Journal of The Japanese and International Economies 58 (2020) 101110

Contents lists available at ScienceDirect

Journal of The Japanese and International Economies

journal homepage: www.elsevier.com/locate/jjie

Job tasks and wages in the Japanese labor market: Evidence from wage functions

Toru Kobayashi [a], Isamu Yamamoto [b,*]

[a] Faculty of Economics, Takasaki City University of Economics, 1300 Kaminamie, Takasaki city, Gunma prefecture 370-0801, Japan
[b] Faculty of Business and Commerce, Keio University, 2-15-45, Mita, Minato-ku, Tokyo 108-8345, Japan

A R T I C L E I N F O

JEL classification:
J24
J31
O33

Keywords:
Job task
Wage function
Self-selection
ROY model
Technological change

A B S T R A C T

Based on the microdata from the *Basic Survey on Wage Structure* and the original survey, we estimate the Mincerian wage function, incorporating job tasks, to examine the importance of job task wage premiums as well as long-term changes in the Japanese labor market. In the estimation, we found that the association between abstract tasks and wages is positive and that a one standard deviation increase in the abstract task scores was associated with a 21.2% wage premium, while that of routine and manual task wage premiums are negative. We also found that the total explanatory power of three task scores (routine, abstract, and manual tasks) is higher than that of the education dummies or the major occupation group dummies. We also confirmed two testable implications from the Roy model regarding the workers' self-selection into occupations in the Japanese labor market. These findings are similar to those obtained by Autor and Handel (2013). On the other hand, we found no major changes between 2005 and 2016 in the coefficients of routine, abstract, or manual task scores as well as their explanatory powers in the wage function. We then observed that demand for labor increased in many occupations involving many non-routine or manual tasks, but at the same time, the supply of labor to those occupations also increased. Therefore, we discussed that the change in labor demand and supply may be one of the reasons for the stable relationship between job tasks and wages.

1.Introduction

Job polarization has been observed in many countries. The employment shares of middle-wage positions such as blue-collar and clerical jobs containing a significant number of routine tasks have decreased, whereas those of high-wage jobs that involve many non-routine cognitive or abstract tasks as well as low-wage jobs that involve many manual tasks have increased. A number of studies, including Autor et al. (2003), Autor and Dorn (2013), Goos et al. (2009), and Reenen (2011) found that recent advancements in the field of information technology (IT) caused job polarization. In addition to technological progress, many studies, including Blinder (2007) and Jensen and Klezer (2010), focused on immigration or offshoring as possible factors causing job polarization.

All these studies adopted the task approach wherein changes in skill demands of workers due to technological progress or globalization result in changes in job task distribution, such as routine, manual, and abstract ones. As Autor and Handel (2013) emphasized, the task approach potentially offers a demand-side microfoundation of the relationship between job tasks and skills (or human capital). In fact, similar to the frequently estimated returns to skills, recent studies attempted to estimate the return to job tasks. For example, Cortes (2016) found that the wage premium in occupations involving routine tasks has been falling over the long run in the United States (US), even as there has been a rise in non-routine occupations. Cavaglia and Etheridge (2017) also discovered a similar tendency in the wage premium of all tasks in the United Kingdom (UK). Additionally, Fonseca et al. (2018) reported that, in Portugal between 1986 and 2007, the wage premium of abstract and routine-cognitive tasks increased whereas that of routine-manual tasks decreased.[1]

According to the findings of Ikenaga and Kambayashi (2016), an increase in the employment share of high- and low-wage jobs with

* Corresponding author.
E-mail address: yamamoto@fbc.keio.ac.jp (I. Yamamoto).

[1] Even if the labor demand for non-routine tasks continues to increase, the wage premium of non-routine tasks may not change when it causes a simultaneous increase in the labor supply. Thus, these findings on wage increases for non-routine tasks are more likely to indicate that the increase in labor demand for non-routine cognitive tasks superseded those in the labor supply.

https://doi.org/10.1016/j.jjie.2020.101110
Received 17 March 2020; Received in revised form 11 October 2020; Accepted 17 October 2020
Available online 24 October 2020

non-routine tasks, as well as a decrease in middle-wage jobs with routine tasks, was observed, even in Japan. It is thus likely that the wage structure across job tasks in the Japanese labor market also exhibits a pattern similar to that of other countries considering that technological progress and globalization are advancing without exception in Japan. However, regarding the relationship between wages and job tasks and its long-term changes, little can be found in the previous literature. Therefore, one of this study's objectives is to investigate the descriptive relationship between wages and job tasks in the Japanese labor market.

Note that when estimating the returns to job tasks to understand the job demands of a worker's skills, the conventional ordinary least square (OLS) estimates from the Mincerian wage functions with task measures are not likely to identify the structural parameters for the returns to job tasks. Unlike human capital or its proxy variables, such as years of schooling and tenure, workers can adjust a bundle of job tasks depending on changes in job demand, which indicates that job tasks are highly endogenous because of a worker's self-selection into each occupation or job. As a first attempt to examine the relationship between wages and job tasks in the Japanese labor market, we estimate the Mincerian wage function with task measures and the testable empirical implications of the Roy model developed by Autor and Handel (2013) to derive the findings for how such self-selection should be considered.

Regarding estimations and task measures, Acemoglu and Autor (2011) estimated the wage functions for every year using the variables of task scores, education, occupation, and other factors and then compared the explanatory power of each factor with partial R-squared calculations. According to their results, education had the most explanatory power for wage determination up until the 20th century, but as of the 21st century, it was surpassed by the explanatory power of task measures. Similarly, Autor and Handel (2013) found that the variance in task scores of workers who were in the same occupation was not negligible. They used data from the "Princeton Data Improvement Initiative Survey" (PDII) to estimate two types of wage functions. The first was estimated using reported task scores calculated based on several survey questions asking the respondent about the type and contents of his or her job tasks. The second was estimated with task scores obtained by connecting a number of occupations with each occupation's mean of its task scores, using the US Department of Labor's Dictionary of Occupational Titles(DOT) and the Occupational Information Network(O*NET). Having found significant differences between two task scores, they recommended the first ones that used the reported task scores of workers.

In this paper, we follow the approach implemented by Acemoglu and Autor (2011) and Autor and Handel (2013). Specifically, we first examine the importance of job tasks in the determination of a worker's wages by estimating the Mincerian wage functions incorporating job tasks. The data used are the microdata from the original survey, the *Survey for Construction of Collaborative Task Model of Human and AI System* (SCCHA). The SCCHA was conducted through the Japan Science and Technology Agency's project entitled "Research on the task models to cooperate with the human and AI systems," based on an Internet questionnaire rolled out to representative samples of approximately 10, 000 workers in January 2018 to investigate the task details of various workers along with their wages and individual characteristics. The SCCHA's questions are related to job tasks by which we can compile the reported task scores for routine, abstract, and manual tasks, as did Autor and Handel (2013), who also used the survey PDII. As previously stated, we also estimate the testable empirical implications of a worker's self-selection into each occupation derived by the Roy model of Autor and Handel (2013).

We next examine how the importance of job tasks for wage determination has evolved over the last decade. To examine this, we estimate the Mincerian wage functions with task scores year by year, based on the microdata of the *Basic Survey on Wage Structure* (BSWS, Ministry of Health, Labour and Welfare). Since the BSWS contains no information on job tasks, we assign the average task scores of three types of tasks obtained from the SCCHA to each sample from the BSWS by matching job tasks with the appropriate occupation category.

Our main findings are as follows. First, we find that, in total, the explanatory power of three task scores (routine, abstract, and manual tasks) is higher than that of education dummies or major occupation group dummies. Regarding the sign and magnitude of the coefficients of each task score, the estimation results indicate that the abstract task is significantly positive; a one standard deviation increase in the abstract task score is associated with a 21.2% wage premium, while routine and manual tasks are significantly negative. These results are similar to those obtained by Autor and Handel (2013), implying that as in the US, job tasks are important in Japan in terms of their explanatory power and influence on wage determination.

Second, we estimate the testable implications of the Roy model of Autor and Handel (2013) to confirm that there is a possibility that workers in the Japanese labor market tend to self-select occupations depending on their endowed skills and abilities.

Third, we find no major changes from 2005 through 2016 in the coefficients of routine, abstract, or manual task scores in the wage function as well as the explanatory power of the three task scores. Thus, it is understood that the association between job tasks and wages as well as the explanatory power of job tasks have been basically stable over the last decade in Japan—unlike the findings by Acemoglu and Autor (2011) and others for the US labor market. To discuss the reasons for the stable wage premium in Japan, we observed proxy variables for labor supply and demand. Then, we found that labor demand increased in many occupations that involved many non-routine or manual tasks, but at the same time, the labor supply to those occupations also increased. As a result, it is likely that the gap between labor supply and demand remained unchanged, stabilizing the association with wages and the explanatory power of related job tasks.

The remaining paper is organized as follows. Section 2 explains the empirical specifications and conceptual framework. Section 3 describes the data that are used in the analysis. Section 4 examines the cross-sectional relationships and importance of task scores in wage determination as well as the possibility of a worker's self-selection of occupations. Section 5 investigates time-series changes in the wage premium and the explanatory power of job tasks. Section 6 discusses several issues related to the estimation, including a reason for the stable relationship between job tasks and wages, by focusing on changes in the supply and demand for labor. Finally, Section 7 summarizes and concludes the paper.

2. Empirical specifications and conceptual framework

Using SCCHA and BSWS, we estimate the following descriptive wage function:

$$lnW_i = \alpha + \beta_A A_i + \beta_R R_i + \beta_M M_i + \theta \boldsymbol{X}_i + \varepsilon_i \tag{1}$$

where $W_i$is the individual wage of worker i, and A_i, R_i, and $M_i$denote the intensity of the analytical, routine, and manual task inputs of worker i, respectively. $\boldsymbol{X}_i$is a vector of the standard set of explanatory variables used in the Mincerian wage function, including age, tenure, gender, education, occupation, industry, and firm size.

We estimate Eq. (1) using 2018 cross-section data from SCCHA with the precise task intensity of individual workers. We also estimate this equation year by year using BSWS from 2005 to 2016. Although individual task intensity is only measured at the occupational level, we confirm possible time-series changes in the coefficients of task intensity in the estimation using BSWS. Here, we must assume that the task composition within each occupation does not change during the sample period because we pin down the 2018 occupational task scores using the Japanese occupational task information of SCCHA because no occupational database that is similar to the O*NET of United States and available from 2005 to 2016 in Japan exists.[2] This assumption could bias the estimation. For instance, when more abstract tasks were required and wages increased in a certain occupation possibly as a result of technological progress, the task returns would be underestimated for an abstract task. In contrast, when wages increased in occupations that use intensive abstract tasks and the task requirement did not change over time, our analysis could find increasing task returns for the abstract task.

As Autor and Handel (2013) pointed out, Eq. (1) does not necessarily recover the return on tasks when workers were randomly assigned to occupations. Autor and Handel (2013) proposed a conceptual model based on Roy (1951) theoretical framework wherein the allocation of workers to tasks is not random given that they self-select occupations that maximize their wages based on their skill endowments.

In Roy model of Autor and Handel (2013), workers are endowed a vector of different skills to conduct each task, representing a stock of human capital. Occupations use a vector of different tasks to produce output, and workers are paid the marginal product depending on their tasks and skills. Thus, each worker's problem is to choose the occupation that maximizes his/her wages. In an equilibrium, workers self-select occupations based on a comparative advantage and are employed in the occupation with the highest wages for their bundle of tasks, indicating that task returns are occupation-specific or that task intensity is endogenous. Therefore, without further assumptions, the OLS estimates of Eq. (1) do not identify the structural parameters, including returns on tasks.

Instead of estimating structural task parameters using panel data, such as in Cortes (2016), Autor and Handel (2013) further investigated Roy model to derive testable restrictions on the relationship between tasks and wages because they only use cross-section data in their empirical analysis. The first testable restriction is that "the cross-occupation covariance among task returns cannot be uniformly positive across task pairs" (Proposition 2 of Autor and Handel (2013)); otherwise, some workers can be better off by changing occupations. To check this concept, Autor and Handel (2013) separately estimated the following Eq. (2) by occupation:

$$lnW_{ij} = \alpha_j + \beta_{j1}A_i + \beta_{j2}R_i + \beta_{j3}M_i + \varepsilon_{ij} \tag{2}$$

Then, they conducted the following bivariate regressions using the estimated parameters to observe if task returns are negatively correlated for at least one task category:

$$\widehat{\beta_A} = a_1 + b_1\widehat{\beta_R} + e_{AR},\ \widehat{\beta_A} = a_2 + b_2\widehat{\beta_M} + e_{AM}$$

$$\widehat{\alpha} = a_3 + b_3\widehat{\beta_A} + e_A,\ \widehat{\alpha} = a_4 + b_4\widehat{\beta_R} + e_R,\ \widehat{\alpha} = a_5 + b_5\widehat{\beta_M} + e_M \tag{3}$$

Autor and Handel (2013) confirmed a nonzero number of negative relationships among task returns within an occupation.

The second testable restriction is that "if the correlation between worker abilities in each task is not too high, workers will self-select occupations that offer high returns to the tasks in which they are particularly well endowed" (their Proposition 3) because workers can choose their occupation based on their skill endowments.

To check this testable restriction, Autor and Handel (2013) estimated the following equation:

$$lnW_i = \alpha + \beta_A A_i + \beta_R R_i + \beta_M M_i + \delta_A \overline{A_j} + \delta_R \overline{R_j} + \delta_M \overline{M_j} + \gamma_A A_i \times \overline{A_j} + \gamma_R R_i \times \overline{R_j} + \gamma_M M_i \times \overline{M_j} + \theta \boldsymbol{X}_i + \varepsilon_i \tag{4}$$

where $\overline{A_j}$, $\overline{R_j}$, and $\overline{M_j}$indicate the average abstract, routine, and manual task intensity, respectively, within occupation *j*. If workers self-select each occupation on the basis of their endowment, task returns will be higher in occupations that intensively use each task, implying the estimated parameters of cross-terms between each worker's task intensity and its occupational average will be positive ($\gamma_A > 0, \gamma_R > 0,\ \gamma_M > 0$).

Because we only have cross-section or repeated cross-section data, we follow Autor and Handel (2013) and estimate Equations (1), (2), and (3) to drive the descriptive evidence on the relationship between wages and tasks in Japanese labor markets instead of structurally identifying the return to tasks.

3. Data

Our sample is comprised of microdata from the BSWS for the years between 2005 and 2016. Since 1948, the BSWS has been conducted annually by the Ministry of Health, Labour, and Welfare to obtain reliable statistical information about wages. It collects and records wage information according to a variety of employee demographic characteristics such as educational background, employment status, tenure, and firm size.[3] Because several pieces of information are not investigated, we must exclude part-time workers, workers at firms with under 100 employees, temporary workers, and workers at public institutions from our sample.[4] Additionally, following the methodology used by Cortes (2016) and Acemoglu and Autor (2011), we also limit the sample to full-time workers and people under the age of 64.[5] Using the wage information provided by the BSWS, we define wages by calculating yearly income[6] divided by the number of annual work hours.

We assign three types of task scores[7] to each employee in the BSWS by connecting the occupational category of BSWS samples with the occupational average task scores generated using the SCCHA,[8] which was implemented in January 2018 using an Internet questionnaire that was rolled out to representative samples to investigate the task details of various workers aged 20–59.[9] The questions related to job tasks in the SCCHA were constructed by referring to the PDII. For example, to

[2] In Japan, the "Career Matrix" database, which is similar to the O*NET of the United States, was available until 2011 in Japan. However, after the government abolished the database, there was no way to measure occupational task scores in Japan.

[3] The details regarding the implementation of the BSWS, such as the target and construction of the survey, are reported by the HP of the Ministry of Health, Labour, and Welfare (*see* https://www.mhlw.go.jp/english/ database/db-slms/dl/slms-04.pdf).

[4] For example, the educational background of part-time workers and detailed occupational information about managerial workers at small firms are not recorded in the BSWS.

[5] We excluded respondents who reported in the BSWS questionnaire that they were part-time workers.

[6] Annual income is monthly income × 12 + the annual bonus. It includes overtime pay but excludes transportation costs and family allowance.

[7] The task scores are the abstract, manual, and routine task scores. Using the responses from the SCCHA, these task scores are calculated using the same method as Autor and Handel (2013). We calculated the principal component scores using the answers to multiple questions about each task, and standardized the respondents' principal component scores. Afterwards, we calculated the averages of the scores for each occupation as categorized according to a three-digit level. Finally, we assigned each of the three scores summarized by each occupation to BSWS respondents based on their occupations. The detailed task scores of the three-digit level occupations are reported in the Appendix.

[8] The survey was conducted through the Japan Science and Technology Agency's project entitled "research on the task models to cooperate with the human and AI systems" (representative: Isamu Yamamoto).

[9] Ikenaga and Kambayashi (2016) used the average occupational task scores generated by the "Career Matrix" database until 2011 before this database was discontinued by the Japanese government.

Table 1
Descriptive statistics of the SCCHA.

	Mean	Standard deviations
log real wages	0.631	0.704
Task scores		
Abstract	0.000	1.000
Routine	0.000	1.000
Manual	0.000	1.000
Male dummy	0.560	0.496
Age	40.681	10.202
Tenure	10.610	9.072
Tenure squared	194.863	298.870
Education dummy (base=high or Jr. High)		
University or more (Science)	0.077	0.266
University or more (Arts)	0.417	0.493
College or less	0.239	0.426
# of observations	10126	

Table 2
Estimation results of task scores with male, education, occupation, and industry dummies and age, tenure, and tenure squared.

	Abstract task score		Routine task score		Manual task score	
	(1)	(2)	(3)	(4)	(5)	(6)
Male dummy	0.392	0.275	-0.128	-0.066	0.167	-0.008
	[0.020]***	[0.020]***	[0.021]***	[0.022]***	[0.020]***	[0.020]
Age	-0.008	-0.009	0.013	0.013	-0.005	-0.003
	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***
Tenure	0.034	0.027	-0.027	-0.027	-0.013	-0.002
	[0.003]***	[0.003]***	[0.003]***	[0.003]***	[0.003]***	[0.003]
Tenure squared	-0.001	-0.001	0.000	0.001	0.000	0.000
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]	[0.000]
Education dummy (base=high or Jr. High)	Education dummy (base=high or Jr. High)					
University or more (Science)	0.74	0.378	-0.226	-0.062	-0.449	-0.205
	[0.037]***	[0.037]***	[0.040]***	[0.040]	[0.038]***	[0.037]***
University or more (Arts)	0.373	0.201	-0.199	-0.071	-0.444	-0.175
	[0.022]***	[0.022]***	[0.024]***	[0.024]***	[0.023]***	[0.022]***
College or less	0.133	0.073	-0.131	-0.066	-0.159	-0.075
	[0.025]***	[0.024]***	[0.027]***	[0.026]**	[0.026]***	[0.024]***
Detailed occupation dummies (289)	no	yes	no	yes	no	yes
Indusstry and firm size dummies	yes	yes	yes	yes	yes	yes
# of observations	10,126	10,126	10,126	10,126	10,126	10,126
Adjusted R-squared	0.236	0.348	0.117	0.229	0.165	0.369

Note: Numbers in parentheses are robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

investigate the degree of abstract tasks, SCCHA framed four questions as follows: (1) the length of the longest document that must be read; (2) the frequency with which knowledge of mathematics such as algebra, geometry, trigonometry, probability/statistics, and calculus is required; (3) the frequency of solving problems that require at least 30 minutes to find a good solution; and (4) the proportion of the workday spent managing or supervising other workers. Additionally, to investigate the degree of routine tasks, four questions are included to elicit the following information: (1) the proportion of the workday spent performing short and repetitive tasks; (2) the proportion of jobs that require face-to-face interaction with customers; (3) their status as either suppliers or contractors; and (4) their status as either students or trainees. Finally, to investigate the degree of manual tasks, a single question is asked regarding the proportion of the workday spent performing physical tasks such as standing, operating machinery or vehicles, and making or fixing things by hand. Following Autor and Handel (2013), for abstract and routine task scores, we combined the answers to four questions and extracted the first principal component. Then, we standardized each task score for routine, abstract, and manual tasks.

Currently, there is no other available database that encompasses task scores in Japan. Ikenaga and Kambayashi (2016) used the average occupational task scores created by the "Career Matrix" database. However, this database was abolished by the Japanese government in 2011. This is why we, instead, utilize an original survey, the SCCHA, to assign task scores to each occupation.

Please note that samples of individuals aged over 60 in SCCHA cannot be used because of its survey design. Including this sample when following Autor and Handel (2013) might be better. However, we regard that the relationship between wages and job tasks of the sample of individuals aged over 60 tends to be affected by the institutional factors for mandatory retirement in Japan. For example, the continuous employment system (referring to a system of continuing to employ an elderly person currently employed after the mandatory retirement age) in the framework of the Law for Stabilizing Employment of the Elderly is concerned that workers aged over 60 tend to face changes in occupation and wages around the mandatory retirement age. Thus, their self-selection into occupation and job tasks might be serious enough to cause significant biases in the wage function parameters.[10]

4. Cross-sectional relationship and importance of task scores in wage determination

4.1. Task score properties

Before estimating the wage function, we confirm how the three task scores are distributed among workers to consider the validity of individual-level task scores. Following Autor and Handel (2013), we regressed task scores on individual characteristics, such as education dummies, occupation dummies, age, tenure, tenure-squared, gender dummy, industry dummies, and firm size dummies, based on SCCHA microdata. The descriptive statistics of SCCHA are summarized in Table 1, and the estimation results are shown in Table 2.

Columns (1) and (2) of Table 2 show significantly positive associations among male, high educational status, and long tenure with the abstract task score. With occupation dummies, the explanatory power increases from 23.6% to 34.8%. Columns (3) and (4) show significantly negative associations of male, high education, and long tenure with the routine task score. With occupation dummies, the explanatory power of the routine task score increases from 11.7% to 22.9%. Columns (5) and (6) show significantly negative associations between age and high education and significantly positive associations between male and tenure with the manual task score. With occupation dummies, the explanatory

[10] In the analysis using BSWS, we confirmed that the results are not much different whether or not the over 60 age sample is included. The differences in the coefficients of three task scores obtained from each sample do not exceed +/–0.01 every year.

Table 3
Real wages and task scores by each occupation.

	Real Wage per hour (unit:100yen)	routine task score	abstract task score	manual task score	employment share by occupation
Managers	46.4	-0.228	0.835	-0.501	8.0
Professionals and engineers	29.4	-0.197	0.483	-0.067	22.1
Clerical workers	24.0	0.190	-0.089	-0.593	27.8
Sales	20.9	-0.513	-0.286	0.469	9.1
Service	18.4	-0.288	-0.390	0.434	12.9
Security	22.5	0.174	0.136	0.259	1.1
manufacturing process workers	23.2	0.938	-0.370	0.861	6.5
Transport and machine Operators	24.3	0.237	-0.659	1.104	1.6
Architectural Laborers	27.7	0.019	0.132	0.608	1.5
Laborers	16.1	0.647	-0.806	0.977	2.4
Other	23.7	0.143	-0.307	0.181	7.1

Note: Shaded fields indicate the largest task value for each occupational group.

power of the manual task score increases from 16.5% to 36.9%.

These findings on the determinants of task scores from Table 2 are generally similar to that from Table 4 of Autor and Handel (2013); thus, these task scores are likely to accurately measure the type and quantity of the job tasks that each worker conducts. We can also understand that the individual-level task measure is more important than the occupation-level task measure in wage determination considering that most individual characteristics are significant even after controlling for detailed occupation dummies.

4.2. The overall relationship between occupation, tasks, and wages

Using the microdata from the SCCHA based on major occupational groups, we present an overview of the relationships between average occupational task scores for routine, abstract and manual tasks and the corresponding average real wages for each occupational group in Table 3.

The table shows that the occupational groups “managers” and “professionals and engineers” are the highest-wage groups, and that they feature high abstract task scores and low routine task scores. The table also demonstrates that the “clerical” and “manufacturing process” are middle-wage groups, and these occupations have a higher routine task score, which is similar to findings in previous studies. Looking at other occupations, we find lower wages for occupations with higher manual task scores, except for the “architectural laborers,” which features relatively high wages, possibly because of the greater risk of industrial accidents. In sum, Table 3 illustrates the fact that the relationship between occupations, task scores, and wages is very similar to those determined by previous studies such as Autor and Dorn (2013) and Goos et al. (2009, 2010).

4.3. Descriptive wage regression with individual-level job task scores

Next, we investigate how important the task scores are to wage determination as compared with other typical factors, such as occupation and education dummies, by estimating the descriptive Mincerian wage functions using task scores based on the SCCHA microdata. Since it is a cross-sectional survey, we estimate the relationship between wages and the precise information of an individual-level worker’s task score as well as their partial R-squared values for 2018. As previously stated, the estimated coefficients of task scores are noted as not necessarily able to be interpreted as structural parameters for the return on tasks because job tasks can be endogenous given the self-selection into occupations.

In the descriptive Mincerian wage functions, we use log hourly wage as a dependent variable, and three task scores (abstract, routine, and manual), education dummies (college, university with BA or MA, university with BSc or MSc), occupation dummies (the 12 group or the 289 group), and other control variables including age, tenure, tenure-squared, gender dummy, industry dummies, and firm size dummies as independent variables.

Table 4
Estimation results of the descriptive wage function with job tasks.

	log hourly wage			
	(1)	(2)	(3)	(4)
Task scores				
Abstract		0.212***	0.080***	0.056***
		(0.007)	(0.007)	(0.008)
Routine		-0.022***	-0.043***	-0.038***
		(0.007)	(0.007)	(0.007)
Manual		-0.111***	-0.065***	-0.052***
		(0.007)	(0.006)	(0.007)
Male dummy	0.301***		0.275***	0.249***
	(0.013)		(0.014)	(0.015)
Age	0.000		0.001*	0.001
	(0.001)		(0.001)	(0.001)
Tenure	0.028***		0.023***	0.020***
	(0.002)		(0.002)	(0.002)
Tenure squared	-0.000***		-0.000**	-0.000*
	(0.000)		(0.000)	(0.000)
Education dummy (base=high or Jr. High)				
University or more (Science)	0.318***		0.220***	0.165***
	(0.025)		(0.025)	(0.027)
University or more (Arts)	0.254***		0.187***	0.155***
	(0.015)		(0.016)	(0.016)
College or less	0.077***		0.051***	0.033*
	(0.017)		(0.017)	(0.017)
Detailed occupation dummies (289)	no	no	no	yes
Industry and firm size dummies	yes	yes	yes	yes
# of observations	10,126	10,126	10,126	10,126
Adjusted R-squared	0.275	0.137	0.298	0.329

Note: Numbers in parentheses are robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4 shows the estimation results of the descriptive Mincerian wage functions with three task scores compiled according to the methodology presented by Autor and Handel (2013). Looking at Table 4, we find that all variables have comparable signs and magnitudes to those in the standard Mincerian wage functions in Column (1) where the standard set of explanatory variables is used in the estimation. Besides industry and firm size dummies, Column (2) only includes three task scores, and we can see that although the R-squared in Column (2) is lower than that in Column (1), only three task variables can explain 13.7% of wage variations. The estimated coefficients in Column (2) indicate that abstract task scores tend to increase wages while routine and manual task scores tend to decrease them. From the coefficient of abstract task scores, we can understand that a one standard deviation difference in abstract tasks corresponds to an approximately 20% difference in wages. This magnitude is regarded as sizable and is similar to estimates calculated by Autor and Handel (2013) using US data. In Columns (3) and (4), where individual characteristics and occupation dummies are included with task scores, we can still find significant coefficients for task scores although the magnitude is smaller, especially

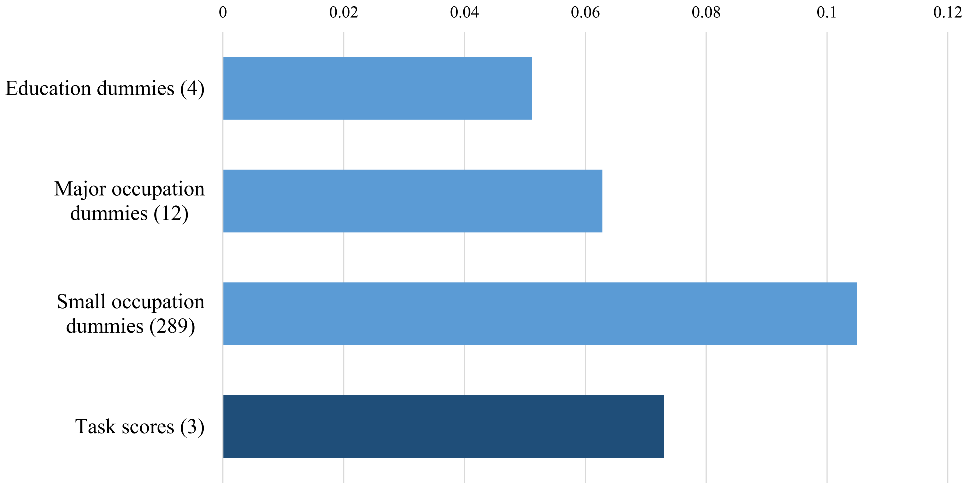

Fig. 1. Partial R-square of education, occupation, and tasks in the wage function.
Note: The partial R-square is the proportion of the log hourly wage variations explained by four education dummies, 12 or 289 occupation dummies, or three task scores that cannot be explained by the standard set of explanatory variables: age, tenure, tenure-squared, gender dummy, industry dummies, and firm size dummies. For example, we calculated the partial R-square of Task Scores ($R^2(ts|st)$) as follows:

$$R^2(ts|st) = \frac{SSR(ts|st)}{SSE(st)} = \{\mathrm{SSR}(\mathrm{ts}, \mathrm{st}) - \mathrm{s}, \mathrm{s}(\mathrm{st})\}/\mathrm{SSE}(\mathrm{st}) = \{R^2(ts, st)SST - R^2(st)SST\}/[\{1 - R^2(st)\}SST] = \{R^2(ts, st) - R^2(st)\}/\{1 - R^2(st)\}$$

where $\mathrm{SSR}(\mathrm{st})$ is the sum of the squares regression obtained by a model containing only the standard set of explanatory variables, $\mathrm{SSR}(\mathrm{ts},\mathrm{st})$ is the sum of the squares regression obtained by adding three task scores to a model already containing only the standard set of explanatory variables, and $\mathrm{SSE}(\mathrm{st})$ is the sum of the squares error obtained by a model containing only the standard set of explanatory variables.

for abstract tasks.

Fig. 1 shows the partial R-square for education dummies, occupation dummies, and task scores. The partial R-square is the proportion of the log hourly wage variation—explained by four education dummies, 12 or 289 occupation dummies, or three task scores—that cannot be explained by the standard set of explanatory variables, including age, tenure, tenure-squared, gender dummy, industry dummies, and firm size dummies. In short, the partial R-square indicates the partial explanatory power of specific groups (*i.e.*, education, occupation, or task). All employees confirmed that the partial R-square of the task scores (indicated by a dark bar) is higher than that of the education dummies or major occupation group dummies. Although the partial R-square is lower than that of the small occupation group dummies, we can interpret that only three task score variables have sufficiently large explanatory power considering that the small occupation group dummies consist of approximately 290 dummy variables.

4.4. *Descriptive wage regression with occupational-level job task scores*

Many studies that adopted the task approach used not individual- but occupational-level information on the task scores based on O*NET or DOT. To judge the validity of the occupational-level task scores in the wage functions in the Japanese labor market, we calculated and assigned occupational average task scores to each SCCHA respondent based on the 289 occupation categories and included them in the descriptive wage functions.

The estimation results are shown in Table 5, which follows Table 6 of Autor and Handel (2013). Column (1) includes three occupational task score means as well as industry and firm size dummies. In Column (2), the standard set of explanatory variables is added. These columns show that, although routine task scores are not statistically significant in Column (1), all three task scores in Column (2) are significant, and the sign and magnitude of the parameters of the three task scores and the R-square are comparable with those of the individual-level task scores shown in Column (3) of Table 4. Columns (3) and (4), which include individual- and occupational-level task scores, we can confirm that some occupational-level task scores are not significant, whereas all the individual-level scores are significant. A comparison of the R-square between Columns (2) and (4) shows that the explanatory power does not increase much even when individual task scores are included in the explanatory variables. These findings are similar to those of Autor and Handel (2013).

Therefore, it is understood that occupational-level task scores are generally useful for determining the relationship between wages and job tasks in the Mincerian wage function, but individual-level task scores are more useful when they are available.

4.5. *Testable implications from Roy model regarding self-selection*

To check the first testable restriction mentioned in Section 2, we confirm whether the cross-occupation covariance among the estimated job task parameters cannot be uniformly positive. To do so, we first estimated the wage function of Eq. (2) as explained in Section 2, by using 216 out of 289 occupations containing at least five observations. Next, using the estimated parameters, including intercepts as a dataset, we ran the bivariate regressions described in Eq. (3) by weighting the sum of the workers within each occupation. The results are shown in Table 6.

Table 6 shows that three of the six coefficients are negative, and two coefficients are significant. Compared with Table 7 of Autor and Handel (2013), although the results of b(abstract) and b(routine) are different, that the coefficients of b(manual) in Column (3) and Column (6) are positive is similar to Autor and Handel (2013). Thus, we determine that the predictions obtained from Roy model mentioned in Proposition 2 of Autor and Handel (2013) are consistent in the Japanese labor market.

Next, to check the second testable restriction mentioned in Section 2, we estimate Eq. (4) using cross-terms of occupation level and individual task scores as explanatory variables. According to Roy model, at least one of the three coefficients of the cross-terms becomes significantly positive. The estimation results of Eq. (4) are shown in Table 7. Table 7 shows that the coefficient of the cross-term for an abstract task is significantly negative; however, those for the routine and manual tasks are positive. In particular, the coefficients for the cross-term for manual are significantly positive in Columns (4) and (6). These results are similar to Autor and Handel (2013); thus, workers are thought to have the tendency to self-select occupations in the Japanese labor market that offer high returns to the tasks in which they are particularly well endowed.

5. Time-series changes in the explanatory power and wage premiums of task scores

To explore time-series changes in the fitness and magnitude of task

Table 5
Estimation results of the descriptive wage function with occupational-level and individual-level task scores.

	(1)	(2)	(3)	(4)
Task scores (individual-level)				
Abstract			0.124 [0.011]***	0.054 [0.007]***
Routine			-0.033 [0.008]***	-0.035 [0.008]***
Manual			-0.083 [0.012]***	-0.052 [0.010]***
Task scores (occupational-level)				
Abstract	0.245 [0.025]***	0.087 [0.015]***	0.177 [0.026]***	0.068 [0.015]***
Routine	-0.002 [0.015]	-0.038 [0.011]***	0.013 [0.015]	-0.022 [0.011]**
Manual	-0.029 [0.017]*	-0.034 [0.013]***	0.021 [0.018]	-0.004 [0.015]
Male dummy		0.273 [0.017]***		0.258 [0.017]***
Age		0 [0.001]		0.001 [0.001]
Tenure		0.025 [0.002]***		0.023 [0.002]***
Tenure squared		0 [0.000]***		0 [0.000]**
Education dummy (base=high or Jr. High)		Education dummy (base=high or Jr. High)		
University or more (Science)		0.207 [0.033]***		0.175 [0.031]***
University or more (Arts)		0.189 [0.022]***		0.167 [0.021]***
College or less		0.054 [0.018]***		0.044 [0.017]***
Detailed occupation dummies (289)	no	no	no	no
Industry and firm size dummies	yes	yes	yes	yes
# of observations	10126	10126	10126	10126
Adjusted R-squared	0.139	0.296	0.174	0.305

Note: Numbers in parentheses are robust standard errors clustered by occupation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

scores in the wage determination with BSWS, we first conduct an overview of the relationship between real wages and task scores for 2005 and 2016. Fig. 2 presents a scatter plot of average real wages and task scores for 10 major occupations. This figure shows that negative associations exist between average real wages with routine or manual task scores and positive associations with abstract task scores, which is consistent with Table 3. However, a comparison of the 2005 and 2016 figures indicates no major changes in the relationship between average real wages and each task score.

Then, to check whether this stable relationship between real wages and task scores is also confirmed in wage functions with task scores, we estimate the Mincerian wage functions year by year using the data matched with the BSBW and the SCCHA. Fig. 3 shows the estimated wage premium of each task score across the years, from the regression of log real wages on three task scores—age, tenure, tenure-squared, and dummies for education, industry, firm size, gender, and regular work contract. The descriptive statistics for the variables used in the estimation using the BSWS are also listed in Table 8.

Looking at Fig. 3, we find that the estimated wage premium for all three task scores are basically stable. They are large and positive for abstract tasks whereas they are small and positive, or around zero, for manual or abstract tasks, and this tendency does not change over time. These stable trends are different from those in the US or the UK and Germany as shown by Cortes (2016) or Cavaglia and Etheridge (2017), respectively. Such studies indicate that the disparity in returns from tasks has been expanding in recent years. Specifically, the returns from non-routine cognitive and abstract tasks have been rising compared to other task sectors.

We compare the results with SCCHA and found that the estimated parameters of three task measures in Fig. 3 are larger than those in Column (3) of Table 4 or Column (2) of Table 5. These differences might arise from the approach to match occupation-level task scores obtained from another survey. Autor and Handel (2013) also estimated the wage function using individual-level task scores matched from O*NET. According to Table 6, the parameters of the occupation-level abstract task from O*NET are larger than those of the individual-level abstract task score and those of the individual-level routine and manual task scores are negative, whereas those of the occupation-level routine and manual task scores are positive.

Next, we plot the partial R-square of the three standardized occupational-level task scores, as well as the education and occupation dummies in Fig. 4. Note that the explanatory power of the task scores is lower than that of the major occupation dummies, which might be because of the matched data feature that does not provides individual-level task scores.

The time-series changes of the partial R-square for the task scores show that, although the explanatory power of task scores, education, and occupation seems to increase from 2014, they are basically stable. This tendency is different from other countries. For instance, Acemoglu and Autor (2011) discovered an increasing trend in the explanatory power of job tasks in the United States.

Table 6
Relationships among coefficients obtained from the wage function for each occupation.

	b(manual) (1)	b(abstractl) (2)	b(routine) (3)	Intercept (4)	Intercept (5)	Intercept (6)
b(abstract)	0.167 [0.161]			-0.585 [0.227]**		
b(routine)		0.383 [0.079]***			-0.528 [0.190]***	
b(manual)			0.088 [0.072]			-0.275 [0.247]
# of observations	216	216	216	216	216	216
Adj-R-squared	0.018	0.142	0.005	0.076	0.061	0.018

Note: Numbers in parentheses are robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are given in parentheses. Regressions are weighted by the sum of the workers in each occupation. Means (and standard deviations) of the variables used in these models are 0.08 (0.38) for b(abstract), –0.05 (0.41) for b(routine), –0.03(0.46) for b(manual), and 0.72 (0.71) for intercept.

Table 7
Estimation results of wage function with interactions between worker task intensity and occupational mean task use intensity.

	log hourly wage (1)	(2)	(3)	(4)	(5)	(6)
Abstract(individual-level)	0.124	0.135	0.09	0.099	0.069	0.076
	[0.011]***	[0.009]***	[0.008]***	[0.008]***	[0.007]***	[0.008]***
Routine(individual-level)	-0.033	-0.032	-0.034	-0.034	-0.031	-0.03
	[0.008]***	[0.008]***	[0.008]***	[0.008]***	[0.008]***	[0.008]***
Manual(individual-level)	-0.083	-0.088	-0.078	-0.085	-0.055	-0.059
	[0.012]***	[0.012]***	[0.013]***	[0.013]***	[0.010]***	[0.010]***
Abstract(occupational-level)	0.322	0.366	0.201	0.237	0.146	0.175
	[0.047]***	[0.045]***	[0.037]***	[0.035]***	[0.027]***	[0.027]***
Routine(occupational-level)	0.028	0.027	-0.025	-0.031	-0.02	-0.023
	[0.031]	[0.031]	[0.029]	[0.028]	[0.028]	[0.027]
Manual(occupational-level)	0.035	0.059	-0.044	-0.028	-0.009	0.004
	[0.030]	[0.029]**	[0.029]	[0.028]	[0.028]	[0.027]
Abstract(individual) × Abstract(occupational)		-0.088		-0.069		-0.059
		[0.013]***		[0.012]***		[0.012]***
Routine(individual) × Routine(occupational)		0.001		0.012		0.011
		[0.018]		[0.016]		[0.016]
Manual(individual) × Manual(occupational)		0.032		0.043		0.024
		[0.023]		[0.019]**		[0.014]*
Male dummy			0.355	0.352	0.261	0.259
			[0.021]***	[0.020]***	[0.017]***	[0.017]***
Age					0	0
					[0.001]	[0.001]
Tenure					0.023	0.023
					[0.002]***	[0.002]***
Tenure squared					0	0
					[0.000]	[0.000]
Education dummy (base=high or Jr. High)						
University or more (Science)					0.212	0.219
					[0.032]***	[0.031]***
University or more (Arts)					0.193	0.188
					[0.023]***	[0.023]***
College or less					0.055	0.052
					[0.019]***	[0.019]***
# of observations	10126	10126	10126	10126	10126	10126
Adjusted R-squared	0.174	0.178	0.224	0.228	0.287	0.289

Note: Numbers in parentheses are robust standard errors clustered by occupation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6. Discussion

6.1. *Timing of changes in the task premium*

We found that that although job task is an important factor in wage determination, the explanatory power and wage premium of job tasks have been basically stable during the last decade in Japan, unlike the findings by Acemoglu and Autor (2011) and others for the US labor market. It might be the case that most of the changes in the explanatory power and wage premium of job tasks had occurred in the Japanese labor market before 2005–2016. In fact, Ikenaga and Kambayashi (2016) showed that the average wage in Japan increased for non-routine task-intensive occupations while they decreased for routine task-intensive occupations between 1970 and 2005. However, considering the recent findings that task premium changes are observed even during the 2000s and 2010s in other countries, the stable tendency between 2005 and 2016 in Japan is regarded unique. Cortes (2016) confirmed the changes in the coefficients of tasks in the wage function in the mid-2000s in the United States. Cavaglia and Etheridge (2017) also found changes in the coefficients of tasks in the wage function after 2005 in the United Kingdom and Germany.

This tendency can also be confirmed in Fig. 5, which plots the time-series changes in real wages by occupation during the last two decades. As Fig. 5 shows, we find no remarkable changes in real wages by occupation except the period during which the classification of occupations in BSWS was revised significantly. Wages for non-routine task-intensive occupations such as “managers,” “professionals and engineers,” and “service” did not increase. Conversely, the wages of “managers” and “professionals and engineers” decreased slightly during this period. Moreover, the “manufacturing process,” which is a routine task-intensive occupation, did not exhibit a decreasing trend in wages. Meanwhile, only the wages of the “sales” and “clerical” occupations exhibit slight increases.

6.2. *Possible explanation for stable task premiums and explanatory power*

We postulate that these time-series changes in occupational wages along with wage premiums of job tasks may have been affected by the changes in demand and supply. To explore this possibility, Fig. 6 plots two series of indices: “the number of “employment + unemployment” as a proxy index of labor supply and “the number of employees + vacancies” as a proxy index of labor demand, using the *Labor Force Survey* (conducted by the Ministry of Internal Affairs and Communications) and *Survey on Employment Trends* (conducted by the Ministry of Health, Labour, and Welfare). In Fig. 6, for the year 2005 we normalize the numbers of demand and supply to 100 for each occupation.

Both demand and supply have changed together in occupations such as “service and security,” “professionals and engineers,” and “manufacturing process,” where wages have been stable during the last decade, as shown in Fig. 6. This observation indicates that although the labor demand for non-routine or manual tasks may have increased in the “service and security” and “professionals and engineers” occupations, the number of workers who can supply those tasks has also increased, and thus the gap between supply and demand has remained unchanged, thus keeping wages stable. Conversely, as both the labor demand and supply for routine tasks have decreased in the routine task-intensive “manufacturing process” occupations, changes in the occupational wages and the wage premium of routine tasks have also been stable.

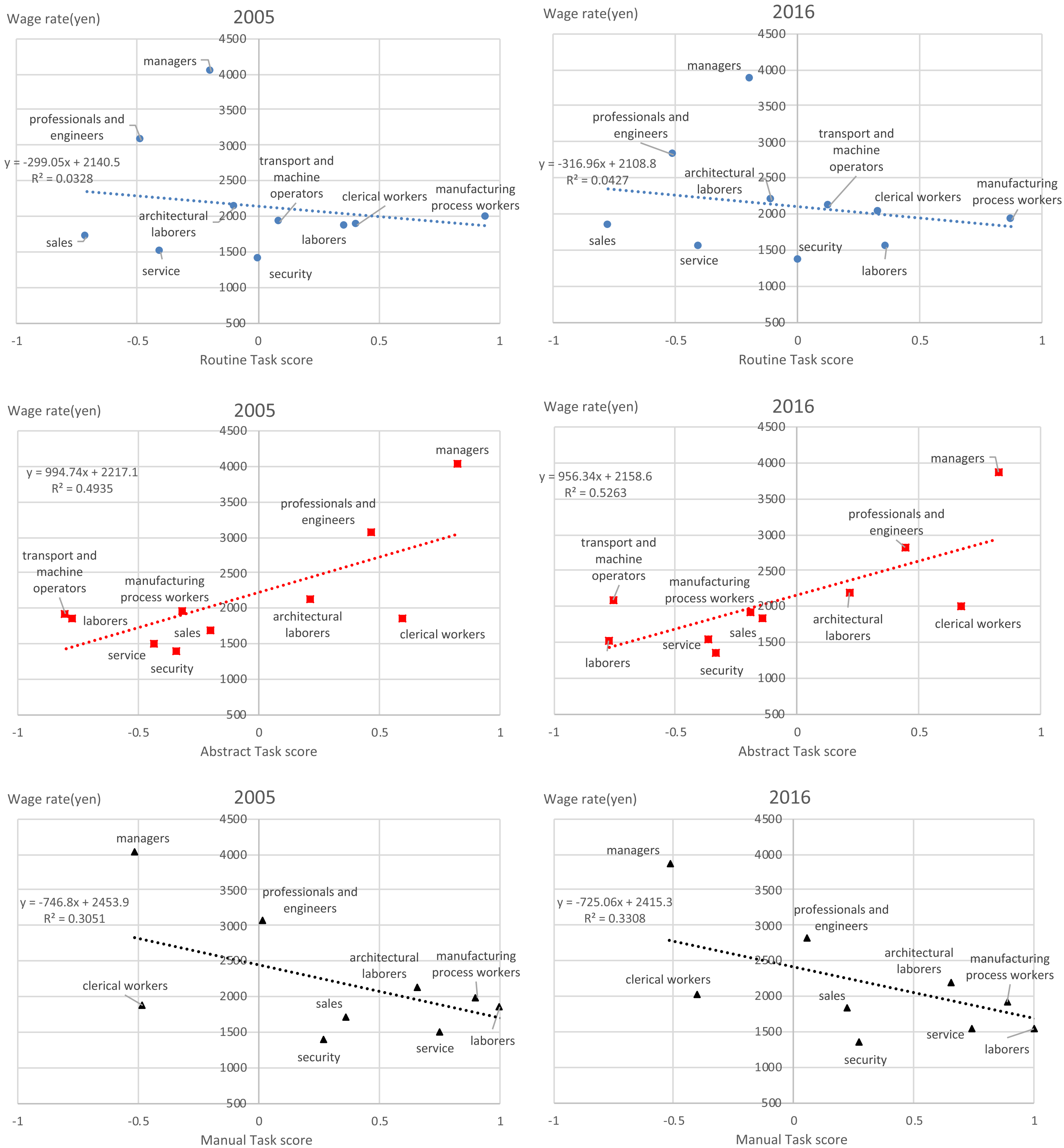

Fig. 2. Real wages and task scores, 2005 and 2016.

As we confirmed in Table 3, the workers in the "clerical" occupation category seem to engage in routine tasks rather than abstract or manual tasks. However, abstract "clerical" task scores are not large (0.19) relative to that of the "manufacturing process" in Japan, and we can confirm in Fig. 6 that they exhibit an increasing labor demand but a stable labor supply. This relative increase in labor demand seems to be consistent with this occupation's slight increase in real wages as illustrated in Fig. 5. A similar relative increase in demand is also observed in the "sales" occupation, which may be related to the slight increase in real wages as shown in Fig. 5.

To summarize, in Fig. 6 we find that although a labor demand increase is observed in many occupations involving large non-routine (abstract) or manual tasks, but the labor supply to those occupations also increased. At the same time, there has been an opposite trend in the routine task market. As a result, it is likely that the gap between the

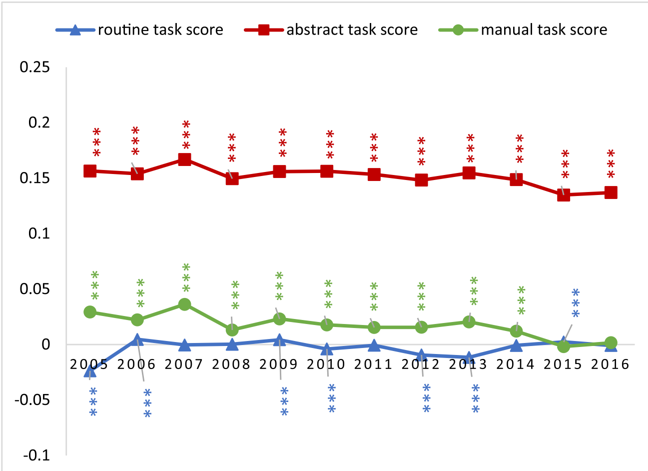

Fig. 3. Coefficients of task scores in the wage function, 2005–2016.
Note: Stars denote the level at which the estimated coefficients are significantly different from zero (*10%, **5%, ***1%). The figure shows the coefficients of the three task scores obtained from the yearly Mincerian wage functions. The dependent variable is log hourly wage. The explanatory variables are education dummies (college or less, university or more), three task scores, age, tenure, tenure-squared, gender dummy, industry dummies, regular dummy, and firm size dummies.

supply and demand for labor remained unchanged[11] such that the explanatory power or wage premium of job tasks has remained stable over the last decade. In Fig. 4, regarding the stable explanatory power of job tasks for wages, the stability of the partial R-square of other factors such as education shown in Fig. 4—together with the stable job task coefficients—is interpreted as serving as stability.

6.3. *Heterogeneity in task premium*

One possible factor for a supply adjustment is an increase in university graduates that engage in non-routine abstract tasks. Considering that the number of Japanese university graduates has recently increased,[12] we expect that the Japanese labor market might exhibit a different inclination than that of other countries.

As the demand for abstract tasks and supply of university graduates increase, the abstract task premium for university graduates may not change, whereas the abstract task premium for high school graduates decreases. To confirm this statement, we added the interaction terms of education dummies and each task score to the wage function and plotted the time-series change in the task wage premium by each educational group in Fig. 7.

Fig. 7 allows us to confirm that the abstract task premium of "high school or junior" is gradually declining, whereas that of "university or more" is stable. Similarly, the routine task premium of "high school or

[11] Fig. 6 illustrates that there is a gap between supply and demand in the abstract task-intensive "administrative and managerial" occupation. However, the employment share of this occupation is only 0.6%–1.2% (2005–2016); therefore, the effect of a change in the "administrative and managerial" occupation on total abstract task input is negligible.

[12] According to the statistical abstract (2016) reported by the Ministry of Education, Culture, Sports, Science, and Technology (MEXT), approximately 550,000 university graduates entered the labor market every year this decade—specifically, 551,016 in 2005 and 564,035 in 2015. Kawaguchi and Mori, 2016 reported that the wage inequality attributable to educational status in Japan was smaller than that in the United States because of the increasing supply of college-graduate workers. A verification of the regression of abstract task scores on education dummies is reported in the Appendix; the coefficients of college-educated dummies are positive and statistically significant.

Table 8
The descriptive statistics of the BSWS.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	All
log real wages	7.853	7.864	7.862	7.852	7.839	7.831	7.838	7.857	7.845	7.838	7.833	7.833	7.846
	(0.586)	(0.592)	(0.599)	(0.594)	(0.593)	(0.579)	(0.573)	(0.571)	(0.573)	(0.565)	(0.564)	(0.553)	(0.579)
Task scores													
Abstract	-0.032	0.027	0.002	0.007	-0.032	-0.016	-0.022	0.029	-0.001	0.027	0.011	-0.003	0.000
	(1.041)	(1.006)	(0.994)	(1.001)	(1.006)	(0.995)	(0.997)	(0.989)	(1.012)	(0.981)	(0.986)	(0.987)	(1.000)
Routine	-0.034	-0.015	-0.013	0.033	0.005	-0.008	-0.006	0.049	0.039	-0.012	-0.013	-0.018	0.000
	(0.987)	(0.999)	(0.990)	(1.002)	(1.033)	(0.992)	(1.001)	(1.008)	(0.994)	(1.001)	(0.979)	(1.013)	(1.000)
Manual	0.025	-0.024	-0.007	-0.007	0.017	0.017	0.021	-0.016	0.005	-0.024	-0.016	0.012	0.000
	(1.013)	(0.996)	(0.993)	(1.005)	(1.009)	(1.001)	(0.996)	(0.997)	(1.005)	(0.990)	(0.994)	(0.998)	(1.000)
Male dummy	0.732	0.751	0.739	0.760	0.736	0.744	0.743	0.756	0.758	0.737	0.731	0.721	0.742
	(0.443)	(0.432)	(0.439)	(0.427)	(0.441)	(0.436)	(0.437)	(0.430)	(0.428)	(0.440)	(0.444)	(0.449)	(0.437)
Age	41.964	42.191	42.159	42.111	42.040	42.283	42.446	42.707	42.891	42.888	42.928	42.934	42.470
	(11.118)	(11.077)	(11.095)	(11.152)	(11.270)	(11.131)	(11.079)	(10.980)	(11.040)	(10.904)	(10.956)	(10.975)	(11.069)
Tenure	14.599	15.113	15.035	15.108	14.673	14.900	15.079	15.310	15.227	15.406	15.222	14.861	15.044
	(11.292)	(11.416)	(11.386)	(11.494)	(11.470)	(11.339)	(11.260)	(11.334)	(11.320)	(11.309)	(11.320)	(11.289)	(11.354)
Tenure squared	340.642	358.730	355.689	360.359	346.879	350.577	354.151	362.868	360.002	365.229	359.835	348.293	355.233
	(407.784)	(417.264)	(413.792)	(420.219)	(416.528)	(412.790)	(411.881)	(417.859)	(417.456)	(416.896)	(416.508)	(411.140)	(415.039)
Education dummy (base=high or Jr. High)													
University or more	0.155	0.136	0.142	0.135	0.146	0.150	0.152	0.150	0.150	0.157	0.163	0.169	0.151
	(0.362)	(0.343)	(0.349)	(0.341)	(0.353)	(0.357)	(0.359)	(0.357)	(0.357)	(0.363)	(0.369)	(0.375)	(0.358)
College or less	0.370	0.380	0.375	0.377	0.369	0.384	0.389	0.399	0.392	0.404	0.406	0.404	0.388
	(0.483)	(0.485)	(0.484)	(0.485)	(0.483)	(0.486)	(0.488)	(0.490)	(0.488)	(0.491)	(0.491)	(0.491)	(0.487)
# of observations	286244	283264	269539	262130	259290	263780	253323	269158	274682	280056	285442	301176	3288084

Note: Numbers in parentheses are standard deviations.

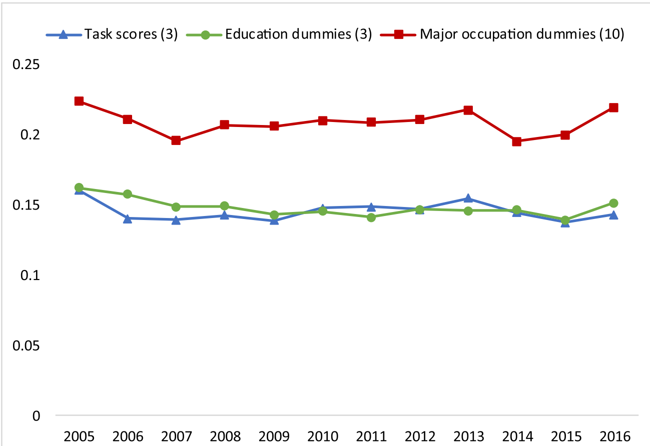

Fig. 4. Changes in Partial R-Square of Education, Occupation, and Tasks in the Wage Function.
Note: The partial R-square is the proportion of log hourly wage variations explained by three education dummies (high school or junior high, college or less, university or more), 10 major occupation group dummies, or three task scores that cannot be explained by the standard set of explanatory variables: age, tenure, tenure-squared, gender dummy, industry dummies, regular dummy, and firm size dummies.

junior" is gradually declining, whereas that of "university or more" is stable. The routine task premium of "high school or junior" is stable but that of "university or more" is increasing. Thus, the relative value of high school graduates can be considered to have declined because of the increase in university graduates.

Next, to confirm the differences in the time-series changes of the coefficients for gender, we estimated the wage function by gender and plotted the coefficients in Fig. 8. Fig. 8 enables us to confirm that the male and female coefficients are almost stable in this decade. However, the coefficients of the manual task scores for females are significantly larger than those for males. This difference may reflect the different occupational distributions across gender. For example, nurses and flight attendants are more likely to be observed for females, and these occupations have high manual task scores with high wages.

6.4. Differences in labor mobility across ages and occupations

The adjustment of the labor supply may have been achieved by both recruitment and retirement in the Japanese labor market. In Japan, most new graduates start to enter the labor market right after graduation, and they tend to work for the same firm for a longer period than most other countries. Conversely, many workers who reach age 60 or 65 have to change their careers due to the mandatory retirement system. Therefore, it can be considered that the Japanese labor supply adjustment is driven by workers who are either between approximately 20 and 30 years of age or 60 years of age or older.

To confirm this, Fig. 9 shows the employment share of each occupation across age groups in Japan in 2005 and in 2016. Looking at Fig. 9, we find that the changes in the employment share are evident under-35 and over-55 age groups. For the under-35 age group, non-routine intensive occupations, including "service and security" and "managers and professionals," have clearly increased, while routine task-intensive occupations, such as "clerical" and "blue-collar and agriculture" occupations, have decreased. Likewise, for the over-55 age group, non-routine intensive occupations, including "service and security" and "managers and professionals," have increased, while routine task-intensive occupations, including "blue-collar and agriculture," have decreased. On the other hand, we cannot find such changes in the 35–54 age group, as the employment share of each occupation is generally stable. These facts may indicate that the Japanese reconstruction of task supply occurred mainly due to younger and older employees.

To confirm whether this supply-side adjustment was driven by each employee's occupational transfers, Table 9 shows the transition matrices across occupations for job changers in 2005 and 2016 using the Survey on Employment Trends (Ministry of Health, Labour, and Welfare). The differences in the occupational transfers to "managers and professionals" and "service and security," which are confirmed in the increases in Fig. 8, only allow for the slight increase in the transfer from "sales" to "managers and professionals" (6.9 to 7.4%) and the increase from "blue collar and agri" to "service and security" (9.2 to 12.7%) to be confirmed. Thus, some of the supply-side adjustments were understood to be driven by job changers' occupational transfers. Notably, in Table 9, the occupational transfer from "manager and professionals" to "clerical" increased significantly from 5.2% to 9.3%. This change may be brought about by the institutional change in the mandatory retirement system attributable to the amendment of the Law for Stabilizing Employment of

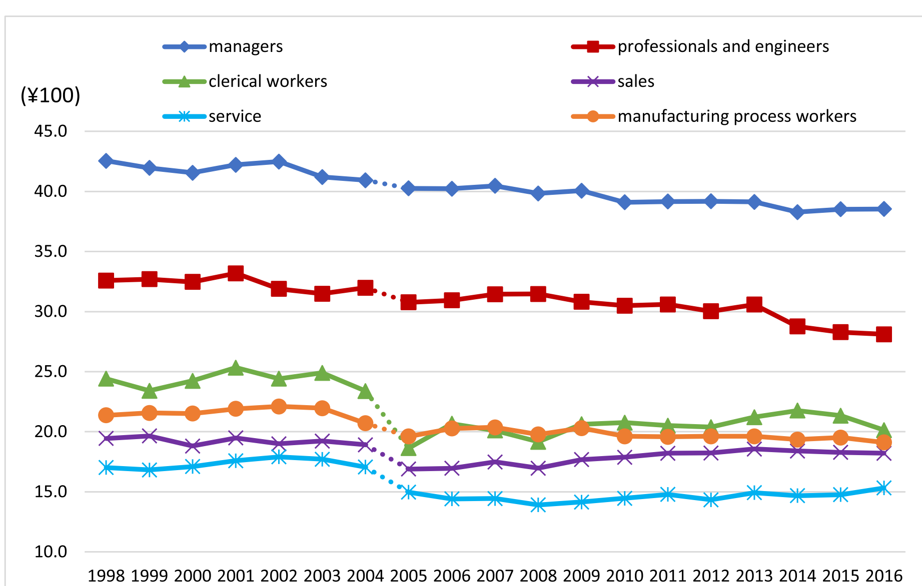

Fig. 5. Changes in Real Wage by Occupation, 1998–2016.
Note: Because the classification of occupation has changed since 2005, no time-series continuity exists between 2004 and 2005.

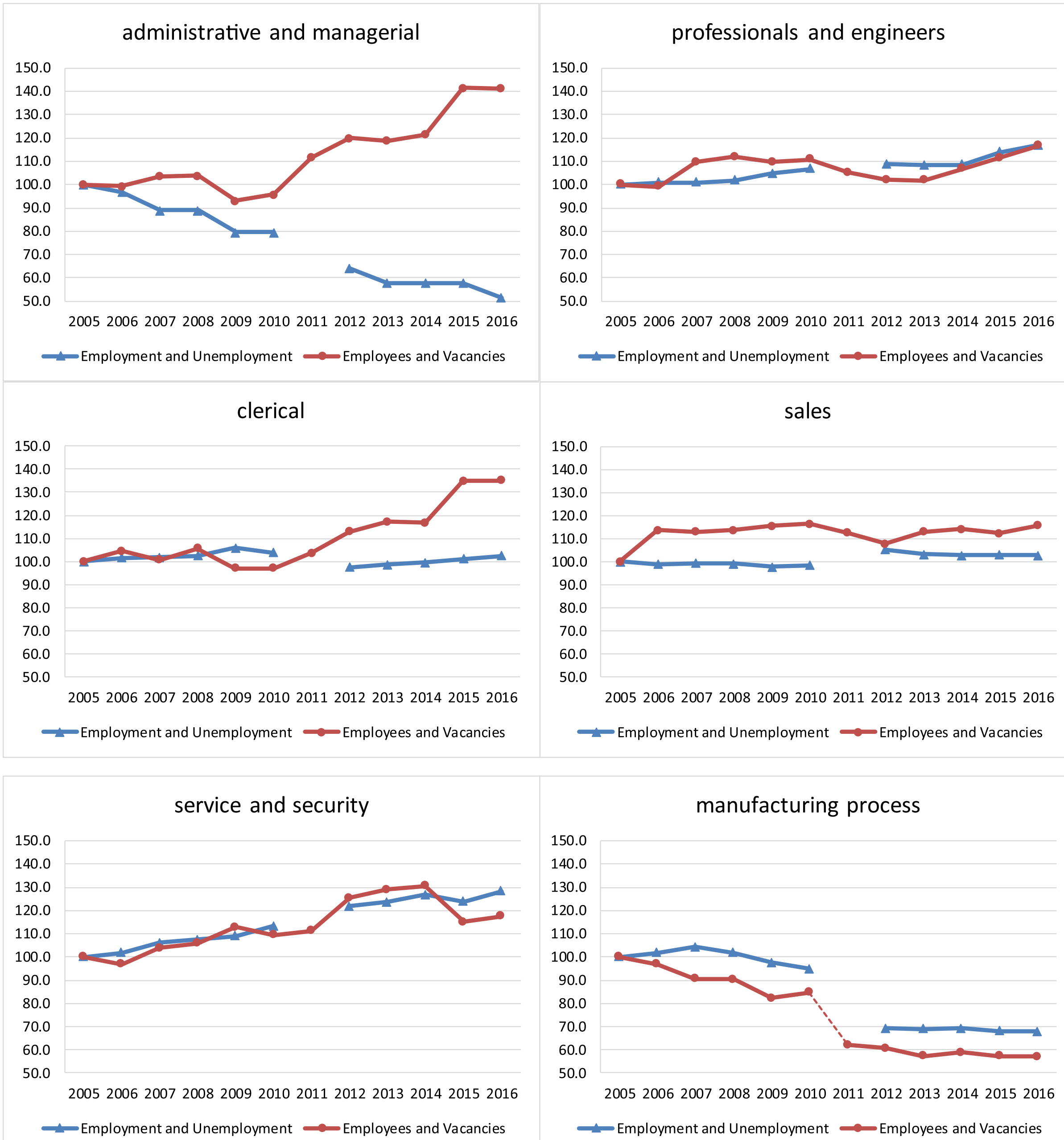

Fig. 6. Trends in Labor Supply and Demand for Each Occupation Type (2005 = 100), 2006–2016.
Note: In the Labour Force Survey (Detailed Tabulation), the "manufacturing process" was categorized as the "manufacturing process, machine operator, and architectural laborer" before 2010. In the Survey on Employment Trends, the "manufacturing process" was categorized as the "manufacturing process and related laborer" before 2010.
Source: Information on employees and vacancies were obtained from the Ministry of Health, Labour, and Welfare Survey on Employment Trends. Employment and unemployment rates were obtained from the Statistics Bureau, Ministry of Internal Affairs and Communications' Labour Force Survey (Detailed Tabulation).

the Elderly, which encouraged firms to re-employ their workers until the age of 65. Workers aged over 60 tend to change their employment contracts and get re-employed in a different position, such as clerical workers.

7. Conclusion

This study used cross-section data to investigate the relationship between wages and job tasks in the Japanese labor market. We first examined the importance of job tasks in the determination of wages by estimating the Mincerian wage functions incorporating individual-level job task data. From the estimation results of Mincerian wage functions, we found that the association between abstract tasks and wages is significantly positive, whereas that between routine and manual tasks is significantly negative. We also found that the explanatory power of three task scores in total is higher than that of education dummies or major occupation group dummies. Additionally, we found that individual-level task scores might be better than occupation-level task scores when including them in the wage function. We also confirmed the two testable implications from Roy model regarding workers' self-selection into occupations in the Japanese labor market. These results are similar to those obtained by Autor and Handel (2013).

We next examined how the association of job tasks with wages has changed over the last decade. To examine this, we estimated the

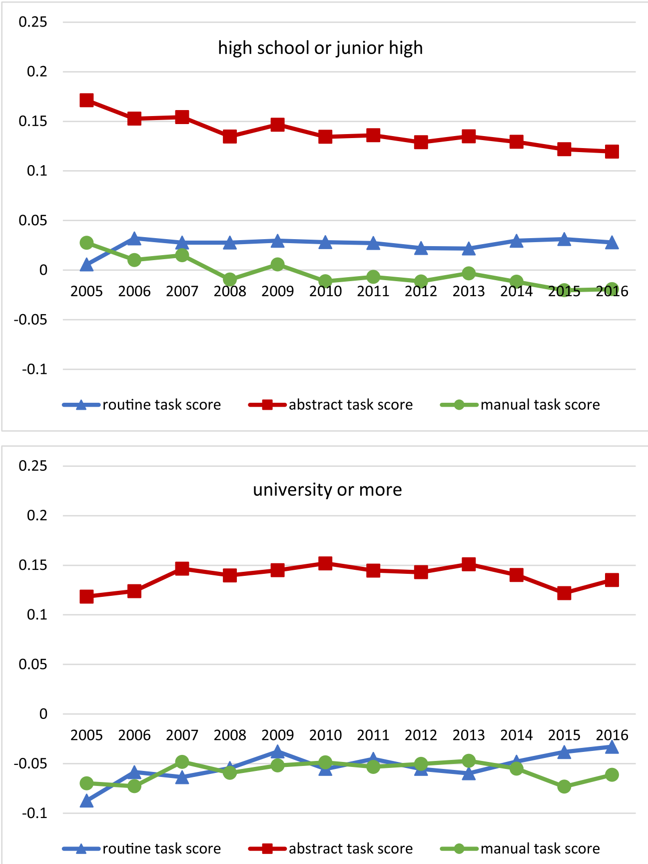

Fig. 7. Wage Premium of Three Tasks by Educational Groups, 2005–2016.
Note: The figure on "high school or junior high" shows the coefficients of the three task scores obtained from the yearly log-hourly-wage functions containing the following explanatory variables: education dummies (college or less, university or more), three task scores, interaction variables (college or less dummy x each task score, university or more dummy x each task score), age, tenure, tenure-squared, gender dummy, industry dummies, regular dummy, and firm size dummies. The figure for "university or more" shows the coefficients of the three task scores plus the coefficient of the three interaction variables of "university or more" obtained from the previously described wage function. Almost all of the coefficients are statistically significant (1%). The coefficient of the 2007 "university or more dummy x abstract task scores" is statistically significant (5%). The coefficient of the 2013 manual task scores is statistically significant (10%). The coefficients of the 2008 and 2015 "university or more dummy x abstract task scores" are not significant.

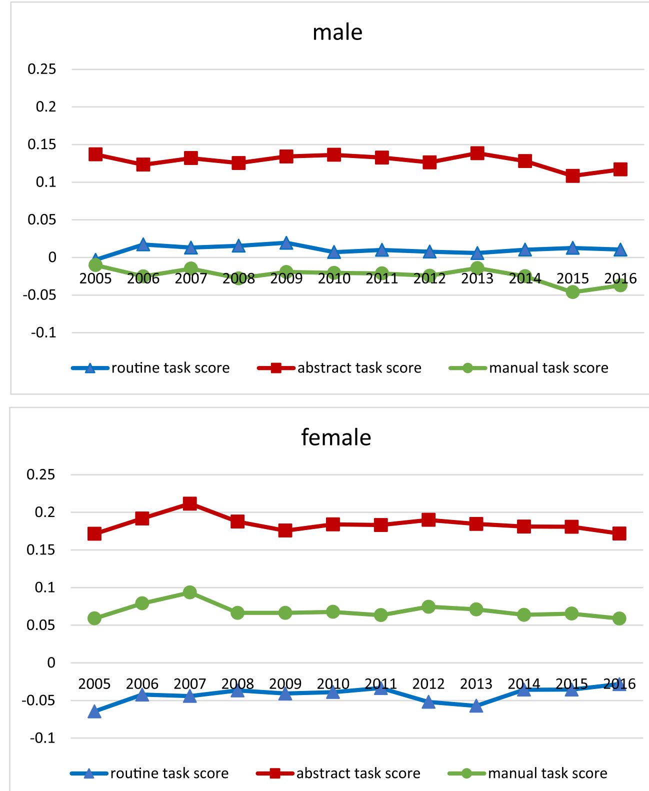

Fig. 8. Wage Premium of Three Tasks by Gender, 2005–2016.
Note: The figure on "male or female" shows the coefficients of the three task scores obtained from the yearly log-hourly-wage functions by gender. The explanatory variables used in the analysis are education dummies (college or less, university or more), three task scores, age, tenure, tenure-squared, industry dummies, regular dummy, and firm size dummies. All coefficients indicated in Fig. 8 are statistically significant (1%).

Mincerian wage functions with task scores year by year, based on the BSWS microdata assigned the occupation-level average task scores obtained from the SCCHA. We then found no major changes in the coefficients of routine, abstract, or manual task scores as well as their explanatory powers in the wage function. Thus, it is understood that association with wages and the explanatory power of job tasks have been basically stable over the last decade in Japan, unlike findings for the United States, the United Kingdom, and Germany.

To discuss the reasons for the stable wage premium, we observed proxy variables for supply and demand for labor. We then found that labor demand increased in many occupations involving large non-routine or manual tasks, but at the same time labor supply to those occupations has also increased. Additionally, we found a tendency indicating that both labor demand and supply have decreased in routine task-intensive occupations. As a result, it is likely that the gap between labor supply and demand remained unchanged so that the wage premiums and explanatory powers of job tasks have remained stable during the time period of our study.

Therefore, it may be possible to interpret that the similar changes in task demand were occurring even in Japan in the sense that labor demand for non-routine or manual tasks increased, but labor supply factors might mask the effects of the increase in task demand on wages. If this interpretation is valid, assuming that the labor supply is stable, the prevalence of new technology may affect wage determinations or wage differentials. For example, wages for the jobs involving larger tasks that are substitutable by new technologies would decline even in the Japanese labor market.

Although this study provided evidence of the relationship between job tasks and wages and the possibility of an endogeneity bias in the wage function with task scores attributable to a worker's self-selection into occupations in the Japanese labor market, limitations exist with respect to the data.

First, because we only use cross-section data, the estimated wage functions should be regarded as not structural but as descriptive in the sense that a worker's self-selection into occupations and the resulting endogeneity bias attributable to task scores are not considered. According to Autor and Handel (2013), we empirically checked the testable restrictions of their Roy model and confirmed the possibility that Roy model is valid in the Japanese labor market. Therefore, further investigating a structural relationship between job tasks and wages to measure true wage premiums of job tasks by controlling the endogeneity of a worker's self-selection based on panel data and exogenous instrumental variables is important as future research.

Second, as stated in Section 2, in our analysis using BSWS to observe time-series changes, we assume that the task score within each occupation does not change over because of a data limitation. This may cause

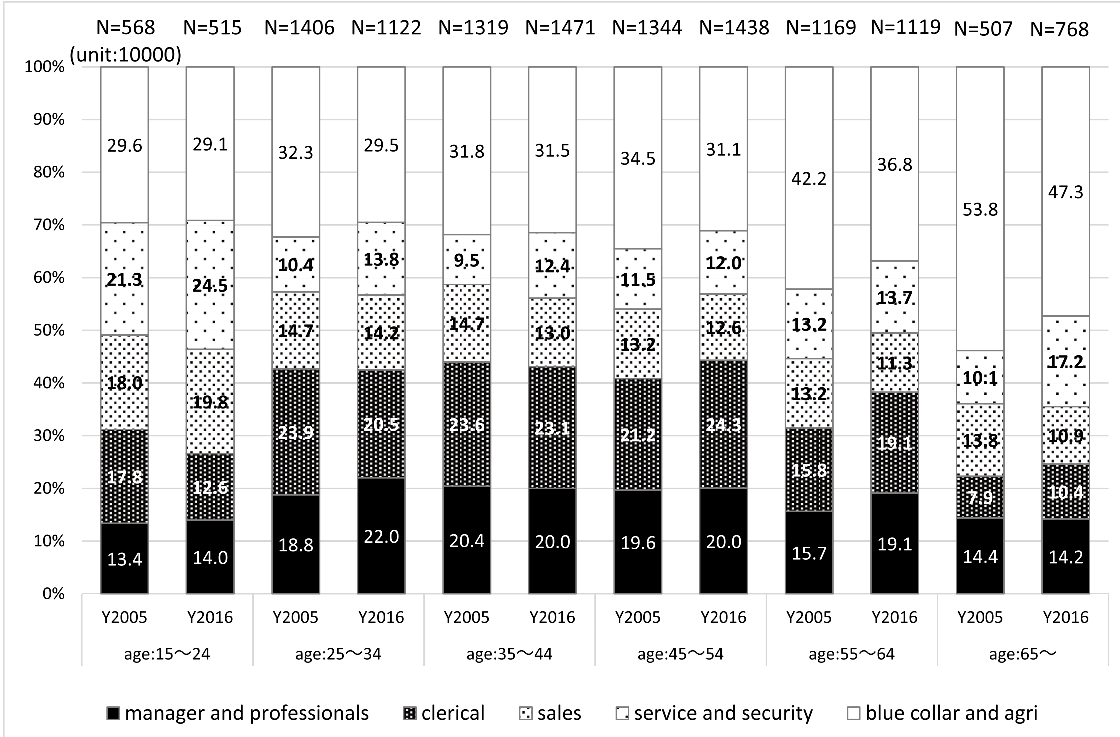

Fig. 9. Changes in Occupational Composition Ratio by Age Class, 2005–2016.
Note: A sample size unit for each age class is 10,000.
Source: Statistics Bureau, Ministry of Internal Affairs and Communications' Labour Force Survey (Detailed Tabulation).

Table 9
Job changers' occupational transfers from previous to present jobs.

2005							
		present jobs					N(unit:1000)
		maneger and professionals	clerical	sales	service and security	blue collar and agri	
previous jobs	manager and professionals	79.8	5.2	2.8	5.9	6.3	945
	clerical	5.6	79.8	3.9	6.2	4.6	657
	sales	6.9	12.3	51.6	17.2	12.1	511
	service and security	6.1	7.2	9.8	63.4	13.5	939
	blue collar and agri	4.9	4.9	4.8	9.2	76.2	954
all		23.2	18.7	11.3	21.7	25.1	4,006
		age:~29	age:30~39	age:40~49	age:50~59	age:60~	all
proportion		40.2	24.7	15.9	12.6	6.6	4,006
2016							
		present jobs					N(unit:1000)
		maneger and professionals	clerical	sales	service and security	blue collar and agri	
previous jobs	manager and professionals	78.1	9.3	2.6	5.3	4.7	1,148
	clerical	5.4	79.7	3.4	6.1	5.4	924
	sales	7.4	15.1	49.9	14.5	13.0	442
	service and security	5.8	12.4	9.8	60.4	11.6	860
	blue collar and agri	5.0	4.5	5.4	12.7	72.4	836
all		27.3	22.0	10.5	20.4	19.9	4,210
		age:~29	age:30~39	age:40~49	age:50~59	age:60~	all
proportion		30.4	23.1	21.1	13.4	12.0	4,210

over or underestimation regarding the association between job tasks and wages if the required tasks within each occupation had significantly changed.

Third, we observed time-series changes in labor demand and supply based on their proxy variables to explore the reasons for the stable relationship between job tasks and wages during the sample period. Judging from the changes in the proxy variables of labor demand and supply, we can understand that the changes in labor demand would be consistent with the story of the RBTC, which is also confirmed in Ikenaga and Kambayashi (2016). However, a further analysis should be needed to structurally identify the reasons for the stable relationship.

Fourth, considering the large share and the increase in non-regular employees, such as fixed-term contract workers or part-time, contract, and dispatch workers in Japanese labor markets, examining how the relationship between job tasks and wages would be different depending on employment status (regular or non-regular employment) is important. SCCHA data showed that the distribution of task scores is very different between regular and non-regular employees (average score of abstract, routine, and manual tasks are 0.24, –0.09, and –0.12 for regular employees, and –0.61, 0.22, and 0.30 for non-regular employees,

Table A1
Part of the code list of the BSWS and the SCCHA.

SCCHA occupation category	SCCHA data				BSWS occupation category							
	observation	Mean of routine task score	Mean of abstract task score	Mean of manual task score	department managers	section managers	other mangers	Chemical analysts	System engineers	Computer programmers	Medical doctors	Dentists
Legislators	2	-0.95	1.03	0.19								
Senior government officials	10	0.10	1.00	-0.64								
Senior regional officials	37	-0.27	1.04	-0.73								
Chief executives	10	-0.64	1.33	0.05								
Managing directors	478	-0.16	0.82	-0.60	1	1						
Managing directors of other agency	25	-0.30	0.62	-0.56								
Other managers	171	-0.27	0.83	-0.28			1					
Chemical engineers (development)	30	0.39	0.77	0.01				1				
Chemical engineers (except for development)	2	-0.03	1.39	-0.15				1				
System consultants	16	-0.28	0.86	-0.85					1			
System designers	69	-0.09	0.99	-0.78					1			
Information processing project managers	34	-0.17	1.00	-0.89					1			
Software creators	142	0.33	0.72	-0.75						1		
medical doctors (physicians)	18	-0.75	-0.18	0.12							1	
dentists	2	-1.14	-0.09	-0.50								1
weighted average score of routine task					-0.16	-0.16	-0.27	0.37	-0.14	0.33	-0.75	-1.14
weighted average score of abstract task					0.82	0.82	0.83	0.81	0.97	0.72	-0.18	-0.09
weighted average score of manual task					-0.60	-0.60	-0.28	0.00	-0.82	-0.75	0.12	-0.50

Table A2
Detailed task scores of the SCCHA's three-digit level occupations.

Occupation category of SCCHA		observation	routine task Mean	abstract Mean	manual task Mean
Senior regional officials		37	-0.267	1.040	-0.729
Managing directors		478	-0.162	0.822	-0.605
Managing directors of other agency		25	-0.300	0.622	-0.558
Other manager		171	-0.271	0.830	-0.283
professional and engineering	Researchers in natural science	52	-0.012	1.434	-0.315
	Food Engineer (Development)	26	0.244	0.315	-0.101
	Electrical and telecommunication engineers (development)	97	0.315	0.998	-0.402
	Mechanical engineer (development)	63	0.246	1.156	-0.281
	Automotive Engineer (Development)	36	-0.174	1.191	-0.135
	Chemical engineer (development)	30	0.394	0.773	0.008
	Other manufacturing engineers (development)	59	0.330	0.900	-0.078
	architectural engineers	62	-0.293	0.799	-0.413
	civil engineers	49	-0.226	1.378	-0.289
	System designer	69	-0.090	0.989	-0.775
	Information processing project manager	34	-0.173	0.997	-0.892
	Software creator	142	0.329	0.722	-0.748
	System operation manager	54	0.283	0.493	-0.709
	information technology engineers	29	0.308	0.606	-0.479
	other information technology engineers	41	0.245	0.643	-0.775
	other engineers and technicians	102	-0.037	0.713	-0.011
	pharmacists	33	-0.693	0.358	0.046
	public health nurses	31	-0.768	0.472	0.307
	nurses	105	-0.709	-0.211	0.765
	Medical radiologist	24	-0.001	-0.443	0.223
	Clinical laboratory technician	20	0.020	-0.192	0.124
	Physiotherapist, occupational therapist	46	-1.085	-0.093	0.452
	nursery school teachers	25	-0.578	-0.382	0.584
	social welfare service professionals	34	-0.773	0.082	0.420
	elementary school teachers	27	-0.526	0.558	0.788
	junior high school teachers	32	-0.939	0.682	0.347
	high school teachers	43	-0.984	0.733	0.227
	Professional workers not classified elsewhere	112	-0.069	0.135	0.231
clerical	General affairs clerk	403	0.253	-0.042	-0.527
	HR clerks	81	-0.113	0.332	-0.623
	planning clerks	138	-0.115	0.566	-0.538
	receptionists/information clerks	54	-0.517	-0.363	-0.348
	Telephone reception clerk	34	0.557	-0.058	-0.831
	general affairs	468	0.071	0.090	-0.568
	other office clerks	302	0.331	-0.190	-0.625
	accounting clerks	186	0.424	-0.057	-0.799
	other accounting clerks	29	0.579	-0.252	-0.911
	transportation clerks	21	0.193	-0.129	-0.403
	sales clerks	184	-0.285	0.062	-0.408
	other sales clerks	43	-0.025	0.194	-0.584
sales	retail shop owners	39	-0.429	0.095	0.623
	shop salespersons	231	-0.551	-0.335	0.725
	Pharmaceutical sales workers	22	-1.022	0.149	0.194
	Machine equipment sales workers (excluding communication equipment)	34	-0.823	0.050	-0.011
	Finance and insurance sales workers	55	-1.022	0.052	-0.325
	other sales and sales-related workers	94	-0.675	-0.040	-0.051
	Care staff (medical care, welfare facilities)	88	-0.311	-0.206	0.701
	Other health service workers	30	-0.518	-0.488	0.101
	cooks	37	-0.284	-0.456	0.985
	waiters/waitresses	28	-0.304	-0.618	0.916
	tour guides	31	-0.494	-0.391	0.531
	entertainment facility service workers	35	-0.402	-0.406	0.771
	Service workers not classified elsewhere	350	-0.246	-0.088	0.079
	Security guard	37	0.004	-0.339	0.269
	other metal products workers	20	0.857	-0.530	0.961
	food makers	45	0.998	-0.690	1.061
	Other manufacturing workers (except metal products)	24	1.052	-0.334	0.775
	manufacturing laborer	59	0.905	-0.386	0.678
	similar manufacturing laborer	24	0.693	-0.507	0.659
	Truck driver	57	0.038	-0.817	1.245
	other construction worker	41	0.071	0.093	0.398
	Civil engineer	32	0.293	0.554	0.673
	Warehouse worker	25	1.044	-0.796	0.947
	transportation workers	23	-0.061	-0.870	0.982
	Other workers in transportation, cleaning, packaging	20	0.361	-0.772	0.995
	not elsewhere classified	415	-0.051	-0.044	0.098

Note: Table A2 is restricted to only occupations with over 20 respondents.

respectively). In other words, regular employees tend to engage in abstract tasks, whereas non-regular employees tend to perform routine and manual tasks. However, regarding the difference in job tasks across employment status, the possibility of self-selection exists; thus, identifying the causal relationship using cross-section data is difficult. Therefore, this analysis is left to a future research agenda.

Acknowledgment

This study was conducted as part of the "Research on the task models to cooperate with the human and new technology: Evaluating the impacts on labor market" project undertaken at the Research Institute of Science and Technology or Society (RISTEX), Japan Science and Technology Agency (JST). This study utilizes the micro data from the "Basic Survey on Wage Structure" conducted by the Ministry of Health, Labour, and Welfare. This research was also supported by a Grant-in-Aid for Scientific Research (C) no.18K0165 (Yamamoto) from the Ministry of Education, Culture, Sports, Science and Technology. We sincerely thank the anonymous referees for reading the paper carefully and providing thoughtful comments.

Appendix: The SCCHA and BSWS

To investigate the effect of technological change on the employment environment, we implemented the SCCHA in January of 2018. The survey was conducted using an Internet-based questionnaire of 11,543 respondents, consisting of nationwide workers in the 20-59 age group with gender, age, and work regularity compositions following those used in the "labor force survey." However, we used only the task score information of 6,897 respondents who were working in the private sector for over 35 hours per week and were not temporary contract workers. Additionally, the occupational categories in the SCCHA were the same three-digit standard occupational categories (more than 300 categories), whereas the occupational categories of BSWS is original (136 categories). Therefore, using the official material 2-3 of the BSWS, which explains how to align the standard occupation categories with the original occupation categories of the BSWS, we assigned task scores by each occupation to BSWS respondents such as those listed in Table A1 in the Appendix.

For example, the BSWS category of "department managers" and "section managers" could be matched with only "managing directors." Thus, we assigned the mean task scores for "managing directors" to "department managers" and "section managers." However, the BSWS category of "chemical analysts" could be matched with "chemical engineers (development)" and "chemical engineers (except for development)" of the SCCHA category. Therefore, we assigned the weighted average task score of the two occupations to the single BSWS category of "chemical analysts." Additionally, Table A2 in the Appendix shows three task scores according to the SCHHA's occupational categories. SCCHA's occupational categories are more general than the BSWS categories. Moreover, all management occupations involved affluent, abstract tasks. Conversely, all manufacturing occupations involved affluent routine and manual tasks, and all service occupations involved only manual tasks. Meanwhile, the characteristics of professional and engineering, clerical, and sales occupations are much more complicated that such categories would suggest. There is a mixture of job classifications with high abstract task scores and job classifications with high manual or high routine task scores.

References

Acemoglu, D., Autor, D.H., 2011. Skills, tasks and technologies: implications for employment and earnings. In: Ashenfelter, O., Card, D. (Eds.), Handbook of Labor Economics, 4. Amsterdam: Elsevier, North Holland, pp. 1043–1171.

Autor, D., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118 (4), 1279–1333.

Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. Am. Econ. Rev. 103 (5), 0553–1597.

Autor, D.H., Handel, M.J., 2013. Putting tasks to the test: human capital, job tasks, and wages. J. Labor Econ. 31 (2), S59S96.

Blinder, Alan, 2007. How Many U.S. Jobs Might be Offshorable? Princeton University. Princeton University Center for Economic Policy Studies Working Paper no. 142 (March).

Cavaglia, C., and Etheridge, B 2017. Job polarization, task price and the distribution of task returns,. ISER Working Paper Series. No. 2017-09, June 2017.

Cortes, G.M., 2016. Where have the middle-wage workers gone? A study of polarization using panel data. J. Labor Econ. 34, 63–105.

Fonseca, T., Lima, F., Pereira, S.C., 2018. Job polarization, technological change and routinization: evidence for Portugal. Labour Econ. 51, 317–339.

Goos, MaartenM., Alan Manning, A., Anna Salomons, A, 2009. Job polarization in Europe. Am. Econ. Rev. 99 (2), 58–63.

Goos, M., Manning, A., Salomons, A., 2010. Explaining Job Polarization in Europe: the Roles of Technology. Globalization and Institutions. CEP Discussion Paper No. 1026.

Ikenaga, T., Kambayashi, R., 2016. Task polarization in the Japanese labor market: evidence of a long-term trend. Ind. Relat. 55 (2), 267293.

Jensen, Bradford J., Kletzer, Lori G., 2010. Measuring tradable services and the task content of offshorable services jobs. In: Abraham, Katharine, Harper, Mike, Spletzer, James (Eds.), Labor in the New Economy. University of Chicago Press, Chicago, pp. 309–335.

Kawaguchi, D., Mori, Y., 2016. Why has wage inequality evolved so differently between Japan and US? The role of the supply of college-educated workers. Econ. Educ. Rev. 52, 2950.

Roy, A.D. 1951. Some thoughts on the distribution of earnings. Oxford Economic Papers 3, no. 2:135-46.

Van Reenen, J., 2011. Wage inequality, technology and trade: 21st century evidence. Labour Econ. 18 (6), 730–741.