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The Impact of Long Working Hours on Mental Health Status in Japan: Evidence from a National Representative Survey*

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Abstract

Using the long-term Comprehensive Survey of Living Conditions (CSLC), a nationally representative survey conducted in Japan from 2003 to 2019, we examine the impact of long working hours on mental health in Japan while addressing the endogeneity issue arising from non-random selection bias. Additionally, we assess variations in the effect of long working hours on mental health across different groups.

This study yields three primary conclusions. First, individuals working longer hours (55 hours or more per week) exhibit a higher likelihood of developing mental illness compared to those working regular or fewer hours. Second, the negative effect of long working hours on mental health is more pronounced among non-regular workers than among regular worker groups. These conclusions are corroborated by results obtained through the propensity score matching method. Third, the effect of long work hours on mental health varies among different demographic groups, with greater impact observed among women, managers, non-regular workers, employees in small or large-sized firms, and those in smaller cities compared to their counterparts.

The results suggest that, in order to enhance worker productivity, the Japanese government should address the issue of long working hours to improve the mental well-being of employees. Initiatives aimed at promoting work-life balance, family-friendly policies, and measures to ameliorate working conditions, such as reducing the wage gap between non-regular and regular workers, are expected to help mitigate the challenges associated with long working hours and mental health issues, especially among non-regular workers.

Keywords: mental health, long working hours, regular worker, non-regular worker, Japan

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1. Introduction

Mental illness, often referred to as a mental health disorder, and long working hours, represent two significant issues impacting employees worldwide (Lee, 2007; Dattani et al., 2022; WHO, 2022). In 2017, approximately 792 million individuals around the globe were reported to be living with a mental illness, accounting for 10.7% of the global population – slightly exceeding 1 in 10 people (Dattani et al., 2022).

In Japan, the prevalence of workplace stress among workers is steadily increasing, leading to concerning implications for mental health. According to the Survey on State of Employees' Health conducted by the Ministry of Health, Labour, and Welfare (MHLW), the percentage of workers experiencing strong anxiety, worry, or stress in their work or working life has risen from 55.0% in 1987 to 61.5% in 2002. This rise in workplace stress is also evident in the alarming increase in number of mental disorder patients and suicides nationwide. The total number of mental disorder patients in Japan increased from 4.33 million in 2013 to 17.21 million in 2022 (**Figure 1**). The total number of suicides in Japan surged from 27,282 in 2013 to 21,881 in 2022 (**Figure 2**), even as the number of employed persons decreased from 9,401 in 2013 to 7,862 in 2016 while increased to 8,576 in 2022 (**Figure 3**). *The 2008 White Paper on Suicide Countermeasures*, published by the Cabinet Office, revealed that "health problems" accounted for the largest proportion of causes and motives for suicide at 63.3%. A critical factor contributing to these issues is the long working hours in Japan. In 2004, the MHLW published a report on the "*Study Group on Overwork and Mental Health Countermeasures*," which selected employees based on the fact that they had worked long overtime hours. It recommended creating a mechanism for checking employees' health. In recent times, the Japanese government has promoted reducing long work hours and improving mental health in workplaces. However, when compared internationally, Japan, along with the United States, had the longest average annual working hours of 1,800 hours or more among developed countries during the 2000s.

Given the high medical care expenses associated with mental illness (Dattani et al., 2022; WHO, 2022), and considering that mental illness can reduce labor productivity, thereby negatively affecting human capital accumulation in most countries, exploring the determinants of mental illness becomes a critical issue in the field of public health. Therefore, investigating the association between long working hours and mental health problems, particularly in Japan, is of utmost importance.

Several empirical studies have shed light on potential determinants of mental illness, including individual attributes such as education, age, and sex (Sparks et al., 1997; Bannai and Tamakoshi, 2014; Kopasker et al., 2018; McIsaac et al., 2021). Additionally, social capital has been identified as a factor influencing the risk of developing mental illness (Verduin et al., 2014; Ma et al., 2020), along with life events such as marriage and fertility (Symoens et al., 2014; Jace and Makridis, 2021; Jiang and Yang, 2022). Understanding these factors can significantly contribute to addressing mental health challenges and implementing effective public health interventions.

Furthermore, work-life conflict has been identified as a factor that may increase the risk of mental illness (Kim and Cho, 2021; Pitt et al., 2021). Among various work environment factors that can adversely affect workers' mental health status, prior empirical research has consistently highlighted long working hours as a significant risk factor. Numerous studies have found a strong association between long working hours and a higher risk of developing mental disorders (Sparks et al., 1997; Mishra and Smyth, 2013; Bannai and Tamakoshi, 2014; Afonso et al., 2017; Kopasker et al., 2018; Wong et al., 2019; Sato et al., 2020; McIsaac et al., 2021) in both developing and developed countries.

This study focuses on the issue in Japan, which has been the subject of several studies from occupational health and epidemiology perspectives. For instance, Fujino et al. (2006) conducted a systematic literature review based on 17 papers addressing this issue. Recent survey data have been utilized by other researchers, such as Ogawa et al. (2018), Hino et al. (2018), Tsuno et al. (2019), Kikuchi et al. (2020), and Ochiai et al. (2022), who also examined the relationship between long working hours and the likelihood of developing mental disorders, such as depression and stress, in Japan. However, many of these studies from occupational health or medical perspectives did not adequately consider endogeneity issues.

From an economics perspective, a few empirical studies have explored this issue.

Three papers are particularly relevant to this study. Ma (2009b) and Kuroda and Yamamoto (2019) investigated the association between long working hours and mental health, using longitudinal survey data and employing fixed effect (FE) models to address individual heterogeneity. Okamoto (2019) used longitudinal survey data and instrumental variable (IV) methods to discover that long working hours may lead to reduced sleep hours and an increased probability of becoming obese. However, these three studies did not adequately account for non-random sample selection issues between long and non-long working hour groups. Additionally, they did not explore potential differences in the effects of long working hours on mental health status between regular and non-regular workers. This study aims to address these gaps in the existing literature.

Using Japanese long-term national survey data from 2000 to 2019 and the propensity score matching (PSM) method, this study aims to investigate the association between long working hours and mental illness in Japan while considering the endogeneity issue arising from non-random selection bias.

This study makes notable contributions to the related literature in three keyways. First, unlike most studies that relied on cross-sectional survey data and overlooked the endogeneity issue, we aim to address this limitation. While Ma (2009b), Kuroda and Yamamoto (2019) and Okamoto (2019) attempted to tackle the problem using the fixed-effects (FE) model or instrumental variable (IV) method to investigate the causal relationship between long work hours and mental health, they did not sufficiently account for the endogeneity issue arising from non-random selection bias. In contrast, our study employs the propensity score matching (PSM) method to address this concern. To the best of our knowledge, this study is the first to explore the relationship between long working hours and Japanese mental health based on the PSM method, thereby enriching the evidence on this issue.

Second, unlike previous studies that focused on a single definition of "long working hours," we introduce various definitions (e.g., different cut-off values) to perform robustness checks. We compare the effects of work hours on mental health among different weekly working hour groups, such as the 40-, 45-, 50-, 55-, and 60-hours groups.

Third, we extend our investigation by comparing the impact of long working hours on mental health among different groups (by regular and non-regular workers, gender, occupation, employment status, firm size, and regional group), offering valuable insights into potential variations in this relationship.

The rest of this paper is structured as follows: Section 2 provides a comprehensive review of the channels and summarizes the findings of previous empirical studies related to the issue. Section 3 outlines the methodology employed in this study, including the models used, data sources, and variables considered. In Section 4, descriptive statistics of the data are presented. Section 5 presents and discusses the empirical results obtained. Finally, Section 6 summarizes the conclusions.

2. Literature Review

Regarding the relationship between long working hours and mental illness, two models from the perspectives of occupational health and human resource management theories have been advocated to suggest that long working hours negatively affect mental health. First, the job demand-control model (Karasek, 1979) posits that involuntary long working hours may lead to mental illness due to the imbalance between work responsibility (the reality of long working hours) and authority (wherein employees lack the authority to determine their own working hours). Second, according to the effort-reward imbalance model (Siegrist, 1996), when the efforts involved in involuntary long working hours are not adequately rewarded (e.g., through unpaid overtime or a low overtime premium), the probability of developing mental illness may be higher among those working long hours.

From the perspectives of labor and family economics theory, based on the individual/household utility model, individuals aim to maximize their utility while considering income and time constraints. An individual's time allocation can be divided into three parts: market work, housework, and leisure (Gronau, 1977; Becker, 1985). This division implies a trade-off relationship between working hours and the hours devoted to housework and leisure activities. Consequently, long working hours may reduce the time available for housework and leisure, leading to work-life conflict. This conflict may be particularly pronounced for female workers during their motherhood period, as they face additional responsibilities and time constraints. This reduction in housework/leisure time and the resulting work-life conflict may ultimately lead to a decline in an individual's utility and increase the risk of developing mental illness (Hill et al., 2010; Henly and Lambert, 2014).

Numerous studies have found that long working hours are a primary contributor to mental illness among the working-age population (Sparks et al., 1997; Mishra and Smyth, 2013; Bannai and Tamakoshi, 2014; Afonso et al., 2017; Kopasker et al., 2018; Wong et al., 2019; Sato et al., 2020; McIsaac et al., 2021), in addition to demographic factors (Sparks et al., 1997; Bannai and Tamakoshi, 2014; Kopasker et al., 2018; McIsaac et al., 2021), family-related factors (Symoens et al., 2014; Jace and Makridis, 2021; Jiang and Yang, 2022), and social factors such as social participation and social capital (Verduin et al., 2014; Ma et al., 2020). These studies have reported that long working hours negatively affect mental health (Sparks et al., 1997; Mishra and Smyth, 2013; Bannai and Tamakoshi, 2014; Afonso et al., 2017; Kopasker et al., 2018; Wong et al., 2019; Sato et al., 2020; McIsaac et al., 2021).

In Japan, there is a series of studies focusing on this issue from both occupational health and epidemiology perspectives. Fujino et al. (2006) conducted a systematic literature review based on 17 papers exploring this topic. Additionally, using recent survey data, several other researchers, including Ogawa et al. (2018), Hino et al. (2018), Tsuno et al. (2019), Kikuchi et al. (2020), and Ochiai et al. (2022), have also concentrated on this issue. Their findings consistently indicate that long working hours may increase the likelihood of developing mental disorders, such as depression and stress, in Japan.

A few empirical studies have addressed the issue from an economic perspective, and three of them are closely related to this study. Ma (2009) utilized survey data from the 2004-2008 Keio Household Panel Survey (KHPS 2004-2008) and employed the fixed-effect model with lagged variables to address endogeneity concerns. Their empirical analysis investigated the impact of long working hours on the mental health status of workers in Japan and found that long working hours may increase the probability of developing mental disorders. Furthermore, the study found that the impact of long work hours on mental health varies across different groups: it is more significant for workers in the private sector, workers in large-size firms, low-education workers, low-income workers, female workers, and male non-managerial occupational workers compared to their counterparts.

Kuroda and Yamamoto (2016) used four-wave longitudinal data from the Survey of Companies and Employees on Human Capital Development and Work-Life Balance, which has been conducted annually since 2012 by the Research Institute of Economy, Trade, and Industry. Their investigation focused on how the number of work hours, job characteristics, and workplace circumstances affect workers' mental health. The study found that long work hours significantly contribute to deteriorations in respondents' mental health, even after controlling for individual fixed effects and other characteristics. Furthermore, it observed that the relationship between work hours and mental health is not linear, as working more than 50 hours per week notably erodes the mental health of workers.

Using longitudinal survey data from the Japan Household Panel Survey/Keio Household Panel Survey of 2004-2017 and the instrumental variable (IV) method, Okamoto (2019) analyzed the effects of work hours on body mass index, smoking, and sleeping hours in Japan. The study found that longer work hours led to reduced sleep hours and increased the probability of obesity among workers.

However, the studies from the occupational health and medical perspectives did not adequately address the endogeneity issues inherent in the relationship between long work hours and mental health. While Ma (2009b), Kuroda and Yamamoto (2019), and Okamoto (2019) attempted to tackle the endogeneity problems from economic perspectives, they did not fully account for the non-random selection bias resulting from endogeneity, nor did they compare the differences in the effects of long working hours among regular and non-regular work groups. This study aims to fill these gaps in the existing literature by comprehensively addressing the endogeneity issues and exploring potential variations in the impact of long working hours on mental health between regular and non-regular workers.

3. Methodology

3.1 Model

As the benchmark, we employ the logistic regression model to estimate the association between long working hours and mental illness, as expressed by Eq. (1).

$$MI_i = a + \beta_{LWH} WH_i + \beta_{NR} NR_i + \beta_{LNR} \mathrm{WH}NR_i + \sum_n \delta_n X_{ni} + \varepsilon_i, \quad (1)$$

where MI denotes the risk of becoming mental illness; $i$and n denote the individual and number of covariates, respectively; LWH represents a set of indicators of work hours (e.g., 40-, 45-, 50-, 55-, 60-hours); NR represents the non-regular workers; $\mathrm{WH}NR$ represents the interaction term of WH and NR; X denotes the covariates; β and δ are the coefficients, respectively, a is a constant term; and ε is an error term.

The group that works long hours and the group with regular or shorter work hours may not have been randomly selected. Some unobservable variables could influence the probability of working long hours. To address this endogeneity problem, we employ the propensity score matching (PSM) method, which is a statistical technique for matching that estimates the effect of a treatment (in this case, working long hours). PSM aims to reduce bias stemming from confounding variables that may affect the treatment effect estimate when comparing outcomes between units that received the treatment and those that did not (Rosenbaum & Rubin, 1983). The propensity score matching method makes the observed data more akin to randomized experimental data through matching and resampling, thereby minimizing selectivity bias and counterfactual states in the sample composition.

Using propensity score matching, we can calculate the average treatment effect on the treated group, the average treatment effect on the untreated group, and the overall average treatment effect as follows: First, we select appropriate control variables for resampling in propensity score matching. Second, we run a Probit regression to estimate the propensity score. Third, we match the propensity score based on the selected control variables. Finally, we calculate the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU), and the overall average treatment effect (ATE) based on the matched samples. We will report the results of ATT.

$$ATT = E(MI_{it}(1) - MI_{it}(0)|LWH = 1) \quad (2)$$

$$ATU = E(MI_{it}(1) - MI_{it}(0)|LWH = 0), \quad (3)$$

$$ATE = E\big(C_{it}(1) - C_{it}(0)\big), \quad (4)$$

where $MI_{it}(1)$ expresses the risk of mental illness when works in long hours and $MI_{it}(0)$ represents the risk of mental illness when not work in long hours. We also reran the PSM method to compare the effect of long work hours on mental health among different groups by using subsamples.

3.2 Data and variable setting

This study utilizes data from the Comprehensive Survey of Living Conditions (CSLC), a long-term National Representative Survey conducted by the MHLW in Japan from 2003 to 2019. The CSLC is a large-scale survey conducted on households and household members throughout Japan.

To collect household and health records, all households and household members within 5,530 districts were stratified and randomly sampled from postal codes 1 and 8 of the national censuses. For nursing care records, individuals requiring nursing care and support under the Long-Term Care Insurance Act within 2,500 districts were stratified and randomly sampled from the 5,530 districts. Additionally, income and savings certificates were stratified and randomly sampled from postal code 1 of the aforementioned 5,530 districts. Moreover, a survey was conducted on all households and household members within a 2,000-unit districts. The CSLC serves as a representative national survey on health status, income, and nursing care in Japan.

The dependent variable in the risk of mental illness function is the mental health score, calculated based on six questions as follows:

(a) Did you feel nervous?

(b) Did you feel hopeless?

(c) Did you feel restless?

(d) Did you feel depressed and like nothing could clear your mind?

(e) Did you feel difficulty doing anything?

(f) Did you feel worthless?

We assigned scores to each item based on the response options as follows: 5 = every time; 4 = often; 3 = sometimes; 2 = not often; 1 = no. A higher value indicates a greater probability of experiencing mental illness. By summing the scores from the following questionnaire items, we calculated the total mental illness score based on the respondent's answers, which ranges from 5 to 25.

The key independent variable in the mental health function is work hours. We created a set of weekly work hours (which are the total numbers of work hours, including main and side jobs) dummy variables as follows:

(a) 40 hours (1 = 40 hours, 0 = otherwise)

(b) 45 hours (1 = 45 hours, 0 = otherwise)

(c) 50 hours (1 = 50 hours, 0 = otherwise)

(d) 55 hours (1 = 55 hours, 0 = otherwise)

(e) 60 hours (1 = 60 hours, 0 = otherwise)

The covariate variables are utilized in the mental health function based on the OLS method. To account for the differences in work conditions between regular work and non-regular work groups, we created a regular worker dummy variable (1 = regular worker, 0 = non-regular worker). We defined the non-regular worker based on the questionnaire items of CSLS including part-time worker, albeit (temporary) worker, dispatched worker, contract worker, and entrusted worker. Additionally, we incorporated an interaction term of work hours and the regular worker dummy variable to estimate the difference in the effect of long working hours on mental health status between these two groups.

We utilized the following variables in the probability function for matching:

(1) A female dummy variable (1 = females, 0 = males) was used to control the

gender gap in work hours, as numerous studies have reported that work hours differ by gender, with men generally working longer hours than women.

(2) To account for potential differences in work hours among age groups (younger generations, middle-aged, and older generations), we included the age variable in the analysis.

(3) The coresident relation dummy variable was used to control the influence of family members on mental health status.

(4) Occupational dummy variables were employed in the analysis to categorize workers into 9 types of occupations: (a) manager; (b) professional job; (c) clerk; (d) sales job; (e) service job; (f) security job; (g) agriculture, forestry, and fishery job; (h) elementary job; and (i) other occupations.

(5) To account for the influence of firm size on mental health status, we included 8 types of firm size dummy variables: (a) 129 employees; (c) 3099 employees; (d) 100299 employees; (e) 300499 employees; (f) 500999 employees; (g) 1000~4999 employees; (h) 5000 or more; (i) government office.

(6) We considered the impact of non-earned income on labor supply and included household income.

(7) Spouse's employment status was categorized using 7 types of dummy variables: (a) regular worker; (b) part-time worker; (c) albeit (temporary worker); (d) dispatched worker; (e) contract worker; (f) entrusted worker; (g) other employment status excepting the above types.

(8) To control for the influence of childcare on work hours, we constructed a variable representing the number of children.

(9) We created 5 types of dummy variables representing regions based on the number of populations in cities to control for the influence of city size on mental health status: (a) city with a population of less than 50 thousand; (b) city with a population of 50-149 thousand; (c) city with a population of 150 thousand; (d) large city; and (e) countryside.

4. Results of descriptive statistics

The descriptive statistics of the variables are presented in **Table 1**. We compared the mean value gap for each variable between the group with weekly work hours of 55 or more (long working hour [LWH]) and the group with weekly work hours less than 55 (non- long working hour [non-LWH]).

First, the mental health score among the LWH group (3.536) is higher than that among the non-LWH group (3.205), suggesting a higher probability of mental illness among the LWH group compared to the non-LWH group.

Second, individual attributes (gender and age), family structure factors (number of children, household income), work-related factors (occupation, firm size), and regions differ between these two groups. For example, the proportion of regular workers among the LWH group (93.0%) is larger than that among the non-LWH group (58.6%); the proportion of female workers among the LWH group (12.1%) is smaller than that among the non-LWH group (48.9%). The proportion of managers among the LWH group (11.4%) is larger than that among the non-LWH group (6.5%). These differences suggest that these factors may potentially influence the probability of being a worker with long work hours, which can lead to an endogeneity issue due to the non-random selection between the long work hour group and the regular work hour group. Therefore, it is necessary to address this issue in the analysis.

Table 2 presents the average work hours across heterogeneous groups. The results reveal that weekly working hours differ among various groups. It is observed that the weekly working hours are longer for male workers, middle-aged workers (aged 30-49), well-educated workers, managers, and regular workers than those for their counterpart groups (female workers, younger and older aged generations, low- and middle-level educated workers, non-managerial workers, and non-regular workers). It is assumed that the effect of long working hours may differ among these groups. Hence, we also examine the impact of long working hours on mental health within these heterogeneous groups in this study.

The raw relationship between long working hours and mental illness is illustrated in **Figure 4**. First, the mental illness score among non-regular workers is higher than that among regular workers, indicating a higher probability of mental health disorders among non-regular workers compared to their counterparts. Second, the relationship between working hours and mental illness varies between regular and non-regular workers. For regular workers, the mental illness score tends to increase with the growth of working hours in the range of 0-10 hours, while it tends to decrease with the growth of working hours in the range of 10-55 hours. However, the mental illness score then tends to increase with the growth of working hours when the working hours exceed 55 hours.

Although the descriptive statistics show differences in individual attributes between long working hours workers and non-long working hours workers, variations in work hours across heterogeneous groups, and differences in the relationship between work hours and mental illness between regular and non-regular workers, these results have not accounted for other factors that may also influence mental health status. In the following section, we will investigate the association between long working hours and mental illness while considering these other factors to obtain a more comprehensive understanding of the relationship.

5. Econometric analysis results

5.1 Results based on the OLS method

Table 3 presents the basic results obtained using the OLS method. To compare the impact of long work hours on mental illness between regular and non-regular workers, we included an interaction term of working hours and non-regular worker dummy variables in the analysis. Additionally, considering that the impact of working hours on mental health status may vary depending on the length of working hours, we used a set of working hour dummy variables (40-, 45-, 50-, 55-, and 60-hours), with the reference group being 45 hours.

We distinguished five models by using different indicators of work hours and the interaction term of work hours and the regular worker dummy variable as follows:

(1) Model 1: using the working hours variable and excluding the interaction term.

(2) Model 2: using the 40 hours dummy variable and including the interaction term.

(3) Model 3: using the 50 hours dummy variable and including the interaction term.

(4) Model 4: using the 55 hours dummy variable and including the interaction term.

(5) Model 5: using the 60 hours dummy variable and including the interaction term.

For Models 2-5, we used 45 hours as the reference group. The main findings are as follows.

First, the coefficients of the regular worker dummy variable in Models (1)-(5) are negatively valued and significant at the 1% level, indicating that when the other factors are held constant, the probability of experiencing mental illness is higher among non-regular workers than among regular workers.

Second, regarding the impact of work hours on mental health status, the coefficients of work hours in Models (2)-(4) are all negatively valued and significant at the 1% level, suggesting that when work hours are 40 or more, the probability of experiencing mental illness increases. Comparing the magnitude of coefficients for the 40, 50, 55, and 60 work-hour dummy variables, the coefficient is greatest for 60 or more hours (1.994) and lowest for 40 or more hours (0.695), indicating that as work hours become longer, the probability of experiencing mental illness significantly increases. These results are consistent with the findings of previous studies (Ma, 2022).

Lastly, the interaction terms of work hours and the regular worker dummy variable are negative values and significant at the 1% level in Models (1)-(4). These results indicate that the impact of long working hours on mental health status is greater for non-regular workers than for regular workers. The findings can be explained by the effort-reward imbalance model (Siegrist, 1996), which suggests that when the efforts involved in involuntary long working hours are not adequately rewarded, the probability of experiencing mental illness may become higher among those working long hours. In Japan, there still exists a wage gap between regular and non-regular workers, and when non-regular workers receive lower wages while working long hours, the probability of experiencing mental illness among non-regular workers is likely to be higher than that among regular workers.

5.2 Results based on the PSM method

Tables 4 and 5 present the results of the probability of individuals working long hours for regular workers (Table 4) and non-regular workers (Table 5), respectively. Columns 1-4 display the results for (1) 40 hours; (2) 50 hours; (3) 55 hours; and (4) 60 hours. We used 45 hours as the cutoff value to construct the control group in the PSM method. The variables used for matching include gender, age, coresident relation, employment status, occupation, firm size, income, number of children, and city size. The results indicate that the probability of individuals working long hours is higher for men, managers, workers in small- or middle-size firms, non-regular workers, and those residing in large cities in Japan. We used these results to construct the matched samples.

Table 6 summarizes the results of the Average Treatment Effect on the Treated for the control and treatment groups. Based on the findings in Tables 1-3 and Figure 4, we defined the control group as individuals working 45 hours and less. We conducted three estimations for 50, 55, and 60 hours and used two models: Model 1, which excludes the covariates, and Model 2, which includes the covariates.

All results indicate that compared to the group working 45 hours or less per week, the probability of experiencing a mental disorder increases for the group working 55 hours or more, or the group working 60 hours or more. For instance, for the group working 55 hours or more (Estimation 2), in Model 1, the gap of mental illness score between treatment group (55 hours or more group)) and control group (45 hours or less) is 0.353 and significant at the 10% level, indicating that compared to the group working 45 hours or less per week, the probability of experiencing a mental disorder increases for the group working 55 hours or more per week. In Model 2, the gap is 0.454 and significant at the 10% level. The results also support the finding that long work hours of 55 hours or more per week increase the probability of developing a mental disorder.

5.3 Results by heterogenous group based on the PSM method

The results for heterogeneous groups are presented in **Table 7**, based on Model 2 of Estimation 2 in Table 6. We reran the estimations using the PSM method for gender (panel [a]), occupation (panel [b]), employment status (panel [c]), firm size (panel [d]), and city (panel [e]) groups. The main findings are as follows:

First, long working hours (LWH) negatively affect the mental health of both female and male workers, with the effect of LWH being greater among female workers (0.718) than among male workers (0.430).

Second, LWH negatively affects the mental health of both manager and non-manager workers, with the effect of LWH being greater among manager workers (0.767) than among non-manager workers (0.430).

Third, LWH negatively affects the mental health of both regular and non-regular workers, with the effect of LWH being greater among non-regular workers (0.518) than among regular workers (0.457). These results confirm the findings in Figure 4 and Table 3.

Fourth, LWH negatively affects the mental health of workers in small, middle, large-size firms, or government offices, with the effect of LWH being especially pronounced among workers in small-size firms (with 1-99 employees) and large-size firms (with 300 or more employees) compared to other groups.

Lastly, LWH negatively affects the mental health of workers in small, middle, and large cities, with the effect of LWH being greater among workers in middle and small-size cities than among workers in large cities.

5. Conclusions

Using the long-term Comprehensive Survey of Living Conditions (CSLC), a nationally representative survey conducted in Japan from 2003 to 2019, we examine the impact of long working hours on mental health in Japan while addressing the endogeneity issue arising from non-random selection bias. Additionally, we assess variations in the effect of long working hours on mental health across different groups.

This study yields three primary conclusions. First, in general, individuals working longer hours (55 hours or more weekly) have a higher probability of developing mental illness compared to those working regular or fewer hours. Second, the negative effect of long working hours on mental health is greater for regular workers than for non-regular worker groups. These conclusions have been confirmed based on the results obtained using the propensity score matching method. Third, the effect of long working hours on mental health differs among various groups. It is greater for women, managers, non-regular workers, workers in small or large-size firms, and workers in small cities than for their counterparts.

The policy implications based on the empirical study can be considered as follows: First, our findings suggest that compared to the group with 45 work hours or less, the group with 55 work hours or more potentially has a higher risk of developing mental disorders. The results support the policy of promoting weekly work hours of less than 45 hours, as enforced by the Japanese government (Ministry of Health, Labour and Welfare) in the current period. Since the results indicate that weekly work hours exceeding 55 hours will increase the risk of mental illness, setting the upper limit for long work hours at 55 hours in work hour regulations may be advisable.

Second, the results indicate that the negative effect of long working hours on mental health among non-regular workers is greater than that among regular workers. Most non-regular workers have less job authority than their counterparts (regular workers), and there exists a significant wage gap between regular and non-regular workers (Ma, 2008, 2009a; Arita et al., 2023). Based on the job demand-control model (Karasek, 1979) and the effort-reward imbalance model (Siegrist, 1996), long working hours may harm the mental health of non-regular workers much more than that of regular workers. Japan faces the issue of working poor due to the substantial wage gap between non-regular and regular groups among non-regular workers with long working hours (Guston and Kishi, 2007). A policy aimed at reducing the wage gap between the two groups is expected to mitigate the negative effects of long working hours, especially for non-regular workers. Meanwhile, implementing work-life balance initiatives, family-friendly policies, and measures to improve working conditions are expected to enhance overall mental health.

Third, regarding the determinants of becoming long-hour employees, our results (see Appendix Table A1) suggest that, in general (as shown in Column 1, which includes the total sample of both men and women), younger workers aged 16-29 and middle-aged and older workers aged 40 and over, workers with low household income, widowers, workers with lower levels of education, non-managers, employees in micro-firms with

1-4 employees, workers with a spouse who is a regular employee, and those working in large cities with populations of 15 million or more, are at a higher risk of becoming long-hour employees compared to their counterparts. These counterparts include senior younger workers aged 30-39, married workers, employees with high household income, workers who graduated from senior high school, managers, employees working in middle- and large-sized firms, workers whose spouses do not work, and those working in middle- and small-sized regions. The results among female and male groups (as shown in Columns 2 and 3) are almost similar to those observed in the total sample. The results suggest that workers with young children and disadvantaged workers (those without spouses, low-income workers, individuals with lower education levels, non-managers, and employees in small-sized firms) are more likely to have long work hours. The differences in socioeconomic status contribute to the inequality in work hours between disadvantaged and advantaged groups, indicating that the issue of working poverty may be more severe among the disadvantaged group than among the advantaged group. Policies aimed at reducing work hours may lead to lower earned income levels, potentially worsening the life situations of the disadvantaged group. Therefore, it is essential to emphasize policies aimed at improving wages or earned income, such as reducing the wage gap between regular and non-regular workers (for example, enforcing the implementation of equal pay for equal work policy), alongside the implementation of work hour regulation policies.

Finally, it should be noted that this study has the following limitations: First, long working hours may have effects on physical health (e.g., chronic diseases) beyond mental health, which should be explored in future research. Second, although we controlled for covariate variables as thoroughly as possible based on the CSLC, some factors (such as spouse's attributes and work situation, housing, personal relationships and work conditions in workplace) may potentially affect an individual's mental health. Since we could not obtain this information from the long-term CSLC dataset used in this study, exploring the empirical relationship considering these factors is a future research avenue. Lastly, as this study utilized repeated cross-sectional survey data, we were unable to examine the dynamic changes in the effect of long working hours on mental health and unable to address the individual heterogeneity problem. Conducting a study based on panel data would be valuable for addressing this issue in the future.

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Unit: 1000 persons

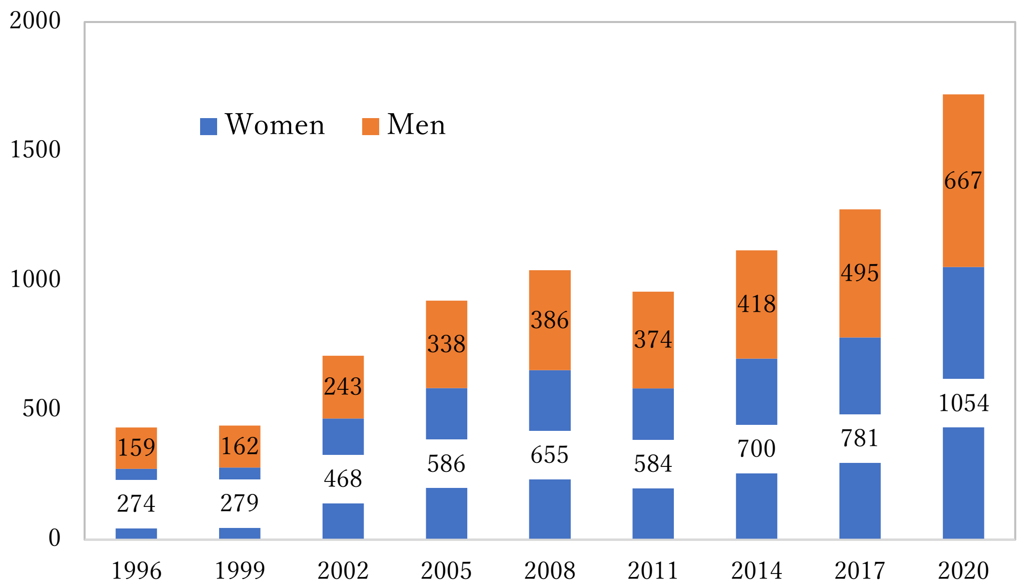

Figure 1 The number of mental illness patients in Japan (1996-2020)

Source: Creation by authors based on the data from Patient Survey conducted by the MHLW in October every three years for medical facilities nationwide in Japan. The total number of patients with mood disorders (depression, manic depression, dysthymia, etc.) are shown in the figure.

Unit: Persons

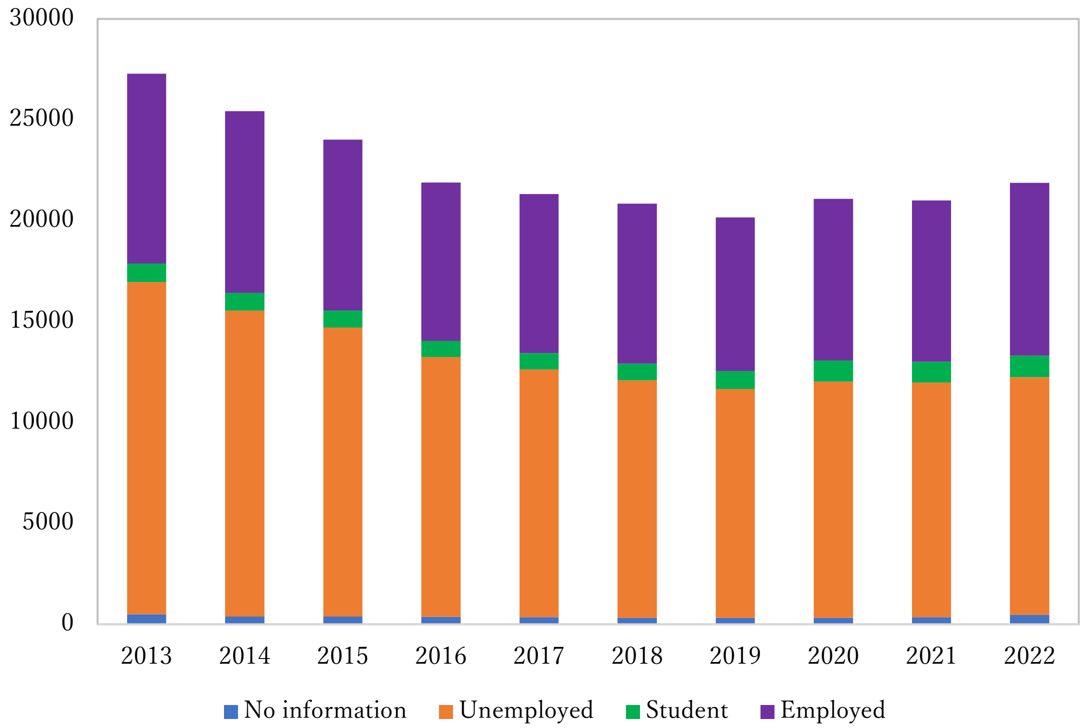

Figure 2 The number of suicides in Japan (2013-2022)

Source: Creation by authors based on the data from Metropolitan Police Department, Japan. R4jisatsunojoukyou.pdf (npa.go.jp)

Unit: Persons

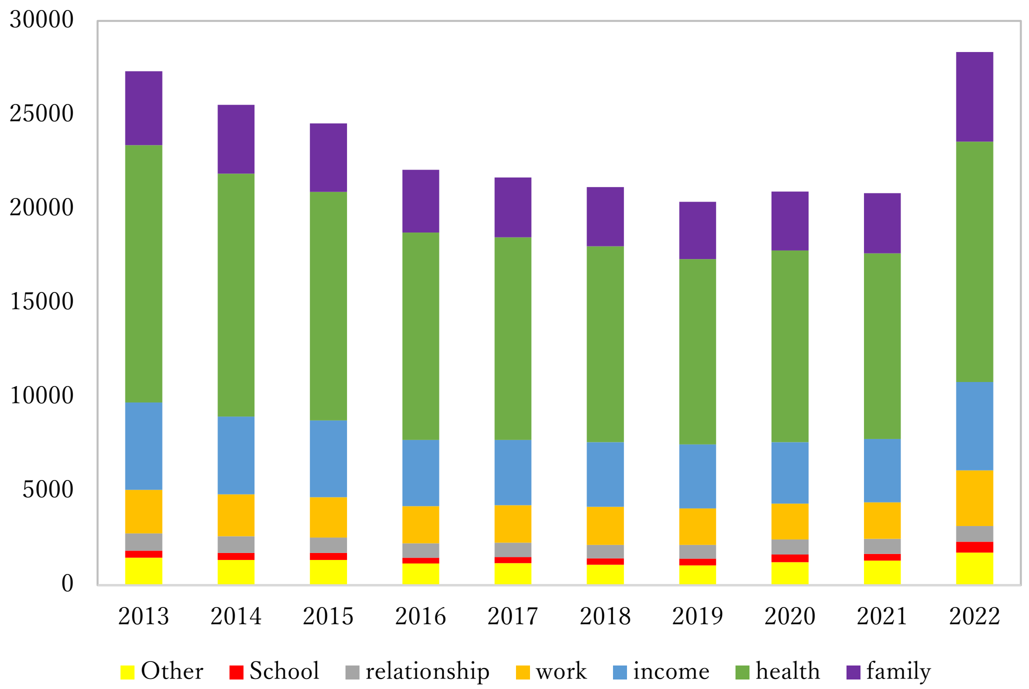

Figure 3 The number of suicides by reason of suicide in Japan (2013-2022)

Source: Creation by authors based on the data from Metropolitan Police Department, Japan. R4jisatsunojoukyou.pdf (npa.go.jp)

Table1 Descriptive statistics of variables

	Weekly Working Hour>55 (N=5931)		Weekly Working Hour<=55 (N=52446)		Gap
	Mean(a)	S.D.	Mean(b)	S.D.	a-b
Mental health score	3.536	4.387	3.204	4.086	0.332
Weekly work hour	64.375	7.066	36.264	12.785	28.111
Female dummy	0.121	0.327	0.489	0.500	0.368
Log of age	3.772	0.239	3.863	0.260	-0.091
Having a spouse	0.083	0.276	0.380	0.485	0.297
Number of Children	0.018	0.136	0.017	0.136	0.001
Log of family income	6.432	0.568	6.325	0.662	0.107
Family Income	721.765	418.416	673.128	403.529	48.637
Employment status					
Non-regular worker	0.070	0.255	0.414	0.493	-0.344
Regular worker	0.930	0.255	0.586	0.493	0.344
Occupation					
Managers	0.114	0.318	0.065	0.247	0.049
Professional	0.312	0.463	0.259	0.438	0.053
Clerk	0.067	0.251	0.172	0.377	-0.105
Sale job	0.102	0.302	0.076	0.265	0.026
Service job	0.113	0.317	0.167	0.373	-0.054
Security job	0.030	0.170	0.016	0.125	0.014
Agriculture, forestry and fishery job	0.010	0.100	0.010	0.097	0.000
Elementary job	0.229	0.420	0.198	0.399	0.031
Not elsewhere classified	0.022	0.148	0.037	0.188	-0.015
Firm size					
1-4	0.029	0.168	0.046	0.209	-0.017
5-29	0.185	0.388	0.203	0.402	-0.018

30-99	0.176	0.380	0.173	0.378	0.003
100-299	0.144	0.351	0.147	0.354	-0.003
200-499	0.063	0.244	0.063	0.242	0.000
500-999	0.062	0.242	0.069	0.253	-0.007
1000-4999	0.107	0.309	0.104	0.306	0.003
5000-	0.103	0.304	0.105	0.307	-0.002
Government office	0.131	0.337	0.091	0.288	0.040
Spouse's type of employment status					
Not in work	0.494	0.500	0.458	0.498	0.036
Regular worker	0.213	0.410	0.342	0.474	-0.129
Part-time worker	0.224	0.417	0.133	0.339	0.091
Albeit (temporary worker)	0.021	0.144	0.017	0.130	0.004
Dispatched worker	0.010	0.101	0.006	0.080	0.004
Contract worker	0.024	0.154	0.027	0.162	-0.003
Entrusted worker	0.009	0.095	0.012	0.110	-0.003
Other	0.004	0.062	0.004	0.066	0.000
Scale of resident city (thousands)					
Large city more than 150)	0.262	0.440	0.228	0.419	0.034
Population Scale 150	0.311	0.463	0.298	0.457	0.013
Population Scale 50-149	0.255	0.436	0.272	0.445	-0.017
Population Scale 149 or less	0.066	0.249	0.085	0.279	-0.019
County	0.106	0.308	0.116	0.321	-0.010
Survey year					
2010	0.261	0.439	0.223	0.416	0.038
2013	0.297	0.457	0.274	0.446	0.023
2016	0.248	0.432	0.255	0.436	-0.007
2019	0.193	0.395	0.248	0.432	-0.055

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.

Table 2 Average work hours by heterogenous groups

	Mean	SD	Min	Max
(1) Gender				
Male	45.05	13.18	0	89
Female	31.92	13.81	0	88
(2) Age				
Aged 16-29	40.52	16.25	0	89
Aged 30-49	41.22	15.17	0	89
Aged 50 and above	36.95	14.31	0	89
(3) Education				
Low education	38.09	14.41	0	89
Middle education	36.29	15.06	0	89
High education	43.24	15.03	0	89
(4) Occupation				
Non-managers	38.58	15.04	0	89
Managers	46.32	11.75	0	85
(5) Region				
Small cities	39.14	15.46	0	89
Large cities	39.09	14.40	0	88
(6) Employment status				
Non-Regular workers	28.43	12.91	0	88
Regular workers	45.81	11.92	0	89

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.

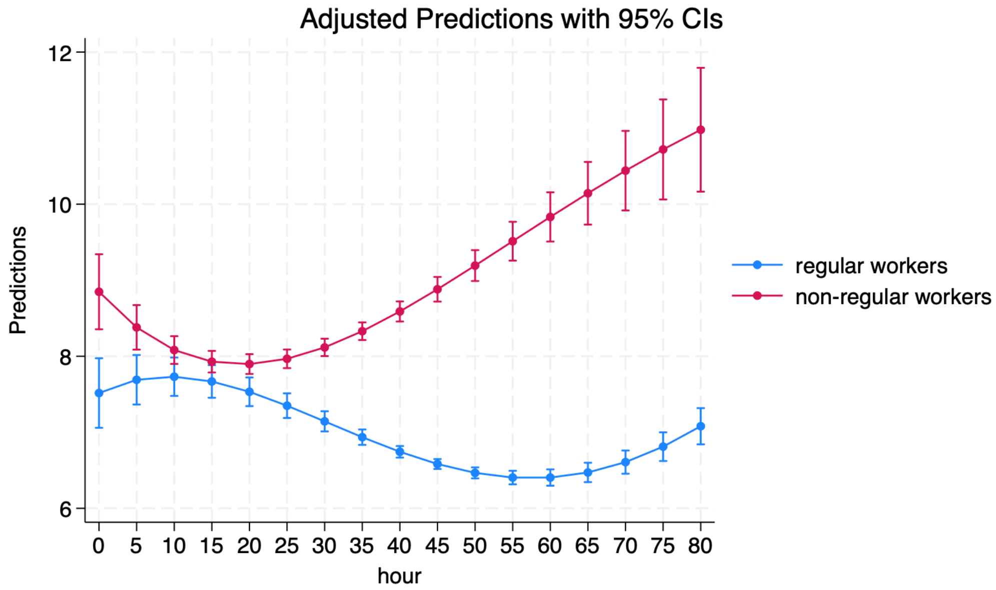

Figure 4 The raw relationship between work hours and MI

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.

Notes: The calculations are based on the model as $M_i = \alpha + \beta_1 WH_i + \beta_2 WH_i^2 + \beta_3 WH_i^3 + \beta_4 HW_i^4 + \epsilon_i$; WH represents the work hours. Non-regular workers include part-time worker, temporary employees, dispatched worker, contract worker, and entrusted worker.

Table 3 Results based on the OLS method

	(1)		(2)		(3)		(4)		(5)	
Regular	0.249	***	-0.155	***	-0.187	***	-0.175	***	-0.158	***
	(3.04)		(10.69)		(14.45)		(14.30)		(13.07)	
WH	-0.038	***								
	(7.33)									
WH*Regular	-0.047	***								
	(10.45)									
WH^2	0.0011	***								
	(6.45)									
WH^2*Regular	0.0008	***								
	(6.26)									
WH^3	-0.000007	***								
	(4.25)									
WH^2*Regular	0.000	**								
	(2.07)									
Ref. 45WH										
40WH			0.218	***						
			(7.36)							
40WH*Regular			-0.105	***						
			(3.20)							

50WH					0.386	***				
					(9.01)					
50WH*Regular					-0.125	***				
					(2.76)					
55WH							0.472	***		
							(7.79)			
55WH*Regular							-0.086			
							(1.36)			
60WH									0.617	***
									(8.30)	
60WH*Regular									-0.238	***
									(3.08)	
Control variables	Yes		Yes		Yes		Yes		Yes	
Number of Observations	549524		549524		549524		549524		549524	
Adjuster R-square	0.002		0.001		0.001		0.001		0.001	
Log Likelihood	-1566039		-1566407		-1566274		-1566217		-1566265	
F statistics	42.44		16.68		28.79		33.96		29.55	
Prob>F	0.000		0.000		0.000		0.000		0.000	

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.
Note: t-value is in the parentheses. * p<0.1, ** p<0.05, *** p<0.01. t-values are in paratheses.

Table 4 Probability of become workers with long work hours (regular worker)

	(1) 40WH		(2) 50WH		(3) 55WH		(4) 60WH	
Female	-0.462	***	-0.512	***	-0.559	***	-0.609	***
	(17.65)		(17.71)		(15.80)		(15.05)	
lnage	-0.689	***	-0.811	***	-0.720	***	-0.737	***
	(22.45)		(25.94)		(20.65)		(19.71)	
Having a spouse	-0.190	***	-0.173	***	-0.133	***	-0.123	**
	(6.17)		(5.02)		(3.13)		(2.51)	
ln family income	0.198	***	0.236	***	0.199	***	0.174	***
	13.49		14.85		10.75		8.62	
Occupation [Manager]								
Professional	-0.081	***	-0.089	***	-0.053	*	-0.056	*
	(3.21)		(3.56)		(1.88)		(1.84)	
Clerk	-0.381	***	-0.462	***	-0.456	***	-0.450	***
	(13.36)		(15.51)		(12.95)		(11.41)	
Sales workers	0.145	***	0.169	***	0.209	***	0.230	***
	(4.26)		(5.01)		(5.68)		(5.82)	
Service workers	-0.069	**	-0.053		0.029		0.085	**
	(2.14)		(1.64)		(0.79)		(2.16)	
Protective Service Workers	-0.258	***	-0.339	***	-0.165	***	-0.085	
	(4.79)		(6.20)		(2.76)		(1.34)	
Agriculture, forestry and fishery workers	0.025		-0.124		0.029		-0.002	
	(0.30)		(1.44)		(0.30)		(0.02)	
Elementary occupations	-0.039		-0.165	***	-0.060	**	-0.026	
	(1.43)		(6.05)		(1.96)		(0.78)	
Not elsewhere classified	-0.264	***	-0.230	***	-0.146	**	-0.104	

	(5.04)		(4.24)		(2.38)		(1.58)	
Firm size (number of employees)								
5-29	0.114	***	0.138	***	0.190	***	0.178	***
	(2.86)		(3.17)		(3.70)		(3.18)	
30-99	0.067	*	0.153	***	0.191	***	0.181	***
	(1.66)		(3.48)		(3.70)		(3.21)	
100-299	-0.033		0.098	**	0.092	*	0.043	
	(0.82)		(2.21)		(1.75)		(0.76)	
200-499	-0.060		0.071		0.058		0.016	
	(1.33)		(1.46)		(1.00)		(0.26)	
500-999	-0.067		0.098	**	0.025		-0.047	
	(1.48)		(2.03)		(0.44)		(0.76)	
1000-4999	-0.087	**	0.027		0.006		-0.025	
	(2.06)		(0.58)		(0.10)		(0.43)	
5000-	-0.130	***	-0.024		-0.056		-0.133	**
	(3.09)		(0.53)		(1.05)		(2.26)	
Government office	0.024		0.240	***	0.336	***	0.300	***
	(0.56)		(5.15)		(6.20)		(5.05)	
Spouse's employment status [non-work]								
Regular worker	-0.102	***	-0.115	***	-0.128	***	-0.111	***
	(5.25)		(5.69)		(5.57)		(4.39)	
Part-time	0.054	***	0.007		-0.024		0.017	
	(2.79)		(0.37)		(1.10)		(0.72)	
Albeit (temporary worker)	0.022		-0.006		0.012		0.061	
	(0.42)		(0.12)		(0.20)		(0.98)	
Dispatched worker	0.048		0.072		0.022		0.118	
	(0.60)		(0.91)		(0.25)		(1.29)	
Contract worker	0.019		0.060		0.016		-0.019	
	(0.40)		(1.27)		(0.30)		(0.32)	

Entrusted worker	0.015		0.009		0.021		0.018	
	(0.20)		(0.13)		(0.26)		(0.20)	
Other	-0.004		0.094		0.070		0.050	
	(0.03)		(0.84)		(0.57)		(0.36)	
Number of children	0.027		-0.015		0.057		0.102	*
	(0.53)		(0.29)		(0.99)		(1.68)	
City Scale [Large city] (thousands)								
Population 150	-0.047	**	-0.070	***	-0.046	**	-0.073	***
	(2.50)		(3.63)		(2.15)		(3.15)	
Population 50-149	-0.080	***	-0.111	***	-0.103	***	-0.118	***
	(4.12)		(5.55)		(4.55)		(4.84)	
Population 149 or less	-0.101	***	-0.169	***	-0.163	***	-0.234	***
	(3.57)		(5.75)		(4.82)		(6.21)	
County	-0.097	***	-0.148	***	-0.126	***	-0.173	***
	(3.89)		(5.74)		(4.30)		(5.38)	
Constant term	2.480	***	2.153	***	1.435	***	1.514	***
	(17.94)		(15.33)		(9.03)		(8.76)	
Number of observations	35870		35870		35870		35870	
Psuedo R-Square	0.063		0.071		0.067		0.073	
Log Likelihood	-23109		-21585		-16013		-13163	
Chi2 Statistics	2868.900		2830.200		1907.500		1613.600	
Prob>Chi2	0.000		0.000		0.000		0.000	

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.
Note: t-value is in the parentheses. * p<0.1, ** p<0.05, *** p<0.01. t-values are in paratheses.

Table 5 Probability of become workers with long work hours (non-regular worker)

	(1)		(2)		(3)		(4)	
	40WH		50WH		55WH		60WH	
Female	-0.200	***	-0.317	***	-0.307	***	-0.432	***
	(4.68)		(5.65)		(4.15)		(4.91)	
lnage	-0.699	***	-0.762	***	-0.690	***	-0.707	***
	(13.79)		(12.17)		(8.80)		(7.80)	
Spouse of household	-0.357	***	-0.207	***	-0.160	*	-0.149	
	(7.40)		(3.21)		(1.86)		(1.41)	
ln family income	0.102	***	0.115	***	0.125	***	0.106	**
	(4.69)		(4.15)		(3.55)		(2.48)	
Typ of work [Part-time]								
Dispatched worker	0.01		-0.02		0.05		-0.07	
	(0.21)		(0.37)		(0.68)		(0.76)	
Contract worker	0.45	***	0.38	***	0.35	***	0.33	***
	(8.16)		(5.60)		(3.83)		(3.08)	
Entrusted Worker	0.66	***	0.52	***	0.46	***	0.39	***
	(19.65)		(12.18)		(8.45)		(5.95)	
Occupation [Manager]	.		.		.		.	
Professional	0.069		0.130		0.032		0.077	
	(0.76)		(1.17)		(0.23)		(0.44)	
Clerk	-0.060		-0.073		-0.218		-0.306	
	(0.64)		(0.62)		(1.44)		(1.53)	
Sale	0.038		0.048		0.080		0.162	
	(0.39)		(0.39)		(0.52)		(0.84)	
Service	0.101		0.136		0.195		0.310	*
	(1.11)		(1.20)		(1.38)		(1.75)	
Security	0.375	***	0.417	***	0.360	**	0.435	**
	(3.04)		(2.85)		(1.97)		(2.03)	

Agriculture, forestry and Fishery workers	0.341	**	0.394	**	0.285		-0.132	
	(2.52)		(2.38)		(1.37)		(0.42)	
Elementary	0.356	***	0.272	**	0.210		0.242	
	(3.97)		(2.45)		(1.51)		(1.40)	
Not elsewhere classified	0.036		0.022		0.019		0.135	
	(0.35)		(0.17)		(0.12)		(0.68)	
Firm size [1-4] (number of employees)								
5-29	-0.075		-0.123		-0.145		-0.053	
	(1.26)		(1.61)		(1.52)		(0.45)	
30-99	-0.017		-0.036		-0.063		-0.013	
	(0.27)		(0.48)		(0.66)		(0.11)	
100-299	-0.018		-0.058		-0.083		-0.080	
	(0.29)		(0.73)		(0.84)		(0.65)	
200-499	-0.033		-0.096		-0.177		-0.128	
	(0.44)		(1.02)		(1.48)		(0.89)	
500-999	-0.025		-0.074		-0.231	**	-0.218	
	(0.35)		(0.81)		(1.97)		(1.52)	
1000-4999	-0.072		-0.146	*	-0.255	**	-0.292	**
	(1.07)		(1.67)		(2.28)		(2.09)	
5000-	-0.222	***	-0.212	**	-0.317	***	-0.348	**
	(3.11)		(2.35)		(2.70)		(2.30)	
Government office	-0.560	***	-0.347	***	-0.224	*	-0.230	
	(6.57)		(3.35)		(1.75)		(1.44)	
Spouse's employment status [non-work]								
Regular worker	-0.226	***	-0.284	***	-0.297	***	-0.282	***
	(5.63)		(5.43)		(4.32)		(3.34)	
Part-time	0.058		0.076		0.071		0.042	
	(1.32)		(1.44)		(1.08)		(0.55)	

Albeit (temporary worker)	0.060		-0.038		0.044		0.184	
	(0.68)		(0.33)		(0.32)		(1.26)	
Dispatched worker	0.060		0.224		0.008		-0.397	
	(0.38)		(1.30)		(0.04)		(1.04)	
Contract worker	-0.012		-0.041		0.024		-0.071	
	(0.17)		(0.45)		(0.22)		(0.51)	
Entrusted worker	-0.106		-0.060		-0.067		-0.099	
	(0.92)		(0.43)		(0.37)		(0.42)	
Other	-0.243		-0.007					
	(1.07)		(0.03)					
Number of children	0.088		0.202	*	0.204		0.193	
	(0.99)		(1.85)		(1.52)		(1.16)	
City Scale [Large city] (thousands)								
Population 150	0.060	*	0.006		0.049		0.007	
	(1.73)		(0.15)		(0.87)		(0.10)	
Population 50-149	0.083	**	-0.020		-0.037		-0.054	
	(2.35)		(0.43)		(0.62)		(0.77)	
Population 149 or less	0.128	**	0.083		0.078		-0.051	
	(2.57)		(1.32)		(0.95)		(0.49)	
County	0.196	***	0.097	*	0.161	**	0.086	
	(4.46)		(1.73)		(2.30)		(1.04)	
Constant term	1.422	***	1.249	***	0.540		0.677	
	(5.93)		(4.22)		(1.48)		(1.58)	
Number of observations	21884		21884		21798		21798	
Psuedo R-Square	0.135		0.122		0.110		0.124	
Log Likelihood	-6278		-3577		-2030		-1353	
Chi2 Statistics	1803.500		848.600		423.300		303.100	
Prob>Chi2	0.000		0.000		0.000		0.000	

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.
Note: t-value is in the parentheses. * p<0.1, ** p<0.05, *** p<0.01. t-values are in paratheses.

Table 6 Results based on the PSM method

	(1)		(2)	
	Coef.	SE.	Coef.	SE.
(1)50WH				
ATT	0.306	0.048	0.403	0.051
Covariates	No		Yes	
(2)55WH				
ATT	0.353	0.059	0.454	0.061
Covariates	No		Yes	
(3)60WH				
ATT	0.324	0.068	0.435	0.069
Covariates	No		Yes	

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.

Note: The PSM method was used. We used the 45 hours weekly as the control group. Covariate variables include gender, age, income, occupation, employment status, firm size and city size.

Table 7 Results by heterogenous groups based on the PSM method

(a) gender

	(1) Men			(2) Women		
	Coef.		SE.	Coef.		SE.
ATT	0.430	***	0.063	0.718	***	0.160
Covariates	Yes			Yes		

(b) occupation

	(1) manager			(2) non-manager		
	Coef.		SE.	Coef.		SE.
ATT	0.767	***	0.161	0.430	***	0.063
Covariates	Yes			Yes		

(c) Employment status

	(1) Regular			(2) No-regular		
	Coef.		SE.	Coef.		SE.
ATT	0.457	***	0.061	0.518	**	0.277
Covariates	Yes			Yes		

(d) firm size (number of employees)

	(1) Small (1-99)			(2) Middle (100-299)			(3) Large (300 or more)			(4) Government office		
	Coef.		SE.	Coef.		SE.	Coef.		SE.	Coef.		SE.
ATT	0.547	***	0.135	0.285	***	0.105	0.612	***	0.098	0.411	***	0.156
Covariates	Yes			Yes			Yes			Yes		

(e) Region

	(1) Large city			(2) middle-size city			(3) small-size city		
	Coef.		SE.	Coef.		SE.	Coef.		SE.
ATT	0.415	***	0.078	0.531	***	0.089	0.547	***	0.135
Covariates	Yes			Yes			Yes		

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.
Note: The PSM method was used. We used the 55 and more hours weekly as the indicator of long work hours in the analysis. Covariate variables include gender, age, income, occupation, employment status, firm size and city size.

Appendix Table A1 Results of Probability of becoming long-work hour employees

	Total		Male		Female	
	dF/dx		dF/dx		dF/dx	
Age group [Ref.: Age30-39]						
Age15-29	0.060	***	0.081	***	-0.015	*
	(0.005)		(0.005)		(0.009)	
Age40-49	0.030	***	-0.013	***	0.033	***
	(0.004)		(0.004)		(0.007)	
Age50+	0.189	***	0.243	***	0.073	***
	(0.004)		(0.005)		(0.007)	
Ln Family Income	-0.116	***	-0.084	***	-0.115	***
	(0.002)		(0.003)		(0.004)	
Marital status [Married]						
Unmarried	-0.015	***	0.089	***	-0.189	***
	(0.005)		(0.006)		(0.009)	
Widow/Widower	0.092	***	0.014		-0.022	
	(0.012)		(0.016)		(0.015)	
Divorced	-0.015	**	-0.009		-0.168	***
	(0.007)		(0.009)		(0.010)	
Education [Ref.: Senior high school]						
Junior high school	0.060	***	0.072	***	0.053	***
	(0.007)		(0.008)		(0.013)	
Training college	-0.007		-0.007		-0.023	***
	(0.005)		(0.006)		(0.007)	
Junior college/technical college	0.094	***	-0.008		0.023	***
	(0.006)		(0.010)		(0.007)	
University	-0.070	***	-0.002		-0.045	***
	(0.004)		(0.004)		(0.007)	
Graduated school	-0.093	***	-0.005		-0.065	**
	(0.011)		(0.011)		(0.025)	

Occupation [Ref.: Manager]						
Technician	0.138	***	0.055	***	0.215	***
	(0.006)		(0.006)		(0.020)	
Clerk	0.234	***	0.081	***	0.277	***
	(0.007)		(0.007)		(0.020)	
Sales workers	0.353	***	0.118	***	0.542	***
	(0.008)		(0.008)		(0.021)	
Service workers	0.458	***	0.251	***	0.556	***
	(0.007)		(0.008)		(0.020)	
Security workers	0.168	***	0.151	***	0.072	
	(0.014)		(0.013)		(0.050)	
Agriculture, forestry and fishery workers	0.271	***	0.156	***	0.506	***
	(0.018)		(0.018)		(0.036)	
Elementary occupations	0.214	***	0.099	***	0.482	***
	(0.007)		(0.006)		(0.021)	
Not elsewhere classified	0.438	***	0.272	***	0.565	***
	(0.011)		(0.013)		(0.023)	
Firm Size [Ref: 1-4 workers]						
5-29	-0.011		-0.015		-0.007	
	(0.008)		(0.010)		(0.012)	
30-99	-0.023	***	0.002		-0.046	***
	(0.009)		(0.010)		(0.012)	
100-299	-0.035	***	0.002		-0.062	***
	(0.009)		(0.010)		(0.012)	
200-499	-0.050	***	-0.010		-0.068	***
	(0.010)		(0.011)		(0.014)	
500-999	-0.027	***	0.008		-0.034	**
	(0.010)		(0.011)		(0.014)	
1000-4999	-0.031	***	-0.009		-0.013	
	(0.009)		(0.011)		(0.013)	
5000+	-0.051	***	-0.018	*	-0.033	**
	(0.009)		(0.011)		(0.014)	

Government office	-0.072	***	-0.050	***	-0.049	***
	(0.010)		(0.011)		(0.014)	
Spouse's employment status [Ref.: Non-work]						
Regular worker	0.146	***	-0.062	***	0.042	***
	(0.005)		(0.006)		(0.007)	
Part-time	-0.138	***	-0.041	***	0.026	
	(0.005)		(0.005)		(0.022)	
Albeit [Temporary worker]	-0.005		0.024	*	0.041	
	(0.013)		(0.015)		(0.028)	
Dispatched worker	-0.024		-0.029		0.051	
	(0.022)		(0.022)		(0.045)	
Contract worker	0.081	***	0.018		0.092	***
	(0.012)		(0.014)		(0.018)	
Entrusted worker	0.127	***	0.040	*	0.113	***
	(0.017)		(0.023)		(0.025)	
Other	0.046		-0.015		0.049	
	(0.029)		(0.032)		(0.047)	
Number of children	0.194	***	0.111	***	0.246	***
	(0.012)		(0.011)		(0.019)	
City Scale [Ref.: Large city] [thousands]						
Population150	.		.		.	
	-0.027	***	-0.015	***	-0.039	***
Population 50-149	(0.005)		(0.005)		(0.007)	
	-0.031	***	-0.017	***	-0.050	***
Population 50 or less	(0.005)		(0.005)		(0.007)	
	-0.051	***	-0.026	***	-0.083	***
County	(0.006)		(0.007)		(0.009)	
	-0.052	***	-0.032	***	-0.082	***
Constant term	(0.006)		(0.006)		(0.009)	
Number of Observations	75,602		40,396		35,206	
Psuedo R-squares	0.153		0.199		0.182	
Log Likelihood	-41931.3		-15866.9		-19772.6	
Chi2	12785		6598.7		7160.1	

Source: Calculated based on the data from Comprehensive Survey of Living Conditions (CSLC) of 2003-2019 conducted by the MHLW.
Note: The value of standard error is in the parentheses. * p<0.1, ** p<0.05, *** p<0.01. The

dependent variable is a binary variable (1 if work hours are 45 hours or more, 0 if work hours are less than 45 hours).