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Who Can Work from Home?
The Roles of Job Tasks and HRM Practices*

Daiji Kawaguchi[†] and Hiroyuki Motegi[‡]

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Abstract

This paper examines the characteristics of remote work using a unique Japanese survey dataset that provides information on engagement in remote work together with the specific job task and human resource management (HRM) characteristics workers face. We show that the opportunity to work remotely was more likely to be available to those in professional occupations, characterized by non-routine, analytical and non-interactive tasks, and less likely to be available to service sector workers requiring face-to-face interactive tasks or manual laborers, characterized by routine and manual tasks. We also find that workers subject to HRM practices that presuppose that worker performance is measurable are more likely to engage in remote work. The implications of these findings for income transfer policies and management practices in light of the COVID-19 pandemic are also discussed.

1 Introduction

Throughout 2020, the spread of COVID-19 and the implementation of social distancing policies have confined millions of workers to their homes. While primarily a public health measure, the economic impact of social distancing has been profound, but its effect on the aggregate labor supply and any distributional consequences will be determined largely by the extent to which remote work is possible. Against this backdrop, there has been a heightened interest in better understanding which jobs can and are being performed remotely. Studies using job task descriptions to estimate the proportion of jobs that can technically be accomplished from home have arrived at numbers ranging from 37% in the US to 56% in Germany. This study takes a different approach by documenting who worked from home just prior to the COVID-19 crisis to identify the specific job characteristics that permit a remote work arrangement and to articulate any expected challenges as remote work expands.

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For our analysis, we utilize a unique panel data set from Japan that includes job task characteristics and human resource management conditions. As of December 2019, 9% of Japanese workers worked outside of their official workplace, and while we find that the prevalence of remote work does not vary much across industries, it does vary considerably across occupations, with workers involved in non-routine and non-manual tasks and those employed under performance-based human resource management (HRM) practices significantly more likely to work from home. Together, these results indicate that the extent to which employers can prevent "shirking from home" by, for example, quantifying work output is a critical determinant in the adoption of remote work. We show that task and HRM characteristics, which vary considerably within a given 2-digit occupation or 1-digit industry category, largely explain the remote work experience conditioned on industry and occupation.

Further, as the determinants of earnings and remote work potential are positively related, the burden of social distancing policies disproportionately falls on low income earners, with the approximately 40% of consultants who worked remotely earning 5.5 million yen annually while the 10% of care workers working remotely earned only 2.8 million yen annually. More generally, those who worked remotely earned 27.6% more than those who only worked at their official place of work. We further find that the propensity to work outside of the workplace as predicted by job and demographic characteristics is positively correlated with annual earnings, with a one percentage point increase in the potential for remote work increasing annual earnings by 0.039 log points.

Since the outbreak of COVID-19, numerous studies have investigated the potential for working remotely based on occupation. Dingel and Neiman (2020), for example, determine whether a job can be performed remotely from responses to an O*NET questionnaire on "work context" and "generalized work activities". By aggregating feasibility according to the distribution of the 6-digit standard occupational classifications published by the U.S. Bureau of Labor Statistics, they conclude that 37% of U.S. jobs can be performed from home.[1] Using a similar mapping, Boeri et al. (2020) find that 24-31 % of jobs can be performed at home in major European countries, and Holgersen et al. (2020), who determine the potential for working remotely through detailed ISCO-08 job descriptions and the marginal distribution of occupations through online job advertisements, similarly find that 36% of jobs in Norway can be performed from home. Meanwhile, Alipour et al. (2020) find from employee surveys that 56% of jobs in Germany can be performed from home. Finally, Brussevich et al. (2020) and Hatayama et al. (2020) independently calculate the possibility of remote work for more than 50 countries based on task characteristics recorded in the OECD Survey of Adult Skills (PIAAC) and find that per capita GDP and prevalence of remote work are positively associated. They also report that

[1] Mongey et al. (2020) validates this measure using SafeGraph cell phone mobility data and actual labor market outcomes from the March 2020 *Current Population Survey.*

women, college graduates, and salaried and formal workers have jobs that are more amenable to working from home than the average worker.

In addition to these studies of the *potential* for remote work based on occupation, research is beginning to appear on the proportion of the workforce that is actually working from home in the midst of the COVID-19 crisis. Based on a survey conducted from April 1-5, 2020, Brynjolfsson et al. (2020) find that 15% of U.S. workers had already been working remotely and that 38% of those workers who formerly commuted were now working from home. Bick et al. (2020) reports that the proportion of newly remote workers rose from 8% in February to 35% in May, but Adams et al. (2020) notes substantial heterogeneity in the roll-out of remote work within industries and occupations. Meanwhile, in Japan, Okubo (2020) indicates that the percentage of remote workers in 2020 was 6% in January, 10% in March and 17% in June, but Morikawa (2020) finds the proportion in June to be higher, at 32%, based on a June 2020 survey.

This paper contributes to the literature by examining the relationship between job characteristics and the potential for remote work by exploiting the unique features of a Japanese worker panel data set which directly surveys whether a worker worked remotely. In addition, it records two measurable variables that are important determinants of the potential for remote work: the direct measurement of job task characteristics and the specific HRM style that characterizes each employee's work environment.

The high explanatory power of these variables has two important implications. First, on redistribution policy, the likelihood of working remotely is strongly associated with a negative income shock (Mongey et al., 2020), and transfer policies have focused on targeting heavily hit workers (Mongey et al., 2020; Brussevich et al., 2020; Kikuchi et al., 2020). However, since the negative impact of COVID-19 has been felt differently across occupations and skill levels (Adams et al., 2020), we need to pay close attention to this heterogeneity. Any redistribution policy that only targets the industry or occupational level will not likely be optimal.

Second, this study has important implications for the human resource management policies of private companies in terms of maintaining productivity. There is a strong relationship between HRM practices based on individual performance measures (such as pay for performance, management by key performance indicator, or management by objectives) and the potential for remote work, implying that remote work can occur only when output is observable and measurable (Allen et al., 2015; Bloom et al., 2015; Sewell and Taskin, 2015; Groen et al., 2018). However, the output of certain jobs is inherently difficult to observe or quantify, and this potential for "shirking from home" is the major reason why some workers are not permitted to work remotely. Despite this concern, however, the sudden implementation of social distancing policies during the COVID-19 pandemic has forced firms to encourage remote work even for those in jobs deemed unsuitable for it. Thus, unless firms take measures to improve their observation of worker effort or output, the remote work phenomenon is likely to lead to reduced productivity in certain jobs, mainly because worker effort is difficult to sustain in the remote work environment.

2 Data

This paper uses the *Japanese Panel Study of Employment Dynamics (JPSED)*, a panel survey with a standard set of demographic and labor market variables conducted by the Recruit Works Institute every year since 2015. JPSED is a nationwide survey that is representative of all men and women over the ages of 15 years old and is conducted by an internet monitor registered to Intage Corporation. The first wave of the survey included 49,131 people, and while JPSED has contracted and expanded through panel attrition and sample addition, it collects around 50,000 observations each year. The surveys, which are conducted each January, ask about the work situation in the previous month and previous year. We use the 2020 wave of the survey conducted from January 9-31, 2020, when the outbreak of COVID-19 in China was initially covered by media but Japan was as yet virtually unaffected. In addition, a supplemental 2020 survey about the Human Resource Management conditions workers face was conducted between January 15th and February 5th for those who responded on the main survey that they had worked in December 2019 (see Appendix A.1 for the specific questions asked about remote work, task characteristics and human resource management practices). The original 2020 wave includes 57,284 observations, consisting of 47,833 continuing observations, 5,025 additional observations, and 4,426 revived observations. We restrict our analysis sample to only those who are employed, excluding the self-employed because we are interested in assessing the impact of human resource management conditions on the potential for remote work. Dropping invalid variables further reduces the sample size to 38,292 observations, and this basic analysis sample consists of employed men and women whose ages are 15 years old or above. Among them, 24,729 observations have valid responses to the supplemental survey.

A unique feature of this survey is the set of questions on engagement in remote work. The first question is hours worked remotely per week in December 2019, where remote work includes work from home, satellite offices, coffee shops or restaurants. Respondents provide a continuous number representing the exact hours worked, which may include zero hours. The second question addresses company rules about remote work, with respondents choosing from 1) the company sets the rule and it applies to the respondent, 2) the company sets the rule but it does not apply to the respondent, 3) the company does not set a rule, and 4) do not know. Other questions ask about the range of workers who are allowed to work remotely and the actual place the respondent worked the previous December.

This array of questions allows us to define remote workers in two alternative ways. The first definition is those workers who actually worked remotely in December 2019, while the second definition is those workers who were allowed to work remotely according to the company rule. Table 1 shows the proportion of workers who reported positive remote hours worked in each of the above company rule categories. We see that while only 4% of respondents answered that their companies set the rule for remote work and it applied to them, 55% of these respondents actually worked outside of the workplace. On the other hand, 6 to 8% of those for whom the rule on remote work did not apply or those who did not know about the rule actually reported positive hours worked outside of the workplace. Given that a large number of workers actually worked outside the workplace irrespective of the formal work rule, we define the remote worker as one who actually worked outside of the work place.

Thus, in total, 9% of workers engaged in remote work in December 2019, which is higher than the 3-4% for 2016-2017 reported by Kazekami (2020) and 5.2% for 2017 reported by Morikawa (2018), but close to the 10% for January 2020 reported by Okubo (2020), which indicates that the prevalence of remote work has been increasing over time even before the COVID-19 outbreak.[2] According to the descriptive statistics reported in Table 2, average hours worked per week was 37.6 hours, of which 0.68 hours occurred remotely. Those who engaged in remote work spent 19% of their working hours out of the workplace.

The other unique feature of the JPSED survey is the question about task characteristics, which asks respondents to characterize the tasks required by their current job along the following three dimensions: 1) routine vs. non-routine, 2) manual vs. cognitive, and 3) working alone vs. working interactively with others. As described in detail in Section A.1, respondents choose the task characteristics in terms of percentages using the slide bar on the computer screen. For example, if the respondent chooses that routine tasks comprise 60% of the job, then the remaining 40% is automatically counted as the proportion of non-routine tasks. Table 2 shows that non-remote workers describe their job tasks as 61% routine, 44% manual, and 46% interactive, while remote workers describe their job tasks as 49% routine, 35% manual, and 44% interactive. Thus we see that remote workers are much less likely to engage in routine and manual tasks.

Next, we find that the reported task characteristics depend heavily on occupation. Figure 1 shows the percentage of routine work for 45 occupation categories, and while as much as 80% of the job tasks are routine for workers in transportation and communication occupations other than drivers, only 35% are routine for consultants. Similarly, Figure 2 shows that the proportion of manual tasks varies significantly across occupations, from 10% for OA operator to 80% for manual laborers other than production workers in the manufacturing sector. Likewise, Figure 3 shows that the percentage of interactive tasks also varies significantly across occupations, from 20% for drivers to above 60% for chefs, customer service representatives and waiters, and social welfare professionals (care workers).

[2] In addition, our numbers are higher than those reported by Kazekami (2020) and Morikawa (2018) because we define the remote worker more broadly by including those who were not officially permitted to work remotely but who actually did.

While occupation explains a portion of the job task characteristics a worker faces, non-negligible heterogeneity remains. To examine how much variation in task characteristics is explained by the 45 occupation codes and 15 industry codes, we regress the task content score on an array of occupation dummy variables, industry dummy variables, occupation and industry dummy variables, and the interaction of these industry and occupation dummy variables. Table 3 reports the R^2 of the ANOVA regressions, and Column 1 shows that 3.6% of the total variation in reported routine scores is explained by industry, 10.4% by occupation, 11.2% by industry and occupation, and 13.2% by industry $\times$ occupation. Column 2 shows that 14.4% of the manual task score is explained by industry, 41.5% by occupation, 43.3% by industry and occupation, and 45.3% by industry $\times$ occupation, while Column 3 shows that 3.9% of interactive task score is explained by industry, 8.8% by occupation, 10% by industry and occupation, and 12.4% by industry $\times$ occupation. The low R^2 for routine and interactive tasks imply that these task characteristics vary significantly within an industry and an occupation, so crude industry or occupation codes are not suitable for capturing the routine and interactive characteristics of jobs. In contrast, the high R^2 for the manual task with occupation dummy variables implies that occupation codes capture about the half of the manual task characteristics of each job within that occupation. The only moderate correlation between task content and industry or occupation indicates that significant variation in the task characteristics remains within an industry-occupation cell, casting doubt on the common use of industry or occupation codes to determine the potential for remote work unless very detailed occupational categories are available, as in some previous studies (Dingel and Neiman, 2020; Holgersen et al., 2020; Alipour et al., 2020).

Turning now to the implications of human resource management (HRM) practices for remote work, basic contract theory demonstrates that wages are strongly associated with output when the output depends heavily on the effort of workers, given that employers are risk neutral and employees are risk averse (Milgrom and Roberts, 1992). On the other hand, if output is difficult to measure or it depends heavily on factors other than individual effort, wages are less dependent on output and a fixed wage prevails instead, provided that employers can monitor worker effort, for workers will otherwise completely slack off. Worker effort is more difficult to observe in a remote work setting, as reflected in the phenomenon of "shirking from home" (Bloom et al., 2015). Indeed, Sewell and Taskin (2015) and Groen et al. (2018) both find a positive association between remote work and the adoption of output control measures; reviewing the broad literature, Allen et al. (2015) claim that the availability of output measures lowers the hurdle for engaging in remote work, so we expect that output that is easily observed will induce the adoption of remote work arrangements. As this mechanism entails a positive association between HRM practices that presuppose individual performance (output) measures and the availability of remote work, we test this hypothesis using a battery of questions from the JPSED supplementary survey in which respondents describe the human resource management conditions applicable to them. To identify HRM style, we pay particular attention to the following three variables which all involve output measures: pay-for-performance in determining compensation, management based on key performance indicators (KPI), and a system of management by objectives (MBO). Survey responses are recorded on a 5-point Likert scale ranging from not applicable to applicable, and we characterized those who responded either "applicable" or "if anything, applicable" (1 or 2 on the scale) as workers for whom that specific HRM variable applies. Table 2 shows that pay-for-performance is applicable to 25% of workers, KPI to 18% and MBO to 20%.

3 Job Characteristics of Remote Workers

Before presenting our empirical specification for investigating the effects of task and HRM characteristics on the potential for remote work in Section 4, in this section, we discuss the relationship between remote work and specific job characteristics independently.

3.1 Industry and Occupation

Figure 4 reports the percentage of workers allowed to work outside of workplace by industry. Compared to the overall average of 9%, the variation across industries is rather small, with highest being 17% in the telecommunication industry and the lowest 5% in the public sector. The high prevalence of remote work in the telecommunication (and information) industry is understandable given that their work is computerized. On the other hand, workers in transportation and the postal industry, who are considered essential workers, are less likely to engage in remote work.

While we observe little variation in remote work by industry, there is substantial variation across occupations. Figure 5 shows that remote work is close to zero in hospitality positions such as chef, customer service and waitperson, as well as in blue collar jobs such as security guard, driver, manufacturing process worker. Meanwhile, the percentage is 20% or higher for occupations such as planning and sales clerk, sales personnel, brokerage business, internet professional, writer and reporter, and consultant. Employers presumably allow this latter group to work from home because they work independently and their output is easily observable. Also notable is that the large observed variation in remote work across occupations but small variation across industries is indicative of the heterogeneity of remote work among occupations that is averaged out when observed by industry.

3.2 Annual Income

The variation in remote work by occupation suggests that the distribution of earnings may also be related to the prevalence of remote work. Figure 6 shows that workers who did not work from home earned less than remote workers.[3] In particular, the majority of those who did not work from home earned less than 5 million yen in 2019, while a large fraction of those who worked from home earned more than 5 million yen. This finding supports the claim that low earners suffer more from social distancing policies because they cannot work from home.

To articulate the relationship between remote work and earnings by occupation, Figure 7 plots the proportion of workers who worked from home and average annual earnings by occupation. We see that occupation is an important mediator of the relationship between the prevalence of remote work and earnings, and that the proportion of workers engaging in remote work and average annual earnings are positively correlated. Consultants and Drivers provide a striking example of this pattern, with the propensity for Consultants to engage in remote work about 42% and income about 5.5 million yen annually, while fewer than 5% of Drivers engage in remote work and annual income is 3.8 million yen. There are a few notable outliers such as Medical doctors, who are less likely to engage in remote work but yet earn a high income. However, with few exceptions, the plot shows a general pattern that high-income occupations tend to have a higher proportion of remote workers.

3.3 Task Characteristics

Digging deeper than the occupation level for a more fine-grained analysis, we next examine the potential for remote work based on the specific characteristics of the tasks associated with each worker's job. Figure 8 shows the distribution of routine, manual and interactive scores by remote work status as of December 2019, and all three panels show that the task characteristics of non-remote workers and remote workers overlap. However, by comparing the median of the two groups, some differences can be identified. The first two panels show that remote workers are less likely to engage in routine and manual tasks, with the latter finding consistent with our occupation analysis from Figure 2 that blue collar workers are less likely to engage in remote work than white collar workers. The third panel shows that task interactivity has little to say about the potential for remote work, which is probably related to the different types of interaction that might occur on the job. At one extreme, managerial jobs require interaction with subordinates, superiors and colleagues to coordinate tasks, while at the other extreme, service sector jobs such as restaurant wait staff or cashier requires interaction with customers. These varying types of interaction with others are arguably

[3] The JPSED survey records the respondent's annual income without an upper limit but for our analysis, we top-coded income at 20 million yen annually.

the reason why we find a similar distribution of task interactivity between remote and non-remote workers.

3.4 Human Resource Management Style

In this subsection, we examine the association between remote work and human resource management, focusing on three variables that capture whether the respondent is subject to pay-for-performance style HRM practices: whether compensation is determined by Pay-for-Performance (PFP), whether performance is managed by Key Performance Indicators (KPI) and whether the respondent is subject to Management by Objective (MBO). Table 2 shows that 37% of remote workers were paid according to their performance compared to 23% of those without remote work experience. Similarly, remote workers are more likely to be managed by KPI and MBO. Overall, remote workers were as much as 82% more likely to experience some form of pay-for-performance style HRM practice, which is consistent with the hypothesis that workers whose output is easily observable are more likely to engage in remote work because there is less concern about "shirking from home."

4 Determinants of Remote Work

The analysis thus far has discussed the relationship between remote work potential and various occupation and task characteristics independently. In this section, we analyze how task characteristics, basic demographic characteristics, and HRM practices together affect the status of working from home by estimating the following probit model:

$$Y_i^* = X_i'\beta + Z_i'\alpha + \theta_{ind} + \eta_{occ} + \epsilon_i \tag{1}$$

$$Y_i = \begin{cases} 1 & (Y_i^* \geq 0) \\ 0 & (Y_i^* < 0) \end{cases} \tag{2}$$

where Y_i is a binary variable indicating whether the respondent engaged in remote work; X_i is a set of demographic variables including age and its square and indicator variables for whether the respondent was female, had a child age 6 or younger, and was a university graduate; Z_i is the set of job characteristic variables including routine, manual, and interactive task characteristics, and indicator variables for working under a non-regular employment contract and firm size; and θ_{ind} and η_{occ} are industry and occupation dummy variables. We report the specifications with and without industry and occupation dummy variables to demonstrate the extent to which these dummy variables capture the effect of demographic and job characteristics on the remote work experience.

Column 1 of Table 4 shows the marginal effects of the probit regression of remote work status on demographic and job characteristic variables. While there is no gender gap in the probability of working from home, respondents with younger children are 14 percentage points more likely to work from home. This result is not surprising, as the majority of working mothers with pre-school children use child care facilities that typically operate from 7:30 AM to 5:30 PM, and firms often allow working mothers with young children to engage in remote work to facilitate this.

The relationship between age and working from home forms a U shape, bottoming at 42 years old. This is perhaps because those in middle management positions are likely to work at the office while those who are earlier or later in their careers may be more free to work remotely. Additionally, university graduates are about 18 percentage points more likely to work from home, while workers classified as non-regular (on a fixed-term contract, working part time or dispatched from temporary help agencies) are 21 percentage points less likely to work from home.

In terms of task characteristics, workers engaged in routine, manual and interactive tasks are less likely to work from home, conditional on workers' characteristics such as educational background or age. The relationship between firm size and probability to work from home is U-shaped. Compared with the workers in small firms with less than 100 employees, workers in medium scale firms with 100-999 employees are about 10 percentage points less likely to work from home, while workers in large firms with 1000-4999 employees are equally likely to work from home as those in small firms, and workers in mega-sized firms with more than 5000 employees are about 8 percentage points more likely to work from home than them. The reasons why remote work is prevalent in both small and mega-sized firms probably differ, for small firms tend to have more casual and informal employee control while mega-sized firms have a formalized network system and human resource management practices that can permit employees to work from home. It is also possible that mega-sized firms want to cultivate reputations for having flexible work environments in order to appeal to potential workers. Altenatively, mega-sized firms may have better designed HRM practices to manage its workers remotely. We test the last hypothesis in the following analysis using the sub-sample that includes the information on the HRM practices that workers face. Also notable is that compared to employees of private firms, public sector workers are about 40 percent less likely to work from home.

Column 2 of Table 4 shows the regression results conditional on industry fixed effects, and we find three notables changes in the estimated coefficients. First, the size of the coefficient for university graduates is reduced by a third, which indicates that the difference in the prevalence of remote work according to educational background is partially due to industry distribution by educational background. Second, the size of the coefficient for mega-firms with more than 5000 employees is raised by about 50%, which indicates that the potential for remote work at mega-firms is amplified further when conditioned on industry. Third, the coefficient for the public sector dummy variable becomes statistically insignificant because industry category includes a “public sector”. Next, adding occupation fixed effects as reported in Column 3 attenuates the effect of university education and non-regular employment on remote work. These changes imply that the difference in the prevalence of remote work is partially due to occupational sorting, but it is worth noting that even after conditioning on industry and occupation fixed effects, a substantial difference remains for educational background and labor contract type.

Columns 5 - 8 report the Tobit estimates using hours worked outside of the workplace and total hours worked as the dependent variable, with the dependent variable taking zero if the worker is not engaged in remote work. The results using the intensive margin of the remote work hours does not change the probit estimation results substantially, which suggests that it is the extensive margin, whether to work outside the workplace or not, that is important. One notable change is the attenuation of the coefficient for non-regular employment, which implies that regular workers are more likely to engage in remote work than non-regular workers but that the hours worked remotely as a proportion of total hours is not substantial.

The results of the analysis thus far indicate that there are substantial differences in the potential for remote work by task and demographic characteristics within an industry or occupation. Although we did not find a gender gap in remote work, those workers performing routine and manual tasks are less likely to engage in remote work even within the same industry or occupation, as are middle-aged workers in their mid 40s, those on part-time or contingent contracts, and those working for mid-sized firms. By contrast, university educated workers are more likely to engage in remote work.

Now turning to the impact of HRM characteristics, Table 5 reports on our analysis when HRM variables are added to the set of explanatory variables and the analysis sample is adjusted to include only those who provided valid responses to the supplemental survey, which reduces the sample size by about a third. First, we confirm that the estimation results from the restricted sample (see Appendix Table A1) do not change significantly from the main results reported in Table 4. Next, we notice from Table 5 that the estimated coefficients for HRM style indicate that those subject to pay-for-performance (PFP), KPI and MBO are 20, 27 and 10 percentage points more likely to engage in remote work, respectively. These partial correlations are economically significant. Here, we do not attempt to claim the relationship as causal, but simply that the employer’s ability to accurately observe each worker’s output is indicative of HRM style and the potential for remote work. It is worth noting that the positive correlation between employment at mega-firms and remote work disappears once HRM style is conditioned, which implies that mega-firms can permit workers to work from home because they adopt HRM practices that ensures employees do not “shirk from home”.

Our basic findings have implications for both income transfer policies and corporate management. First, regarding income transfer policy, we find significant variation in the potential for remote work both across and within occupations, and even within an industry, there are workers who can work from home and those who cannot. Thus, policies that target specific industries or occupations are not sufficiently fine-grained to accurately target those workers who are most severely impacted by a lack of opportunity to work remotely. We must be cognizant that some workers might fall through the cracks such as those who may not be able to work remotely in an industry in which many can work from home and, further, that there is presumably substantial variation in the earnings shock or possibility of job loss within an industry in addition to the potential for remote work. Second, we find that policies targeting small companies that are typically seen as most vulnerable are not targetting those firms that experience the most difficulty in adapting to remote work environment, given the U-shaped relationship between firm size and the potential for remote work. The fact that those workers who cannot work from home are spread across industries and firm sizes suggests that the government cannot precisely target workers in need via company-based rescue policies such as special loan programs or employment subsidies targeting certain industries or firm sizes. Instead, an income transfer policy based on household income would seem to be a better targeted policy.

Regarding advice for corporate managers, we've found a strong correlation between HRM style and engagement in remote work that has important implications for managers seeking to expand the opportunities for remote work. Our results suggest that "shirking from home" was indeed a practical concern of employers in adopting remote work arrangements. When a manager cannot observe the output or effort of each worker, moral hazard can cause a worker to slack off. However, the current social distancing policy forces firms to allow certain workers to work from home regardless of their ability to effectively observe worker output or effort. This could have a detrimental impact on the firms' productivity unless managers can reorganize the job design and compensation scheme so that the effort or output of individual workers is accurately measured and workers rewarded accordingly. However, even if this output measurement issue is resolved, there remains the usual problem of multitasking that arises from pay-for-performance incentive schemes, whereby a worker with a multiple-task assignment will focus excessively on the task whose output is measured relatively easily. For example, middle-level managers of a sales team who are expected to both expand sales and coach subordinates will put more effort on expanding sales if the effect of coaching subordinates is not properly measured and rewarded. While professionals who were permitted to work remotely before COVID-19 are presumably not subject to a serious multitasking problem, these output measurement and multitasking issues pose a serious challenge for managers who want to introduce a remote work arrangement in response to the spread of COVID-19.

To this point we have intentionally omitted annual earnings as an explanatory variable in the probit regression because we wanted to articulate the relationship between job and worker characteristics and the potential for remote work, so we provide some insight on annual earnings here. Using the propensity score from the probit model as the summary measurement of remote work prevalence, we investigate the correlation between the propensity to engage in remote work and the binned average of annual earnings. Figure 9 clearly shows that the higher the propensity to work remotely, the higher the annual earnings. This relationship is nicely captured by the quadratic function, as the positive association between remote work propensity and income becomes weaker as the propensity increases. The regression coefficient shows that a one percentage point increase in the propensity increases annual earnings by 0.039 log points at the mean of the propensity score. As the propensity score captures all job and worker characteristics including educational background and only 9% of workers engage in remote work, the estimated size of the impact seems reasonable.

5 Geographic Distribution of Remote-Workable Jobs

Finally, we discuss the geographic distribution of the proportion of workers who participated in remote work as of December 2019. This geographic dimension is important to the analysis, as infectious diseases such as COVID-19 are considered to be more urban phenomena. Indeed, as of August 1, 2020, the number of infections per 1 million people in Japan was highest in Tokyo prefecture at about 900, followed by Osaka prefecture at about 500.[4] However, while urban areas may be more susceptible to infection, they may be more amenable to adapting to remote work.

To investigate this, Figure 10 shows the proportion of workers who worked from home. As white collar occupations are concentrated in urban areas, the proportion is understandably high in the Tokyo and Osaka metro areas. Interestingly, however, the proportion is also high in the less populated prefectures contiguous to Tokyo and Osaka such as Yamanashi and Shiga. Presumably, those who live on the outskirts of urban business centers are working from home and occasionally commuting to the urban center. However, the area around Nagoya, the third largest urban metropolis in Japan, does not show such a pattern in terms of the prevalence of remote work. Presumably, this is due to the high concentration of the manufacturing sector in the Nagoya area, for in Japan's manufacturing industry, workers often work in the field.

Next, Figure 11 shows the prevalence of remote work by prefecture, adjusted for the geographic heterogeneity of occupation/industry structures and worker demographics.[5] The general tendency is almost identical to that of Figure 10. In the dark red areas such as Tokyo, Yamanashi, and Fukui prefectures, more workers engage in remote work than predicted even after controlling for industry, occupation and other variables. In contrast, in white areas such as Yamaguchi and Saga prefectures, there are unobserved factors that hinder remote work. In sum, as expected, while urban areas may be more susceptible to infectious

[4]The number of COVID-19 infections by prefecture was compiled by Sapporo Medical College at `https://web.sapmed.ac.jp/canmol/coronavirus/japan.html` and viewed on August 3, 2020.

[5]We adjusted for heterogeneity by using the regression residual of Column (4) of Table 4 by first calculating the propensity score and then defining the difference between the actual outcome and the propensity score as the "residual."

disease, they also seem more resilient in terms of the proportion of workers who can work from home.

6 Concluding remarks

As a preliminary analysis of the potential for remote work in Japan, this paper documents who worked from home as of December 2019, the period just before the breakout of COVID-19. The opportunity to work remotely was more likely to be available to those in professional occupations, characterized by non-routine, analytical and non-interactive tasks, and less likely to be available to service sector workers requiring face-to-face interactive tasks or manual laborers, characterized by routine and manual tasks. Furthermore, workers subject to HRM practices that presume the measurability of individual output were more likely to engage in remote work. Moreover, reflecting the heterogeneity of job characteristics within a given occupation or industry, high income earners were more likely to engage in remote work, which implies that the cost of social distancing policies does indeed disproportionately fall on low income earners. On top of the disproportionate probability of job loss among the poor as pointed out by Kikuchi et al. (2020), this finding calls for a household income-based transfer policy targeted toward the poor to compensate for the limited opportunity to work from home.

Additionally, the strong association between pay-for-performance type HRM practices and the prevalence of remote work, conditional on industry, occupation, and task characteristics suggests that the phenomenon of "shirking from home" is a legitimate concern that discourages employers from adopting remote work arrangements. Thus, any adoption of remote work as a countermeasure to COVID-19 will require management to adopt a style of human resource management that ensures that individual worker effort and output can be accurately monitored in the remote work setting. This poses a significant challenge to company management.

Finally, exploiting the panel feature of the data set, future work should address how adaptability to remote work has translated into the severity of the income shock. Those who could work from home during the implementation of social distancing policies presumably suffered less in terms of job loss and earnings impairment. The next wave of the panel in 2021 which records the status as of December 2020 will enable us to test this hypothesis.

References

Adams, Abigail, Teodora Boneva, Marta Golin, and Christopher Rauh, "Work Tasks That Can Be Done From Home: Evidence on Variation Within & Across Occupations and Industries," CEPR Discussion Papers 14901, C.E.P.R. Discussion Papers June 2020.

Alipour, Jean-Victor, Oliver Falck, and Simone Schüller, "Germany's Capacities to Work from Home," Technical Report April 2020.

Allen, Tammy D., Timothy D. Golden, and Kristen M. Shockley, "How effective is telecommuting? Assessing the status of our scientific findings," *Psychological Science in the Public Interest*, 2015, *16* (2), 40–68.

Bick, Alexander, Adam Blandin, and Karel Mertens, "Work from home after the COVID-19 Outbreak," Technical Report 2020.

Bloom, Nicholas, James Liang, John Roberts, and Ying Zhichun Jenny, "Does Working From Home Work ? Evidence From A Chinese Experiment," *The Quarterly Journal of Economics*, 2015, *130* (1), 165–218.

Boeri, Tito, Alessandro Caiumi, and Marco Paccagnella, "Mitigating the work-safety trade-off," *Covid Economics*, 2020, *2*, 60–66.

Brussevich, Mariya, Era Dabla-Norris, and Salma Khalid, "Who will Bear the Brunt of Lockdown Policies ? Evidence from Tele-workability Measures Across Countries," Technical Report, IMF Working Paper No. 20/88 2020.

Brynjolfsson, Erik, Daniel Rock, John Horton, Adam Ozimek, Garima Sharma, and Hong Yi Tu Ye, "COVID-19 and Remote Work : An Early Look at US Data," Technical Report 2020.

Dingel, Jonathan and Brent Neiman, "How Many Jobs Can be Done at Home?," Technical Report March 2020.

Groen, Bianca A.C., Sander P. van Triest, Michael Coers, and Neeke Wtenweerde, "Managing flexible work arrangements: Teleworking and output controls," *European Management Journal*, 2018, *36* (6), 727–735.

Hatayama, Maho, Mariana Viollaz, and Hernan Winkler, "Jobs' Amenability to Working from Home: Evidence from Skills Surveys for 53 Countries," *Covid Economics*, 2020, *19*.

Holgersen, Henning, Zhiyang Jia, and Simen Svenkerud, "Who and How Many Can Work from Home? Evidence from Task Descriptions and Norwegian Job Advertisements.," Technical Report 1 2020.

Kazekami, Sachiko, "Mechanisms to improve labor productivity by performing telework," *Telecommunications Policy*, 2020, *44* (2), 101868.

Kikuchi, Shinnosuke, Sagiri Kitao, and Minamo Mikoshiba, "Heterogeneous Vulnerability to the COVID-19 Crisis and Implications for Inequality in Japan," Technical Report, Research Institute of Economy, Trade and Industry (RIETI) 2020.

Milgrom, Paul and John Roberts, *Economics, organization and management*, Prentice-hall, 1992.

Mongey, Simon, Laura Pilossoph, and Alex Weinberg, "Which Workers Bear the Burden of Social Distancing Policies?," Technical Report, NBER Working Paper No. 27085 2020.

Morikawa, Masayuki, "Long Commuting Time and the Benefits of Telecommuting," Technical Report 2018.

_ , "Productivity of remote workers under the COVID-19: Analysis based on workers' survey," Technical Report 2020.

Okubo, Toshihiro, "Spread of COVID-19 and telework: Evidence from Japan," *Covid Economics*, 2020, *32*, 1–25.

Sewell, Graham and Laurent Taskin, "Out of Sight, Out of Mind in a New World of Work? Autonomy, Control, and Spatiotemporal Scaling in Telework," *Organization Studies*, 2015, *36* (11), 1507–1529.

Table 1: Firm's introduction of remote work as of December 2019 (JPSED2019, Employee)

	Fraction	Actual remote work
Introduced and applied	0.04	0.55
Introduced but not applied	0.05	0.08
Not introduced	0.72	0.06
Not knowing	0.18	0.07
Total	1.00	0.09
Observations	32892	

Note: 1. Fraction is the fraction that each item is applicable.

2. Actual remote work is the conditional probability of working remotely within each category.

Table 2: Summary statistics by remote work status (JPSED2019, Employee)

	Remote worker	Non-remote worker	Difference
Routine	49.16	61.17	-12.01
	(27.44)	(28.64)	(0.52)
Manual	34.80	43.90	-9.10
	(27.46)	(31.07)	(0.56)
Interactive	43.94	45.89	-1.95
	(28.16)	(30.61)	(0.56)
PFP (pay for performance)	0.37	0.23	0.13
	(0.48)	(0.42)	(0.01)
KPI (key performance indicator)	0.31	0.17	0.14
	(0.46)	(0.37)	(0.01)
MBO (management by objective)	0.31	0.20	0.12
	(0.46)	(0.40)	(0.01)
Remote work hours per week	8.04	0.00	8.04
	(12.07)	(0.00)	(0.06)
Work hours per week	41.15	37.32	3.83
	(16.51)	(14.47)	(0.27)
Annual earnings (10,000 yen)	433.20	339.54	93.66
	(294.85)	(239.80)	(4.52)
Observations	3258	35034	

Note: 1. Mean values and standard deviations are reported. Standard deviations are in parentheses.

2. t-test is conducted in difference column. Standard errors are in parentheses.

Table 3: The regression R^2 of task variables on industry and occupation dummy variables

	(1)	(2)	(3)
Dependent variables	Routine	Manual	Interactive
Independent variables			
Industry	0.036	0.144	0.039
Occupation	0.104	0.415	0.088
Industry and Occupation	0.112	0.433	0.100
Industry $\times$ Occupation	0.132	0.453	0.124
Observations	38292	38292	38292

Note: R squared when regressing each task variable.

Figure 1: Percentage of routine tasks by occupation

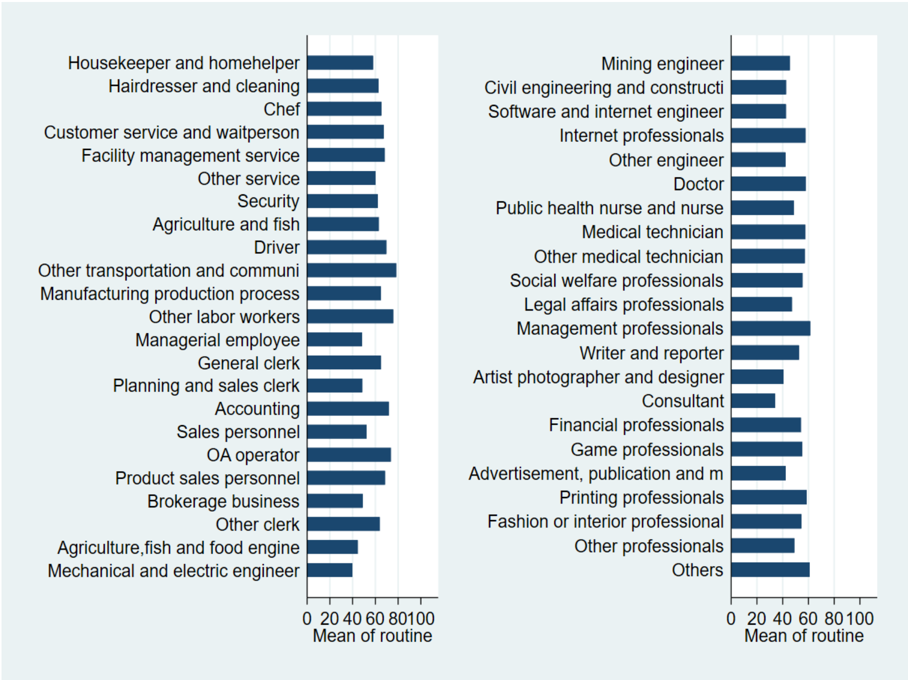


Figure 2: Percentage of manual tasks by occupation

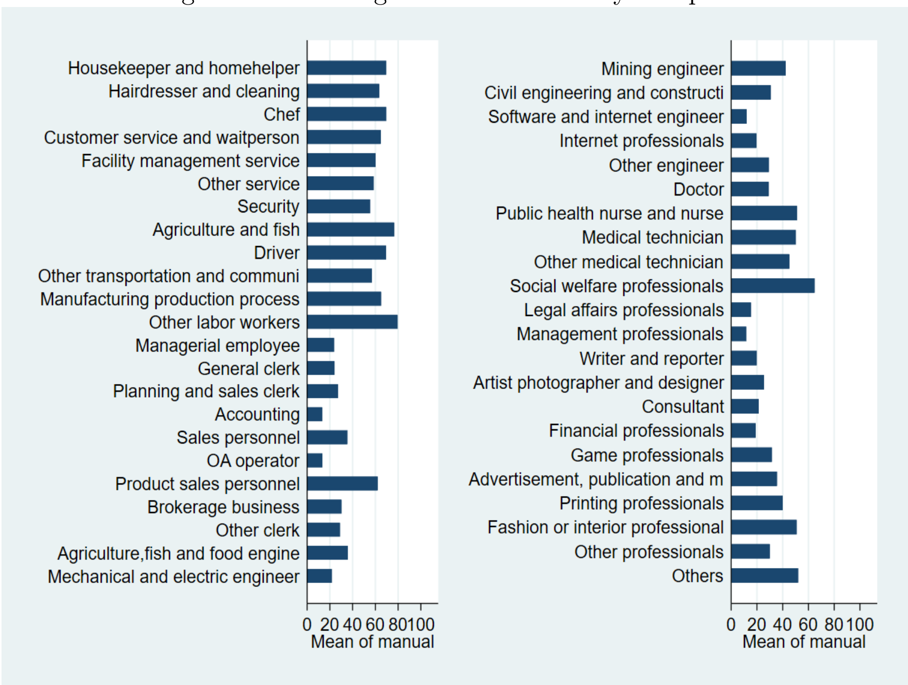


Figure 3: Percentage of interactive tasks by occupation

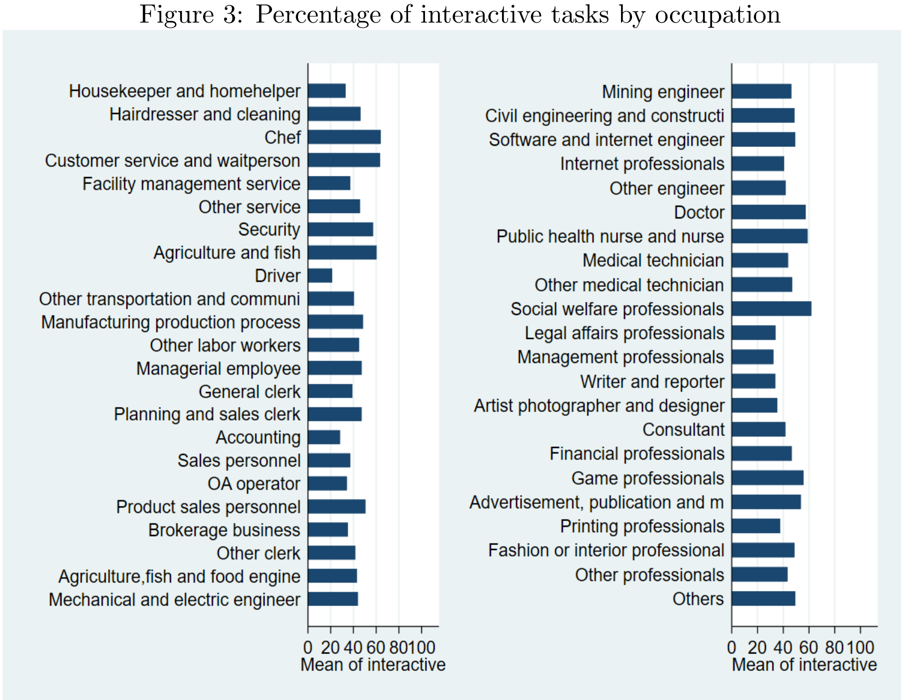


Figure 4: Prevalence of remote work by industry

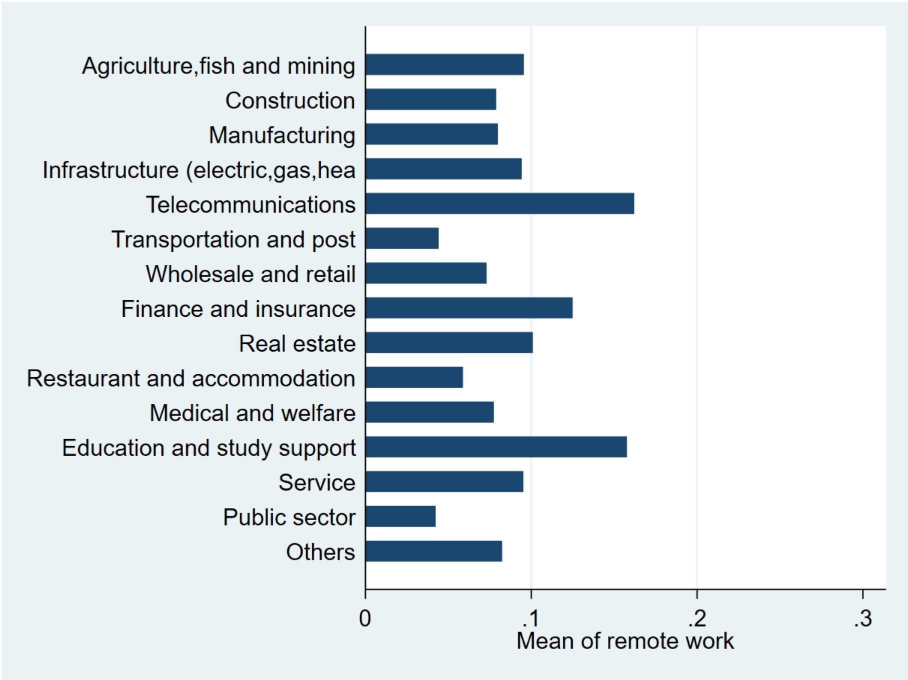


Figure 5: Prevalence of remote work by occupation

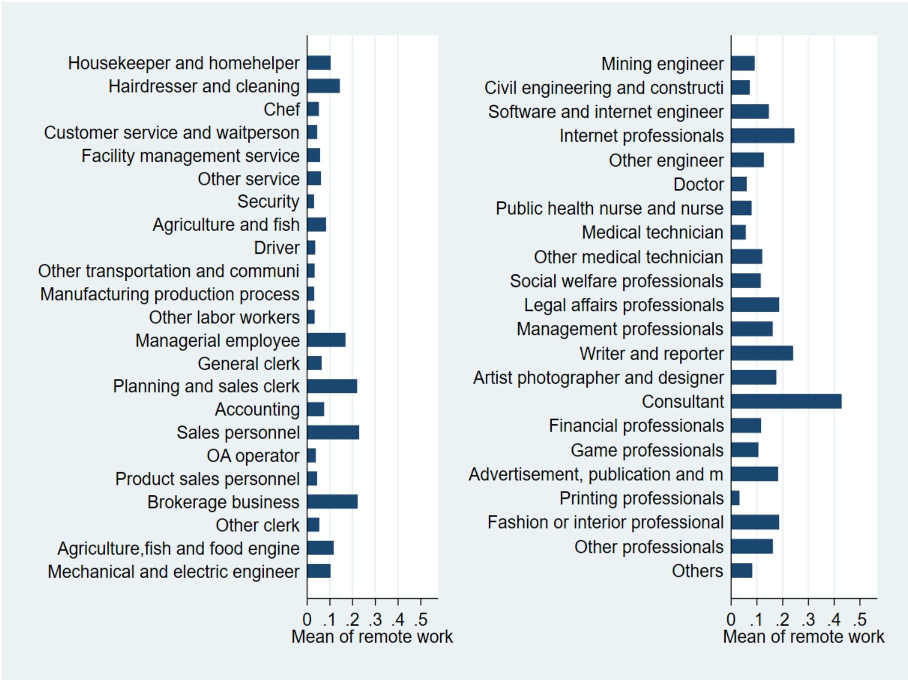


Figure 6: Relationship between annual earnings and remote work

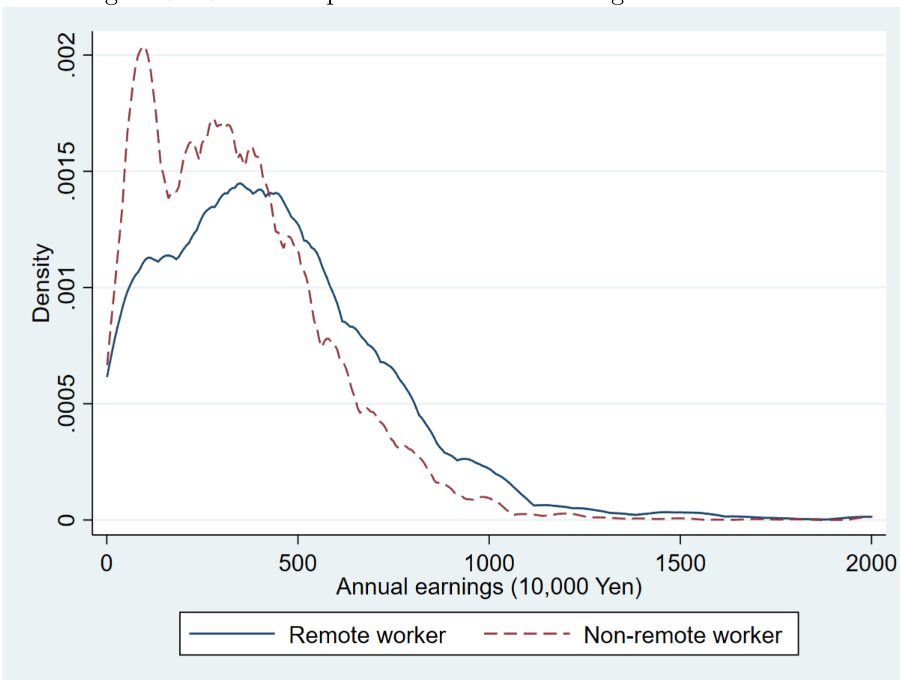


Figure 7: The prevalence of remote work and average annual earnings by occupation

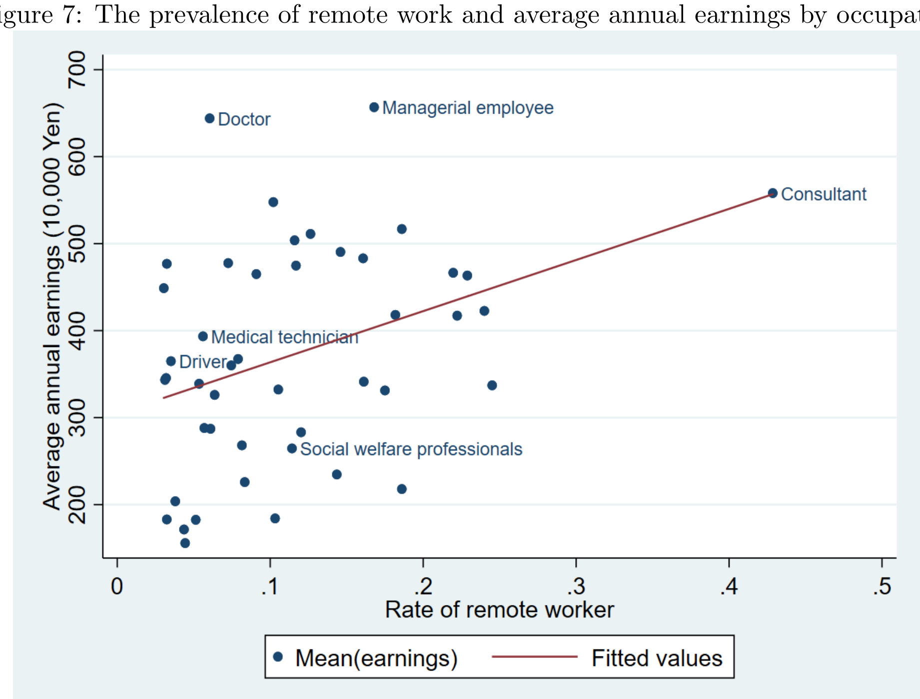
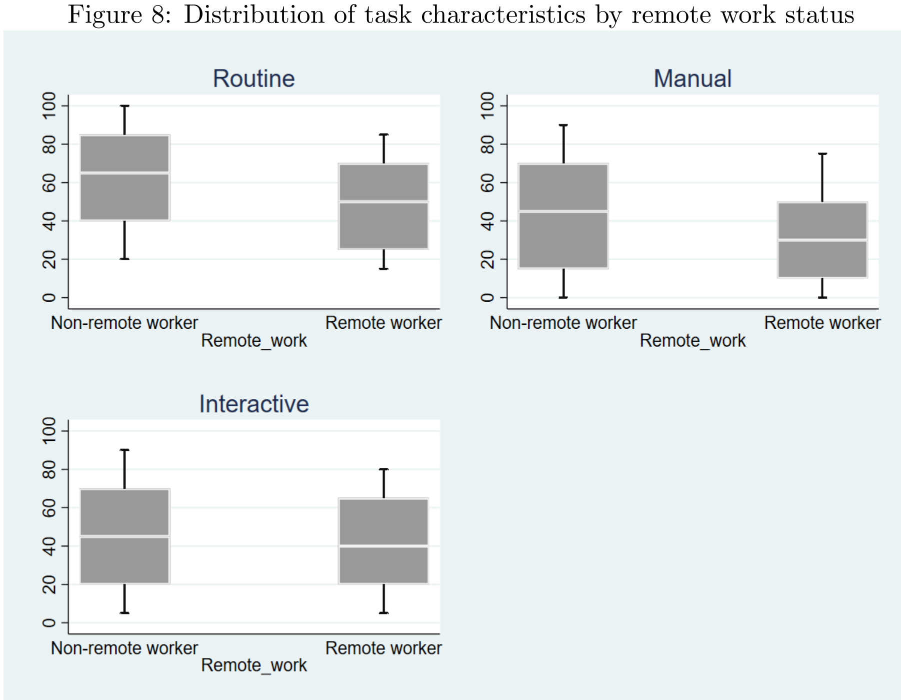
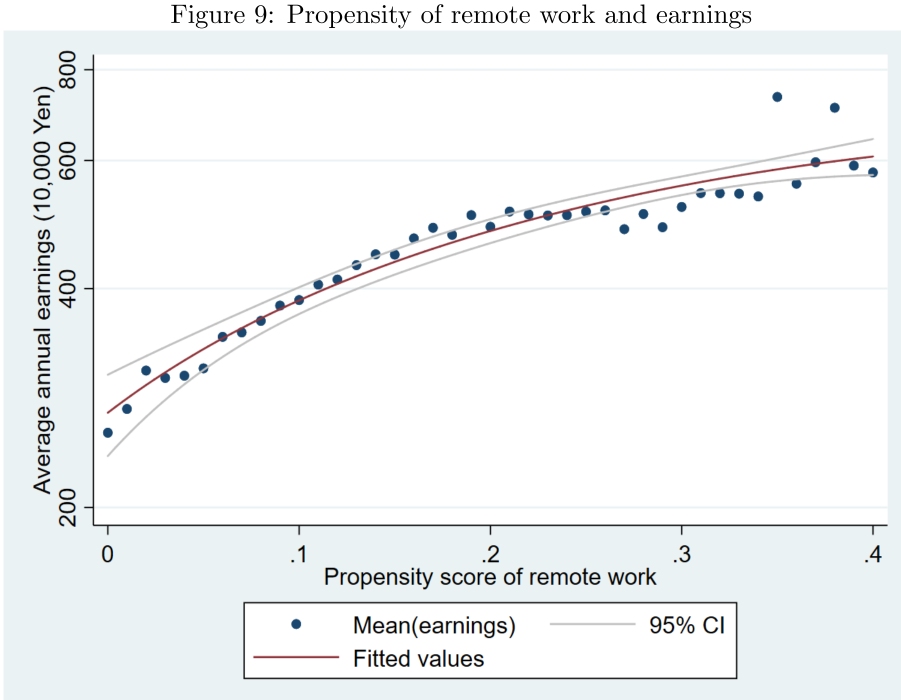


Figure 8: Distribution of task characteristics by remote work status



Note: The box plot displays a box bordered at the 25th and 75th percentiles of each task variable with a median line at the 50th percentile. From the box, we further extend a line vertically to the 90th and 10th percentile values, which are capped by short horizontal lines.

Figure 9: Propensity of remote work and earnings



Note: 1. We calculated the mean of log(earnings) for each category with propensity scores in every 0.01 range. A propensity score with a value of 0.4 or higher is in one category.

2. We regressed log(earnings) on propensity score (PS) and its square by OLS. Standard errors robust against heteroskedasticity are in parentheses.

$log(\widehat{earnings}) = 5.28(0.01) + 3.91(0.09) \times PS - 7.05(0.53) \times (PS - \overline{PS})^2$

Table 4: Determinants of remote work

	(1) Probit Remote=1	(2) Probit Remote=1	(3) Probit Remote=1	(4) Probit Remote=1	(5) Tobit $\frac{Remoteh}{Workh}$	(6) Tobit $\frac{Remoteh}{Workh}$	(7) Tobit $\frac{Remoteh}{Workh}$	(8) Tobit $\frac{Remoteh}{Workh}$
Female	0.006	-0.021	-0.004	-0.004	0.014	-0.000	0.011	0.010
	(0.022)	(0.023)	(0.025)	(0.025)	(0.016)	(0.017)	(0.018)	(0.018)
With child age 6 or younger	0.143***	0.154***	0.149***	0.145***	0.101***	0.108***	0.104***	0.098***
	(0.026)	(0.026)	(0.027)	(0.027)	(0.019)	(0.019)	(0.020)	(0.020)
Age	-0.030***	-0.028***	-0.030***	-0.029***	-0.024***	-0.023***	-0.024***	-0.023***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Age squared/100	0.035***	0.034***	0.034***	0.033***	0.029***	0.028***	0.028***	0.027***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
University	0.184***	0.138***	0.085***	0.083***	0.119***	0.093***	0.060***	0.057***
	(0.021)	(0.022)	(0.023)	(0.023)	(0.016)	(0.016)	(0.016)	(0.016)
Routine/100	-0.596***	-0.572***	-0.478***	-0.481***	-0.404***	-0.385***	-0.319***	-0.314***
	(0.033)	(0.034)	(0.036)	(0.036)	(0.033)	(0.032)	(0.032)	(0.032)
Manual/100	-0.261***	-0.183***	-0.117***	-0.129***	-0.189***	-0.135***	-0.094***	-0.101***
	(0.035)	(0.037)	(0.045)	(0.046)	(0.028)	(0.029)	(0.035)	(0.035)
Interactive/100	-0.114***	-0.139***	-0.135***	-0.144***	-0.097***	-0.112***	-0.104***	-0.105***
	(0.033)	(0.034)	(0.036)	(0.036)	(0.025)	(0.026)	(0.027)	(0.027)
Nonregular	-0.208***	-0.241***	-0.168***	-0.177***	-0.105***	-0.125***	-0.081***	-0.083***
	(0.025)	(0.026)	(0.027)	(0.028)	(0.019)	(0.020)	(0.020)	(0.020)
100-299	-0.099***	-0.079**	-0.074**	-0.076**	-0.071***	-0.056**	-0.051**	-0.052**
	(0.030)	(0.031)	(0.031)	(0.032)	(0.023)	(0.023)	(0.023)	(0.023)
300-999	-0.111***	-0.088***	-0.069**	-0.072**	-0.097***	-0.078***	-0.063***	-0.063***
	(0.031)	(0.032)	(0.033)	(0.033)	(0.023)	(0.023)	(0.023)	(0.023)
1000-4999	0.018	0.044	0.065**	0.061*	0.002	0.021	0.035	0.031
	(0.032)	(0.032)	(0.033)	(0.034)	(0.023)	(0.024)	(0.025)	(0.025)
5000+	0.079***	0.125***	0.136***	0.140***	0.047**	0.079***	0.085***	0.086***
	(0.029)	(0.031)	(0.032)	(0.033)	(0.021)	(0.023)	(0.024)	(0.024)
Public sector	-0.418***	-0.079	-0.050	-0.037	-0.291***	-0.076	-0.057	-0.053
	(0.044)	(0.098)	(0.098)	(0.099)	(0.035)	(0.065)	(0.065)	(0.063)
Industry	No	Yes	Yes		No	Yes	Yes	
Occupation	No	No	Yes		No	No	Yes	
Industry × Occupation				Yes				Yes
Observations	36457	36457	36457	35506	36323	36323	36323	36323
Pseudo R^2	0.046	0.057	0.084	0.098	0.040	0.048	0.071	0.094

Note: 1. Standard errors are in parentheses and are heteroskedastic consistent.

2. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

3. Coefficients are marginal effects for all estimation methods. All effects are evaluated at the means of the other variables.

Table 5: Determinants of remote work with human resource management style

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probit	Probit	Probit	Probit	Tobit	Tobit	Tobit	Tobit
	Remote=1	Remote=1	Remote=1	Remote=1	$\frac{Remoteh}{Workh}$	$\frac{Remoteh}{Workh}$	$\frac{Remoteh}{Workh}$	$\frac{Remoteh}{Workh}$
Female	-0.030	-0.058**	-0.053*	-0.062*	-0.007	-0.023	-0.020	-0.027
	(0.028)	(0.029)	(0.031)	(0.032)	(0.023)	(0.024)	(0.026)	(0.026)
With child age 6 or younger	0.145***	0.155***	0.157***	0.149***	0.121***	0.128***	0.128***	0.120***
	(0.036)	(0.036)	(0.037)	(0.038)	(0.030)	(0.030)	(0.030)	(0.031)
Age	-0.029***	-0.028***	-0.030***	-0.029***	-0.027***	-0.026***	-0.027***	-0.025***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Age squared/100	0.034***	0.033***	0.034***	0.032***	0.031***	0.030***	0.030***	0.029***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
University	0.203***	0.161***	0.116***	0.117***	0.151***	0.124***	0.093***	0.091***
	(0.026)	(0.027)	(0.028)	(0.029)	(0.022)	(0.023)	(0.023)	(0.023)
PFP (pay for performance)	0.178***	0.178***	0.165***	0.163***	0.130***	0.129***	0.117***	0.113***
	(0.027)	(0.028)	(0.028)	(0.029)	(0.023)	(0.023)	(0.023)	(0.023)
KPI (key performance indicator)	0.241***	0.243***	0.225***	0.232***	0.179***	0.181***	0.166***	0.166***
	(0.033)	(0.033)	(0.034)	(0.034)	(0.028)	(0.028)	(0.028)	(0.029)
MBO (management by objective)	0.084***	0.083**	0.066**	0.068**	0.052**	0.053**	0.043	0.044*
	(0.032)	(0.032)	(0.033)	(0.034)	(0.026)	(0.026)	(0.026)	(0.027)
Routine/100	-0.589***	-0.562***	-0.492***	-0.502***	-0.462***	-0.440***	-0.381***	-0.378***
	(0.042)	(0.042)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Manual/100	-0.199***	-0.127***	-0.019	-0.034	-0.165***	-0.109***	-0.030	-0.040
	(0.045)	(0.047)	(0.057)	(0.058)	(0.039)	(0.041)	(0.050)	(0.050)
Interactive/100	-0.185***	-0.208***	-0.198***	-0.207***	-0.162***	-0.176***	-0.161***	-0.157***
	(0.042)	(0.043)	(0.045)	(0.046)	(0.037)	(0.037)	(0.038)	(0.039)
Nonregular	-0.141***	-0.173***	-0.110***	-0.122***	-0.074***	-0.096***	-0.055**	-0.059**
	(0.031)	(0.032)	(0.033)	(0.034)	(0.026)	(0.026)	(0.027)	(0.027)
100-299	-0.111***	-0.096**	-0.085**	-0.089**	-0.087***	-0.073**	-0.063*	-0.066**
	(0.038)	(0.039)	(0.039)	(0.040)	(0.033)	(0.033)	(0.033)	(0.032)
300-999	-0.160***	-0.145***	-0.122***	-0.127***	-0.142***	-0.128***	-0.110***	-0.109***
	(0.040)	(0.040)	(0.041)	(0.042)	(0.033)	(0.033)	(0.034)	(0.034)
1000-4999	-0.050	-0.030	-0.003	-0.002	-0.044	-0.027	-0.006	-0.005
	(0.041)	(0.041)	(0.042)	(0.043)	(0.034)	(0.034)	(0.035)	(0.035)
5000+	-0.031	0.008	0.023	0.020	-0.027	0.004	0.013	0.011
	(0.039)	(0.040)	(0.041)	(0.043)	(0.032)	(0.033)	(0.034)	(0.034)
Public sector	-0.365***	-0.051	-0.021	-0.018	-0.296***	-0.082	-0.062	-0.067
	(0.057)	(0.126)	(0.124)	(0.126)	(0.049)	(0.092)	(0.090)	(0.090)
Industry	No	Yes	Yes		No	Yes	Yes	
Occupation	No	No	Yes		No	No	Yes	
Industry × Occupation				Yes				Yes
Observations	23762	23762	23762	22770	23687	23687	23687	23687
Pseudo R^2	0.061	0.071	0.096	0.112	0.050	0.058	0.079	0.106

Note: 1. Standard errors are in parentheses and are heteroskedastic consistent.

2. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

3. Coefficients are marginal effects for all estimation methods. All effects are evaluated at the means of the other variables.

Figure 10: Proportion of of workers working from home, December 2019

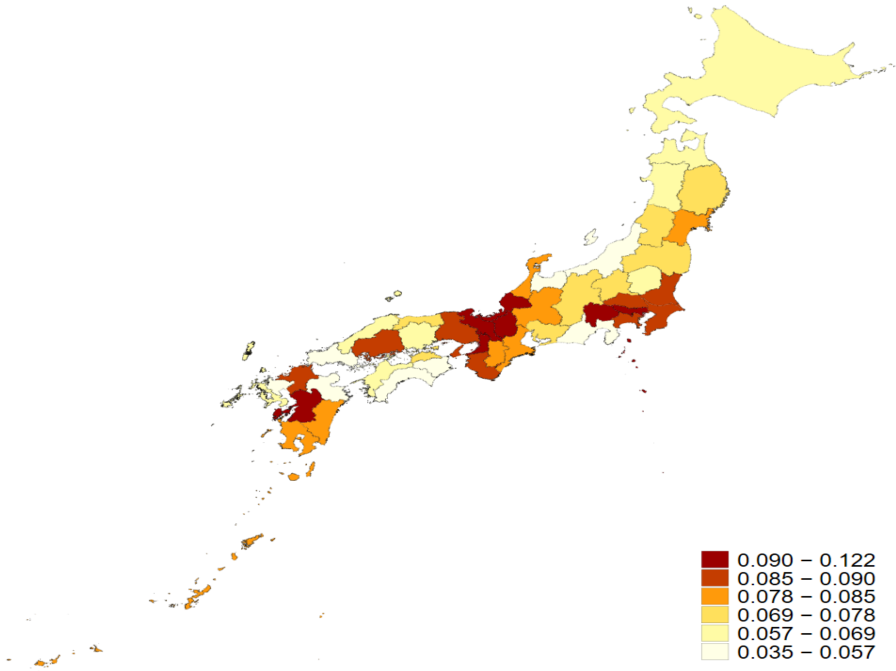
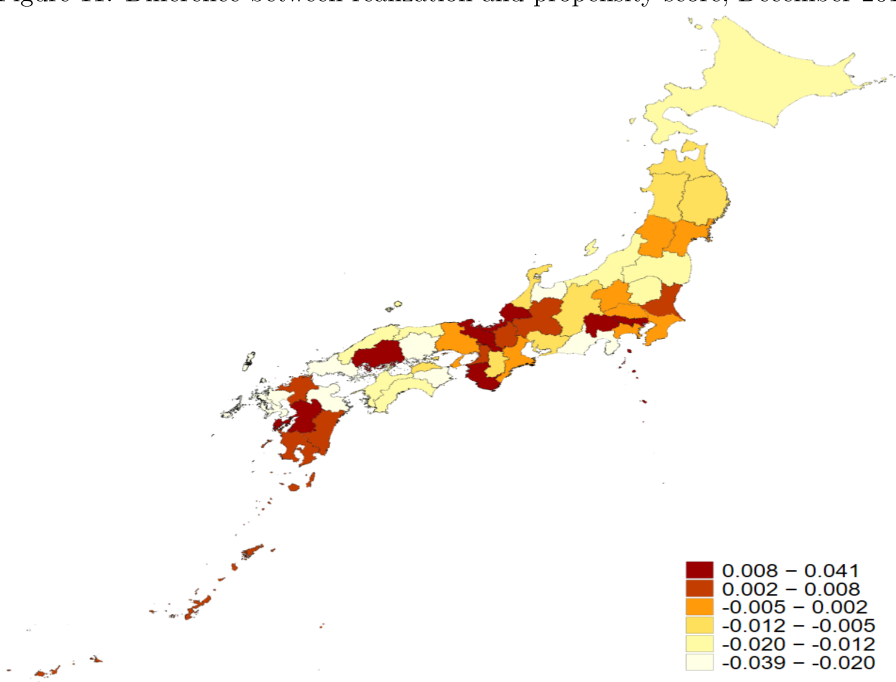


Figure 11: Difference between realization and propensity score, December 2019



A Appendix

A.1 JPSED Questionnaire

This appendix provides the complete JPSED questionnaire used to construct the variables for this study.

- Questions about remote work

  As of last December, how long did you engage in remote work per week? Remote work is defined as working from your home, a satellite office, a cafe/family restaurant, or a workplace (This refers to working at a location other than the company and its customers).

  Total hours per week: (XXX) hours

  As of last December, you did remote work for a total of XXX hours in an average week. The answer is "yes". If there are no mistakes, please click the "Next Page" button. If you need to make a correction, please click the "Back" button and try again.

- Questions about the remote work system

  As of last December, did your workplace have a remote work system in place? Were you eligible for the system and did you apply for it? Please choose the response below that applies to you. A remote work system refers to a system that allows employees to work from locations other than the workplace (your company and your customers), such as your home, a satellite office, or a cafe/family restaurant.

  1. It was introduced as a system and applied to me.
  2. It was introduced as a system, but did not apply to me.
  3. It had not been introduced as a system.
  4. I don't know.

- Questions about task characteristics

  What percentage of each of the following tasks did you engage in your job in last December? Drag the translucent button and slide it to the position that you think fits your job.

  routine/ non-routine

  manual/ cognitive

  working alone/ working interactively

  Percentage of work ( ) / Percentage of work ( )

  If you enter a number on one side, it will automatically calculate the total to be 100%.

- Questions about human resource management

  We would like to ask you about your work at your workplace over the last year (January - December 2019).

  Do any of the following apply at your workplace?

  – Results are more important than age or seniority in your personnel evaluations.
  – Results are managed through KPI and other measures.
    KPI are metrics to manage your performance and actions that you look back on regularly to achieve your goals.
  – There is a system for setting clear goals for work, such as the management by objectives (MBO) system.

  1. applicable
  2. if anything, applicable
  3. I can't say either.
  4. if anything, not applicable
  5. not applicable

A.2 Regression results with the restricted sample

We conducted the same analysis as in Table 4 after restricting the sample to those observations with valid responses to the supplementary survey.

Table A1: Determinants of remote work (robustness: restricted sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probit	Probit	Probit	Probit	Tobit	Tobit	Tobit	Tobit
	Remote=1	Remote=1	Remote=1	Remote=1	$\frac{Remoteh}{Workh}$	$\frac{Remoteh}{Workh}$	$\frac{Remoteh}{Workh}$	$\frac{Remoteh}{Workh}$
Female	-0.026	-0.050*	-0.042	-0.052	-0.004	-0.019	-0.014	-0.021
	(0.027)	(0.028)	(0.031)	(0.032)	(0.023)	(0.024)	(0.025)	(0.026)
With child age 6 or younger	0.154***	0.165***	0.163***	0.156***	0.128***	0.136***	0.134***	0.127***
	(0.036)	(0.036)	(0.037)	(0.038)	(0.030)	(0.030)	(0.031)	(0.031)
Age	-0.032***	-0.031***	-0.033***	-0.032***	-0.029***	-0.028***	-0.029***	-0.027***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Age squared/100	0.037***	0.036***	0.037***	0.035***	0.033***	0.032***	0.032***	0.031***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
University	0.208***	0.167***	0.120***	0.122***	0.156***	0.129***	0.096***	0.095***
	(0.026)	(0.027)	(0.028)	(0.028)	(0.022)	(0.023)	(0.023)	(0.023)
Routine/100	-0.618***	-0.592***	-0.513***	-0.524***	-0.485***	-0.464***	-0.398***	-0.395***
	(0.041)	(0.042)	(0.045)	(0.046)	(0.047)	(0.046)	(0.046)	(0.047)
Manual/100	-0.260***	-0.178***	-0.064	-0.078	-0.211***	-0.147***	-0.063	-0.071
	(0.044)	(0.047)	(0.056)	(0.058)	(0.040)	(0.041)	(0.050)	(0.050)
Interactive/100	-0.159***	-0.180***	-0.174***	-0.183***	-0.143***	-0.155***	-0.144***	-0.141***
	(0.042)	(0.043)	(0.044)	(0.046)	(0.036)	(0.037)	(0.038)	(0.039)
Nonregular	-0.177***	-0.209***	-0.138***	-0.151***	-0.101***	-0.124***	-0.075***	-0.080***
	(0.030)	(0.031)	(0.033)	(0.034)	(0.026)	(0.026)	(0.027)	(0.027)
100-299	-0.074**	-0.061	-0.053	-0.057	-0.060*	-0.048	-0.041	-0.044
	(0.038)	(0.038)	(0.039)	(0.040)	(0.032)	(0.033)	(0.033)	(0.032)
300-999	-0.097**	-0.085**	-0.066	-0.068	-0.098***	-0.086***	-0.071**	-0.068**
	(0.039)	(0.040)	(0.041)	(0.042)	(0.033)	(0.033)	(0.033)	(0.034)
1000-4999	0.040	0.053	0.074*	0.076*	0.022	0.034	0.049	0.050
	(0.040)	(0.040)	(0.041)	(0.042)	(0.034)	(0.035)	(0.035)	(0.036)
5000+	0.082**	0.110***	0.117***	0.115***	0.054*	0.077**	0.080**	0.078**
	(0.037)	(0.038)	(0.040)	(0.041)	(0.031)	(0.033)	(0.034)	(0.034)
Public sector	-0.335***	-0.025	-0.001	0.003	-0.278***	-0.065	-0.049	-0.054
	(0.056)	(0.124)	(0.123)	(0.125)	(0.048)	(0.091)	(0.089)	(0.090)
Industry	No	Yes	Yes		No	Yes	Yes	
Occupation	No	No	Yes		No	No	Yes	
Industry × Occupation				Yes				Yes
Observations	23762	23762	23762	22770	23687	23687	23687	23687
Pseudo R^2	0.048	0.058	0.086	0.102	0.041	0.048	0.071	0.099

Note: 1. Standard errors are in parentheses and are heteroskedastic consistent.

2. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

3. Coefficients are marginal effects for all estimation methods. All effects are evaluated at the means of the other variables.