then we would expect that by controlling for the AI and RT variables, the gap vis-à-vis the reference groups should shrink.

Table 5 shows the estimation result for the probabilities of employer- and worker-initiated training using sex, employment status, and education as explanatory variables. Moreover, we also include the industry, employer size, and fresh-graduate-recruit dummies used for constructing groups in the calculation of RT. This is to take into account the possibility that these factors directly affect workers' job-training probability through technological aspects of production activities and worker heterogeneity. The results in columns (1) and (3) do not include AI and RT, while those in columns (2) and (4) do.

Comparing the results for employer-initiated training, we find that in column (1) the difference between men and women is 3.5 percentage points, but by controlling for AI and RT in column (2), the difference shrinks to 1.4 percentage points. That is, more than half of the difference between men and women in the probability of receiving employer-initiated training can be explained by the two factors of how much longer someone will continue to be employed in the labor market (AI) and how much longer he or she will continue to work for the present employer (RT). In contrast, only about one fifth of the low training probability for the less educated can be explained by these factors. This suggests that while the length of the investment-payoff period explains some of the difference in training probabilities by level of educational attainment, a large part of the difference is caused by differences in the returns from job training (that is, differences in learning efficiency) and differences in the discount rate for future earnings. Finally, for nonregular workers, the differences do not diminish even when AI and RT are included.

In sum, our results indicate that differences in labor-market attachment and expected remaining tenure at the present employer affect training probabilities in a way that is consistent with the predictions of human-capital theory. Moreover, the results show that these factors partly explain the low probabilities of training participation for women and the less educated. Concerning the low probability of training participation among nonregular workers, however, other factors are more important. Although we do not clearly know the reasons for the difference in training probabilities between regular and nonregular workers, we speculate that a large part of the difference in training probabilities between regular and nonregular workers is caused by differences in the type of work they do and the resulting skill requirements.

5. Competition in local labor markets and training participation

The analysis in the previous section finds that an index for "remaining tenure" to a specific firm explains participation in employer-initiated training. This relation could emerge when part of the return to training is captured by the firm that offers training opportunities to its workers. A firm can capture a part of the return when participants' outside option does not increase because of firm specificity of the accumulated skill or friction in a local labor market. This section further explores the implication of local labor-market friction on participation to employer-initiated training. Specifically, we first examine whether local labor-market friction, measured by proxy variables, increases the probability of participating in employer-initiated training. Second, we examine whether the relation between "remaining tenure" and participation in employer-initiated training is stronger in a market with a higher degree of local labor-market friction.

The friction of the local labor market is measured by two indexes defined at prefecture level. The first index is the number of employees per square kilometer, defined as $\mathrm{D_1}$. This index captures the ease with which a worker can find another potential employer, as adopted by previous literature (Brunello and Gambarotto (2007) and Brunello and De Paola(2008)). The second index is industry specialization, i.e., a share of the number of workers in a specific industry among all workers in a prefecture. More specifically, the index for a worker in industry k in prefecture j is defined as $\mathrm{D_2} = \frac{\mathrm{E_{kj}}}{\sum_{\mathrm{k}} \mathrm{E_{kj}}}$. This index captures the ease with which a worker can find another employer in the same industry as the current employer. As shown in the previous literature (Neal (1995)), part of the human capital formed on the job, including the one accrued through training participation, could well be industry-specific. If part of human capital is industry-specific, a worker in an industry agglomeration is more likely to find another employer who appreciates her skill. In fear of workers being poached, an employer in an industry agglomeration may offer less employer-initiated training opportunities to its workers. The higher both D_1 and D_2s are, the more competitive the local labor market should be, with a higher probability that a worker will be poached by another firm.

In addition to the degree of local labor-market friction, several other local labor-market conditions may affect the probability of training participation. Workers' higher skill level in a region enhances the efficiency of human-capital accumulation (Moretti (2004)). Part of this efficiency-enhancement effect is capitalized to local land price and local wage (Roback (1982)). If the efficiency enhancement effect is not fully offset by an increase in the opportunity costs of training, however, the higher average skill of regional workers increases the probability of training participation. To capture this local spillover effect of human capital, prefectural-level average years of education or fraction of college-educated workers is included in the specification.

To examine the effects of local labor-market characteristics on the probability of training participation by worker i in prefecture j, the following probit model is estimated:

$$\Pr\left(\text{Training}_{ij} = 1 \middle| z, x_i\right) = \Phi\left(\gamma_0 + \gamma_1 z_{1j} + \gamma_2 z_{2ij} + \gamma_3 z_{3j} + x_i \beta\right),$$

where z_{1j} is the number of workers per 1,000 square kilometer in prefecture j,[9] z_{2ij} is the share of workers in the industry that worker i works for in prefecture j, and z_{3j} is the average years of education or fraction of college-educated workers in prefecture j. Vector x_i includes individual characteristics of worker i that are: female dummy, employment-type dummies, age dummies, industry dummies, occupation dummies, employer size dummies, and dummies for years of job tenure. To capture poaching effects related to industry-specific skill more clearly, we disaggregate "manufacturing" into 7 more specific subcategories[10] in obtaining z_{2ij}.

Table 6 reports the results of regressions. Column 1 indicates that a higher density of workers, measured by the number of workers per 1,000 square kilometer and the fraction of workers in the same industry, suppresses the probability of participating in employer-initiated training. The size of the

9 Area data in each prefecture are obtained from the Population Census in 2005.

10 (a) food, beverage, tobacco and feed; (b) textile, apparel, and leather products; (c) wood products, furniture, pulp, paper products, and printing; (d) chemicals; (e) metals; (f) machinery; and (g) others.

coefficients is unaffected by the inclusion of the regional average of human capital, as reported in Columns 2 and 3. These findings are consistent with the notion that less competition in the local labor market encourages employers to provide training opportunities. Higher local average human capital also increases the probability of participating in employer-initiated training.

In contrast, Table 6 Column 4 shows that the higher density of workers per square kilometer increases the probability of participating in worker-initiated training, while a higher share of workers in the current employer's industry decreases it. Even when including prefecture-level average years of education or a fraction of college graduates, the local density does not significantly suppress the probability of participating in worker-initiated training, but the share of workers in the industry of the current employer decreases it. Less friction in the local labor market, represented by a higher density of workers, does not discourage worker-initiated training, but lower local specialization in the industry of the current employer, meaning a differentiated local labor market, encourages worker-initiated training. These results are sensible if higher possibilities for workers to transit to another industry encourage workers to be more involved in worker-initiated training and to accumulate skills not necessarily specific to the industry in which workers are employed. In addition, the magnitude of local spillover effects of regional education, measured by average years of education or the ratio of college graduates, on worker-initiated training are estimated to be substantially large.

As we find in the preceding section, the higher the AI or RT, the higher is the probability of employer-initiated training. Then we examine how this relation differs by the degree of local labor-market friction. We divide the sample into two areas. The area is defined as dense if the ratio of workers in the same industry each worker faces, $\mathrm{D}_2 = \frac{\mathrm{E}_{\mathrm{kj}}}{\sum_{\mathrm{k}} \mathrm{E}_{\mathrm{kj}}}$, is the median value of the whole sample or more. The area is defined as sparse if otherwise. Figures 4 and 5 compare the relation between AI and RT across dense and sparse areas. Both figures indicate that the probability of training in the sparse area, i.e., the area of a less competitive local labor market, has a steeper slope, implying that the positive relation between AI or RT and employer-initiated training is stronger in areas where the local labor market is supposed to be more frictional. The effects of RT on employer-initiated training are especially different between dense and sparse areas. Overall, results for employer- and worker-initiated training and the difference of the results for two types of training activities do not refute the hypothesis that employers operating in a local labor market with high friction are more likely to offer employer-initiated training to their workers because they can reap part of the return to workers' skill accumulation.

6. Conclusion

Using microdata from the 2007 *Employment Status Survey*, this study empirically examined determinants of workers' participation in employer- and worker-initiated training. By calculating each worker's expected labor-market attachment – that is, how much time that worker will spend in the labor market until retirement – and each worker's remaining tenure – that is, how many years each worker with given attributes will continue to work for his/her present employer – we examined the relation of these variables with training participation. We particularly focused on the low participation probabilities for women, the less educated, and non-regular workers, and examined the extent to which expected labor-market attachment and remaining tenure explain these workers' low training probabilities.

Our main findings were as follows. First, controlling for age, employer size, years of tenure, industry, and occupation, we found that training probabilities for women, the less educated, and non-regular workers were lower than for the relevant reference groups. The differences were particularly large for employer-initiated training. In contrast, for worker-initiated training, there was almost no difference by sex, and the differences by age and by employer size were also small. This pattern could be interpreted as suggesting that women and workers at small firms try to make up for receiving less employer-initiated training by participating in worker-initiated training. Differences between the less educated and the better educated were even greater for worker-initiated training than for employer-initiated training, however. A likely explanation for this is that learning ability and discount rates for future earnings differ across those with different levels of educational attainment. Second, we estimated how training participation depends on workers' attachment to the labor market, represented by the attachment index (AI), and how long a worker can be expected to continue working for his current employer, represented by remaining tenure (RT). The results indicated that the higher the AI (i.e., the greater the predicted future labor-market attachment), the higher are the training probabilities. In addition, there were no substantial differences in the shapes of the curves for employer- and worker-initiated training. We also found that the higher the value of RT, the higher the training is likely to be, but the slope of the curve showing the effect of RT was much greater for employer-initiated training than for worker-initiated training. This shows that whereas greater length of future employment increases job-training participation at the initiative of both workers and employers, differences in the predicted years of employment at a specific firm raise job-training participation mainly at the firm’s initiative. Moreover, these results suggest that there is firm-specificity in the formation of skills through employer-initiated training because of technology-related factors and/or market friction.

Third, women’s lower participation rate in employer-initiated training is largely explained by AI and RT in the estimation. In contrast, for non-regular workers, the negative coefficient remains largely unchanged even when controlling for AI and RT. These results imply that the difference in training participation between men and women is explained by the difference in their future prospects of labor-market attachments, while the difference between regular and non-regular workers is not explained by this factor. Although it is now only a conjecture, a likely reason seems to be that nonregular workers are only assigned tasks that require little training to begin with. More in-depth research on the causes of disparities in job training between regular and nonregular workers is necessary to reach a definitive conclusion.

Fourth, workers in more competitive local labor markets are less likely to participate in employer-initiated training, conceivably because of higher poaching risk. This fact is consistent with the notion that part of human capital formed by firm-initiated training is firm-specific and that firms can reap the return to their human-capital investment. Higher average human capital in a region is found to encourage the workers' participation in both employer-initiated training and especially worker-initiated training. This evidence is consistent with human-capital spillover.

Overall, the results obtained in this paper are consistent with the prediction from the standard human-capital theory that the investment-planning horizon plays a crucial role in investment decisions. Moreover, firms' expectations about whether they can reap the returns to human-capital investment are shown to be a crucial determinant for firm-initiated training. This result is consistent with predictions from a strand of literature on who finances on-the-job training (Hashimoto (1981), Stevens (1994), Chang and Wang (1996) and Acemoglu and Pischke (1999)).

The results obtained in this paper imply that institutional practices that enable women to stay in the labor market or specific firm for longer period, such as work-life balance policy, would at the same time enhance women’s training participation. Government policies that encourage firms to adopt such practices may well contribute to narrowing the gap of human-capital formation between men and women and consequently contribute to narrowing the gender wage gap. In contrast to the clear implication for women, results in this paper do not illustrate the reasons behind the low training-participation rate among nonregular workers. The possible reasons for lower participation may be rigid labor-market institutions that prevent a transition from nonregular to regular jobs. Nonregular workers may conceivably be confined to dead-end jobs without a chance to upgrade their job career, resulting in a lower return to human-capital investment. Shedding more light on the reasons for the lower training-participation rate among nonregular workers is left for future research.

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Table 1: Descriptive statistics of analysis sample, N＝374,468

	Mean	Std. Dev.
Female	0.464	0.499
Regular employees	0.697	0.460
Part-time and casual workers	0.209	0.407
Dispatched workers from temporary labor agencies	0.027	0.162
Contract employees	0.050	0.217
Primary or junior-high school (reference)	0.070	0.255
Senior-high school	0.468	0.499
Vocational school, junior college	0.228	0.419
College, graduate school	0.222	0.416
Age	40.8	11.242
15 to 19	0.010	0.099
20 to 24	0.078	0.269
25 to 29	0.111	0.314
30 to 34	0.130	0.336
35 to 39	0.133	0.339
40 to 44	0.127	0.333
45 to 49	0.133	0.339
50 to 54	0.133	0.340
55 to 59	0.145	0.352
Firm Size：1 to 9 persons	0.138	0.345
10 to 29	0.136	0.343
30 to 99	0.159	0.366
100 to 299	0.136	0.343
300 to 499	0.056	0.230
500 to 999	0.061	0.240
1,000 and over	0.189	0.391
Government	0.118	0.322
Tenure	11.47	10.677
0 to 4 years	0.382	0.486
5 to 9	0.169	0.374
10 to 14	0.120	0.325
15 to19	0.108	0.310
20 to 24	0.069	0.253
25 to 29	0.062	0.241
30 to 34	0.050	0.218
35 to 39	0.033	0.177
40 and over	0.008	0.089
New graduates dummies	0.235	0.424
AI	11.73	8.409
RT	-1.73	8.353
Number of employees per 1,000 square kilometer	0.281	0.466
Industry specialization	0.089	0.054
Average years of education	13.262	0.344
Ratio of college graduates	0.195	0.054

Table 2: Job-training participation by workers' characteristics (%)

	Any job training	Employer-initiated training	Worker-initiated training
Total	41.7	33.6	20.1
Sex			
Male	44.8	37.1	20.2
Female	37.7	29.3	19.9
Employment status			
Regular employees	47.9	40.3	22.5
Part-time and casual workers	22.5	15.1	11.5
Dispatched workers from temporary labor agencies	29.6	16.9	17.9
Contract employees	40.6	29.1	21.7
Education			
Primary or junior high school	17.9	14.9	5.5
Senior high school	32.1	26.8	11.8
Vocational school, junior college	45.4	36.0	23.2
College, graduate school	59.3	47.0	33.9
Age			
Average	38.5	38.7	37.9
15 to 19	36.7	32.0	11.3
20 to 24	48.2	39.5	23.1
25 to 29	47.2	36.7	25.4
30 to 34	43.9	34.2	22.7
35 to 39	41.5	32.7	20.4
40 to 44	41.8	33.9	20.2
45 to 49	42.2	35.0	19.8
50 to 54	38.2	32.0	16.6
55 to 59	32.1	26.9	13.2
Industry			
Agriculture, forestry and fisheries	21.7	13.7	11.8
Mining, construction	35.2	27.8	15.2
Manufacturing	34.4	28.6	13.3
Electricity, gas, heat supply, and water	63.6	55.5	28.3
Information and communications	52.4	38.7	30.9
Transport	28.5	23.9	9.9
Wholesale and retail trade	33.1	26.5	13.9
Finance and insurance	62.9	55.8	27.8
Real estate	44.1	31.2	25.7
Eating and drinking places, accommodations	23.6	15.4	12.4
Medical, health care, and welfare	59.1	49.2	33.2
Education, learning support	69.3	56.6	43.6
Compound services	58.9	54.2	20.5
Services not elsewhere classified	40.3	30.2	20.9
Government not elsewhere classified	58.3	49.7	27.5

(continued)

	Any job training	Employer-initiated training	Worker-initiated training
Occupation			
Specialist and technical workers	66.3	54.2	40.6
Administrative and managerial workers	65.8	60.0	27.6
Clerical workers	42.8	33.1	21.3
Sales workers	41.0	34.3	16.8
Service workers	37.8	29.0	18.8
Security workers	57.8	49.5	25.0
Agriculture, forestry, and fishery workers	24.5	15.8	13.4
Transport and communication workers	25.9	22.2	7.9
Production process and related workers	28.9	23.9	10.2
Size of employer (number of employees)			
1 to 9 persons	25.2	15.3	14.6
10 to 29	29.4	21.3	14.7
30 to 99	33.9	25.9	16.1
100 to 299	40.4	32.9	18.4
300 to 499	44.7	36.7	20.3
500 to 999	47.2	39.7	21.1
1,000 and over	51.1	43.9	22.6
Government	64.3	55.9	34.9
Tenure			
Average	11.5	12.3	10.5
0 to 4 years	38.7	28.6	20.7
5 to 9	39.5	31.9	19.2
10 to 14	41.2	34.4	18.7
15 to19	44.8	38.1	19.8
20 to 24	48.8	42.5	22.0
25 to 29	50.9	45.5	21.9
30 to 34	49.5	44.0	20.6
35 to 39	44.1	39.5	16.0
40 and over	35.1	31.1	10.8

Source: Authors' calculation based on data from the 2007 *Employment Status Survey*, Ministry of Internal Affairs and Communications.

Table 3: Probit analysis of job-training probabilities

	Employer-initiated training				Worker-initiated training			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.024	-0.036	-0.014	-0.037	0.035	0.000	0.000	-0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Part-time and casual workers	-0.193	-0.171	-0.185	-0.168	-0.075	-0.062	-0.064	-0.056
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dispatched workers	-0.199	-0.171	-0.176	-0.163	-0.044	-0.020	-0.018	-0.012
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Contract employees	-0.102	-0.100	-0.096	-0.096	-0.016	-0.017	-0.010	-0.012
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Senior-high school	0.081	0.070	0.064	0.065	0.074	0.067	0.059	0.059
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Vocational school, junior college	0.195	0.133	0.130	0.115	0.199	0.150	0.133	0.124
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
College, graduate school	0.213	0.160	0.135	0.132	0.288	0.242	0.207	0.201
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age: 20 to 24	-0.018	-0.031	-0.018	-0.030	0.023	0.016	0.022	0.016
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age: 25 to 29	-0.067	-0.078	-0.065	-0.077	0.025	0.019	0.025	0.019
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Age: 30 to 34	-0.090	-0.101	-0.087	-0.099	0.025	0.020	0.025	0.020
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Age: 35 to 39	-0.099	-0.113	-0.098	-0.111	0.020	0.013	0.019	0.013
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Age: 40 to 44	-0.092	-0.110	-0.093	-0.109	0.021	0.011	0.019	0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Age: 45 to 49	-0.093	-0.115	-0.092	-0.112	0.012	0.001	0.012	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Age: 50 to 54	-0.117	-0.136	-0.114	-0.133	-0.007	-0.017	-0.004	-0.013
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age: 55 to 59	-0.141	-0.158	-0.138	-0.156	-0.021	-0.030	-0.018	-0.026
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Size: 10 to 29	0.090	0.084	0.085	0.082	-0.003	-0.005	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Size: 30 to 99	0.140	0.136	0.135	0.134	0.002	-0.001	-0.002	-0.001
	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Size: 100 to 299	0.201	0.200	0.195	0.198	0.009	0.008	0.004	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
Size: 300 to 499	0.243	0.244	0.238	0.241	0.023	0.026	0.018	0.023
	(0.004)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Size: 500 to 999	0.258	0.266	0.255	0.262	0.026	0.035	0.022	0.030
	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Size: 1,000 and over	0.300	0.314	0.304	0.309	0.043	0.060	0.046	0.054
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Size: Government	0.362	0.287	0.316	0.278	0.118	0.047	0.065	0.037
	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)

(Continued)

	Employer-initiated training				Worker-initiated training (Self-development)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenure: 5 to 9	0.020	0.022	0.020	0.021	-0.024	-0.023	-0.025	-0.024
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure: 10 to 14	0.029	0.036	0.032	0.035	-0.032	-0.028	-0.031	-0.029
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure: 15 to 19	0.042	0.055	0.042	0.052	-0.028	-0.021	-0.030	-0.025
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure: 20 to 24	0.070	0.081	0.066	0.076	-0.017	-0.011	-0.023	-0.018
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure: 25 to 29	0.093	0.100	0.086	0.094	-0.010	-0.007	-0.019	-0.015
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure: 30 to 34	0.099	0.105	0.089	0.096	-0.005	-0.002	-0.016	-0.012
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure: 35 to 39	0.098	0.108	0.085	0.098	0.002	0.007	-0.010	-0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Tenure: 40 and over	0.084	0.092	0.071	0.083	0.006	0.010	-0.005	-0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)
Industry dummies	No	Yes	No	Yes	No	Yes	No	Yes
Occupation dummies	No	No	Yes	Yes	No	No	Yes	Yes
Observations	374,468	374,468	374,468	374,468	374,468	374,468	374,468	374,468
Pseudo R2	0.109	0.135	0.125	0.140	0.080	0.103	0.104	0.111

Notes: Marginal effects at the means of the independent variables are reported. Standard errors robust to misspecification are reported in parentheses.

Table 4: Means and standard deviation of AI and RT by demographic characteristics

	Attachment index		Remaining tenure 0 and over	
	Mean	Std. Dev.	Mean	Std. Dev.
Male	14.923	9.344	5.101	4.442
Female	8.054	5.125	3.186	3.131
Regular employees	12.744	8.549	5.185	4.283
Part-time and casual workers	8.307	6.928	2.010	1.465
Dispatched workers from temporary labor agencies	13.784	7.789	0.940	0.894
Contract workers	11.387	8.469	1.866	1.982
Primary or junior-high school	7.893	8.096	5.056	5.132
Senior high school	11.109	8.501	4.604	4.157
Vocational school, junior college	12.196	7.856	3.286	3.072
College, graduate school	13.934	8.251	4.089	3.900

Table 5: The Attachment Index (AI), Remaining Tenure (RT), and training probabilities

	Employer-initiated training		Worker-initiated training (Self-development)	
	(1)	(2)	(3)	(4)
Female	-0.035	-0.014	0.001	0.006
	(0.002)	(0.002)	-0.002	(0.002)
Part-time and casual workers	-0.186	-0.185	-0.060	-0.058
	(0.002)	(0.002)	(0.002)	(0.002)
Dispatched workers from temporary labor agencies	-0.174	-0.180	-0.005	-0.007
	(0.004)	(0.004)	(0.004)	(0.004)
Contract employees	-0.108	-0.111	-0.011	-0.011
	(0.003)	(0.003)	(0.003)	(0.003)
Senior-high school	0.074	0.060	0.074	0.068
	(0.004)	(0.004)	(0.003)	(0.003)
Vocational school, junior college	0.141	0.117	0.166	0.154
	(0.004)	(0.004)	(0.004)	(0.005)
College, graduate school	0.154	0.128	0.257	0.245
	(0.004)	(0.004)	(0.005)	(0.005)
AI	No	Yes	No	Yes
RT	No	Yes	No	Yes
Observations	374,468	374,468	374,468	374,468
Pseudo R2	0.133	0.135	0.100	0.103

Note: Marginal effects at the means of the independent variables are reported. Standard errors robust to misspecification are reported in parentheses. Industry, size of employer, and new graduate dummies are also included in each estimation.

Table 6: Probit analysis of job-training probabilities by regional characteristics

	Employer-initiated training			Worker-initiated training		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of employees per 1,000 square kilometer	-0.021	-0.026	-0.025	0.014	-0.002	-0.002
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Industry specialization	-0.139	-0.133	-0.134	-0.122	-0.098	-0.097
	(0.040)	(0.040)	(0.040)	(0.031)	(0.031)	(0.031)
Average years of education		0.009			0.030	
		(0.003)			(0.003)	
Ratio of college graduates			0.045			0.191
			(0.023)			(0.017)
Female	-0.035	-0.035	-0.035	-0.009	-0.009	-0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Part-time and casual workers	-0.167	-0.167	-0.167	-0.057	-0.057	-0.057
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dispatched workers from temporary labor agencies	-0.165	-0.166	-0.166	-0.013	-0.014	-0.014
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Contract employees	-0.097	-0.096	-0.097	-0.012	-0.011	-0.011
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Senior-high school	0.062	0.062	0.062	0.059	0.058	0.059
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Vocational school, junior college	0.114	0.114	0.114	0.123	0.121	0.121
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
College, graduate school	0.134	0.133	0.133	0.198	0.194	0.194
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age: 20 to 24	-0.030	-0.030	-0.030	0.016	0.016	0.016
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age: 25 to 29	-0.076	-0.076	-0.076	0.019	0.019	0.019
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Age: 30 to 34	-0.098	-0.099	-0.099	0.020	0.019	0.019
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Age: 35 to 39	-0.110	-0.110	-0.110	0.012	0.012	0.012
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age: 40 to 44	-0.108	-0.108	-0.108	0.010	0.010	0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age: 45 to 49	-0.112	-0.112	-0.112	0.002	0.002	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age: 50 to 54	-0.132	-0.132	-0.132	-0.013	-0.014	-0.013
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age: 55 to 59	-0.154	-0.154	-0.154	-0.026	-0.027	-0.027
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)

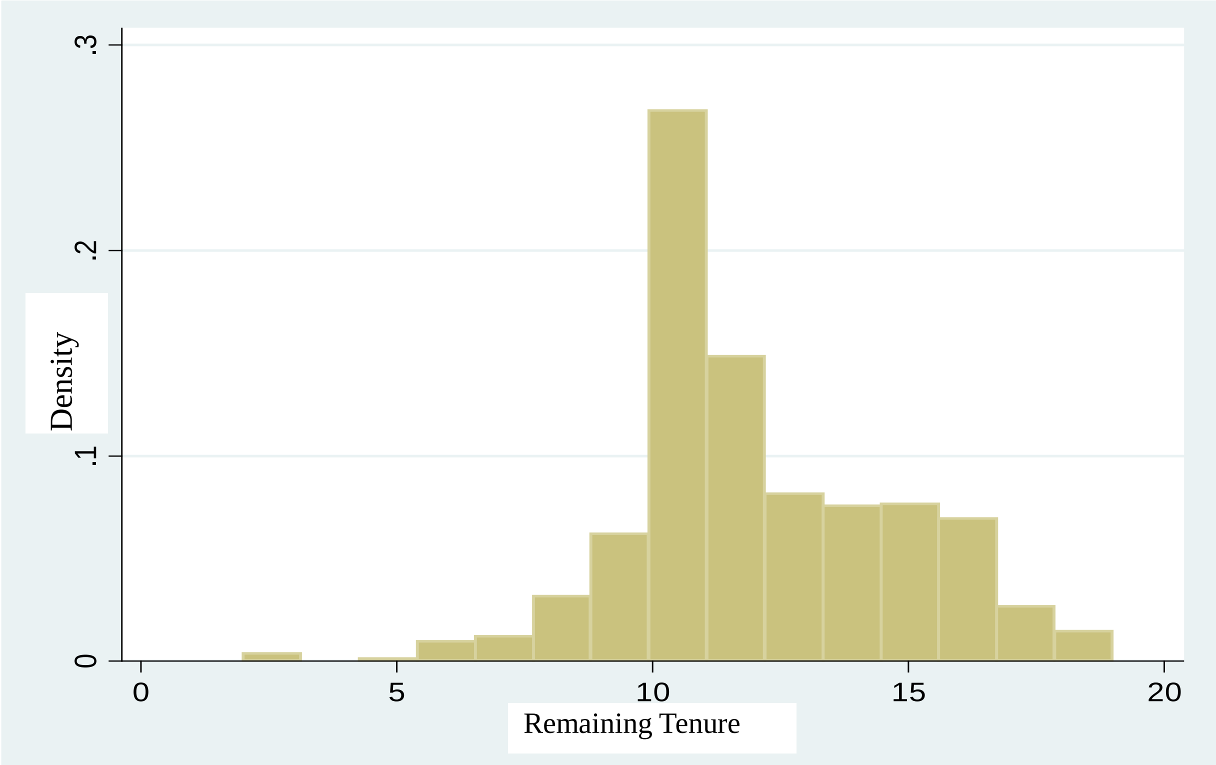
(continued)

	Employer-provided training			Self-development		
	(1)	(2)	(3)	(4)	(5)	(6)
Tenure: 5 to 9	0.021	0.021	0.021	-0.024	-0.024	-0.024
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Tenure: 10 to 14	0.035	0.035	0.035	-0.029	-0.029	-0.029
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Tenure: 15 to 19	0.052	0.052	0.052	-0.025	-0.025	-0.025
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Tenure: 20 to 24	0.075	0.075	0.075	-0.018	-0.018	-0.018
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Tenure: 25 to 29	0.093	0.093	0.093	-0.014	-0.014	-0.014
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Tenure: 30 to 34	0.095	0.095	0.095	-0.012	-0.012	-0.012
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Tenure: 35 to 39	0.096	0.096	0.096	-0.005	-0.006	-0.006
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Tenure: 40 and over	0.081	0.080	0.080	-0.001	-0.002	-0.002
	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)
Industry dummies	yes	yes	yes	yes	yes	yes
Occupation dummies	yes	yes	yes	yes	yes	yes
Size of employer dummies	yes	yes	yes	yes	yes	yes
Observations	374,468	374,468	374,468	374,468	374,468	374,468
Pseudo R2	0.141	0.141	0.141	0.112	0.112	0.112

Notes: See Table 2.

Figure 1. Remaining Tenure: 30-year-old male regular employees who have graduated from college or graduate school

Fresh graduate recruits (median=12.000, mean=12.126)



Mid-career recruits (median=2.000, mean=2.203)

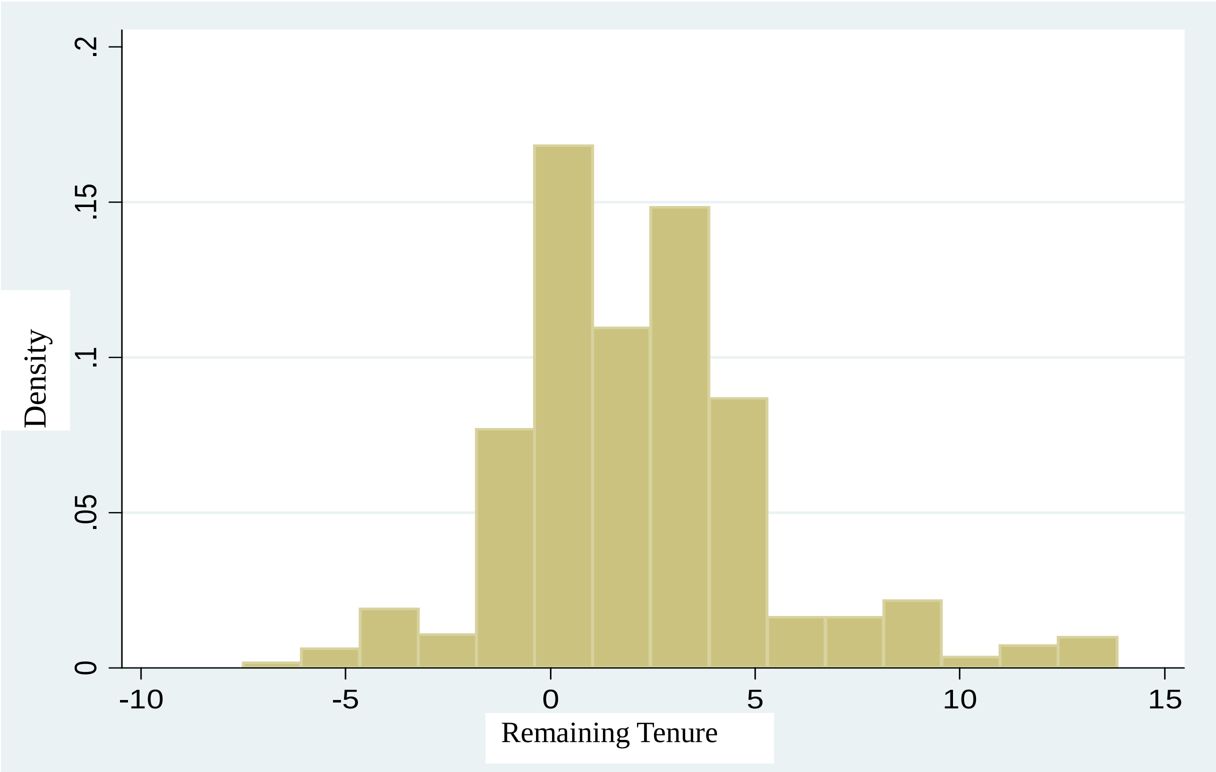
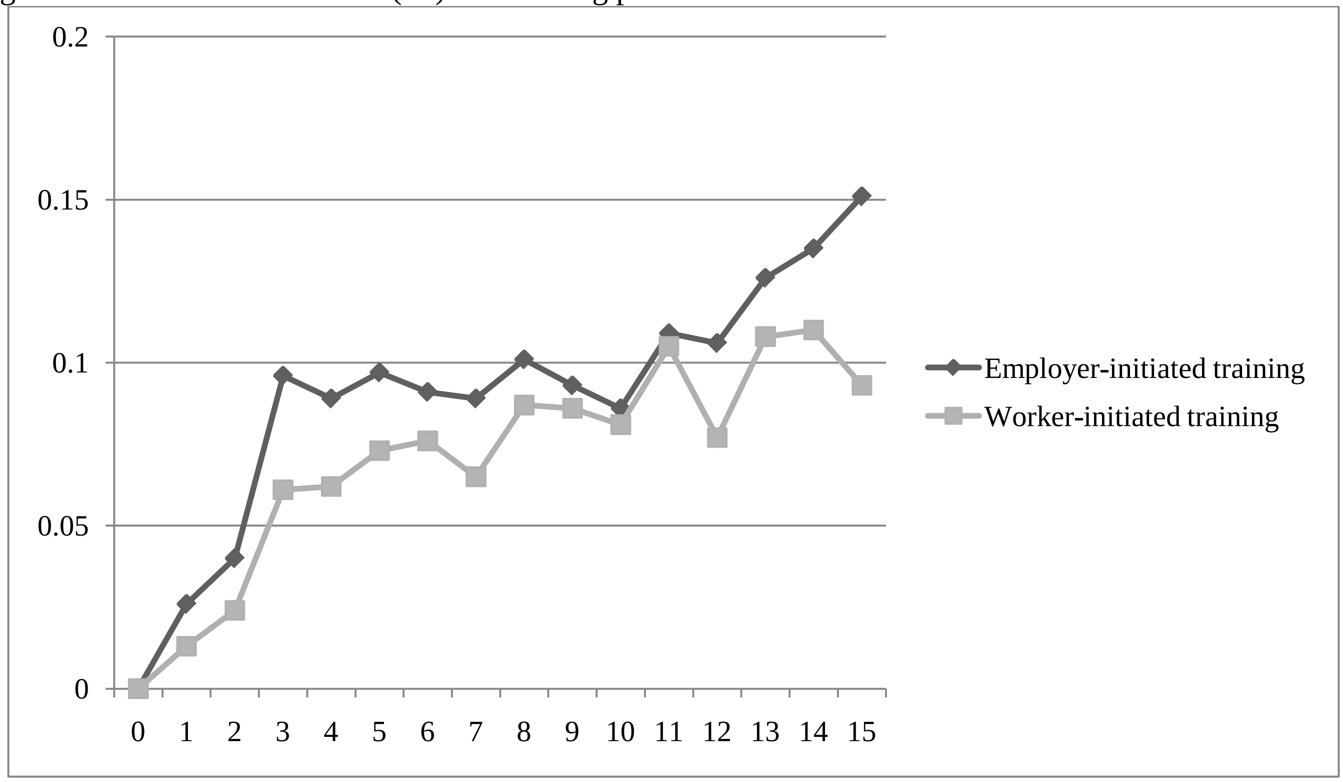
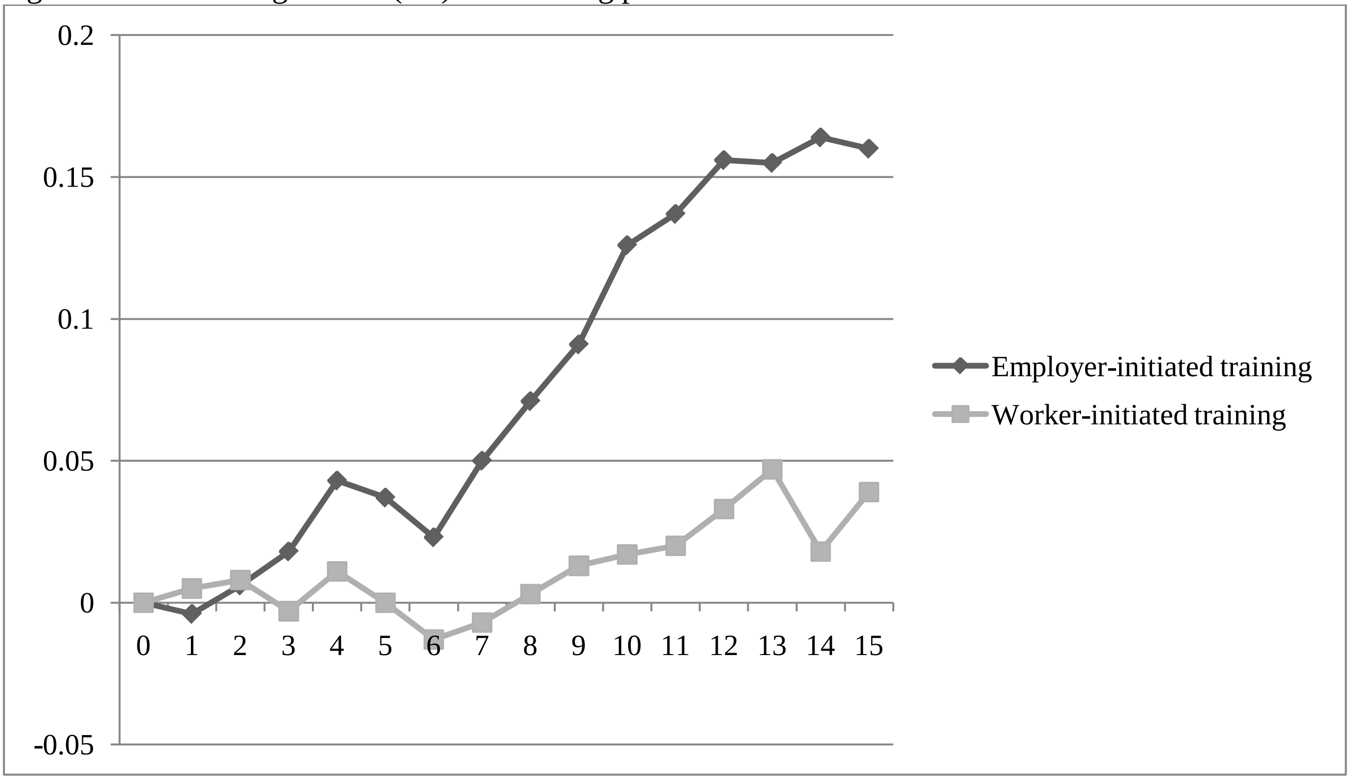


Figure 2: The Attachment Index (AI) and training probabilities



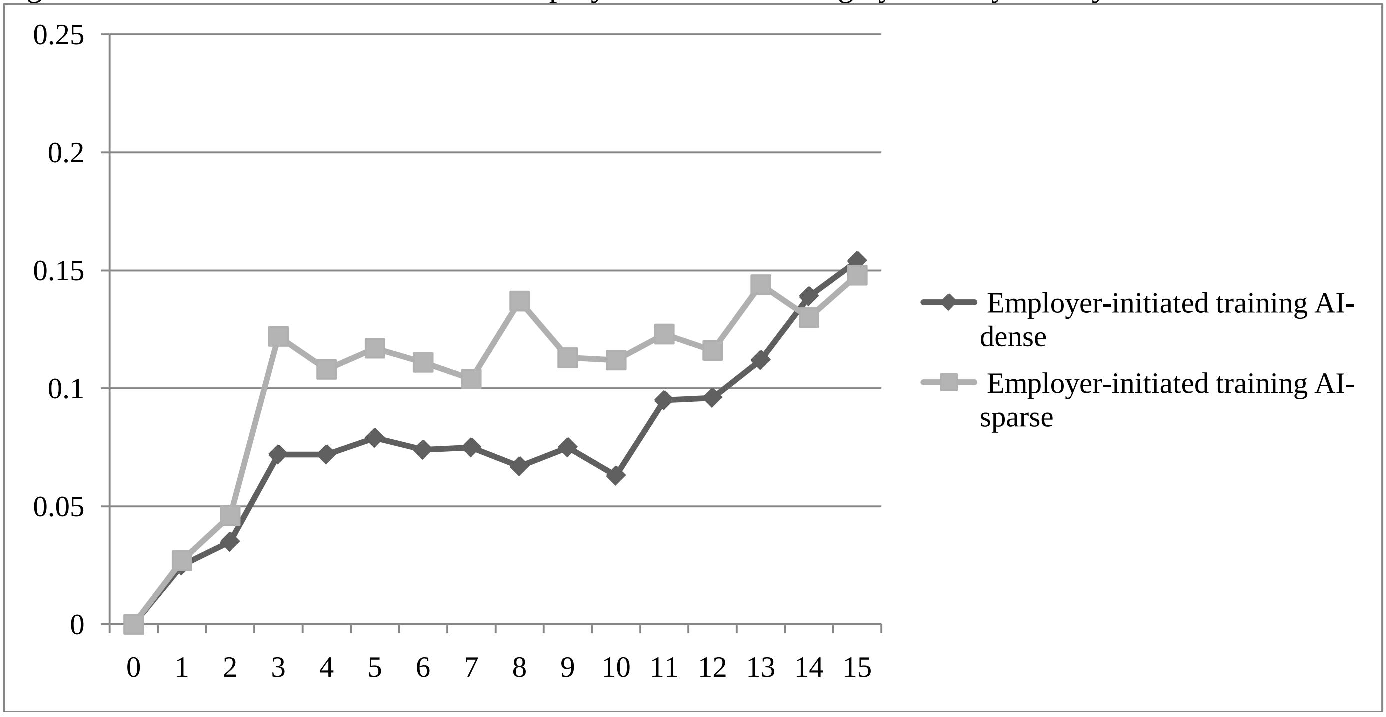
Note: Probit regression coefficients on dummy variables $\mathrm{AI_i}$ in $\Pr(\mathrm{Training_i} = 1|\mathrm{AI_i}, \mathrm{RT_i}) = \Phi(\beta_0 + \mathrm{AI_i}\beta_1 + \mathrm{RT_i}\beta_2)$ are reported on the vertical axis. Marginal effects at the means of independent variables are reported. All coefficients are statistically different from zero.

Figure 3. Remaining Tenure (RT) and training probabilities



Note: Probit regression coefficients on dummy variables RT_i in $\Pr(\text{Training}_i = 1 | AI_i, RT_i) = \Phi(\beta_0 + AI_i\beta_1 + RT_i\beta_2)$ are reported on the vertical axis. Marginal effects at the means of independent variables are reported. The coefficients for "Employment-initiated training" are significant for RT values from 3 and up. The coefficients for "Worker-initiated training" are significant for RT values of 1, 2, 4, 6, and 9 and up.

Figure 4: Labor-market attachment and employer-initiated training by industry density



Note: See Figure 2. All coefficients are statistically different from zero.

Figure 5: Remaining tenure and employer-initiated training by industry density

Note: See Figure 3. The coefficients for “RT-dense” are statistically different from zero for RT values of 2, 4, 5, and 8 and up. The coefficients for “RT-sparse” are significant for RT values from 2 and up.