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

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

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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 tasks and human resource management (HRM) characteristics workers face. We show that the opportunity to work remotely was more likely to be available to those engaged in non-routine and non-interactive tasks as well as to workers subject to HRM practices presupposing that worker performance is measurable. The implications of these findings for income transfer policies and management practices in light of the COVID-19 pandemic are also discussed.

Keywords Remote work, Human resource management, Pay for performance, Key performance indicators, Job tasks, Shirking

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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, social distancing has had a profound economic impact, 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 actually worked from home just prior to the COVID-19 crisis and identifying their specific job characteristics. In contrast to the literature, this approach allows us to understand the conditions facilitating a remote work arrangement and to articulate any expected challenges as remote work expands. To accomplish this, we utilize a unique panel data set from Japan that includes job task characteristics and human resource management conditions. As of December 2019, 8% of Japanese workers worked outside of their official workplace, and while the prevalence of remote work does not vary much across industries, it does vary considerably across occupations. In particular, workers involved in non-routine and non-manual tasks and those employed under performance-based human resource management (HRM) practices are significantly more likely to engage in remote work. Together, these results indicate that workers engaging in manual or interactive tasks are less likely to work remotely, as previous studies have found, and also 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 job 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.

In addition, as the determinants of earnings and remote work potential are positively related, the burden of social distancing policies disproportionately falls on low income earners. For instance, while the 50% of consultants who worked remotely earned 6 million yen annually, the 10% of care workers who worked remotely earned only 2.8 million yen annually. More generally, those who worked remotely earned 23.4% more than non-remote workers. However, we find that remote workers did not earn more than non-remote workers when conditioned on observed job and demographic characteristics, which suggests that income transfer policies conditioned on observable characteristics or socioeconomic status would mitigate the disadvantage experienced by non-remote workers under the hardships caused by the pandemic.

Remote work increased from 8% in December 2019 to 14% in December 2020, and we further examine how the determinants of remote work evolved during the COVID-19 pandemic by examining the job characteristics associated with the increase in remote work using the latest wave of the panel survey implemented in December 2020. We examine the impact of job characteristics on December 2019 on the engagement in remote work in December 2020, and find that as remote work expanded, workers engaging in interactive tasks, holding a university degree, and belonging to larger firms caught the wave, while workers engaging in manual tasks were left behind. Thus, the increase in remote work during COVID-19 exacerbated the pre-existing inequality.

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. (2021), 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 women, college graduates, and salaried and regular-contract 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 appears 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. (2021) 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

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

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 characteristics of each employee's work environment. The survey was implemented just before the outbreak of COVID-19 pandemic, and this makes this data set ideal for examining the natural determinants of the possibility for remote work. Further, identifying these natural determinants is useful for foreseeing the problems that might arise when employers are forced to adopt a remote work arrangement.

The high explanatory power of job characteristics variables has two important implications. First, on redistribution policy, the literature demonstrates that the negative impact of COVID-19 is heterogeneous across occupations and skill levels (Adams et al., 2020; Mongey et al., forthcoming; Brussevich et al., 2020; Kikuchi et al., 2021) and the likelihood of working remotely is strongly associated with a negative income shock (Mongey et al., forthcoming). Thus, our finding of a heterogeneous probability of engaging in remote work according to job tasks within a standard industry/occupation category implies that a heterogeneous negative income shock will exist even within the category. This therefore calls for a careful examination of the current income change and a much more fine-grained transfer policy to compensate for any earnings loss due to COVID-19.

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).[2] 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 workers 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] Another mechanism that enables remote work without productivity loss is to make the job task fun and self rewarding (Dutcher, 2012).

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 that has been 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.[3] 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. For this study, we use the 2020 wave of the survey conducted from January 9-31, 2020, when the outbreak of COVID-19 in China had been covered by the 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 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, of which 24,728 observations had valid responses to the supplemental survey. This basic analysis sample consists of employed men and women whose ages are 15 years old or above.

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

[3] We compare the distribution of worker characteristics of the 2019 JPSED with the 2015 Census. Appendix A.5 demonstrates that the distributions of types of employment and industry are fairly close to the distribution based on the Census.

who reported positive remote hours worked in each of the above company rule categories. We see that while only 4% of respondents replied that their companies set the rule for remote work and it applied to them, 58% 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 a remote worker as one who actually worked outside of the work place.

Thus, in total, 8% 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). Our number is 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. According to the descriptive statistics reported in Table 2, average hours worked per week was 38.7 hours, of which 8.81 hours occurred remotely, indicating that those who engaged in remote work spent 23% of their working hours outside 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 Appendix A, respondents choose the task characteristics in terms of percentages using a 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 62% routine, 43% manual, and 44% interactive, while remote workers describe their job tasks as 49% routine, 33% manual, and 42% interactive. Thus we see that remote workers are much less likely to engage in routine and manual tasks. The analysis in Appendix A demonstrates that although the task measures are highly associated with the two-digit occupation codes, significant variation remains within an occupation code, suggesting that task measurement in addition to the two-digit occupation code is needed to accurately capture job heterogeneity.

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 facilitate 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 applies to 37% of remote workers, KPI to 31% and MBO to 31%. In the Appendix, we examine how the HRM characteristics are associated with occupation.

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

As the literature has typically used occupation to define the feasibility of working from home (see Dingel and Neiman (2020), for example), we first document the prevalence of remote work by industry and occupation. Figure 1 reports the percentage of workers allowed to work outside of workplace by industry, and compared to the overall average of 8%, the variation across industries is rather small, with the highest being 17% in the telecommunications industry and the lowest being 5% in the transportation and the postal industry. The high prevalence of remote work in the telecommunications (and information) industry is understandable given that their work is computerized. On the other hand, workers in transportation, the postal industry and the public sector, 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 2 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, and 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 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 3 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 medians 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 A2 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 require interaction with customers. These varying types of interaction with others are arguably the reason why we find a similar distribution of task interactivity between remote and non-remote workers.

3.3 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 61% more likely to experience some form of pay-for-performance style HRM practice, which is consistent with our 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."

3.4 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, and Figure 4 shows that workers who did not engage in remote work earned less than remote workers.[4] In particular, the majority of those who did not engage in remote work 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 5 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 50% and income about 6.0 million yen annually, while fewer than 5% of drivers engage in remote work and annual income is 3.4 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.

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:

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

[4] 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.

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

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, indicator variables for HRM practices (Pay for Performance, Key Performance Indicator, Management by Objective), as well as 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.

4.1 Basic Results

Column 1 of Table 3 shows the marginal effects of the probit regression of remote work status on job characteristic and demographic variables. In terms of task characteristics, workers performing routine and interactive tasks are less likely to engage in remote work, conditional on job and demographic characteristics and industry×occupation fixed effects. This finding gives support to the approach of attempting to identify remote-workable jobs through task characteristics (Dingel and Neiman, 2020; Boeri et al., 2020; Holgersen et al., 2021; Alipour et al., 2020) and, further, indicates that important variation in job tasks remains within an industry×occupation cell.

We next focus on the estimated coefficients for HRM style variables. Those workers subject to pay-for-performance (PFP), KPI and MBO are 2.3, 3.3 and 1.0 percentage points more likely to engage in remote work, respectively, and these partial correlations are economically significant. While the partial correlations are not causal, they do show that the employer's ability to accurately observe each worker's output, approximated by the HRM style, is associated with the potential for remote work. Further, the magnitudes of these coefficients are large when considering that only 8% of employees work remotely. This finding is consistent with the prediction that firms that are concerned about workers "shirking from home" tend to be reluctant to adopt a remote work arrangement. Furthermore, workers classified as non-regular (on a fixed-term contract, working part time or dispatched from temporary help agencies) are 1.7 percentage points less likely to engage in remote work, which suggests that employers may be less able to discipline a worker's shirking behavior without a long-term and continuing relationship.

Workers' demographic characteristics also play an important role in determining remote work status.

University graduates are about 1.6 percentage points more likely to engage in remote work, and while women are slightly less likely to engage in remote work, workers with younger children are 2.1 percentage points more likely to do so. 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. Further, 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.

In addition to age, the relationship between firm size and remote work is also U-shaped. Compared with workers in small firms with less than 100 employees, workers in medium-sized firms with 100-299 or 300-999 employees are about 1.2 or 1.8 percentage points, respectively, less likely to engage in remote work. In contrast, workers in large firms with 1000-4999 and 5000+ employees are equally likely to engage in remote work as those in small firms. The reason why remote work is prevalent in both small and mega-sized firms is probably different, for small firms tend to have more casual and informal employee control that might permit flexibility while mega-sized firms have a formalized network and HRM practices that can facilitate remote work while maintaining appropriate monitoring.

As previous studies used different analysis samples to analyze the relationship between firm size and the prevalence of remote work, we here attempt to replicate findings of previous studies by using a consistent analysis sample. Specifically, Okubo (2020) included self-employed workers while our main analysis sample has excluded them, so Column (7) of Table 3 reports the regression result using a sample that includes self-employed workers. We see that when we also include self-employed workers, our results are consistent with Okubo (2020) in that self-employed workers are 7.2 percentage points more likely to engage in remote work. These secondary results support both our main findings and those of Okubo (2020) of a U-shaped relationship between firm size and the prevalence of remote work in the pre- COVID-19 period.

The basic results heretofore indicate that there are substantial differences in the engagement in remote work according to job and demographic characteristics within an industry or occupation. These findings suggest that a firm's ability to suppress its workers' incentive to shirk is an important determinant of remote work adoption. In addition, task characteristics, educational background, presence of pre-school age children, and age are also important determinants of the remote work engagement.

4.2 Alternative Definitions of Remote Work

In order to ensure that our analysis is not affected by the definition we have chosen for remote work, in this section we implement several robustness checks by varying the definition.[5] While our main analysis defined a remote worker as anyone who reported any positive hours worked outside of the work place, this definition could include those who worked only a very few hours at home or at a cafe on the commuting route. Therefore, our first robustness check is to include only those who worked more substantial hours outside of the workplace, which we consider here to be 3 (alternatively, 6) hours or more. The regression results based on these alternative definitions of the remote worker are reported in Columns 2 and 3 of Table 3, and show that the results do not change qualitatively, except for the estimated impact of the manual task intensity, which we discuss below.

Another consideration is whether there might be a difference in the total hours worked between remote and non-remote workers, and how this might affect the results. To adjust for any potential difference in the total hours worked per week, in this next robustness check we define the dependent variable as the hours worked remotely divided by the total hours worked, and estimate using the Tobit model, because the variable *Remote/Work* is left-censored at 0 and right-censored at 1. The results reported in Column 4 of Table 3 using the intensive margin of remote work hours does not change the probit estimation results substantially, which suggests that these characteristics are determinants not only of the extensive margins but also of the intensive margins of remote work.

We next define a remote worker not by actual hours worked but as a worker who is formally permitted to work outside of the workplace by the employer. As discussed above, while 8% of workers reported positive hours worked outside of the workplace, only 4% of workers were formally allowed to do so (Table 1). Column 5 shows the results based on this alternative definition, and we see that the results do not change substantially except for two things. Firstly, workers engaging in manual tasks are much less likely to work under a formal remote work arrangement. Combined with the previous result that manual workers are less likely to work outside of the workplace for more than 6 hours, we can infer that while manual workers are less likely to be in a formal remote work arrangement, they do perform some of their work tasks outside of the workplace. Secondly, while those who work for large firms with 1,000 employees or more are significantly more likely to be in a formal remote work arrangement, this is in contrast to our finding about their actual remote work engagement. This suggests that while workers in large firms may be given the right to work remotely, in reality they do not exercise it often.

[5] We report the regression results without using a sampling weight because our JPSED analysis sample is fairly similar to the 2015 Census in terms of worker characteristics. To confirm this, we conducted a probit estimation applying sampling weights. The results in Column (6) of Table 3 show that, as expected, the estimated marginal effects are sufficiently close to the estimates obtained without using a sampling weight.

4.3 Adoption of Remote Work in December 2020

Our main analysis has focused on the determinants of the adoption of remote work as of December 2019, before the onset of COVID-19, in order to identify the nature of jobs that fit well with remote work in normal times. However, the rapid spread of COVID-19 forced many firms to quickly adopt remote work arrangements on an ad hoc basis, with remote work increasing from 8% in 2019 to 14% in 2020. Because the nature of jobs adopting remote work in an emergency may well be different from that during normal times, it is natural to ask how the determinants of remote work adoption differ before and after the onset of COVID-19. To answer this question, we draw on the 2020 wave of the JPSED that was implemented in December 2020. For this analysis, we use engagement in remote work in December 2020 as the dependent variable, but for comparability, we continue to use the job characteristics as of December 2019. As a result, this analysis sample includes only those who worked for the same firm in both 2019 and 2020.

This comparison of remote work determinants in 2019 and 2020 reveals that the further penetration of remote work in 2020 exacerbated pre-existing inequalities. Table 4 compares the determinants of remote work engagement across different timelines and, for ease of comparison, Column (1) reproduces Column (1) of Table 3 to show the baseline results in December 2019. Restricting the analysis sample to those who worked for the same firm in both December 2019 and 2020 reduces the sample size from 22,769 to 16,341, and Column (2) reports the probit regression results with the same dependent and independent variables based on this restricted sample. We see that the estimated coefficients are broadly similar to the baseline coefficients in Column (1), which indicates that replacing the analysis sample does not change the estimation results in any meaningful way. Column (3) reports the probit regression results in December 2020, and Column (4) presents the difference in the estimated coefficients of Columns (2) and (3) to show the difference in the determinants of remote work engagement in 2019 and 2020. Column (4) reveals that workers engaged in manual tasks became substantially less likely to engage in remote work in 2020, indicating that manual workers did not benefit from the increased penetration of remote work during COVID-19, becoming *relatively* less likely to engage in remote work.

On the other hand, the relative disadvantage of interactive workers in terms of remote work engagement disappeared in 2020. Furthermore, the advantage of holding a university degree or working for a large firm was enhanced in 2020. In particular, the impact of firm size on remote work engagement grew substantially. For instance, while in December 2019, workers at firms with 5000+ employees were equally likely to engage in remote work as those at firms with less than 100 employees, workers at larger firms became as much as 8.6% more likely to work remotely in December 2020. Also, the probability of engaging in remote work monotonically increases as the firm size increases in December 2020. This finding is consistent with the finding by Morikawa (2020) based on the sample after the onset of COVID-19. In sum, as workers with advantageous characteristics in the labor market such as higher education or employment at a large firm benefited more from the expansion of remote work in 2020, it increased existing inequalities.

The results reported in Table 4 suggest the presence of adjustment costs to adopt a remote work setting. Using the same analysis sample and the same set of explanatory variables, the probit model predicts the adoption of remote work in 2020 much better than the adoption of remote work in 2019, as indicated by the substantial increase in Psuedo R^2. The improvement of the goodness of fit implies that the relationship between job characteristics and the adoption of remote work settings becomes more distinct during COVID-19. Arguably, the pandemic nudged the firms to adopt remote work settings if it is technically possible.

4.4 Implications

Policy Implication

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. 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, including those who may not be able to work remotely in an industry in which many can indeed work from home. Additionally, there is presumably substantial variation in the earnings shock or possibility of job loss within an industry beyond merely the potential for remote work. Second, we argue that policies that target small and medium-sized firms (SMEs) to promote the adoption of remote work settings are justified. Our findings show that smaller firms have a lower probability of adopting remote work by December 2020, arguably due to limited financial and human resource capacities. Removing these barriers through policy intervention is justified because remote work adoption is an effective non-pharmaceutical intervention to reduce mobility and generate a positive externality. Of course, we do not intend to justify the general company-based rescue policies such as special loan programs or employment subsidies targeting specific industries or firm sizes. Instead, our findings speak to specific policies to promote the adoption of remote work settings of SMEs.

Managerial Implication

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. When a manager cannot observe the output or effort of each worker, moral hazard can cause a worker to slack off, and our results suggest that "shirking from home" was indeed a practical concern of employers in adopting remote work arrangements. 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 re-design the job or compensation scheme so that the effort or output of individual workers is accurately measured and appropriately compensated. 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 or expand remote work arrangements in response to the spread of COVID-19.

5 Effect of Remote Work on Earnings

To this point we have demonstrated that workers in high-earning occupations or with high human capital are more likely to engage in remote work. Now we ask if engagement in remote work affects earnings after conditioning on observable job and demographic characteristics. This exercise is important for deriving implications for government transfer policies, for if remote work and earnings are positively correlated through observed job and demographic characteristics, an income transfer policy based on these observed characteristics would effectively mitigate inequality-exacerbating negative shocks. On the other hand, if engagement in remote work and earnings are positively correlated conditional on observed characteristics, then even after receiving income transfers based on these characteristics, workers who cannot engage in remote work remain low earners. Thus, if the government aims at mitigating a negative income shock, an income transfer policy based on the possibility of remote work engagement should be considered. With this policy implication in mind, we next examine the impact of remote work engagement on earnings, conditional on job and demographic characteristics.

Panel A in Table 5 lays out the estimation results of log annual earnings in 2019 on engagement in remote work. While Column (1) shows that remote workers earn 0.234 log points more than non-remote workers, Column (2) shows that remote workers do not earn more than non-remote workers when conditioned on the job characteristics and demographic variables used in the regression analysis reported in Table 3. This result does not change by adding Industry × Occupation dummy variables to the conditioning set. These results demonstrate that the positive association between remote work engagement and earnings is induced by job and earnings characteristics.

We next address any concerns that job and demographic characteristics of remote and non-remote workers do not overlap by conducting a propensity score matching (PSM) estimation. While we confirm that engagement in remote work varies substantially within an industry and an occupation (Figures 1 and 2), the high dimension of the job and demographic characteristics vector may nonetheless entail no overlap in the characteristic variables between remote and non-remote workers. If there is no overlap in characteristics, OLS is estimated by extrapolation, assuming that treatment and outcome out of common support is parametric linear. We then relax this assumption in our PSM estimation.

Figure A7 shows the distribution of the propensity score, and we see that there is a substantial degree of overlap between the treatment and control groups, indicating that PSM estimation is appropriate. Column (4) of Table 5 shows the results for nearest-neighbor matching, and while we see that a remote worker can earn 0.3% less than non-remote workers, this is a small effect and not significant. Next, we conduct kernel matching and local linear regression (LLR) matching, and Columns (5)-(7) show similar results that remote workers do not earn more than non-remote workers. Column (8), which shows the results of inverse probability weighting (IPW), obtains similar results. Consistent with the overlap of the propensity scores between remote and non-remote workers, the observations do not drop in Table 5 except for kernel matching. In sum, the PSM estimation confirms that engagement in remote work and earnings are not partially correlated, conditional on job and demographic characteristics.

The policy implication derived from the analysis in this subsection is straightforward: while non-remote workers are low earners in general, after any earnings loss is compensated based on job and demographic characteristics, remote work status does not need to be included in the policy targeting variable. While targeting an income-supplementary policy based on the vast range of job and demographic characteristics is not realistic, taxable income in the previous year may be considered a plausible proxy, or sufficient statistics, for the set of job and demographic characteristics.

A final consideration is that the labor economics literature typically uses hourly wage instead of annual earnings as a measurement of income. The main analysis did not use hourly wage because the data set does not contain information on annual hours worked corresponding to the annual earnings. However, to obtain results comparable with standard results in the literature, we calculate annual hours worked by multiplying monthly hours worked in December 2019 by twelve by restricting the sample to the workers who worked for 12 full months. Panel B in Table 5 reports the regression results using the natural logarithm of hourly rate of pay as the dependent variable, and Column (1) in Panel B shows that remote workers earn 0.170 log points more than non-remote workers per hour. This wage differential remains even after conditioning on the job characteristics and demographic variables. Column (2) in Table 3 indicates that remote workers receive higher wages than non-remote workers by 0.033 log points, but this difference disappears when Industry × Occupation fixed effects are added to the conditioning set, indicating that the positive association between remote work engagement and wages is induced by industry and occupation characteristics. These results do not change by using propensity score matching to allow for flexible functional form on the impact of workers' characteristics on wages. Overall, the hourly wage analysis confirms our main analysis that engagement in remote work does not affect wages in a causal sense.

6 Concluding Remarks

This paper analyses remote work in 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 performing 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. (2021), this finding calls for a transfer policy based on household income and targeted at the poor to compensate for their more 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.

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

	Percentage	Actual remote work engagement
Introduced and applied	4%	58%
Introduced but not applied	5%	8%
Not introduced	76%	6%
Do not know	15%	8%
Total	100%	8%
Observations	24728	

Note: 1. Data source is Japanese Panel Study of Employment Dynamics.

2. Percentage is the proportion of workers who chose that item.

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

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

	Non-remote worker	Remote worker	Difference
Routine	61.58	49.22	-12.36
	(28.73)	(27.47)	(0.66)
Manual	42.61	33.26	-9.35
	(31.26)	(27.60)	(0.71)
Interactive	43.91	41.59	-2.33
	(30.63)	(28.14)	(0.70)
PFP (pay for performance)	0.23	0.37	0.13
	(0.42)	(0.48)	(0.01)
KPI (key performance indicators)	0.17	0.31	0.14
	(0.37)	(0.46)	(0.01)
MBO (management by objective)	0.20	0.31	0.12
	(0.40)	(0.46)	(0.01)
Remote hours per week	0.00	8.81	8.81
	(0.00)	(12.58)	(0.08)
Work hours per week	36.36	38.73	2.36
	(13.80)	(15.60)	(0.32)
Annual earnings (10,000 yen)	338.44	438.79	100.35
	(247.64)	(317.35)	(5.89)
Observations	22679	2049	

Note: 1. Data source is Japanese Panel Study of Employment Dynamics.

2. Mean values and standard deviations are reported. Standard deviations are in parentheses.

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

Table 3: Determinants of remote work engagement as of December 2019

	(1) Probit Remote>0	(2) Probit Remote≥3	(3) Probit Remote≥6	(4) Tobit Remote/Work	(5) Probit Remote Institute	(6) Probit (Weight) Remote>0	(7) Probit (Self-employed) Remote>0
Routine/100	-0.071***	-0.051***	-0.034***	-0.023***	-0.024***	-0.068***	-0.073***
	(0.007)	(0.005)	(0.005)	(0.002)	(0.005)	(0.007)	(0.006)
Manual/100	-0.005	-0.004	-0.013**	-0.003	-0.034***	-0.001	-0.015*
	(0.008)	(0.007)	(0.006)	(0.003)	(0.007)	(0.008)	(0.008)
Interactive/100	-0.029***	-0.021***	-0.017***	-0.011***	-0.010**	-0.027***	-0.023***
	(0.007)	(0.005)	(0.005)	(0.002)	(0.005)	(0.007)	(0.006)
PFP	0.023***	0.014***	0.007**	0.007***	0.012***	0.021***	0.028***
	(0.004)	(0.003)	(0.003)	(0.001)	(0.003)	(0.004)	(0.004)
KPI	0.033***	0.020***	0.014***	0.010***	0.028***	0.030***	0.034***
	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)
MBO	0.010**	0.007*	0.003	0.003	0.013***	0.010**	0.013***
	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)
Nonregular	-0.017***	-0.006	-0.003	-0.004**	-0.020***	-0.017***	-0.015***
	(0.005)	(0.004)	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)
Female	-0.009*	-0.002	-0.001	-0.002	-0.001	-0.008*	-0.009*
	(0.004)	(0.004)	(0.003)	(0.002)	(0.004)	(0.005)	(0.004)
With child age 6 or under	0.021***	0.016***	0.012***	0.008***	0.014***	0.019***	0.020***
	(0.005)	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.006)
Age	-0.004***	-0.003***	-0.002***	-0.002***	-0.002**	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Age squared/100	0.005***	0.004***	0.003***	0.002***	0.002***	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
University	0.016***	0.015***	0.010***	0.006***	0.015***	0.015***	0.018***
	(0.004)	(0.003)	(0.003)	(0.001)	(0.003)	(0.004)	(0.004)
100-299	-0.012**	-0.005	-0.003	-0.005**	-0.013**	-0.013**	-0.014**
	(0.006)	(0.005)	(0.004)	(0.002)	(0.005)	(0.006)	(0.006)
300-999	-0.018***	-0.015***	-0.017***	-0.007***	-0.002	-0.015**	-0.020***
	(0.006)	(0.005)	(0.005)	(0.002)	(0.005)	(0.006)	(0.006)
1000-4999	-0.000	0.005	0.000	-0.001	0.014***	-0.003	-0.002
	(0.006)	(0.005)	(0.004)	(0.002)	(0.005)	(0.006)	(0.007)
5000+	0.003	0.008*	0.006	-0.000	0.040***	-0.002	0.000
	(0.006)	(0.005)	(0.004)	(0.002)	(0.004)	(0.006)	(0.006)
Self-employed							0.072***
							(0.006)
Industry × Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.11	0.11	0.10	0.11	0.20	0.11	0.12
Observation	22769	22328	21174	23686	21546	22741	25755

Note: Data source is Japanese Panel Study of Employment Dynamics. $^{*}p < .10,^{**} p < .05,^{***} p < .01$. Coefficients are average marginal effects for all estimation methods. Heteroskedasticity robust standard errors are in parentheses. Remote>0 means whether remote working more than 0 hour or not. Remote>3 (6) means whether remote working 3 (6) hours or more or not. Remote/Work is ratio of remote work hours per week of working hours in main work place per week. Remote institute is the indicator if the remote working is allowed by the employer and the institution applies to the worker. Three HRM variables 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. PFP indicates if the worker's compensation is determined by pay for performance, KPI indicates if the worker is subject to the management based on the Key Performance Indicator, MBO indicates if the worker is subject to the management by objectives. The baseline of nonregular is regular workers, and nonregular workers include part time jobs, dispatched workers, contract workers and part time employees. The base category of firm size category variables is less than 100 people. The difference of sample size between each column are due to a perfect prediction for the case of probit estimation.

Table 4: The determinants of remote work engagement as of December 2019 and December 2020

	(1) Probit Remote>0 2019	(2) Probit Remote> 0 2019 Restricted	(3) Probit Remote>0 2020 Restricted	(4) (3)-(2)
Routine/100	-0.071***	-0.070***	-0.068***	0.002
	(0.007)	(0.008)	(0.009)	(0.012)
Manual/100	-0.005	-0.006	-0.141***	-0.135***
	(0.008)	(0.010)	(0.012)	(0.016)
Interactive/100	-0.029***	-0.030***	0.002	0.032***
	(0.007)	(0.008)	(0.009)	(0.012)
PFP	0.023***	0.020***	0.007	-0.013*
	(0.004)	(0.005)	(0.006)	(0.007)
KPI	0.033***	0.036***	0.036***	0.000
	(0.005)	(0.006)	(0.006)	(0.009)
MBO	0.010**	0.010*	0.025***	0.015*
	(0.005)	(0.006)	(0.006)	(0.008)
Nonregular	-0.017***	-0.023***	-0.031***	-0.008
	(0.005)	(0.006)	(0.007)	(0.009)
Female	-0.009*	-0.008	-0.002	0.006
	(0.004)	(0.005)	(0.006)	(0.008)
With child age 6 or under	0.021***	0.022***	0.013*	-0.009
	(0.005)	(0.006)	(0.008)	(0.010)
Age	-0.004***	-0.005***	-0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Age squared/100	0.005***	0.006***	0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
University	0.016***	0.014***	0.047***	0.032***
	(0.004)	(0.005)	(0.005)	(0.007)
100-299	-0.012***	-0.029***	-0.007	0.021**
	(0.006)	(0.007)	(0.008)	(0.011)
300-999	-0.018***	-0.027***	0.020**	0.047***
	(0.006)	(0.007)	(0.008)	(0.011)
1000-4999	-0.000	-0.004	0.059***	0.063***
	(0.006)	(0.007)	(0.008)	(0.011)
5000+	0.003	-0.004	0.086***	0.089***
	(0.006)	(0.007)	(0.008)	(0.011)
Industry × Occupation	Yes	Yes	Yes	
Pseudo R^2	0.11	0.11	0.24	
Observation	22769	16341	16332	
Mean of dependent variables	0.08	0.08	0.14	

Note: Data source is Japanese Panel Study of Employment Dynamics. $^{*}p < .10,^{**} p < .05,^{***} p < .01$. Coefficients are average marginal effects for all estimation methods. Heteroskedasticity robust standard errors are in parentheses. Remote>0 means whether remote working more than 0 hour or not. Remote>3 (6) means whether remote working 3 (6) hours or more or not. Remote/Work is ratio of remote work hours per week of working hours in main work place per week. Remote institute is the indicator if the remote working is allowed by the employer and the institution applies to the worker. Three HRM variables 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. PFP indicates if the worker's compensation is determined by pay for performance, KPI indicates if the worker is subject to the management based on the Key Performance Indicator, MBO indicates if the worker is subject to the management by objectives. The baseline of nonregular is regular workers, and nonregular workers include part time jobs, dispatched workers, contract workers and part time employees. The base category of firm size category variables is less than 100 people. We restricted our sample in column (2) and (3) to those who had not quit their job in 2019 and 2020. The difference of sample size between column (2) and (3) are due to a perfect prediction for the case of probit estimation.

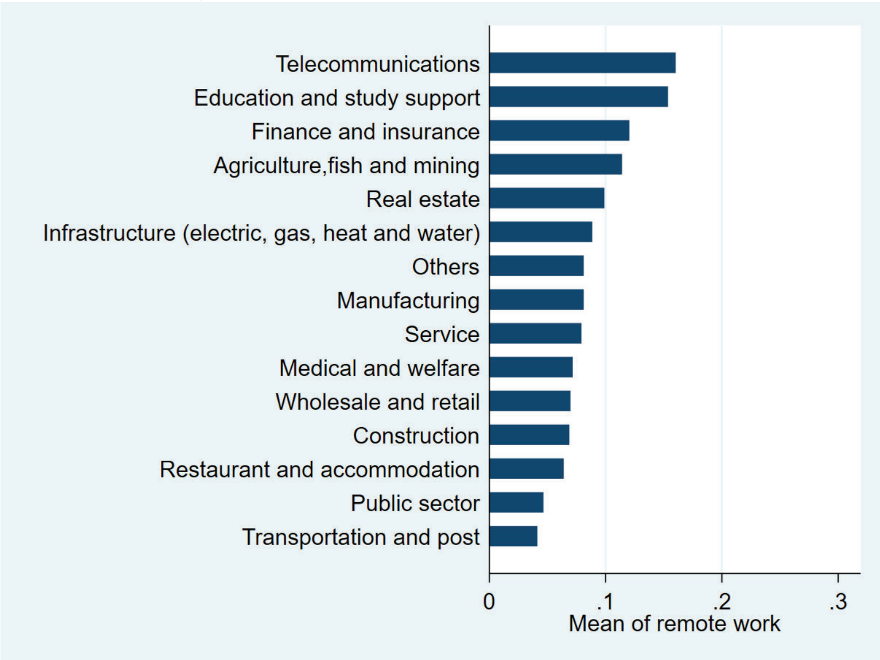
Table 5: Effect of remote work on ln annual earnings (Average Treatment Effect on Treated)

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(income)	Log(income)	Log(income)	Log(income)	Log(income)	Log(income)	Log(income)	Log(income)
	OLS	OLS	OLS	PSM(nn)	PSM(LLR;0.01)	PSM(LLR;0.02)	PSM(Kernel)	IPW
Remote work	0.234***	-0.007	-0.017	-0.003	-0.010	-0.007	-0.009	-0.005
	(0.024)	(0.018)	(0.018)	(0.027)	(0.033)	(0.033)	(0.025)	(0.018)
Control	No	Yes	Yes					
Industry × Occupation	No	No	Yes					
Observations	24432	23495	23495	23495	23495	23495	23490	23495

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)	Log(wage)
	OLS	OLS	OLS	PSM(nn)	PSM(LLR;0.01)	PSM(LLR;0.02)	PSM(Kernel)	IPW
Remote work	0.171***	0.033*	0.011	0.033	0.021	0.022	0.021	0.023
	(0.020)	(0.018)	(0.018)	(0.023)	(0.026)	(0.026)	(0.021)	(0.018)
Control	No	Yes	Yes					
Industry × Occupation	No	No	Yes					
Observations	21935	21297	21297	21297	21297	21297	21293	21297

Note: Data source is Japanese Panel Study of Employment Dynamics. $^{*}p < .10,^{**}p < .05,^{***}p < .01$. Standard errors are parentheses and are heteroskedastic consistent for OLS, and are robust Abadie-Imbens type for PSM and IPW. Coefficients are marginal effects for all estimation methods. nn means nearest neighbor. LLR means local linear regression and subsequent number is bandwidth. Epanechnikov kernel is used for LLR matching and kernel matching. Wage is calculated by dividing annual income by the number of hours worked per week × 52. We cannot calculate the annual hours worked because we do not know the weeks worked, so that we restrict the sample to those who worked in all months. This restriction resulted in the difference in sample size between Panel A and B. Control variables include three task variables, three HRM variables, employment types, female, whether having child age 6 or under, age, age squared, university or more, firm size, industry and occupation. The actual analyzed sample sizes are 3916 and 3662 for the case of PSM(nn) in panel A and B respectively.

Figure 1: Prevalence of remote work by industry



Note: The industry classification of JPSED is according to Japan Standard Industry Classification system.

Figure 2: Prevalence of remote work by occupation

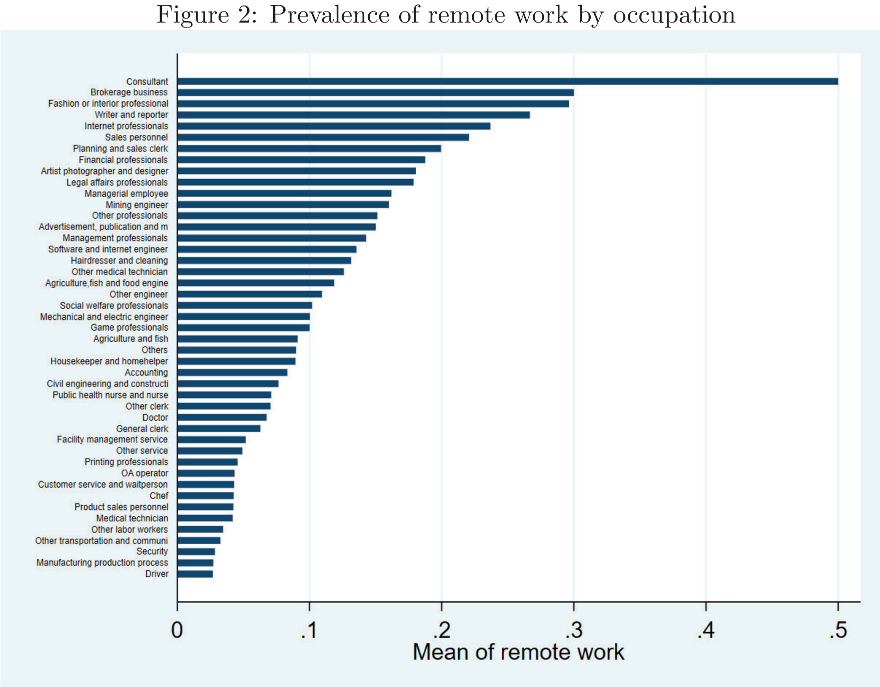
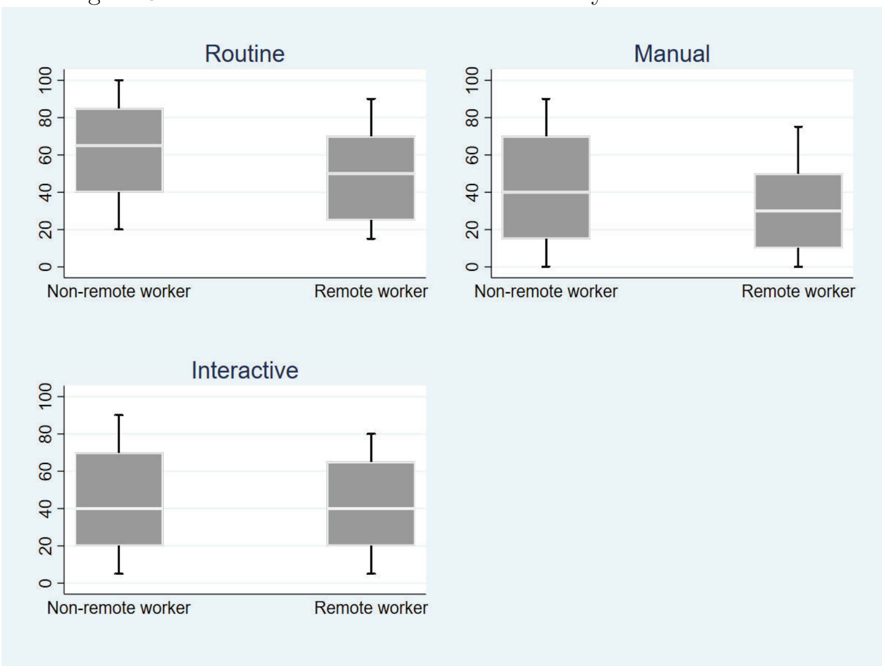


Figure 3: Distribution of task characteristics by remote work status



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 4: Relationship between annual earnings and remote work

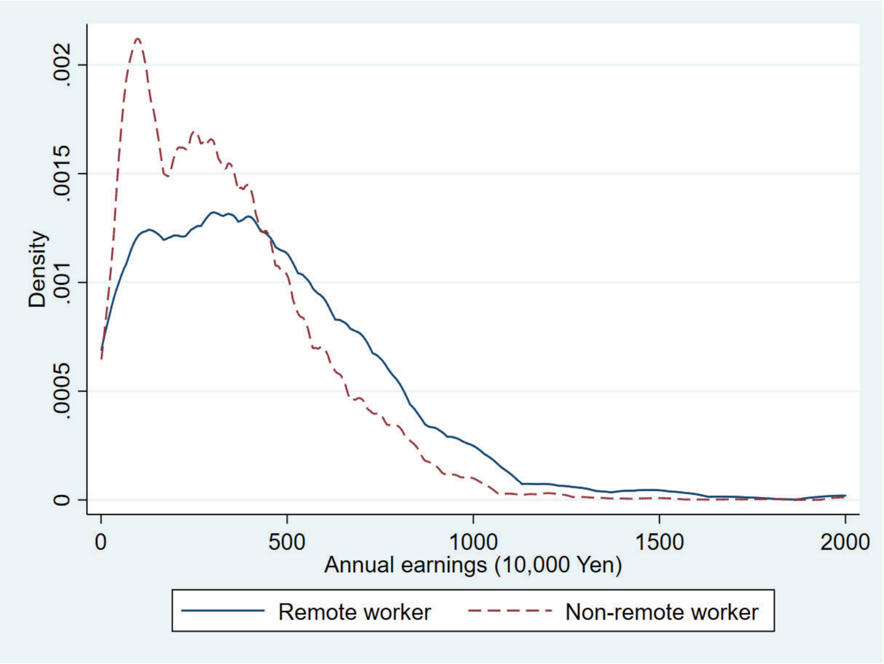
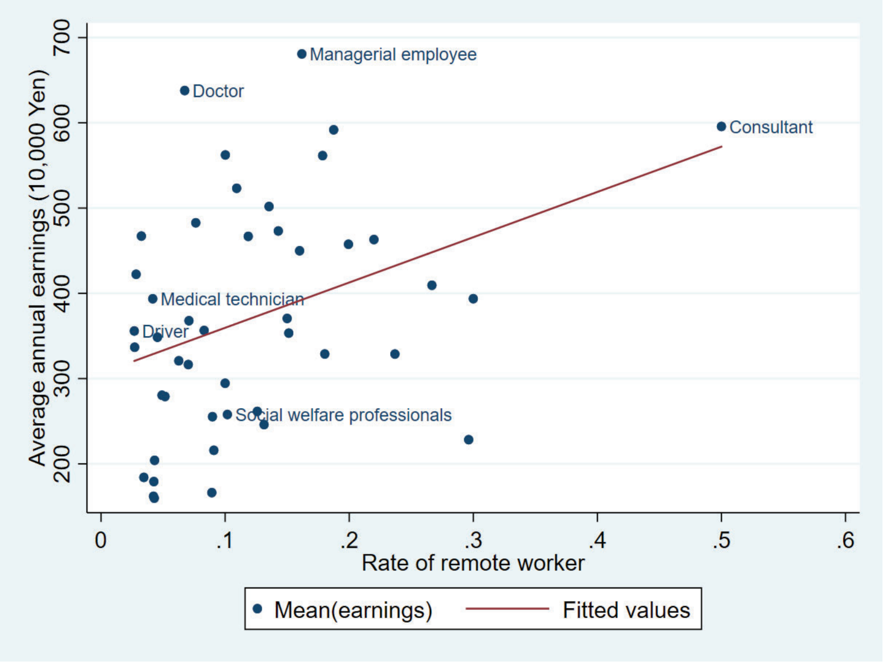


Figure 5: The prevalence of remote work and average annual earnings by occupation



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: ( ) hours

  As of last December, you did remote work for a total of (*Previous Answer*) 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 Task characteristics and occupation

The reported task characteristics depend heavily on occupation. Figure A1 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 A2 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 A3 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).

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 A1 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., 2021; Alipour et al., 2020).

Table A1: The regression R^2 of task variables on industry and occupation dummy variables

	(1)	(2)	(3)
Dependent variables	Routine	Manual	Interactive
Independent variables			
Industry	0.034	0.139	0.036
Occupation	0.113	0.436	0.088
Industry and Occupation	0.120	0.449	0.098
Industry $\times$ Occupation	0.145	0.471	0.127
Observations	24728	24728	24728

Note: 1. Data source is Japanese Panel Study of Employment Dynamics.
2. R squared when regressing each task variable.

Figure A1: Percentage of routine tasks by occupation

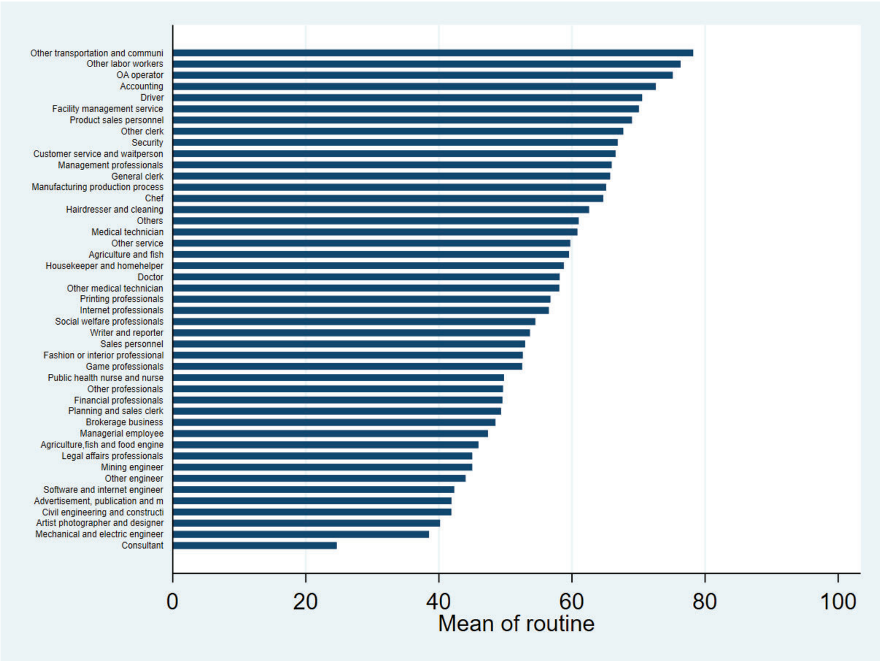


Figure A2: Percentage of manual tasks by occupation

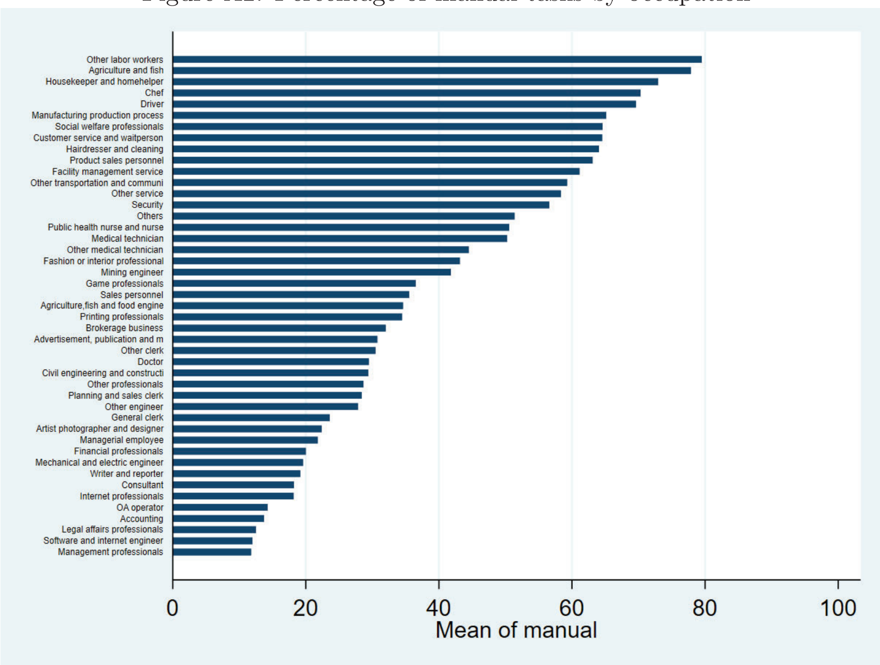
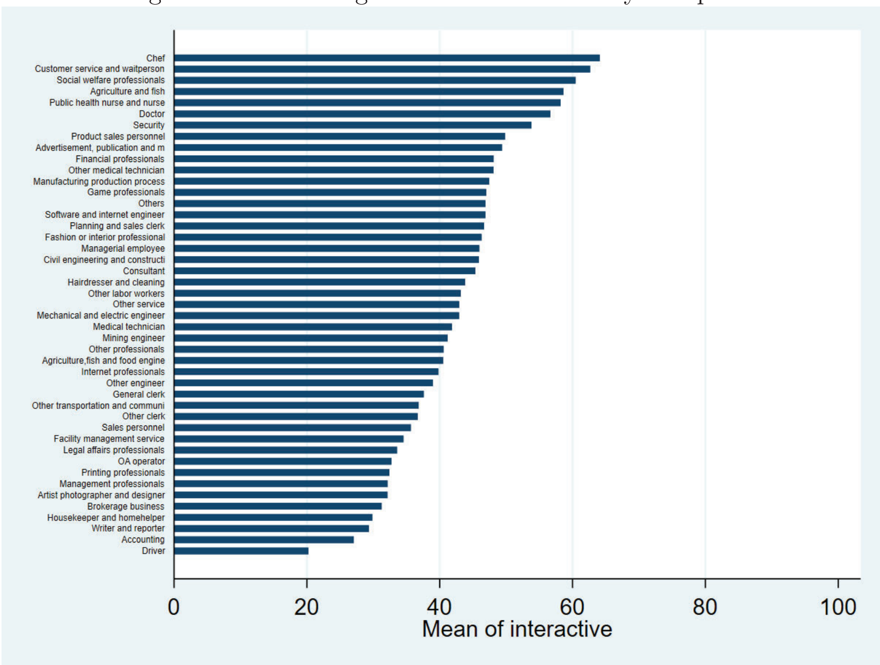


Figure A3: Percentage of interactive tasks by occupation



A.3 HRM characteristics and occupation

The HRM characteristics depend heavily on occupation. Figure A4 shows the percentage of Pay for Performance (PFP) for 45 occupation categories, and while PFP applies to as many as 56% of financial professionals, only 18% apply for agriculture and fishing. Similarly, Figure A5 shows that Key Performance Indicator (KPI) is more likely to apply to workers who are financial professionals, internet professionals and planning and sales clerks (43, 32 and 36%, respectively). In contrast, KPI applies to only 3% workers in agriculture and fishing. Likewise, Figure A6 shows that the applications of MBO also varies significantly across occupations, from 3% for agriculture and fishing to 40% for legal affairs professionals.

A.4 Distribution of propensity scores by remote and non-remote workers

Figure A4: Rate of PFP (pay for performance) by occupation

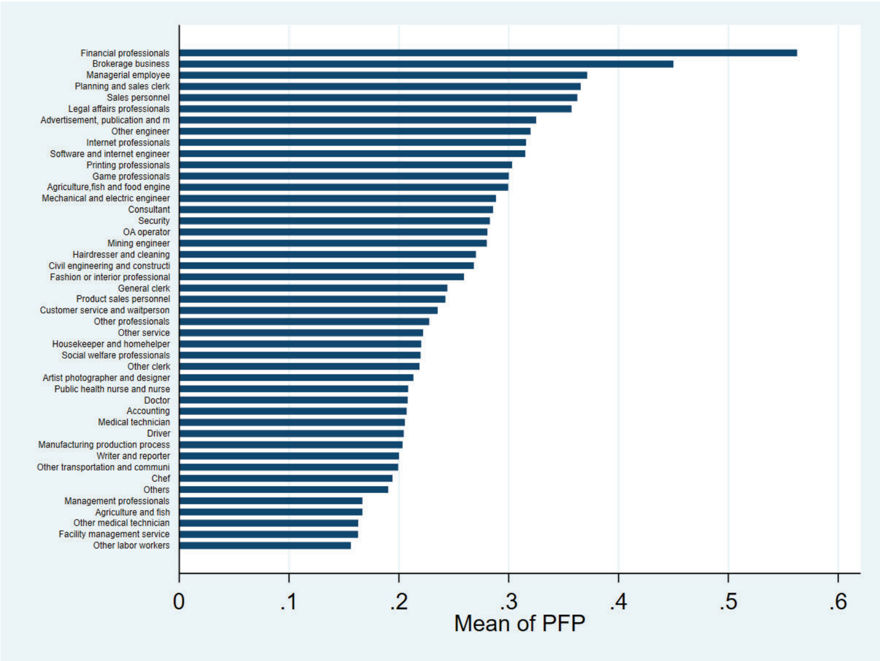


Figure A5: Rate of KPI (key performance indicator) by occupation

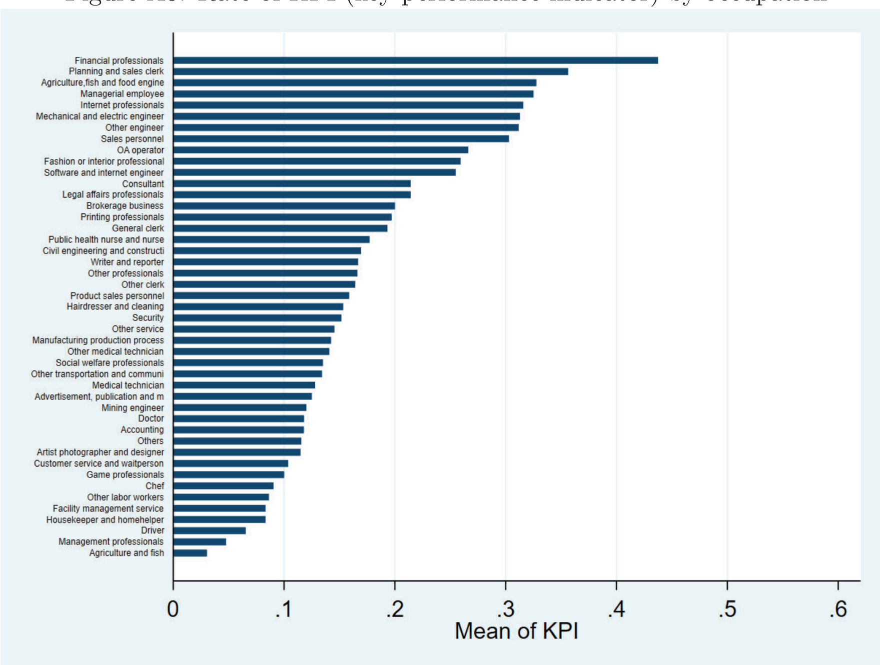


Figure A6: Rate of MBO (management by objective) by occupation

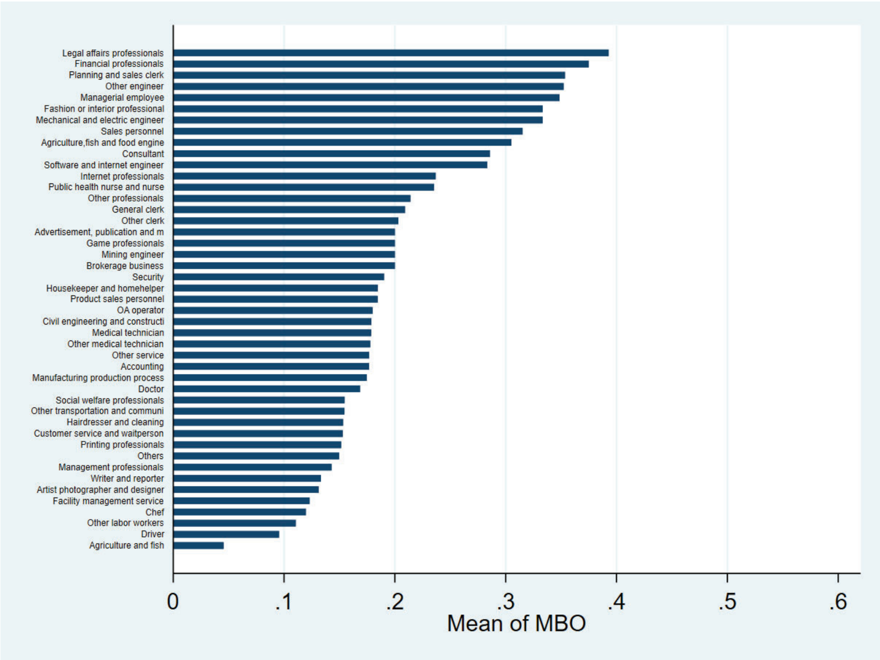
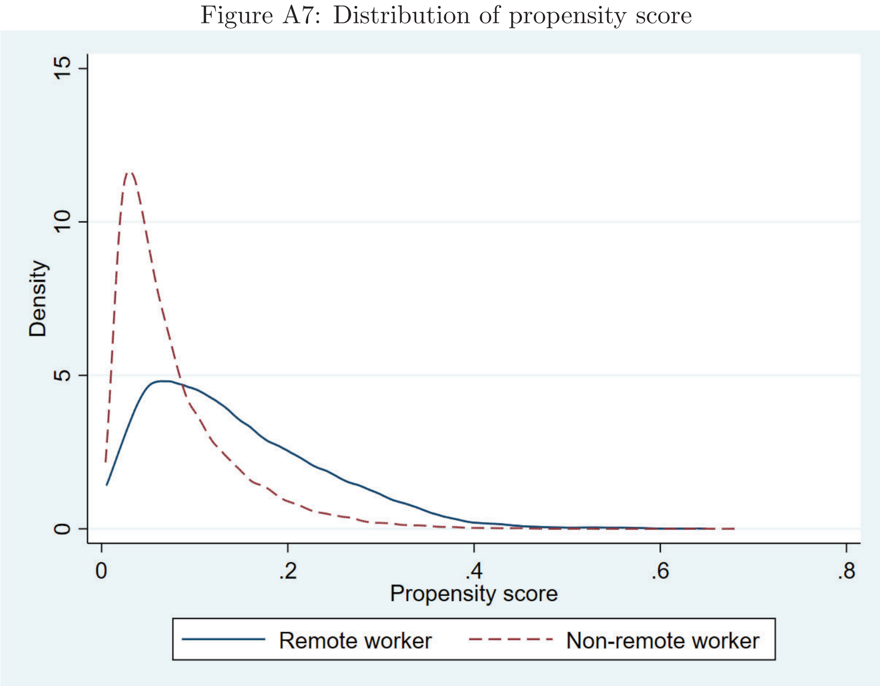


Figure A7: Distribution of propensity score



A.5 Comparison between JPSED and Census

JPSED is designed to be a nationally representative survey covering those who are 15 years of age or older. To confirm this sampling design, we compared our data to the 2015 Census, restricting our sample to those who were working because the analysis sample includes only working people. We pay particular attention to the gaps in types of employment and the distribution of industries of workers. The distributions of these workers' characteristics of the 2019 JPSED are broadly similar to the distribution based on the 2015 population census.

Table A2: The distribution of employment types and industry of workers in the 2019 JPSED and the 2015 Census

Panel A: Employment types	Census (2015)	JPSED (2019)
Regular workers	53.6	53.7
Dispatched workers	2.7	3.0
Part time jobs	26.0	29.1
Officers	5.1	4.0
Self-employed workers	9.0	7.4
Family employee	3.4	1.7
Internal employment	0.2	1.2

Panel B: Industry	Census (2015)	JPSED (2019)
Agriculture, Fish and mining	3.8	1.2
Construction	7.4	5.1
Manufacturing	16.2	16.0
Infrastructure(electric, gas, heat and water)	0.5	1.3
Telecommunications	2.9	5.9
Transportation and post	5.2	6.6
Wholesale and retail	15.3	11.7
Finance and insurance	2.4	3.6
Real estate	2.0	2.0
Restaurant and accommodation	5.5	5.1
Medical and welfare	11.9	10.6
Education and study support	4.5	4.9
Service	13.6	10.7
Public sector	3.4	6.2
Others	5.4	9.3

Note: Data sources are Japanese Panel Study of Employment Dynamics and Census.