Job Tasks, Skill Formation, and Wages: An Internal Labor Market Approach

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This study highlighted the institutional aspects of the task approach and quantitatively showed the mechanisms of tasks, skills, and wage determination through the operations of the internal labor market. As a skill measure, intellectual skills to deal with changes and problems in the workplace were employed. Using an original survey from Japan, it was found that the internal labor market-oriented skill formation system affects task allocation. The most important finding was that task polarization occurs through the skill-formation system as a subsystem of internal labor market. This result suggests the possibility of controlling task distribution through internal labor market design. Furthermore, we found that non-routine tasks positively affect intellectual skills. Finally, in estimating the wage function, we found that abstract task increases wages, while routine and manual tasks decreases wages. This result is consistent with previous studies and robust regardless of skill measure controls. Our findings suggest that task polarization and wage returns of tasks in previous studies can be interpreted from the aspects of internal labor market, and the importance of model analysis from such perspectives in the future.

Keywords: Job tasks; Skills; Wage determination; Internal labor market; Japan

JEL classification codes: J24, J31, J40

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1 Introduction

This study is an attempt to incorporate the internal labor market-oriented skill formation model into the task approach (pioneered by Autor, Levy, and Murnane ,2003). Several studies have used the task approach to interpret the polarization in earnings distribution in terms of task allocation among workers (Autor, Levy, and Murnane 2003; Autor and Dorn 2009; Goos, Manning, and Salomons 2009; Acemoglu and Autor 2011; Michaels, Natraj, and Van Reenen 2014; Ikenaga and Kambayashi 2016). The novelty of the task approach lies in the separation of production factors (e.g., labor or capital) and tasks in the workplace. According to Autor, Levy, and Murnane (2003), job tasks can be roughly divided into *routine* tasks that conduct a limited and well-defined set of cognitive and manual activities, and *non-routine* tasks that conduct problem-solving and complex communication activities. In Autor and Handel (2013), non-routine tasks are further divided into *abstract* tasks, including abstract problem-solving and creative, organizational, and managerial tasks; and *manual* tasks, including non-routine manual tasks that require physical adaptability. Task allocation partly depends on the set of tasks experienced during on-the-job training within the enterprise. For example, Doeringer and Piore (1971, 19) described on-the-job training through task experience.

> In many respects, on-the-job training might best be described as one of a rolling readjustment of tasks between experienced and inexperienced workmen. The experienced workman begins by assigning novices the simpler parts of the jobs which he originally performed. He then gradually assigns more complicated tasks connected with teaching and supervision. As the workman shifts more complex tasks to the trainee,

he also reduces his supervisory and teaching efforts, and reabsorbs some of the simpler tasks to allow the trainee time to master the complex work (Ibid., 19).

The economic efficiency of on-the-job training through task readjustment depends on the nature of the tasks. Among the literature on internal labor market, Williamson, Wachter, and Harris (1975) focus on 'idiosyncratic tasks' that require the knowledge of 'particular circumstances of time and place' (Hayek 1945). Idiosyncrasies in tasks include anticipating trouble, diagnosing, repairing workplace-specific equipment quickly, and operating effectively with workplace-specific team members.[1] Suppose the idiosyncratic tasks work substantially in the workplace and the skills required to perform the tasks are nurtured through on-the-job training in the internal labor market. Subsequently, the task approach needs to explicitly incorporate the organizational aspect of skill-formation.

Previous studies using task approach provide evidence that technological change has resulted in biased allocation to non-routine tasks and clarify that the effect on wages differs depending on task type. However, they have not explicitly considered the workings of external and internal labor markets in task allocation, so it has not been possible to discuss how the market should be designed to control task polarization. The first contribution of this study is to elucidate the mechanism by which the internal labor market induces task polarization.

Task allocation influences worker's skill formation through on-the-job training. According to the major previous studies in this segment, Yamaguchi (2012) found that occupations characterized by more complex tasks promote the growth of workers' skills.

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[1] See Doeringer and Piore (1971, 15–16) and Williamson, Wachter, and Harris (1975, 256).

On the other hand, Liu and Fleisher (2022) clarified that non-routine task experience through on-the-job learning enhances cognitive skills, and points out the importance of work design for cognitive skill development. The second contribution of this study is to shed new light on the effect of on-the-job task experience on skills from the perspective of the internal labor market.

The third contribution is advancing Autor and Handel's (2013) analysis of job tasks on wages. We estimate the effects of job tasks on wages, conditional on skills. Previous research has analyzed the relationship between task measures and wages without explicitly controlling for skills, and has clarified that while abstract tasks increase wages, routine and manual tasks decrease wages (Autor and Handel, 2013; Kobayashi and Yamamoto, 2020). However, if the skills enhanced by abstract task increase wages, returns on abstract task in previous studies may reflect the effect of skills rather than task themselves. In this study, we examine how the wage return on tasks changes by explicitly introducing internal labor market-oriented skill measures into wage function.

To summarize, there are three main research questions in this study. (1) How does the internal labor market-oriented skill formation system affect task allocation? (2) What are the effects of task allocation on skill levels? (3) To what extent are wage returns of task affected by skill controls? This study is a challenging attempt to check whether an internal labor market-oriented skill formation model yields the results consistent with those of previous studies on task polarization and wage returns of tasks.

The rest of the paper is organized as follows. Section 2 explains the internal labor market-oriented skill formation model. Section3 presents the estimation models and hypothesis. Section4 describes the dataset and variables. Section5 presents the empirical results. Section 6 concludes by discussing the implications of the empirical results.

2 Internal Labor Market-Oriented Skill Formation Model

In this study, we focus on the internal labor market in Japan and analyze the skills formed through the skill formation system within enterprise. Among previous studies, Koike (1990, 1995, 1998, 2002) provides a comprehensive analysis of 'skills' and 'skill formation' from an institutional perspective. The original concept presented in these studies are *intellectual skills*: the skills to deal with changes and problems in the workplace. According to these studies, the system to promote workers' development of intellectual skills comprises the following two subsystems of the internal labor market: (1) breadth of job experience and (2) late screening of candidates assigned to managerial positions. The former focuses on the horizontal experience through the placement of workers. In contrast, the latter focuses on vertical experiences through long-term competition among workers. Late screening encourages many workers to continuously upgrade their skills in hope that they will be selected as the elite. Intellectual skills are based on the ability to diagnose the causes of changes and problems in the workplace. As these causes are a combination of factors associated with specific job tasks within the organization, task experience is necessary to integrate fragmentary knowledge distributed across job tasks. Intellectual skills can be developed through moderate vertical and horizontal task experiences to analyse and deal with 'uncertainty' in the workplace.

We introduce intellectual skills as a skill measure in the task approach to advance conventional task analysis. In previous studies, empirical analysis of the intellectual skills model has been conducted mainly by interview surveys (Koike 1998, 2002). This study aims to reproduce empirical research on intellectual skills in the framework of task approach. The advantage of using intellectual skills as a skill measure lies in the universality of the conceptual framework. Conceptually, intellectual skills correspond to Welch's (1970) *allocative ability* and Schultz's (1975) *ability to deal with disequilibria* that diagnosing the cause of disequilibrium and efficient allocation time to activities. There are studies created a skill measure from NLSY and O*NET (Guvenen et al. 2020; Lise and Fabien Postel-Vinay, 2020) and studies created a measure from PIACC (Martínez-Matute and Villanueva, 2021; Liu and Fleisher, 2022). However, their research lacks an analysis of the skill formation process. On the other hand, Cunha et al. (2006) and other studies model skill formation within the framework of the generalization of human capital theory; in that sense, it is a model with general applicability. The uniqueness of our research lies in limiting the scope of analysis to skills to deal with the uncertainties that occur in the workplace and to analyse skills and skill formation systems in the context of institutions.

3 Empirical Models

If skill formation through on-the-job training is task readjustment among workers, and intellectual skills are formed through task experience, the skill formation system—a proxy variable for stream of tasks experienced in the past—is an important determinant of current task allocation and intellectual skills formation. Intellectual skills are skills to deal with idiosyncratic tasks. Therefore, intellectual skills have high affinity for non-routine (abstract and manual) tasks, including idiosyncrasies. By incorporating the tasks into the intellectual skills model, it is predicted that skill-formation system of moderately broad job experience and the late screening of candidates promote individual placement in non-routine tasks and, consequently, enhance intellectual skills. In the following analysis, we test the hypotheses that (1) moderately broad job experience and late screening promote individual placement in non-routine tasks and (2) non-routine task use enhances intellectual skills.

To estimate the wage function, we follow Autor and Handel (2013) and use their analytical framework. We estimate the following wage function to determine the effect of task and intellectual skills measures on wages:

$$\ln W_i = \alpha + \beta_A A_i + \beta_R R_i + \beta_M M_i + \beta_S S_i + \theta X_i + \varepsilon_i, \tag{1}$$

where W_i is the log hourly wage of a worker i; A_i, R_i, M_i, and S_i denote the intensity of worker $i's$ abstract, routine, manual task inputs, and intellectual skills measures, respectively. X_i is a vector of the observable and unobservable characteristics. In wage estimation, we explicitly add intellectual skills measure to the conventional estimation model as explanatory variables and verify whether there is a difference in the conventional estimation results regarding the effect of the task measures on wages. Moreover, we estimate different models for controlling task and intellectual skills measure, and compare the power to predict wages in each variable based on R-squared.

4 Dataset

The dataset used for the analysis was based on a questionnaire survey, the General Survey on Jobs and Working Conditions (GSJW), conducted by Rakuten Research (now Rakuten Insight), affiliated with Rakuten, a major Internet shopping site, and it has a survey monitor covering about 2.5 million people. The GSJW collects detailed information about occupations, work content, working conditions, knowledge, and employees' abilities. The survey was conducted in March 2018, targeting male and female employees aged 15–64 years, excluding executives and students. Sampling was performed to ensure the generality of the analysis so that the distribution by sex, age group, and educational background would be the same as the distribution in the 2012 survey results of the Basic Survey on Employment Structure (EES), a representative government statistic. First, we investigated the enrolment status, educational background, employment status at the time of the survey, and employment status of monitors aged 15–64 years. Second, we collected the samples until the sample size was pre-allocated. The number of valid responses was 17,848 (the valid recovery rate was 35.7%). The bottom 5% and top 5% of the response time distribution were excluded to avoid answers with short and extended response times. Consequently, a total of 15,914 samples were obtained. Figure 1 compares the distribution of occupations: an important variable for task analysis, with EES.

[Insert Figure 1 here]

Notably, the GSWJ has an exceptionally high proportion of administrative and managerial workers and professional and engineering workers compared to the EES. The GSWJ includes question items referring to O*NET in the United States, the Skills Survey in the United Kingdom, and PIACC in the OECD. However, our primary interest was a task that would be measured based on the content and nature of the respondent's job. Therefore, based on Acemoglu and Autor (2011), we calculated three task measures using O*NET: abstract, routine, and manual.

As our study focuses on a specific skill-formation model and the economic consequences of long-term OJT, we limited the sample to male regular workers. Regarding the definitions of the variables, the hourly wage was calculated as follows. First, as the GSWJ asks about the income of the previous year by category, we calculated the median value for each category and used it as annual income. As the GSWJ asks about the usual weekly working hours, including overtime, we converted it to annual working hours and divided the previously calculated annual income by the annual working hours to obtain the hourly wage. In this survey, the following questions related to performance were asked to create task measures: *'How important are the following activities and abilities, etc.?'*; *'How much freedom do you have in the following matters?'*; *'How much time do you spend on the following things?'* Table 1 shows the content of each question classified into abstract, routine, and manual tasks. There were five answers to each question. We assigned numbers 5 to 1, depending on the question.[2] Subsequently, the assigned numbers were summed for each abstract, routine, and manual task ('raw' task score) and converted into a standardized variable (a variable with a mean of 0 and a standard deviation of 1) to create a task score.

[Insert Table 1 here.]

This survey is unique as it directly questions the worker's intellectual skills. We created an intellectual skills measures and an index that measures the organizational system promoting intellectual skills, following Tomita's (2001) definition. Regarding the intellectual skills measures, the questionnaire included: *'Are you currently doing the following things at your company?'* for each of the five items listed in Table 2.

[Insert Table 2 here]

The following four options are available for each of the five questions: *'I always do it' = 4*, *'I do it to some extent' = 3*, *'I do it a little' = 2*, and *'I do not do it' = 1*. Similar to

[2] See Appendix1 for details on how to calculate annual income and task measures.

the task measures, we created a standardized intellectual skills measures, a variable with a mean of 0 and a standard deviation of 1 for each of the five items.

According to Acemoglu and Autor (2011), a task is 'a unit of work activity that produces output', and skill is 'a worker's endowment of capabilities for performing various tasks'. Comparing the task measures in Table 1 and the intellectual skills measures in Table 2, many questions do not appear to overlap. However, some of the task and intellectual skills measures imply the same activities. Specifically, '*Guidance, instructions, and motivation for subordinates'* and '*Coaching and training for others'*, components of the abstract task in Table 1—conceptually correspond to the intellectual skill of Training newcomer: '*When newcomers are assigned to the workplace, I am in charge of instruction and training'*. Therefore, to quantitatively assess the independence of the task and intellectual skills measures, we calculated the Spearman's rank correlation between the ordinal scale for components of the above abstract task and intellectual skill of Training newcomer. Our calculations revealed that both rank correlations are 0.4: not considerably large. Thus, it can be inferred that our task and intellectual skills measures can be distinguished as independent variables. [3] In the following, we statistically examine the average relationship between aggregated task and intellectual skills measures consisting of independent components.

Additionally, the index of skill formation system that promotes intellectual skills, the degree of a broad range of work experience, and the timing of screening were also created. Regarding the degree of a broad range of work experience, we used the question, *'What*

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[3] The lessons to be learned from this analysis is that tasks and skills that appear to overlap in worker characteristics do not necessarily match, and may capture different aspect of worker characteristics. A clearer identification method for tasks and skills is a future topic.

kind of work experience have you gained in your company or organization?' The following four answers were offered: *'One job in one department all the time'*; *'Wide range of work experience in one department'*; *'Experienced work closely related to each other in several departments'*; and *'Experienced various jobs in several departments'*. We created dummy variables using the narrowest range of experience: *'One job in one department all the time'* as the base category. Regarding the timing of screening, the question *'In your company/organization, how old is it that there is a clear difference in ability and achievements even if the age and educational background are almost the same?'* is used. Among the answers of *'20–24 years old'*, *'25–29 years old'*, *'30–34 years old'*, *'35–39 years old'*, *'40–44 years old'*, *'45 years old and over'*, and *'I do not know'*, the timing of screening was defined as early or late compared to *'30–34 years old'*.[4]

Hamaguchi (2011, 2013) defines Japanese-style regular employment as other Japanese-specific factors that affect the internal labor market. Employees flexibly accept work content, working hours, and work location ordered by the employer as *membership-based employment*. It is contrasted with Western-style *job-based employment* with limited content. To examine the impact of membership-based employment on tasks, intellectual skills, and wages, we use the question of whether respondents have experienced personnel changes, including changes in work content or work location over the past 4 years, and create a dummy variable that takes the value of 1 when experienced at least once.

An analytical constraint is that the data used were cross-sectional; therefore, individual-specific factors could not be controlled. To address this issue, our survey included

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[4] Table 3 shows that the percentage of people who answered 'I don't know' is 0.197, and over 50% of them are inexperienced workers at the current company for 10 years or less. The number 0.197 is the second highest after 0.271 of people who answered '30–34 years old'. As this size cannot be ignored, it is included in the sample.

questions about the personality of respondents. The questionnaire asked how well the respondents know themselves and their personalities, with the following options: *'Lively and extroverted (Lively)'*, *'Dissatisfied with others and prone to dispute (Dissatisfied)'*, *'Firm and strict to myself (Firm)'*, *'Anxious and easy to get upset (Anxious)'*, *'Like new things and have strange ideas (Strange)'*, *'Modest and docile (Modest)'*, *'Kind and cares for people (Kind)'*; *'Sloppy and careless (Careless)'*; *'Calm and stable (Calm)'*; *'Lacking creativity and mediocre (Mediocre)'*. The answer options were *'Completely different'*, *'Approximately different'*, *'A little different'*, *'Neither'*, *'I think so a little'*, *'I think so'*, and *'I strongly think so'*. Here, we create a dummy variable that takes 1 when answering any of *'I think so a little'*, *'I think so'*, and *'I strongly think so'*. We include personality dummies in both regressions for the determinants of task allocation and wages. Individual personalities may be correlated with task measures; for example, 'lively' personality has an incentive-enhancing effect on the activity of 'establishing and maintaining relationships' included in abstract tasks. If individual personalities are also correlated with hourly wages through productivity (Bowles, Gintis, and Osborne 2001; Nyhus and Pons 2005), the use of personality variables leads to dealing with the possibility of omitted variable bias in the regression of wage on task measures.

Table 3 summarizes the descriptive statistics. The routine intensity of the task is low, and the average skill of 'handling trouble' and 'stating opinion' are relatively high. With regard to the breadth of experience, many people have limited experience within one department. Additionally, the timing of screening is gently distributed mainly among aged 30–34 years, except for the answer 'I do not know'. Other variables, such as personnel changes, union membership, and personality, have no distinctive characteristics and are moderately distributed.

Table 4 shows the distributions of hourly wages, task and intellectual skills measures for each occupation. Regarding task measures, routine and manual scores tend to be high and abstract scores low in ‘manufacturing process’ and ‘transport and machine operation’. However, abstract scores are high for ‘clerical’, ‘sales’, and ‘services’. In the case of intellectual skills, ‘administrative and managerial’ workers have the highest score for all skills except ‘helping others’. For most other occupations, ‘stating opinions’ are relatively high.

[Insert Table 3 here]

[Insert Table 4 here]

5 Empirical results

5.1 Determinants of Task Allocation

Table 5 presents the regression results of individual-level task measures on the skill formation system index and socioeconomic characteristics including personnel change experience, union membership, and personality. A list of occupation dummies is presented in Appendix Table A1. As shown in Table 5, while graduates are more engaged in abstract tasks, education levels reduce routine and manual tasks; tenure and years of experience generally lower task measures. Mainly, tenure reduces the intensity of routine and manual tasks, whereas years of experience reduce the intensity of abstract and routine tasks. Interestingly, the effects of the breadth of experience and timing of screening—indicators of skill formation systems through the internal labor market—highlight the differences between non-routine (abstract and manual) and routine tasks.

First, in the non-routine task group, the breadth of work experience enhanced task use regardless of breadth, whereas in the routine task group, cross-department experience did not lead to task use. This result is consistent with our hypothesis that a broad past task experience promotes individual placement in non-routine tasks. As for the timing of screening, unlike our hypothesis, it is estimated that screening at the age of 25–29 years, earlier than the reference timing, increases the use of non-routine tasks. [5] The interpretation of this result is that those screened earlier may experience more intensive non-routine activities, resulting in a lower cost of performing non-routine tasks. Estimates that broad work experience and early selection encourage non-routine task use suggest that task polarization between non-routine and routine tasks is partly determined by the skill formation system as a subsystem of the internal labor market. Personnel change with changes in work content enhances all tasks used. By contrast, changes in work location enhance abstract task use, and union membership strongly encourages routine task. The personalities likely to be related to the abstract task are 'lively', 'firm', 'strange', 'kind', 'careless', and 'calm', and those likely to be related to the routine task are 'dissatisfied', 'firm', and 'modest'. Finally, the personalities related to the manual task are 'dissatisfied', 'strange', and 'modest'.

[Insert Table 5 here]

5.2 Determinants of Intellectual Skills

Table 6 shows the regression results of task experience on intellectual skills measures. Predictably, abstract task enhances intellectual skills; above all, the effect size is largest in 'making judgment'. The manual task shows the same qualitative tendency as the

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[5] Screening over 45 years significantly enhanced abstract and routine use. However, as shown in Table 2, the ratio of screening 'over 45 years is only 6.7%, and it is difficult to derive economic implications from this result. Therefore, we focused only on the early screening results.

abstract task, but the effect size is smaller than the abstract task. Furthermore, routine task positively and significantly affects only ‘training newcomers’ and ‘helping others’. In most cases, the breadth of experience has a positive effect. In summary, the results show that non-routine task experience enhances intellectual skills; this is in line with the estimated results of Yamaguchi (2012) and Liu and Fleisher (2022). Estimating without the task measures almost halves the adjusted R-squared, indicating that job tasks are an important explanatory factor for intellectual skills level.

[Insert Table 6 here]

5.3 Estimation of the Wage Equation

Autor and Handel (2013) emphasize the significance of clarifying the quantitative relationship between individual-level task measures and wages. Our unique attempt to estimate the wage equation introduces a new dimension of internal labor market-oriented intellectual skills into their estimation model. We regressed the individual-level log hourly wages on self-reported tasks, intellectual skills measures, and socioeconomic characteristics (Table 7). As expected, educational attainment and union membership increase wages. Variables such as tenure, years of experience, and their squares also show the expected results. Abstract task increases wages, while routine and manual tasks negatively impact wages, and the wage decrease is more significant for routine task. This result is consistent with Autor and Handel (2013) and Kobayashi and Yamamoto (2020). Regarding intellectual skills, mixed results are obtained regarding the effects on wages: the ‘handling trouble’ and ‘stating opinion’ tend to push wages up; however, ‘helping others’ tends to push wages down. The different model specifications do not produce significant qualitative differences in the estimation results. Comparing the adjusted R-squared for each specification suggests that job tasks and intellectual skills have similar explanatory power for wages. Personality is also related to wages, while ‘lively’, ‘calm’, and ‘mediocre’ are positively correlated with wages, ‘modest’ and ‘careless’ negatively affect wages. Finally, as Autor and Handel (2013) highlight, the wage return of tasks can include the effect of self-selection of workers into tasks; potentially efficient workers in a particular task are sorted into such tasks, resulting in higher returns on the allocated tasks. Therefore, we tested the self-selection hypothesis following Autor and Handel (2013) and found that self-selection hypothesis is not supported.[6]

[Insert Table 7 here]

6. Conclusion

This study highlighted the institutional aspects of the task approach and quantitatively showed the mechanisms of tasks, skills, and wage determination through the working of internal labor market. Our analysis reveals that systems such as country-specific skill formation and personnel change significantly impact worker task intensity. This result shows the importance of inter-country comparative research on the relationship between country-specific internal labor markets and task allocations.

Previous studies have highlighted the existence of polarization between non-routine (abstract and manual) and routine tasks. Our analysis of the relationship between the intra-firm skill formation system and job tasks shows a similar trend in task polarization: the breadth of work experience and the early screening of workers enhances non-routine task use. This result suggests the possibility of controlling task distribution through the

[6] See Appendix 3 for the estimation model and estimated results.

internal labor market design. It is also found that non-routine tasks positively and significantly affect all intellectual skills.[7]

In estimating the wage return of the task measures by explicitly controlling the skill measures, we found that abstract task increases wages, while routine and manual tasks decrease wages. This result is consistent with previous studies and robust regardless of skill measures controls.

Our findings suggest that task polarization and wage returns of tasks in previous studies can be interpreted from the aspects of internal labor market, and the importance of model analysis from such perspectives in the future. Our empirical results are subject to measurement errors in the data because of the nature of the handled objects, and the distinction between tasks and skills is not perfect. Therefore, this is a tentative study of the institutional approach to task and skill analysis. Detailed inter-country comparative studies based on more explicit identification strategies for institution-oriented tasks and skills are required for future research.

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[7] These estimation results suggest that a wide range of work experience and early screening of workers enhance non-routine task intensity, and promoting intellectual skill formation. The result that early screening enhances intellectual skills overturns the conventional wisdom in Japanese labor market that late screening enhances intellectual skills.

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Tables

Table 1. Task measures.

Abstract task	Non-routine analysis task	Analysis of Data and Information
		Creative thinking
		Explanation of the meaning of information to others
	Non-routine mutual task	Establishing and maintaining relationships
		Guidance, instructions, and motivation for subordinates
		Coaching and training for others
Routine task	Routine cognitive task	Continuous, repetitive mental, and physical activities
		Extremely strict and accurate
		Freedom of work
	Routine manual task	Machine and process control
		Maintaining a pace determined by machines and equipment
		Repeated operation
Manual task	Non-routine manual task	Mechanical equipment and vehicle control
		Touching, operating, or manipulating the objects, tools, or control devices
		Manual dexterity
		Spatial cognitive ability

Note: The “freedom of work” in the routine task is included in the question “How much freedom do you have in the following matters?”; “repeated operation” in routine task and “touching, operating, or manipulating the objects, tools, or control devices” in manual task is included in the subject of the question, “How much time do you spend on the following things?” All other items are included in the subject of the question, “How important are the following activities and abilities, etc.?”

Table 2. Intellectual skills measures.

Kind of Intellectual Skills	Question Item
Making judgment	"I am making judgment and devising by myself."
Training newcomer	"When newcomers are assigned to the workplace, I am in charge of instruction and training."
Handling trouble	"When a trouble and abnormality occur, I handle the problem myself."'
Stating opinion	"I state my opinion on how to proceed with the work of the entire workplace."
Helping others	"I do other work than my charge, such as substituting for a person who took a vacation."

Table 3. Descriptive statistics.

	Mean		Mean
Log hourly wages	7.592	The breadth of experience:	
Tenure	13.379	One job in one dept.	0.289
Work experience	21.612	Wide range jobs in one dept.	0.378
Task measures:		Related jobs in several depts.	0.165
Abstract	0.224	Various jobs in several depts.	0.167
Routine	0.033	Timing of screening:	
Manual	0.245	20–24	0.042
Intellectual skills measures:		25–29	0.175
Making judgment	0.105	30–34	0.271
Training newcomer	0.177	35–39	0.156
Handling trouble	0.243	40–44	0.092
Stating opinion	0.280	over 45	0.067
Helping others	0.106	I do not know	0.197
Education dummy:		Personnel change:	
Junior high school and below	0.043	Changes in work content	0.425
High school	0.442	Changes in work location	0.351
Vocational school	0.069	Union membership	0.379
Technical/junior college	0.033	Personality:	
University	0.365	Lively	0.331

Graduate school	0.048	Dissatisfied	0.149
Employee size:		Firm	0.292
99 or less	0.369	Anxious	0.380
100–999	0.310	Strange	0.391
Over 1000	0.283	Modest	0.358
Job rank:		Kind	0.531
Ordinary employee	0.574	Careless	0.293
Foreman/group leader	0.084	Calm	0.372
Subsection chief	0.137	Mediocre	0.313
Section chief	0.117		
Manager	0.059		
Miscellaneous	0.030		

Table 4. Hourly wages and task/Intellectual skills measures by occupations.

	Hourly Wage (yen)	Abstract	Routine	Manual	Making Judgment	Training Newcomer	Handling Trouble	Stating Opinion	Helping Others	Employment Share
Administrative and managerial	2896	0.477	-0.219	0.078	0.358	0.551	0.496	0.868	0.132	8.7
Professional and engineering	2276	0.423	0.061	0.400	0.322	0.245	0.380	0.380	0.147	28.9
Clerical	2263	0.104	-0.120	-0.193	-0.075	0.034	0.096	0.138	0.009	16.2
Sales	2080	0.336	-0.279	-0.115	0.154	0.188	0.450	0.320	0.191	8.5
Service	1736	0.178	-0.064	0.023	0.015	0.228	0.207	0.256	0.206	8.1
Security	2190	0.280	0.260	0.509	-0.118	0.400	0.170	0.291	0.278	1.9
Agriculture, forestry, and fishery	1378	-0.123	0.025	0.537	-0.033	0.222	0.013	0.471	0.349	0.4
Manufacturing process	1865	0.124	0.686	0.687	-0.051	0.149	0.111	0.131	0.154	9.7
Transport and machine operation	1779	-0.328	0.188	0.820	-0.045	-0.119	-0.003	-0.123	-0.008	4.9
Construction and mining	1765	0.105	0.297	0.918	0.092	0.022	0.165	0.243	-0.011	2.9
Carrying, cleaning, packaging, and related	1713	-0.292	0.007	0.402	-0.334	-0.183	-0.194	-0.222	-0.055	2.1
Other	2105	0.035	-0.082	0.123	-0.095	0.060	0.063	0.098	-0.021	7.8

Note. All are average values.

Table 5. Regressions of task measures on the internal labor market and personal characteristics.

	Abstract		Routine		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)
Breadth of experience						
Wide range jobs in one department	0.171*** (0.030)	0.163*** (0.030)	0.073** (0.032)	0.065** (0.032)	0.156*** (0.033)	0.159*** (0.032)
Closely related jobs in several departments	0.174*** (0.037)	0.163*** (0.038)	0.049 (0.040)	0.051 (0.040)	0.124*** (0.041)	0.132*** (0.041)
Various jobs in several departments	0.156*** (0.040)	0.148*** (0.040)	0.049 (0.043)	0.056 (0.043)	0.092** (0.045)	0.108** (0.044)
Timing of screening						
20–24	0.079 (0.063)	0.083 (0.063)	0.091 (0.074)	0.094 (0.074)	0.135* (0.076)	0.139* (0.074)
25–29	0.105*** (0.035)	0.102*** (0.036)	0.029 (0.039)	0.034 (0.038)	0.077** (0.039)	0.083** (0.039)
35–39	-0.002 (0.036)	0.001 (0.036)	-0.059 (0.040)	-0.046 (0.040)	-0.023 (0.042)	-0.008 (0.041)
40–44	0.015 (0.045)	0.016 (0.045)	0.075 (0.047)	0.085** (0.046)	0.010 (0.049)	0.034 (0.048)
over 45	0.103** (0.052)	0.107** (0.052)	0.149*** (0.055)	0.132** (0.055)	0.083 (0.058)	0.080 (0.056)

I do not know	-0.239*** (0.037)	-0.223*** (0.037)	-0.120*** (0.039)	-0.114*** (0.039)	-0.166*** (0.040)	-0.148*** (0.039)
Less than high school	-0.040 (0.062)	-0.048 (0.062)	0.041 (0.068)	0.016 (0.068)	0.080 (0.068)	0.004 (0.068)
Vocational school	0.040 (0.047)	0.010 (0.048)	-0.010 (0.054)	0.030 (0.054)	-0.048 (0.055)	-0.034 (0.055)
Junior (technical) college	-0.091 (0.068)	-0.117* (0.068)	-0.201*** (0.073)	-0.178** (0.072)	-0.092 (0.075)	-0.098 (0.073)
University	0.018 (0.028)	0.010 (0.029)	-0.231*** (0.030)	-0.163*** (0.031)	-0.263*** (0.032)	-0.191*** (0.032)
Graduate school	0.239*** (0.057)	0.191*** (0.061)	-0.349*** (0.060)	-0.299*** (0.062)	-0.204*** (0.064)	-0.240*** (0.065)
Tenure	-0.003 (0.004)	-0.004 (0.004)	-0.010** (0.005)	-0.012** (0.005)	-0.008* (0.005)	-0.009* (0.005)
Sq. of tenure/100	0.005 (0.011)	0.007 (0.011)	0.029** (0.012)	0.032*** (0.012)	0.016 (0.013)	0.019 (0.013)
Work experience	-0.018*** (0.005)	-0.016*** (0.005)	-0.018*** (0.006)	-0.017*** (0.006)	-0.006 (0.006)	-0.006 (0.006)
Sq. of work experience/100	0.012 (0.011)	0.009 (0.011)	0.007 (0.012)	0.008 (0.012)	-0.003 (0.012)	-0.002 (0.011)
Personnel change with changes in work content	0.110*** (0.028)	0.118*** (0.029)	0.152*** (0.032)	0.158*** (0.032)	0.085*** (0.033)	0.119*** (0.032)

Personnel change with changes in work location	0.113***	0.102***	0.063**	0.075**	0.047	0.042
	(0.029)	(0.029)	(0.032)	(0.032)	(0.033)	(0.033)
Union	0.052*	0.064**	0.148***	0.138***	0.097***	0.084***
	(0.027)	(0.027)	(0.030)	(0.030)	(0.031)	(0.030)
Lively	0.155***	0.152***	0.024	0.030	0.048	0.045
	(0.029)	(0.029)	(0.031)	(0.031)	(0.033)	(0.032)
Dissatisfied	0.050	0.046	0.090**	0.085**	0.076**	0.068*
	(0.035)	(0.035)	(0.038)	(0.037)	(0.038)	(0.038)
Firm	0.090***	0.088***	0.102***	0.092***	0.042	0.041
	(0.028)	(0.028)	(0.031)	(0.030)	(0.031)	(0.031)
Anxious	0.043	0.047*	0.045	0.048	0.012	0.023
	(0.027)	(0.027)	(0.030)	(0.030)	(0.030)	(0.029)
Strange	0.174***	0.168***	0.023	0.033	0.119***	0.114***
	(0.026)	(0.026)	(0.028)	(0.028)	(0.030)	(0.029)
Modest	0.013	0.008	0.119***	0.119***	0.061*	0.062**
	(0.028)	(0.028)	(0.031)	(0.030)	(0.031)	(0.031)
Kind	0.092***	0.088***	0.005	-0.003	0.011	0.003
	(0.027)	(0.027)	(0.029)	(0.029)	(0.030)	(0.029)
Careless	0.094***	0.092***	0.052	0.049	0.045	0.034
	(0.029)	(0.029)	(0.032)	(0.031)	(0.032)	(0.031)
Calm	0.058**	0.057**	-0.048	-0.042	0.003	0.003
	(0.027)	(0.027)	(0.029)	(0.029)	(0.030)	(0.029)

Mediocre	-0.026 (0.028)	-0.018 (0.028)	-0.019 (0.031)	-0.014 (0.030)	-0.047 (0.031)	-0.026 (0.030)
Occupation dummies	no	yes	no	yes	no	yes
Industry, employee size, and job rank dummies	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.192	0.202	0.106	0.130	0.125	0.172

Note. n=5515. All models include a constant. Robust standard errors are noted in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Occupations are controlled by 63 types of occupation dummies with a sample size of 20 or more and classified. Base categories are "high school graduate: for educational attainment, :30–34 years old: for the timing of screening, and "I've been doing one job in one department all the time" for the breadth of experience.

Table 6. Regressions of intellectual skills measures on task measures.

	Making Judgment		Training Newcomer		Handling Trouble		Stating Opinion		Helping Others	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Abstract	0.331*** (0.017)		0.307*** (0.016)		0.293*** (0.016)		0.314*** (0.015)		0.189*** (0.017)	
Routine	-0.098*** (0.019)		0.052*** (0.019)		-0.012 (0.019)		-0.026 (0.019)		0.088*** (0.020)	
Manual	0.149*** (0.018)		0.048*** (0.018)		0.104*** (0.018)		0.092*** (0.018)		0.118*** (0.020)	
<u>Breadth of experience</u>										
Wide range in one department	0.121*** (0.031)	0.206*** (0.032)	0.120*** (0.030)	0.193*** (0.031)	0.105*** (0.030)	0.181*** (0.031)	0.100*** (0.028)	0.177*** (0.030)	0.139*** (0.031)	0.203*** (0.032)
Mutually relevant in several departments	0.130*** (0.038)	0.208*** (0.040)	0.059 (0.037)	0.126*** (0.039)	0.039 (0.037)	0.108*** (0.039)	0.093*** (0.036)	0.163*** (0.038)	0.087** (0.039)	0.144*** (0.041)
Various job tasks in several departments	0.174*** (0.040)	0.242*** (0.043)	0.066* (0.038)	0.127*** (0.042)	0.101*** (0.039)	0.163*** (0.041)	0.130*** (0.037)	0.192*** (0.040)	0.139*** (0.041)	0.190*** (0.043)
<u>Timing of screening</u>										

20–24	0.008 (0.061)	0.048 (0.065)	-0.023 (0.064)	0.016 (0.066)	-0.057 (0.062)	-0.017 (0.066)	-0.067 (0.060)	-0.029 (0.064)	-0.089 (0.064)	-0.047 (0.067)
25–29	0.075** (0.035)	0.120*** (0.037)	0.010 (0.035)	0.049 (0.037)	0.025 (0.035)	0.066* (0.036)	-0.002 (0.034)	0.039 (0.036)	-0.018 (0.038)	0.016 (0.039)
35–39	-0.100*** (0.037)	-0.105*** (0.039)	-0.013 (0.035)	-0.023 (0.037)	-0.038 (0.037)	-0.046 (0.038)	-0.040 (0.034)	-0.047 (0.036)	-0.032 (0.038)	-0.042 (0.039)
40–44	-0.154*** (0.046)	-0.164*** (0.050)	-0.029 (0.043)	-0.028 (0.046)	-0.052 (0.044)	-0.055 (0.047)	-0.027 (0.040)	-0.032 (0.044)	-0.039 (0.045)	-0.032 (0.047)
over 45	-0.165*** (0.053)	-0.147** (0.058)	-0.010 (0.051)	0.018 (0.055)	-0.086* (0.052)	-0.063 (0.057)	-0.054 (0.048)	-0.032 (0.052)	0.019 (0.052)	0.049 (0.057)
I do not know	0.011 (0.037)	-0.088** (0.040)	-0.049 (0.036)	-0.144*** (0.038)	-0.026 (0.036)	-0.119*** (0.038)	-0.064* (0.035)	-0.159*** (0.037)	-0.022 (0.038)	-0.102*** (0.040)
Tenure	-0.010** (0.004)	-0.014*** (0.005)	0.013*** (0.004)	0.009* (0.005)	0.010** (0.004)	0.006 (0.005)	-0.001 (0.004)	-0.005 (0.004)	0.014*** (0.004)	0.009* (0.005)
Sq. of tenure/100	0.019 (0.012)	0.025** (0.012)	-0.031*** (0.012)	-0.023* (0.012)	-0.022* (0.012)	-0.015 (0.013)	0.002 (0.011)	0.009 (0.012)	-0.033*** (0.012)	-0.024* (0.012)
Work experience	0.030*** (0.005)	0.026*** (0.006)	0.014*** (0.005)	0.009 (0.006)	0.025*** (0.005)	0.021*** (0.005)	0.016*** (0.005)	0.012** (0.005)	0.010* (0.005)	0.006 (0.006)

Sq. of work experience/100	-0.047*** (0.011)	-0.047*** (0.012)	-0.026** (0.011)	-0.025** (0.011)	-0.044*** (0.011)	-0.044*** (0.011)	-0.028*** (0.010)	-0.028** (0.011)	-0.029*** (0.011)	-0.028** (0.012)
Personnel change with changes in work content	-0.043 (0.030)	0.009 (0.032)	0.015 (0.030)	0.075** (0.031)	-0.069** (0.029)	-0.014 (0.031)	-0.014 (0.028)	0.040 (0.030)	0.056* (0.032)	0.114*** (0.033)
Personnel change with changes in work location	-0.015 (0.030)	0.012 (0.032)	0.086*** (0.030)	0.117*** (0.031)	0.025 (0.030)	0.053* (0.031)	0.078*** (0.029)	0.106*** (0.030)	0.025 (0.032)	0.051 (0.033)
Union	-0.005 (0.026)	0.017 (0.030)	0.045* (0.027)	0.077*** (0.029)	-0.006 (0.027)	0.022 (0.029)	0.056** (0.026)	0.081*** (0.028)	0.106*** (0.028)	0.141*** (0.029)
Occupation dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry, employee size, and job rank dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.188	0.072	0.228	0.116	0.183	0.074	0.253	0.142	0.162	0.068

Note. n=5515. Robust standard errors are noted in parentheses. All models include constant and educational attainment dummies. Robust standard errors are noted in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Occupations are controlled by 63 types of occupation dummies with a sample size of 20 or more and are classified.

Table 7. Effects of task/intellectual skills measures on log hourly wages.

	(1)	(2)	(3)	(4)	(5)	(6)
Abstract			0.034*** (0.006)	0.031*** (0.006)	0.027*** (0.006)	0.024*** (0.006)
Routine			-0.029*** (0.007)	-0.028*** (0.007)	-0.026*** (0.007)	-0.026*** (0.007)
Manual			-0.012* (0.007)	-0.012* (0.007)	-0.013** (0.007)	-0.013* (0.007)
Making judgment	-0.006 (0.006)	-0.008 (0.006)			-0.008 (0.006)	-0.010 (0.006)
Training newcomer	-0.011 (0.007)	-0.007 (0.007)			-0.011 (0.007)	-0.007 (0.007)
Handling trouble	0.023*** (0.007)	0.020*** (0.007)			0.024*** (0.007)	0.021*** (0.007)
Stating opinion	0.038*** (0.007)	0.034*** (0.007)			0.034*** (0.007)	0.032*** (0.007)
Helping others	-0.028*** (0.006)	-0.024*** (0.006)			-0.023*** (0.006)	-0.019*** (0.006)

Less than high school	-0.109*** (0.029)	-0.103*** (0.028)	-0.108*** (0.029)	-0.103*** (0.029)	-0.106*** (0.029)	-0.102*** (0.028)
Vocational school	0.041** (0.019)	0.034* (0.019)	0.043** (0.019)	0.036* (0.019)	0.040** (0.019)	0.034* (0.019)
Junior college or technical college	0.071*** (0.027)	0.068*** (0.026)	0.069** (0.027)	0.066** (0.027)	0.068** (0.027)	0.065** (0.026)
University	0.136*** (0.011)	0.126*** (0.011)	0.129*** (0.011)	0.120*** (0.011)	0.127*** (0.011)	0.119*** (0.011)
Graduate school	0.285*** (0.021)	0.274*** (0.022)	0.274*** (0.021)	0.263*** (0.023)	0.268*** (0.021)	0.259*** (0.022)
Tenure	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)
Square of tenure/100	-0.015*** (0.005)	-0.016*** (0.005)	-0.014*** (0.005)	-0.015*** (0.005)	-0.014*** (0.005)	-0.015*** (0.005)
Work experience	0.024*** (0.002)	0.025*** (0.002)	0.025*** (0.002)	0.026*** (0.002)	0.024*** (0.002)	0.025*** (0.002)
Square of work experience/100	-0.040*** (0.005)	-0.041*** (0.004)	-0.041*** (0.005)	-0.042*** (0.005)	-0.040*** (0.005)	-0.041*** (0.004)
Personnel change with changes in work content	0.019* (0.011)	0.014 (0.011)	0.016 (0.011)	0.013 (0.011)	0.020* (0.011)	0.016 (0.011)

Personnel change with changes in work location	0.025** (0.011)	0.019* (0.011)	0.027** (0.011)	0.021* (0.011)	0.025** (0.011)	0.019* (0.011)
Union	0.043*** (0.011)	0.045*** (0.011)	0.045*** (0.011)	0.047*** (0.011)	0.046*** (0.011)	0.048*** (0.011)
Lively	0.024** (0.011)	0.021* (0.011)	0.025** (0.011)	0.022** (0.011)	0.022* (0.011)	0.019* (0.011)
Dissatisfied	-0.004 (0.013)	-0.005 (0.013)	0.000 (0.013)	-0.001 (0.013)	-0.002 (0.013)	-0.002 (0.013)
Firm	-0.002 (0.011)	0.000 (0.011)	0.002 (0.011)	0.004 (0.011)	-0.001 (0.011)	0.001 (0.011)
Anxious	-0.014 (0.010)	-0.016 (0.010)	-0.014 (0.010)	-0.015 (0.010)	-0.014 (0.010)	-0.015 (0.010)
Strange	0.013 (0.010)	0.012 (0.010)	0.014 (0.010)	0.012 (0.010)	0.011 (0.010)	0.010 (0.010)
Modest	-0.036*** (0.011)	-0.038*** (0.011)	-0.033*** (0.011)	-0.036*** (0.011)	-0.032*** (0.011)	-0.034*** (0.011)
Kind	0.004 (0.010)	0.004 (0.010)	0.004 (0.010)	0.004 (0.010)	0.002 (0.010)	0.002 (0.010)
Careless	-0.021* (0.011)	-0.019* (0.011)	-0.024** (0.011)	-0.022* (0.011)	-0.022* (0.011)	-0.020* (0.011)

Calm	0.038*** (0.010)	0.037*** (0.010)	0.037*** (0.010)	0.036*** (0.010)	0.035*** (0.010)	0.035*** (0.010)
Mediocre	0.024** (0.011)	0.024** (0.010)	0.020* (0.011)	0.021** (0.011)	0.023** (0.011)	0.024** (0.011)
Occupation dummies	no	yes	no	yes	no	Yes
Industry, firm size, and job rank dummies	yes	yes	yes	yes	yes	Yes
Adjusted R-squared	0.404	0.421	0.404	0.422	0.409	0.425

Note. n=5515. All models include a constant. Robust standard errors are noted in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
Occupations are controlled by 63 types of occupation dummies with a sample size of 20 or more and classified.
Base categories are “high school graduate” for educational attainment, “30–34 years old” for the timing of screening, and “I’ve been doing one job in one department all the time” for the breadth of experience.

Figures

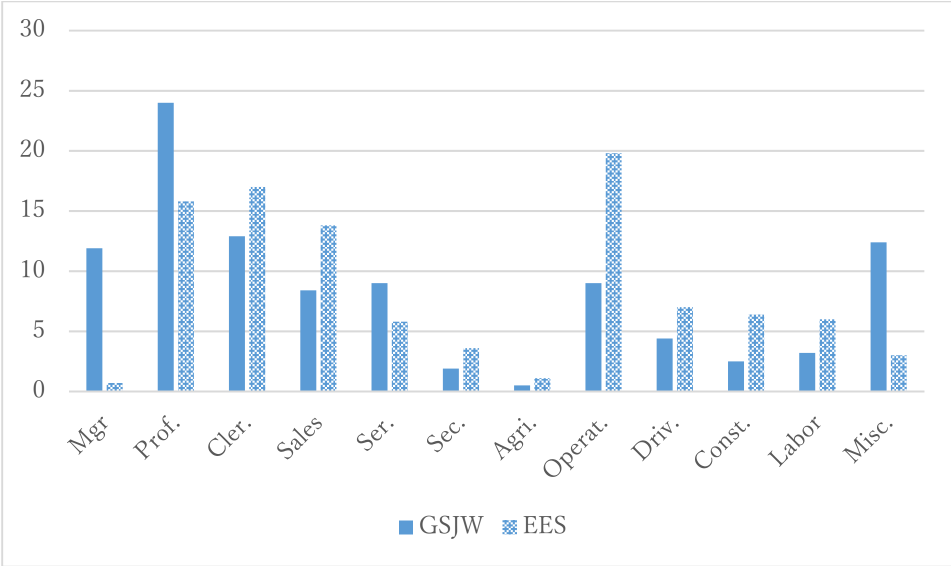

Figure 1.

Figure captions

Figure 1. Occupational distribution of employees (men, 15–64 years old), excluding executives of GSWJ and EES (October 2012).

Note. Administrative and managerial workers (Mgr.); professional and engineering workers (Prof.); clerical workers (Cler.); sales workers (Sales); service workers (Ser.); security workers (Sec.); agriculture, forestry, and fishery workers (Agri.); manufacturing process workers (Operat.); transport and machine operation workers (Driv.); construction and mining workers (Const.); carrying, cleaning, packaging, and related workers (Labor); and other workers not classified by these occupations (Misc.)

Appendices

Appendix 1. Calculations of annual income and task measures.

The categories of annual income were as follows: none, <700,000 yen, 700,000–1 million yen, 1 million–1.3 million yen, 1.3 million–1.5 million yen, 1.5 million–2.5 million yen, 2.5 million–3.5 million yen, 3.5 million–4.5 million yen, 4.5 million–5.5 million yen, 5.5 million–6.5 million yen, 6.5 million–7.5 million yen, 7.5 million–8.5 million yen, 8.5 million–10 million yen, 10 million–12 million yen, 12 million–14 million yen, 14 million–16 million yen, 16 million–18.5 million yen, 18.5 million–23 million yen, and >23 million yen.

For each category, the following values are assigned: 0, 350000, 850000, 1.15 million, 1.4 million, 1.75 million, 3 million, 4 million, 5 million, 6 million, 7 million, 8 million, 9.25 million, 11 million, 13 million, 15 million, 17.25 million, 21 million, and 23 million.

Among the task-related questions listed in Table1, the question “How important are the following activities and abilities, etc.?” it is assigned that “Not at all important” = 1, “Not very important” = 2, “important” = 3, “Pretty important” = 4, and “Very important” = 5.

On the other hand, for the question “How much time do you spend on the following things?” “No” = 1, “Less than half” = 2, “About half” = 3, “More than half” = 4, and “Continuously” = 5 were assigned.

The numbers are assigned in reverse order to the question “How much freedom do you have in the following matters?”: “no freedom at all” = 5, “very little freedom” = 4, “limited freedom” = 3, “some degree of freedom” = 2, and “quite a lot of freedom” = 1.

Appendix 2. Occupations list.

Table A1. Task measures of three-digit level occupations.

	Obs.	Abstract	Routine	Manual
Administrative workers				
Administrative local civil servant	27	0.475	-0.382	0.004
Company executive	33	0.294	-0.208	0.080
Company management staff	235	0.516	-0.256	0.031
Other corporations and organizations management staff	27	0.520	-0.450	-0.272
Other administrative workers	135	0.426	-0.125	0.224
Professional/technical workers				
Natural sciences researcher (not including the university faculty)	43	0.643	0.135	0.622
Electrical/electronic/telecommunications engineer (development)	42	0.639	0.083	0.594
Mechanical engineer (development)	48	0.578	0.226	0.799
Other manufacturing engineers (development)	38	0.593	-0.066	0.300
Electrical/electronic/telecommunications engineer (excluding development)	30	0.311	0.126	0.413
Mechanical engineer (excluding development)	70	0.476	0.738	1.243
Automotive engineer (excluding development)	20	0.355	0.261	0.862
Other manufacturing engineers (excluding development)	58	0.156	0.218	0.706
Building engineer	78	0.357	0.125	0.746
Civil engineer	91	0.100	-0.127	0.441
System designer	46	0.609	-0.141	0.039
Information processing project manager	21	0.734	-0.236	-0.021
Software creator	85	0.298	-0.244	-0.151
System operation administrator	35	0.364	-0.018	0.031
Communication network technician	30	0.090	-0.128	0.127
Other information processing/communication engineers	41	0.477	0.136	0.026
Other technicians	192	0.235	0.201	0.707

Nurses	29	0.517	-0.141	-0.188
Physical therapist	33	0.855	-0.285	0.089
Other social welfare professionals	26	0.234	-0.494	-0.176
Elementary school teacher	24	0.694	-0.352	-0.091
High school teacher	35	0.568	-0.448	-0.198
Professional occupations not classified elsewhere	111	0.115	0.043	0.316
Office worker				
General affairs clerk	167	-0.070	-0.197	-0.164
HR clerk	34	0.320	-0.325	-0.341
Planning clerk	81	0.512	-0.405	-0.276
General clerk	116	0.314	-0.065	-0.171
Other general office workers	161	-0.116	-0.062	-0.227
Accounting clerk	86	0.012	0.121	-0.301
Other accounting office workers	27	0.139	-0.245	-0.336
Production site clerk	24	0.200	0.197	0.184
Sales/sales clerk	83	0.220	-0.297	-0.195
Salesperson				
Retail store owner/clerk	31	0.491	-0.281	0.098
Sales clerk	97	0.247	0.021	-0.027
Grocery sales professional	29	0.420	-0.141	0.098
Machinery and equipment sales professionals	39	0.290	-0.337	0.265
Communication/information system sales professional	23	0.840	-0.166	-0.024
Financial/insurance sales professionals	34	0.623	-0.352	-0.653
Real estate sales professional	27	0.242	-0.365	-0.241
Other sales professionals	129	0.220	-0.466	-0.231
Service worker				
Facility care worker	58	0.159	-0.208	-0.267
Cook	34	0.397	-0.025	0.063
Ryokan/hotel/vehicle customer service workers	25	0.622	0.161	-0.038
Service workers not classified elsewhere	197	0.030	-0.047	0.046
Security workers				
Police officer	24	0.556	0.255	0.339
Security guard	26	-0.149	-0.174	-0.176

Production process worker				
Other product manufacturing/processing workers (metal products)	20	0.268	0.596	0.590
Chemical production workers	22	0.492	1.162	0.974
Other product manufacturing/processing workers (excluding metal products)	46	0.059	0.518	0.599
Other production-related/production-like employees	109	-0.060	0.453	0.557
Transportation / mechanical operator				
Train driver	21	-0.163	1.052	1.071
Bus driver	29	-0.518	0.250	0.869
Passenger car driver	24	-0.906	-0.516	0.626
Lorry driver	129	-0.409	0.042	0.822
Construction and mining workers				
Other construction workers	43	0.294	0.301	1.008
Civil engineering worker	43	0.014	0.194	0.995
Workers in transportation, cleaning, packaging, etc				
Land handling/transportation workers	26	-0.344	-0.183	0.375
not classified elsewhere	484	0.090	-0.043	0.138

Note: It shows the average task measures for occupations with ≥20 observations.

Appendix 3. Estimated model and results for self-selection test.

Regarding the estimation of the wage function, as Autor and Handel (2013) point out, the wage return of tasks can include the effect of self-selection of workers into tasks—potentially efficient workers in a task are sorted into such tasks, resulting in higher returns on the allocated tasks. Therefore, as in Autor and Handel (2013) and Kobayashi and Yamamoto (2020), we test the self-selection hypothesis. In both studies, the following two types of self-selection test were performed: The first test estimates task returns for each occupation and shows that the correlation of task returns between tasks is not uniform. The second test estimates the wage function by adding the average task intensity calculated for each occupation and cross terms with each task measures to the explanatory variables and tests whether the cross terms are positive. In our dataset, enough sample size cannot be obtained for each occupation; the first test causes variations in the reliability of the estimate of task returns for each occupation. Therefore, we performed only the second test, using the following estimation formula:

$$\ln W_i = \alpha + \beta_A A_i + \beta_R R_i + \beta_M M_i + \delta_A \overline{A_j} + \delta_R \overline{R_j} + \delta_M \overline{M_j} + \gamma_A A_i \times \overline{A_j} + \gamma_R R_i \times \overline{R_j} + \gamma_M M_i \times \overline{M_j} + \varepsilon_i, \quad \text{(A1)}$$

where, $\overline{A_j}$, $\overline{R_j}$, and $\overline{M_j}$ indicate the occupation-level averages of abstract, routine, and manual task intensity for occupation j, respectively.

If at least one of γ_A, γ_R, or γ_M is significantly positive, the self-selection hypothesis is supported. In previous studies, the cross-term of average task use at the worker and occupation levels was positive and significant in the routine tasks of Autor and Handel (2013) and manual tasks of Kobayashi and Yamamoto (2020). The estimation results are presented in Table A2. Regarding the estimates of the cross-term of average task use at the worker and occupation levels, the qualitative tendency of being negative in the abstract task and positive in the routine and manual tasks is consistent with Autor and Handel (2013) and Kobayashi and Yamamoto (2020). However, our results are not statistically significant, and qualitative and quantitative tendencies do not change, even if the estimation model is altered.

Table A2. Effects of individual and occupational task measures on log hourly wages.

	(1)	(2)	(3)	(4)
Abstract (individual level)	0.029***	0.033***	0.030***	0.034***
	(0.006)	(0.008)	(0.006)	(0.008)
Routine (individual level)	-0.023***	-0.025***	-0.022***	-0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
Manual (individual level)	-0.015**	-0.018**	-0.015**	-0.018**
	(0.006)	(0.008)	(0.006)	(0.007)
Abstract (occupational level)	0.126***	0.130***	0.121***	0.126***
	(0.039)	(0.040)	(0.039)	(0.040)

Routine (occupational level)	-0.104**	-0.124**	-0.098**	-0.117**
	(0.046)	(0.048)	(0.046)	(0.048)
Manual (occupational level)	0.067*	0.071*	0.064*	0.068*
	(0.036)	(0.037)	(0.036)	(0.037)
Abstract (individual level)		-0.020		-0.021
×Abstract (occupational level)		(0.026)		(0.026)
Manual (individual level)		0.026		0.023
×Manual (occupational level)		(0.021)		(0.021)
Routine (individual level)		0.015		0.016
×Routine (occupational level)		(0.019)		(0.018)
Making judgment			-0.005	-0.006
			(0.009)	(0.009)
Training newcomer			-0.037**	-0.037**
			(0.015)	(0.016)
Handling trouble			0.041***	0.041***
			(0.013)	(0.013)
Stating opinion			0.023	0.024
			(0.018)	(0.017)
Helping others			-0.047***	-0.047***
			(0.017)	(0.017)
Adjusted R-squared	0.408	0.408	0.410	0.410

Note. N=5515.

All models include a constant, educational attainment dummies, tenure, square of tenure/100, work experience, square of work experience, industry, firm size, job rank, job rotation, union memberships, and personality dummies. Cluster robust standard errors are noted in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.