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Labor Market of Regular Workers in Japan: A Perspective from Job Advertisement Data*

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Abstract

We analyze labor market tightness and wages for regular workers in Japan, using online job advertisement big data from 2015 to 2022 (approximately 5.8 million samples). The analysis reveals several aspects of the labor market which cannot be captured by official statistics. First, the ratio of job postings matched to job applicants (job-filling rate) has been declining, which suggests that firms may be facing greater difficulties in hiring workers than indicated by macro indicators such as jobs-to-applicants ratio. Second, the decline in the job-filling rate is in part driven by an increase in skill requirements of firms. This is related to the observed acceleration in the accumulation of intangible assets, which has a complementary effect in raising demand for high skilled workers. Third, posted wages are clearly rising under tightening labor market conditions, driven by an increase in demand for high skilled workers. Fourth, an increase in posted wages spills over to average wages of regular workers with some time lag. As for this spillover mechanisms, our empirical results support the existence of (1) a channel in which firms raise wages in order to retain workers as it becomes easier for them to move to higher paying jobs, and (2) a channel in which firms raise wages for fairness consideration as newly hired workers are paid high wages within a firm.

JEL Classification: J23, J24, J30
Keywords: Job advertisement, Alternative data, Posted wages, Labor demand, Skill requirement

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1. Introduction

Understanding trends in labor market conditions and wages are essential for assessing the state of the economy, but it is difficult to grasp the full picture with a limited source of statistics. In particular, the Japanese labor market is characterized by a "dual structure" of regular and non-regular workers, which has different wage determination mechanisms (Fukunaga et al. (2023), etc.). Wages of regular workers tend to be less responsive to fluctuations in labor market conditions due to long-term contracts, seniority-wage system with low labor mobility. However, in recent years, labor mobility of regular workers has been increasing, especially among younger workers, and there is also a trend toward adopting job-type employment (as opposed to the traditional membership-type employment).

Against this background, we analyze the online job posting market for regular workers in Japan, using online job postings data.[1] Specifically, we first summarize characteristics of regular workers' job posting market in recent years. We then analyze the relationship between posted wages and average wages of regular workers. Traditionally, statistics, such as the *Employment Referrals for General Workers*, which are collected at the Public Employment Service Center, are used to analyze developments in regular workers' job market. However, in recent years, online job boards have become a more common tool to find jobs (Figure 1). In addition, by using online job postings data, we can obtain highly granular information at the individual job level such as offered wages. In the following analysis, we utilize this granularity to analyze labor tightness and its drivers, as well as the impact of changes in labor tightness on posted wages. We also analyze how posted wages transmit to average wages of regular workers.

The main results are summarized as follows. First, the job-filling rate -- ratio of online job postings that are actually filled by applicants -- has been declining in recent years. This suggests that labor tightness faced by firms may be tighter than the level indicated by the jobs-to-applicants ratio. Second, we find that this decline in the job-filling rate is driven by the increase of skill requirements of Japanese firms. This is related to the observed acceleration in the accumulation of intangible assets and R&D investments, which has a complementary effect in raising demand for high skilled workers. Third,

[1] Various types of employment are posted on online job boards in addition to regular workers, such as part-time jobs. Available information contents differ by employment type; for example, information on qualifications is often more detailed for regular workers than for part-time jobs. Hence, it is desirable to analyze job ads by employment type. Regular workers account for about 60 percent of all employees in terms of number of workers and about 80 percent in terms of income.

posted wages have accelerated. Although wages of regular workers are not very sensitive to labor tightness (Bank of Japan (2023)), our analysis finds that posted wages are more responsive to labor tightness. Such increases in posted wages are widespread across a range of industries, occupations, firms, and regions, and they are particularly larger in professional and engineering jobs and the IT (information and telecommunications) industry. We show that increases in demand for high skilled workers, particularly in these fields, are primary drivers for rising posted wages. Moreover, while the labor market has become tighter overall and posted wages are rising for a wide range of jobs including those with low skill requirements, posted wages for jobs with high skill requirements are rising rapidly driven by strong demand. Fourth, an increase in posted wages has an effect to push up average wages of regular workers with some time lag. As for the spillover mechanisms, the analysis suggests the existence of (1) a channel in which firms raise wages in order to retain workers as it becomes easier for them to move to higher paying jobs and (2) a channel in which firms raise wages for fairness consideration as newly hired workers are paid high wages within the firm.

Research using micro data on posted jobs is a relatively new field, and previous studies in Japan are scarce compared to those for the U.S. Many of the results in this paper, such as those pertaining to skill requirements and job-filling rates for posted jobs and their relationships with posted wages, can be obtained only by using micro data on job ads. Consequently, they provide us with new insights into the labor market in Japan. In particular, to the best of our knowledge, this paper is the first attempt to analyze the spillover from posted wages of job ads to average wages of regular workers. This paper demonstrates that posted jobs contain valuable information in assessing future trends in wages of regular workers.

The structure of this paper is as follows. First, Section 2 reviews the previous literature; Section 3 provides an overview of data on posted jobs used in this analysis; Section 4 then discusses labor tightness faced by firms (job-filling rate) and trends in the skill requirements; Section 5 summarizes trends in posted wages; Section 6 discusses spillovers from posted wages of job ads to the average wages of regular workers; and Section 7 concludes.

2. Literature Review

This paper is related to three strands of literature: usage of job posting data to capture trends in the labor market and posted wages; skill requirements of posted jobs; and the relationship between outside options and workers' wages. We look at them in this order.

First, a growing number of studies use information on posted jobs to capture trends in labor market conditions and posted wages; Adrjan and Lydon (2019) measure labor tightness from the number of jobs and "clicks" on online job boards by job category and find that the level and the growth rate of posted wages are higher for jobs for which the labor market is tight. Turrell et al. (2019) use data on the number of jobs posted on online job boards and the number of applicants obtained from official statistics to measure labor tightness at the job level. For Japan, Fukui et al. (2020) use information on jobs posted on the Public Employment Service Center and find that during the COVID-19 pandemic, number of job openings tended to decrease in areas with higher rates of voluntary curfew and that the decrease in job openings was smaller for occupations with higher work-from-home rates. A similar trend is also found in the U.S., where analyses using job ads show that decline in labor tightness following the pandemic was highly heterogeneous across occupations and regions (Campello et al. (2020), Forsythe et al. (2020a, b)).

Data on job ads is also used to gauge developments of posted wages. Adrjan and Lydon (2022) calculate the average posted wages by industry and occupation in European countries and find that the recent increase in posted wages is much higher than before the pandemic, and that the range of occupations with rising posted wages are widening. Crump et al. (2022) calculate the growth rate of the wages of jobs posted by the same firms with the same address and the same job type in the U.S. and find that this measure has accelerated since 2019.

Second, there is a strand of literature that focuses on the skill requirements of posted jobs. Previous studies in the U.S. measure the level of skill requirements of posted jobs based on information such as education requirements and job descriptions, and show that skill requirements become upgraded in economic downturns (Hershbein and Kahn (2018), Modestino et al. (2018), Modestino et al. (2020), Blair and Deming (2020)). As for the factors behind this upgrading, it has been pointed out that high degree of slackness in the labor market causes firms to demand higher skill levels (Modestino et al. (2020)), and that the shocks prompt firms to update their production processes, which require higher skills (Hershbein and Kahn (2018)). Among them, Hershbein and Kahn (2018) uses information on job postings in the U.S. before and after the global financial crisis and finds that firms in urban areas which experienced large negative shocks and firms investing in capital, had relatively higher demand for more educated and experienced workers with better cognitive and computational skills. Furthermore, they show that the demand for these high skilled workers remained high until 2015, when the effects of the financial crisis had dissipated, pointing to the possibility that the increase in skill requirements is a medium- to long-term phenomenon.[2]

Third, since posted wages can be interpreted as representing outside options for workers (i.e., the value that workers obtain by changing jobs), this paper is also related to the literature on the relationship between outside options for workers and their wages. On the theoretical side, number of studies have shown that workers' wages increase when the value of outside options increases. Possible mechanisms include the increase in workers' bargaining power (Mortensen and Pissarides (1994), Burdett and Mortensen (1998), and Hagedorn and Manovskii (2008), Hall and Milgrom (2008)) and an incentive for employers to prevent workers from shirking (Shapiro and Stiglitz (1984)). Other relevant studies include an empirical analysis by Card et al. (2012), where they conducts a randomized controlled experiment on University of California employees and demonstrate that employees who learn that their wages are lower compared to their colleagues become less satisfied with their jobs and more willing to change jobs. The paper also argues that the "relative income hypothesis" (Clark and Oswald (1996)), which states that workers' utility is determined by the relative level of their income, may be a relevant factor for this phenomenon. Section 6 of this paper discusses the mechanism by which posted wages of job ads spillover to average wages of regular workers based on the findings of these previous studies.

3. Data

Our analysis uses information on job ads posted on a major private online job board, obtained by HRog, Inc. through web scraping.[3] Specifically, we use monthly data (scraped as of the last Monday of each month) from January 2015 to December 2022 posted on a major private online job board. The total sample size of the data is approximately 5.8 million job posts. Looking at the industry composition of job posts, shares of manufacturing and IT industry are high and the share of medical and welfare

[2] Blair and Deming (2020) also demonstrate that skill requirements for jobs in the U.S. became upgraded after the financial crisis and remained so even around 2019.

[3] Fukui et al. (2020), one of the earlier studies in Japan, also uses HRog's data. The paper analyzes job ads of not only regular workers but also of part-time workers.

industry are lower compared to regular workers' job openings at the Public Employment Service Center and the stock of regular workers (Figure 2).[4]

The information of job ads used in this paper includes information on wages, occupations, locations, job descriptions, and skill requirements for individual jobs, as well as the names and addresses of firms postings jobs (Figure 3).[5] We also use the *Basic Survey of Japanese Business Structure and Activities*[6] conducted by the Ministry of Economy, Trade and Industry (METI) and the *Basic Survey on Wage Structure*[7] conducted by the Ministry of Health, Labour and Welfare (MHLW). We use these data by matching them with the job ads data. While the frequency of these surveys is an annual basis, they provide granular information at a firm or establishment level. The *Basic Survey of Japanese Business Structure and Activities* provides the financial information of firms[8] and the *Basic Survey on Wage Structure* provides information on wages of individual employees at each establishment.

4. Changes in Labor Market Conditions gauged by Job Posting Data

In this section, we analyze labor tightness faced by firms and its drivers based on individual job ads.

[4] This can be attributed to a number of factors, including the fact that major private online job boards are often used by large manufacturing firms because of the high cost of posting jobs; that the nature of online job boards means that jobs ads for IT engineers and other information communication-related jobs are more likely to be posted online; and that medical and welfare-related industries have dedicated job boards other than the one we use in the analysis.

[5] As for posted wages, job ads often list a range such as "5-7 million yen per year". In this paper, numerical information on the lower and upper annual salary limits for each job (5 million yen and 7 million yen in this example, respectively) is extracted, and the average (6 million yen in this example) is used as the posted wage.

[6] The *Basic Survey of Japanese Business Structure and Activities* is a survey of the financial information of firms with 50 or more employees and capital of 30 million yen or more.

[7] The *Basic Survey on Wage Structure* is a survey of private-sector business establishments employing five or more full-time workers that examines information such as the length of working hours and wages at the individual level for employees randomly selected from each establishment. Here, "firm" refers to a corporation and "establishment" refers to a head office or branch office of a firm.

[8] We combine the job ads data and the *Basic Survey of Japanese Business Structure and Activities* based on information about the location of the firms' headquarters, such as zip code and street address. In this analysis, approximately 17,000 of the about 100,000 firms that posted job ads during the sample period are matched to the survey. In terms of the number of job postings, those linked to the *Basic Survey of Japanese Business Structure and Activities* account for about half of the total number of job postings.

4-1. Labor Tightness Faced by Firms in the Job Market for Regular Workers

As we showed in Section 1, the number of job postings for regular workers temporarily dropped around the spring of 2020 in response to the pandemic and has been on the rise since then (Figure 1). We attempt to measure labor tightness by taking into account trends on the supply side (job applicants) as well as the demand side (firms). Specifically, we calculate the job-filling rate, which is the share of job postings that are considered to be ultimately filled by applicants. The job-filling rate is considered to represent labor tightness faced by firms in the sense that it measures how easy it is for them to hire workers. The concept is also discussed in previous studies such as Davis et al. (2012), Davis et al. (2013), Carrillo-Tudela et al. (2020). The theoretical background of the job-filling rate can be summarized as follows. In labor economics, the relationship between the number of matches m, job postings v, and applicants u is generally described by a Cobb-Douglas type matching function (Mortensen and Pissarides (1994)),

$$m = \mu v^{\alpha} u^{1-\alpha}, \tag{1}$$

where μ represents the matching efficiency, and α is a constant that takes a value between 0 and 1. Defining the job-filling rate as m/v, this can be expressed using Equation (1), as follows;

$$\frac{m}{v} = \mu / \left(\frac{v}{u}\right)^{1-\alpha}. \tag{2}$$

Equation (2) shows that the job-filling rate depends on two factors; the number of job postings per job applicant (v/u) and the matching efficiency (μ). Decline in the job-filling rate can be caused by either an increase in the number of job postings per applicants or a decline in the matching efficiency. Number of job postings per applicants is conceptually equivalent to the jobs-to-applicants ratio in the *Employment Referrals for General Workers*. The job-filling rate can be interpreted as capturing the "labor tightness faced by firms" as it takes into account the matching efficiency as well as the overall balance of job postings and applicants as measured by the jobs-to-applicants ratio.

In this analysis, we identify the matching status of each job posting by using the information on its posting period. Specifically, given that majority of job postings are scheduled to be posted for a period of three months, we consider job postings that are posted for less than three months to be filled by an applicant.[9] The job-filling rate is then

[9] We assume that firms have an incentive to withdraw job postings before the scheduled end date of the posting if it is filled by an applicant. That is, if they do not, they have to continue to respond to new

calculated as the ratio of newly posted jobs each month that are ultimately filled by applicants.

Looking at trends in the job-filling rate, we observe that it moves counter-cyclically; it declines during periods of economic expansions and rises during recessions (Figure 4).[10] However, in recent months, while the jobs-to-applicants ratio of the *Employment Referrals for General Workers* has not recovered to the level before the pandemic, the job-filling rate has remained below it, indicating a clear divergence between the two. As Equation (2) shows, this suggests that it is becoming more difficult for firms to hire workers than is indicated by the jobs-to-applicants ratio due to the decline in the matching efficiency. Looking at the job-filling rate by occupation and industry during this period, while it has declined in all categories, it is particularly low in professional and engineering jobs and the IT industry. Intuitively, these occupations and industries are likely to have more high skilled workers. Thus, we next analyze job postings in terms of skill requirements in order to get a more detailed picture of the background to the decline in the matching efficiency.

4-2. Background of the Decline in the Matching Efficiency: Impact of Changes in the Workers Demanded by Firms

In this section, we analyze the background of the decline in the matching efficiency (μ in Equation (2)) focusing on whether there has been a change in skill requirements by firms. As will be discussed later, skill requirements of job postings are related to posted wages and the matching efficiency, and are therefore important factors for capturing labor market trends.

Skills Requirements of Job Postings and Matching Efficiency

When analyzing skill requirements of job postings, prior studies often quantify them based on criteria such as level of education, length of employment, or specific words included in the job descriptions. For example, Modestino et al. (2020) define high skilled jobs as those that require education levels of a college degree or higher. Hershbein and Kahn (2018) define high skilled jobs as those that, in addition to requiring certain levels of education and years of employment, include words in the job descriptions that are

applicants, which incurs additional costs. Indeed, the job-filling rate moves consistently with the jobs-to-applicants ratio, suggesting the validity of this assumption where we can identify the job filling status with a good degree of accuracy.

[10] Previous studies in the U.S. also indicate that job-filling rates fluctuate countercyclically (Davis et al. (2012), Davis et al. (2013)).

considered to be related to computational or cognitive skills (e.g., " computation," etc.). However, these approaches can be somewhat arbitrary in terms of which conditions are chosen. Hence, this paper proposes a more general method to measure skill requirements using text information in the job description. Specifically, denoting nouns $w_{i,k}$ $(k = 1,2,\dots,K)$, contained under the "qualifications" of job posting i, skill requirement of this job $skill_i$ is calculated as follows;[11]

$$skill_i = \alpha_{w_{i,1}} + \alpha_{w_{i,2}} + \cdots + \alpha_{w_{i,K}}, \tag{3}$$

where α_w is the weight given to each word. A higher value of $skill_i$ means higher skill requirement for job i. Individual weights α_w are determined by how high posted wages are for job postings which includes the word in the "qualifications" text. Specifically, weight α_w of a word w is calculated as follows;[12]

$$\begin{aligned}\alpha_w = {}&[\text{Average posted wages of job ads whose qualifications include } w] - \\ &[\text{Average posted wages of job ads whose qualifications do not include } w].\end{aligned} \tag{4}$$

In this analysis, we calculate Equation (4) for approximately 500 nouns that appear most frequently in the qualification texts in order to comprehensively capture skill requirements.[13]

We then classify job postings in the upper quartile of skill requirements as "high skilled jobs," those in the lower quartile as "low skilled jobs," others as "middle skilled jobs." Looking at the number of job postings by skill levels, growth rate of the number of job postings for high skilled jobs has been higher than other categories throughout the sample period, which indicates strong demand for high skilled labor (Figure 5). Looking at post pandemic developments, the initial drop in the first half of 2020 is relatively smaller for high skilled jobs, while the pace of recovery is faster for those jobs.[14]

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[11] This method of quantifying text data by simply adding up predefined weights pertaining to words that appear in a sentence is widely used the literature (e.g., Picault and Renault (2017), Arratia et al. (2021)).

[12] We also checked that our results are robust to other specification of equation (4). That is, when we calculate α_w as the coefficient obtained by regressing dummy variables for whether particular words appear in the qualification texts of the posted job on its wage. In addition, we also estimated a random forest model to allow the possibility that $skill_i$ is a nonlinear function of α_w, but the qualitative features of our results were unchanged.

[13] Words with larger (smaller) values of α_w indeed represent skills that are intuitively higher (lower). For example, words with large α_w values include "machine learning" and "investment," while words with small α_w values include "no-experience" or "customer service."

[14] This suggests that, during the period of the pandemic and the economic downturn, firms reduced job postings if they could be replaced by the existing workforce in the short term (i.e., low skilled jobs), while

In general, labor supply of high skilled workers is relatively low compared to other skill levels, and an increase in labor demand will likely tighten labor market conditions. To confirm this point, we estimate the following regression;

$$matched_{i,t} = \beta skill_{i,t} + \alpha_{pref_i} + \delta_{occ_i} + \mu_t + \varepsilon_{i,t,} \quad (5)$$

where $matched_{i,t}$ is a variable that takes the value of 1 when job i posted at time t is filled by an applicant and 0 otherwise, and $skill_{i,t}$ is the skill requirement of job i. α_{pref_i}, δ_{occ_i}, and μ_t are fixed effects of prefecture, occupation, and time, respectively.[15] We control macroeconomic factors with the time effects, since job-filling rate moves counter cyclically, as we saw in Section 4-1.[16] The estimation results show that β is negative and statistically significant, suggesting that a one standard deviation increase in skill requirements reduces the probability of a match by about 2.5 percent (Figure 6, left panel). Moreover, there is a reasonable difference in the job-filling rate for different occupations even after controlling for differences in skill requirements. For example, the probability of a professional and engineering job being matched is about 13 percent lower than that for a clerical job (Figure 6, right panel). These estimates indicate that the recent decline in the matching efficiency is due to the increased share for high skilled jobs that are relatively difficult to match.

Background of the Increase in High Skilled Job Postings

We now analyze the background of the recent increase in high skilled job postings. Hershbein and Kahn (2018) shows that skills required for posted jobs become higher as capital and the number of computers owned by firms increases. Furthermore, they attribute this to the fact that skills required for production activities become more sophisticated with technological progress.[17] In order to investigate whether a similar trend exists in Japan, we estimate the following equation using a database combining

they continued to hire for positions that were important in the long term (i.e., high skilled jobs). Prior studies in the U.S. (Hershbein and Kahn (2018), Modestino et al. (2020), Blair and Deming (2020)) generally find that degree of skill requirements for jobs moves counter-cyclically (i.e., low skilled job postings tend to decrease substantially during economic downturns).

[15] In this paper, we follow previous studies such as Campello et al. (2020) and Modestino et al. (2020) in controlling for the effects of different attributes such as region, occupation, and time point by including corresponding fixed effects (dummy variables).

[16] In addition, although not included in our estimation due to data limitations, Davis et al. (2012) point out that recruitment intensity, which cannot be directly observed, affects the job-filling rate.

[17] Technological change that increases demand for high skilled labor is called skill-biased technological change, and previous studies have pointed out that IT investments and R&D investments induce demand for high skilled labor (e.g., Berman et al. (1998)).

information on job ads and the *Basic Survey of Japanese Business Structure and Activities*;

$$skill_{i,j,t} = \beta X_{j,t} + \alpha_{sector_j} + \delta_{occ_i} + \mu_t + \varepsilon_{i,j,t}, \tag{6}$$

where $skill_{i,j,t}$ denotes skill requirement of job i posted by firm j at time t. α_{sector_j} and δ_{occ_i} represent fixed effects of firm j's industry, occupation job i, and μ_t represent time effects. $X_{j,t}$ is a vector of control variables representing firm j's capital formation and/or the degree of technological progress. In this analysis, we include the following variables in $X_{j,t}$; the logarithmic values of tangible fixed assets per worker, intangible fixed assets per worker, and R&D expenditures per worker.[18] Since the demand for high skilled workers may increase as the size of the firm increases due to specialization, we also estimate a specification including dummy variables to control for firm size in $X_{j,t}$.[19]

Estimation results are summarized in Figure 7, which shows that estimated coefficients are positive and statistically significant for all variables in specifications without firm size controls (specification (1)-(4)). However, when firm size controls are included (specification (5)), the coefficient for tangible fixed asset becomes insignificant whereas intangible fixed assets and R&D expenditures are still positive and statistically significant. Note also that estimated coefficients for intangible fixed assets and R&D expenditures are relatively larger compared to fixed tangible assets. This suggests that increases in investments for intangible fixed assets to promote digitalization by firms and R&D expenditures in fast growing areas have a complementary effect in increasing demand for high skilled jobs (Figure 8).[20]

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[18] Variables are nominal values. Deflators common among firms are taken into account by including time effects.

[19] Specifically, we define firm size depending on the size of capital; firms with capital of less than 100 million yen as small firms, capital between 100 million yen and 1 billion yen as medium-sized firms, and capital greater than 1 billion yen as large firms.

[20] The literature also shows that different types of capital have different degree of complementarity to skills. For example, Correa et al. (2019), using data from Chilean manufacturing plants, show that intangible fixed assets, mainly software, has larger complementary effect on the demand for high skilled labor than tangible fixed capital.

5. Impact of Tightening Labor Market Conditions on Posted Wages

In this section, we review the characteristics of posted wages and then analyze the impact of tightening labor conditions and increase in demand for high skilled workers on posted wages.

5-1. Characteristics of Posted Wages in the Regular Workers' Market

First, we summarize characteristics of posted wages for regular workers in the major online board. Looking at the average posted wages, we see a continuous increase since 2018 (Figure 9); average posted wage (annual salary) as of December 2022 is approximately 5.65 million yen, which is approximately 650 thousand yen higher from the 5 million yen in January 2015. Looking more closely, average posted wage increased sharply in the early spring of 2020 when the first state of emergency was declared in response to the pandemic, and the growth rate continued to exceed the pre-pandemic level by about one percentage point since then. Looking at the developments by occupation and industry, while average posted wages have been on an upward trend in recent years for all occupations and industries, growth has been particularly higher in occupations and industries with relatively low job-filling rates, such as professional and engineering jobs and the IT industry (Figure 10).

These trends in posted wages differ from average wages of regular workers. In fact, a comparison of these two wages shows that while both were growing similarly before the pandemic, the growth of posted wages has clearly outpaced that of average wages of regular workers since the pandemic (Figure 11). This difference is also observed by comparing distributions of posted wages and average wages of regular workers (Figure 12). Looking at the distribution by industry, the entire distribution, including areas around the lower bound, has clearly shifted to the right in the IT industry. On the other hand, in manufacturing and wholesale and retail trade industries, the distributions of posted wages has skewed to the right, that is, peaks around 5 million yen have collapsed, indicating an increase in the higher end of wages where areas near the lower tail has hardly changed.

5-2. Background of the Increase in Posted Wages

Next, we analyze the background to these recent increases in posted wages.

Decomposition of the Increase of Posted Wages

First, we decompose changes in posted wages into three factors; within effect (contribution from changes in posted wages by firms that continue to post jobs), exit effect (contribution from firms exiting the online job posting market), and entry effect (contribution from firms entering the online job posting market). According to this decomposition, in the phase immediately following the outbreak of the pandemic, a large increase in the exit effect pushed up posted wages (Figure 13).[21] This is likely due to the fact that, in response to the pandemic and public health measures, job postings in face-to-face service industries with relatively low posted wages were withdrawn, pushing up the average posted wages of the remaining posted jobs. Since then, the contribution of the within effect has been significant.[22] Based on the analysis of labor market conditions in the previous sections, such an increase in the within effect can be attributed to; (a) an increase in posted wages for a wide range of occupations and industries due to an overall tightening of the labor market, (b) a substantial increase in posted wages for high skilled job postings due to an increase in the demand for high skilled workers, and (c) an increase in the share of high skilled job postings (the composition effect).

Next, we examine which of the factors (a), (b), and (c) have contributed to the increase in posted wages.

Tightening of the Labor Market and Posted Wages

In relation to (a), we examine the relationship between labor tightness and posted wages using the following equation, which makes use of the highly granular nature of the job postings data;

$$\Delta W_{i,t}^{potsted} = \beta MatchRate_{i,t} + \gamma \Delta \overline{skill}_{i,t} + \alpha_{sector_i} + \mu_t + \varepsilon_{i,t}, \tag{7}$$

where ${W^{posted}}_{i,t}$ is the average wage of jobs for regular workers posted by firm i in year t, and Δ denotes its year-on-year change (the rate of change between ${W^{posted}}_{i,t}$ and ${W^{posted}}_{i,t-1}$). The $MatchRate_{i,t}$ is the share of job postings by firm i in year t that are considered to be ultimately filled by applicants which represents labor tightness faced by firm i in year t. We identify whether a job posting is filled by an applicant by the same criteria as in section 4-1. $\overline{skill}_{i,t}$ denotes the average skill requirements for job postings by firm i in year t, and Δ is the difference from the previous year (the difference between $\overline{skill}_{i,t}$ and $\overline{skill}_{i,t-1}$). As discussed in section 4-2, since skill requirements of posted jobs are related to the job-filling rate, we add $\Delta\overline{skill}_{i,t}$ as an

[21] Note that throughout the sample period, the exit effect contributes positively and the entry effect contributes negatively. This reflects the high turnover of firms with low levels of posted wages.

[22] After the pandemic (January 2021-December 2022), the contribution of the within effect averages around 3.3%pt annualized, while it was around 1.8%pt before the pandemic (January 2015-December 2019).

explanatory variable to control for the correlation between $\Delta W^{posted}{}_{i,t}$ and $MatchRate_{i,t}$ due to skill requirements (the relationship between skill requirements and posted wages is discussed shortly). α_{sector_i} and μ_t represent fixed effects for industry and time, respectively. Estimation results are summarized in Figure 14 where it shows that β is negative and statistically significant. This suggests that a decline in the job-filling rate, i.e., an increase in labor tightness faced by firms, has an effect to raise growth of posted wages.

Given the fact that the job-filling rate has declined in a wide range of industries and occupations in recent years, the overall tightening of the labor market is expected to have pushed up posted wages of many job posts. In fact, the share of the same jobs (jobs posted by the same firm with the same work address and of the same occupation) for which posted wages increased year-over-year has increased in a wide range of industries in recent years (Figure 15). In addition, growth rate of posted wages of the same type of job ads, which is unaffected by the composition effect (factor (c) above), has remained at a higher level than before the pandemic (Figure 16). Since this measure reflects mainly the effect of tightening of the labor market (factor (a) above), this indicates that posted wages are reasonably sensitive to labor tightness. This is in contrast to the average wages of the regular workers, which are not very sensitive to fluctuations in labor tightness.

Impact of Increased Demand for High Skilled Workers

While this overall tightening of the labor market has pushed up posted wages, the degree of tightness could be heterogeneous across industries, occupations, and skill requirements. In light of the estimation results in Figure 14, it can be expected that high skilled job postings with relatively low job-filling rates would have higher-than-average increases in posted wages. In fact, looking at developments of posted wages for each skill category, the increase in posted wages for high skilled jobs is larger than other categories (factor (b) above, Figure 17). Heterogeneities are also observed in the share of posted jobs whose wages have increased, with the increase being particularly high for high skilled jobs (Figure 18).

This heterogeneity in the development of posted wages depending on skill requirements may lead to wider wage gaps between skill levels if a relative increase in demand for high skilled workers continue. In order to check this point, we plot a simple cross-sectional relationship between the relative strength of demand for high skilled workers (the difference between the shares of high skilled job postings and low skilled job postings) and the relative level of posted wages for high skilled job postings (the ratio of posted wages for high skilled job postings to those for low skilled ones) in Figure 19 panel (a). It shows that the wage gaps tend to widen in prefectures with relative high demand for high skilled jobs. This suggests that, while an overall tightening of the labor market led to an increase in posted wages for a wide range of jobs including low skilled jobs, the relative strength of demand for high skilled workers has led to a particularly strong increase in posted wages for high skilled jobs.[23] These characteristics are also confirmed by the panel regression in panel (b) of Figure 19.

The composition effect, (c) -- the average posted wage is pushed up by an increase in the share of high-wage job postings --, is also an important factor in the high growth of posted wages. Figure 20 shows a simple cross-sectional relationship between the required skill level and posted wages, where a one standard deviation increase in the level of skill requirements is associated with an increase of approximately 830 thousand yen in posted wages (correlation coefficient of 0.53). Based on this relationship, the increase in skill requirements by firms can explain about 30% of the increase in the average posted wage (the composition effect) (Figure 21).

We can summarize these results as follows: First, posted wages of job ads for regular workers are sensitive to labor tightness. Therefore, if labor demand increases as economic activities recover, posted wages are likely to increase to a greater extent than average wages of regular workers. Second, the recent increase in posted wages has been driven in large part by an increase in demand for high skilled workers. This is due to both a significant increase in posted wages for high skilled job postings and an increase in the share of high skilled job postings in the online job posting market. Given the analysis in Section 4, if R&D expenditures in areas of high growth and digital-related investments continue to expand, the accompanying increase in demand for high skilled workers could further push up posted wages for regular workers.

6. Spillover from Posted Wages to Wages of Regular Workers

What implications do posted wages, discussed in the previous sections, have for the wage formation of (existing or stock) regular workers? In this section, we first investigate

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[23] These results suggest that the wage gap among workers may widen with technological progress. Prior studies have pointed to various factors besides technological progress that lead to wage inequality, including international trade (Helpman et al. (2017), Furusawa et al. (2020)) and institutional factors (Jaumotte and Buitron (2015)). The literature that points to the impact of technological progress on wage inequality includes Acemoglu and Autor (2010), Adachi et al. (2022), Adachi (2023), among others.

the time-series relationship between posted wages and average wages of regular workers. We then examine the spillover mechanism from the former to the latter using micro data.

6-1. Relationship between Posted Wages and Average Wages

We begin by estimating a simple vector autoregression model (VAR) to investigate the time series property between posted wages and average wages of regular workers. Specifically, we estimate a three-variable VAR which includes the unemployment rate, the month-on-month change rate of posted wages, and the month-on-month change rate of average wages of regular workers. The sample period is from January 2015 to December 2022. We calculate the cumulative impulse response of regular workers' wage to a 1 percent positive shock to posted wages.[24,25] In doing so, we report two results; one with Cholesky decomposition with the same ordering as above, and another with generalized impulse responses which are independent of variable ordering. The lag is set to six periods based on the results of the Bayes-Information-Criterion (BIC).

The results suggest that after a shock to posted wages occurs, regular workers' wages also increase with a lag of about 6 months and that a 1 percent increase in the former leads to a 0.3 percent increase in the latter (Figure 22). Moreover, a Granger causality test from posted wages to regular workers' wages is statistically significant with a p-value of 1.3 percent.

Next, we examine the usefulness of posted wages in predicting average wages of regular workers. Specifically, we estimate two models that predict future growth rate of regular workers' average wages. In the first model, we use only the lag terms of regular workers' average wages and the unemployment rate, while in the second model we add lag terms of the growth rate of posted wages. We then compare the explanatory power of both models (R-square adjusted for degrees of freedom).[26] Figure 23 shows that the explanatory power of the model which includes a lag term for posted wages is higher for both one-month and 12-month time horizons, which indicates that developments of posted wages have some explanatory power for forecasting average wages of regular workers 12 months into the future.

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[24] Here, we use a simple average of posted wages in each month.

[25] Given that posted wages experienced temporal large fluctuation at the onset of the pandemic (around spring 2020), we re-estimated the same VAR model with the estimation period from January 2015 to December 2019 to confirm that the cumulative impulse response does not materially change.

[26] As in the VAR model, we take lags of six periods for each variable.

These time-series analyses suggest that changes in posted wages spill over to regular workers with some time lag. Therefore, the recent high growth of posted wages is likely to push up wages for regular workers over the next 6 months to 1 year. Based on the 12-month forward-looking forecast model estimated in Figure 23, the recent increase in posted wages is expected to push up the growth rate of average wages of regular workers by about 0.17 percentage points over the next year.

When we think about the mechanism relating posted wages and wages of existing regular workers, it may seem obvious that an increase in posted wages leads to an increase in average wages of regular through job changes. However, since the share of workers in Japan who change jobs in the previous 12 months is about 5 percent, a simple back of the envelope calculation indicates that 1 percent increase in posted wages would only have a modest effect of 0.05 percentage point on average wages. On the other hand, the time-series analysis above shows that a 1 percent increase in posted wages raises average wages of regular workers by about 0.3 percent. This discrepancy suggests that there is a mechanism other than the direct effect –through job transition– in the spillover from posted wages to average wages of regular workers. In the next subsection, we discuss this spillover mechanism based on the literature survey in Section 2.

6-2. Spillover Mechanisms from Posted Wages to Average Wage of Regular Workers

In this section, we proceed with our analysis by classifying the spillover mechanisms from posted wages to average wages of regular workers into two types of effects. The first is the mechanism by which an increase in posted wages raises average wages of regular workers of firms other than the ones that are posting the jobs. We call this effect the "external pressure effect." The second mechanism is that an increase in posted wages raises average wages of regular workers of firms that are actually posting the jobs. We call this effect the "internal pressure effect." The external pressure effect is primarily related to the literature on the relationship between outside options and workers' wages. That is, if the posted jobs act as outside options for regular workers at different firms, an increase in posted wages may lead to an increase in the wages for regular workers at other firms (Mortensen and Pissarides (1994), Burdett and Mortensen (1998), and Hagedorn and Manovskii (2008), Hall and Milgrom (2008)). On the other hand, the internal pressure effect is mainly related to the literature on the relative income hypothesis (Clark and Oswald (1996), Card (2012)). If wages for jobs posted by a firm increases and new employees are hired at higher wages than existing employees, existing employees' satisfaction with their current jobs will decrease and they become more willing to change jobs. As a result, the firm may have an incentive to raise wages for existing employees in order to prevent turnover. Although the previous literature and the above two effects do not correspond strictly on a one-to-one basis, this approach helps to understand the issues regarding the impact of posted wages on average wages of regular workers.

In this paper, we use micro data to examine whether both of these effects exist.[27] Specifically, we consider the following formulation;

$$\Delta W_{i,t}^{worker} = \beta \Delta W_{i,t-1}^{posted} + \gamma X_{i,t} + \alpha_{sector_i} + \mu_t + \varepsilon_{i,t}, \tag{8}$$

where $\Delta W_{i,t}^{worker}$ and $\Delta W^{posted}{}_{i,t-1}$ represent the rates of change in average wages of regular workers and posted wages of job ads associated with firm (or establishment) i in year t, respectively. Here, in order to properly test for the external and internal pressure effects, we use suitable variables for each effect, which we describe below.[28] To alleviate the endogeneity problems due to the inclusion of contemporaneous variables, the variable on posted wages is taken with one period lag. $X_{i,t}$ is a vector of variables controlling for the performance of firm (or establishment) i. In addition, time and industry effects are added to control for business cycle factors and industry specific characteristics. In Equation (8), β represents the spillover effect from posted wages to average wages of regular workers.

An Examination of the External Pressure Effect

To verify whether the external pressure effect is at work, we use a database that combines the job ads with the *Basic Survey on Wage Structure*. Specifically, in Equation (8), $W^{posted}{}_{i,t-1}$ is average wages of job ads posted in year $t-1$ by firms in the same industry within the same prefecture as establishment i, and $W_{i,t}^{worker}$ is the total salary for regular workers at establishment i in year t. Given that the population mobility across prefectures is low at about 2 percent per year and that about 50 percent of job changers switch jobs within the same industry, it is valid to interpret posted wages in the same prefecture and industry as representing outside options for employees at establishment i. To control for the business conditions of each establishment, we also include total hours worked per employee (year-on-year change rate) for each

[27] Note that the analysis in this subsection only verifies whether both mechanisms exist as spillover channels and is not intended to estimate the relative magnitude of the contributions from each mechanism. The relative size of contributions of both mechanisms is a subject for future analysis.

[28] $\Delta W^{posted}{}_{i,t-1}$ represents the strength of pressure on wages of regular workers through the external and internal pressure effects. Here, we also confirmed that the results are unchanged when we use $\Delta W^{posted}{}_{i,t-1} - \Delta W_{i,t-1}^{worker}$ instead of $\Delta W^{posted}{}_{i,t-1}$.

establishment as an additional explanatory variable.

Here, it should be noted that if the job ads from which ${W^{posted}}_{i,t-1}$ is calculated including a non-negligible share of jobs posted by establishment i itself, ${W^{posted}}_{i,t-1}$ may no longer serve as a proxy for outside wage option for the employees of establishment i. In addition, if firm i itself hires new employees through the online job board, $W_{i,t}^{worker}$ and ${W^{posted}}_{i,t-1}$ may be correlated through the internal pressure effect. Regarding the first issue, we checked that the sample size of job postings in this analysis is large enough so that no single firms have significant impacts on average posted wages in the same prefecture and industry. That said, for the sake of robustness, we also address this issue by conducting estimation by restricting the sample to establishments with a small number of employees. Regarding the second issue, we eliminate the impact of the internal pressure effect by restricting the sample to establishments that are not hiring. Specifically, the sample is restricted to establishments that meet the following two conditions: (1) the number of regular workers do not increase over the previous year, and (2) all randomly selected regular workers in the *Basic Survey on Wage Structure* have been with the firm for at least one year. We believe that these conditions allow us to identify establishments that are not hiring new employees with a reasonable degree of accuracy.[29]

The estimation results summarized in Figure 24 shows that the value of β is positive and statistically significant in all specifications, suggesting the existence of the external pressure effect. Comparing the estimation results between a specification with the whole sample and an alternative specification with smaller the number of employees, the latter specification has larger value of β. This suggests that smaller establishments are more likely to be affected by posted wages of job ads by other firms. Prior studies indicate that the degree to which employees' wages are affected by labor tightness is greater for smaller establishments (Munakata and Higashi (2016), Bank of Japan (2023)), which is consistent with the estimation results in this paper.

An Examination of Internal Pressure Effects

To verify the internal pressure effect, we use the database combining the job ads data

[29] Establishments that are excluded under these conditions (those with an increase in the number of regular workers compared to the previous year or those with regular workers who have been with the firm for less than one year) are by definition making new hires. Looking at establishments with a small number of employees (30 or less), the share of establishments that are excluded under these conditions (one that are certain to be hiring new employees) is about the same as the share of establishments that have hired new employees during the year according the official statistics (about 30 percent of all establishments).

and the *Basic Survey of Japanese Business Structure and Activities*. As discussed above, for the internal pressure effect, it is essential that posted jobs actually get filled by applicants. Therefore, for $W^{posted}{}_{i,t-1}$ in Equation (8), we use the average posted wage of job ads by firm i in year $t-1$ that are considered to be filled by applicants, which we denote as $W^{posted,match}{}_{i,t-1}$. For $W_{i,t}^{worker}$, we use the total salary per employee of firm i. We use the same method as in Section 4 to identify whether a posted job is filled by an applicant. To control for business conditions of each firm, we also add sales per employee or value added per employee for each firm as an additional control variable.

Here, if firm i refers to posted wages by competitors in setting their own posted wages, then $\Delta W^{posted,match}{}_{i,t-1}$ and $\Delta W_{i,t}^{worker}$ can also be correlated through the external pressure effect. Therefore, we perform a placebo test by re-estimating Equation (8) using the average wages of all posted jobs by firm i in year $t-1$ as $W^{posted}{}_{i,t-1}$, which we denote as $W^{posted,all}{}_{i,t-1}$. If the value of β is statistically significant only in the former case and not in the latter case, then $\Delta W^{posted,match}{}_{i,t-1}$ and $\Delta W_{i,t}^{worker}$ can be interpreted as being correlated through the internal pressure effect.

The estimation results for the internal pressure effect is summarized in Figure 25, where we observe that β is positive and statistically significant only when we use $\Delta W^{posted,match}{}_{i,t-1}$ as the value of $\Delta W^{posted}{}_{i,t-1}$. As discussed above, this suggests that internal pressure effect is at work.

7. Conclusion

In this paper, we analyzed the labor market for regular workers in Japan using information from online job boards.

The results of the analysis can be summarized as follows. First, the share of job postings filled by applicants (job-filling rate) has been declining. This implies that it has become more difficult for firms to hire workers than indicated by the jobs-to-applicants ratio. Second, the decline in the job-filling rate is driven by the growing demand for high skilled workers among firms. Demand for such workers is increasing likely due to R&D investments in high growth areas and increased investment in intangible fixed assets backed by digitalization demand. Third, posted wages are clearly rising with tightening labor market conditions. While the average wages of regular workers tend to be insensitive to labor tightness, posted wages seem to be reasonably sensitive. It is also indicated that the recent increase in demand for high skilled workers is driving the overall increase in posted wages, both in terms of the increase in posted wages for high skilled job postings and the increase in the share of such job postings. As the demand for high skilled workers increases, the wages of high skilled job postings are also increasing relative to other job postings. Fourth, we find that the increase in posted wages boosts average wages of regular workers with some time lag. As a specific spillover mechanism, we confirmed that both "external pressure effects" and "internal pressure effects" are functioning.

There are also some topics that are constructive for future research using job ads data. First, it will be fruitful to see if the mechanisms highlighted in this paper, such as the propagation from posted wages to existing regular workers, are at work at other large economies. As for topics for Japan, given the dual structure of Japan's labor market, it would be useful to gain more insight into the wage determination mechanism of non-regular (part-time) employees. In Japan, the expansion of labor demand, mainly for non-regular workers, was met by an increase in the labor supply of women and the elderly in the 2010s. However, the baby boomer generation that supported the increase in the labor supply of the elderly is now entering the age of mid-70s, and the pace of increase in their labor participation rate has plateaued since around 2020. Under these circumstances, it is necessary to monitor closely wage trends for non-regular employees, who have high employment mobility and are more responsive to labor tightness. Second, while this paper analyzed labor tightness for regular workers and their impact on posted wages, in general, wages are also affected by consumer price trends. In addition, in the wage determination mechanism for regular workers at individual firms, the annual wage revision negotiations (*shunto*) in Japan has a large impact, particularly for large firms. Investigating the impact of these factors on posted wages - or, alternatively, determining the impact of consumer price trends on average wages of regular workers based on movements in posted wages - is an important topic for future research.

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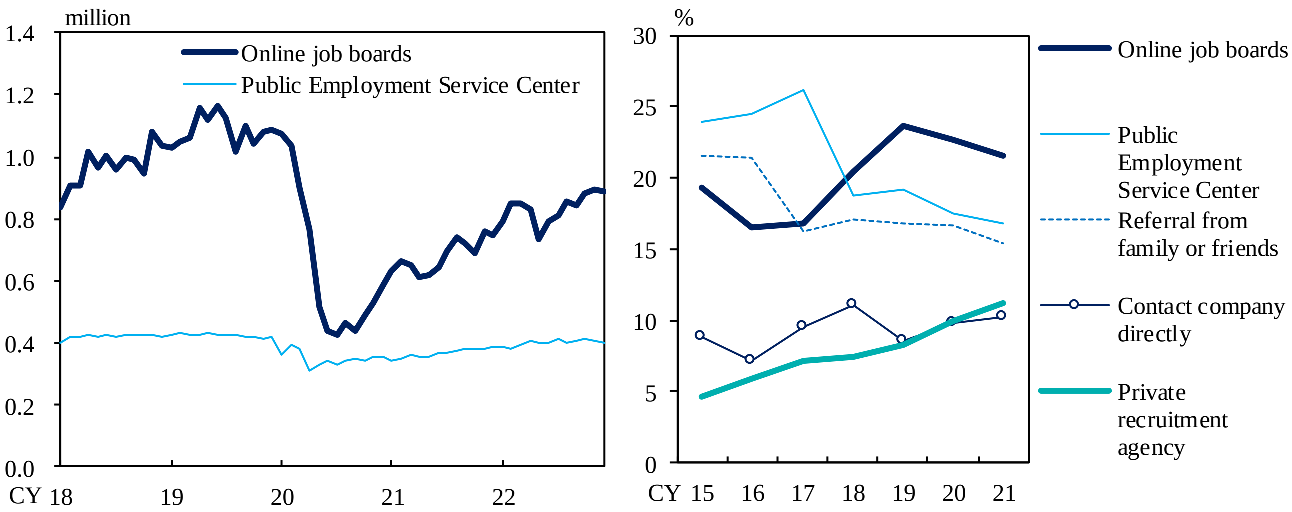
Figure 1. Job Market for Regular Workers

(a) Number of Job Postings (b) Share in Job Switching

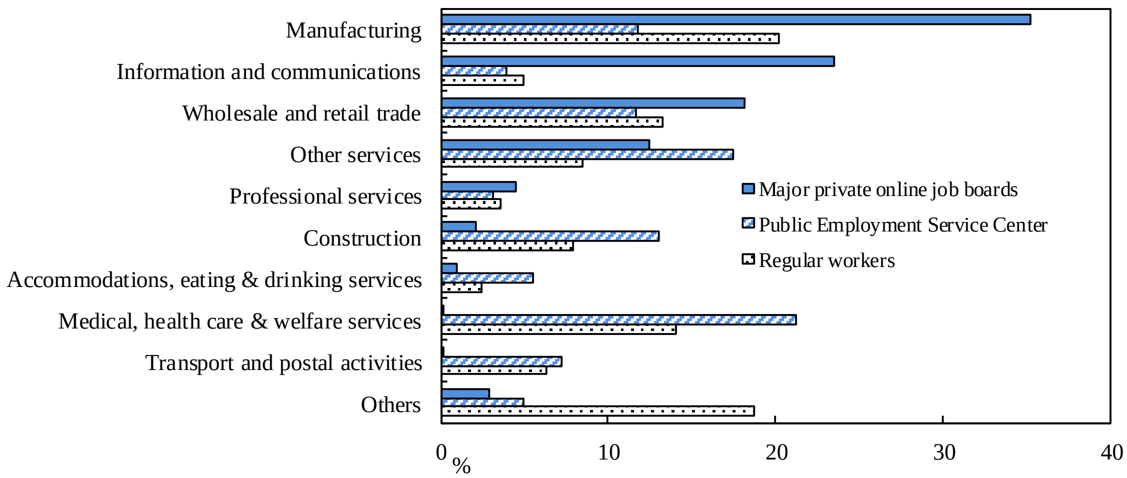


Note 1: The number of jobs posted on online job boards is the average number of job ads posted for regular workers each month at the 15 major online job boards. The number of jobs at the Public Employment Service Center is the number of new full-time job vacancies.

Note 2: The right panel shows the share of regular workers who have switched jobs through each route within a year, based on the *Japanese Panel Study of Employment Dynamics*, released by the Recruit Works Institute. The *Survey on Employment Trends*, released by the Ministry of Health, Labour and Welfare, also shows that "advertisements" including online job boards are the most common route for regular workers to switch jobs.

Sources: Association of Job Information of Japan, Ministry of Health, Labour and Welfare (MHLW), Recruit Works Institute.

Figure 2. Industry Shares



Note: "Major private online job boards" refers to the number of job postings for regular workers listed in the media; "Public employment service center" refers to the number of new job postings for full-time workers listed in the media; "Regular workers" refers to the number of workers employed as regular workers. Data are averaged from January 2015 to December 2022.

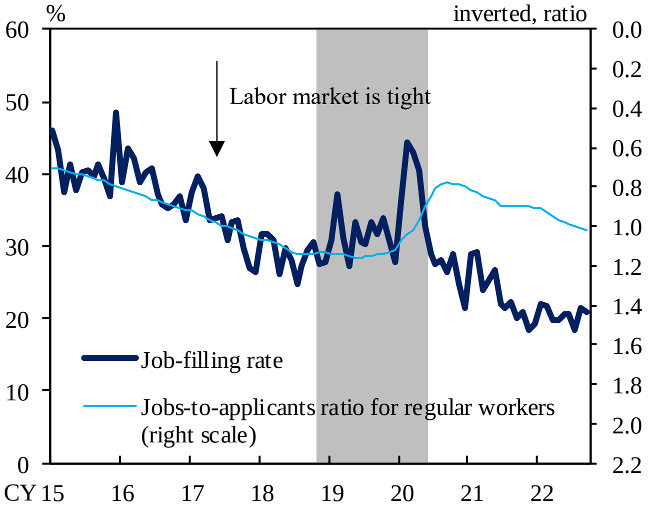
Sources: Authors' calculation based on data job postings data provided by HRog and the *Basic Survey of Japanese Business Structure and Activities* provided by the Ministry of Economy, Trade and Industry (METI), Association of Job Information of Japan, MHLW.

Figure 3. Major Items of Job Ads

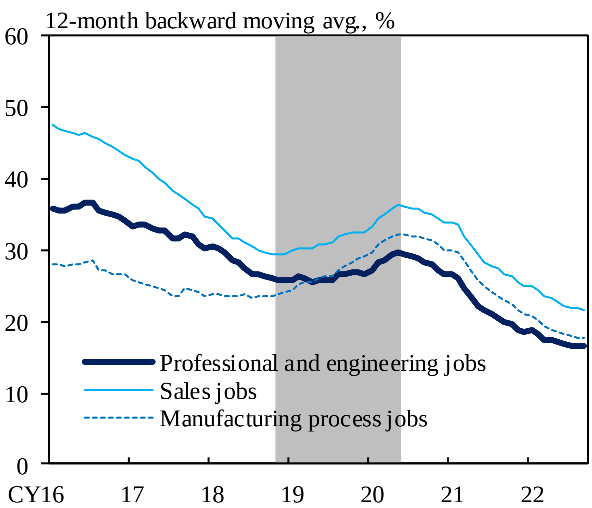
Major items	Description
Date of data acquisition	Date the job posting is retrieved by web scraping (last Monday of each month)
Firm name	Name of the firm that posts the job
Occupation	Occupation of the job
Address of work	Address of the place of work
Address of firm	Address of the firm that posts the job
Posted wage	Posted wage of the job
Job description	Text data about the content of the job
Qualifications	Text data on requirements for applicants (e.g., requirements related to educational background, specific skills, etc.)
First date of posting	Date of the first day the job is posted
End date of posting	The last scheduled date the job will be posted on the website

Figure 4. Job-filling Rate of Posted Jobs

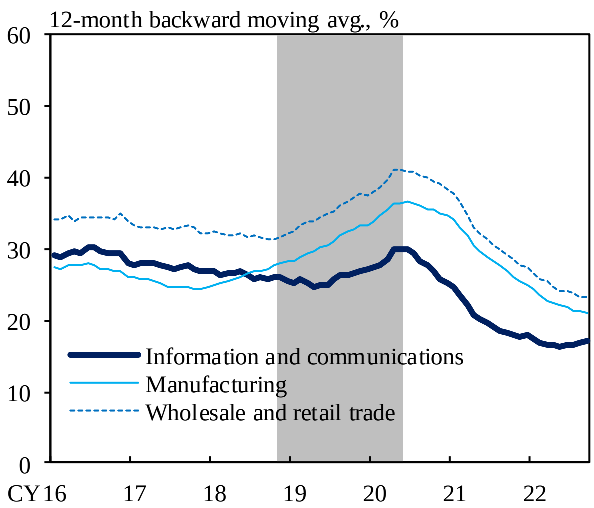
(a) All job postings



（b） By occupation

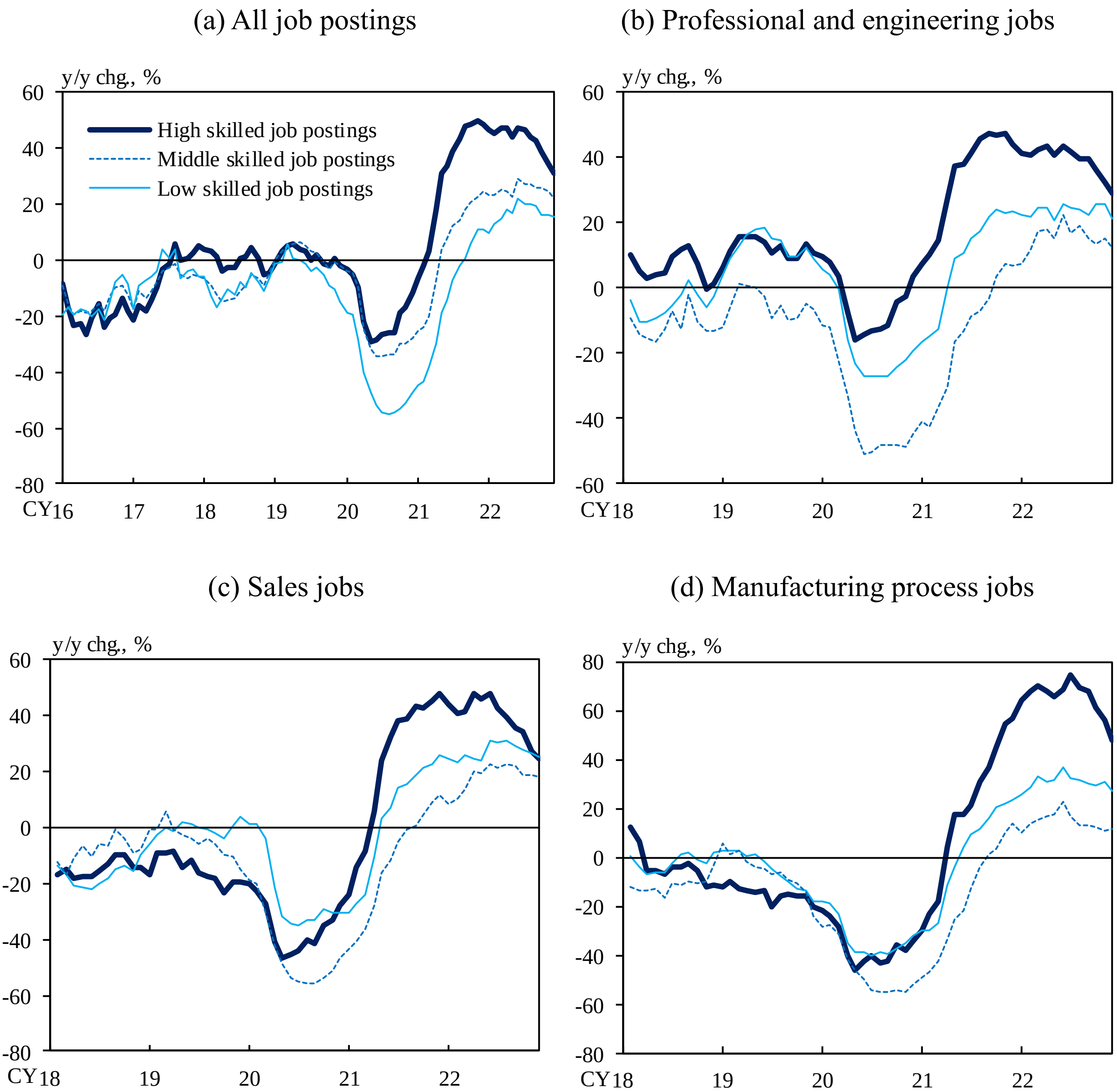


(c) By industry



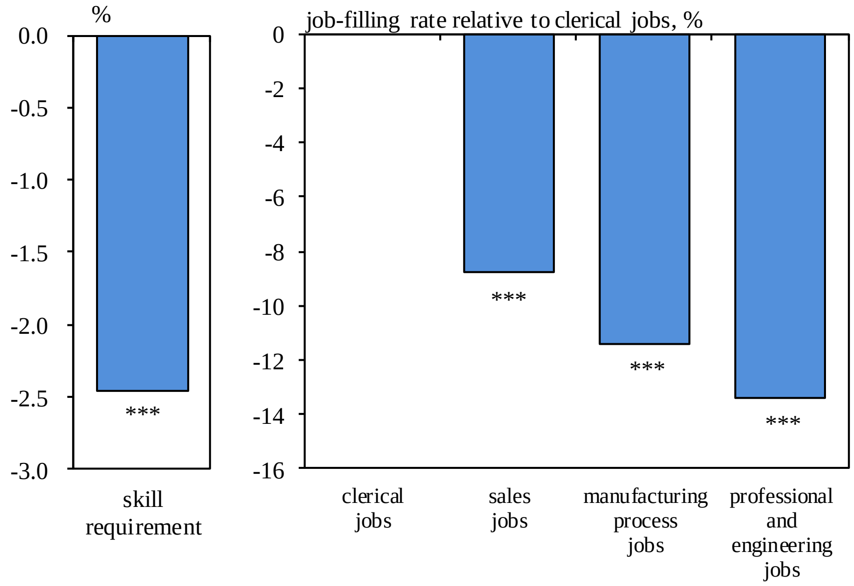
Note 1: Share of new jobs posted in each month that are posted for less than three months.
Note 2: Shadow (November 2018 to May 2020) represents the recessionary period.
Sources: Authors' calculation based on data job postings data provided by HRog and the *Basic Survey of Japanese Business Structure and Activities* provided by METI, MHLW.

Figure 5. Number of Job Postings by Skill Requirement Category



Note: In each month, we calculate the year-on-year change in the number of job postings after restricting our sample to firms that posted jobs in the current month and the same month the year before.
Source: Authors' calculations based on job postings data provided by HRog.

Figure 6. Job Postings' Characteristics and Job-filling Rate



Note 1: The left panel shows how much the job-filling rate decreases when skill requirements increase by one standard deviation.
Note 2: The right panel shows how much the job-filling rate decreases for each occupation relative to clerical jobs.
Note 3: *** indicates statistical significance at the 1% level. The estimation period is from January 2015 to December 2022.

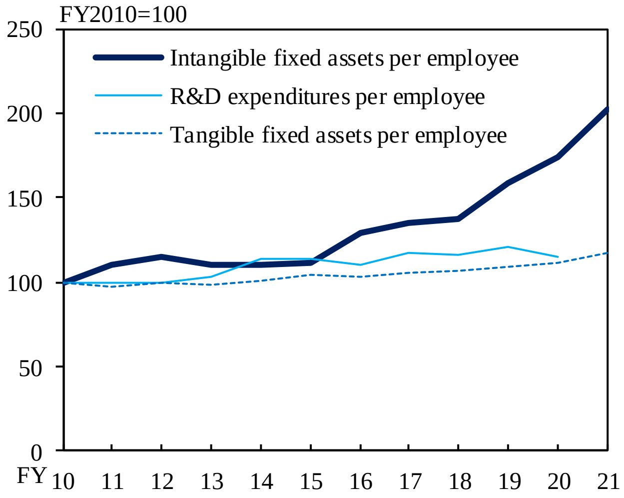
Figure 7. Skill Requirement of Posted Jobs and Firms' Financial Activities

Dependent variable: skill requirement

	(1)	(2)	(3)	(4)	(5)
Tangible fixed assets per employee (logarithm)	0.04 *** (0.00)			0.02 *** (0.00)	0.00 (0.00)
Intangible fixed assets per employee (logarithm)		0.11 *** (0.00)		0.08 *** (0.00)	0.07 *** (0.00)
R&D expenditures per employee (logarithm)			0.13 *** (0.00)	0.10 *** (0.00)	0.09 *** (0.00)
Midium-sized firm dummy					0.06 *** (0.00)
Large firm dummy					0.19 *** (0.01)
Time FE	✔	✔	✔	✔	✔
Occupation FE	✔	✔	✔	✔	✔
Industry FE	✔	✔	✔	✔	✔
Adj. R^2	0.20	0.23	0.23	0.24	0.24
Obs.	425116	415591	233079	208727	208727

Note 1: The medium-sized firm dummy equals one when the capital of the firm posting jobs is between 100 million yen and 1 billion yen. The large firm dummy takes the value of 1 when the firm's capital is at least 1 billion yen.
Note 2: Figures in parentheses indicate standard errors. *** denotes statistical significance at the 1% level. The estimation period is January 2015 to December 2020.

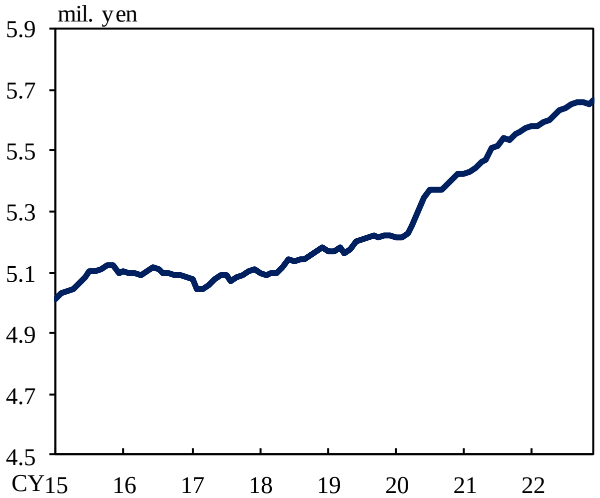
Figure 8. Financial Activities by Firms



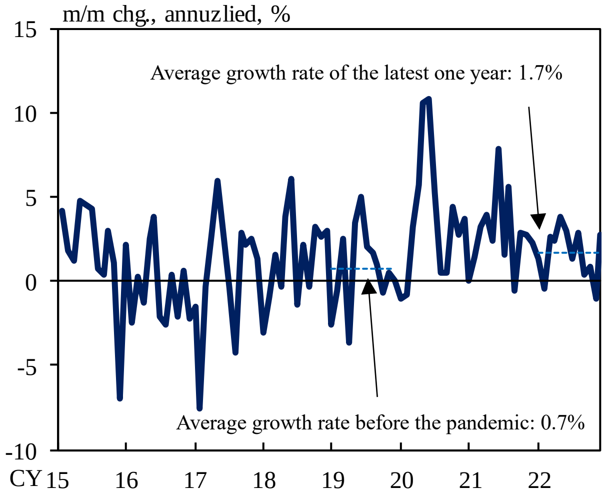
Sources: Ministry of Finance, METI.

Figure 9. Posted Wages

(a) Level



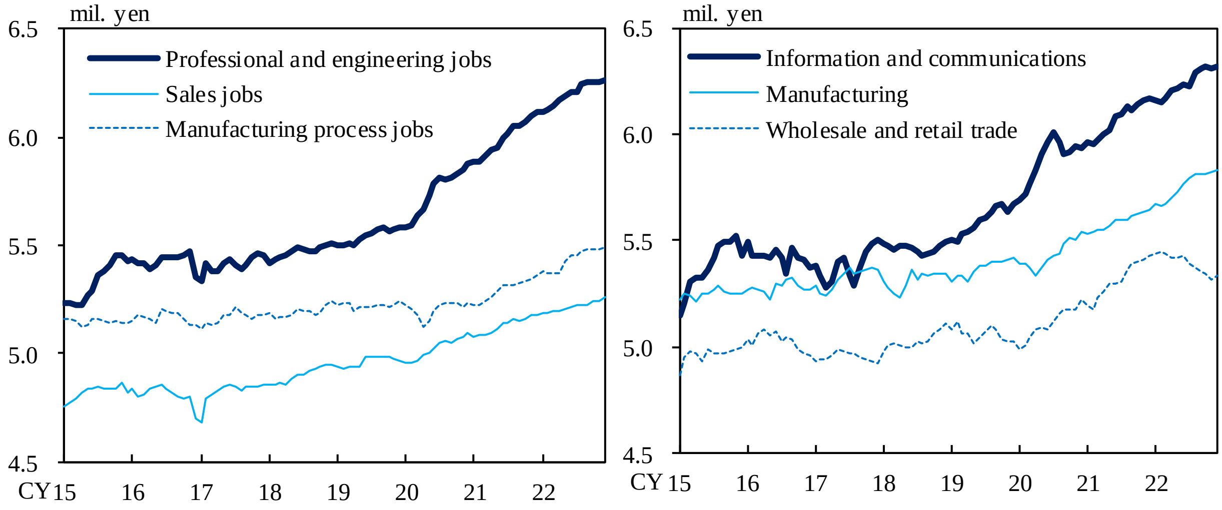
(b) Month-on-month change rate



Source: Authors' calculations based on job postings data provided by HRog.

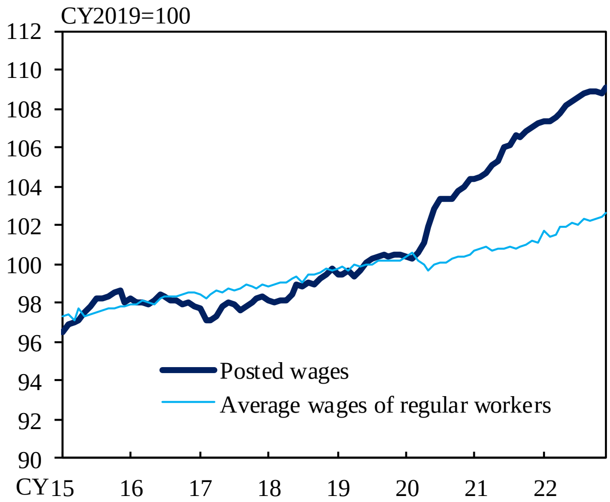
Figure 10. Posted Wages by Occupation and Industry

(a) By occupation (b) By industry



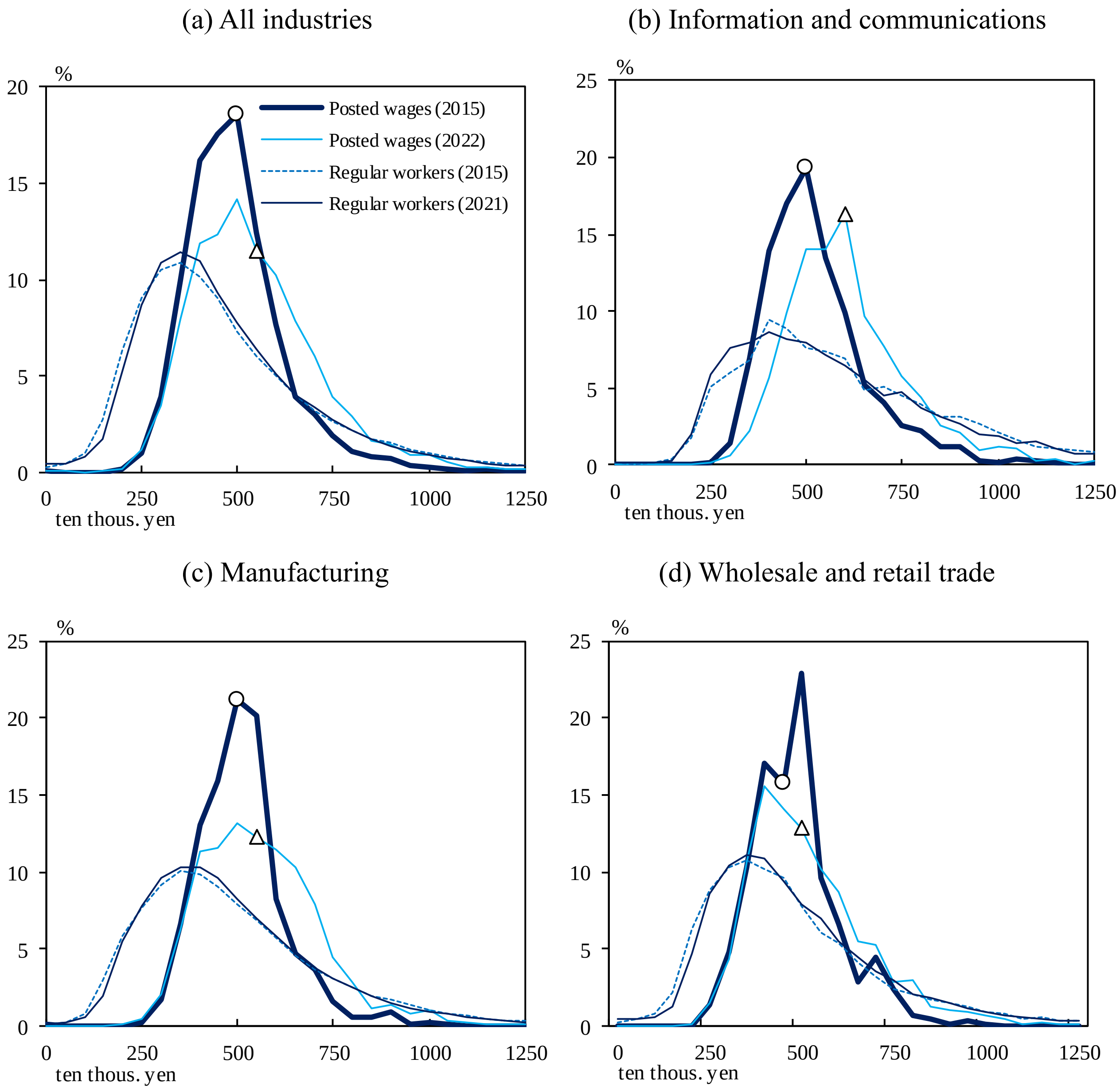
Source: Authors' calculation based on data job postings data provided by HRog and the *Basic Survey of Japanese Business Structure and Activities* provided by METI.

Figure 11. Posted Wages and Average Wages of Regular Workers



Note: Average wages of regular workers are based on the *Monthly Labour Survey*.
Sources: Authors' calculation based on data job postings data provided by HRog and the *Basic Survey of Japanese Business Structure and Activities* provided by METI, MHLW.

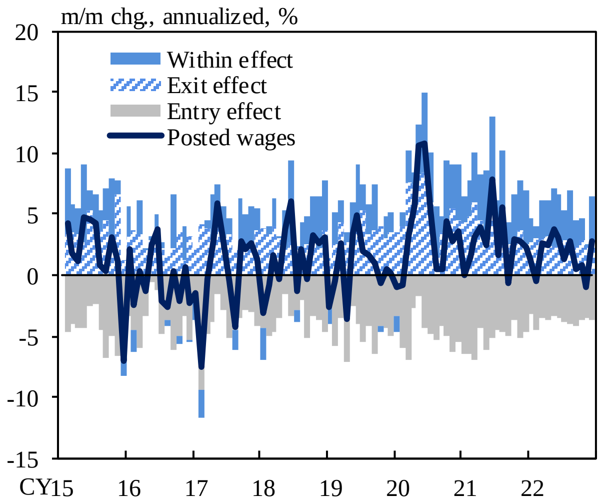
Figure 12. Distribution of Posted Wages and Average Wages of Regular Workers



Note: The markers show the average values in each year.

Source: Authors' calculation based on data job postings data provided by HRog and the *Basic Survey on Wage Structure* provided by MHLW.

Figure 13. Decomposition of Changes in Posted Wages



Note 1: We follow Melitz and Polanec (2015) in decomposing changes in posted wages.
Note 2: The within effect is a contribution from changes in posted wages by firms that continue to post jobs, the exit effect is a contribution from firms exiting the job market, and the entry effect is a contribution from firms entering the job market.
Source: Authors' calculations based on job postings data provided by HRog.

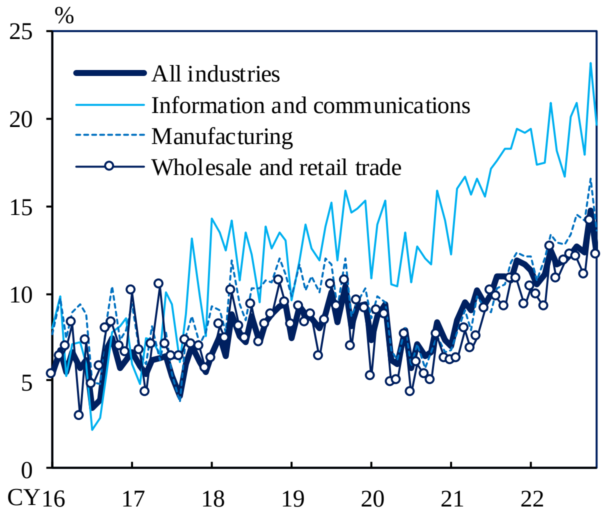
Figure 14. Posted Wages and Labor Tightness

Dependent variable: posted wages (year-on-year change rate)

	(1)	(2)	(3)	(4)
job-filling rate	-0.01 ***	-0.01 **	-0.01 **	-0.01 **
	(0.00)	(0.00)	(0.00)	(0.00)
skill requirement (chg. from previous year)			5.56 ***	5.53 ***
			(0.22)	(0.21)
Time FE	✔		✔	
Industry FE	✔		✔	
Time x Industry FE		✔		✔
Adj. R^2	0.00	0.01	0.04	0.05
Obs.	25816	25816	24924	24924

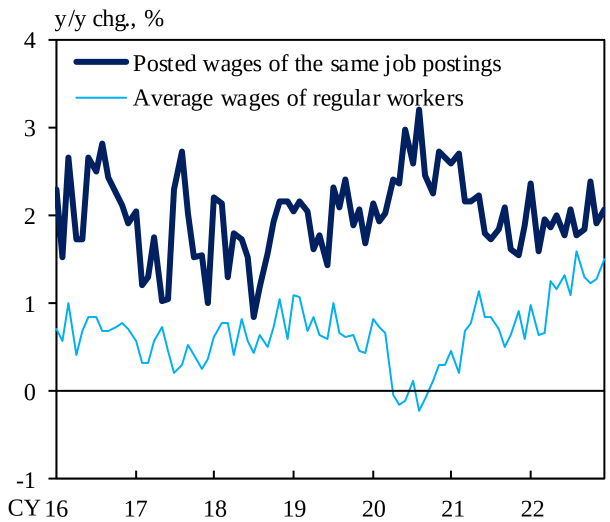
Note: Figures in parentheses represent HAC standard errors. ** and *** denotes statistical significance at the 5% level and the 1% level, respectively. The estimation period is 2015-2020.

Figure 15. Spread of Posted Wages Increases



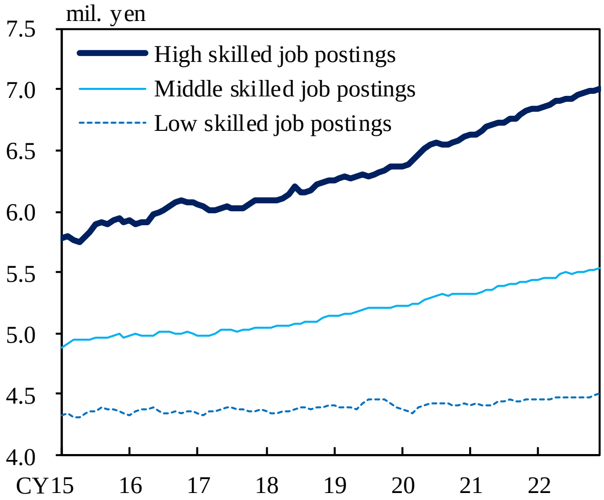
Note: The figure shows the share of jobs defined by firm, address, and occupation whose wages increased compared to the same month of the previous year.
Source: Authors' calculation based on data job postings data provided by HRog and the *Basic Survey of Japanese Business Structure and Activities* provided by METI.

Figure 16. Growth Rate of the Same Jobs



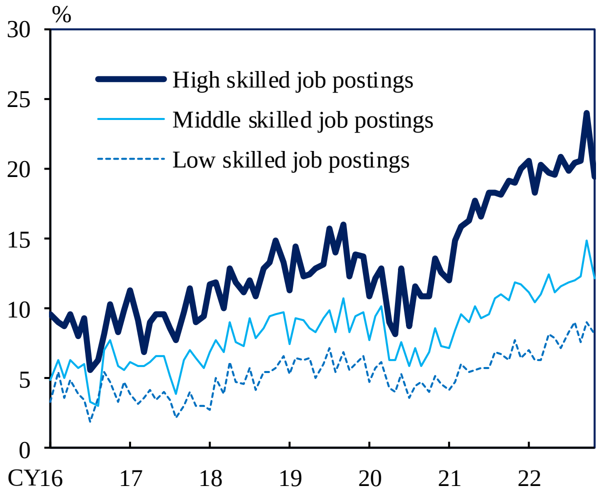
Note: "Posted wages of the same job postings" shows the share of jobs defined by firm, address, and occupation whose wages increased compared to the same month of the previous year. "Average wages of regular workers" are based on the *Monthly Labour Survey*.
Sources: Authors' calculations based on job postings data provided by HRog, MHLW.

Figure 17.　Posted Wage by Skill Requirement



Source: Authors' calculations based on job postings data provided by HRog.

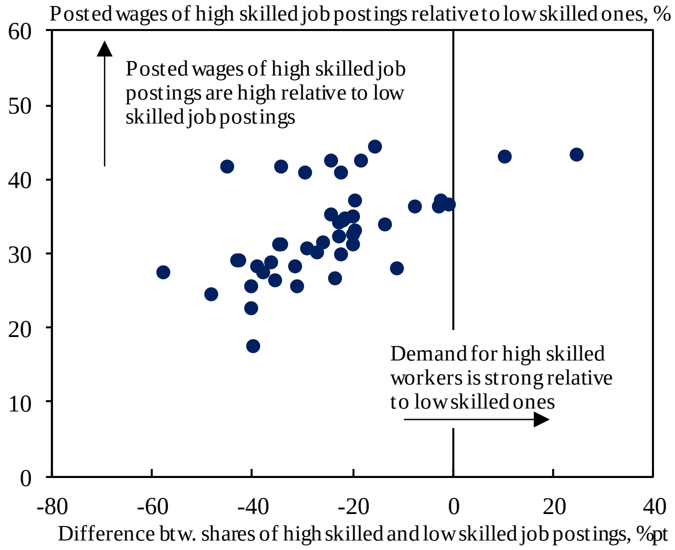
Figure 18.　Spread of Posted Wages Increases by Skill Requirement



Note: The figure shows the share of jobs defined by firm, address, and occupation whose wages increased compared to the same month of the previous year.
Source: Authors' calculations based on job postings data provided by HRog.

Figure 19. Posted Wages and Relative Demand for High Skilled Workers

(a) Scatter plot



Note 1: The horizontal axis shows the difference between the shares of high skill job postings and low skilled job postings. The vertical axis shows the relative level of posted wages of high skilled job postings compared to the average wage of low skilled ones.
Note 2: The data are averaged values between January 2015 and December 2022 for each prefecture.
Source: Authors' calculations based on job postings data provided by HRog

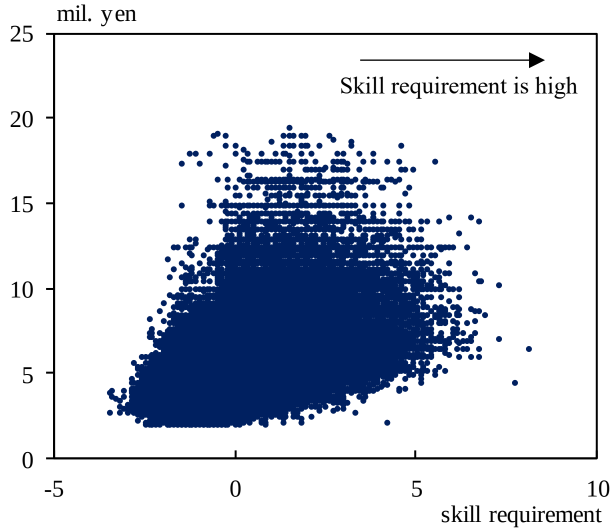
(b) Panel regression

Dependent variable:
posted wages of high skilled job postings relative to low skilled ones, %

	(1)	(2)
difference of shares in high skilled job postings and low skilled ones, %pt	0.21 *** (0.04)	0.09 ** (0.04)
Time FE	✔	✔
Prefecture FE		✔
Adj. R^2	0.21	0.42
Obs.	4010	4010

Note 1: Panel estimates are based on data aggregated by prefecture and month. The dependent variable is the level of posted wages of high skilled job postings relative to low skilled job postings (%), and the explanatory variable is the difference between the shares of high skilled job postings and low skilled job postings (%pt).
Note 2: Figures in parentheses show HAC standard errors. ** and *** denote statistical significance at the 5% level and the 1% level, respectively. The estimation period is from January 2015 to December 2022.

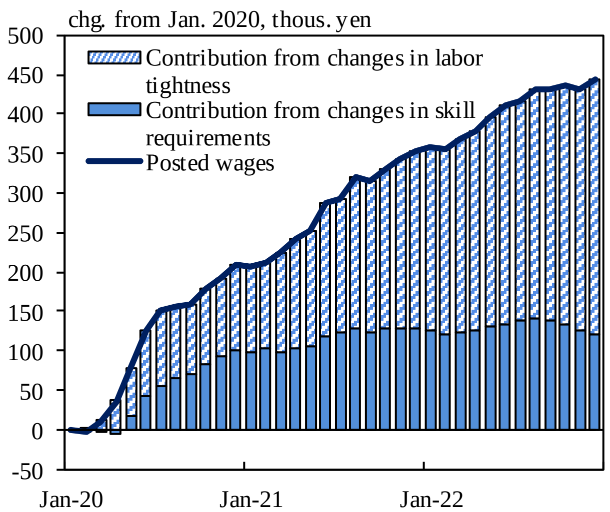
Figure 20. Skill Requirement and Posted Wages



Note: The relationship between the degree of skill requirements (standardized so that the sample mean is 0 and the standard deviation is 1) and posted wages is shown for individual job postings in the online job board between January 2015 and December 2022.

Source: Authors' calculations based on job postings data provided by HRog.

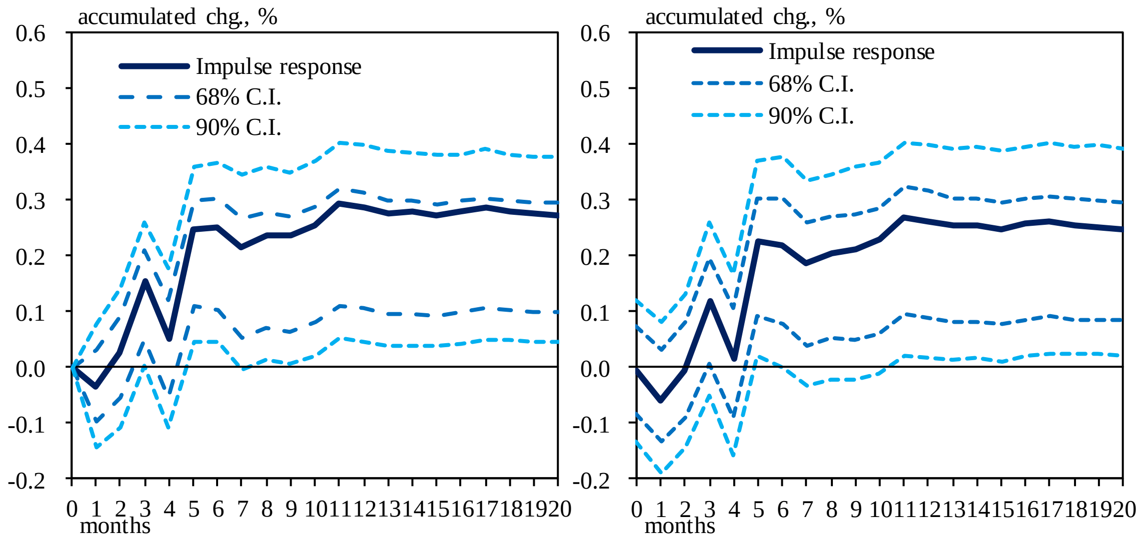
Figure 21. Decomposition of Posted Wages



Source: Authors' calculations based on job postings data provided by HRog.

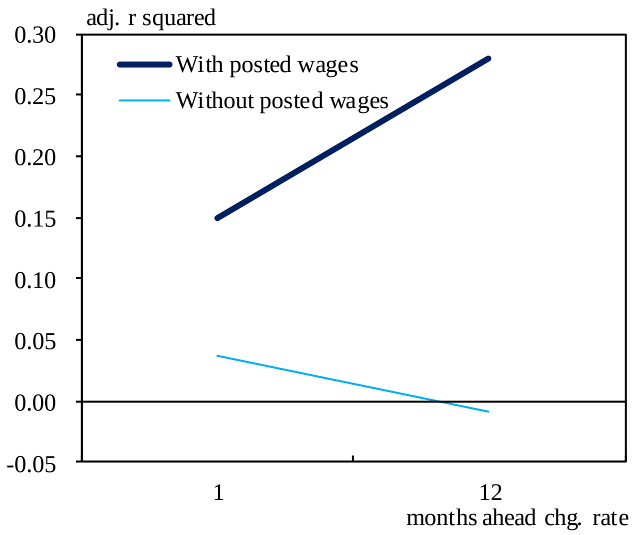
Figure 22. Impulse Response of Average Wages of Regular Workers to Posted Wages

(a) Cholesky decomposition (b) Generalized impulse response



Note: We estimate a VAR model with three variables: unemployment rate, average wages of regular worker (month-on-month change rate), and average posted wages (month-on-month change rate), and calculate the cumulative impulse response of average wages of regular workers when average posted wages increase by 1%. The dashed line is the confidence interval based on the bootstrap method (2000 iterations). The left panel shows the impulse response by Cholesky decomposition (in the above variable order). The right panel shows the value of the generalized impulse response that does not depend on variable order. The estimation period is from January 2015 to December 2022.

Figure 23. Explanatory Power of Posted Wages to Average Wages of Regular Workers



Note: We estimate models that explain the forward-looking growth rate of average wages of regular workers by (i) lag terms of average wages of regular workers and the unemployment rate and (ii) lag terms of the posted wages in addition to the aforementioned two variables. We then compare the explanatory power of the two models in term of degree-of-freedom-adjusted coefficient of determination. In the figure, the first model is labeled as "Without posted wages" and the second as "With posted wages." The estimation period is from January 2015 to December 2022.

Figure 24. External Pressure Effect

Dependent variable: total salary per employee (year-on-year change rate)

	(1) All establishments	(2) less than 30 employees	(3) less than 10 employees
Posted wages in the same industry and the same prefecture (y/y chg.)	0.04 * (0.02)	0.09 ** (0.05)	0.15 ** (0.07)
Working hours per employee (y/y chg.)	0.25 *** (0.01)	0.38 *** (0.03)	0.44 *** (0.04)
Time FE	✔	✔	✔
Industry FE	✔	✔	✔
Prefecture FE	✔	✔	✔
Adj. R^2	0.06	0.12	0.16
Obs.	11023	2248	1127

Note: Figures in parentheses represent HAC standard errors. *, ** and *** denote statistical significance at the 10% level, the 5% level, and the 1% level, respectively. The estimation period is 2015-2021.

Figure 25. Internal Pressure Effect

Dependent variable: total salary per employee (year-on-year change rate)

	(1)	(2)	(3)	(4)
posted wages of matched job postings (y/y chg.)	0.04 ** (0.02)	0.03 * (0.02)		
posted wages of all job postings (y/y chg.)			0.04 (0.03)	0.03 (0.03)
sales per employee (y/y chg.)	0.40 *** (0.02)		0.41 *** (0.02)	
value added per employee (y/y chg.)		0.40 *** (0.02)		0.40 **** (0.02)
Time FE	✔	✔	✔	✔
Industry FE	✔	✔	✔	✔
Adj. R^2	0.15	0.31	0.15	0.31
Obs.	2682	2703	2686	2708

Note: Figures in parentheses represent HAC standard errors. *, ** and *** denote statistical significance at the 10% level, the 5% level, and the 1% level, respectively. The estimation period is 2015-2020.