博士論文

Internal Labor Markets, Workers' Career, and Human Capital in Japanese Firms

(日本企業における内部労働市場、労働者のキャリア、人的資本)

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Contents

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Chapter 1

Overview

1. Introduction

Over the past few decades, the fields of personnel and organization economics have examined the employment practices and norms of internal labor markets that are governed by different rules from external labor markets, under the assumption that firms and employees make their decisions rationally. The internal labor market (ILM) is a concept developed by Doeringer and Piore (1971) and refers to an administrative system for allocating human resources (Barron and Kreps 1999). Doeringer and Piore (1971) suggest that ILMs have ports of entry, systems of internal promotion, job ladders, and wage policies related to job characteristics. Many theoretical and empirical studies have investigated the incentive mechanism of ILMs using concepts such as human capital and contracts. Furthermore, increased access to the personnel records of firms has allowed researchers to more precisely examine the dynamics of ILMs (Bagger and Seltzer 2014).

There are some critical issues that have remained unexplored in studies of ILMs. Much of the previous literature has focused on human capital in a dichotomous manner, e.g., general and firm-specific human capital, and ignored other types of worker heterogeneity. However, with the advancement of female labor participation, the progress of technology, and an increasingly information-based society, it becomes more important to examine the relationship between the firm’s decision and additional types of worker heterogeneity, such as gender, career histories, and skill sets. This dissertation addresses three themes pertaining to those ignored but important sides of ILMs: the gender gap in career outcomes within ILMs, differences in promotion incentives across occupations, and workers' mental health as an issue that affects the maintenance of general human capital. Regarding the first research theme, the gender wage gap is one phenomenon that has been intensively investigated, and some literature attributes the source of this gap to job segregation in ILMs (Bayard et al. 2003). The theoretical study by Lazear and Rosen (1990) explains differential promotion prospects by gender within ILMs in terms of job assignments. Their model suggests that firms maintain a higher ability threshold for women to be promoted and provide only the most able women with managerial training, implying the positive selection of women for intensive training. Mainly due to a lack of information about job assignments and promotions within firms, there are only a few empirical studies testing that model (e.g., Pema and Mehay 2010, Winter-Ebmer and Zweimuller 1997, Jones and Makepease 1996). Chapter 2 considers job rotation as a proxy for managerial training and, using personnel records, examines how gender differences in job assignments are associated with the gender gap in pay and promotion.

Next, previous literature on job assignments and promotions within ILMs has focused on workers' firm-specific human capital and ignored heterogeneity across occupations (Baker et al. 1994, Lazear and Oyer 2004), while recent literature on human capital accumulation focuses on occupation-specific human capital (Kwon and Milgrom 2014). If the relative importance of occupation-specific human capital is significant in some occupations, experience in a particular occupation is more valued than experience within a firm, and patterns of job assignments and promotions may be different than within other occupations. Using survey data for Japanese male workers, Chapter 3 examines whether the relationship between job change and promotion, including the specialist system, varies across occupations.

Thrid, I highlight the importance of mental health problems for personnel management in ILM. Health is regarded as one form of endogenous human capital (Grossman 1972); it may be increased by investment and decreased by heavy workloads. Because ILM assumes long-term relationships between firms and their employees

(Barron and Kreps 1999), it is efficient for management to keep employees healthy and free of illness so that they can work long-term. In particular, workers' mental health has been a major focus in recent years because mental illness is prevalent worldwide and causes major economic losses, as many people of working age suffer from mental illness (Layard 2017). Previous literature in the fields of medicine, occupational health, and epidemiology has suggested a strong relationship between working hours and workers' mental health. However, due to endogeneity issues, it is difficult to establish the causal effect of working hours on employees' mental health. Furthermore, while some literature has reported that working at night and on weekends may be associated with the deterioration of workers' health, little research has comprehensively confirmed the association among work style, which includes not only the duration of work but also the timing of work (that is, night or day, weekday or weekend), duration of rest time, and workers' mental health. Chapter 4 explores how various characteristics of the work schedule affect workers' mental health using detailed attendance records of a Japanese firm.

Finally, I explain the significance of using the data from Japanese firms and employees' survey. Japan is known for the larger gender pay gap among the developed countries (Estévez-Abe, 2013). Therefore, it is assumed that the relationship between the factors that the previous western literature has pointed out to be the main source for gender pay and promotion gap and promotion/wage may appear more strongly. As much literature pointed out, the long-term relationship between firms and employees has been pervasive in Japan and Japanese firms tend to evaluate firm-specific human capital. However, as described in Chapter 3, this Japanese employment system has changed and job change has become more common than before. There is little research that examines whether the importance of occupation-specific human capital may be replicated in Japanese firms. Japan is also known as having the tendency for long working hours and "karo-shi" has become the word representing the Japan's work culture favoring overwork.

Therefore, the effect of long working hours and burdensome work style on workers' mental health may be more likely to be extracted using Japanese firm's dataset.

The remainder of this chapter is organized as follows. First, in section 2, I explain the characteristics of the personnel records that are used in two of the three essays in this dissertation. Next, in section 3, I briefly introduce the three essays.

2. Personnel Data and Internal Labor Markets

Personnel data are datasets that are mainly managed by the personnel function of a firm; they include information about employees' individual characteristics, compensation, and job assignments. Among the three essays in this dissertation, two use personnel records from large Japanese companies. In this subsection, I explain the characteristics of these personnel records and introduce some major literature that uses personnel records and is related to my essays.

Angrist and Krueger (1999) defined the data produced as a byproduct of administrative functions and corporate activities as administrative data. They emphasized the advantages of these data, which include large samples and many critical variables used in decision-making by firms and administrations. These characteristics allow us to identify causal effects of management practices by analyzing the data in the panel format before and after their changes and to conduct more precise estimations controlling for many variables. On the other hand, the data have some drawbacks—for example, weak external validity due to analyzing only one administration or firm and lack of specific variables related to the research agenda.

I now describe the detailed characteristics of personnel records, which have the same merits and demerits described above in the context of administrative data. Personnel records usually include the following information: employees' individual characteristics (age, tenure, gender, education, marriage, etc.), compensation (wages, bonuses), attendance records, evaluation records, and career history (entry, leave, department, transfer). The data are recorded for each employee during an employment spell. Usually, the information is stored in separate fields or folders based on various categories in the database. Therefore, when data are retrieved from the database, merging multiple files using employee IDs and time variables as keys is inevitable if one wants to construct a panel dataset suitable for analyses of employees' promotions and wage growth. The results obtained from personnel records may not necessarily be applied to all companies, and we should be careful in deriving implications from the results. However, personnel records may allow us to use precise information that is not available in public-use survey data and to study how firms/employees make choices within the organization.

There are two different research strategies that can be pursued using personnel records. One is to understand the incentive systems within the firm, and researchers often use experimental methodology to estimate causal effects. The other is to reveal the structure of internal labor markets in larger firms (Bagger and Seltzer 2014). I focus on the latter type of literature because the objective of this dissertation is to derive the implications of the structure of ILMs for human capital accumulation and the employer-employee relationship. The pioneering empirical study investigating internal labor markets using personnel records is Medoff and Abraham (1980). They use the personnel records of two U.S. manufacturing companies and show that labor market experience was not correlated with evaluations from supervisors but with wages. This result implies that wage growth cannot be explained by productivity. Another representative study using personnel records is Baker, Gibbs, and Holmstrom (1994a, 1994b), who use the personnel data of a U.S. financial services company. The authors confirmed that the firm had a career ladder and a fast track, which are characteristics of internal labor markets, but found scarce evidence for an existing "port of entry" within the firm. They also found cohort effects on wages where those who were offered higher wages were likely to maintain their wage advantage over time. Ever since these three famous studies, other studies have used personnel records to examine the structure of internal labor markets and offered valuable findings (e.g., Treble et al. 2001, Gibbs and Hendricks 2004, Seltzer and Merrett 2000).

Some studies explore the structure of ILMs using the personnel records of Japanese companies. In this section, I refer to the literature that focuses on the issues studied in this dissertation: promotion incentives and the gender gap in careers within a firm. These studies utilize evaluation from supervisors and the frequency of transfer within firms, which are rarely included in public-use surveys but are included in personnel records. Ariga, Ohkusa, and Brunello (1999) and Ariga (2006) use the personnel records of a large Japanese manufacturing company. They have found that externally hired employees were promoted more slowly than stayers without outside experience and that those who have experienced job transfers within the firm and acquired multiple skills are likely to be promoted. Kato, Kawaguchi, and Owan (2013), Kato, Ogawa, and Owan (2016), Hashimoto and Sato (2014) have examined gender gaps in careers within a firm using the same Japanese manufacturing company's personnel records. These studies have shown that the return to working long hours may be different between male and female employees and that there may be gender job segregation within a firm in that particular departments and sections have a high proportion of female employees. These results imply that statistical discrimination against female employees may lead firms to use different assignment policies for females and males.

3. Introduction of the Essays

In this subsection, I briefly introduce the three essays of this dissertation. These essays attempt to reveal some of the mechanisms of ILMs: the relationship between gender and career differences, the difference in promotion incentives between job changers and stayers, and the effect of working style on workers' mental health. Analyzing personnel records and survey data allows confirmation of the causal effect of employees' career history and work style on the outcome of interest.

Chapter 2 focuses on gender pay and promotion differences within a firm. Past literature has shown that job segregation by gender is one major cause of the widely observed gender pay gap and that there are also gender differences in developmental job assignments that affect broader job experience. Using the personnel records of a Japanese manufacturing company, this essay uses the entire lateral transfer experience recorded in the personnel management system and examines how gender differences in job assignments are associated with the gender gap in pay and promotion. One of the major findings is that broader work experience through job transfers across establishments is associated with a higher promotion probability and future wages for employees of both genders, but this relationship is especially strong for women, which is consistent with the selection and signaling explanations based on statistical discrimination against women. Furthermore, according to our fixed effects model estimation of wage function, broader work experience leads to higher wages for men but not for women, implying that compared with men, women accept promotions with smaller pay raises, which is consistent with the sticky floors model.

Chapter 3 investigates the relationship among occupation, firm size, and promotions in the ILM. Previous literature shows that among candidates with equivalent general human capital, companies prefer to promote "stayers" from the internal labor market rather than job changers. However, few studies have examined the relationship among occupation, firm size, and promotions in the ILM. This paper focuses on technical workers and specialized professionals because they are likely to accumulate occupation-specific human capital and their labor market tends to be established. Then, this paper uses the "Working-Person Survey" to examine how the promotion probability of managers and senior specialists is related to job-change histories, occupation, and firm size. Three main conclusions are summarized as follows. First, the promotion probability of job-changing managers is lower on average than that of stayers. This result is consistent with previous findings (Ariga, Ohkusa, and Brunello 1999). Second, among administration and sales workers, it is difficult for job changers to be promoted to managerial positions as firm size increases. This result supports the theory of DeVaro and Morita (2013). On the other hand, this pattern is not observed among technical workers and specialized professionals, suggesting that the theory of DeVaro et al. applies only to nontechnical and nonspecialized professionals. Third, regarding promotions to senior professional positions, it turns out that job changers are not disadvantaged when compared with stayers.

Chapter 4 investigates how various work schedule characteristics affect workers' mental health. Although the prior literature has examined the relationship between work schedule characteristics and worker mental health, establishing the causal effect of work schedule characteristics is challenging because of endogeneity issues. This paper investigates how various work schedule characteristics affect workers' mental health using employee surveys and actual working hours recorded over seventeen months in a Japanese manufacturing company. Our major findings are as follows: long working hours cause the mental health of white-collar workers to deteriorate even after controlling for individual fixed effects. Furthermore, working on weekends is associated with mental ill health—the negative effect of an hour increase in weekend work is one and a half to two times larger than that of weekday overtime work for white-collar workers. On the other hand, short rest periods are not associated with mental health for them. Our results indicate that taking a relatively long rest period on weekends is more important for keeping white-collar workers healthy than ensuring a sufficient daily rest period. Regarding blue-collar workers, our analysis reveals that working after midnight is associated with mental ill health, whereas short rest periods are not associated with their mental health. This suggests that the strain of night work is a more important determinant of mental health for blue-collar workers. The differences in the relationship between work schedule characteristics and workers' mental health for white-collar and blue-collar workers can be explained in terms of different work styles, different expectations, and different degrees of selection.

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Chapter 2

Gender Differences in Career[1]

[1] This study is a joint work with Yuki Hashimoto, and Hideo Owan. This is based on the Author's Accepted Manuscript of an article published in Journal of Japanese and International Economies, 2019, vol.53, available online https://doi.org/10.1016/j.jjie.2019.04.001. This study was conducted as part of the project "Economic Analysis of Human Resource Allocation Mechanisms within the Firm: Insider econometrics using HR data" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). The authors are grateful for helpful comments and suggestions by Masaru Sasaki (Osaka University), Daiji Kawaguchi (University of Tokyo.), Ayako Kondo (University of Tokyo), Ryuichi Tanaka (University of Tokyo) and Discussion Paper seminar participants at RIETI. This work was also supported by JSPS KAKENHI Grant Number JP25245041 and 18H03632.

Abstract

Chapter 2 focuses on gender pay and promotion differences within a firm. Past literature has shown that job segregation by gender is one major cause of the widely observed gender pay gap and that there are also gender differences in developmental job assignments that affect broader job experience. Using the personnel records of a Japanese manufacturing company, this essay uses the entire lateral transfer experience recorded in the personnel management system and examines how gender differences in job assignments are associated with the gender gap in pay and promotion. One of the major findings is that broader work experience through job transfers across establishments is associated with a higher promotion probability and future wages for employees of both genders, but this relationship is especially strong for women, which is consistent with the selection and signaling explanations based on statistical discrimination against women. Furthermore, according to our fixed effects model estimation of wage function, broader work experience leads to higher wages for men but not for women, implying that compared with men, women accept promotions with smaller pay raises, which is consistent with the sticky floors model.

Chapter 3

The relationship between labor market experience outside the firm and promotion in the internal labor market[2]

[2] The data for this secondary analysis, “Working Person Survey 2004, 2006, 2008, 2010, 2012, 2014” were provided by The Social Science Japan Data Archive, Center for Social Research and Data Archives, The Institute of Social Science, The University of Tokyo. This is a revised version of an Author’s Accepted Manuscript of an article published in *The Japanese Journal of Labour Studies*, No.695, 2018, pp.80-97.

1. Introduction

Long-term employment relationships have been regarded as a distinguishing feature of the Japanese employment practice. However, in recent years, some studies have suggested that changes have occurred in this pattern: long-term employment relationships have been weakened regardless of firm scale and industry, and the age-wage profile has been flattening (Kawaguchi and Ueno 2013; Hamaaki et al., 2012). Job changes have also been increasing slightly. Data from the "Survey on Employment Trends" by the Ministry of Health, Labour and Welfare show that the job-changer entry ratio (the ratio of newly recruited regular employees who worked elsewhere in the previous year) rose by approximately 0.4 percentage points for men and approximately 2.7 percentage points for women from 1990 to 2014.

This paper focuses on the promotions of job changers after their job change and investigates career processes in the internal labor market by occupation type. In terms of human capital theory, employees who have experienced a job change are likely to be disadvantaged because they have less firm-specific human capital than those who have not experienced a job change (stayers). Many Japanese studies on job change explore wage growth among job changers. However, few studies have considered job changers' promotions and assignments at their new companies, although promotion is one of the major incentive systems in internal labor markets (ILM).

One of the major characteristics of the promotion system in Japanese firms is "late selection" on the premise of long-term employment relationships. Under this system, employees usually transfer between different functions in ILM to acquire the coordination skills that are required for future management positions. This personnel policy is suitable for developing generalists who have a variety of skills but is unsuitable for cultivating specialists who have expertise in specific areas (Yashiro, 2011).

However, with the advancement of technology and the development of an information-based society, demand for advanced expertise is increasing in Japanese firms.

Given this change, a personnel system that provides incentives for employees with highly specialized knowledge and skills has become more prevalent in Japanese firms since the 1980s[3]. This paper uses the term “specialists” to refer to in-house professionals (Haraguchi 2003) in general corporations; these individuals are employed in a highly specialized occupation and job domain. This paper also uses the term “specialist system” to refer to the personnel system that manages these specialists. The specialist system is usually a dual-ladder career system targeting white-collar workers (Kameshima, 2016), and provides career ladders for both conventional line managers and specialist positions, ensuring that the organization retains and makes efficient use of specialists (Konno and Sato, 2002).

I briefly explain the difference between line managers and specialists. Yashiro (2002) defines line managers as "people who contribute to the organization through managing others" and specialists as "people who contribute to the organization through their expertise." The former are needed to coordinate between functions and departments. Coordination ability is developed through experience in various departments within a firm and can be considered firm-specific human capital. On the other hand, the latter position requires skills and expertise specific to a particular field or service that is considered to be valued across firms. Under the promotion system of Japanese firms, employees who are trained to be managers are likely to acquire broad but shallow skills and are unlikely to have specialized knowledge and skills pertinent to specific fields. The assignment policy for specialist positions may be different from that for line-manager positions because climbing up the specialist career ladder may require occupation-specific human capital rather than firm-specific human capital.

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[3] Ohi (2005) investigated the change in managerial ratio by using the 1979-2004 Wage Censuses and reveled the increase of in "other managerial posts," which are the managerial positions other than department chief, section chief, chief clerk, and foreman. This finding may be attributed to the increase of introducingin the introduction of the professional system.

The contribution of this paper is threefold. First, this paper explores the relationship between job change and the promotion system, including the specialist system, using an econometric approach. If firm-specific human capital is prioritized, the firm prefers internal promotion, and job changers are disadvantaged with regards to promotion. On the other hand, job changers who have accumulated occupation-specific human capital will not necessarily be handicapped with regard to promotion in the specialist system, which focuses on highly specialized knowledge and skills. However, there is little literature on the specialist system. This paper reveals how experiencing job change is associated with the probability of promotion for each path of advancement, i.e., line managers and professionals.

Second, this paper focuses on the relationship between occupation, especially technical workers and specialized professionals (tech-pro workers), and the promotions of job changers in new workplaces. Previous literature has suggested the importance of occupation-specific human capital in determining wages, and that occupation-specific human capital is relatively important for determining wages in technology and professional occupation (Shaw 1987, Sullivan 2010, Zangelidis 2008). The difference in the relative importance of firm-specific human capital to occupation-specific capital may also lead to differences in job assignment patterns across occupations. Additionally, the specialist system, which is the dual-track career ladder for line managers and advanced specialists, is considered to be effective in the management of tech-pro workers (Imano 1986, Haraguchi 2003). Therefore, this paper predicts that for job changers engaged in technology and professional occupations, the possibility of promotion to a specialist position would be higher (due to their higher level of occupation-specific human capital) than that of stayers, who may have the variety of skills that characterize generalists.

Finally, this paper applies DeVaro and Morita's (2013) theory of ILM to the specialist system and examines the hypothesis for the relationship among job changers, occupation type, and promotion. This theory refers to the strong association between firm size and a firm’s preference for internal promotion. Therefore, this paper uses an econometric approach to investigate whether job changers are disadvantaged in promotion depending on firm size.

In summary, the empirical analyses of this paper reveal the following three points: First, for line managers, the promotion probability of job changers is lower on average than that of stayers, regardless of occupation type. This result is consistent with previous literature that has compared the promotions of job changers and stayers within the internal labor market (Ariga, Ohkusa and Brunello 1999, Baker, Gibbs and Holmstrom 1994, Chan 1996). Second, among nontechnical and nonspecialized professionals, which we call administrative and sales workers (admin-sales workers), it is difficult for job changers to be promoted to line managers as firm size increases. This result supports the theory of DeVaro and Morita (2013). On the other hand, this tendency was not observed among tech-pro workers, suggesting that the theory of DeVaro et al. applies only to admin-sales workers.Third, regarding promotions to a specialist ladder, it turns out that job changers are not disadvantaged when compared with stayers. While the theory of ILM has suggested that firms prefer internal promotion, this result implies that job changes are unlikely to be disadvantageous for promotion in the specialist system, which emphasizes workers’ specialized skills and knowledge in specific fields, that is, occupation-specific human capital. This result is consistent with the previous literature, which has found that not only firm-specific human capital but also occupation-specific human capital is important in promotion and hiring (Kwon and Milgrom 2014).

The rest of the article is organized as follows. Section 2 surveys the related literature, Section 3 explains the dataset, and Section 4 presents the empirical strategy. Section 5 explains the results, and Section 6 provides a discussion and conclusions.

2. Previous Literature

2-1. Job Changers and Promotion

The literature on internal labor markets has suggested that firms prefer internal promotion when filling vacancies in managerial positions. This preference can be explained by two approaches. The first is the human capital theory (Lazear 1979). Compared to stayers, job changers have less firm-specific human capital; thus, if changers and stayers have equal amounts of general human capital, the productivity of job changers would be lower than that of stayers. Therefore, companies give priority to stayers over job changers. The second is the perspective of incentives based on tournament theory (Chan 1996). If employers fill a managerial position with an external candidate, stayers will be less incentivized because their probability of promotion becomes lower. Therefore, employers hesitate to promote job changers from the external labor market in order to maintain incentives for stayers to remain at the organization.

Some empirical studies have supported this theory and suggested that job changers are promoted more slowly than stayers (Ono 1995, Ariga, Ohkusa and Brunello 1999, Baker, Gibbs and Holmstrom 1994). However, these studies of internal labor markets have not considered job rank and have ignored occupations, although recent literature has suggested that occupation-specific human capital is valued and that firm-specific human capital is not necessarily significant in determining not only wages, but also promotion and hiring (Kwon and Milgrom 2014).

2-2. Occupation specific human capital and promotion

As mentioned above, recent literature in labor economics has focused on the importance of occupation-specific human capital in determining wages and job assignments, and its relative importance varies across occupations. Specifically, research has suggested that occupation-specific human capital is more valued in professional occupations, e.g., engineers, accountants, and technologists (Kambourov and Manovskii 2009, Sullivan

2010, Zangelidis 2008).

A similar implication is obtained from studies on the Japanese labor market. Using data from the "Survey on Employment Trends" and the "Labor Force Survey", Toda (2010) reported that occupation-specific work experience has a greater effect than age on wages. Literature based on data from surveys of Japanese workers and firms implies that the importance of occupation-specific human capital in determining wages depends on the occupation itself: those in sales, technology, and R&D-related jobs experienced more wage growth from job changes than did those in manufacturing jobs (Ohashi, and Nakamura 2002, Yugami 2001, Naganuma 2014, Kishi 1998).

Because the wage system in ILM corresponds to the job ranking system in general, occupation-specific human capital may also affect promotion and hiring. Although there is little literature that examines the relationship between occupation-specific human capital and promotion or hiring, Kwon and Milgrom (2014) have found that both firm- and occupation-specific human capital are valued in promotion and hiring and that the relative importance of occupation- and firm-specific human capital varies across occupations. However, there is no literature that has comprehensively examined the relationship between Japan’s relatively new promotion system, the specialist system, and different occupations. Furthermore, it is not yet clear whether decreases in firm-specific human capital followed by job changes are associated with promotion in the specialist system.

2-3. Analysis of the Promotions of Technical Workers and Specialized Professionals

This subsection describes the relationship between technology and professional occupation in the specialist system. As mentioned in “1. Introduction”, the specialist system is considered to be effective for managing certain types of professional workers, such as those engaged in R&D, engineering, and IT system integration (Imano 1998, Haraguchi 2003). The details of the system are described as follows: The specialist system is a human resource management system that exclusively manages employees with advanced expertise, skills, and experience in specific fields. The employees are managed according to their skills and career orientation. This system was introduced to Japanese firms mainly for the following three reasons: (1) a lack of managerial positions in the firms, (2) increased specialization in a variety of businesses due to the advancement of knowledge and skills, and (3) changes in career awareness, such as an increase in workers seeking to build expertise (Haraguchi 2003)[4]. The number of Japanese firms introducing the specialist system is increasing; more than half of firms with 5000 or more employees had already adopted it by 2002 (Table 1), according to Ministry of Health, Labour and Welfare's "Personnel Management Survey (Koyo-kanri Chosa)".

Thus, in a worker’s career, where is the fork in the road between the line manager ladder and the specialist ladder? I discuss this issue according to the HRM grade system, the personnel system used by Japanese firms that separates grades from positions. Under this HR system, when firms are filling a managerial position, they select an employee from those who have moved up to a certain grade that corresponds to a certain managerial position (Yashiro, 2002). Therefore, it is assumed that employees have the possibility of being assigned to a managerial position or a specialist position when they have reached those grades that correspond to the managerial level[5].

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[4] Yashiro (1995) pointed out that in case studies of trust banks, two reasons for the why companies to may introduce the specialist system include the facts that are as follows: (1) due to increased business sophistication and intensified competition, it is no longer possible to deal with conduct human resource development centered on conventional rotation and (2) it is necessary to proactively develop those who are not suited to managerial positions.

[5] Yashiro (1995) pointed out that when deciding one's profession, from the viewpoint of training costs, the timing of deciding the area of specialization of employees is moreit is more efficient for employees to choose their area of specialization when it takes place early in one's their career in the company. On the other hand, he also insists on the importance of establishing a period during which an employee can search for a suitable job specialization.

As introduced in “2-2. Occupation-specific human capital and promotion”, occupation-specific human capital is significant in determining not only wages but also promotion and hiring, and the importance of such human capital is relatively high in professional occupations. Because the specialist system offers a career ladder to those who have the highly specialized skills and knowledge necessary for specific jobs, tech-pro workers with advanced expertise may be highly productive even when switching firms and are likely to be promoted to the specialist career ladder. However, it has also been argued that the specialist system is actually a "receptacle" for those who are unable to attain managerial positions and does not truly work as a system to retain people with expert knowledge and skills (Yashiro 2002). This issue will be examined below based on the information obtained from the data.

3. Theoretical Background and Hypotheses

The framework of this paper builds on the literature of ILM, specifically the theory of DeVaro and Morita (2013). Their model focuses on internal promotion versus external recruitment in managerial positions and extends the job assignment and human capital accumulation model for promotion developed by Gibbons and Waldman (1999). Based on the assumption of heterogeneity across firms, they developed a model in which firms prefer internal promotion as opposed to external hiring.

The summary of the model of DeVaro et al. is described as follows: This model assumes that the number of managerial positions is limited and each company has only one manager's position that can be filled either by internal promotion or by hiring mid-career staff from other companies. Because stayers have firm-specific human capital, internally promoted managers tend to have higher productivity than job changers do. Because a firm that has a higher return on managerial capability tends to employ more young workers as managerial candidates and provide managerial training, a firm that favors more internal promotion tends to be larger. In other words, because a large-sized firm that has a fully developed internal labor market has a large enough contestant pool from which to select managers, such a firm needs not recruit managerial candidates from the external labor market. Even if a new employee is hired from another company, his or her prospects for promotion to a managerial position will be lower than the prospects stayers due to their scarcity of firm-specific human capital.

According to that model, this paper considers the case of a firm with a dual-career track personnel system with parallel career paths to managerial positions and specialist positions. This paper assumes that workers are promoted along either the specialist ladder or the managerial ladder according to their accumulated ability and skills. The firm decides whether to prioritize internal promotion or external recruitment for specialist positions and for managerial positions. When tech-pro workers are recruited as mid-career employees and they advance to a job grade that corresponds to a managerial position in the new company, it is difficult for them to be further promoted as line managers, as described above.

On the other hand, for job changers, the probability of promotion up the specialist ladder may not necessarily be lower than that of stayers for the following reasons. First, specialists are required to perform tasks limited to specific technologies and fields of expertise, and such tasks do not require the ability to manage subordinates and coordinate across functions and divisions. Even if someone’s firm-specific human capital is reduced by job changes, tech-pro workers can offer highly developed occupation-specific human capital as long as their occupation remains the same, and there is little difference between job changers and stayers with regard to their abilities to perform the duties required of professional jobs. Moreover, firms may employ job changers who have high-level skills that cannot be developed through internal training. Such highly skilled personnel from the external labor market may have a higher probability of being assigned to a demanding post, that is, a specialist position, because they have higher productivity than stayers when it comes to a specific field or job[6]. I refer to professionals in positions equivalent in rank to managerial positions as "senior specialists." Because senior specialists are not engaged in management, there is no limit on the number of possible positions to fill; thus, the promotion decision can be decided based on more absolute evaluations. Therefore, in terms of incentives associated with promotion, it is no longer necessary to delay the promotions of job changers in order to maintain incentives for stayers, as discussed in Chan (1996).

Based on the above explanation, this paper examines the following hypotheses regarding the promotion of job changers to managerial positions and the promotion to senior specialists.

<Hypothesis 1> The larger the company size is, the smaller the number of job changers.

<Hypothesis 2> Job changers are less likely to be promoted to managerial positions when compared to workers with no job-change experience (“stayers”) who have the same educational background and years of experience.

<Hypothesis 3> The larger the company size is, the stronger the chances of stayers being promoted to managerial positions compared to job changers with the same educational background and years of experience.

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[6]In addition to highly accumulated job skills, there are the following possible reasons for why the job changer has higher occupational-specific human capital:1) the job changer may have a valuable job experience in the previous firms, 2) a job change experience itself may function a signal for his or her higher ability enough to transfer to a new company, 3) if there is an occupation-specific skill standard (e.g. system engineers), he or she may objectively prove his or her occupational-specific human capital to a new firm.

<Hypothesis 4> Job changers engaged in technical and professional fields are more likely to be promoted to senior specialists than are stayers with the same educational background and years of experience.

4. Analysis Framework

4-1. Data

For the analysis, we used answers from individual respondents in the "Working Person Survey 2004, 2006, 2008, 2010, 2012, 2014" (Recruit Works Institute); this survey is archived in the Social Survey and Data Archive Research Center's SSJ data archive at the University of Tokyo Institute for Social Science. This paper uses data for six years, namely, 2004, 2006, 2008, 2010, 2012, and 2014. This survey is a questionnaire survey given to male and female workers from 18 to 59 years of age working within 50 km of the Tokyo Metropolitan Area; it includes those who are working as regular employees, nonregular employees, dispatched subcontractors, and part-time employees. Until 2008, the survey was conducted through the placement method, and since 2010, it has been conducted as an Internet survey. This survey is suitable for investigating the relationship between job changes and occupations because it includes many questions on career change and work experience. However, it should be noted that the survey target is limited to employees within 50 km of the Tokyo Metropolitan Area, and the results obtained do not necessarily represent Japan's entire labor market. The sample used in the analysis is restricted to those who are regular employees and work for companies with 11 or more employees in order to examine the promotion of white-collar workers in the internal labor market. The analysis excludes the following samples for the same reason: those who work in medical occupations or as independent businesspeople, such as doctors, lawyers, accountants, nurses, and radiation technicians; those who work for government offices; and those who are considered blue-collar workers (those in agriculture, forestry, fisheries, production and manufacturing, and those who are difficult to classify). This paper focuses on job changers who have not changed their field of expertise; thus, I exclude samples of those whose occupations were different in their previous jobs in terms of occupation classification as used in the Employment Status Survey (clerical work, sales, marketing, engineering, specialized fields, etc.)[7]. The sample is also restricted to males only in order to maintain the homogeneity of samples because for women, marriage and childbirth may affect retirement and job changes.

4-2. Variables

The answers to the question "about your current job position" on the questionnaire are used to identify the current position of workers. I set those who selected “section chief” or “department chief” as "line manager," and those who selected "professional at a section-chief level" or "professional at a department chief level" as "senior specialists". Among job classifications, we created the "technical workers and specialized professionals(tech-pro workers)" dummy variable, which takes 1 if employees are engineers and those engaged in finance /R&D/ IT-related professions and 0 if they are engaged in the occupations of sales, administration, marketing, and accounting; these employees are called “sales-admin workers”.[8] In addition, we defined "those who changed jobs even once in the past" as "job changers" and created a "job changer dummy variable." As mentioned in the previous section, we excluded those who were in different occupations before and after their job changes. Therefore, the definition of the job change dummy variable here is as follows: "1" for "those who have the experience of changing jobs even once in the past, with the former and current occupational classifications being the same," and "0" for "those who have never changed jobs."

[7] The number of job changers with changing occupation is 3163, and that of without changing occupation is 3562. The latter group is used for analysis as the job changers sample.

4-3. Empirical Strategy

(1) The Relationship Between Company Size and Probability of Job Change

To verify Hypothesis 1, we estimate the relationship between the probability of job changes and current firm size to investigate whether the ratio of job changers decreases as the firm size becomes smaller. As described below, we set the job change dummy as a dependent variable. In addition to the current firm size, explanatory variables include the worker’s individual and firm characteristics such as education, age, tenure, type of industry and survey year. I estimate the following probit model for experiencing job change:

$$Pr(D = 1) = \begin{cases} 1 & if \quad Y_i \geq 0 \\ 0 & otherwize \end{cases}$$

$$Y_i = X_i\beta + \sum \gamma_k firmsize_k + \varepsilon_i$$

D is a dummy variable representing job changes, with "1" used for those who have changed jobs, and "0" used for those who have not. Y_i represents a latent variable for D. X_i represents a vector of control variables including education, age, age squared, potential years of experience and potential years of experience squared, occupation, and industry of worker i. We also control the dummy variable of the survey year. $firmsize_k$ represents five categories of firm size: "99 or fewer people," "100 to 299 people," "300 to 999 people," "1000 to 4999 people," and "5000 or more people." ε_i is an error term.

(2) Estimation for Promotion Probability Using a Propensity Score Matching Method

The objective of this paper is to examine the relationship between experiencing job change and promotion in the dual career ladder system. However, when evaluating the influence of career change experience on subsequent career processes in a nonexperimental setting, there is an issue of self-selection in decision-making for job change. To verify Hypotheses 2, 3, and 4, this paper employs the propensity score matching method.

The propensity score matching method allows us to compare those who have experience changing jobs with those who do not have such experience but have similar individual characteristics using the predicted probability (propensity score) of the job change. Controlling for the propensity score ensures that we are comparing those who have the same range of characteristics that may affect the decision to change jobs. Murakami (2003) has identified the following variables as factors that may affect workers' job change decisions: the worker's age, educational background, occupation, and company size.

I make the following two assumptions, considering the case in which the decision about a job change depends on the value of the individual attribute X.

$$(Y_1, Y_0) \perp D \vee X \tag{1}$$

$$0 < P(D = 1 \vee X) < 1 \tag{2}$$

Equation (1) is called a strongly ignorable treatment assignment (Rosenbaum and Rubin, 1983). Y is the current promotion status. Conditioning the value of the individual attribute X, which is a covariate, means that the simultaneous distribution of the potential outcome Y_1 in the case of job change experience (D = 1) and the potential outcome Y_0 in the case of no job change experience are independent regardless of having the experience of a job change. Equation (2) is called an overlap assumption, which means that there are people who have no job change experience but have similar attributes corresponding to all those who have experienced a job change. Under assumption (1), conditional on the probability of experiencing a job change, $Pr(D = 1|X_i)$, having experience of a job change and potential outcomes Y_1 and Y_0 become independent. This $Pr(D = 1|X_i)$ is estimated from the data and is defined as the propensity score. This paper uses the following probit model to estimate the propensity score.

$$P(X_i) = Pr(D = 1|X_i) = \Phi(X\beta) \qquad (3)$$

D is a dummy variable indicating the experience of job changes. X represents a vector of control variables including potential labor market experience after graduation, the square of potential experience, the cube of potential experience, highest level of education, industry, occupation, and company size. For those employees with experience changing jobs, the industry, occupation, and company size of their former companies are used.

Next, samples are divided into two occupational subgroups, tech-pro workers and admin-sales workers. For each subgroup, analysis for the relationship between experiencing job change and promotion probability is conducted after adjusting the covariates using the propensity score obtained from Equation (3). The promotion status of workers is classified into three groups: (1) those with no position, (2) senior specialists, and (3) line managers. Using a multinomial probit model, I estimate the probability of the firm's deciding each assignment. I consolidate section manager level and department chief level into one managerial position in estimating the promotion probability. Y_i = 0 stands for individuals *i* without positions, Y_i = 1 for senior specialists, and Y_i = 2 for general managers. Assuming that the quasi-rents resulting from each job position are R_{i0}, R_{i1}, and R_{i2}, the estimation model is a multinomial probit model as follows[8].

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[8] The multinomial probit model allows relaxation of the IIA assumption, in which the choice between two pairs of alternatives in the dependent variable must be simply a binary probit model (Cameron and Trivedi 2010).

$$Y_i = \begin{cases} 0 & if \quad R_{i0} \geq R_{i1}, \quad R_{i0} \geq R_{i2} \\ 1 & if \quad R_{i1} \geq R_{i0}, \quad R_{i1} \geq R_{i2} \\ 2 & if \quad R_{i2} \geq R_{i1}, \quad R_{i2} \geq R_{i0} \end{cases}$$

$$R_{ij} = X_i\beta + \gamma_1 external + \sum \sigma_k external * firmsize_k + \varepsilon_{ij} \qquad (4)$$

R_{ij} represents a quasi-rent in position j of worker i. X_i represents a vector of control variables that consists of individual characteristics of employees that include age, age squared, tenure, tenure squared, a marriage dummy variable, an educational dummy variable, and corporate factors that include firm size categories, industry categories, and year dummy variable. $external$ represents a job change dummy that is set to 1 if one has job change experience and 0 if one does not. $firmsize_k$ represents the five categories of firm size as used to estimate Equation (1). To verify the relationship between firm size and internal promotion as presented in Hypothesis 2, we add an interaction term for each firm size category and a job change dummy variable. The estimate of Equation (4) employs the weighted least squares method, which uses propensity scores as weights. This method, which was proposed by Hirano, Imbens, and Ridder (2003) and Hirano and Imbens (2001), is a Horvitz-Thompson type estimation method that weighs the reciprocal of the treatment assignment probability. The weighting ω_i of Equation (5) is created from the propensity score calculated by Equation (3). Then, we estimate Equation (4) by using the weighted maximum likelihood method using this calculated weight.

$$\omega_i = \sqrt{\frac{D_i}{P(X_i)} + \frac{1-D_i}{1-P(X_i)}} \qquad (5)$$

When performing a propensity score matching estimation, we exclude samples of those who have changed jobs when there are not corresponding samples of those who have not changed jobs, and we only perform an analysis when there is common support in cases when a person who has changed jobs and a person who has not changed jobs match on a propensity score.

5. Descriptive statistics

Summary statistics for the variables used in the analysis are shown separately in Table 2 for job changers and stayers. Let us discuss whether the position of senior specialists is just the pool of line-manager candidates who have queued for promotion. If senior specialist positions serve as an alternative for those who cannot become managers regardless of occupation, it is likely that the ratios of senior specialists will be similar among both tech-pro workers and admin-sales workers. It is also likely that there will be growing wage disparities between senior specialists and line managers. Below, these issues are examined separately at the level of each managerial position.

First, for the section-chief level, Table 3-1 shows the ratios of senior specialists and managerial workers depending on firm size, type of occupation and experience of job change. The table shows that the ratio of senior specialists is smaller than that of line managers regardless of occupation and firm size, and this tendency becomes more salient in larger companies. However, when analyzed by occupation, this gap in the ratio of senior specialists is larger among admin-sales workers than among tech-pro workers. In comparisons between job changers and stayers, at firms with no more than 999 employees, tech-pro workers experiencing job change are more likely than stayers to become senior specialists. On the other hand, this relationship does not hold for admin-sales workers. For the department chief level, Table 3-2 shows similar results.

Tables 4-1 and 4-2 show the average annual income for the same categories. For section-chief level, Table 4-1 shows that the average wage for senior specialists among admin-sales workers is lower than that of line managers in the same occupation regardless of firm size. However, this gap is narrower in tech-pro workers than in admin-sales workers. Among tech-pro workers at firms with 100-999 employees, senior specialists earn as much as line managers do. This result indicates that among tech-pro workers, the senior specialist path is not an alternative for those who cannot become line managers, at least in medium-sized firms. Among job changers who are tech-pro workers, senior specialists on average earn higher wages than line managers do at companies with at least 300 workers. This finding indicates that people who engage in professional work after changing jobs may be more productive than those who become line managers.

For the department chief level, Table 4-2 shows the average wage. For both occupations, the average wage for senior specialists is lower than that of those in managerial positions when job changers and stayers are combined. This finding implies that senior specialist positions do not provide a career path equivalent to that of line manager positions. Among job changers, senior specialists of both occupations at companies with at least 1,000 workers earn wages equivalent to those of line managers. However, among stayers, senior specialists have lower average wages than line managers do regardless of occupation and firm size. At companies with at least 1,000 workers, senior specialists who are job changers earn as much as stayers regardless of occupation. This finding indicates that job changers who have strong skills may be highly productive in their new positions as specialized professionals.

In summary, there are fewer senior specialist positions than line manager positions regardless of occupation. This tendency is particularly noticeable among larger companies. However, among administrative/sales workers, the difference in ratios between senior specialists and line managers is larger than among tech-pro workers. This finding implies that there are more senior specialist positions among tech-pro workers. With respect to remunerations, senior specialists who are tech-pro workers at medium-sized companies earn wages comparable to those earned by line managers, indicating that they may be on an independent career path. At the department-chief level, senior specialists have lower average wages regardless of occupation and firm size. Thus, they are not on a career track comparable with that of line managers. However, it is also suggested that at medium- and large-sized companies, highly skilled persons who are senior specialists may be more productive in specialist positions than those in line manager positions. For at least the section-chief level, at small- and medium-sized companies, tech-pro workers who are senior specialists earn wages on par with those of line managers, and thus, they may be on an independent career track. The next section will analyze the results of estimates regarding job changers' promotions by controlling for various factors.

6. Estimate results

6-1. The relationship between the probability of job changes and company size

Table 5 presents the results of probit estimation for the share of employees with job change. The table only shows the coefficients and the marginal effects of each firm size category. Each category shows a significant negative coefficient compared with companies with no more than 99 employees, which is used as a reference group for firm size categories. The coefficient and the marginal effect increase in absolute value as the company's size increases. Even after controlling for workers' education, years of experience, and the industries to which the companies belong, the proportion of job changers is lower in the large firms. These results support Hypothesis 1, suggesting that large companies with a well-developed internal labor market are less willing to recruit mid-career workers.

6-2. Estimates for propensity scores

Table 6 shows the results of probit estimates for job changes described in Equation (3). Table 6 shows that individual and firm characteristics are significantly related to the probability of job changes. The larger the potential years of experience and the lower the educational level, the larger the probability of job changes. The probability of job changes is also significantly higher for those in transport and telecommunications than those in services, while the probability is low among those who have clerical positions. With respect to industries, the probability of job changes is significantly high for those in finance, insurance, and other fields compared with those in agriculture, forestry, and fisheries. There is also a significant relationship between firm size and the probability of job changes; the larger the company is, the lower the probability of job changes.

6-3. Matching estimates

Tables 7-1 and 7-2 show the results of matching estimates – using the propensity scores – regarding employees' promotions to section chiefs or higher managerial positions. Model 1 adds only a job-change dummy to control variables, while Model 2, without including the main effects of a job-change dummy, has an interaction term for firm size categories and a job-change dummy to confirm the relationship between job changes and promotions by firm size.

Table 7-1 shows the results of tech-pro workers. For promotions to senior specialists, the coefficient of the job-changing dummy is not significant for Model 1, and this result does not support Hypothesis 4. In Model 2, the coefficients for the interaction term with all firm-size categories are not significant. For tech-pro workers, the probability of promotion to senior specialists is not associated with an experience of changing jobs or with firm size. For promotion to line managerial positions, the coefficient of the job-change dummy for Model 1 is significantly negative at the 10 percent level. This means that job changers in technology and professional occupations are unlikely to advance to managerial positions, supporting Hypothesis 2. In Model 2, only the coefficient of the interaction term between firms with 11 and 99 employees and the job change dummy show a significantly negative value. Thus, it cannot be established that the larger the company, the harder it is for job changers to be promoted to line managers. Consequently, Hypothesis 3 is not supported.

Table 7-2 shows the results for admin-sales workers. For promotion to senior specialist, the coefficient of the job-changing dummy in Model 1 is not significant, and the coefficients of the interaction term between job changes and firm size categories in Model 2 are not significant either. Among administrative workers, neither experience of job changes nor company size are related to promotion to senior specialist. For promotions to line managers, in Model 1, the coefficient of the job change dummy is negative, meaning that job changers in admin-sales occupations are unlikely to be promoted to line managers. However, this relationship is weak because the figure is not statistically significant. In Model 2, the coefficient of the interaction term with companies with 11–99 employees has a significantly positive value, while the coefficient of the interaction term for companies with over 5,000 employees has a significantly negative value. This shows that job changers in admin-sales occupations at large firms are unlikely to be promoted to line managers. This result is consistent with Hypothesis 3.

In summary, Hypothesis 1 is supported; there are few mid-career employees in the large firms. According to DeVaro and Morita (2013), large-sized firms are reluctant to hire mid-career employees and prefer internal promotion due to the sufficient managerial candidate pools available in the internal labor market. Next, Hypothesis 2 is supported. Job changers are unlikely to be promoted to line manager positions, which is an important post in the management of the firm regardless of occupation type. Hypothesis 3 is supported only for administrative and sales occupations. Job changers in admin-sales occupations are unlikely to be promoted to line managers at large companies with a well-developed internal labor market. However, this tendency is not observed for tech-pro workers. Table 3-1 also shows that admin-sales workers have a relatively high ratio of being promoted to line managers. These results suggest that DeVaro et al.'s theory applies only to admin-sales workers, who are often trained to become line managers. Firm-specific human capital is more valuable in admin-sales occupations, and large firms tend to provide employees with internal training to foster management personnel in that occupational field. As a result, job changers with less firm-specific human capital are disadvantaged with regards to promotion to line manager positions.

On the other hand, in the case of tech-pro workers, with the exception of small firms, the probability of promotion to line manager positions among job changers is not significantly lower than among stayers. The previous case study, which interviewed the system integration company, found that the tasks of some project managers were standardized to a great extent and that firm-specific knowledge was relatively less important (Senda et al. 2008). Furthermore, some empirical studies have found that skills in professional occupations are primarily occupation-specific (Sullivan 2010, Shaw 1987, Zangelidis 2008). These findings imply that firm-specific human capital is less important for line managers in tech-pro occupations and, for this reason, firms need not foster personnel within the internal labor market. The premise of DeVaro et al.'s theory is that emphasis on firm-specific human capital among line managers may not apply to tech-pro workers, and this explanation is consistent with our estimation result: among tech-pro workers, the probability of promotion to line manager positions does not seem to be related to the size of firms. In terms of incentives, there is a trade-off between motivating stayers and acquiring mid-career persons with high-level skills. There may be cases in which hiring people externally would be more efficient even though the motivation of stayers would decrease.

While Hypothesis 4 was not supported, our estimation results imply that regardless of occupation, job changers are not at a disadvantage in terms of being promoted to senior specialist positions when compared with stayers. The specialist system evaluates workers' specialized skills and knowledge, which is included in occupation-specific human capital. Thus, whether or not someone has experienced job change may not be associated with promotion to senior specialist positions.

These results do not take into account the problem of endogeneity involving job changers' decisions to quit their positions. Thus, there is a possibility that the estimated values may be biased. The analysis that follows considers this endogeneity and examines the soundness of the aforementioned results.

7. Robustness Check: Analysis Restricted to Samples with Negative Turnover Reasons

Additional analysis is conducted with restricted job changers who had negative reasons for quitting their previous jobs to examine the robustness of the results obtained in "3 Matching Estimates." Previous literature has suggested that the difference in reasons for turnover may affect wage growth in job change due to the difference in the extent of job matches (the degree to which the skills and aptitudes of individual workers match the requirements of their jobs) in firms after job change (Ohashi and Nakamura 2002). Those with high capabilities and a strong likelihood of successfully changing jobs may search for a new job and leave their current firm to improve job matches and, as a result, may be likely to be promoted at their new workplace. Conversely, those who changed jobs for reasons other than matching improvement tend to see their matching decrease at their new workplace. As a result, they may not be easily promoted. Thus, to confirm the robustness of the results of Tables 7-1 and 7-2, an analysis was conducted regarding promotions among job changers who left their previous work for reasons other than matching improvement.

This paper employs the same categories of reasons for turnover as those used in Ohashi and Nakamura (2002), who classified the reasons for turnover into the following four categories: 1) "company circumstances," such as dismissals and mandatory retirements, 2) an attempt to "improve job matching" by those who believe that their jobs are not suited to their abilities and aptitudes, 3) an "elimination of dissatisfactions" related to problems at work, such as those of human relations and 4) "family circumstances" such as marriage and childrearing. This paper adds one more category: 5) “other/no answer” to the above classification and adds “Starting one’s own business/becoming independent by acquiring necessary work credentials” to the category of 2) “improving matching.”

Using the above categories, two types of analysis were conducted. First, an analysis was conducted to investigate whether there are any differences between the two types of occupations with respect to the ratios of the reasons for turnover. The results are shown in Table 8. Among firms with fewer than 5,000 employees, no major differences were observed between tech-pro workers and admin-sales workers in the ratios of the reasons for leaving jobs. Therefore, it cannot be confirmed that the number of employees who quit their jobs to “improve matching” is particularly high among tech-pro workers. However, for firms with over 5,000 employees, the percentage of tech-pro workers who quit because of “company circumstances” or “dissatisfaction with organizational or human relationships” is lower compared with admin-sales workers. Instead, among admin-sales workers, there is a greater percentage of people who quit to “improve matching”. These results imply that tech-pro workers who have felt unmatched to their previous firms are likely to move to larger organizations to improve their matching.

Next, to confirm the robustness of the results of Tables 7-1 and 7-2, analysis was conducted restricted to the sample of job changers based on their reasons for quitting. As mentioned above, those who changed jobs for reasons other than matching improvement tend to see their matching decrease at their new workplace, and they may not be easily promoted. We analyzed promotions among job changers who left their work for reasons other than matching improvement; these reasons are “company circumstances,” “family circumstances,” or an attempt to “eliminate dissatisfaction.” These three reasons are consolidated to one category and are referred to as “company circumstances/ negative” reason for turnover. As in the case of Table 7, a multinomial probit model estimate was conducted using propensity score matching. Table 9-1 shows the results for tech-pro workers. For promotion to senior specialists, the coefficient of the job-change dummy is significantly negative in Model 1. For Model 2, only the coefficient for the interaction term of companies with at least 5,000 employees shows a significantly negative value. The probability of promotion to senior specialist positions is lower for tech-pro workers than in the main analysis represented in Table 7-1. This result may be due to the elimination of those have quit their jobs to improve their matching, as Table 8 shows that among tech-pro workers, the percentage of those who quit to improve their matching is relatively high. For promotions to line managers, the results are similar to those in Table 7-1, which shows that in tech-pro occupations, firm size seems not to be associated with the relationship between job changes and promotions to managerial positions.

For admin-sales workers, Table 9-2 shows the results of estimation, which are similar to Table 7-2 with respect to promotions to senior specialist and line management positions. That is, admin-sales workers with job changes have difficulty being promoted to managerial positions at larger companies. This tendency is not observed among tech-pro workers with job changes. As is the analysis of Table 7-2, DeVaro et al.'s theory only applies to admin-sales workers.

8. Conclusion

This paper examined the relationship between job changes and promotion by focusing on occupation type using questionnaire survey data for male white-collar regular workers. This paper also conducted a propensity score matching method to correct for biases derived from the endogeneity of self-selection for job change. The main conclusions are summarized in the following three points.

First, large firms are reluctant to hire mid-career workers from external labor markets. According to the theory of DeVaro and Morita (2013), larger companies have a sufficient candidate pool when hiring managers and prefer internal promotion. This result can also be interpreted in terms of the wage seniority system theory (Lazear

1979). The larger a company is, the more likely it is to use the wage seniority system, which assumes lifetime employment. Hence, it is difficult for these companies to accept job changers from external labor markets.

Second, regardless of occupation, the probability that job changers will be promoted to line managers is lower, on average, than that of stayers. Line managers are so critical to management and so essential to coordination within the organization that stayers with enough firm-specific human capital are likely to be promoted to this position. Furthermore, it is found that admin-sales workers with job changes are unlikely to be promoted to line managers as firm size increases. This result supports the theory of DeVaro and Morita (2013). On the other hand, this relationship was not confirmed for tech-pro workers, suggesting that the theory of DeVaro et al., which emphasizes firm-specific human capital, may apply only to admin-sales occupations. The reason why, for tech-pro workers, there was no clear association between the probability of being promoted to line manager and firm size is that firm-specific human capital is relatively unimportant among tech-pro workers and firms need not necessarily have a large candidate pool for these types of jobs. Therefore, looking at firm size, there is little difference in the relationship between job change and promotion to line manager; this finding indicates the thickness of the internal labor market. Consequently, DeVaro's premise may not apply to tech-pro workers. This explanation is valid in terms of previous literature that has suggested relative importance of occupational-specific human capital in technology and professional occupations (Shaw 1978, Sullivain 2010, Zangelidis 2008).

In terms of incentive theory, firms may derive such a large return from the advanced skills and knowledge of tech-pro workers that there is a trade-off between incentives for stayers and the returns obtained by acquiring skilled personnel from external labor markets. It has been noted that in recent years, managers are required to take up the role of "playing-manager," which means they serve as both players and managers (Ohi, 2005). This implies that even line managers often have to simultaneously perform both coordination and task duties. Further investigation is necessary to describe in more detail the new role of line managers in technical/specialized jobs.

Third, the analysis shows that when compared with stayers, job changers are not disadvantaged with regards to promotions to senior specialist positions. Previous studies have shown that those with experience changing jobs are less likely to be promoted (Ariga et al. 1999, Lazear 1979, Chan 1996), but the analysis reveals that this tendency may not be applicable to the specialist system, which emphasizes workers' occupational human capital, such as specialized knowledge and skills, in specific occupational fields. Based on the comparison of annual incomes among job changers (see Table 4-2), it has been suggested that in large companies, regardless of occupation, senior specialists have higher income in their new firms than those in line manager positions. This finding may imply the importance of professional vocational ability in career change. I pointed out in "III. Theoretical Background and Hypothesis" that in the specialist system, workers are more likely to be evaluated purely on criteria for promotion. Strict examinations for promotion are usually conducted for manager candidates, but in the specialist system, particularly in industries such as IT, there is a tendency towards establishing a promotion standard in accordance with skill levels based on industry-wide standards (Yatsushiro 1995, Senda et al. 2008). If promotion to senior specialist positions is based on objective skill standards pervasive in occupations across firms, then external recruiting for higher positions may not necessarily lead to a decrease in motivation for stayers. Professional workers may compete for promotions among workers in the same occupation rather than among workers within the internal labor market. The recruitment of mid-career staff is also becoming common in Japanese companies, and since the introduction of the specialist system in more than half of Japan's large companies, it is presumed that the existence of job changers in the specialist system is not a special case. Elucidating how firm size and the acceptance of job changers fit into the specialist system is a subject for later discussion.

Finally, I cite remaining challenges and future prospects. Professional jobs have not necessarily been precisely evaluated, and those engaged in such jobs often have to expect high costs when they change jobs (Higuchi 2001). Technical vocational ability forms the basis of industrial development and has occupied an important position in the economic development of Japan. It is hoped that technological development will end Japan's economic stagnation. It is desirable to have a system in which legitimate evaluations and rewards are granted to those with technical and specialized vocational abilities. This paper uses cross-sectional data to analyze the current promotion status of job changers. In the future, examining – using a panel dataset – whether there are differences between job changers and stayers in the speed of promotion and the frequency of transfer to other functions will elucidate the career paths of job changers in the internal labor market. Using personnel data for each company will provide details on workers and long-term promotion/transfer information. It is desirable to accumulate research using insider econometrics focusing on individual companies. To further clarify the incentive structure of the internal labor market, it is also necessary to examine the relationship between promotions and wages. We will need to further analyze this point again in the future.

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Table 1: The ratios of firms that use the specialist system

Firm Size	1981	1987	1990	1993	1996	1999	2002
Total	7.1	13.0	16.2	18.1	19.9	18.2	19.5
5000 over	36.2	43.5	57.8	60.3	58.9	51.5	50.7
1,000 ～ 4,999	28.1	32.9	43.0	45.3	44.9	39.2	43.3
300 ～ 999	14.0	28.1	36.2	33.5	34.0	35.3	37.3
100 ～ 299	8.1	19.6	17.9	22.8	23.6	21.9	23.1
30 ～ 99	5.6	9	13.0	14.2	16.5	14.7	15.9

Data Source: Ministry of Health, Labour and Welfare. “Survey of Employment Management (Koyo Kanri Chosa)”

Table 2: Summary statistics

	Stayers			Job Changers		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Age	9572	39.064	10.504	3,562	40.530	8.791
Tenure	9572	16.401	10.736	3,562	7.427	7.135
Education	9572	15.146	2.112	3,562	14.390	2.353
Annual Income (Yen)	9049	655.591	305.747	3,372	583.606	258.808
Line Manager	9572	0.247	0.431	3,562	0.181	0.385
Senior Specialist	9572	0.092	0.289	3,562	0.090	0.286
Technology and Profession	9572	0.412	0.492	3,562	0.401	0.490
Agriculture	9572	0.002	0.048	3562	0.001	0.024
Infulastructure	9572	0.022	0.145	3562	0.008	0.090
Service	9572	0.371	0.483	3,562	0.469	0.499
Communication and Transport	9572	0.079	0.269	3,562	0.101	0.301
Finance	9572	0.083	0.276	3562	0.056	0.230
Manufacturing	9572	0.388	0.487	3562	0.287	0.453
Medical Welfare	9572	0.021	0.142	3562	0.031	0.174
Others	9572	0.034	0.182	3562	0.046	0.210
Firm size(less than 99)	9572	0.149	0.356	3562	0.387	0.487
Firm size(100-299)	9572	0.125	0.331	3562	0.193	0.395
Firm size(300-999)	9572	0.182	0.386	3562	0.171	0.377
Firm size(1000-4999)	9572	0.243	0.429	3562	0.139	0.346
Firm size(5000 over)	9572	0.302	0.459	3562	0.111	0.314

Table 3-1: The ratioSECs of line manager and senior specialists (section-chief level)

Firm Size		99 or less		100-299		300-999		1000-4999		5000 and over	
		Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager
Tech-pro Workers	Stayers	5.70	8.94	6.62	9.49	6.17	11.36	8.46	14.96	7.32	15.84
	Job Changers	8.15	6.52	7.22	9.51	9.24	7.23	7.89	12.22	6.67	12.11
	Total	6.96	7.70	6.84	9.50	6.96	10.29	8.37	14.51	7.24	15.39
Admin-sales workers	Stayers	3.99	9.08	5.44	13.81	5.54	18.77	6.55	18.81	7.80	22.00
	Job Changers	4.09	10.11	4.94	12.47	5.26	16.34	6.91	14.14	6.54	8.88
	Total	4.04	9.57	5.26	13.33	5.47	18.14	6.62	17.93	7.65	20.49

Table 3-2: The ratios of line manager and senior specialists (department-chief level)

Firm Size		99 or less		100-299		300-999		1000-4999		5000 and over	
		Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager
Tech-pro Workers	Stayers	3.04	7.22	3.53	6.62	2.95	6.17	2.46	7.19	2.07	8.68
	Job Changers	3.26	7.43	2.28	7.22	4.82	4.42	3.68	3.16	1.67	2.78
	Total	3.15	7.33	3.07	6.84	3.43	5.72	2.65	6.55	2.02	7.94
Admin-sales workers	Stayers	2.88	8.19	2.39	11.82	1.85	11.38	2.13	10.97	3.35	9.14
	Job Changers	2.29	11.19	1.18	8.24	2.77	5.54	2.96	6.58	3.27	6.07
	Total	2.60	9.63	1.95	10.53	2.09	9.86	2.29	10.14	3.34	8.79

Table 4-1: The average annual income of line manager and senior specialists (section-chief level)

Firm Size		99 or less		100-299		300-999		1000-4999		5000 and over	
		Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager
Tech-pro Workers	Stayers	549.62	648.18	762.41	661.20	753.59	771.71	818.27	866.48	943.79	992.24
	Job Changers	618.45	643.43	700.78	706.82	742.39	673.33	825.33	798.57	1092.73	976.19
	Total	592.13	646.08	738.81	677.39	749.44	753.26	819.34	857.99	960.51	990.62
Admin-sales workers	Stayers	578.00	652.64	663.41	694.94	679.43	767.06	825.92	857.76	876.86	990.81
	Job Changers	594.38	608.65	701.00	671.55	704.38	751.85	874.25	827.00	872.54	1074.39
	Total	585.94	630.22	675.74	687.51	685.13	763.61	835.30	853.38	876.46	994.97

Table 4-2: The average annual income of line manager and senior specialists (department-chief level)

Firm Size		99 or less		100-299		300-999		1000-4999		5000 and over	
		Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager	Senior Specialist	Line Manager
Tech-pro Workers	Stayers	660.13	718.33	780.00	900.71	887.89	889.05	937.92	1103.29	1032.92	1189.60
	Job Changers	584.38	753.23	796.67	917.22	809.00	891.82	1063.33	968.33	1000.00	1100.00
	Total	622.25	736.48	784.55	907.17	860.69	889.62	963.00	1092.35	1029.26	1185.41
Admin-sales workers	Stayers	632.92	813.19	745.29	891.11	873.47	969.82	950.00	1093.53	1034.42	1221.31
	Job Changers	622.58	744.89	920.00	943.87	836.50	953.16	951.11	948.95	1221.43	1185.38
	Total	628.35	775.15	785.00	905.58	859.78	967.42	950.29	1075.45	1056.61	1218.33

Table 5: Estimation of the probability of job changes

	Coefficient		Marginal Effect	
Firm size(100-299)				
	-0.3233	***	-0.0917	***
	[0.0392]		[0.0110]	
Firm size(300-999)				
	-0.6224	***	-0.1770	***
	[0.0382]		[0.0105]	
Firm size(1000-4999)				
	-0.9323	***	-0.2650	***
	[0.0387]		[0.0103]	
Firm size(5000 over)				
	-1.1359	***	-0.3220	***
	[0.0403]		[0.0105]	
Tenure、Age、Education	Yes			
Occupation, Industry, Year	Yes			
N	13,342			
Loglikelihood Ratio	-6881.5478			

Notes: The reference group is Firm size (less than 99)

Significance levels: ***p<0.01, **p<0.05, *p<0.1,

Table 6: Estimation of propensity score (Probit Model)

Y:Job change dummy	Coefficient		Marginal Effect	
Security				
	0.0182		0.0053	
	[0.2036]		[0.0587]	
Communication and Transportation				
	0.5634	***	0.1620	***
	[.08917]		[0.0256]	
Administration				
	-0.1647	***	-0.0475	***
	[.05444]		[0.0157]	
Sales				
	0.0433		0.0125	
	[.05561]		[0.0160]	
Technology				
	0.0690		0.0199	
	[.05223]		[0.0151]	
Profession				
	-0.1341		-0.0386	*
	[0.0808]		[0.0233]	
Firm size(20〜29)				
	-0.0459		-0.0132	
	[0.0789]		[0.0227]	
Firm size(30〜49)				
	-0.0432		-0.0124	
	[0.0728]		[0.0210]	
Firm size(50〜99)				
	-0.1242	*	-0.0358	*
	[0.0668]		[0.0192]	
Firm size(100〜299)				
	-0.3571	***	-0.1030	***
	[0.0612]		[0.0176]	
Firm size(300〜499)				
	-0.5445	***	-0.1570	***
	[0.0684]		[0.0196]	
Firm size(500〜999)				
	-0.6449	***	-0.1860	***
	[0.0657]		[0.0187]	
Firm size(1000〜1999)				
	-0.7496	***	-0.2160	***
	[0.0667]		[0.0189]	
Firm size(2000〜4999)				
	-0.9515	***	-0.2740	***
	[0.0666]		[0.0188]	
Firm size(5000 and over)				
	-1.1066	***	-0.3190	***
	[0.0621]		[0.0173]	
Tenure、Age、Education	Yes			
Industry, Year	Yes			
N	13231			
Loglikelihood Ratio	-6750.7609			

Notes: The reference group is Service occupation, Firm size (10-19)

Significance levels: ***p<0.01, **p<0.05, *p<0.1,

Table 7-1: Propensity score matching estimation (Tech-pro workers)

	Model 1				Model 2			
	Senior Specialist		Line Manager		Senior Specialist		Line Manager	
	Coef	ME	Coef	ME	Coef	ME	Coef	ME
Job change dummy	-0.0790	0.0022	-0.2497 *	-0.0327 *				
	[0.1386]	[0.0146]	[0.1369]	[0.0179]				
Firm size(11〜99)×Job change	-	-	-	-	-0.2409	-0.0067	-0.4652 **	-0.0566 *
	-	-	-	-	[0.2102]	[0.0220]	[0.2294]	[0.0301]
Firm size(100～299)×Job change	-	-	-	-	-0.1352	-0.0202	0.0995	0.0206
	-	-	-	-	[0.2372]	[0.0253]	[0.2279]	[0.0307]
Firm size(300～999)×Job change	-	-	-	-	0.3272	0.0459 *	-0.1731	-0.0401
	-	-	-	-	[0.2358]	[0.0253]	[0.2258]	[0.0301]
Firm size(1000～4999)×Job change	-	-	-	-	-0.0452	0.0045	-0.2141	-0.0290
	-	-	-	-	[0.230]	[0.0243]	[0.24170]	[0.0321]
Firm size(5000 and over)×Job change	-	-	-	-	-0.2094	-0.0093	-0.3278	-0.0380
	-	-	-	-	[0.2406]	[0.0260]	[0.21308]	[0.0287]
Year, Education, Industry	Yes				Yes			
Age、Tenure	Yes				Yes			
N	5376				5376			
Loglikelihood Ratio	-6132.6768				-6118.1			

Notes: Significance levels: ***p<0.01, **p<0.05, *p<0.1,

Table 7-2: Propensity score matching estimation (Admin-sales workers)

	Model 1				Model 2			
	Senior Specialist		Line Manager		Senior Specialist		Line Manager	
	Coef	ME	Coef	ME	Coef	ME	Coef	ME
Job change dummy	0.0943	0.0155	-0.1100	-0.0243 *				
	[0.1198]	[0.0122]	[0.1029]	[0.0172]				
Firm size(11〜99)×Job change	-	-	-	-	0.2158	0.0079	0.3159 **	0.0461 *
	-	-	-	-	[0.1962]	[0.0197]	[0.1570]	[0.0261]
Firm size(100〜299)×Job change	-	-	-	-	-0.1540	-0.0104	-0.1267	-0.0152
	-	-	-	-	[0.1956]	[0.0198]	[0.1714]	[0.0289]
Firm size(300〜999)×Job change	-	-	-	-	0.0731	0.0153	-0.1557	-0.0313
	-	-	-	-	[0.1919]	[0.0195]	[0.1575]	[0.0266]
Firm size(1000〜4999)×Job change	-	-	-	-	0.2410	0.0307 *	-0.1007	-0.0296
	-	-	-	-	[0.1827]	[0.0186]	[0.1807]	[0.0302]
Firm size(5000 and over)×Job change	-	-	-	-	-0.0493	0.0250	-0.6282 ***	-0.1099 ***
	-	-	-	-	[0..2200]	[0.0225]	[0.1978]	[0.0332]
Year, Education, Industry	Yes				Yes			
Age、Tenure	Yes				Yes			
N	7758				7758			
Loglikelihood Ratio	-9687.8785				-9648.7			

Notes: Significance levels: ***p<0.01, **p<0.05, *p<0.1,

Table 8: Distribution of reason for turnover by occupation and firm size

		99 or less		100-299		300-999		1000-4999		5000 and over	
		Admin-sales	Tech-pro	Admin-sales	Tech-pro	Admin-sales	Tech-pro	Admin-sales	Tech-pro	Admin-sales	Tech-pro
Company dircumstances	N	135	107	59	43	52	33	41	29	25	12
	%	16.92	19.89	14.25	16.41	14.61	13.52	13.76	15.26	11.90	6.70
Improving job matching	N	424	271	223	130	191	139	149	95	110	117
	%	53.13	50.37	53.86	49.62	53.65	56.97	50.00	50.00	52.38	65.36
Elimination of dissatisfactions	N	165	112	89	58	84	45	80	53	60	33
	%	20.68	20.82	21.50	22.14	23.60	18.44	26.85	27.89	28.57	18.44
Family circumstances	N	30	14	22	5	5	11	8	1	3	2
	%	3.76	2.60	5.31	1.91	1.40	4.51	2.68	0.53	1.43	1.12
Others	N	44	34	21	26	24	16	20	12	12	15
	%	5.51	6.32	5.07	9.92	6.74	6.56	6.71	6.32	5.71	8.38
Total	N	798	538	414	262	356	244	298	190	210	179
	%	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 9-1: Propensity score matching estimation restricted to job changers with negative reason for turnover(Tech-pro workers)

	Model 1				Model 2			
	Senior Specialist		Line Manager		Senior Specialist		Line Manager	
	Coef	ME	Coef	ME	Coef	ME	Coef	ME
Job change dummy	-0.5353 **	-0.0405 *	-0.4994 **	-0.0428 *	-	-	-	-
	[0.2532]	[00242]	[0.2310]	[0.0253]	-	-	-	-
Firm size(11〜99)×Job change	-	-	-	-	-0.5134	-0.0258	-0.8069 ***	-0.0838 **
	-	-	-	-	[0.3258]	[0.0325]	[0.2808]	[0.0324]
Firm size(100～299)×Job change	-	-	-	-	-0.3492	-0.0307	-0.2175	-0.0143
	-	-	-	-	[0.3580]	[0.0362]	[0.3547]	[0.0417]
Firm size(300～999)×Job change	-	-	-	-	0.0717	0.0233	-0.3846	-0.0525
	-	-	-	-	[0.4228]	[0.0430]	[0.3773]	[0.0432]
Firm size(1000～4999)×Job change	-	-	-	-	-0.5518	-0.0500	-0.3073	-0.0179
	-	-	-	-	[03972]	[0.0397]	[03825]	[0.0447]
Firm size(5000 and over)×Job change	-	-	-	-	-1.3450 **	-0.1277 *	-0.5965	-0.0236
	-	-	-	-	[05660]	[0.0600]	[0.4537]	[0.0552]
Year, Education, Industry	Yes				Yes			
Age、Tenure	Yes				Yes			
N	4502				4510			
Loglikelihood Ratio	-4765.3499				-4818.8			

Notes: Significance levels: ***p<0.01, **p<0.05, *p<0.1,

Table 9-2: Propensity score matching estimation restricted to job changers with negative reason for turnover (Admin-sales workers)

	Model 1				Model 2			
	Senior Specialist		Line Manager		Senior Specialist		Line Manager	
	Coef	ME	Coef	ME	Coef	ME	Coef	ME
Job change dummy	0.2867	0.0367 *	-0.1655	-0.0421	-	-	-	-
	[0.2012]	[0.0195]	[0.2040]	[0.0324]	-	-	-	-
Firm size(11〜99)×Job change	-	-	-	-	0.1300	0.0079	0.2352	0.0461 *
	-	-	-	-	[0.2686]	[0.0197]	[0.2590]	[0.0261]
Firm size(100～299)×Job change	-	-	-	-	-0.0803	0.0290	-0.3044	-0.0708
	-	-	-	-	[02960]	[0.0289]	[0.3061]	[0.0510]
Firm size(300～999)×Job change	-	-	-	-	0.3039	0.0220	-0.0163	-0.0329
	-	-	-	-	[0.3649]	[0.0311]	[0..2723]	[0.0555]
Firm size(1000～4999)×Job change	-	-	-	-	0.3915	0.0443	0.1146	-0.0770
	-	-	-	-	[0.2948]	[0.0297]	[0.3819]	[0.0516]
Firm size(5000 and over)×Job change	-	-	-	-	0.4905	0.0795 **	-0.9100 **	-0.1961 ***
	-	-	-	-	[03388]	[0.0340]	[0.4277]	[0.0622]
Year, Education, Industry	Yes				Yes			
Age、Tenure	Yes				Yes			
N	6480				6480			
Loglikelihood Ratio	-7747.7322				-7694.1			

Notes: Significance levels: ***p<0.01, **p<0.05, *p<0.1,

Chapter 4

Mental Health Effects of Long Work Hours, Night and Weekend Work, and Short Rest Periods [9]

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[9] This study is a joint work with Sachiko Kuroda, and Hideo Owan. This is based on the Accepted Manuscript of an article published in Social Science & Medicine, 2020, 246, 112774, available online https://doi.org/10.1016/j.socscimed.2019.112774. This study was conducted as part of the project “Economic Analysis of Human Resource Allocation Mechanisms within the Firm: Insider econometrics using HR data” undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This work was also supported by JSPS KAKENHI Grant Number JP17H06591, 18H03632, 16K03715 and 25245041.

1. Introduction

Mental health problems in working populations are prevalent in many countries. The OECD (2013) has estimated that approximately 20% of working-age adults have mental health problems, which range from severe psychiatric impairments such as schizophrenia, and bipolar disorders to "milder" forms of mental disorders such as anxiety and depression. These problems not only induce personal suffering but also burden our society economically. The ILO has reported that the cost of work-related mental health problems, including both expenditures for treatment and loss of potential labor supply, amounts to 3-4% of the gross domestic product in Europe (ILO 2000).

Evidence is growing that various types of job stressors, including workplace conditions, can influence the onset and progress of mental health problems (Memish et al. 2017, Deloitte 2017). One of the main conditions affecting workers' mental health is working hours. Some empirical research suggests a close relationship between working hours and workers' mental health (e.g. Martens et al. 1999, Kim et al. 2013, Kato et al. 2014, Kuroda and Yamamoto 2016). In addition to the number of working hours, however, other work schedule characteristics, such as the frequency of night work and short daily rest periods (quick return), can affect workers' health as work-related stressors (Caruso et al. 2006, Vedaa et al. 2016, Costa et al. 2003). This issue of how working unusual hours may affect worker health is attracting more attention because social and industrial changes have increased flexibility in work schedules; an increasing number of workers are required to work the night shift or otherwise irregular hours (Johnson and Lipscomb 2006). The purpose of this paper is to investigate which of four work schedule characteristics (long work hours, night work, weekend work, and short rest period) affect workers' mental health and to what extent by combining personnel data, administrative attendance records and mental status information collected from an employee survey provided by a Japanese manufacturing company.

While some literature has examined the relationship between working schedule characteristics and worker mental health, establishing the causal effect of work schedule characteristics is challenging. For example, there is individual heterogeneity in vulnerability to mental health problems, and much of that heterogeneity is unobserved and omitted from analyses. Workers with mental toughness may remain healthy even if they work long hours. By contrast, workers with mental health problems are likely to have lower productivity, which in turn forces them to work longer than healthy workers would. Such endogeneity of working hours may cause estimation bias. Except for a very small number of studies using longitudinal data, a majority of prior studies do not control for unobserved worker heterogeneity (e.g. Flo et al. 2014). Moreover, measurement error may also bias the estimation, as the previous literature has often used retrospective data for working hours, which may be influenced by the respondent's mental health. Another type of endogeneity bias that may come from using self-reported longitudinal survey data is that workers with mental ill health are more likely to drop out of the cohort sample. This attribution problem is called the "healthy worker effect" (Li and Sung 1999, Watanabe et al. 2014).

Given these challenges, the main contributions of this paper are threefold. First, while most other studies use self-reported retrospective data for hours worked in a particular week, we use actual working hours recorded by the firm's attendance management system over seventeen months, which may contribute to reducing measurement errors. Moreover, since the turnover rate is very low in this firm, using this firm's administrative data, which covers all regular employees, minimizes sample attrition biases. As in the case of most large manufacturing firms in Japan, the annual turnover rate (from 2015 to 2016; the time period on which this paper focuses) of this firm was less than 2 percent. Therefore, selection bias due to voluntary quits should be less of a concern. Second, the use of attendance records also allows us to exploit detailed information on work schedules (i.e. from the start to the end of each day), enabling us to experiment with various types of work schedule characteristics, including overtime working hours, hours worked after midnight, frequency of short rest periods, and frequency of weekend work. Note that much of the previous literature has investigated only one type of work schedule characteristic. This paper addresses multiple work schedule characteristics of workers at the same firm so that we can more comprehensively examine what work schedule patterns affect workers' mental health status.

Third, by combining these data with longitudinal personnel records, we can prevent firm, occupation, or worker heterogeneity from confounding the relationship between work schedule characteristics and mental health. All of the workers in the study sample work for the same firm, and the occupation and workplace information allow us to control for the influence of differences in tasks and workplace environment. We further account for unobservable individual characteristics by estimating the model with worker fixed effects.

In summary, our empirical analyses reveal that long working hours may cause white-collar workers' mental health to deteriorate even after controlling for individual fixed effects. Furthermore, we find that working on weekends may be associated with white-collar workers' mental ill health. These relationships hold when all four work schedule characteristics measures are simultaneously included in the estimation model. The negative effect toward mental health of an hour increase in weekend work is one and a half to two times larger than that of weekday overtime work. When this is translated to the one-standard-deviation increase in overtime hours of 35.2 hours, such increases in overtime hours for weekdays and weekends raise the probability of feeling mental burden by 7.4% and 11.6%, respectively. On the other hand, short rest periods are not associated with mental health for white-collar workers. Our findings imply that the negative effect of working long hours, especially during weekends is substantial and that ensuring a prolonged weekly rest period is more effective than securing a minimum daily rest period, at least for white-collar workers. Regarding blue-collar workers, our analysis found that working after midnight may be associated with mental ill health, whereas short rest periods are not associated with mental health for blue-collar workers. The difference between job types in the relationship between work schedule characteristic measures and mental health may be explained in terms of different work styles and the resulting differences in expectations and selection of workers. This is discussed in the next section.

The rest of the article is organized as follows. Section 2 surveys the related literature, Section 3 explains the dataset, and Section 4 presents the empirical strategy. Section 5 explains the results, and Section 6 provides a discussion and conclusions.

2. Related Literature

Based on Caruso et al. (2006), this paper focuses on four work schedule characteristics that affect worker health problems: overall working hours, night work, frequency of short rest periods, and working on weekends. The following sections briefly review (A) related mechanisms and (B) the previous literature on the relationship between each of the four work schedule characteristics and workers' mental health.

(A) Review of mechanisms

The theory of job stressors explains that not only workload but also work characteristics are key factors in the deterioration of workers' health (Karasek 1979, Siegrist 1996). Caruso et al. (2006) provided a comprehensive framework for the study of long work hours and their health and safety effects. Their framework described that long working hours and other work schedule characteristics such as night and weekend shifts and short rest periods can lead to increased exposure to work-related stress and reduced time for other activities that enable recovery from work. Such unbalance between workload and recovery from exhaustion can be associated with a wide variety of outcomes, such as physical and mental illness.

The number of people working during nonstandard and irregular operating hours is increasing as a result of changes in macrolevel social factors such as the growth of the service industry (Johnson and Lipscomb 2006). Night work can have a negative effect on workers' health and well-being in terms of biological and social dimensions. From a biological viewpoint, night work can disturb normal circadian rhythms related to the sleep/wake cycle (Biovin et al. 2014). With respect to the social dimension, workers who perform night work have difficulties maintaining normal relationships with family and community members (Costa 1996).

Taking enough rest after work can prevent worker fatigue from reaching unhealthy levels. The Council of the European Working Time Directive requires organizations to ensure that every worker is entitled to a minimum daily rest period of 11 consecutive hours per 24-hour period (European Parliament, Council of the European Union 2003). Moreover, not only daily short rest periods but also longer rest periods, such as weekends, are important factors that affect individual health and performance (Sonnentag and Bayer 2005). Most employees usually exploit their weekends as an opportunity to recover from the exhaustion accumulated during their workweek.

(B) Evidence of the effect on worker mental health

Although several review articles have been published that address the influence of working long hours on workers' mental health (van der Hulst 2003, Fujino et al. 2006, Bannai and Tamakoshi 2014, Virtanen et al. 2018), the evidence they provide is inconclusive. For example, Fujino et al. (2006) report that, of seventeen studies reviewed, seven find positive association, one shows a negative association, and nine reveal no significant relationships between working hours and mental burden indicators such as self-reported depression symptoms. In a recent review and meta-analysis of prospective cohort studies from 35 countries, Virtanen et al. (2018) find that long working hours are modestly associated with an increased risk of new-onset depressive symptoms (odds ratio of 1.14 when long working hours is defined as working 55 hours or more). Moreover, they also reveal that although a moderate association between working hours and depressive symptoms is found in Asian countries, the association is weak for European countries and absent for North America.

Previous studies, however, have had difficulty establishing the causal impact of working hours on workers' mental health because they have not necessarily addressed the problem of biases derived from the endogeneity of working hours (van der Hulst 2003). For example, workers with mental toughness may remain healthy even if they work long hours, which tends to negatively bias the association between working hours and mental health indicators. By contrast, workers with mental health problems are likely to have lower productivity, which in turn forces them to work longer than healthy workers would, resulting in a positive but not causal association between the two factors. There may be other confounding factors that could either reinforce or reduce the correlation between working hours and mental health, such as work characteristics including job demand, job control, superiors' and coworkers' support in the workplace. Consequently, the estimated impact of hours worked using OLS regression can be either upward or downward biased. Heterogeneity in the estimated effect reported in prior studies may simply imply that different sources of endogeneity bias dominate in one direction or the other in different contexts.

To the best of our knowledge, only two studies utilize longitudinal information in order to account for time-invariant confounding factors (Oshio et al. 2015, Kuroda and Yamamoto 2016). Both apply fixed-effects models to longitudinal data on Japanese workers and show that long working hours could be one of the main sources of deterioration in workers' mental health even after controlling for worker characteristics and various workplace and job conditions. In addition to controlling for individual fixed effects, our paper aims to achieve higher internal validity by using information collected not from a retrospective survey but from administrative attendance records and focusing on workers whose job heterogeneity is relatively small (i.e. work-related confounding factors are limited). Namely, in contrast to Oshio et al. (2015) and Kuroda and Yamamoto (2016), who use samples of a wide variety of workers employed in different firms, this paper utilizes samples of non-managerial workers from the same firm and controls for major job characteristics.

With respect to the relationship between night work and workers' mental health, based on a review of the literature, Angerer et al. (2017) conclude that although there is evidence that nighttime shift work increases the risk of depression (at least in occupations outside the health sector), the evidence is not sufficiently strong. Angerer et al. (2017) note that such studies also need to account for individual heterogeneity because there is a "healthy worker effect" in which sick individuals are likely to switch from shift work to daytime work; that is, only healthy workers continue to work after midnight. For example, among eldercare and health care workers, Nabe-Nielsen et al. (2011) report that shift workers have higher vitality and better mental health than day workers. Some studies attempt to account for the healthy worker effect by using cohort data, such as Thun et al. (2014), who report that nurses who changed from day work to night work during the study period do not differ from day workers in terms of symptoms of anxiety or depression (see also Norder et al. (2015) reporting similar results using data of male production workers). On the contrary, Beltagy et al. (2018) report evidence that changing from day to night work (or night to day work) is statistically associated with increased (decreased) odds of acquiring mental disorders. None of these studies however, account for individual unobserved heterogeneity in order to cope with the healthy worker effect. Our paper further investigates whether the findings reported in these previous articles remain when a fixed-effects model is used.

Most studies of short rest periods focus on workers engaged in shift or rotating work. Veeda et al. (2016) perform a systematic review of five papers examining nurses or physicians and two papers studying workers performing shift work at manufacturing companies. They find no associations between short rest periods and mental health. Only a few papers analyze the consequences of short rest periods for the mental health of general workers who usually work daytime schedules. Ikeda et al. (2017) and Tuchiya et al. (2017) are two of the few studies examining the association between a daily rest period and mental health for white-collar workers with no shift or rotating work. Based on observations of fifty-four daytime employees at a company for a month, Ikeda et al. (2017) find that a short daily rest period of fewer than 13 hours is not adequate for participants to recover from fatigue. Tuchiya et al. (2017) examine 1811 daytime employees and find that short daily rest periods are associated with high psychological distress. However, this association disappears after controlling for covariates such as age, gender, hours worked per week, workload and social support. The same endogeneity issues associated with the effect of long working hours on workers' mental health are present for the relationship between short rest periods and mental health. Most of the papers described above do not control for time-invariant factors among individuals or any changes in work characteristics.

Lastly, regarding the effect of weekend work, using longitudinal data, Frits and Sonnentag (2005) find that social activity during the weekend negatively predicts burnout and poor general well-being. This result implies that working on weekends may deprive workers of the chance to recover from fatigue and may decrease time spent with family and friends. Using data on British munition workers in the 1930s, Pencavel (2015) provide evidence that the loss in output from denying workers a day of rest on Sunday is approximately 10%. Although these studies incidentally provide evidence of a negative effect of working weekends, few papers specifically examine the relationship between working on weekends and mental health. One exception is Tucker et al. (2015), who investigate this relationship using cross-sectional data. Although those authors show that weekend work is not significantly associated with burnout, stress and fatigue, the results may be biased due to the "healthy worker effect". We still need to investigate the relationship between weekend work and mental health while controlling for various confounding factors using a longitudinal design.

3. Data and measures

3.1 Data

This paper uses the personnel records provided by a Japanese consumer goods manufacturing company, C-Dur Corporation, which is a fictitious name used to protect the company's privacy. C-Dur Corporation was established in the 1940s and employs over 10,000 regular employees, including affiliated firms. This dataset includes (1) employees' daily attendance records, (2) responses to the employee survey, (3) employee characteristics (gender, age, education, marital status, etc.), (4) pay and benefit records, and (5) job assignment history records, which identify the department unit to which each employee belongs. For blue-collar workers, daily attendance records are derived from employees' time card data. Although data for white-collar workers are based on self-reported attendance records, HR staff investigated any cases that showed persistent differences between the time reported by the employee and the time when the employee shuts down his/her personal computer. This verification process should ensure the accuracy of daily attendance data for white-collar workers. These time attendance data are available from July 2015 to November 2016. Therefore, we use the personnel records for two years, 2015 and 2016.

3.2 Work Schedule Characteristics

As the time and attendance data include work start and end times for each date, we can construct four measures of work schedule characteristics. The first is the number of overtime hours worked. C-Dur Corporation sets regular work hours as 7 hours and 55 minutes per day. Consequently, we define overtime hours as hours worked over 7 hours and 55 minutes each day. The second is the number of hours worked after midnight, which measures hours worked between 12 o'clock midnight and the end time for work. The third measure is the frequency of short daily rest periods, which is defined as the incidence of fewer than 11 hours between the end time of work and the start time of work on consecutive days. The last measure is the frequency of working on weekend days, namely, Saturday and Sunday. If a worker works on both Saturday and Sunday, regardless of the total hours, the count is two weekend workdays per week.

We use two months as a measurement period for calculating each work schedule characteristic. Thus, we examine the effect of two-month accumulated fatigue before the employment survey (for more details, see section 3.3) is conducted. In the appendix, we also report two additional measurement periods besides two months before the employee survey was conducted, i.e. one month and two weeks, to examine whether the effect varies by the length of the measurement period.

3.3 Employee's Mental Status

We use a section of responses to the annual employee survey, which started in 2010 in consultation with the firm's occupational physicians. All regular employees of C-Dur Corporation answer this survey every year with a response rate of nearly 100% (white and blue-collar, 98% and 94%, respectively)—only those who are on temporary assignments abroad or those on leave are missing. This survey is conducted for two weeks period at the end of September and includes a question that asks the employees to self-assess their mental health status. The respondent chooses the most appropriate description of their mental health status among four choices as follows: "1. My mental status is healthy"; "2. I feel a little mental burden"; "3. I feel a considerable mental burden"; and "4. I am consulting a doctor for my mental health problem." According to our analysis of the responses in 2011-2016, the transition probabilities from the above answers 1, 2, and 3 in year *t* to 4 in year *t+1* are 0.3%, 1.19%, and 3.48%, respectively, implying that the measure could be used as a risk indicator of the onset of depressive disorders.

3.4 Sample

We restricted the sample to regular employees in nonmanagerial positions. We also excluded those who selected the final option in the mental health status question ("4. I am consulting a doctor for my mental health problem") in the employee survey because according to C-Dur Corporation, workers who chose "4" are put under special consideration with a reduced assignment and forced to work less hours. This is a typical measure recommended for employers based on Japan's Labor Contracts Act (for further details, see Section 6). We omit these samples in order to exclude reverse causality. Eighteen (2%) and fourteen (1.5%) employees chose this most serious mental health status in 2015 and 2016, respectively. We believe the selection bias caused by this omission is negligible as we discuss more formally later because the share of employees who are receiving medical treatment for mental illness was relatively small and unchanged between the two years. We also dropped those who had no attendance during the measurement period because these employees may be taking leave or seconded to a subsidiary.

The sample has two occupational subgroups: blue-collar workers engaged in manual production tasks in factories and white-collar workers engaged in other functions, mostly in offices. We conducted estimations for both types of workers separately because their jobs are governed by different work rules. White-collar workers are daytime workers and usually off on weekends. On the other hand, blue-collar workers are shift workers who are engaged in day, night, and weekend shifts. More detailed description for the differences in work style between white-collar workers and blue-collar workers is included in the Appendix 5. Despite the differences in their work schedules, we employ all the four work schedule measures for both groups because of the non-negligible shares of both work after midnight and during weekends—according to the department-level aggregate data, employees work after midnight for more than an hour on average in 4%

and 16% of the white-collar and blue-collar departments, respectively, while they work for a day or more during weekends per month in 67% and 53% of the white-collar and blue-collar departments, respectively. Although working during weekends is quite common for both white and blue-collar workers, the percentage of working after midnight for white-collar workers is relatively small compared to that of blue-collar workers. Therefore, we need to keep in mind that the coefficient of working after midnight is likely to be biased due to this selection for white-collar workers. Those who work after midnight are likely to be limited to special roles, such as engineers solving plant process/quality problems, campaign organizers in marketing or task force staff for managerial missions, etc.

Our sample restrictions result in final samples of 1334 white-collar workers and 786 blue-collar workers.

3.5 Descriptive Statistics

Summary statistics are presented in Table 1 for white-collar workers and Table 2 for blue-collar workers. We compare those figures with the means which are calculated using the data from the "Basic Survey on Wage Structure" by the Ministry of Health, Labour, and Welfare between 2015 and 2016. For the manufacturing company with more than 1000 employees, "Basic Survey on Wage Structure" shows that the average age, tenure, and overtime hours for a month of the college-graduates and above are 41.65, 15.95, and 11.5 hours respectively. For blue-collar workers, "Basic Survey on Wage Structure" shows that the average age, tenure, and overtime hours for a month of the high school-graduates are 42.70, 17.15, and 20.05 hours respectively. While these figures imply that the average age and tenure of the sample are lower than, and the average overtime hours is higher than those of the ordinary Japanese large manufacturing company, regardless of occupation, this difference may occur because the sample of this paper is restricted to the non-managerial employees. On average, the mental health indicator for both worker groups is between 1 and 2, that is, somewhere between healthy and feeling a little mental burden. The average of the mental health indicator of blue-collar workers is higher than that of white-collar workers and this is consistent with the previous studies for comparing mental health between both workers using the samples of Japanese workers (Kawasaki et al. 2015, Inoue et al. 2010). Average overtime work hours of blue-collar workers are longer than those of white-collar workers. Average working hours after midnight and frequency of working on weekends are much higher for blue-collar workers than for white-collar workers, as blue-collar workers perform shift work and experience night shifts and weekend shifts from time to time.

Tables 3 and 4 compare the means of each work characteristic measure for the two-month measurement period in 2015 and 2016 by level of mental health status for each job subgroup. Table 3 shows that white-collar workers with worse mental status tend to have worked longer, worked more hours after midnight, worked more often on weekends, and returned more often after very short rest periods. These findings imply that not only the length of working hours but also working the night shift, short rest periods and working on weekends may be associated with workers' mental health, at least for white-collar workers. On the other hand, Table 4 does not show such a systematic relationship for blue-collar workers.

Tables 5 and 6 compare the distribution of mental health status by the levels of each work schedule characteristic measure which have been made according to the 75the and 90 the percentile values of each work schedule characteristic measure for the two-month measurement period in 2015 and 2016 for each job group. For white-collar workers, table 5 shows that longer overtime working hours, and more experiencing weekend work tend to increase the rates of “Having a little mental burden” and “Having a great mental burden”. Table 5 also shows that more longer working midnight hours and more experiencing short rest period to tend to increase the rate of “Having a great mental burden”. For blue-collar workers, table 6 shows that longer overtime working hours tend to increase the rates of "Having a little mental burden" and "Having a great mental burden" and that longer midnight working hours tend to increase the rate of "Having a little mental burden". However, table 6 does not show that short rest periods and working on weekends have such a systematic relationship with mental health status for blue-collar workers.

4. Estimation strategy

4.1 Linear Probability with Fixed-Effect Model

First, we convert the category variable representing mental health status into a binary dependent variable and estimate linear probability models because the simple ordered logit model does not allow us to include worker fixed effects. We estimate the following linear probability model with individual fixed effects in which the dependent variable is the indicator of having mental burdens:

$$Y_{it} = \beta_k Work\ Schedule_{kit} + \gamma' X_{it} + \alpha_i + u_{it} \qquad (1)$$

Y_{it} denotes the indicator variable of having mental burdens, which takes a value of 1 if worker *i* chose either "2. I feel a little mental burden" or "3. I feel a considerable mental burden" and 0 if he or she chose "1. My mental status is healthy" as his/her mental health status in the employee survey conducted in year *t*. $Work\ Schedule_{kit}$ represents the four work schedule characteristic measures denoted by *k*, including total overtime hours worked, total work hours after midnight, the total number of returns to work after a daily rest period of fewer than 11 hours, and the total number of incidents of working on weekend days. X_{it} represents a vector of control variables including age, age squared, hourly wage (annual income divided by annual total hours worked), salesperson dummy, year dummy, the number of working days and the number of business trips during the measurement period. α_i represents the worker fixed effect, which represents the influence of time-invariant individual characteristics. Heteroskedasticity robust standard errors are used. Note that the year dummy is dropped during the estimation since we use a two-year panel dataset and therefore the year dummy has multicollinearity with age.

One of the concerns we have is selection bias. As noted in Section 3.4, workers who reported that they were consulting with doctor for their mental health problem were omitted from the sample in order to avoid reverse causality. Let d_{it} be the indicator of being in the sample for worker *i* in year *t*. A sufficient condition for our model to be consistent is $\mathrm{E}\left[\mathrm{u}_{it} - \mathrm{u}_{is} \middle| X_{it}, X_{is}, Work\ Schedule_{kit}, Work\ Schedule_{kis}, d_{it} = d_{is} = 1\right] = 0$.

This condition holds if the distribution of u_{it} conditional on d_{it} =1 does not change from year *t* to year *s*. Given the very stable workforce with limited turnover, the major factor that affects the conditional distribution of u_{it} should be the business environment for C-Dur Corporation, which determines the resources available for workplaces. The business environment did not change between 2015 and 2016, with low return on equity (ROE) at the 3-4% level reflecting a weak economy in both years. Another piece of evidence in support of this claim is that the number of employees who reported to be consulting a doctor for their mental health problem did not change noticeably between the two years (twenty-five and twenty-one, respectively). Furthermore, the number of individuals who were dropped due to lack of reporting was minimal, and thus systematic sorting is very unlikely. We judge that selection bias should be negligible.

The linear probability model with worker fixed effects controls for time-invariant unobserved individual characteristics. However, if there are unobserved time-variant, individual factors, u_{it} may still be correlated with the incidence of certain work schedule characteristics causing bias in the estimation results for the fixed effect model.

4.2 Latent Variable Model

Next, we estimate the following latent variable model with ordered multiple outcomes and unobserved individual heterogeneity:

$$Y_{it}^{*} = \beta_k Work\ Schedule_{kit} + \gamma' X_{it} + \alpha_i + u_{it}$$
$$Y_{it} = \mathrm{j} \quad \text{if} \quad \mu_j < Y_{it}^{*} \leq \mu_{j+1} \quad \mathrm{j} \in \{1,2,3\} \qquad (2)$$

Y_{it}^{*} is a latent variable for Y_{it}, which denotes the category of the mental health status (i.e. the three levels explained in Section 3.3) that a worker *i* chose. Explanatory variables are the same as those in equation (1). α_i represents time-invariant, individual fixed effects.

We estimate the Blow-up and Cluster (BUC) model, which Baetshmann et al. (2015) propose as an extension of conditional maximum likelihood estimators for a fixed-effects logit model to a model with ordered limited dependent variables. The parameters in the above model are estimated inconsistently when we use the ordered logit model with individual dummy variables because the incidental parameter problem exists (Lancaster 2000). This problem contaminates the estimation of parameters, as each α_i depends on finite T period observations, but there are too many α_i since the total number of observations NT grows infinitely. The BUC model is a remedy for this incidental parameter problem, The BUC estimate is a variant of the CML (Conditional Maximum Likelihood) estimators, and it dichotomizes the ordered variable at each cut-off point *j*. The standard errors are computed by clustering at the individual level. The BUC model uses all available information and produces consistent estimators (Baetshmann et al. 2015). Riedl and Geishecker (2014) report that the BUC estimator performs best in finite samples when comparing linear and nonlinear ordered response estimators in terms of consistency and efficiency by running Monte Carlo simulations. For reference, we also report our estimation results using a simple ordered logit model for comparison in the appendix.

5. Results

5.1 Linear Probability Model with Fixed Effects

Table 7 shows the results from the analysis of the fixed-effect linear probability model for white-collar workers. In all of our model specifications, age, age squared, hourly wage, salesperson dummy, the number of working days, and the number of business trips are controlled for but omitted from the table. In models 1 to 4, we include each work schedule characteristic measure separately, whereas in model 5, we include all four measures at once. The coefficients of *overtime* and *working on weekends* are significantly positive in models 1 and 4. By contrast, the coefficients of the two other work characteristic measures are positive but not significant, as shown in models 2 and 3. When all four work schedule characteristics are simultaneously included in model 5, the coefficients of *overtime* and *working on weekends* still remain the same in magnitude and statistically significant. These results indicate that long working hours may deteriorate workers' mental health, although the effects of strain coming from midnight work or short rest periods cannot be confirmed.

To check the robustness and the effect size, we further included two different overtime variables; the number of overtime hours worked only during weekdays and the number of work hours during weekends. The results are shown in models 6 and 7. The results indicate that an hour increase in overtime work during weekdays raises the probability of feeling mental burden by 0.21 percent, whereas an hour increase in weekend work lifts the probability by 0.33 percent, which is one and a half times as large as the effect of an overtime hour during weekdays. When this is translated to the one-standard-deviation increase in overtime hours of 35.2 hours, such increases in overtime hours for weekdays and weekends raise the probability of feeling mental burden by 7.4% and 11.6%, respectively. Our results indicate that the negative effect of working long hours, especially during weekends, is substantial and that taking a relatively long rest period on weekends is more important for keeping white-collar workers healthy than ensuring a sufficient daily rest period.

Table 8 shows the results for blue-collar workers using the same model specifications as for white-collar workers. In models 2, 5, and 7, the coefficient of *working after midnight* is significantly positive. A one-hour increase in night work raises the probability of feeling mental stress by 0.17%. When hours of night work increases by one standard deviation, which is 38.6 hours, , this probability increases by 6.6%. Once again, ensuring a sufficient daily rest period does not help to relieve this burden.

5.2 Latent Variable Model

Table 9 shows the results of the BUC model for white-collar workers. In this estimation, the sample size was substantially reduced due to the fact that mental health status in almost two thirds of the sample was unchanged for two consecutive years (note that the BUC model does not use samples with no change in the dependent variable). However, we notice that the results in Table 9 are not qualitatively different from those obtained in the linear probability model in Table 7: *overtime* and *working on weekends* are significantly associated with deteriorating mental health, and those relationships are not affected even if other work schedule measures are controlled for. Table 10 shows the results of the BUC model for blue-collar workers. The coefficient of *Working after midnight* is significantly positive in models 2 and 5, consistent with the linear probability model in Table 8.

The key results obtained from Tables 7 to 10 are summarized as follows: (1) working long hours may cause mental health to deteriorate even after correcting for biases due to time-invariant individual heterogeneity for white-collar workers; (2) working on weekends is also likely to impose risks to the mental health of white-collar workers; (3) working after midnight for a relatively long period may also cause a strain on blue-collar workers' mental health. However, this relationship does not hold for white-collar workers: (4) although having a sufficient rest period has been emphasized as important among practitioners, a *short rest period* is not associated with deteriorating mental health for either white- or blue-collar workers in our analysis. The difference between job types in the relationship between work schedule characteristic measures and mental health may be explained in terms of different work styles and the resulting differences in expectations and selection of workers. This is discussed in the next section.

6. Discussion and Conclusion

By combining personnel data, administrative attendance records and mental health status information collected from employee surveys provided by a Japanese manufacturing company, this paper takes into account individual heterogeneity and investigates the causal relationship between work schedule characteristics and workers' mental health. Specifically, this paper examines how four work schedule characteristics (long work hours, night work, weekend work, and short rest periods) affect workers' mental health. We obtain four valuable findings.

First, long working hours are associated with workers' deteriorating mental health even after correcting for a bias derived from unobservable individual heterogeneity for white-collar workers. This result is consistent with previous studies (Kuroda and Yamamoto 2016, Virtanen et al. 2011, 2012 and 2018) and implies that working long hours may cause white-collar workers to have a higher risk of onset of depressive disorders. For the purpose of comparison with prior studies, we calculated the odds ratio for feeling mental burden associated with long working hours exceeding 55 hours per month based on the linear probability with a fixed-effects model where bias due to individual heterogeneity is controlled for (not reported in the paper). The obtained odds ratios are 1.922 and 1.306 for white-collar and blue-collar workers, respectively, which is higher than the average of 1.14 from the meta-analysis in Virtanen et al. (2018). We have confirmed that the difference can be mostly explained by the fact that the bias due to individual heterogeneity is corrected for in our study (see our discussion in Appendix A3). Many previous studies are presumably affected by the healthy worker effect.

Second, we find that working on weekends for a relatively long period may cause white-collar workers' (but not blue-collar workers') mental health to deteriorate, consistent with previous studies (Beltagy et al. 2018). Working on weekends deprives workers of not only respite time but also time with family and friends. Some empirical research has shown the importance of weekends for recovery. Karhula et al. (2017) examine the relationship between objective work schedule characteristics and work–life conflict in day and shift work using longitudinal data and find that weekend work is associated with work–life conflict. Binnewies et al. (2010) find that psychological detachment from work, relaxation, and experiencing challenging off-job activities during the weekend predict a better recovery state after the weekend. Along the same line of thought, it may be effective policy for reducing the mental stress to encourage workers to take their full holiday entitlement. Given the fact that average paid days taken per year in Japan is eight to nine days, which is only about 50 percent of annual entitlement, many Japanese firms now set this goal to make their employees to stay health and productive.

Third, working after midnight for a relatively long period causes blue-collar workers' mental health to worsen. Fourth, short rest periods are not associated with mental health for both white-collar and blue-collar workers. These findings imply that guaranteeing a prolonged weekly rest period is more important than ensuring a minimum daily rest period, at least for white-collar workers, and that the strain coming from night work is a more important determinant of mental health for blue-collar workers.

When comparing the effect sizes of the four work schedule characteristics, our results indicate that the negative effect of an hour increase in work hours during weekends on mental health is one and a half to two as large as that of overtime hours during weekdays. Another implication from the results is that not only managing the amount of total working hours but also ensuring a relatively long weekly rest period—at least a day or two–are important, especially for white-collar workers.

The difference between white-collar vs. blue-collar workers in the relationship between working on weekends/after midnight and mental health may have a number of explanations. First, the blue-collar workers in C-Dur Corporation primarily work in shifts, and therefore most of them work on weekends once in a while. On the other hand, the white-collar workers in C-Dur Corporation are daytime workers and are usually off on weekends; therefore, working on weekends is not taken as a matter of course for them, except for a small number of jobs such as production engineers. In fact, Tables 1 and 2 show that the mean hours of weekend work for blue-collar workers is more than twofold greater than that for white-collar workers. Then, the prospect theory would predict that the reference point for most white-collar workers is not to work during weekends (i.e. spend quality time with their family and friends), and their loss aversion is likely to make them feel conflicted when they are compelled to work unexpectedly on weekends.

The second interpretation is a difference in the degree of selection between blue-collar workers and white-collar workers. Working after midnight is less uncommon among shift workers, and thus a majority of blue-collar workers experience night work once in a while. On the other hand, it is much rarer for white-collar workers to experience working after midnight, and such experiences are usually limited to special roles, such as engineers solving plant process/quality problems, campaign organizers in marketing or task force staff for managerial missions, etc. Therefore, the result that working after midnight has no significant effect on white-collar workers may come from the fact that it is solely based on the variation for a small group of employees, and may be subject to the "healthy worker effect."

There are three issues that need to be addressed or explored in our future research. First, the results obtained in this paper are derived from only one firm's dataset, so external validity may be rather limited. Specifically, two areas of study are particularly important. One of our findings suggests that the effects of work schedule characteristics on mental health may differ depending on the job type. This finding may imply that although many countries employ universal work-hour regulations for various types of workers, more segmental rules based on systematic studies across different occupations may be desirable. In addition, because C-Dur Corporation is a highly regarded company, the distribution of working hours has a very thin tail. Namely, there were no extremely long working hour samples in our data. One reason why we did not find any relationship between short rest periods and mental health may be the lack of a tail in the distribution. Datasets from other companies with more variations in working patterns are needed to investigate which regulations regarding the rest period are necessary to maintain good mental health for workers in the future.

Second, the measure of mental health used in this paper is weak in terms of validity, and thus reexamination with different valid psychometric measures is necessary in the future. The Japanese government introduced a new occupational health policy called the Stress Check Program with the amendment of the Industrial Safety and Health Law in 2014, which became effective on December 1, 2015. The program screens for workers with high psychosocial stress at least once per year in all establishments with 50 or more employees. According to Tsutsumi et al. (2018), the Japanese stress check program screening tool predicts employee long-term sickness absence. The primary reason why we did not attempt to use the stress check data for this study is that there is a strict regulation that requires a firm to obtain approval from each employee to use the micro data. Using stress check data linked with administrative data to reexamine our findings remains as a future challenge.

Last but certainly not least is that although we have accounted for time-invariant factors by using fixed effects, we should also consider time-variant factors that would affect both changes in mental health status and work hours. For example, workers who work in a growing market may find many opportunities to develop businesses that lead to long working hours but at the same time may find the job rewarding and feel engaged by achieving performance goals. As shown in this example, the positive or negative work environment could cause a spurious correlation between mental health and working hours.

The study by Kuroda and Yamamoto (2016) is one of a few attempts to examine the causal relationship between working long hours and workers' mental health using the aggregate level of average work hours as an instrumental variable in order to control for unobserved time-variant and time-invariant individual heterogeneity. However, it is difficult to find valid and strong instruments to control for time-variant factors. Controlling for time-variant factors by using appropriate instruments remains for future work.

Appendix

AI. Institutional Background

Readers who are not familiar with the healthcare system in Japan may wonder why C-Dur Corporation is asking its employees about their mental health and why they are expected to answer the question truthfully. In order to understand the background, it would help to briefly explain the Industrial Safety and Health Law in Japan. Establishments with over 50 employees are required to hire an occupational physician under the Japanese Industrial Safety and Health Act (those with over 3,000 employees must have at least two or more occupational physicians). Major responsibilities of occupational physicians include: (1) overseeing medical examinations and follow-up work and providing health consultations; (2) conducting workplace inspections according to a schedule agreed-upon in advance in order to keep the work environment safe, (3) providing health education and recommending policies to maintain and enhance the health of employees; and (4) preventing illness and injuries due to overwork by meeting employees who work long hours and advising their superiors.

In the past two decades, long working hours have attracted public attention because of the media coverage of increased depression and suicide cases attributable to overwork. According to the national patient survey from the Ministry of Health, Labour, and Welfare, the number of patients suffering from emotional disorders such as depression increased from 441 thousand in 1999 to 1,195 thousand in 2017. In an effort to reverse this trend, since 2008, the Industrial Safety and Health Act has stipulated that all establishments with 50 or more employees provide consultations with occupational physician to workers who work more than one hundred hours of overtime per month upon the worker's request. In 2019, the act was further strengthened, and a consultation with an occupational physician was made mandatory for workers who work more than eighty hours of overtime per month. C-Dur Corporation introduced the questions about mental health in the employee survey in this setting in order to identify those who might need a consultation with the occupational physician and to monitor the workplace climate.

Employees also have a proper incentive to answer the question truthfully, as psychiatric services are covered by Japan’s National Health Insurance; moreover, mentally ill employees cannot be easily fired because Article 16 of the Labor Contract Act prohibits “unfair” firing. Article 5 of the law further requires employers to give necessary consideration to allow workers to work under healthy and safe conditions. Thus, when an employer finds that her employee is mentally ill, she must reduce the person’s workload, transfer him to a less-demanding job, or allow him to take a leave. We note, however, that there remains a possibility that an employee who does not want such an arrangement may conceal their health problem until it becomes serious.

Our findings would offer useful advice to those occupational physicians: we should focus not only on the total number of overtime hours but also the number of weekly rest days (with less focus on the daily rest period).

A2. The Estimation Results for the Measurement Period of 1 Month and 2 Weeks

In the main text, we focused on the measurement period of two months. In this appendix, using a fixed-effect linear probability model, we compare measurement periods of different lengths, i.e. two weeks and one month, in order to examine whether the effect of accumulated fatigue varies by the length of the measurement period (Table A1). There is a lack of systematic research on how long workers can work long hours without causing mental illness.

The results for white-collar workers indicate that the coefficients of *overtime* are significantly positive for all three measurement periods and that the coefficients of *working on weekends* are significantly positive for the measurement periods of 1 and 2 months but not for the two-week period. We interpret that people can endure having no weekend rests for a week or two, but weekends for one or more months may become intolerable. As for the results of blue-collar workers, the coefficients of *working after midnight* are positive but not significant for both measurement periods of two weeks and one month.

In summary, based on the comparison of the results for the three different measurement periods, we can point out the following relationship between work schedule measures and mental health: for white-collar workers, fatigue due to overtime work affects mental health in a relatively short period of time (i.e., two weeks), whereas fatigue due to working on weekends needs to accumulate for a month or more before mental health deteriorates. For blue-collar workers, fatigue due to night work needs to accumulate for approximately two months before mental health is affected.

A3. Comparison between Ordered Logit and BUC models

In order to examine how unobservable individual heterogeneity affects the estimated effect in models without individual fixed effects, we ran ordered logit model estimations and compared the results with our BUC model estimation. Table A2 shows the comparison. Interestingly, the effects of overtime hours and working on weekends, which are significant in the BUC models, are no longer significant. The coefficients are also much smaller in the ordered logit model. These results imply that the estimated coefficients in the ordered logit models are downward biased, possibly due to the “healthy worker effect”.

The difference in the estimation between the two models is much smaller for blue-collar workers. Although the coefficient is somewhat smaller in the ordered logit model, it is significant at the 1% level, whereas it is only weakly significant in the BUC model. We interpret that the healthy worker effect bias is negligible for blue-collar workers because most shift workers experience midnight work once in a while.

A4. Fixed-effect linear probability models and BUC models (Full version)

We show the estimation results of fixed-effect linear probability models and BUC models with all the coefficients and standard errors of the explanatory variables that are included in each model in tables A3-A6, respectively.

A5. The differences in work style by occupation type

We explore precisely the differences in work style between white-collar workers and blue-collar workers. As mentioned in section 3.4, while most white-collar workers are daytime workers, and blue-collar workers are shift workers who are engaged in day and night shifts. White-collar workers usually work in weekdays and off on weekends. Although they work under the flex-time system of shift scheduling, their standard working hours are set as 9:00 to 17:40. On the other hand, blue-collar workers usually work under 3 shift schedule, day shift, night shift, and midnight shift. Each type of shift consists of multiple shift schedules with different start time. Table A7 shows the distribution of the shift that the blue-collar workers sample used for fixed effect estimation experienced during 2 months from July 20 to September 20 in 2015 and 2016, respectively. The findings for the work style of blue-collar workers from this table are as follows: for the day shifts, the blue-collar workers experienced more frequently two types of shifts, "Day shift (7:00-15:40)" and "Day shift (8:00-16:40)". Among the night shifts, the most frequent shift which the blue-collar workers experienced is "Night shift (16:20-25:00)". Midnight shifts are less frequent, the sum of the rates for "Midnight shift (21:20-30:00)" and "Midnight shift (22:20-31:00)" is 2.0-2.3%. The rate of the shifts which include time periods after 24:00 is 16.33 %. These figures imply that the blue-collar workers often work earlier in the morning than the white-collar workers and experience working in irregular night hours.

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Table 1. Basic statistics for white-collar workers

White-collar workers (N=1334)				
Variable	Mean	SD	Min	Max
Age	37.013	9.245	23	59
Tenure	10.947	9.820	0	36
Marriage	0.642	0.480	0	1
Female	0.319	0.466	0	1
Mental Health Status	1.470	0.616	1	3
Mental Health Dummy	0.405	0.491	0	1
Hourly Wage(Yen)	2124.197	1013.025	1325.096	32196.520
Sales Dummy	0.314	0.464	0	1
Working Style Variables (Measurement period: Two months)				
Total Workdays	40.050	2.768	5	56
Number of Trips on Business	1.121	3.569	0	48
Overtime (total)	65.835	35.246	0	223
Working after Midnight	4.930	18.116	0	136
Short Rest Period	2.286	3.860	0	26
Working on Weekends	2.495	3.088	0	15
Overtime (weekdays)	57.793	30.459	0	194.090
Overtime (weekends)	7.042	11.544	0	107.500

Note: Hourly wage is annual income in units of Japanese yen divided by annual work hours. The year-end exchange rate of US$1 to Japanese Yen was 121.61 and 117.49 for 2015 and 2016, respectively.

Table 2. Basic statistics for blue-collar workers

Blue-collar workers (N=786)				
Variable	Mean	SD	Min	Max
Age	38.085	9.506	19	59
Tenure	12.948	10.883	0	40
Marriage	0.565	0.496	0	1
Female	0.280	0.449	0	1
Mental Health Status	1.635	0.633	1	3
Mental Health Dummy	0.551	0.498	0	1
Hourly Wage(Yen)	1787.273	424.336	1015.859	3832.522
Working Style Variables(Measurement period: Two months)				
Total Workdays	40.132	3.114	28	52
Number of Trips on Business	0.196	1.483	0	22
Overtime (total)	68.091	40.269	0	201.070
Working after Midnight	30.560	38.642	0	215.250
Short Rest Period	1.190	1.977	0	20
Working on Weekends	7.282	4.188	0	15
Overtime (weekdays)	51.487	29.185	0	172.910
Overtime (weekends)	16.604	15.051	0	86.570

Note: Hourly wage is annual income in units of Japanese yen divided by annual work hours. The year-end exchange rate of US$1 to Japanese Yen was 121.61 and 117.49 for 2015 and 2016, respectively.

Table 3. Mean work schedule characteristics measures by the level of mental health status: White-collar workers

Work Schedule Characteristic Measure (unit of measurement) Measurement period:2 months	Mental Health Status			
	Keeping mentally healthy (N=794)	Having a little mental burden (N=453)	Having a great mental burden (N=87)	Total (N=1334)
Overtime(total)(hours)	64.717	66.283	73.702	65.834
Working after Midnight(hours)	4.235	5.657	7.478	4.930
Short Rest Period(times)	2.207	2.313	2.874	2.286
Working on Weekends(times)	2.445	2.556	2.632	2.494

Table 4. Mean work schedule characteristics measures by the level of mental health status: Blue-collar workers

Work Schedule Characteristic Measure (unit of measurement) Measurement period:2 months	Mental Health Status			
	Keeping mentally healthy (N=353)	Having a little mental burden (N=367)	Having a great mental burden (N=66)	Total (N=786)
Overtime(total)(hours)	67.728	68.960	65.189	68.091
Working after Midnight(hours)	24.990	35.126	34.953	30.560
Short Rest Period(times)	1.107	1.297	1.030	1.189
Working on Weekends(times)	7.107	7.476	7.136	7.282

Table 5. The distribution of mental health status by the level of work schedule characteristics measures: White-collar workers

Work Schedule Characteristic Measure (unit of measurement) Measurement period:2 months	Range 1: 0－75th percentile values 2: 75th－90th percentile values 3: 90th percentile value－	Mental Health Status Keeping mentally healthy	Having a little mental burden	Having a great mental burden	Total (%)
Overtime(total)	1: 0－86.82	60.94	32.97	6.09	100.00
(hours)	2: 86.82－113.54	57.50	35.50	7.00	100.00
	3: 113.54－	51.88	39.10	9.02	100.00
Working after Midnight	1: 0	59.83	33.94	6.23	100.00
(hours)	2: 0－4	68.89	24.44	6.67	100.00
	3: 4－	59.52	37.31	8.96	100.00
Short Rest Period	1: 0－3	58.63	35.26	6.10	100.00
(times)	2: 3－8	64.47	28.51	7.02	100.00
	3: 8－	57.55	33.81	8.63	100.00
Working on Weekends	1: 0－3	60.15	33.51	6.35	100.00
(times)	2: 3－8	58.74	34.53	6.73	100.00
	3: 8－	56.67	36.00	7.33	100.00

Table 6. The distribution of mental health status by the level of work schedule characteristics measures: Blue-collar workers

Work Schedule Characteristic Measure (unit of measurement) Measurement period:2 months	Range 1: 0－75th percentile values 2: 75th－90th percentile values 3: 90th percentile value－	Mental Health Status Keeping mentally healthy	Having a little mental burden	Having a great mental burden	Total (%)
Overtime(total)	1: 0－96.25	45.50	45.67	8.83	100.00
(hours)	2: 96.25－123.57	36.97	58.82	4.20	100.00
	3: 123.57－	52.56	35.90	11.54	100.00
Working after Midnight	1: 0－56.25	48.56	43.80	7.64	100.00
(hours)	2: 56.25－85	34.19	54.70	11.11	100.00
	3: 85－	33.75	56.25	10.00	100.00
Short Rest Period	1: 0－2	46.92	44.11	8.96	100.00
(times)	2: 2－3	37.78	55.56	6.67	100.00
	3: 3－	40.94	51.97	7.09	100.00
Working on Weekends	1: 0－10	43.66	47.74	8.60	100.00
(times)	2: 10－12	45.57	45.15	9.28	100.00
	3: 12－	50.00	45.24	4.76	100.00

Table 7. Estimation for Linear Probability with Fixed-Effects Model (White-collar Workers)

Measurement period: 2 months Dependent variable: Mental health status dummy (0:"Healthy" , 1:"Having a little mental burden" or" Having a great mental burden")							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0017***				0.0019**		
	[0.0007]				[0.0009]		
Working after Midnight		0.0006			0.0000		0.0006
		[0.0020]			[0.0018]		[0.0019]
Short Rest Period			0.0039		-0.0063		-0.0065
			[0.0051]		[0.0066]		[0.0068]
Working on Weekends				0.0252***	0.0209**		
				[0.0083]	[0.0089]		
Overtime (weekdays)						0.0015***	0.0021**
						[0.0007]	[0.0010]
Overtime (weekends)						0.0032**	0.0033**
						[0.0016]	[0.0016]
Controls:							
Age, tenure, working days, hourly wage,	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sales dummy, the number of business trips	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1334	1334	1334	1334	1334	1334	1334

Notes: Robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table 8. Estimation for Linear Probability with Fixed-Effects Model (Blue-collar Workers)

Measurement period: 2 months Dependent variable: Mental health status dummy (0:"Healthy" , 1:"Having a little mental burden" or" Having a great mental burden")							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0012				0.0014		
	[0.0009]				[0.0011]		
Working after Midnight		0.0016**			0.0017**		0.0017**
		[0.0007]			[0.0007]		[0.0007]
Short Rest Period			0.0063		-0.0079		-0.0072
			[0.0121]		[0.0131]		[0.0132]
Working on Weekends				0.0096	0.0068		
				[0.0065]	[0.0067]		
Overtime (weekdays)						0.0005	0.0010
						[0.0011]	[0.0012]
Overtime (weekends)						0.0031	0.0033
						[0.0020]	[0.0020]
Controls:							
Age, tenure, working days, hourly wage,	Yes	Yes	Yes	Yes	Yes	Yes	Yes
the number of business trips	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	786	786	786	786	786	786	786

Notes: Robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table 9. Estimation for BUC Model (White-collar Workers)

Measurement period: 2 months Dependent variable: Mental health status (1:"Healthy" , 2:"Having a little mental burden", 3:"Having a great mental burden")							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0146**				0.0224**		
	[0.0065]				[0.0094]		
Working after Midnight		0.0077			0.0019		0.0088
		[0.0113]			[0.0077]		[0.0109]
Short Rest Period			0.0258		-0.0828		-0.0751
			[0.0390]		[0.0607]		[0.0596]
Working on Weekends				0.2443***	0.2355***		
				[0.0824]	[0.0812]		
Overtime (weekdays)						0.0137***	0.0217***
						[0.0066]	[0.0094]
Overtime (weekends)						0.0367*	0.0354*
						[0.0912]	[0.0197]
Controls:							
Age, tenure, working days, hourly wage,	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sales dummy, the number of business trips	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	418	418	418	418	418	418	418

Notes: Cluster robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table 10. Estimation for BUC Model (Blue-collar Workers)

Measurement period: 2 months
Dependent variable: Mental health status
(1:"Healthy" , 2:"Having a little mental burden", 3:"Having a great mental burden")

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0103				0.0119		
	[0.0083]				[0.0113]		
Working after Midnight		0.0142**			0.0134*		0.0135*
		[0.0070]			[0.0069]		[0.0069]
Short Rest Period			0.0397		-0.0748		-0.0802
			[0.0987]		[0.1256]		[0.1253]
Working on Weekends				0.0382	0.0018		
				[0.0491]	[0.0531]		
Overtime (weekdays)						0.0105	0.0134
						[0.0099]	[0.0123]
Overtime (weekends)						0.0099	0.0099
						[0.0152]	[0.0157]
Controls:							
Age, tenure, working days, hourly wage,	Yes	Yes	Yes	Yes	Yes	Yes	Yes
the number of business trips	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	254	254	254	254	254	254	254

Notes: Cluster robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table A1. Estimation for Linear Probability with Fixed-Effects Model (White- and Blue-collar Workers) Measurement period: two weeks, 1 month and 2 months

Measurement periods: 2 weeks, 1 month and 2 months
Dependent variable: Mental health status dummy
(0:"Healthy", 1:"Having a little mental burden" or "Having a great mental burden")

	White-collar workers			Blue-collar workers		
	2 weeks	1 month	2 months	2 weeks	1 month	2 months
Overtime (total)	0.0063**	0.0026*	0.0019**	0.0026	-0.0001	0.0014
	[0.0025]	[0.0013]	[0.0009]	[0.0039]	[0.0018]	[0.0011]
Working after Midnight	0.0026	0.0005	0.0000	0.0011	0.0015	0.0017**
	[0.0059]	[0.0030]	[0.0018]	[0.0023]	[0.0013]	[0.0007]
Short Rest Period	-0.0271	-0.0032	-0.0063	-0.0114	0.0059	-0.0079
	[0.0200]	[0.0105]	[0.0066]	[0.0397]	[0.0131]	[0.0131]
Working on Weekends	0.0255	0.0409***	0.0209**	-0.0481	0.0155	0.0068
	[0.0318]	[0.0149]	[0.0089]	[0.0390]	[0.0130]	[0.0067]
Controls:						
Age, tenure, working days, hourly wage,	Yes	Yes	Yes	Yes	Yes	Yes
sales dummy, the number of business trips	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1332	1334	1334	786	786	786

Notes: Robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01. The results for the 2-month period are the same as those obtained for model 5 in Tables 5 and 6. In the results for the 2-week period, two samples are dropped because these employees had no attendance during the 2 weeks due to taking leave.

Table A2. Comparison between Ordered Logit and BUC Models (White- and Blue-collar Workers)

Measurement periods: 2 months Dependent variable: Mental health status dummy (1:"Healthy", 2:"Having a little mental burden", 3:"Having a great mental burden")				
	White-collar workers		Blue-collar workers	
	Ologit	BUC	Ologit	BUC
Overtime (total)	0.0022	0.0224**	-0.0042	0.0119
	[0.0030]	[0.0094]	[0.0040]	[0.0113]
Working after Midnight	0.0056	0.0019	0.0073***	0.0134*
	[0.0044]	[0.0077]	[0.0025]	[0.0069]
Short Rest Period	0.0134	-0.0828	0.0203	-0.0748
	[0.0214]	[0.0607]	[0.0493]	[0.1256]
Working on Weekends	-0.0306	0.2355***	-0.0040	0.0018
	[0.0272]	[0.0812]	[0.0241]	[0.0531]
Controls:				
Age, tenure, working days, hourly wage,	Yes	Yes	Yes	Yes
sales dummy, the number of business trips	Yes	Yes	Yes	Yes
Observation	1334	418	776	254

Notes: Cluster robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01. The results for the 2-month period are the same as those obtained in Model 5 in Tables 7 and 8. Female dummy and Education dummy are also included in the ordered logit estimation

Table A3. Estimation for Linear Probability with Fixed-Effects Model : Full Version

(White-collar Workers)

Measurement period: 2 months
Dependent variable: Mental health status dummy
(0:"Healthy" ,1:"Having a little mental burden" or" Having a great mental burden")

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0017***				0.0019**		
	[0.0007]				[0.0009]		
Working after Midnight		0.0006			0.0000		0.0006
		[0.0020]			[0.0018]		[0.0019]
Short Rest Period			0.0039		-0.0063		-0.0065
			[0.0051]		[0.0066]		[0.0068]
Working on Weekends				0.0252***	0.0209**		
				[0.0083]	[0.0089]		
Overtime (weekdays)						0.0015***	0.0021**
						[0.0007]	[0.0010]
Overtime (weekends)						0.0032**	0.0033**
						[0.0016]	[0.0016]
Age	0.1121	0.1456*	0.1368*	0.1739**	0.1186	0.1451*	0.1196
	[0.0802]	[0.0802]	[0.0808]	[0.0797]	[0.0808]	[0.0802]	[0.0808]
Age squared	-0.0010	-0.0015	-0.0014	-0.0017*	-0.0011	-0.0013	-0.0011
	[0.0010]	[0.0010]	[0.0010]	[0.0010]	[0.0010]	[0.0010]	[0.0010]
Workdays	-0.0022	0.0045	0.0043	-0.0017	-0.0037	-0.0077	-0.0050
	[0.0053]	[0.0051]	[0.0051]	[0.0054]	[0.0050]	[0.0055]	[0.0052]
Hourly wage	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
The number of business trips	-0.0027	-0.0018	-0.0024	-0.0033	-0.0034	-0.0031	-0.0025
	[0.0059]	[0.0060]	[0.0060]	[0.0058]	[0.0059]	[0.0058]	[0.0059]
Sales dummy	-0.0057	-0.0254	-0.0212	-0.0263	-0.0091	-0.0109	-0.0083
	[0.1038]	[0.1057]	[0.1047]	[0.1063]	[0.1043]	[0.1054]	[0.1050]
Controls:							
Age, tenure, working days, wage rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sales dummy, the number of business tri	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1334	1334	1334	1334	1334	1334	1334

Notes: Robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table A4. Estimation for Linear Probability with Fixed-Effects Model : Full Version

(Blue-collar Workers)

Measurement period: 2 months Dependent variable: Mental health status dummy (0:"Healthy" ,1:"Having a little mental burden" or" Having a great mental burden")							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0012				0.0014		
	[0.0009]				[0.0011]		
Working after Midnight		0.0016**			0.0017**		0.0017**
		[0.0007]			[0.0007]		[0.0007]
Short Rest Period			0.0063		-0.0079		-0.0072
			[0.0121]		[0.0131]		[0.0132]
Working on Weekends				0.0096	0.0068		
				[0.0065]	[0.0067]		
Overtime (weekdays)						0.0005	0.0010
						[0.0011]	[0.0012]
Overtime (weekends)						0.0031	0.0033
						[0.0020]	[0.0020]
Age	0.0772	0.0628	0.0713	0.0980	0.0808	0.0902	0.0859
	[0.0958]	[0.0949]	[0.0959]	[0.0972]	[0.0961]	[0.0972]	[0.0969]
Age squared	-0.0005	-0.0004	-0.0005	-0.0006	-0.0005	-0.0005	-0.0005
	[0.0012]	[0.0012]	[0.0012]	[0.0012]	[0.0012]	[0.0012]	[0.0012]
Workdays	-0.0036	0.0018	0.0007	0.0011	-0.0046	-0.0028	-0.0038
	[0.0086]	[0.0078]	[0.0079]	[0.0078]	[0.0086]	[0.0082]	[0.0081]
Hourly wage	-0.0002*	-0.0002*	-0.0002*	-0.0002*	-0.0002**	-0.0002*	-0.0002*
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
The number of business trips	0.0207	0.0238*	0.0233*	0.0216	0.0188	0.0194	0.0185
	[0.0142]	[0.0138]	[0.0139]	[0.0139]	[0.0141]	[0.0143]	[0.0142]
Controls:							
Age, tenure, working days, wage rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
the number of business trip	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	786	786	786	786	786	786	786

Notes: Robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table A5. Estimation for BUC Model: Full Version (White-collar Workers)

Measurement period: 2 months Dependent variable: Mental health status (1:"Healthy" ,2:"Having a little mental burden", 3:"Having a great mental burden")							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0146**				0.0224**		
	[0.0065]				[0.0094]		
Working after Midnight		0.0077			0.0019		0.0088
		[0.0113]			[0.0077]		[0.0109]
Short Rest Period			0.0258		-0.0828		-0.0751
			[0.0390]		[0.0607]		[0.0596]
Working on Weekends				0.2443***	0.2355***		
				[0.0824]	[0.0812]		
Overtime (weekdays)						0.0137***	0.0217***
						[0.0066]	[0.0094]
Overtime (weekends)						0.0367*	0.0354*
						[0.0912]	[0.0197]
Age	1.2020**	1.5355**	1.4395**	1.9395***	1.2747**	1.7015***	1.3182**
	[0.6013]	[0.6058]	[0.6086]	[0.6330]	[0.6066]	[0.6422]	[0.6112]
Age squared	-0.0116	-0.0162**	-0.0150*	-0.0206**	-0.0126	-0.0172**	-0.0131
	[0.0079]	[0.0079]	[0.0080]	[0.0082]	[0.0079]	[0.0083]	[0.0080]
Workdays	-0.0652	0.0160	0.0161	-0.0541	-0.1130	-0.1679**	-0.1316
	[0.0692]	[0.0564]	[0.0561]	[0.0649]	[0.0812]	[0.0841]	[0.0872]
Hourly wage	0.0007	0.0004	0.0004	0.0006	0.0007	0.0012	0.0010
	[0.0015]	[0.0014]	[0.0014]	[0.0014]	[0.0015]	[0.0015]	[0.0015]
The number of business trips	0.0221	0.0265	0.0203	0.0069	0.0094	0.0209	0.0303
	[0.0358]	[0.0394]	[0.0396]	[0.0363]	[0.0362]	[0.0375]	[0.0399]
Sales dummy	0.0966	-0.2079	-0.1599	-0.1950	0.1056	0.1125	0.1107
	[0.7250]	[0.7529]	[0.7507]	[0.7504]	[0.7078]	[0.7422]	[0.7377]
Controls:							
Age, tenure, working days, wage rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sales dummy, the number of business tri	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	418	418	418	418	418	418	418

Notes: Cluster robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table A6. Estimation for BUC Model: Full Version (Blue-collar Workers)

Measurement period: 2 months
Dependent variable: Mental health status
(1:"Healthy" ,2:"Having a little mental burden", 3:"Having a great mental burden")

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Overtime (total)	0.0103				0.0119		
	[0.0083]				[0.0113]		
Working after Midnight		0.0142**			0.0134*		0.0135*
		[0.0070]			[0.0069]		[0.0069]
Short Rest Period			0.0397		-0.0748		-0.0802
			[0.0987]		[0.1256]		[0.1253]
Working on Weekends				0.0382	0.0018		
				[0.0491]	[0.0531]		
Overtime (weekdays)						0.0105	0.0134
						[0.0099]	[0.0123]
Overtime (weekends)						0.0099	0.0099
						[0.0152]	[0.0157]
Age	0.6859	0.6336	0.5356	0.6319	0.6886	0.7642	0.7755
	[0.8285]	[0.8099]	[0.8122]	[0.8224]	[0.8354]	[0.8442]	[0.8388]
Age squared	-0.0033	-0.0029	-0.0020	-0.0020	-0.0034	-0.0039	-0.0042
	[0.0106]	[0.0104]	[0.0105]	[0.0104]	[0.0108]	[0.0106]	[0.0108]
Workdays	-0.0554	0.0017	-0.0157	-0.0024	-0.0552	-0.0416	-0.0421
	[0.0675]	[0.0565]	[0.0566]	[0.0582]	[0.0682]	[0.0759]	[0.0708]
Hourly wage	-0.0016	-0.0018	-0.0016	-0.0015	-0.0016	-0.0019	-0.0018
	[0.0012]	[0.0014]	[0.0011]	[0.0012]	[0.0012]	[0.0015]	[0.0015]
The number of business trips	15.0979***	13.3016***	14.3947***	15.0002***	14.3644***	14.2427***	14.2390***
	[1.0314]	[1.0285]	[1.0293]	[1.0438]	[1.0336]	[1.0418]	[1.0335]
Controls:							
Age, tenure, working days, wage rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes
the number of business trip	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	254	254	254	254	254	254	254

Notes: Cluster robust standard errors are reported in parentheses. * p<.1; ** p<.05; *** p<.01.

Table A7. The distribution of shift schedule for Blue-collar Workers

	Period	
	20150720-20150920	20160720-20160920
Type of Shift	N=16574	N=11113
	%	%
Day shift (5:30-14:10)	4.19	3.97
Day shift (10:00-18:40	0.92	0.31
Day shift (6:30-15:10)	6.57	6.32
Day shift (7:00-15:40)	17.15	16.13
Day shift (8:00-16:40)	23.14	24.38
Day shift (9:00-17:40)	1.13	0.83
Night shift (13:20-22:00)	0.59	0.77
Night shift (14:20-23:00)	1.82	1.5
Night shift (15:20-24:00)	5.48	3.5
Night shift (16:20-25:00)	11.72	13.54
Night shift (17:20-26:00)	1.14	1.53
Night shift (18:20-27:00)	1.18	1.56
Midnight shift (21:20-30:00)	1.17	1.49
Midnight shift (22:20-31:00)	1.12	0.51
Others	22.66	23.63
Total	100	100

"N" in the table represents the total number of working days during 2 months, 7/20-9/20 in 2015 and 2016, respectively that summed across the blue-collar workers sample which are used for estimation the fixed effect models.

Chapter 5

Concluding Remarks

1. Summary of Chapters 2, 3, and 4

While the number of studies on labor economics using micro panel data is increasing, there is not much literature on the Internal Labor Market (ILM). Specifically, research on the ILM has not yet addressed topics that have received substantial attention in recent years, such as gender differences and new aspects of human capital. This dissertation has examined three themes that have been ignored in the past literature on ILMs: the gender gap, occupation-specific human capital, and workers' mental health.

Chapter 2 examined how gender differences in job assignments are associated with the gender gap in pay and promotion using the personnel records of a large Japanese manufacturing firm; the data include job assignment history records. One of the major findings is that broader work experience through job transfers across establishments is associated with a higher promotion probability and future wages for employees of both genders, but this relationship is especially strong for women, which is consistent with the selection and signaling explanations based on statistical discrimination against women. This finding implies that because the internal labor market premises a long-term employment relationship, the firm may apply different management policies for female workers who are recognized as belonging to a group with a higher average turnover rate than their male counterparts.

Chapter 3 investigates the relationship among occupation, firm size, and promotions in the internal labor market using data from the "Working-Person Survey". The main finding is that among administration and sales workers, it is difficult for job changers to be promoted to managerial positions as firm size increases. This result supports the theory of DeVaro and Morita (2013). On the other hand, this pattern is not observed among technical workers and specialized professionals, suggesting that the theory of DeVaro et al. applies only to administration and sales workers. Furthermore, regarding promotions to senior professional positions, it turns out that job changers are not disadvantaged when compared with stayers. These findings imply that job changers with highly accumulated occupation-specific human capital are not necessarily disadvantaged with regards to promotion in new firms, although previous theoretical and empirical literature on ILMs has suggested that firms are likely to favor internal promotion in terms of firm-specific human capital and incentives.

Chapter 4 investigates how various work schedule characteristics affect workers' mental health using employee surveys and actual working hours recorded over seventeen months in a Japanese manufacturing company. Our major findings are as follows: for white-collar workers, long working hours and working on weekends cause mental health to deteriorate even after controlling for individual fixed effects. Our results indicate that taking a relatively long rest period on weekends is more important for keeping white-collar workers healthy than ensuring a sufficient daily rest period. For blue-collar workers, our analysis reveals that working after midnight is associated with poor mental health, whereas short rest periods do not seem to affect mental health among this category of workers. This suggests that the strain of night work is a more important determinant of mental health for blue-collar workers than for white-collar workers.

2. The Contribution to the Literature on the Internal Labor Market

In this section, I discuss how this dissertation contributes to the literature on ILMs. The significance of the above three themes corresponds to changes in the socioeconomic environment in recent years. Information about the gender gap, workers' skills, and health status had been unobserved from outside the firms. However, this hidden information has gradually been revealed for the following three reasons: 1) The increase in the introduction of a certification system for firms' gender equality, as well as health and productivity reforms by the government, may decrease asymmetric information. For example, "kurumin" was introduced by the Ministry of Health, Labour and Welfare in 2003 to certify firms with childcare support systems. Another example is the "Health and Productivity Management Award (kenko-keiei-meigara)", which certifies outstanding enterprises engaging in health and productivity management; this certification is awarded by the Ministry of Economy, Trade and Industry. 2) The progress of industry-wide standards for skill levels in the information and technology industry may allow firms to objectively evaluate the skills of job changers (e.g. Skill Standards for IT Professionals (ITSS) by the Information-Technology Promotion Agency (IPA), Japan). 3) The increase in information derived from word-of-mouth due to the prevalence of social networks may help to spread information from insiders. For the above reasons, the firm's commitment to these issues may be more observable than before. Therefore, the firm may obtain returns from their investments in training female workers, occupational skills, and workers' health. The implications of this dissertation should encourage firms to promote gender equality, treat high-skilled workers efficiently, and improve workers' mental health.

Finally, I note the significance of examining workers' mental health in the research on ILMs. In ILMs, the workers are expected to demonstrate their commitment and accept flexible assignments and adjustments in hours worked in exchange for long-term employment security. However, the effects of flexible adjustments in hours worked on workers' health have been unclear, while health is included in workers' general human capital and the basis for productivity improvement and skill development. Impaired worker health due to a burdensome work style may lead to a decrease in the firm's productivity and profit. Although workers' health problems have often been treated as personal matters rather than issues the employer should be responsible for, this attitude has been changing recently. Much literature has suggested that unhealthy workers tend to be less productive (e.g. Kuroda 2018), and more and more firms have realized that they can benefit by investing in workers' health and wellbeing. For example, some literature has found that introducing health and productivity management may significantly increase ROA after two years (Yamamoto and Takizawa 2019). Thus, the study of chapter 4, which has identified a relationship between work schedule characteristics and the deterioration of workers' mental health, may provide valuable implications for recognizing and maintaining workers' health as a part of general human capital, thus improving firms' productivity and profit.

3. Limitation and Future research

Finally, the author would like to mention the limitations of each study in this dissertation and the issues that warrant future research. In chapter 1, we must recognize the uniqueness of the sample firm, MfgJapan. The average number of transfers across establishments for female workers is the same as that of their male counterparts. This tendency is not common in large Japanese firms (Sano et al. 2018). Furthermore, Mfg Japan did not have a large enough female contestant pool for the higher job level because this firm began to recruit female college graduates for the management trainee track in the 2000s. To reveal the gender gap in the relationship between promotion to higher management positions and job experience, we need to use data from firms that have recruited female workers for the management trainee track for a few decades. The second point is the distinction of different purposes of job transfers. Although this study regards job transfers as a proxy of management training, the firm sometimes transfers an employee due to reorganization or adjustment of human resource allocation (JILPT 2015). In general, the firm may transfer a younger employee mainly for the purpose of career development and an older employee for the purpose of reorganization or adjustment. In particular, Japanese firms tend to transfer older employees into their affiliated firms for adjustment reasons (Shukko). We need to analyze job transfers both within and outside the firm, including Shukko, to reveal the whole relationship between job transfers and career outcomes.

In chapter 3, the first limitation is that the number of years that pass before job changers experience the first promotion in their new company after a job change is unclear. Firms may be reluctant to promote the employee immediately after a job change. We need to analyze personnel records, including the history of promotions and assignments, to determine when promotion occurs after job changes and how the accumulation of human capital and experience in the external labor market may be associated with the timing of promotion. The second limitation is that this study cannot precisely examine how much the accumulation of occupational experience is associated with promotion because the dataset we used has little information about how long each employee has been in their current occupation. We need to use a dataset that includes information on occupational experience – including occupation or job tenure for each employee – to measure the effect of accumulated occupation-specific human capital on future promotions.

In Chapter 4, the first limitation concerns the gender difference in stress and mental health. This study has set aside gender differences in mental health and focused on the relationship between work schedule characteristics and mental health problems, but some literature has suggested that females are more likely to be depressed than males regardless of the country being studied (Hopcroft and Bradley 2007, Mirowsky 1996). Previous research has also reported that female workers tend to experience “work-life conflict”, which may lead to an increased tendency toward depression (Kanai 2006). As Japan becomes a more gender-equal society, it will be important to study the relationship between work schedule characteristics and female workers’ mental health.

The second limitation is the accumulation of panel data and the length of measurement periods for work schedule characteristics. This study used a two-year panel dataset and a two-month measurement period of work schedule characteristics due to the restrictions of workers' time attendance records. However, it is necessary to examine the long-term accumulation effects of stress derived from work schedules on workers' mental health. Furthermore, the measure of employees' mental status used in this study may not distinguish chronic mental burden from accurate mental burden. We need to accumulate long-term panel data, including time attendance records and to use the measure that may distinguish accurate and chronic symptoms of mental health

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