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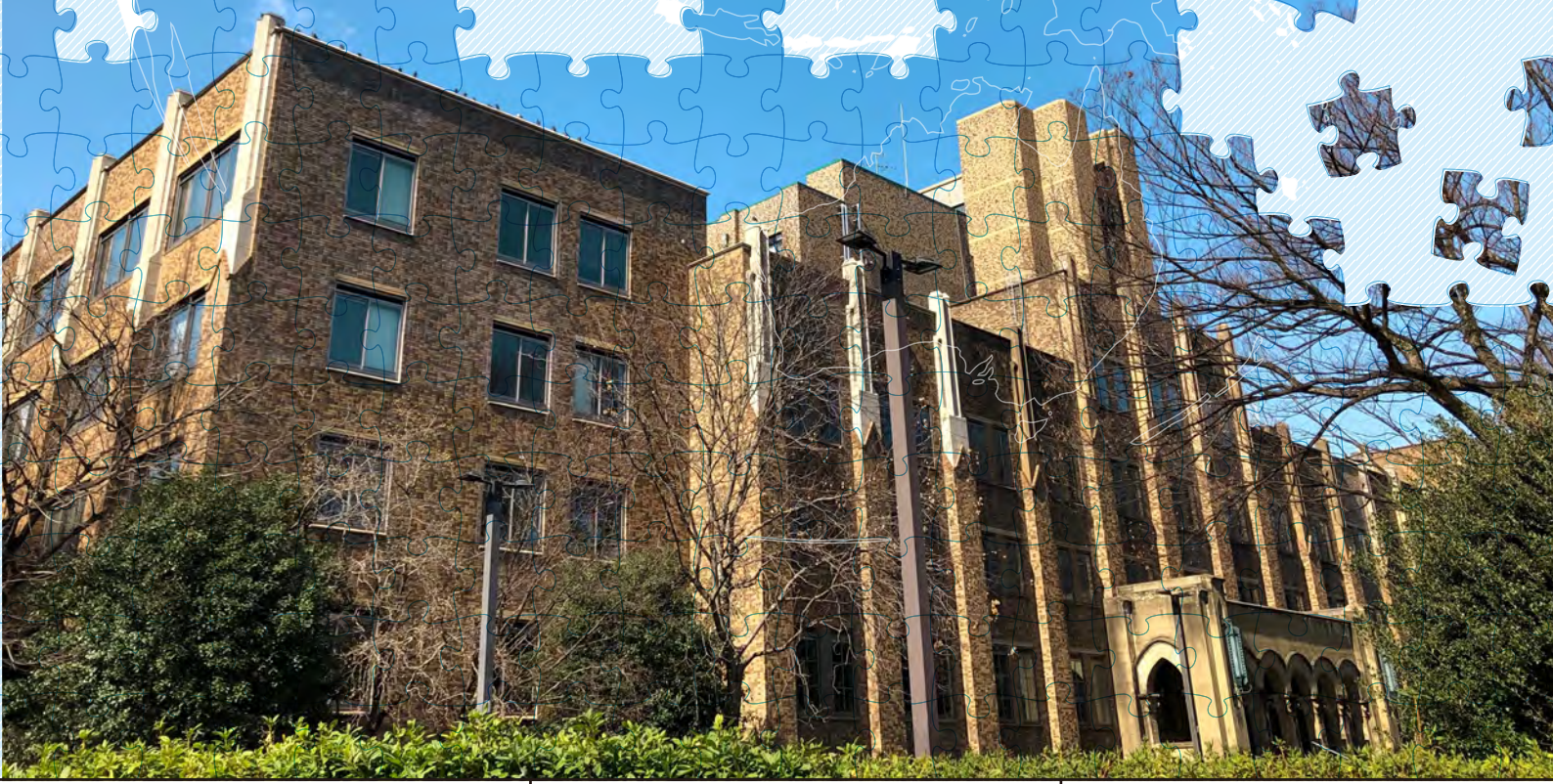
Who Gets Trained? Task Intensity, Coverage and Inequality in Employer-Provided Training in Contemporary Japan



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Abstract

Technological change has reorganized work into task units that differ in terms of their exposure to codification and automation, raising important questions regarding who gains access to employer-provided training. Motivated by the question, "Who gets trained?", we use the 2023 wave of Japanese Panel Study of Employment Dynamics (JSPED) to examine how the "task content" (Autor et al., 2003) of jobs associated with individual workers shapes participation in on-the-job training (OJT) and off-the-job training (OFF-JT), and how each mode of training relates to perceived skill improvements. We estimate corresponding multivariate models using rich controls such as education, age, employment status, firm size, industry, and childcare.

Three main findings emerged. First, workers in routine-intensive jobs were less likely to participate in both OJT and OFF-JT than those in less routine jobs. Second, OJT exhibited a stronger association with perceived skill improvement than OFF-JT, consistent with its close integration into daily tasks. Third, the joint pattern suggests complementarity: structured OFF-JT appears to be reinforced through work-embedded OJT. Simultaneously, routine-heavy settings limit the extent to which training translates into perceived skill gains.

We link the task-based view of technological change to contemporary inequalities in employer-provided training within a single national context. This study offers implications for targeting routine-intensive jobs and for designing bundles of OJT and OFF-JT that better support upskilling.

Keywords: training inequality; OJT; OFF-JT; task content; coverage

1. Introduction

Rapid technological progress has reshaped work organization by reallocating tasks[1] between humans and machines. A large body of literature documents how routine tasks that are codifiable and predictable are increasingly being performed by digital systems and artificial intelligence, while non-routine problem solving and interpersonal tasks remain central to human work (Autor et al. 2003; Acemoglu 2015; Acemoglu and Autor 2011; Acemoglu and Restrepo 2017, 2018). In this environment, employer-provided training[2] has become a pivotal mechanism of continuous skill formation, both in terms of firm productivity and worker mobility, to keep up with and benefit from rapid technological change. However, little is known about whether access to such training is equitably distributed across different task environments within firms, raising questions regarding its coverage and allocation, especially in Japan.

This study asks a simple but consequential question: *Are workers in routine-intensive jobs disadvantaged in terms of access to employer-provided training, and does the mode of training matter for perceived skill improvement?* We focus on two major forms of training: on-the-job training (OJT), which is learning embedded in everyday work under the guidance of supervisors or peers, and off-the-job training (OFF-JT), which consists of structured courses, seminars, or e-learning and occurs outside regular tasks. Although both modes are common in Japan, they differ in terms of their proximity to tasks, costs to firms and workers, and the types of skills they cultivate (Busemeyer 2009; Busemeyer and Trampusch 2012; Thelen 2014).

By answering this question, our study bridges three strands of scholarship. First, human capital research links employer training to productivity and wages but often models training as an undifferentiated input—typically proxied by a dummy variable of participation or hours—with no regard for mode, content, or within-firm allocation across task environments. Second, sociological studies on lifelong learning document lasting inequalities in those who receive training based on education, firm size, and contract status, typically without explicit consideration of task content. Third, task-based accounts of technological change reveal that routine tasks are most exposed to automation; however, task environments are rarely connected to training opportunities or effectiveness. By foregrounding task content, we connect these topics and analyze how routine, cognitive, and collaborative tasks shape participation in OJT and OFF-JT, and their association with perceived skill improvement.

We address these issues using data from the 2023 wave of the Japan Panel Study of Employment Dynamics (JSPED), which provides detailed information regarding workers' task content, participation in OJT and OFF-JT, and perceived skill improvements. Based on the results of our

[1] The term "task" is used to refer to a work activity that produces output (goods and services) according to the definition by Acemoglu and Autor (2011).

[2] Throughout this article, we use "employer-provided training" broadly to cover both formal, structured instruction delivered inside or outside the firm (OFF-JT), and informal, work-embedded learning through guidance and day-to-day tasks (OJT).

analysis, we document a systematic participation gap according to the task environment, where workers in routine-intensive jobs are less likely to participate in both OJT and OFF-JT than workers in less-routine settings. OJT exhibits a stronger association with perceived skill improvement than OFF-JT. Additionally, a joint pattern suggests complementarity, where structured OFF-JT appears to lay the foundation for OJT to consolidate skills on the job. Simultaneously, routine-heavy environments constrain the translation of training into perceived skill gains, suggesting that task redesign may be necessary for training to provide the maximum benefit.

This study makes three main contributions to the literature. First, it links the task-based view of technological change with contemporary inequalities in employer-provided continuing vocational education and training (CVET), focusing on the allocation of training opportunities. Second, by analyzing OJT and OFF-JT within the same framework, we compare their associations with perceived skill improvement and probe their complementarity. Third, we draw implications for firms and policies in a national context, where firm-specific skill regimes (Estevez-Abe et al. 2001) or segmentalist skill-formation regimes (Busemeyer 2009; Busemeyer and Trampusch 2012; Thelen 2014) face shrinking coverage under technological and institutional pressures.

The remainder of this paper is organized as follows. Section 2 establishes the context of this study within the literature on employer-provided training, inequality, and task-based technological change. Section 3 describes the data and measurements of variables used in our analytical models. Section 4 outlines the analytical strategies used in this study. Section 5 reports both baseline results and robustness checks. Section 6 discusses the implications of our findings for firms and policymakers, and concludes this paper.

2. Literature Overview: Employer-Provided Training and the Japanese Context

2.1 From investment to allocation: views on skill training

Human capital theory has long been the dominant framework for analyzing employer-provided training. Following Becker (1964), Mincer (1962, 1974), and Schultz (1961), training is conceptualized as an investment undertaken when expected productivity gains outweigh the associated costs. A large body of research in this tradition demonstrates that workers who receive training earn higher wages, experience faster wage growth, and show improved productivity, thereby establishing training as a central mechanism for skill accumulation within firms and an important determinant of individual careers. However, human capital research typically models training as a homogeneous input. Empirical measures often rely on simple indicators such as a participation dummy or hours of instruction, which may ignore meaningful differences in terms of training mode, content, and within-firm allocation. In this sense, while the literature has convincingly shown that "training pays," there is ambiguity regarding how training practices may generate unequal benefits depending on the nature of work tasks.

A second major strand of research, rooted in the sociology of inequality and lifelong learning,

conceives of training not simply as an investment but as a scarce organizational resource whose distribution reflects broader patterns of stratification. Classic studies emphasize how participation is shaped by status, job design, and institutional rules, producing systematic differences based on education, gender, contract type, and firm size (Blossfeld 1992; Bills and Hudson 2007; Korpi and Tåhlin 2021; Hornberg et al. 2024; OECD 2017, 2021). This line of work has demonstrated that employer-provided training can reinforce, rather than reduce, labor market inequality by privileging those already advantaged in terms of skills, credentials, or employment security. However, despite these insights, sociological studies often treat training in similarly aggregated terms, focusing on whether individuals receive training without systematically considering the substantive task content of work. In this manner, sociology and economics converge in their limitations, where both traditions establish the importance of training but rarely theorize or measure how allocation is contingent on the specific task environments in which workers are embedded.

Our study addresses both perspectives. As technological change reorganizes work into bundles of tasks, expected returns and allocation logic become task contingent and are not simply worker- or firm contingent.

2.2 Why tasks matter for participation gaps

Task-based theories emphasize how technological change reshapes skill demand not simply by occupation but also by the content of tasks. Autor et al. (2003) introduced the "routinization hypothesis," indicating that computerization mainly replaces routine, codifiable activities while complementing non-routine cognitive and interactive tasks. Subsequent research on "routine-biased technological change" has documented how employment shares and wage growth decline in routine-intensive jobs, while expanding in non-routine work (Acemoglu and Autor 2011; Goos and Manning 2007; Goos et al. 2014). This framework highlights the importance of measuring task intensity—defined as the degree to which jobs rely on routine, cognitive, or collaborative activities—as a lens for analyzing labor market inequality and training allocations.

Although task-based theories have illuminated the distributional consequences of technological change, few empirical studies have directly linked task intensity to training. Anger et al. (2023) and Lukowski et al. (2020) demonstrate that routine-intensive workers in Germany receive less employer-sponsored training, while Görlitz and Tamm (2016) show that the complementarity between education and training depends on job tasks. Tamm (2018) further finds that changes in job tasks are associated with training participation. Such studies remain rare, highlighting the novelty and relevance of examining task–training relationships in the Japanese context.

Building on this perspective, we identify three mechanisms linking tasks to training inequality. First, we consider the opportunity structure inside jobs. Highly scripted, throughput-oriented roles limit slack time and discretion for learning by doing or mentoring, and reduce natural "slots" for OJT such as unstructured moments for observation, feedback, or mentoring. Second, we consider the

expected returns on training. If managers, acting as employers or line supervisors making training investment decisions, anticipate automation or reorganization to replace routine work, they may downshift investments in those roles, whereas non-routine jobs promise clearer payoffs from added skills (Autor et al. 2003; Gathmann and Schönberg 2010). Third, we analyze the mode–task fit, which indicates how well a training mode aligns with the nature of tasks. OJT is tied to day-to-day problem solving and social transmission of knowhow, whereas OFF-JT delivers formal curricula that may be foundational but harder to transfer without practice. In routine-intensive contexts, even completed OFF-JT may yield limited perceived skill gains unless it is accompanied by structured OJT or task redesign.

These mechanisms yield several testable predictions. Routine intensity should depress participation in both OJT and OFF-JT. Cognitive and collaborative content should elevate participation. OJT should be more strongly associated with perceived skill improvement and both modes may be complementary, rather than substitutive.

Taken together with the human capital and sociological perspectives reviewed above, task-based accounts provide new explanatory leverage but still neglect the role of labor market institutions. The next section situates Japan within the comparative political economy debates on skill formation regimes before turning to our main research questions.

2.3 The Japanese setting: political economy of skill formation and shrinking coverage

A comparative political economy frames CVET coverage along two axes, namely coordination and scope of coverage, and demonstrates that liberalization can yield divergent paths. In Thelen's (2014) account, "embedded flexibility" emerges when the state sustains inclusive, adult-oriented CVET (as in Denmark), in contrast to deregulated or polarized trajectories. We adopt this perspective to interpret Japan's employer-centered training regime.

Institutional comparisons place Japan in a segmentalist skill regime with limited public involvement in vocational education, strong firm involvement in initial training, and heavy reliance on firms for CVET. Such a configuration that can contract under technological and macroeconomic pressures and risk widening inequality (Estevez-Abe et al. 2001; Hall and Soskice 2001; Busemeyer 2009, 2015; Busemeyer and Trampusch 2012; Thelen 2014). This dependence on firms has historically allowed relatively broad coverage during periods of stable employment and high growth. However, it also makes CVET vulnerable when firms retrench or when non-standard employment expands.

Similarly, domestic scholars note both the centrality and limitations of firm-led training, with coverage stratified by employment status, firm size, and gender (Hara 2014; Kambayashi and Kato 2016; Kawaguchi 2006; Toda and Higuchi 2005; Yokoyama et al. 2019). Existing research highlights how large firms and regular employees enjoy relatively rich opportunities, whereas small firms and non-regular workers remain underserved. In recent years, a long-term decline in OJT and OFF-JT coverage has been demonstrated (Asuyama 2023; Ministry of Health 2023; Miyagawa et al. 2016),

raising concerns regarding the shrinking foundation for skill renewal in the face of technological changes.

In such a system, technological change may interact with existing stratification, where workers in routine-heavy roles, which are the most exposed to automation, may receive little coverage unless organizations or policies explicitly target them. This institutional context motivates our empirical question regarding how task environments shape participation in OJT and OFF-JT, and their perceived returns in Japan's evolving training regime.

2.4 Research questions and hypotheses

Building on the above review, we articulate three research questions concerning (1) who participates in training, (2) how training modes relate to perceived skill improvement, and (3) how these relationships vary by stratification across employment contracts and firm sizes. H1 to H3 represent the core contributions of this study and introduce the task environment as a novel lens for evaluating training participation and effectiveness. Additionally, we include H4 as a confirmatory hypothesis to test whether traditional stratification by employment status and firm size, which has long been emphasized in the literature, persists after task content is accounted for.

RQ1 (Participation). Net education, employment status, and firm attributes: Do workers in routine-intensive jobs exhibit lower participation in employer-provided training (OJT and OFF-JT)?

- **H1.** Routine intensity is negatively associated with OJT and OFF-JT, whereas cognitive and collaborative shares are positively associated.

RQ2 (Mode–task fit and complementarity). How do OJT and OFF-JT relate to perceived skill improvement ("level-up"), and do they operate as complements?

- **H2.** OJT exhibits a stronger association with perceived skill improvement than OFF-JT.
- **H3.** OJT and OFF-JT may be complementary. We consider this hypothesis to be exploratory, probing complementarities without emphasizing the interaction terms in the main models.

RQ3 (Stratification). Do task–training relationships remain robust once stratification by employment status and firm size is taken into account?

- **H4.** Task effects are robust across employment status and firm size, but regular workers and those in larger firms participate more in training than others.

2.5 What "coverage" means for policy and the comparative political economy

Reframing training participation as an organizational outcome shaped by task design shifts the question from "how much training" to "who is covered, under what modes, and with what combinations?" In Japan's firm-specific skill formation systems, overall participation has declined and

coverage remains highly stratified by firm size and contract status, suggesting that the central challenge is inclusiveness and effective mode bundling, rather than simply expanding the volume of training (Sano 2018; Theen 2014).

From a policy perspective, this study highlights two priorities. First, targeted inclusion: workers in routine-intensive jobs who are most exposed to technological displacement should not be excluded from CVET opportunities. Second, mode bundling: modular OFF-JT provides foundations but its impact depends on being paired with structured OJT and a small-scale task redesign that enables the integration of new skills (De Grip 2015; Hamaguchi 2021; Thelen 2014). Without such combinations, training risks remaining symbolic, rather than transformative.

Beyond Japan, this perspective informs comparative political economy debates. In firm-specific skill regimes, shrinking coverage undermines both equity and resilience to technological change. Elevating "coverage" as an analytical category emphasizes that what matters is not simply more training hours but whether opportunities reach vulnerable task environments and whether modes are configured to yield sustained skill renewal.

3. Data and Measures

3.1 Survey data and analytic sample

Our analysis draws on the 2023 wave of the JSPED, a nationally representative survey designed to capture individual employment conditions, workplace practices, and training opportunities. The JSPED provides unusually rich information regarding both formal and informal training, as well as the content of work tasks, making it well suited to examining how training participation varies across task environments.

The analytic sample is restricted to employed persons aged 20 to 59 years who worked at least 30 hours per week. Self-employed individuals and company executives were excluded because their training opportunities differ systematically from those of employees. After these restrictions, the sample size is N = 25,250 for training participation outcomes. For perceived skill improvement, the effective sample size was N = 24,646 as 604 respondents selected "not applicable" on the skills question. Focusing on the 2023 wave, we captured the most recent conditions of employer-provided training while minimizing the transitory disruptions associated with the COVID-19 pandemic. Even with the restriction to employees working 30 hours or more per week, our results indicate clear stratification between regular and non-regular workers, as well as across firm sizes, making ours an analytically meaningful sample.

3.2 Outcomes (dependent variables)

We examined three outcome measures capturing the distinct dimensions of employer-provided training and its perceived effects. Following prior literature, we distinguish between OJT and OFF-JT, as they differ in terms of their proximity to everyday work tasks and the types of skills they cultivate.

Additionally, we assess workers' subjective evaluations of skill change, providing an important complement to the participation measures.

The first outcome is OJT intensity, which is measured on a five-point ordinal scale ranging from "0 = no opportunity" to "4 = formal instruction by supervisors or colleagues.[3]" This scale captures variations in the extent and formality of task-embedded learning from informal observation and ad hoc guidance to structured instruction. In the descriptive data (Table 1), 46.5% of the target respondents reported no opportunity for OJT, while smaller proportions reported informal or formalized instruction.

The second outcome is OFF-JT participation, which is measured using a seven-category ordinal index combining access and hours of instruction. Respondents who report no opportunity are coded "0," whereas those who indicate that an opportunity existed but was not attended are coded "1." The remaining categories reflect increasing amounts of training from "less than 5 hours" to "50 hours or more," as shown in Table 1. Importantly, we treat access and uptake as analytically distinct, where "access" refers to whether any opportunity for training was provided (including those not attended) and "uptake" captures actual participation conditional on access. This distinction allows us to separate organizational provision from individual uptake, which is particularly relevant when analyzing the stratification of training opportunities. In our robustness analyses, we estimate models for both the access and uptake dummies, in addition to the main ordinal index.

The third outcome is perceived skill improvement ("level-up"), which is measured on a five-point scale ranging from "−2 = declined significantly" to "+2 = improved significantly," referencing self-assessed change in skill level over the past year. This measure allows us to evaluate not only whether training occurs but also whether workers perceive it as leading to meaningful skill development. In the analytical sample, the mean score is 0.19 (SD = 0.70), indicating modest but positive average perceptions of skill growth.

Together, these outcomes provide a comprehensive picture of employer-provided training, where OJT captures daily, work-embedded learning, OFF-JT captures formal, structured instruction, access and uptake indicators clarify whether inequalities stem from provision or participation, and perceived skill improvement reflects workers' own evaluations of training effectiveness.

3.3 Task measures (independent variables)

To capture the task environments in which workers are embedded, we draw on respondent-reported assessments of the share of jobs spent on different types of activities. This approach follows task-based theories of technological change, which emphasize that routine, codifiable activities are most susceptible to automation, whereas cognitive and collaborative tasks are increasingly becoming central

[3] The precise wording of the question is as shown in Table 1. According to Recruit Works Institute (2023), these indices of OJT and OFF-JT are included in the "work index" variable group in the JPSED, and their use as continuous variables is introduced for the analysis of accessibility.

to value creation. Measuring task content at the individual level allows us to examine how employer-provided training varies not only across worker or firm attributes but also across the nature of day-to-day work.

The survey asked respondents to allocate the proportion of their work time (0% to 100%) across three domains: routine tasks (repetitive activities that follow standard procedures), cognitive tasks (analytical activities), and collaborative tasks (working and coordinating with others). We use these self-reported shares as continuous predictors in our model. By construction, the three domains are not mutually exclusive, but reflect different facets of job content, with mean values in the analytical sample of 57.8% for routine, 60.5% for cognitive, and 45.9% for collaborative tasks, as shown in Table 1.

In our sensitivity analyses, we re-scaled the task measures in two ways: (i) normalizing them to a 0–1 range and (ii) standardizing them (z-scores). These alternative specifications facilitate the comparability of coefficients across domains and ensure that the results are insensitive to scale choices.

3.4 Controls

All models include a standard set of individual and organizational covariates to account for alternative explanations of training participation and perceived skill growth. At the individual level, we control for sex, age, and education level. These variables have long been shown to shape opportunities for training, as education proxies for prior human capital while gender and age are central to the sociological accounts of unequal access to lifelong learning. We also include employment status (regular versus non-regular) and tenure (years) to reflect the institutionalized segmentation of Japan's labor market, where contract security and job experience condition both firms' willingness to invest and workers' access to training.

At the organizational level, we control for firm size (10 categories), which captures well-documented scale-related differences in training provision and industry/sector dummies, to adjust for structural variation across sectors. A public sector indicator is also included given the distinctive training practices and institutional rules associated with governments and quasi-governmental organizations.

Descriptive statistics for these covariates are presented in Table 1. For example, 81.3% of the target respondents are regular employees, 9.1% work in the public sector, and the largest firm size groups were 10 to 49 employees (17.3%) and 5,000 employees or more (14.9%). Including these covariates allows us to situate task-based inequalities in training within the broader landscape of stratification processes emphasized in the literature on education and lifelong learning.

3.5 Coding notes and planned robustness

Several coding choices warrant further clarification. First, for **OFF-JT participation**, the main specifications uses a seven-category ordinal scale that jointly captures access and hours. To probe

whether the inequalities reflect the provision of opportunities or actual participation, we also estimate models separating **access** (coded "1" if any opportunity existed, including those not attended) from **uptake** (coded "1" only if hours were attended). This distinction allows us to disentangle organizational allocation from individual uptake.

Second, regarding modeling strategy, our main analyses employ ordinary least squares (OLS) regression with robust standard errors. This choice facilitates a straightforward interpretation of the coefficients, where a one-unit change corresponds to a 10-percentage-point shift in the task share. In other words, the coefficients can be interpreted as the expected changes in outcomes associated with a 10-percentage-point increase in routine, cognitive, or collaborative content. Regardless, we also estimated ordered logit and probit models for ordinal outcomes as robustness checks to ensure that the findings do not hinge on the linearity assumption.

Finally, regarding missing data, the only systematic reduction in sample size is associated with perceived skill improvement, for which 604 respondents selected "not applicable." For the other variables, list-wise deletions are applied to the main models. We further confirmed robustness by testing alternative coding of missing responses, where relevant.

3.6 Descriptive statistics

Table 1 summarizes the main variables used in our analysis. For OJT, nearly half of the respondents (46.5%) reported no opportunities for workplace-based learning. Among those with access, 14.0% indicated that they learned primarily by using manuals, 11.5% by observing colleagues, 19.1% through informal instruction, and 8.8% through formalized guidance from supervisors or peers. For OFF-JT, 67.8% reported no opportunity, 9.3% reported that an opportunity existed but was not attended, and 22.9% attended some training hours, with only 1.9% participating for 50 hours or more. These patterns underscore the limited reach of formal training opportunities, particularly in comparison with OJT.

The distribution of the task measures spans the full range of 0 to 100 points. On average, respondents report spending 57.8% of their time on routine activities, 60.5% on cognitive tasks, and 45.9% on collaborative tasks. These averages reflect a mixed task composition typical of many jobs, although the wide dispersion suggests substantial heterogeneity across occupations and individuals.

Regarding controls, the sample is predominantly composed of regular employees (81.3%), with non-regular workers representing a significant minority. Public sector employment accounted for 9.1% of the sample. Firm size distributions are relatively balanced, with the largest categories being firms with 10 to 49 employees (17.3%) and those with 5,000 employees or more (14.9%). The mean age of the respondents is 40.3 years.

Overall, the descriptive statistics highlight two key features of the data: the restricted coverage of OFF-JT relative to OJT and wide dispersion of task content across jobs. These patterns provide an empirical backdrop for the multivariate models presented in Section 4.

Table 1. Descriptive statistics

Variables	Mean / N (% / SD)	minimum	maximum
OJT Score	1.297 (1.432)	0	4
No opportunity	11,736 (46.5%)	0	1
Learned with manual, without instruction	3,547 (14.0%)	0	1
Learned by observing work practices	2,910 (11.5%)	0	1
Received informal instruction from supervisors/colleagues	4,835 (19.1%)	0	1
Received formal instruction from supervisors/colleagues	2,222 (8.8%)	0	1
Off-JT Score	0.870 (1.534)	0	4
No opportunity	17,111 (67.8%)	0	1
Opportunity existed, but not attended	2,344 (9.3%)	0	1
< 5 hours per year	1,995 (7.9%)	0	1
5–9 hours per year	1,315 (5.2%)	0	1
10–19 hours per year	1,229 (4.9%)	0	1
20–49 hours per year	773 (3.1%)	0	1
50+ hours per year	483 (1.9%)	0	1
Task type			
routine	57.841 (27.763)	0	100
cognitive	60.470 (30.157)	0	100
collaborative	45.855 (28.575)	0	100
employment_type			
regular	20,523 (81.3%)	0	1
non-regular	4,727 (18.7%)	0	1
tenure years	12.173 (9.687)	1	43.75
firmsize			
~9	2,197 (8.7%)	0	1
10~49	4,365 (17.3%)	0	1
50~99	2,472 (9.8%)	0	1
100~299	3,611 (14.3%)	0	1
300~499	1,607 (6.4%)	0	1
500~999	1,864 (7.4%)	0	1
1000~1999	1,575 (6.2%)	0	1
2000~4999	1,491 (5.9%)	0	1
5000 and more	3,758 (14.9%)	0	1
Public sector	2,310 (9.1%)	0	1
Sex			
men	15,241 (60.4%)	0	1
women	10,009 (39.6%)	0	1
Age	40.340 (10.167)	20	59
Education			
High school or less	7,963 (31.5%)	0	1
Vocational school （senshugakko)	4,088 (16.2%)	0	1
Junior college	1,963 (7.8%)	0	1
Technical college	317 (1.3%)	0	1
University	10,919 (43.2%)	0	1
Pre_school child			
Yes	21,408 (84.8%)	0	1
No(ref.)	3,842 (15.2%)	0	1
Sector			
Primary industry (agriculture, forestry, fisheries, mining)	178 (0.7%)	0	1
Construction	1,226 (4.9%)	0	1
Manufacturing	5,128 (20.3%)	0	1
Public utilities and infrastructure (electricity, gas, postal	2,557 (10.1%)	0	1
Information and communications industry	1,899 (7.5%)	0	1
Transportation	1,947 (7.7%)	0	1
Wholesale, retail trade, and real estate	2,874 (11.4%)	0	1
Finance and insurance	1,055 (4.2%)	0	1
Accommodation and food services	606 (2.4%)	0	1
Medical care and welfare	3,183 (12.6%)	0	1
Education and learning support	975 (3.9%)	0	1
Service industry	2,317 (9.2%)	0	1
Not classified elsewhere	1,305 (5.2%)	0	1
Level of skill improvement in the past year	0.194(0.701)	-2	2
Significantly improved	897 (3.6%)	0	1
Slightly improved	5,692 (22.5%)	0	1
About the same level	15,887 (62.9%)	0	1
Slightly declined	1,641 (6.5%)	0	1
Significantly declined	529 (2.1%)	0	1
N/A	604 (2.4%)	0	1
Observations	25,250		

4. Analytical Strategy and Model Specification

4.1 Models for training participation

We estimate the linear probability models for the indices of OJT (0–4) and OFF-JT (0–6) using OLS with heteroscedasticity-robust standard errors as follows:

$$Training\_i = \alpha + \beta_1 \cdot Routine\_i + \beta_2 \cdot Cognitive\_i + \beta_3 \cdot Collaborative\_i + \gamma' Z\_i + \varepsilon\_i, \quad (1)$$

where Zi denotes the set of controls described in Section 3.4, including gender, age, education, employment status, tenure, firm size, industry/sector dummies, and public sector indicators. The task shares are entered linearly. The main specification uses OLS for ease of interpretation, whereas the ordered logit and probit models are estimated as robustness checks. We report the OLS models in the following stepwise sequence: (i) baseline models with tasks only, (ii) adding employment status and tenure, (iii) adding firm size and industry or sector, and (iv) full specification with all controls.

4.2 Model for perceived skill improvement

To assess perceived skill development, we regress the "level-up" index on both training modes, task shares, and controls as follows:

$$LevelUp\_i = \alpha + \delta_1 \cdot OJT\_i + \delta_2 \cdot OFFJT\_i + \beta_1 \cdot Routine\_i + \beta_2 \cdot Cognitive\_i + \beta_3 \cdot Collaborative\_i + \gamma' Z\_i + \varepsilon\_i. \quad (2)$$

OJT and OFF-JT are entered jointly to compare their associations with perceived improvement. Because training refers to past-year experience and level-up captures self-assessed outcomes at the time of the survey, the temporal ordering is consistent, although we interpret the results as associations, rather than causal effects.

4.3 Robustness and diagnostics

All models use robust standard errors and two-sided significance tests. We assess robustness in several ways. First, we estimate the ordered logit and probit models for OJT, OFF-JT, and level-up to confirm that the results are not driven by linearity. Appendix Tables A1 and A2 reveal that the signs and significance levels for task variables remain unchanged relative to OLS, where routine intensity is negative and cognitive/collaborative content is positively associated with training participation**.** Second, we rescale task shares (0–1 normalization and z-scores) to ensure comparability across domains. Third, we distinguish access from uptake in OFF-JT by estimating models on separate dummies to clarify whether inequalities arise from opportunity provision or actual participation. Across these checks, the results remain substantively unchanged.

5. Results

5.1 Descriptive patterns

Table 1 summarizes the variables and sample composition. Routine, cognitive, and collaborative tasks share a full range of 0 to 100 points. Additionally, Table 2 shows descriptive contrasts by task tertile (high/middle/low) reveal lower mean OJT and OFF-JT scores at higher routine levels, and higher scores at higher cognitive and collaborative levels. Coverage is also clearly stratified by firm size, where the mean OJT increases from 0.788 in firms with fewer than 10 employees to 1.606 in firms with 5,000 or more employees, and OFF-JT increases from 0.442 to 1.098 over the same range. A similar gradient appears for employment status, where regular workers report higher OJT (1.339) and OFF-JT (0.970) than non-regular workers (1.115 and 0.435, respectively). Public-sector workers exhibit relatively high levels of participation (OJT = 1.528, OFF-JT = 1.262). These descriptive gradients underscore the fact that inequalities are visible in raw participation patterns, motivating the need for multivariate models to isolate task effects.

Table 2. OJT/OFF-JT by task tertiles and firm size/employment status

		OJT Score (mean, SD)	Off-JT Score (mean, SD)
Routine Score	low	1.500 (1.426)	1.106 (1.687)
	middle	1.307 (1.431)	0.873 (1.525)
	high	1.052 (1.401)	0.592 (1.295)
Cognitive Score	low	1.183 (1.443)	0.720 (1.424)
	middle	1.386 (1.441)	0.960 (1.558)
	high	1.384 (1.396)	1.004 (1.642)
Collaborative Score	low	1.110 (1.364)	0.746 (1.447)
	middle	1.326 (1.427)	0.903 (1.540)
	high	1.502 (1.488)	0.990 (1.620)
Firmsize	~9	0.788 (1.227)	0.442 (1.143)
	10~49	1.025 (1.343)	0.646 (1.362)
	50~99	1.130 (1.360)	0.694 (1.404)
	100~299	1.252 (1.417)	0.768 (1.422)
	300~499	1.395 (1.451)	0.927 (1.559)
	500~999	1.418 (1.456)	0.953 (1.591)
	1000~1999	1.550 (1.480)	1.106 (1.674)
	2000~4999	1.575 (1.485)	1.091 (1.644)
	5000 and more	1.606 (1.495)	1.098 (1.690)
	Public sector	1.528 (1.409)	1.262 (1.747)
Employment	regular	1.339 (1.434)	0.970 (1.606)
	non-regular	1.115 (1.409)	0.435 (1.072)
N			25,250

5.2 Multivariate participation gaps

The OLS models for OJT and OFF-JT (Table 3) confirm the descriptive patterns reported above. Routine is negative and statistically significant across all specifications, whereas cognitive and collaborative are both positive and significant. In the most saturated model (model 4), a one-point increase in routine share (0 to 100 scale) is associated with a 0.005 decrease in the OJT index and 0.005 decrease in the OFF-JT index. Cognitive and collaborative exhibit positive associations of 0.002 to 0.004. Interpreted substantively, a 10-percentage-point increase in routine share corresponds to an approximately 0.05 point reduction in OJT participation (approximately 4% of the mean) and a similar

Table 3. OLS for OJT and OFF-JT participation

	Regression models of OJT				regression models of Off-JT			
	model 1	model 2	model 3	model 4	model 1	model 2	model 3	model 4
Task Score*								
Routine	-0.005***	-0.005***	-0.005***	-0.005***	-0.006***	-0.005***	-0.005***	-0.005***
Cognitive	0.004***	0.003***	0.002***	0.002***	0.004***	0.003***	0.002***	0.002***
Collaborative	0.006***	0.005***	0.004***	0.004***	0.004***	0.003***	0.002***	0.002***
Employment								
non-regular (ref.)								
regular			0.191***	0.174***			0.405***	0.368***
Tenure years			-0.016***	-0.016***			-0.007***	-0.006***
Firm size								
~9 (ref.)								
10~49			0.147***	0.146***			0.135***	0.114***
50~99			0.239***	0.237***			0.163***	0.146***
100~299			0.352***	0.346***			0.217***	0.202***
300~499			0.457***	0.450***			0.338***	0.327***
500~999			0.491***	0.484***			0.359***	0.352***
1000~1999			0.593***	0.585***			0.480***	0.484***
2000~4999			0.633***	0.630***			0.456***	0.479***
5000 and more			0.692***	0.695***			0.494***	0.539***
Public sector			0.588***	0.504***			0.596***	0.576***
Sector								
primary industry (agriculture,				0.141				0.032
construction				-0.111*				-0.016
manufacturing				-0.065				-0.083*
public utilities and				0.034				-0.018
information and communications industry				-0.004				0.016
transportation				-0.156***				-0.140**
wholesale, retail trade, and real estate				-0.158***				-0.154***
finance and insurance				0.086				-0.074
accommodation and food services				-0.253***				-0.307***
medical care and welfare				0.029				0.229***
education and learning support				0.059				0.481***
service (ref.)								
not classified elsewhere				-0.127**				-0.059
Sex								
women(ref=men)		0.024	0.048*	0.032		-0.151***	-0.054**	-0.100***
Age		-0.026***	-0.016***	-0.017***		-0.013***	-0.008***	-0.009***
Education								
high school or less (ref.)								
vocational school		0.057*	0.042	0.02		0.089***	0.075**	0.018
junior college		0.063	0.047	0.025		0.164***	0.150***	0.100**
technical college		0.262**	0.176*	0.164*		0.471***	0.389***	0.371***
university		0.312***	0.211***	0.187***		0.363***	0.279***	0.218***
Preschool child (ref=none)		-0.064*	-0.091***	-0.098***		0.034	-0.013	-0.026
Constant	1.059***	2.054***	1.447***	1.559***	0.772***	1.228***	0.594***	0.704***
Adj. R^2*	0.033	0.080	0.106	0.109	0.028	0.051	0.071	0.080
N	25250	25250	25250	25250	25250	25250	25250	25250

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Coefficients are per 1 percentage-point task share. Robust standard errors estimated.

reduction in OFF-JT (approximately 5% of the mean). Comparable gains can be observed for cognitive and collaborative shares. Beyond task types, regular employment and larger firm size are associated with higher participation in both modes, participation in the public sector is strongly positive, and tenure is modestly negative. These associations are robust to the addition of employment status, tenure, firm size, sector, and other factors, as can be confirmed in Figures 1 and 2 that visualize the task effects across models 1 to 4.

Overall, these findings support H1: Routine intensity is negatively associated and cognitive/collaborative content is positively associated with participation in both OJT and OFF-JT.

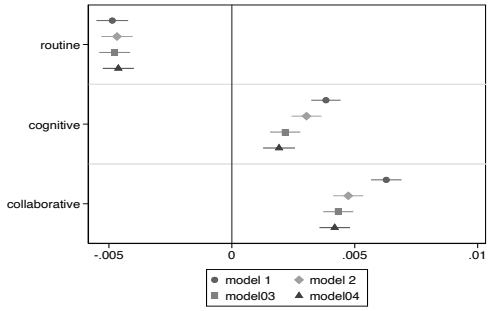

Figure 1. Coefficient plots for task variables: (OJT)

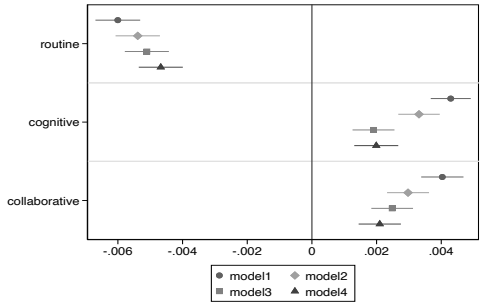

Figure 2. Coefficient plots for task variables (OFF-JT)

Note: Points are coefficients of model 1 to model 4 in Table 3. Bars show 95% Cis.

5.3 Associations with perceived skill growth

Table 4 presents the results of the regression analysis for the level-up index. According to models 1 and 2 in Table 4, OJT has a larger positive association with perceived skill improvement than OFF-JT when both are entered jointly (OJT = 0.126–0.123; OFF-JT = 0.038–0.035). Substantively, moving from no OJT to the informal instruction category (approximately 1 unit on the OJT scale) is associated with a 0.12 point increase in perceived skill improvement, which is equivalent to approximately 17% of the sample mean (0.19). The OFF-JT effects, while still positive, are smaller at approximately 5% of the mean[4]. Task shares also relate to self-reported gains, where routine is negative (approximately −0.001 per percentage point or −0.05 for a 50 percentage point increase, approximately 5% of the mean), cognitive is positive (approximately +0.002), and collaborative is small and not robust.

[4] These percentages are reported relative to the sample mean for ease of interpretation. Technically, they correspond to the ratio of the coefficients to the standard deviation (SD) of the dependent variable (0.70). Thus, the effect of OJT (0.12) equals ≈0.17 SD, and the effect of OFF-JT (0.04) equals ≈0.06 SD.

Table 4. OLS for level-up

		model 1	model 2	model 3
OJT		0.126***	0.123***	
Off-JT		0.038***	0.035***	
OJT	No opportunity			ref.
	Learned with manual, without instruction			0.257***
	Learned by observing work practices			0.383***
	Received informal instruction from supervisors/colleagues			0.436***
	Received formal instruction from supervisors/colleagues			0.386***
Off-JT	No opportunity			ref.
	Opportunity existed, but not attended			-0.059***
	< 5 hours per year			0.052**
	5–9 hours per year			0.108***
	10–19 hours per year			0.128***
	20–49 hours per year			0.176***
	50+ hours per year			0.231***
Task	Routine		-0.001***	-0.001***
	Cognitive		0.002***	0.002***
	Collaborative		0.000	0.000
Employment	non-regular (ref.)	ref.	ref.	ref.
	regular	0.040***	0.018	0.015
Tenure years		-0.002***	-0.003***	-0.003***
Firmsize		0.003*	0.001	0.001
Sex	men (ref.)	ref.	ref.	ref.
	women	0.018	0.003	0.001
Age		-0.004***	-0.004***	-0.005***
Education	High school or less	ref.	ref.	ref.
	Vocational school	-0.011	-0.021	-0.022
	Junior college	0.005	-0.009	-0.011
	Technical college	0.005	-0.029	-0.033
	University	0.046***	0.011	0.003
Preschool child	none (ref.)			
	yes	0.028*	0.022	0.02
Constant		0.096***	0.146***	0.140***
Adj. R^2		0.110	0.117	0.128
N		24646	24646	24646

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Task share coefficients are per 1 percentage point. For interpretability, a one-unit change in OJT corresponds to ≈0.12-point increase in skill improvement (≈17% of the mean). OFF-JT corresponds to ≈5% of the mean. Robust standard errors estimated.

Model 3 in Table 4, which includes categorical specifications of OJT and OFF-JT, reveals clear dose–response patterns, where stronger or longer training corresponds to larger perceived gains. Relative to "no opportunity," higher OJT categories (e.g., informal instruction, formal instruction) and higher OFF-JT hour bands are all positive, whereas "opportunity existed but not attended" is negative, consistent with the importance of uptake. In combination, these findings support the interpretation that structured learning (OFF-JT) is the most effective when reinforced through day-to-day work-embedded learning (OJT), which is consistent with the complementarity hypothesis (H3).

As a robustness check, we standardized OJT and OFF-JT, and re-estimated model 2 in Table 4.

The results are virtually identical, where the standardized coefficients are 0.175 for OJT and 0.054 for OFF-JT (both $p < 0.001$), reinforcing that OJT has a substantially larger association with perceived skill improvement than OFF-JT.

In summary, consistent with H2, OJT exhibits a stronger association with perceived skill improvement compared with OFF-JT. The observed complementarities provide tentative support for H3.

5.4 Heterogeneity and robustness

Participation gaps are larger for non-regular workers and increase with firm size, echoing descriptive gradients. Task effects remain robust across these groups, but stratification persists: regular workers and those in larger firms are more likely to participate in training, while non-regular workers and those in smaller firms remain disadvantaged.

All the main patterns of association reported above—routine tasks showing negative associations, cognitive and collaborative tasks showing positive associations, and OJT being more strongly linked to perceived skill improvement than OFF-JT—are robust across (i) ordered outcome models, (ii) alternative task scaling (0–1 normalization; z-scores), and (iii) specifications separating OFF-JT access from uptake.

6. Discussion and Policy Implications

6.1 Key findings and implications

Three key findings stand out in our analysis. First, participation in employer-provided training is stratified by task environment, where routine intensity is negatively associated with both OJT and OFF-JT, while cognitive and collaborative content are positively associated. Second, when OJT and OFF-JT are entered jointly, OJT exhibits a stronger association with perceived skill improvement, reflecting its close coupling to day-to-day problem solving. Third, the patterns in the results are suggestive of complementarity, where structured OFF-JT appears to be most beneficial when consolidated through work-embedded OJT. An additional detail emerges regarding access versus uptake, where categorical specifications exhibit clear dose–response characteristics, while "opportunity existed but not attended" is negatively associated with perceived gains, underscoring that provision without participation can be counterproductive. Overall, these results highlight an allocation problem in CVET, where those in routine-intensive jobs, precisely where upskilling needs may be the greatest, are least likely to participate and benefit from training.

6.2 Mechanisms and theoretical interpretation

The task perspective clarifies why routine-heavy roles may be disadvantaged. Opportunity structures in scripted, routine-intensive roles restrict mentoring and experimentation, limiting natural "slots" for OJT. Perceived returns on formal courses may also be lower when tasks are codifiable or expected to

be automated, thereby dampening OFF-JT provision. Finally, mode–task fit matters, as structured OFF-JT is harder to translate into perceived gains without subsequent on-the-job consolidation. The negative routine association in the participation models and larger OJT coefficient in the level-up model are consistent with these mechanisms. Although our design does not support causal claims, the coherence of findings across specifications indicates a pathway through which structured learning provides foundations that are consolidated through everyday work.

6.3 Implications for firms and policymakers

The imperative revealed by our analysis is not simply "more training," but who is covered and how modes are bundled. For firms, we present three major principles. First, targeting routine-heavy units is essential. Diagnostic tools can identify high-routine teams, where setting coverage floors for OJT and minimum OFF-JT hours ensure inclusion. Second, the deliberate bundling of modes is important. Modular OFF-JT should be paired with structured OJT such as coached problem cycles so that formal content is applied immediately. Third, firms can create OJT opportunities by introducing micro-assignments or small job-crafting adjustments that create space for observation, feedback, and practice, even in scripted workflows. Tracking access and uptake will allow firms to determine whether coverage translates into learning.

A coverage-first orientation is critical for policy purposes. Incentives or subsidies should be tied to verifiable OJT plans and OFF-JT modules that target routine-intensive roles, particularly for small and medium-sized enterprises. Publicly co-financed micro-credentials and e-learning can expand reach but require complementary firm-side coaching to ensure on-the-job consolidation. Finally, common measurement standards distinguishing between access and uptake would enable clearer accountability and comparative benchmarks. These directions resonate with comparative political economy insights, where sustaining inclusive CVET under liberalizing pressures requires institutions that not only expand volume but also secure equitable coverage and effective bundling of training modes.

6.4 Limitations, future research, and conclusions

There are several limitations to the interpretations presented in this paper. First, the measures are contemporaneous (training in the past year, level-up at the time of the survey), so the analysis identified associations, rather than causal effects. Second, the outcomes are self-reported, and triangulation with performance metrics or administrative records would strengthen inference. Third, task shares are self-assessed. Although alternative scaling yields consistent results, fine-grained task audits are valuable. Additionally, the Japanese case, which is marked by firm-specific skill regime or segmentalist skill formation regime, may limit generalizability. Future research should evaluate whether similar task–training gaps appear in coordinated or state-led systems.

Future studies could exploit panel data or staggered interventions, conduct task redesign

experiments combining OFF-JT modules with OJT coaching, and examine heterogeneity based on employment status, firm size, and exposure to digital tools.

In conclusion, technological change reshapes not only which skills matter, but also who is positioned to acquire them. In Japan's firm-specific skill regime, routine-intensive roles, which are those most exposed to change, receive less training, and perceived skill gains rely more on on-the-job consolidation than formal courses. By highlighting task environments as a determinant of training allocation, this study contributes to human capital, lifelong learning, and task-based literature. It offers practical levers, such as bundling OJT with OFF-JT and targeting coverage in routine-heavy settings, to reduce training inequality and support upskilling under rapid change.

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APPENDIX

Table A1. OJT: OLS vs. Ordered Logit/Probit (Model 4)

		OLS	Ordered Logi	Probit
Task Score	routine	-0.005***	-0.007***	-0.004***
		0.000	0.000	0.000
	cognitive	0.002***	0.004***	0.002***
		0.000	0.000	0.000
	collaborative	0.004***	0.006***	0.003***
		0.000	0.000	0.000
Employment	regular	0.174***	0.266***	0.152***
		-0.025	-0.037	-0.022
	non-regular	0.000	0.000	0.000
		(.)	(.)	(.)
Tenure_years		-0.016***	-0.022***	-0.013***
		-0.001	-0.002	-0.001
Firm size	~9	0	0	0
		(.)	(.)	(.)
	10~49	0.146***	0.258***	0.149***
		-0.032	-0.053	-0.032
	50~99	0.237***	0.413***	0.240***
		-0.037	-0.059	-0.035
	100~299	0.346***	0.552***	0.332***
		-0.035	-0.055	-0.033
	300~499	0.450***	0.689***	0.416***
		-0.044	-0.065	-0.039
	500~999	0.484***	0.744***	0.448***
		-0.042	-0.062	-0.037
	1000~1999	0.585***	0.870***	0.524***
		-0.045	-0.065	-0.039
	2000~4999	0.630***	0.929***	0.563***
		-0.046	-0.067	-0.04
	5000 and over	0.695***	1.024***	0.620***
		-0.037	-0.056	-0.034
	Public_Sec	0.504***	0.745***	0.463***
		-0.064	-0.087	-0.053
Sector	primary industry	0.141	0.163	0.099
		-0.104	-0.153	-0.092
	construction	-0.111**	-0.186***	-0.113***
		-0.046	-0.066	-0.04
	manufacturing	-0.065*	-0.138***	-0.079***
		-0.034	-0.049	-0.029
	public utilities and	0.034	0.048	0.015
		-0.061	-0.08	-0.049
	information and commu	-0.004	-0.036	-0.007
		-0.043	-0.057	-0.034
	transportation	-0.156***	-0.311***	-0.166***
		-0.043	-0.064	-0.038
	wholesale, retail trade, a	-0.158***	-0.252***	-0.146***
		-0.037	-0.054	-0.032
	finance and insurance	0.086	0.095	0.063
		-0.052	-0.068	-0.041
	accommodation and foc	-0.253***	-0.408***	-0.242***
		-0.06	-0.093	-0.055
	medical care and welfar	0.029	0.051	0.035
		-0.039	-0.053	-0.032
	education and learning	0.059	0.095	0.069*
		-0.053	-0.069	-0.042
	service (ref.)			
		(.)	(.)	(.)
	not classified elsewhere	-0.127***	-0.224***	-0.124***
		-0.047	-0.069	-0.041
Sex	men(ref.)			
		(.)	(.)	(.)
	women	0.032	0.034	0.018
		-0.02	-0.028	-0.017
Age		-0.017***	-0.021***	-0.013***
		-0.001	-0.002	-0.001
Education	high school or less (ref.)			
		(.)	(.)	(.)
	vocational school（sen	0.02	0.06	0.035
		-0.027	-0.039	-0.023
	junior college	0.025	0.064	0.026
		-0.035	-0.052	-0.03
	technical college	0.164**	0.250**	0.148**
		-0.081	-0.105	-0.063
	university	0.187***	0.280***	0.153***
		-0.022	-0.031	-0.018
Preschool chi	none (ref.)			
		(.)	(.)	(.)
	yes	-0.098***	-0.133***	-0.082***
		-0.025	-0.033	-0.02
Constant		1.559***		
		-0.069		
	cut1		-0.376***	-0.228***
			-0.102	-0.06
	cut2		0.253**	0.156***
			-0.102	-0.06
	cut3		0.822***	0.499***
			-0.102	-0.061
	cut4		2.297***	1.318***
			-0.103	-0.061
Observations		25250	25250	25250
R-squared (OLS)		0.108		
Pseudo R2 (ord.)			0.043	0.042

Table A2. OFF-JT: OLS vs. Ordered Logit/Probit (Model 4)

		OLS	Ordered Logi	Probit
Task Score	routine	-0.005***	-0.007***	-0.004***
		0.000	-0.001	0.000
	cognitive	0.002***	0.003***	0.002***
		0.000	-0.001	0.000
	collaborative	0.002***	0.004***	0.002***
		0.000	-0.001	0.000
Employment	regular	0.368***	0.600***	0.355***
		-0.022	-0.044	-0.025
	non-regular	0.000	0.000	0.000
		(.)	(.)	(.)
Tenure_years		-0.006***	-0.005**	-0.003***
		-0.001	-0.002	-0.001
Firm size	~9	0	0	0
		(.)	(.)	(.)
	10~49	0.114***	0.259***	0.139***
		-0.032	-0.068	-0.038
	50~99	0.146***	0.329***	0.179***
		-0.037	-0.075	-0.042
	100~299	0.202***	0.471***	0.253***
		-0.035	-0.069	-0.039
	300~499	0.327***	0.647***	0.364***
		-0.046	-0.079	-0.045
	500~999	0.352***	0.669***	0.373***
		-0.044	-0.077	-0.043
	1000~1999	0.484***	0.868***	0.478***
		-0.048	-0.077	-0.044
	2000~4999	0.479***	0.898***	0.497***
		-0.049	-0.078	-0.045
	5000 and over	0.539***	0.951***	0.533***
		-0.038	-0.069	-0.039
	Public_Sec	0.576***	0.963***	0.542***
		-0.074	-0.102	-0.059
Sector	primary industry	0.032	-0.119	-0.021
		-0.107	-0.206	-0.118
	construction	-0.016	-0.099	-0.048
		-0.052	-0.082	-0.047
	manufacturing	-0.083**	-0.172***	-0.105***
		-0.036	-0.057	-0.033
	public utilities and	-0.018	-0.034	-0.013
		-0.071	-0.094	-0.054
	information and comm	0.016	-0.021	-0.01
		-0.048	-0.068	-0.039
	transportation	-0.140***	-0.297***	-0.164***
		-0.043	-0.073	-0.042
	wholesale, retail trade,	-0.154***	-0.320***	-0.175***
		-0.038	-0.066	-0.037
	finance and insurance	-0.074	-0.09	-0.052
		-0.057	-0.079	-0.046
	accommodation and fo	-0.307***	-0.699***	-0.402***
		-0.05	-0.125	-0.067
	medical care and welfa	0.229***	0.357***	0.196***
		-0.042	-0.061	-0.035
	education and learning	0.481***	0.651***	0.359***
		-0.064	-0.078	-0.045
	service (ref.)			
		(.)	(.)	(.)
	not classified elsewhe	-0.059	-0.168**	-0.082*
		-0.049	-0.083	-0.047
Sex	men			
		(.)	(.)	(.)
	women	-0.100***	-0.176***	-0.098***
		-0.022	-0.032	-0.019
Age		-0.009***	-0.015***	-0.008***
		-0.001	-0.002	-0.001
Education	high school or less (ref.)			
		(.)	(.)	(.)
	vocational school（se	0.018	0.062	0.04
		-0.027	-0.045	-0.026
	junior college	0.100***	0.184***	0.101***
		-0.035	-0.059	-0.034
	technical college	0.371***	0.491***	0.296***
		-0.101	-0.122	-0.069
	university	0.218***	0.318***	0.190***
		-0.023	-0.036	-0.021
Preschool chi	none (ref.)			
		(.)	(.)	(.)
	yes	-0.026	-0.007	-0.009
		-0.028	-0.036	-0.021
Constant		0.704***		
		-0.071		
	cut1		1.217***	0.713***
			-0.122	-0.068
	cut2		1.725***	1.014***
			-0.122	-0.068
	cut3		2.278***	1.329***
			-0.122	-0.069
	cut4		2.786***	1.603***
			-0.123	-0.069
	cut5		3.544***	1.983***
			-0.125	-0.07
	cut6		4.548***	2.433***
			-0.13	-0.071
Observations		25250	25250	25250
R-squared (OLS)		0.080		
Pseudo R2 (ord.)			0.042	0.042

Notes: Controls as in Model 4: employment status, tenure, firm size (10), industry/sector, sex, age, education, preschool-child indicator. Ordered-model cutpoints suppressed; coefficients are log-odds (ologit) / latent-index units (oprobit). Results are substantively unchanged: routine tasks show negative associations, cognitive and collaborative tasks show positive associations, consistent with the main results. Robust standard errors estimated.