Labor-Market Attachment and Training Participation[1]

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Toshie Ikenaga and Daiji Kawaguchi[2]

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 more than two thirds of the gender gap in training participation. Employers in less-competitive labor markets are more likely to offer employer-initiated training to their workers.

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[2] Ikenaga: Cabinet Office, Government of Japan; Kawaguchi: Faculty of Economics, Hitotsubashi University, Research Institute of Economy, Trade and Industry, Tokyo Center for Economic Research and IZA. Tel: +81-42-580-8851, Fax: +81-42-580-8851, Email: kawaguch@econ.hit-u.ac.jp (corresponding author).

1. Introduction

Job training and skill development play a central role in the formation of job skills and subsequent wage growth (e.g., Lynch (1992), 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 because of labor-market friction, the costs involved in human-capital investment is paid by firms or shared between firms and employees (Hashimoto (1981), 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 (1997) 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-section of data from the *Employment Status Survey 2007* under a stationary 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 working 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 rates 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, 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. Second, expected labor-market attachment explains more than two thirds 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 their future prospects for labor-market attachment, while differences in job-training participation between regular and nonregular workers arise largely because of the difference in skill requirements between the two groups. Third, firms in more competitive local labor markets are less likely to offer employer-initiated training to their workers, presumably in the face of higher poaching risk.

It should be noted as a caveat that we cannot fully identify the causal effect of the length of planning period on human-capital-investment behaviors because of the usage of a single cross-section data for the analysis. The length of planning period is inferred partly based on exogenous factors, such as sex, but partly based on endogenous factors, such as educational attainment. Since how long an individual receives education is a matter of individual choice, more able individuals may well invest more in human capital through both schooling and training participation. More generally speaking, individuals with higher potential earning capacities arguably plan to stay in the labor market longer and participate in training activities more vigorously. Accordingly, the estimated effect of the planning period on training participation in this paper is likely to be the upper bound of the true causal effect. Having stated this limitation, our contribution to the literature is not offering clean estimates of the causal effect, but articulating the importance of the planning horizon to establish a link between workers' characteristics and training participation.

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 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 4 explores the implications of local labor-market friction on training participation. Section 5 provides conclusions.

2. Data and Descriptive Analysis

The source of our microdata is the 2007 *Employment Status Survey*, which is a household survey of Japan that records employer-initiated and worker-initiated training.[3] Distinguishing between whether training was conducted at the employer's initiative or that of the worker himself, the survey 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.[4] Table 1 reports descriptive statistics of the analysis sample.

In this analysis sample, we reconfirm the findings of previous works on the correlation between

[3] Employer-initiated training refers to the case in which employers offer training opportunities and usually fund training costs. Worker-initiated training refers to the case in which workers participate in training independently.

[4] 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.

workers' characteristics and training participation (Altonji and Spletzer (1991), Green (1993), Pischke (2001), Kurosawa (2001), Kawaguchi (2006), Hara, Kurosawa, and Yamamoto (2009) and Kosugi and Kimura (2009)). Male, regular, younger, educated workers are more likely to participate in employer-initiated training than female, nonregular, older, less-educated workers. Workers in larger firms are more likely to participate in employer-initiated training. The difference in the probability of participating in worker-initiated training by workers' characteristics is not as stark as the case for employer-initiated training. A rather surprising finding is that the participation rate increases with workers' job tenure, with a peak of about 50 percent for those with a tenure of 25-29 years, according to the simple tabulation results. The differences of training participation probability by workers' characteristics are preserved in multivariate frameworks. It is particularly notable that, in the multiple regression analysis, the probability of participating in employer-initiated training increases in an almost linear fashion until 40 years of job tenure. These findings are consistent with the notion of "continuous skill upgrading" in Japanese workplaces (Hashimoto and Raisian (1985) and Hart and Kawasaki (1999)). For the sake of reference, Appendix Table 1 tabulates training participation probability by workers' characteristics, and Appendix Table 2 tabulates Probit regression results.

3. Relations among Labor-Market Attachment, Remaining Tenure, and Job Training

3.1 Measurements of Planning Period

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. A key determinant of the marginal rate of return on investment is the length of the payoff period. In addition, when human capital is firm-specific, the firm reaps part of the gap between workers' marginal productivity and their market wage 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 crucially depends on workers' remaining employment period.

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.

3.1.1 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. The degrees of labor-market attachment presumably differ by workers' characteristics, such as age, sex, or educational background. To gauge this labor-market attachment, we calculate 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:

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

where $\overline{\mathrm{hours}_{\mathrm{t}}}(\mathrm{sex}, \mathrm{education})$ is the average hours worked[5] by workers of t years old, defined by workers' sex and educational backgrounds. The summed hours worked until 59 years old, the general retirement age, is divided by 2,000, 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

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

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.

3.1.2 Remaining tenure (RT)

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. As our second measure, we calculate the expected remaining tenure (RT) for each attribute, which gauges how 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:

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

based on the sample of employed persons from sample B in the previous subsection. 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]).[6] The variable $\overline{\overline{\text{tenure}}}$ 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 distortion from outliers.

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

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. 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 work 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 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 hold jobs that they will continue to work for a long time, and the probability that they will receive employer-initiated training is consequently high.

We should note a caveat about the RT measure here. A preferable measure as a determinant of firm-initiated training participation would be the expected length of completed tenure. Because of a lack of an appropriate longitudinal data set that includes information about completed tenure, we use an available single cross-section of data and construct the RT measure from the distribution of uncompleted tenure. The distributions of uncompleted tenure and completed tenure are generally different. From an age-specific distribution of uncompleted tenure of a single birth-year cohort based on repeated cross-section data, however, the distribution of completed tenure for the birth-year cohort can be recovered. In addition, under an assumption that job-quit behaviour does not differ across birth cohorts, the age-specific distribution of uncompleted tenure is obtained from a single cross-section of data (Hall (1982)). In sum, the expected length of completed tenure is a monotonic increasing function of the RT measure in a stationary environment. Instead of imposing the exact shape of the function that transforms RT to the expected length of completed tenure, we start our examination of the relation between RT and firm-initiated training participation in a non-parametric way without assuming a specific functional form.

3.2 AI, RT, and Training Participations

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 2 tabulates the means and standard deviations of the Attachment Index (AI) and Remaining Tenure (RT) by demographic characteristics and employment status. Here Table 2 focuses only on the statistics of RT with 0 and over. The figures indicate that female workers tend to have a lower average of both 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:

$$\Pr\left(\mathrm{Training}_i = 1 \middle| \mathbf{AI_{i,}}, \mathbf{RT_i}\right) = \Phi\left(\beta_0 + \mathbf{AI_i}\boldsymbol{\beta_1} + \mathbf{RT_i}\boldsymbol{\beta_2} + \mathrm{NegativeRT_i}\beta_3\right),$$

where "$\mathrm{Training}_i$" is a dummy variable indicating whether person i received employer- or worker-initiated training, and $\mathbf{AI_i}$ and $\mathbf{RT_i}$ are sets of dummy variables that correspond to the years of AI or RT of person i. The dummy variable $\mathrm{NegativeRT_i}$ takes one if RT is negative for 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.

We now attempt to further decompose the contents of employer-initiated training. Among the forms of employer-initiated training are those that take place at the workplace, in college/graduate schools, or in training/vocational schools. Training that takes place in workplaces presumably endows human capital that is specific to those particular environments, whereas training that takes place in schools endows human capital that is general across workplaces. Therefore, even among the forms of employer-initiated training participation, the Attachment Index or Remaining Tenure presumably predicts training participation at workplaces better. For the sake of a parsimonious estimation, the indicators of training participation are regressed on linear terms of AI, RT, and an indicator for negative RT. The results of the estimations are reported in Table 3. Column (1) reports the regression results of all employer-initiated training on linear terms of AI and RT. In parallel with Figures 2 and 3, both stronger labor-market attachment and longer expected remaining tenure are associated with a higher probability of employer-initiated training participation. The positive coefficient for the indicator for negative RT needs some explanation. The negative value of RT implies that those workers whose current tenure is longer than the predicted tenure have a particularly strong attachment with the current employer based on unobserved reasons. Thus, the finding that those workers are more likely to participate in employer-initiated training is not particularly surprising.

Decomposing the contents of employer-initiated training by the venues of trainings, the training participation that takes place at workplaces is more strongly associated with AI or RT than the training partition that takes place at schools, as the results reported in Columns (2) to (4) in Table 3 indicate. These results imply that firms choose who will participate in workplace training carefully, based on the workers' expected attachment to the labor market or the current employer. For school-based trainings, other factors, such as general learning ability, are more significant factors for selection than the expected planning period. For the sake of completeness, the results for worker-initiated training are reported in Column (5). We reconfirm that the Attachment Index explains participation in worker-initiated training but Remaining Tenure does not explain it.

3.3 How Much Does the Difference in Planning Period Explain the Difference in Training Participation?

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 2. 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 4 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.

The estimated coefficient of AI is positive and statistically significant as expected, but the coefficient for RT is negative and statistically significant. This negative sign for RT is obtained by the fact that RT does not vary much within a group after conditioning on sex, employment status, education, industry, size of employer, and whether the worker was directly hired from school; the remaining variation is highly collinear with AI. This result implies that separately identifying the effects of AI and RT, conditioning on sex, employment status, education, industry, size of employer, and whether the worker was directly hired from school, is difficult. Our purpose here, however, is not to identify the separate effects of AI and RT, but rather to examine the change of coefficients for sex, employment status, and education dummy variables after controlling for differences in the planning horizon. Therefore, we rely on Column (2) of Table 4 for the following discussion.

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 the linear effect of AI and RT in Column (2), the difference shrinks to 1.0 percentage point and becomes statistically insignificant. That is, more than two thirds 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).[7] In contrast, for nonregular workers, the differences do not diminish even when AI and RT are included, as reported in Column (2). This implies that the nonregular workers choose not to participate in employer-initiated training not simply because their

7 When we include AI and RT separately, significant effects are found only for AI.

expected planning period is short; rather, the different skill requirements for nonregular jobs as compared with regular jobs seems to explain the difference. Finally, 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.

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 explain the low probabilities of training participation for women and the less educated. In contrast, the low probability of training participation among nonregular workers cannot be explained by differences in labor-market attachment or expected length of job tenure. The gap between regular and non-regular workers is not caused simply by the difference of labor-market or specific-firm attachments; rather, it is based on the different skill requirements and consequent careers designed for each type of workers. This result is consistent with Kambayashi's (2010) finding that the classification of workers as "nonregular" at workplaces is more important than the length of contract period as a determinant of training participation by dividing the workers' careers. The distinction of career perspective with the current employer is particularly important in workplaces in Japan, where workers' commitment is an important input for productivity improvement, as reported by Bae et al. (2011).

The determinants for participation in worker-initiated training are reported in Columns (3) and (4) in Table 4. The result in Column (4) implies that male and female workers are equally likely to be involved in worker-initiated training, whereas part-time workers are less likely to become involved in it. Moreover, more educated workers are more likely to be involved in training activities on their own initiative. Inclusion of the Attachment Index (AI) and Remaining Tenure (RT) increases the coefficient for the female dummy variable, as reported in Column (4). This implies that, holding labor-market attachment constant, female workers are 1.0 percentage point more likely to participate in training on their own initiative. This coefficient is identical to the coefficient reported in Column (2). Therefore, holding labor-market attachment constant, female workers are 1.0 percentage point less likely to participate in training initiated by employers, but they are 1.0 percentage point more likely to participate in training on their own initiative. This result can be arguably interpreted as evidence that female workers compensate for their limited training opportunities offered by employers by participating in training programs on their own initiative. In contrast, the coefficients for employment status or educational background dummy variables are virtually unchanged from Column (3). These results again support our conjecture that the skill requirements for regular and nonregular workers are different. Also, learning ability differs across workers by their educational backgrounds.

4. Competition in Local Labor Markets and Training Participation

The analysis in the previous section finds that an index for "remaining tenure" in 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 in 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 markets with a higher degree of local labor-market friction.

Local labor-market friction is measured by two indexes defined at the prefecture level. The first index is the number of employees per square kilometer, defined as z_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 $z_2 = \frac{E_{kj}}{\sum_k E_{kj}}$. 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, part of the human capital formed on the job, including the one accrued through training participation, could well be industry-specific (Neal (1995)). 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 fewer employer-initiated training opportunities to its workers. The higher both z_1 and z_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:

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

where z_{1j} is the number of workers per 1,000 square kilometer in prefecture j,[8] 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

[8] Area data in each prefecture are obtained from the Population Census in 2005.

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[9] in obtaining z_{2ij}.

Before introducing the estimation results, we discuss possible biases of the estimator. In establishing the relationship between local economic characteristics and individual labor-market outcomes, previous studies paid careful attention to the endogeneity of workers' location choice (e.g., Rauch (1993) and Glaeser and Meré (2001)). This possible endogeneity arises mainly because of workers' omitted ability. In these studies, researchers argue that local economic density is likely to be positively correlated with workers' unobserved high ability because local knowledge and individual skill are likely to be complements in the production process. Glaeser and Meré (2001) indeed find evidence that workers with higher unobserved ability tend to reside in metropolitan areas by allowing for individual fixed effects using workers' panel data (*NLSY79* and *Panel Study of Income Dynamics*). In absence of panel data of individual workers, the estimation in this paper cannot be free from endogeneity bias. Since high-ability workers are likely to live in urban areas and vigorously participate in training activities, the estimates for γ_1 presented here are likely to suffer from upward bias.

Table 5 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 coefficients is unaffected by 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. Considering the possible upward bias for γ_1 as discussed above, the negative coefficients estimated here are striking. Higher local average human capital

[9] (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.

is positively associated with the higher probability of participating in employer-initiated training, but any causal inference from this estimation result is hampered by possible endogeneity bias in the regional human capital variable, z_{2ij}.

In contrast, Table 5 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 the fraction of college graduates, 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 current employer's industry, meaning a differentiated local labor market, encourages worker-initiated training. These results are sensible if higher possibilities for workers to move 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.

We acknowledge the endogeneity of proxy variables for local economic activity, z_{1j}, but mere estimation bias does not explain the difference in the estimation results for employer-initiated training and worker-initiated training. The higher the density of population, the lower the probability of participation in employer-initiated training, but no systematic relationship is found between population density and participation in worker-initiated training.

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, $z_2 = \frac{E_{kj}}{\sum_k E_{kj}}$, 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 stronger in sparse areas than in dense areas.

Overall, results for employer- and worker-initiated training and the difference in results for the 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 without the fear of their workers being poached.

5. 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, 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 with 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.

Second, women's lower participation rate in employer-initiated training is largely explained by AI in the estimation. In contrast, for non-regular workers, the negative coefficient remains largely unchanged, even when controlling for AI. 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 attachment, while the difference between regular and non-regular workers is not explained by this factor. This suggests that the difference in careers designed for regular and nonregular workers is not based simply on expected attachments to the labor market or a specific firm.

Third, 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, originating from market friction, and that firms can reap the return to their human-capital investment. Higher average human capital in a region is found to be positively correlated with the workers' active participation in both employer-initiated training and especially worker-initiated training.

Overall, the results obtained in this paper are consistent with the prediction of 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 (1998, 1999)).

The results obtained in this paper imply that institutional practices that enable women to stay in the labor market or a specific firm for longer periods, such as work-life balance policies, 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 careers, 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, Employed Workers 15-59, N＝374,468

	Mean	Std. Dev.
Female (%)	46.4	-
Regular employees (%)	69.7	-
Part-time and casual workers (%)	20.9	-
Dispatched workers from temporary labor agencies (%)	2.7	-
Contract employees (%)	5.0	-
Primary or junior-high school (reference) (%)	7.0	-
Senior-high school (%)	46.8	-
Vocational school, junior college(%)	22.8	-
College, graduate school (%)	22.2	-
Age	40.8	11.2
15 to 19 (%)	1.0	-
20 to 24 (%)	7.8	-
25 to 29 (%)	11.1	-
30 to 34 (%)	13.0	-
35 to 39 (%)	13.3	-
40 to 44 (%)	12.7	-
45 to 49 (%)	13.3	-
50 to 54 (%)	13.3	-
55 to 59 (%)	14.5	-
Firm Size：1 to 9 persons (%)	13.8	-
10 to 29 (%)	13.6	-
30 to 99 (%)	15.9	-
100 to 299 (%)	13.6	-
300 to 499 (%)	5.6	-
500 to 999 (%)	6.1	-
1,000 and over (%)	18.9	-
Government (%)	11.8	-
Tenure	11.5	10.7
0 to 4 years (%)	38.2	-
5 to 9 (%)	16.9	-
10 to 14 (%)	12.0	-
15 to19 (%)	10.8	-
20 to 24 (%)	6.9	-
25 to 29 (%)	6.2	-
30 to 34 (%)	5.0	-
35 to 39 (%)	3.3	-
40 and over (%)	0.8	-
New graduates dummies (%)	23.5	-
Attachment Index (AI)	11.7	8.4
Remaining Tenure (RT) | RT ≥ 0	2.2	3.6
Dummy for RT < 0 (%)	48.12	-
Number of employees per 1,000 square kilometer	0.28	0.47
Industry specialization	0.09	0.05
Average years of education	13.26	0.34
Fraction of college graduates (%)	19.5	-

Table 2: Means and Standard Deviations of AI and RT by Demographic Characteristics, Employed Workers 15-59

	Attachment Index (AI)		Remaining Tenure 0 and Over (RT)	
	Mean	Std. Dev.	Mean	Std. Dev.
Male	14.9	9.3	5.1	4.4
Female	8.1	5.1	3.2	3.1
Regular employees	12.7	8.5	5.2	4.3
Part-time and casual workers	8.3	6.9	2.0	1.5
Dispatched workers from temporary labor agencies	13.8	7.8	0.9	0.9
Contract workers	11.4	8.5	1.9	2.0
Primary or junior-high school	7.9	8.1	5.1	5.1
Senior high school	11.1	8.5	4.6	4.2
Vocational school, junior college	12.2	7.9	3.3	3.1
College, graduate school	13.9	8.3	4.1	3.9

Table 3: Determinants of Training Participation, Probit Estimation, Employed Workers 15-59

	(1)	(2)	(3)	(4)	(5)
Initiative	Employer-initiated Training				Worker-initiated Training
Place	All	Workplace	College or Grad. School	Training or Vocational School	All
Attachment Index / 10	0.044	0.030	0.001	0.002	0.022
	(0.007)	(0.007)	(0.000)	(0.000)	(0.005)
Remaining Tenure / 10	0.086	0.085	0.001	-0.001	0.006
	(0.014)	(0.013)	(0.001)	(0.000)	(0.011)
Remaining Tenure < 0	0.068	0.057	0.000	-0.002	-0.008
	(0.005)	(0.005)	(0.000)	(0.000)	(0.004)
Pseudo R2	0.007	0.006	0.010	0.026	0.004

Note: Number of observations is 374,468 for all estimations. Marginal effects at the means of the independent variables are reported. Standard errors robust to clustering of error terms within groups, defined by sex×education×employment status×industry×size of employer×directly hired from school, are reported in parentheses. Constants are included in all specifications, but the coefficients are not reported.

Table 4: Determinants of Employer-Initiated Training Participation, Probit Estimations, Employed Workers 15-59

	(1)	(2)	(3)	(4)
Initiative	Employer-initiated Training		Worker-initiated Training	
Female	-0.035	-0.010	0.001	0.010
	(0.002)	(0.007)	(0.003)	(0.003)
Part-time and casual workers	-0.186	-0.185	-0.060	-0.058
	(0.002)	(0.006)	(0.004)	(0.004)
Dispatched workers	-0.174	-0.181	-0.005	-0.007
	(0.004)	(0.006)	(0.006)	(0.006)
Contract employees	-0.108	-0.110	-0.011	-0.011
	(0.003)	(0.006)	(0.005)	(0.005)
Senior-high school	0.074	0.057	0.074	0.069
	(0.004)	(0.006)	(0.005)	(0.005)
Vocational school, junior college	0.141	0.112	0.166	0.156
	(0.004)	(0.008)	(0.006)	(0.007)
College, graduate school	0.154	0.125	0.257	0.247
	(0.004)	(0.008)	(0.008)	(0.008)
Attachment Index / 10	-	0.036	-	0.013
		(0.002)		(0.002)
Remaining Tenure / 10	-	-0.020	-	0.004
		(0.006)		(0.004)
Remaining Tenure < 0	-	0.019	-	-0.016
		(0.003)		(0.002)
Pseudo R2	0.133	0.135	0.100	0.102

Note: Number of observations is 374,468 for all estimations. Marginal effects at the means of the independent variables are reported. Standard errors robust to clustering of error terms within groups, defined by sex×education×employment status×industry×size of employer×directly hired from school, are reported in parentheses. Industry, size of employer, and new graduate dummies are also included in estimations in Columns (3) to (5)

Table 5: Probit Analysis of Job-Training Probabilities by Regional Characteristics, Probit Estimations, Employed Workers 15-59

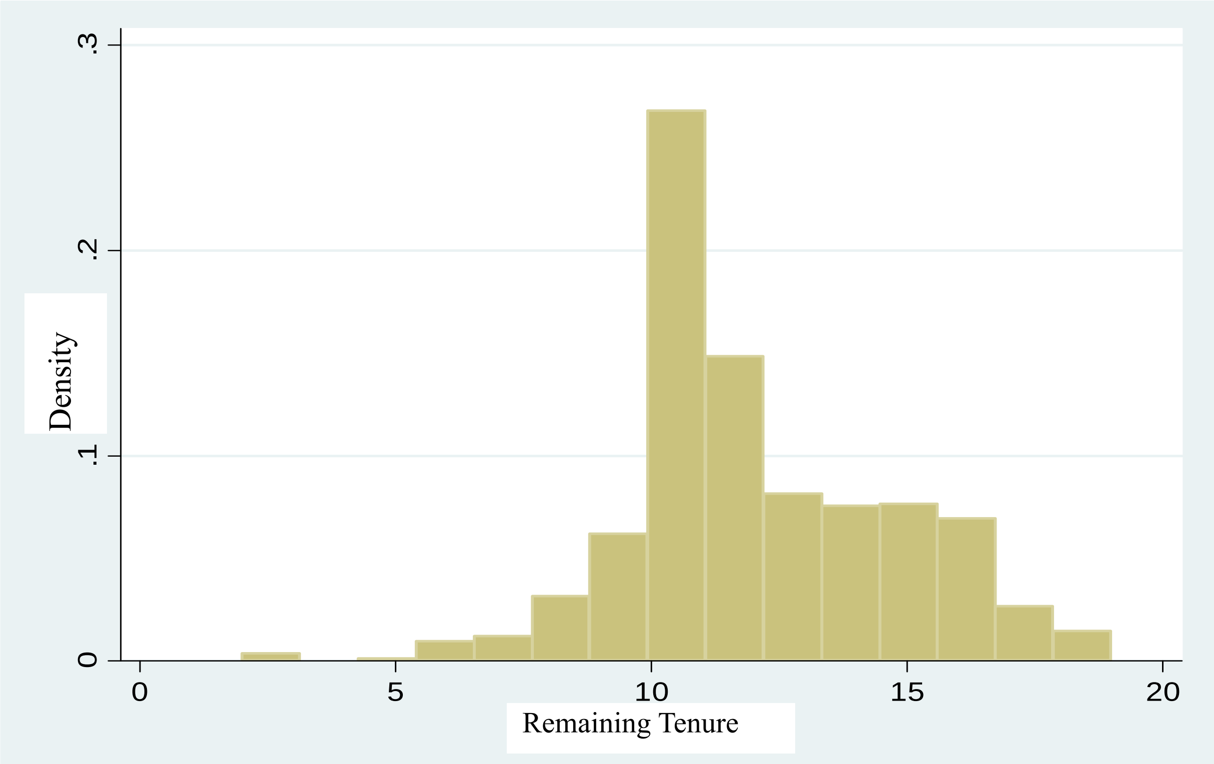
	(1)	(2)	(3)	(4)	(5)	(6)
Initiative	Employer-initiated Training			Worker-initiated Training		
Number of employees per 1,000 square kilometer	-0.021	-0.026	-0.025	0.014	-0.002	-0.002
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Industry specialization	-0.139	-0.133	-0.134	-0.122	-0.098	-0.097
	(0.040)	(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)
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

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

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)

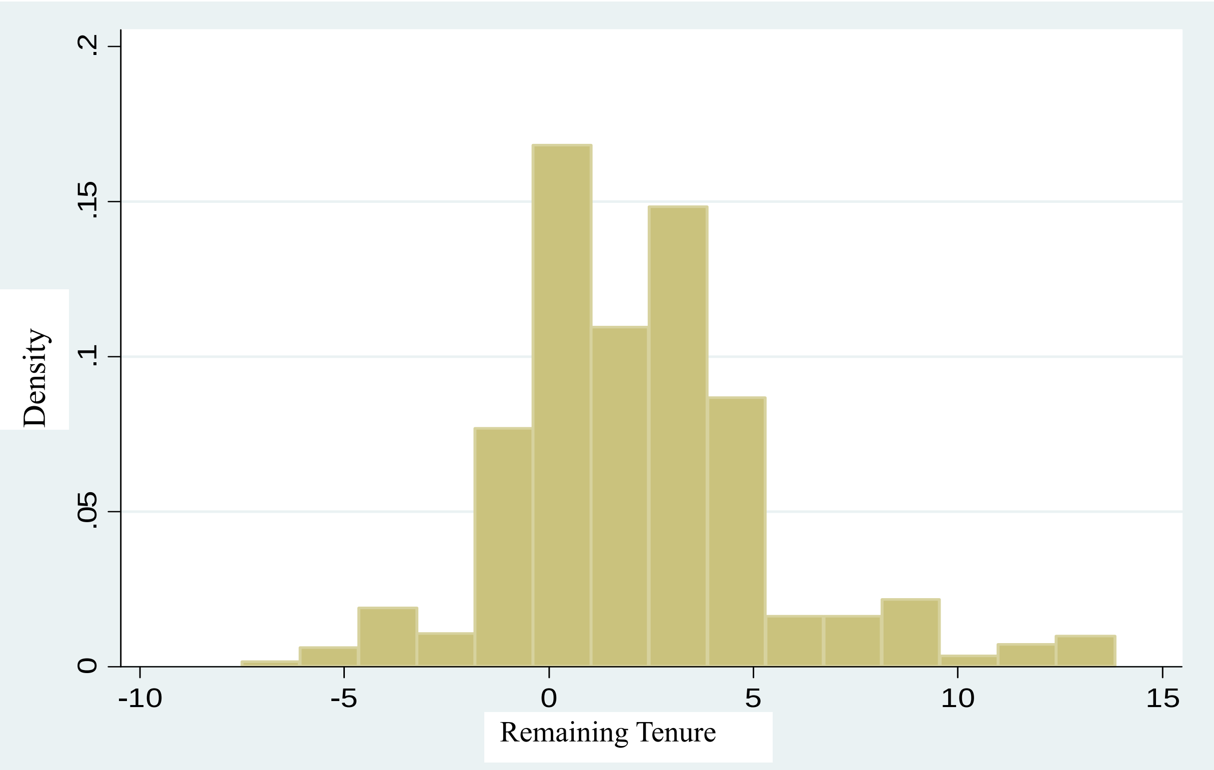
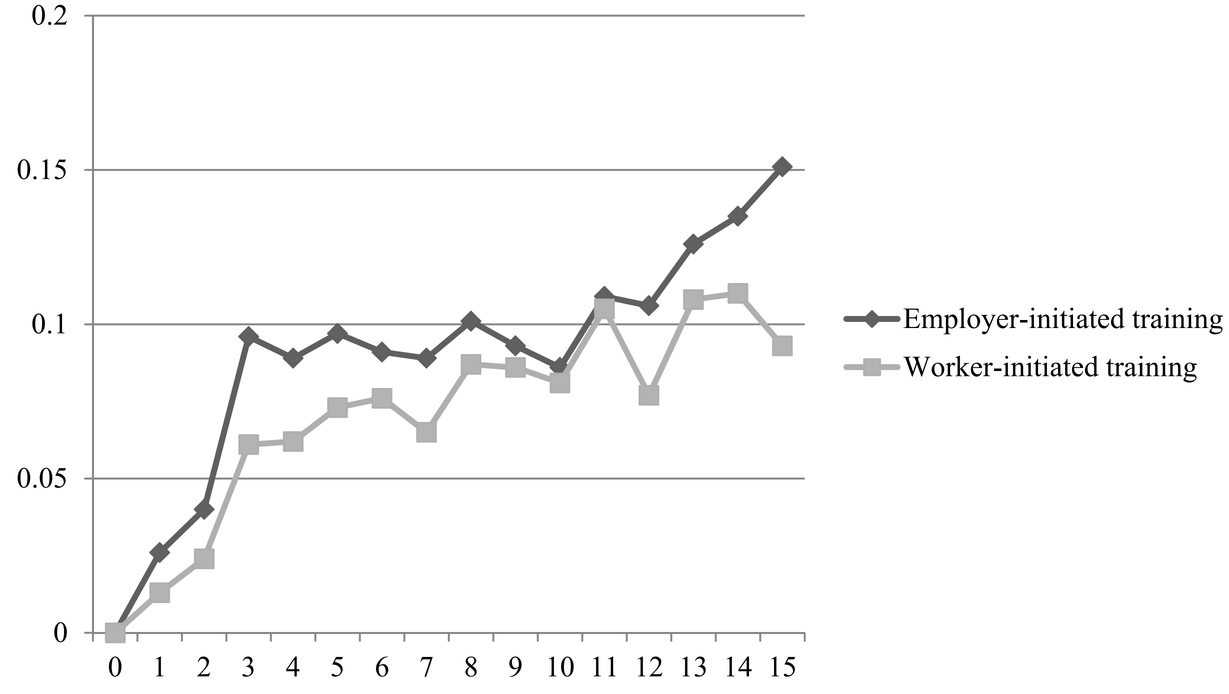
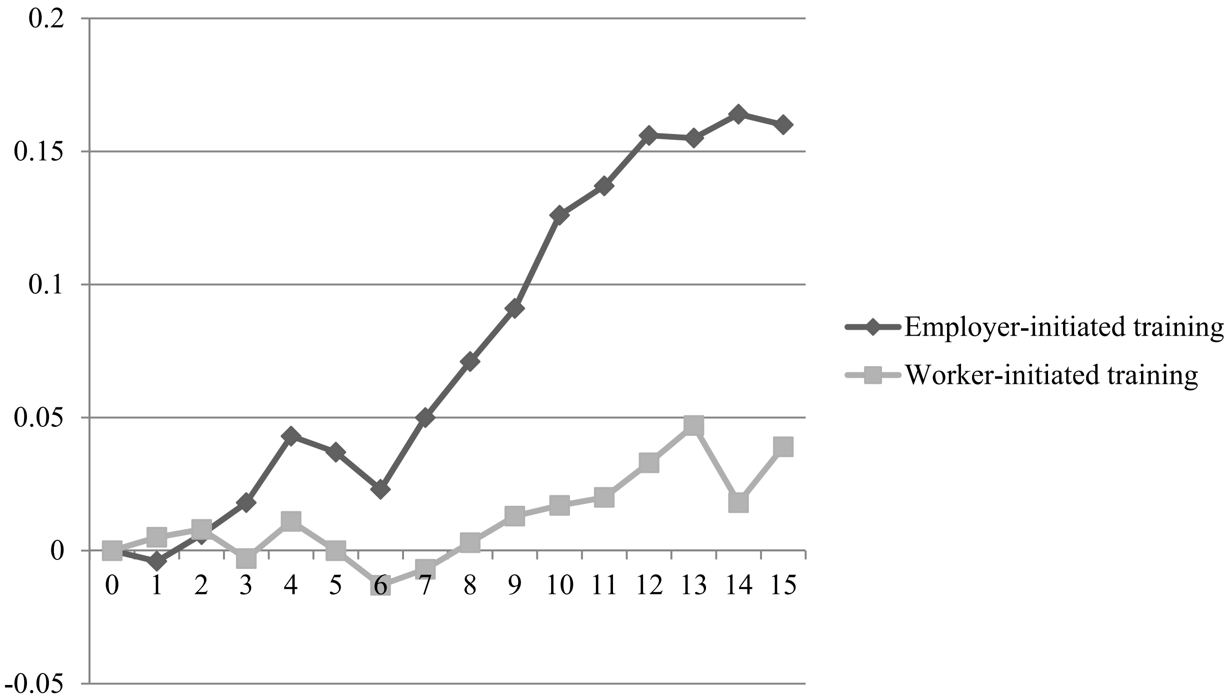


Figure 2: The Attachment Index (AI) and Training Probabilities



Note: Probit regression coefficients on dummy variables $\mathrm{AI_i}$ in $\Pr(\mathrm{Training_i}=1|\mathbf{AI_i},\mathbf{RT_i})=\Phi(\beta_0+\mathbf{AI_i}\boldsymbol{\beta_1}+\mathbf{RT_i}\boldsymbol{\beta_2}+\mathrm{NegativeRT_i}\beta_3)$ are reported on the vertical axis. Marginal effects at the means of independent variables are reported. All coefficients are statistically different from zero.

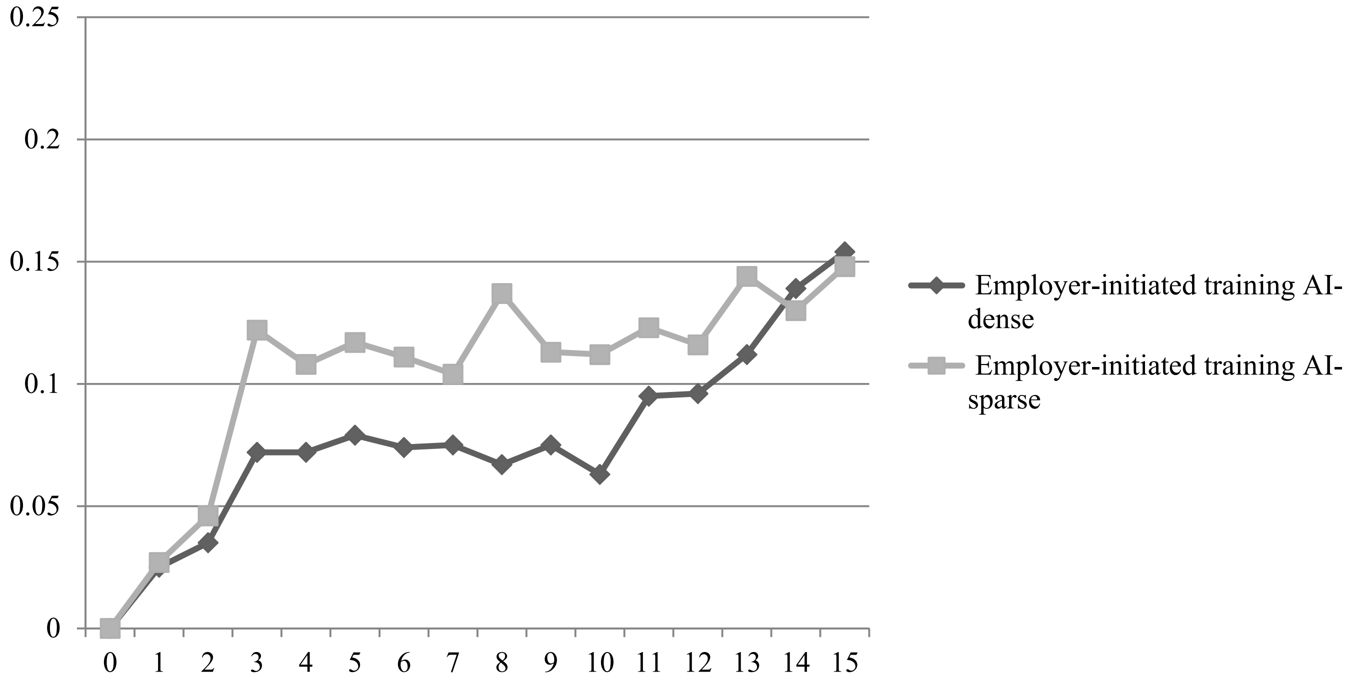
Figure 3: Remaining Tenure (RT) and Training Probabilities



Note: Probit regression coefficients on dummy variables $\mathrm{RT_i}$ in $\Pr(\mathrm{Training_i}=1|\,\mathbf{AI_i},\mathbf{RT_i})=$

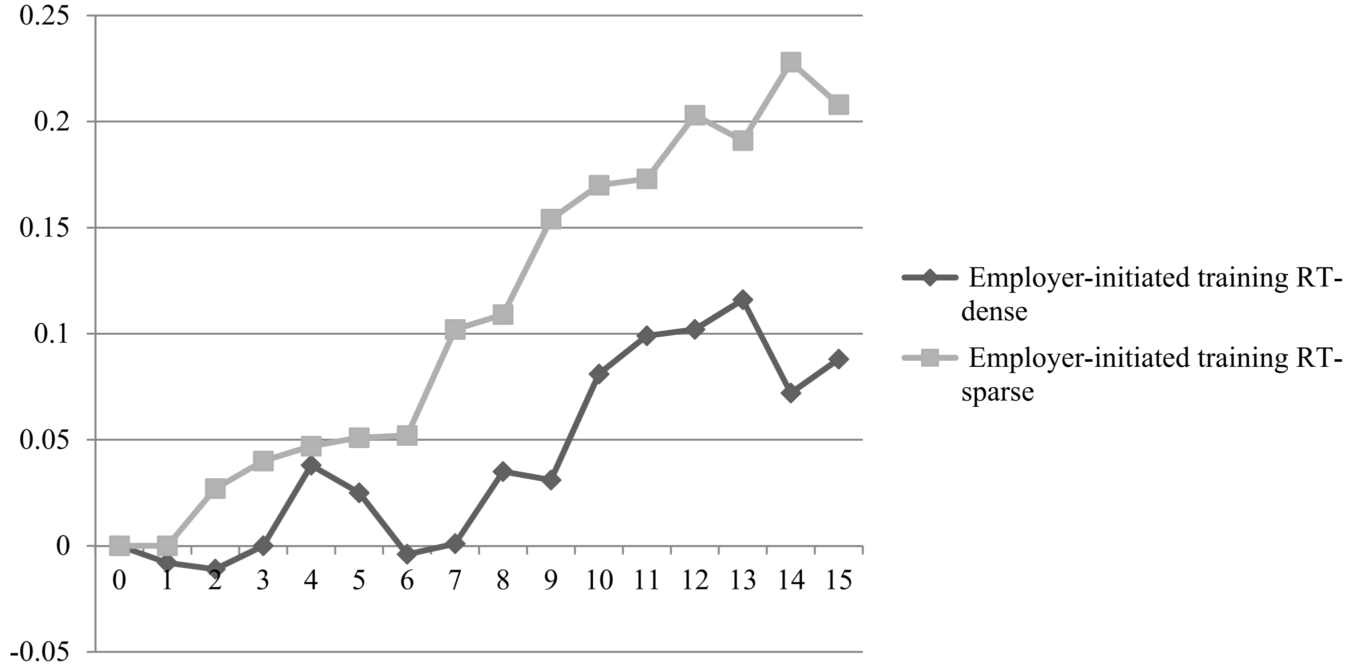
$\Phi(\beta_0 + \mathbf{AI_i}\boldsymbol{\beta_1} + \mathbf{RT_i}\boldsymbol{\beta_2} + \text{NegativeRT}_i\beta_3)$ are reported on the vertical axis. Marginal effects at the means of independent variables are reported. The coefficients for "Employment-initiated training" are significant for RT values 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.

Appendix Table 1: 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			
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			
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.

Appendix Table 2: Determinants of Job-Training Participations, Employed Workers, Ages 15-59

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initiative	Employer				Worker			
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)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initiative	Employer				Worker			
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

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