Discussion Paper Series A No.746

Estimating Recruitment Elasticity in the Multi-stage and Bilateral Job Matching Process

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July 2023

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Estimating Recruitment Elasticity in the Multi-stage and Bilateral Job Matching Process *

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May 20, 2023

Abstract

Estimating recruitment elasticity is complex due to the multi-stage, bilateral decision-making process involving workers and employers in job matching. To measure it, this study uses novel data from a major job-matching intermediary in Japan and investigates the selectivity of vacancies and worker wage elasticities at each stage of the job-matching process from applications to offer acceptances. Our findings reveal that vacancies exhibit greater selectivity for job offers compared to interview invitations. Worker application elasticities range between 0.05 and 0.21, contingent upon previous wage and employment status. However, interview attendance elasticities are statistically insignificant and offer acceptance elasticities of approximately 0.05. These results suggest that workers exhibit reduced sensitivity to wages during interview attendance decisions, anticipating competition from fellow applicants. The elasticities are higher for above-median wage workers compared to their below-median counterparts, supporting this interpretation. Implied recruitment elasticities do not exceed 1, even for the estimated upper bound, reflecting the strong market power of employers.

Keywords: Market power of employers; Monopsony; Job matching intermediary; Recruitment elasticity; Application; Interview; Offer; Control function approach.

JEL code: J20; J30; J42; J64; L13; L40.

*This study was financially supported by KAKENHI 19H00592, 17KK0044, and 16H02020. We thank Yutaro Takayasu and Haruo Kakehi for their research assistance. We also thank Ryota Mugiyama and Kyoko Komatsu for providing the dataset of correspondence between job and task score in the Japanese O*NET. We are also grateful for helpful comments and discussions at seminars at the Hong Kong University of Science and Technology and Jinan University. All errors are our own.

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1 Introduction

The increasing evidence and consensus on non-competitive labor markets (Manning, 2003), concerns regarding the declining labor share (Karabarbounis and Neiman, 2014), and a renewed focus on antitrust enforcement in the labor market (Department of Justice and Commission, 2016) have established a new research agenda aimed at estimating employer market power in the labor market. The estimation of recruitment elasticity, defined as the wage elasticity of the labor supply at the firm level, became crucial to this agenda (Naidu and Posner, 2022).

In labor economics, the labor market has traditionally been conceptualized as a perfectly competitive market. Given this assumption, the elasticity of recruitment is regarded as infinite, rendering the market-level wage elasticity of labor supply the sole aspect of interest. This perspective posits that the heterogeneity among firms is effectively compensated by wage differentials. Consequently, the market-level wage elasticity can be estimated using household panel data, which does not necessarily identify employer-employee relationships (Chetty, 2012). However, when taking into account an imperfectly competitive labor market, the recruitment elasticity becomes a finite value and garners specific attention. Owing to the discrepancy between recruitment elasticity and market-level wage elasticity, it is imperative to employ an alternative estimation methodology for determining wage elasticity.

Nonetheless, data limitations have hindered researchers from directly estimating recruitment elasticity at the firm level. Instead, the literature has assumed that recruitment elasticity is the inverse of quit elasticity (Dube et al., 2020; Horton et al., 2011; Yin et al., 2018) exploiting the equality between quit and recruitment in the steady state, or utilized worker application data from job advertising platforms to estimate recruitment elasticity by the application elasticity (Dal Bó et al., 2013; Dube et al., 2020; Pörtner and Hassairi, 2018; Belot et al., 2018; Azar et al., 2019a; Banfi and Villena-Roldán, 2019; Azar et al., 2019b).

Both approaches have problems: The assumption for the use of inverse quit elasticity is too restrictive and the application elasticity is not equivalent to recruitment elasticity, as applications do not necessarily result in job offers (Manning, 2020). Firstly, there are additional decision-making margins for workers, such as interview attendance and offer acceptance. Secondly, employment is not solely the worker's choice, but rather a bilateral match between the worker and employer, consistent with the widely observed fact that application callback rates are far from 1.[1] To illustrate the problem, suppose that workers are homogeneous and there is only one employer whose capacity is imperfectly flexible. When

[1] The resume audit study reports callback rates of 9.65% for white names and 6.45% for African-American names (Bertrand and Mullainathan, 2004). Kuhn et al. (2020) report that, on a Chinese job board, employers call back only 8.4% of applications (19,245 out of 229,616).

there are n workers and one job posting and n_1 applications lead to $c_1 n_1^{\tau_1}$ interviews and n_2 interviews lead to $c_2 n_2^{\tau_2}$ job offers, the number of recruitment is $p_3(w)\{p_2(w)[p_1(w)n]^{\tau_1}\}^{\tau_2}$ and the recruitment elasticity is $\epsilon_3 + \tau_2\epsilon_2 + \tau_2\tau_1\epsilon_1$ if $p_t(w)$ and $e_t(w)$ are the probability of choice and elasticity at the wage w for application ($t = 1$), interview attendance ($t = 2$), and offer acceptance ($t = 3$). Thus, the offer acceptance elasticity is the lower bound, the sum of all wage elasticities is the upper bound of the recruitment elasticity, and the contribution of application elasticity to recruitment elasticity can be negligible because it is deflated by the elasticities of vacancies' decisions, $\tau_2\tau_1$.

The existing literature has not adequately assessed the implications of these multi-stage and bilateral decisions on recruitment elasticity, as they have relied on employer-employee matched data or job advertising platform data, both of which lack information on post-application processes.

In this study, we address the limitations of previous research by utilizing data from one of the largest job-matching intermediaries in Japan, which encompasses all decisions involved in the job-matching process from applications to offer acceptances. Our data offer several additional advantages: i) coverage of both on-the-job and off-the-job searches; ii) inclusion of employed workers' current income and unemployed workers' previous income; and iii) availability of the posted wage range for all vacancies without any missing values. Leveraging this data, we first investigate how the number of interview calls changes with an increase in the number of applications and how the number of offers increases with the number of interviews conducted. We secondly estimate the worker's wage elasticity of offer acceptance, interview attendance, and application. Finally, we use the estimates of wage elasticities to calculate the implied recruitment elasticity.

Through descriptive analysis, we find that workers anticipate greater competition during the interview attendance decision compared to the application decision. The probability of receiving an interview call after applying is 0.5, while the probability of a job offer after attending an interview is only 0.165. The elasticity of interview calls with respect to the number of applications is 0.495, while the elasticity of job offers with respect to the number of interviews is merely 0.249. This indicates that selection criteria are more stringent and less elastic during the job offer decision stage. Additionally, we observe that wage elasticities vary across each stage of the job-matching process and depend on the worker's economic circumstances. The wage elasticity of applications is relatively high but does not exceed 1, while the wage elasticity of interviews and offer acceptance is considerably lower. Workers with above-median previous wages have higher wage elasticities compared to those with below-median previous wages. These findings support the idea that job offers are more selective than interviews, and workers face varying competitive pressures and costs of action throughout the job-matching process.

We further validate these findings through regression analysis. First, we estimate the worker's offer acceptance decision as a multinomial choice problem, controlling for unobserved vacancy-specific fixed effects using a control function approach (Petrin and Train, 2010). We discover that the elasticity of offer acceptance to the posted wage is positive but quite low, no greater than 0.1 for all worker segments.

Second, we estimate the worker's conditional choice probability for interview attendance decisions by approximating the worker's problem with multiple independent binary decision problems. We find that the interview attendance elasticity is statistically significantly different from zero only for above-median wage workers, with elasticities smaller than 0.01.

Lastly, we estimate the worker's conditional choice probability for application decisions using a model and method similar to the interview attendance problem. We find that the application elasticity is positive and statistically significant for all worker segments. The wage elasticities at the application stage are 0.103 for above-median employed workers, 0.109 for below-median employed workers, 0.213 for above-median unemployed workers, and 0.0474 for below-median unemployed workers. Thus, except for below-median unemployed workers who are less competitive and urgently need a job, the wage elasticities are larger than 0.1.

The recruitment elasticity can be approximated by the sum of offer acceptance elasticity, interview attendance elasticity times the elasticity of offers to interviews, and application elasticity times the elasticity of offers to interviews and the elasticity of interview calls to applications. Consequently, even if the application elasticity is high, the resulting recruitment elasticity can be low if the elasticities of vacancies' decisions are low.

The estimated recruitment elasticities are 0.186 for below-median wage unemployed, 0.125 for below-median employed, 0.390 for above-median unemployed, and 0.241 for above-median employed. Thus, the recruitment elasticities are higher for above-median wage workers than for below-median wage workers, whereas the difference between unemployed and employed is not substantial. Even when ignoring the elasticities of vacancies' decisions and summing up the application, interview attendance, and offer acceptance elasticities, they do not exceed 1, indicating high market power on the vacancy side. These findings suggest that the differentiation of vacancies in the job-matching intermediary can be a source of market power for employers.

1.1 Novelty and Contribution

The competitive model without any market power or institutional influence has long been dominant in labor market analysis. The primary issue in the labor market was the rigidity of nominal wages (Hicks, 1969). In the 1970s, search friction in the labor market became a central focus, but this friction was often encapsulated by a black box of aggregated matching functions. While the micro foundations of these matching functions have been investigated, they have remained highly stylized. The market power of employers was not considered, and the lack of data made analyzing the actual job-matching process challenging.[2]

In the 2000s, interest in employer market power increased due to growing evidence and consensus on the non-competitive labor market (Manning, 2003) and concerns about the declining labor share (Karabarbounis and Neiman, 2014). The need for an antitrust policy for the labor market was rediscovered during this debate (Naidu et al., 2018). Simultaneously, the analysis of the job matching process within actual market institutions emerged due to the growing availability of data from job advertising platforms (Autor, ed, 2009; Marinescu and Wolthoff, 2019). Our paper is the first to use data from a job-matching intermediary and directly identify the multi-stage wage elasticities in the job-matching process.

Manning (2020) distinguishes between monopsony models based on search friction, referred to as modern monopsony models, and those based on worker's taste heterogeneity, known as neoclassical monopsony models. The former includes Burdett and Cunningham (1998), while the latter includes Card et al. (2017). Our paper focuses on the worker's choices after registering with a job-matching intermediary and receiving vacancy recommendations. Therefore, it specifically investigates the employer's market power due to worker taste heterogeneity in an environment where search friction is relatively small.

The estimates of application elasticity in recent studies vary between negative (Marinescu and Wolthoff, 2019), 0.1 to 0.25 (Banfi and Villena-Roldán, 2019), and 0.43 (Azar et al., 2020) in observational studies, and 0.7 (Belot et al., 2019) and 2 (Dal Bó et al., 2013) in experimental studies. Thus, our estimates of application elasticity are in the range of the existing literature. Our paper does not only estimate the application elasticity but also combines the application elasticity estimate with other wage elasticity estimates to evaluate the recruitment elasticity in the multi-stage and bilateral job-matching process.

2 Institutional Background

2.1 Antitrust Laws in the Labor Market

In the United States, antitrust law has exempted collective bargaining by workers since the introduction of Chapter 6 of the Clayton Act in 1914, the Wagner Act in 1935, and the Taft-Hartley Act in 1947. While antitrust law can be applied to the collective behavior of

[2] See Petrongolo and Pissarides (2001) for a literature survey of aggregate matching functions.

employers, there have been very few cases reported until US v. Adobe Systems Inc. et al. in 2010. This case marked a significant shift in the attention given to potential antitrust violations in labor markets, highlighting the growing concern about employer market power and the importance of ensuring fair competition in these markets.

Meanwhile, the growing sharing economy urged regulators to consider the application of antitrust laws to gig workers' contracts because these workers are, by definition, not employed workers that are traditionally protected by labor law (Harris and Krueger, 2015). This, in turn, made regulators reconsider the coverage of antitrust laws. Because some employed workers work under a similar condition to gig workers, regulators began to consider the application of antitrust laws to the contracts of employed workers (Department of Justice and Commission, 2016). Consequently, the US Department of Justice (DOJ) antitrust division began to file no-poach agreements among employers[3] and private conflicts between employers and former employer[4] as civil cases. In 2020, the DOJ filed the first criminal case of wage-fixing behavior among employers. In the following year, the federal district court in Texas released the first statement that concluded that wage-fixing agreements between competing employers are a per se violation of the Sherman Act that can be prosecuted as a criminal case.[5] In 2021, the DOJ also filed the first criminal case of a no-poach agreement[6] and two other cases.[7] In 2022, the DOJ and the Federal Trade Commission (FTC) launched an inquiry to review the merger guideline, and one of the areas of inquiry is the impact of monopsony power, including the labor market. Thus, the application of the antitrust law to the entire labor market for both collective and unilateral behavior of employers was brought back into force.

The Japanese antitrust law also exempts collective bargaining of workers on the basis of the Labor Union Act of 1945. The antitrust law could be applied to the collective behavior of employers and the unilateral relationship between an employer and an employee. However, the Ministry of Labor and the Fair Trade Commission implicitly agreed not to apply the antitrust law on collective behavior by employers, such as information sharing on wage settings and the agreement on the timing of hiring (Ishi, 1947). Following a similar course of argument in the US, the application of antitrust law to the gig workers' contract has begun to be discussed (Ministry of Economy, Trade, and Industry, 2017) and the application of antitrust law to the entire labor market for both collective and unilateral behavior of

[3] *United States v. Knorr-Bremse AG and Westinghouse Air Brake Technologies Corporation.*

[4] *Danielle Seaman v. Duke University and the Duke University Health System* as a case of faculty from medical schools and *Ashlie Harris v. CJ Starr LLC et al.* as a case of fast food franchises.

[5] *US v. Neeraj Jindal.*

[6] *US v. Surgical Care Affiliates, LLC, and SCAI Holdings, LLC.*

[7] *US v. Ryan Hee and VDA OC LLC, formerly Advantage on Call LLC* and *US v. Davita INC. and Kent Thiry.*

employers became in sight (Japan Fair Trade Commission, 2018).

2.2 Law and Regulation of Job Matching Intermediaries

The job matching intermediary is defined as the provider of job placement services under the International Labor Organization (ILO) convention. In the convention, the job placement service and the job advertisement service are strictly distinguished. The placement service is defined as a service that mediates the matching between workers and employers by processing information between them. In contrast, the advertising service cannot process any information between a worker and an employer. It can only offer a marketplace.

This difference in the nature of the service is important to us. We can use detailed characteristics of the worker and the vacancy and track the entire job matching process from the job application, interview call, interview attendance, job offer, and offer acceptance because the job matching intermediary involves these activities. On the other hand, data from a job advertisement service cannot include information after job applications.

In Japan, the Employment Security Act defines and regulates the job-matching intermediary. [8] A job matching intermediary is required to have a license (Article 33), and it can charge fees only to the employer (Article 32-3(2)). [9] The job-matching intermediary cannot intervene in the relationship between the employer and worker once the employment contract is concluded. Due to this regulation, for-profit intermediaries cannot track the worker after matching. Therefore, we cannot use outcomes after matching, such as the retention rate.

In 2019, there existed 25.1 thousand for-profit job-matching intermediaries in Japan. They handled 7.7 million vacancies and 20.0 million workers. In 2014, the year of our data, 17.9 thousand for-profit intermediaries were active and handled 4.4 million vacancies and 15.6 million workers. The for-profit intermediaries created 518 thousand jobs and collected a total amount of fees of 3.3 billion USD. [10] According to the Employment Trend Survey of the Ministry of Health, Labour and Welfare, 5.0 million workers who were employed by companies with more than 5 employees changed jobs in 2014. Thus, approximately 10% of the job changers are through for-profit intermediaries.

Since the beginning of industrialization, the job-matching intermediary has been under regulation. ILO conventions have prohibited for-profit job-matching intermediaries to rule

[8] "[R]eceiving offers for posting job offerings and offers for registering as a job seeker and extending services to establish employment relationships between job offerers and job seekers." (Article 4-1)

[9] "[A] fee-charging employment placement business provider shall not collect any fees from job seekers." This regulation corresponds to C181 of ILO; "Private employment agencies shall not charge directly or indirectly, in whole or in part, any fees or costs to workers." (Article 7-1 C181)

[10] https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/koyou_roudou/koyou/haken-shoukai/shoukaishukei.html

out the exploitation of workers. Matching jobs by for-profit intermediaries was considered hardly distinguishable from trafficking. Consequently, it has been monopolized by a public employment agency in many countries under the Unemployment Recommendation in 1919 (R001) and the Fee-Charging Employment Agencies Convention in 1933 (C034), which was revised in 1949 (C096). 42 countries ratified C034.

However, in the 1990s, regulators started to think that the harm of for-profit job-matching intermediaries has been mitigated because of the improvement of labor laws and regulations and the diffusion of Internet technology. Thus, R001 was withdrawn in 2002, and the ratification of the Convention on Private Employment Agencies in 1997 (C181) automatically overruled C096. Among the 42 countries that ratified C034 (C096), it is no longer in force in 19 countries. For-profit job-matching intermediaries in Japan have also emerged from this wave of deregulation.

2.3 Job Matching Process in the Intermediary

The job-matching intermediary we collaborate with offers a two-sided service, employing agents for both vacancies and workers. These agents are referred to as recruiting advisers (RA) for vacancies and career advisers (CA) for workers. When a vacancy is registered, the RA communicates with the corresponding employer to gather unwritten job details, adjusts the advertisement as necessary, and verifies the qualifications of potential candidates. Meanwhile, the CA meets with registered workers to discuss their goals, job-search scope, and assess their experience and qualifications. The CAs and RAs maintain a close relationship to share information, enabling the CA to recommend suitable vacancies to workers. When a worker applies for a vacancy, the RA conducts an initial screening and forwards the application package of qualified candidates to the employer. The intermediary earns a fixed share of the annual salary (typically 30%) from the vacancy if the worker and the vacancy are successfully matched and the match lasts for at least six months; otherwise, the intermediary receives no compensation.

A worker initiates the job-matching process by registering on the intermediary's website. After registration, they can access vacancy information but can only apply for a vacancy if the CA interviews them and provides a recommendation. Applications without a CA's recommendation are automatically rejected, so the CA's recommendation essentially determines the worker's choice set at the application stage. If the application passes the RA's initial screening, the application package is sent to the employer for review. The rest of the process follows the usual job-matching procedures, with the intermediary not intervening but being informed of events in the system. Based on the application package, the employer decides whom to invite for interviews. Workers then decide which interviews to attend. After the interview, the employer decides whether to extend a job offer. Upon receiving an offer, the worker decides whether to accept it.

2.4 Remarks on the Application Decision

In the following analysis, we treat the worker's application decision in the data as revealing the worker's preference. However, caution is necessary when interpreting this information. While a worker's application decision is theoretically independent of the CA's recommendation, the data indicates that a worker almost exclusively applies to a vacancy if, and only if, the CA recommends it: a worker applies to 96.4% of recommended vacancies and never applies when not recommended. Consequently, the worker's application decision may already be influenced by the CA's preference during their meeting. If this is the case, the application data only reveals the worker's preference after their meeting with the CA.

First, we can think that the estimand can be the preference after the meeting with the CA. Although this introduces a concern for the external validity of the estimated application elasticity in other set-ups, it may not be a substantial problem because similar meetings exist in any other job-matching intermediary. Second, even if the estimand is the worker's preference before meeting with the CA, we could argue that the bias in the estimated application elasticity is negligible. The CA's recommendation accommodates the worker's interest: only 1.2% of the applications recommended by the CA are about vacancies for which the worker did not collect information by themselves, and the worker complies almost all the CA's recommendations above. Thus, if the CA could affect the worker's application decision, it is only by rejecting the recommendation for vacancies that the worker was interested in and not by recommending a vacancy that the worker was not interested in. However, the CA has little reason to reject the application because it is the RA's job to reject it. Therefore, it would be plausible to assume that the CA serves workers as perfect agents rather than strategic agents.

3 Model

We model a job-matching process involving applications, interviews, and offers. We simplify the model of the employer's decision and focus on a registered worker's decision over the application, interview attendance, and offer acceptance. To simplify the description of the dynamic model, we discretize the characteristics of workers and registers.

3.1 Environment

Consider a round of job matching process indexed by r. There are I workers and J vacancies registered on the platform. The number of workers is large and a worker does not incorporate the effect of their own strategy on others. There are observed characteristics of workers that take a value of K distinct points $z \in \{z(1), \ldots, z(K)\}$. There are public characteristics of vacancies that take a value of L distinct points $x \in \{x(1), \cdots, x(L)\}$. There are private characteristics of vacancies that take a value of M distinct points $\xi \in \{\xi(1), \ldots, \xi(M)\}$. There are N levels of posted wages $w \in \{w(1), \ldots, w(N)\}$. Let z_i denote the characteristics of worker i and x_j, ξ_j, and w_j denote the characteristics and posted wage of vacancy j. For the outside option, $x_0 = \xi_0 = w_0 = 0$. That said, the characteristics of the worker's current job are captured by z_i. Let e_r summarize the discrete distribution of registered vacancies' characteristics.

At the beginning of the job matching process, a vacancy observes the public characteristics of registered vacancies and its own private characteristics. Then, the vacancy posts the wage. After the job posting stage, there are application, interview, and offer stages. A worker observes the public characteristics of vacancies but observes the private characteristics only through the interview.

The application stage consists of unit time. A job vacancy's job posting randomly arrives at the worker according to an arrival rate, and the worker decides whether to apply to the vacancy. As the application stage ends, a vacancy decides the arrival rate of the interview calls for each worker type as a function of the number of applications accumulated in the application stage. Thus, the vacancy does not distinguish the workers by the characteristics for deciding the interview calls.

The interview stage also consists of unit time following the application stage. An interview call from a vacancy randomly arrives at the worker according to the arrival rate, and the worker decides whether to attend the interview of the vacancy. As the interview attendance stage ends, the vacancy decides the number of job offers for each worker type as a function of the number of interviews accumulated in the interview attendance stage, and randomly makes offers to fill the number. Thus, the vacancy does not distinguish the workers by the characteristics for deciding the offer. After the interview, the worker observes the private characteristics of the interviewing vacancies.

The offer stage is a one-shot game following the interview stage. A worker chooses one of the offered and current jobs by comparing the posted wage, and public and private characteristics of the jobs. As the offer decisions are made, the matches are realized, and the workers and vacancies receive the surplus.

In the subsequent sections, we characterize the problem backwardly.

3.2 Offer Stage

Consider a worker who has the job offer set $\mathcal{J}_{i3}$ at the beginning of the offer stage. The worker observes the private characteristics ξ_j and idiosyncratic preference shock ϵ_{ij3} for $j \in \mathcal{J}_{i3}$ which are drawn from an i.i.d. standard logistic distribution.

The worker chooses the alternative that maximizes the utility. The utility is

$$u_{ij} \coloneqq u(z_i, w_j, x_j, \xi_j) + \epsilon_{ij3}, \tag{1}$$

for vacancy $j \in \mathcal{J}_{i3}$ and

$$u_{i0} \coloneqq u(z_i, 0, 0, 0) \tag{2}$$

for the current job. This implies the choice probability of

$$P_{ij3}(\mathcal{J}_{i3}) \coloneqq \frac{e^{u(z_i, w_j, x_j, \xi_j)}}{e^{u(z_i, 0, 0, 0)} + \sum_{j' \in \mathcal{J}_{i3}} e^{u(z_i, w_{j'}, x_{j'}, \xi_{j'})}}. \tag{3}$$

3.3 Interview Stage

Consider a worker who has the application set $\mathcal{J}_{i2}$ at the beginning of the interview stage. At time $s \in [0, 1]$, suppose that the worker received an interview call from a vacancy in $\mathcal{J}_{i2}$. Let j denote the vacancy's index. The worker observes the idiosyncratic preference shock ϵ_{ij2} for j, which is drawn from an i.i.d. standard logistic distribution. The idiosyncratic preference shock is only relevant for the interview attendance decision on the vacancy and is independent of everything else.

Let $\mathcal{J}_{i2}(s) \subset \mathcal{J}_{i2}$ be the set of vacancies from which the worker has received an interview call up to time s. Then, the state of the worker is summarized by the time s, the number of vacancies the workers has applied $n_{i2} \coloneqq n_i(\mathcal{J}_{i2}) \in \mathbb{N}^{LMN}$, the number of vacancies that the worker has received interview calls $n_{i2}(s) \coloneqq n_i[\mathcal{J}_{i2}(s)] \in \mathbb{N}^{LMN}$, and the job posting environment e_r.

Let the choice-specific value function of attending vacancy j's interview at time s be

$$V_{ij2}[s, n_{i2}, n_{i2}(s), e_r] = V_2[z_i, w_j, x_j, s, n_{i2}, n_{i2}(s), e_r] + \epsilon_{ij2}, \tag{4}$$

and that of not attending the interview be

$$V_{i02}[s, n_{i2}, n_{i2}(s), e_r] = V_2[z_i, 0, 0, s, n_{i2}, n_{i2}(s), e_r]. \tag{5}$$

The choice-specific value function is functionally related to the structural parameters including the worker's utility u by a Bellman equation. However, we do not specify this equation, because we only estimate the equilibrium choice-specific value function.

The probability that the worker attends the interview is

$$P_{ij2}[s, n_{i2}, n_{i2}(s), e_r] := \frac{e^{V_2[z_i, w_j, x_j, s, n_{i2}, n_{i2}(s), e_r]}}{e^{V_2[z_i, 0, 0, s, n_{i2}, n_{i2}(s)]} + e^{V_2[z_i, w_j, x_j, s, n_{i2}, n_{i2}(s), e_r]}}. \tag{6}$$

At the end of the interview stage, the vacancies make job offers to the interviewed workers. Consider a vacancy that has the interview set $\mathcal{I}_{j2}$. Let $n_j(\mathcal{I}_{j2})$ be the number of interviews for the vacancy. The vacancy randomly makes an offer to $n_{j3} = c_2 n_j(\mathcal{I}_{j2})^{\tau_2}$ interviewed workers. Therefore, the probability for a worker of getting an offer after an interview is $c_2 n_j(\mathcal{I}_{j2})^{\tau_2 - 1}$. This log-log relationship between interviews and job offers, and the relationship between application and interviews in the next section, is in line with the model proposed by Manning (2020). Manning (2020) proposed a model in which $n_{j3} = c_2 n_j(\mathcal{I}_{j2})^{\tau_2 - 1}$ enters the worker's expected utility and equilibrium is determined by the fixed point of n_{j3}.

3.4 Application Stage

Consider a worker who searches for a job. At time $s \in [0, 1]$, suppose that the worker is interested in the application package of a vacancy. Let j denote the vacancy's index. The worker observes the idiosyncratic preference shock ϵ_{ij1} for j, which is drawn from an i.i.d. standard logistic distribution. The idiosyncratic preference shock is only relevant for the application decision to the vacancy and is independent of everything else.

Let $\mathcal{J}_{i1}(s)$ be the set of vacancies to which the worker has applied up to time s. Then, the state of the worker is summarized by the time s, the number of vacancies that the worker has applied $n_{i1}(s) := n_i[\mathcal{J}_{i1}(s)] \in \mathbb{N}^{LMN}$, and the job posting environment e_r.

Let the choice-specific value function of applying to vacancy j at time s be

$$V_{ij1}[s, n_{i1}(s), e_r] = V_1[z_i, w_j, x_j, s, n_{i1}(s), e_r] + \epsilon_{ij1}, \tag{7}$$

and that of not attending the interview be

$$V_{i01}[s, n_{i1}(s), e_r] = V[z_i, 0, 0, s, n_{i1}(s), e_r]. \tag{8}$$

The choice-specific value function is functionally related to the structural parameters including the worker's utility u by a Bellman equation. However, we do not specify this equation, because we only estimate the equilibrium choice-specific value function.

The probability that the worker applies to the vacancy is

$$P_{ij1}[s, n_{i1}(s), e_r] \coloneqq \frac{e^{V_1[z_i, w_j, x_j, s, n_{i1}(s), e_r]}}{e^{V[z_i, 0, 0, s, n_{i1}(s)]} + e^{V[z_i, w_j, x_j, s, n_{i1}(s), e_r]}}. \tag{9}$$

At the end of the application stage, the vacancies make interview call decisions for the applied workers. Consider a vacancy that has the application set $\mathcal{I}_{j1}$. Let $n_j(\mathcal{I}_{j1})$ be the number of applications for the vacancy. The vacancy randomly makes interview calls to $n_{j2} = c_1 n_j(\mathcal{I}_{j1})^{\tau_1}$ applied workers. Therefore, the probability for a worker of getting an interview call after an application is $c_1 n_j(\mathcal{I}_{j1})^{\tau_1 - 1}$.

4 Estimation

4.1 Worker's Offer Acceptance Utility

We approximate a worker's offer-acceptance utility of vacancy j by

$$u(z_i, w_j, x_j, \xi_j) = \alpha_{i3} \log(1 + w_j) + \beta_{i3}' x_j + \xi_j, \tag{10}$$

and that of the current job by

$$u(z_i, 0, 0, 0) = \alpha_{i3} \log(1 + w_{0i}), \tag{11}$$

where w_{0i} is the wage of the current job. Because the data includes unemployed workers and $w_{0i} = 0$ for the unemployed worker, we use the $log(1 + w)$ transformation. The coefficient α_{i3} and β_{i3} can be different across workers due to the observed worker characteristics as

$$\alpha_{i3} \coloneqq \gamma_{i3}' z_i, \beta_{i3} \coloneqq \Pi_{i3} z_i. \tag{12}$$

The private characteristics ξ_j could be correlated with the posted wage. We address the endogeneity problem by using the control function approach (Petrin and Train, 2010).

Assume that the equilibrium wage posting equation is

$$w_j = \delta' x_j + \kappa d(x_j, e_r) + \nu_j, \tag{13}$$

where $d(x_j, e_r)$ is a measure of the distance in the characteristics space of the vacancy from other registered vacancies and $\nu_j = \rho^{-1} \xi_j$ is the function of the private characteristics ξ_j. The idea is that the equilibrium wage depends on the public and private characteristics of the vacancy, and the distance from other registered vacancies influences the wage markdown.

In the first stage, we estimate equation (13). Then, we obtain the residual estimate of

$$\hat{\nu_j} = w_j - \hat{\delta}' x_j - \hat{\kappa} d(x_j, e_r). \tag{14}$$

We insert this into equation (10) to obtain

$$\hat{u}(z_i, w_j, x_j, \xi_j) \coloneqq \alpha_{i3} \log(1 + w_j) + \beta_{i3}' x_j + \rho \hat{\nu}_j. \tag{15}$$

We then estimate the remaining parameters by a maximum likelihood method.

4.2 Estimation of the Conditional Choice Probability

4.2.1 Worker's Interview Attendance Value Function

We next estimate the worker's equilibrium conditional choice probability in the interview. We approximate the choice-specific value function as by

$$V_2[z_i, w_j, x_j, s, n_{i2}, n_{i2}(s), e_r] = \alpha_{i2} \log(1+w_j) + \beta_{i2}' x_j + \lambda_{2s} s + \lambda_{2n}' n_{i2} + \lambda_{2ns}' n_{i2}(s) + \lambda_{2e}' e_r, \tag{16}$$

and

$$V_2[z_i, 0, 0, 0, 0, e_r] = \alpha_{i2} \log(1 + w_{i0}). \tag{17}$$

The industry environment e_r affects the choice-specific value function because it affects the application and interview attendance decisions of other workers and the probability for a worker of receiving an interview call and an offer.

4.2.2 Worker's Application Value Function

We next estimate the worker's equilibrium conditional choice probability in the application stage. We approximate the choice-specific value function by

$$V_1[z_i, w_j, x_j, s, n_{i1}(s), e_r] = \alpha_{i1} \log(1 + w_j) + \beta_{i1}' x_j + \lambda_{1s} s + \lambda_{1ns}' n_{i1}(s) + \lambda_{1e}' e_r, \tag{18}$$

and

$$V_1[z_i, 0, 0, 0, 0, e_r] = \alpha_{i1} \log(1 + w_{i0}). \tag{19}$$

4.3 Specification of the State Variables

We need to specify state variables, s, $n_{i1}(s)$, n_{i2}, $n_{i2}(s)$, and e_r to approximate the value function and to fill in the gaps between our theoretical model and data.

First, in the baseline model, we specify s as elapsed days at the event decision timing since i's registration. Second, we fix the numbers of the distinct points of characteristics to three, that is, set $K = L = M = N = 3$. Here, the specification of K and M does not affect our estimation because these variables are treated as continuous ones. We construct discretized markets using three groups based on the quantile of (1) the number of employees groups (x), (2) posted wage groups (w), three geographical groups (East, Middle, and West), and two job category groups (blue and white collar). Specifically, each worker-date observation observes state variables of at most $54(= 3 \times 3 \times 3 \times 2)$ discretized markets. Then, we construct $n_{i1}(s)$, n_{i2}, and $n_{i2}(s)$ for each discretized market. Finally, we specify r as worker i's registration week. We assume that workers registered before our target period are registered in the 12th week in 2014 (i.e., the first week of our target period) because we could not calculate state variables before our target period consistently. Then, we construct e_r as the number of applications and interviews in week r in the $54(= 3 \times 3 \times 3 \times 2)$ discretized markets.

5 Data

We use proprietary data from a job matching intermediary in Japan from the 12th week to the 52nd week in 2014. The data cover all 47 prefectures in Japan and 39 job categories, as defined by the intermediary. The data records not only the observed characteristics of the registered firms, workers, and vacancies but also the workers' and vacancies' decision process, such as the application, interview attendance, offer acceptance of the workers and interview calls and offers of vacancies. We refer to the data of the workers' decision process as the worker event data. All monetary variables, such as posted wages and previous wages, are represented in US dollars using the average exchange rate between US dollars and Japanese yen in 2014, that is, 105.

5.1 Summary Statistics

We construct data for variables at the worker, vacancy, and match level, respectively. This section describes the summary statistics.

Workers' data contains a number of recommendations, interview calls, and job offers, labor market characteristics including employment, current or previous job wage, category, experience, rank, contract type, and second language fluency, and worker's demographic information including education, gender, age class, and residential area. The job rank is ordered as 9: Director, 8: Manager, 7: Senior Leader, 6: Leader, 5: Junior Leader, 4: Senior Player, 3: Player, 2: Junior Player, and 1: Associate. The second language level has four

Table 1: Summary statistics of *employed* worker's variables for each decision stage

(a) Application stage

	N	mean	sd	min	max
Number of information collection	54718	166.50	147.60	1.00	1034.00
Number of applications	54718	20.65	26.41	0.00	699.00
Current wage (U.S. dollars)	54718	49581.23	22085.42	105.00	378000.00
Number of jobs experienced	54718	1.93	1.28	0.00	34.00
Worker rank	54718	3.92	2.21	1.00	9.00
Second language level	54718	0.92	1.08	0.00	3.00
Full-time dummy	54718	0.86	0.35	0.00	1.00
University graduate dummy	54718	0.83	0.38	0.00	1.00
Male dummy	54718	0.74	0.44	0.00	1.00
Young cohort dummy	54718	0.65	0.48	0.00	1.00

(b) Interview attendance stage

	N	mean	sd	min	max
Number of interview calls	34900	5.43	3.88	1.00	22.00
Number of interview attendance	34900	4.80	3.55	0.00	22.00
Current wage (U.S. dollars)	34900	48449.94	19955.81	420.00	378000.00
Number of jobs experienced	34900	1.84	1.18	0.00	25.00
Worker rank	34900	3.74	2.11	1.00	9.00
Second language level	34900	0.90	1.06	0.00	3.00
Full-time dummy	34900	0.87	0.34	0.00	1.00
University graduate dummy	34900	0.85	0.36	0.00	1.00
Male dummy	34900	0.75	0.43	0.00	1.00
Young cohort dummy	34900	0.69	0.46	0.00	1.00

(c) Offer acceptance stage

	N	mean	sd	min	max
Number of offers	12115	1.22	0.61	1.00	12.00
Number of offer acceptance	12115	0.82	0.39	0.00	2.00
Current wage (U.S. dollars)	12115	48697.28	18444.73	2520.00	304500.00
Number of jobs experienced	12115	1.77	1.11	0.00	23.00
Worker rank	12115	3.69	2.01	1.00	9.00
Second language level	12115	0.87	1.04	0.00	3.00
Full-time dummy	12115	0.88	0.33	0.00	1.00
University graduate dummy	12115	0.85	0.36	0.00	1.00
Male dummy	12115	0.77	0.42	0.00	1.00
Young cohort dummy	12115	0.71	0.45	0.00	1.00

Note: The data also record workers' 39 job category dummies and 47 prefecture dummies. Previous wages for employed workers are NAs, so we omit the variable in the table. The definitions of variables are shown in the main text.

Table 2: Summary statistics of *unemployed* worker's variables for each decision stage

(a) Application stage

	N	mean	sd	min	max
Number of information collection	22711	157.95	143.57	1.00	936.00
Number of applications	22711	26.09	34.10	0.00	616.00
Previous wage	22711	43158.21	22204.82	105.00	367500.00
Number of jobs experienced	22711	1.99	1.36	0.00	31.00
Worker rank	22711	3.55	2.28	1.00	9.00
Second language level	22711	0.84	1.06	0.00	3.00
Full-time dummy	22711	0.79	0.41	0.00	1.00
University graduate dummy	22711	0.79	0.41	0.00	1.00
Male dummy	22711	0.67	0.47	0.00	1.00
Young cohort dummy	22711	0.69	0.46	0.00	1.00

(b) Interview attendance stage

	N	mean	sd	min	max
Number of interview calls	14547	6.00	4.45	1.00	22.00
Number of interview attendance	14547	5.53	4.23	0.00	22.00
Previous wage	14547	41952.17	19605.04	105.00	315000.00
Number of jobs experienced	14547	1.88	1.19	0.00	24.00
Worker rank	14547	3.33	2.13	1.00	9.00
Second language level	14547	0.82	1.05	0.00	3.00
Full-time dummy	14547	0.81	0.39	0.00	1.00
University graduate dummy	14547	0.81	0.39	0.00	1.00
Male dummy	14547	0.67	0.47	0.00	1.00
Young cohort dummy	14547	0.74	0.44	0.00	1.00

(c) Offer acceptance stage

	N	mean	sd	min	max
Number of offers	4833	1.28	0.71	1.00	9.00
Number of offer acceptance	4833	0.83	0.38	0.00	2.00
Previous wage	4833	42721.55	18223.89	105.00	262500.00
Number of jobs experienced	4833	1.77	1.08	0.00	10.00
Worker rank	4833	3.25	2.00	1.00	9.00
Second language level	4833	0.81	1.04	0.00	3.00
Full-time dummy	4833	0.84	0.37	0.00	1.00
University graduate dummy	4833	0.84	0.37	0.00	1.00
Male dummy	4833	0.68	0.47	0.00	1.00
Young cohort dummy	4833	0.77	0.42	0.00	1.00

Note: The data also record workers' 39 job category dummies and 47 prefecture dummies. The log of current wages for unemployed workers are mechanically zeros, that is, current wages for unemployed workers are one, so we omit the variable in the table. The definitions of variables are shown in the main text.

Table 3: Summary statistics of vacancy's variables

	N	mean	sd	min	max
Mean posted wage (U.S. dollars)	156144	55888.07	17655.87	13125.00	304500.00
Lower bound of posted wage	156144	43972.80	12986.50	3675.00	210000.00
Upper bound of posted wage	156144	67803.35	24551.80	13650.00	420000.00
Required number of jobs experienced	156144	1.46	1.40	0.00	10.00
Job rank	156144	5.95	1.80	1.00	9.00
Required second language level	156144	0.26	0.69	0.00	3.00
Eligible education (high)	156144	0.42	0.49	0.00	1.00
Eligible education (vocational)	156144	0.50	0.50	0.00	1.00
Eligible education (college)	156144	0.51	0.50	0.00	1.00
Eligible education (technical)	156144	0.58	0.49	0.00	1.00
Eligible education (undergraduate)	156144	1.00	0.05	0.00	1.00
Eligible education (postgraduate)	156144	0.98	0.13	0.00	1.00
Number of employees	156144	3260.61	14720.80	1.00	344109.00

Note: The data also record vacancies' 39 job category dummies, 47 prefecture dummies. The definitions of variables are shown in the main text.

Table 4: Summary statistics of match-specific variables of realized choice sets

	N	mean	sd	min	max
Duration (week)	11907804	9.04	8.75	0.00	52.00
Log(1 + distance (km))	11907804	2.37	2.20	0.00	7.72
1(posted wage > previous wage)	11907804	0.64	0.48	0.00	1.00
1(job rank > worker rank)	11907804	0.81	0.40	0.00	1.00
Skill distance (math)	11907804	0.01	0.38	-2.00	2.00
Skill distance (negotiation)	11907804	0.01	0.42	-1.00	1.00
Skill distance (operation)	11907804	-0.01	0.56	-2.67	2.67
Skill distance (repairing)	11907804	0.01	0.78	-3.00	3.00
Skill distance (service)	11907804	0.01	0.67	-2.00	2.00

Note: The distance (km) is between the prefecture capital cities of pre-job and posted job. The duration is measure as the period between the vacancy-specific first job post week and the worker-specific application week. The vacancies with long durations are recommended to the workers before our sample period. We require the vacancies for constructing the choice set at the application stage. Each skill distance is measured as the corresponding skill vector (Ikenaga and Kambayashi, 2016) of the job category of worker's former job minus that of the job category of the vacancy. The full list of job categories is upon request from authors.

levels from 0: No knowledge to 3: Very fluent. The required second language is mostly English, with some exceptions. The university graduate dummy takes a value of one if the worker's education rank is "university" or "postgraduate" and zero otherwise. The dummy of the young cohort is one if a worker is younger than 35 years old and is zero otherwise. For estimation, we include the worker's education level as a categorical variable. We drop workers who have the top 10 percentiles of the choice set sizes at each stage as outliers because their behavior and situation will be substantially different from the normal workers.

At the application stage, on average, a worker collects information on 166.5 vacancies and applies to 20.65 vacancies. In the interview attendance stage, which means, among workers who receive at least one call back, a worker receives 5.43 interview calls and attends 4.80 interviews on average. At the offer acceptance stage, on average, a worker receives 1.22 offers if he receives at least one offer and accepts 0.82 offers. These statistics illustrate two notable features. First, the job matching process is competitive, and most of the worker's applications are rejected by the vacancy at a later stage. Second, the multiple-choice behavior of each worker is prevalent in the application and interview attendance stages.

In the application stage, the average current wage is \$48,450 , the number of jobs experienced is 1.84 , and the rank of the job is 3.74 (between the player and the senior player). 87% are full-time, 85% are university graduates, 75% are male, and 69% are younger than 35 years old. The averages of these variables are similar in the interview attendance and offer acceptance stages. Thus, there is no apparent selection based on the observed characteristics.

Table 2 reports the summary statistics of the unemployed workers. The number of unemployed workers is 22,711 at the application stage, 14,547 at the interview attendance stage, and 4,833 at the offer acceptance stage. 64% of the applicants attended some interviews and 21% received some offers. Therefore, although the proportion of unemployed workers who receive interview calls is the same as that of employed workers, the proportion of those who receive some offers is slightly lower.

The current wage for unemployed workers is mechanically zero. The average wage of their previous jobs is \$43,158 at the application stage. The number of jobs experienced is 1.99 and the worker rank is 3.55. Thus, the previous wage of unemployed workers in the intermediary is slightly lower than the current wage of employed workers. The previous job rank is between the player and the senior player but is closer to the player than employed workers. 79% are full-time, 79% are university graduates, 67% are male, and 69% are younger than 35 years old. Unemployed workers consist of fewer full-time workers, fewer university graduates, fewer males, and younger workers than employed workers. The numbers are similar in each stage.

The vacancy data constitutes the registration week and job descriptions including job category, workplace location, lower and upper bounds of wages, job experience, job rank, second language, eligible education level, and firm information including the number of employees. The eligible education (high) takes a value of 1 if a vacancy can accept a high-school graduate worker and zero otherwise. The other eligible educational level is defined analogously. Job rank and language level are defined in the same way as worker data.

The average lower and upper bounds of the posted wage are \$43,973 and \$67,803 . The lower bound is closer to the workers' current and previous wages. The average number of job experience required is 1.46, which is close to the average number of job experience by registered workers. The job rank is on average 5.95, which is between the junior leader and the leader. The rank of the vacancies is higher than the average rank of the jobs of registered workers. The required second language level is 0.26 on average, which means that about 70% of the vacancies do not require the second language level. Almost all vacancies are eligible for university graduates. Approximately half of the vacancies are eligible for an education level less than the university graduate. The number of employees is 3,261 on average, which means that vacancies in this intermediary are mainly posted by large companies.

The match level data consist of variables measuring the duration of the period between the vacancy-specific week of job posting and week of worker application, the relation between a worker and vacancy based on geographic proximity, current or previous and posted wages, and current or previous and posted job ranks. The geographical distance is between the capital cities of the prefecture of the current (if employed) or previous (if unemployed) job and the posted vacancy. In addition, to capture the transition cost between different job categories, we measure the skill distance at the job category level based on the task score of the current or previous job and that of the vacancy (Ikenaga and Kambayashi, 2016).

Table 4 reports the summary statistics of the match-specific variables of the pairs of workers and vacancies in the application stage. The duration is 9.04 on average, and the standard deviation is 8.75 . The log of geographic distance plus one is 2.37 on average, which implies that a sizable number of recommended vacancies for a worker are located in a different prefecture. 64% of the recommended vacancies post a lower bound of wage higher than the current or previous wage of a worker and 81% are of a higher rank. The standard deviation of each skill distance is at least 0.38, which means that some portion of the vacancies in the worker's choice set belongs to job categories different from those of the workers' former jobs.

5.2 Wage Distribution

A vacancy posts a wage range. The literature uses the average of the lower and upper bounds of the posted wage as the posted wage without carefully comparing the range of the posted

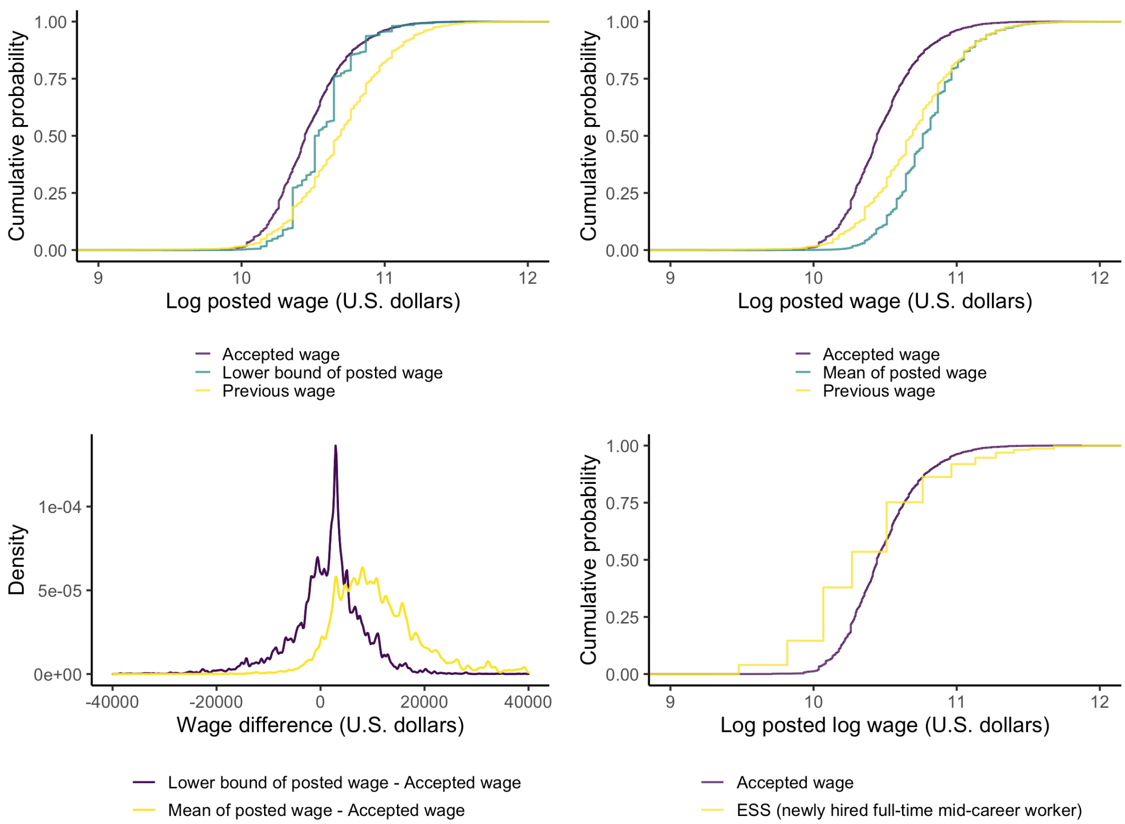


Figure 1: The empirical cumulative distribution of wages

Note: In the right panel, we compare the distribution of the accepted wage in the data with a representative wage distribution in Japan. Specifically, we compare it to the income of newly hired full-time mid-career workers in the Employment Status Survey (ESS) in 2012.

wage to the worker's current wage and the accepted wage because they could not observe those variables. We use the lower bound of the posted wage rather than the average as the posted wage in the model based on the following analysis.

The upper left panel of Figure 1 shows the distribution of the lower bounds of the posted wage, the accepted wage, and the current (if on the job) or previous (if unemployed) wages. The lower bound of the posted wages are slightly lower than the current or previous wages. The accepted wages are also slightly lower than the lower bound of the posted wages but are not substantially different from the lower bounds. The upper right panel of Figure 1 replaces the distribution of the lower bounds with the distribution of the average of the lower and upper bounds. It shows that the mean posted wages are substantially higher than the others. Thus, the lower bound better captures the nature of the vacancy than the average or upper bound of the wage range.

The lower left panel of Figure 1 shows the distribution of the difference between the lower bound of the posted wage and the accepted wage and the difference between the mean of the posted wage and the accepted wage for a matched vacancy. The lower bound of a vacancy's wage range is often higher than the accepted wage, and the mean of a vacancy's wage is even higher. This indicates that the posted wage range is not as strictly binding as the directed search literature assumes.

However, the accepted wage does not seem to be entirely free of the range of posted wages. Table 5 shows the results of regressing the accepted wage on the lower bound of the posted wage. Because the matched wage is observed only for matched pairs, there is a selection in this regression. With this limitation in mind, the coefficient is 0.900 and statistically significant, and the adjusted R-squared is 0.548. After controlling the characteristics of the workers, the coefficient is 0.618 and the adjusted R-squared is 0.687. Thus, the lower bound of the posted wage is not perfect but highly predictive of the accepted wage. The relationship between the posted wage and the matched wage is not as deterministic as assumed in the directed search literature and is not as flexible as assumed in the other search literature.

In the following analysis, we use the posted wage as w_j in the model. Because the matched wage should be observed in the offer acceptance stage and it can be different from the posted wage, the coefficient on the wage would be interpreted as the combination of the worker's preference on money and the predicted difference between the matched and posted wages.

Finally, the lower right panel of Figure 1 compares the distribution of the accepted wage with a representative wage distribution in Japan. Specifically, we compare it with the income of newly hired full-time mid-career workers in the Employment Status Survey (ESS) in 2012. It shows that the accepted wages in the intermediary are higher than the average wages of

Table 5: Regression of accepted wages on the lower bounds of the posted wages

	Accepted wage	Accepted wage
Lower bound of the posted wage	0.900	0.618
	(0.005)	(0.005)
Worker characteristics		Y
Num.Obs.	26056	26056
R2	0.548	0.688
R2 Adj.	0.548	0.687

Note: The observation is the matched pair of workers and vacancies. worker's characteristics include the second language level, worker rank, number of job experiences, education rank, male dummy, young cohort dummy, employed dummy, prefecture, and job category dummies of workers. The numbers in parentheses show the standard errors.

Table 6: The average transition probability

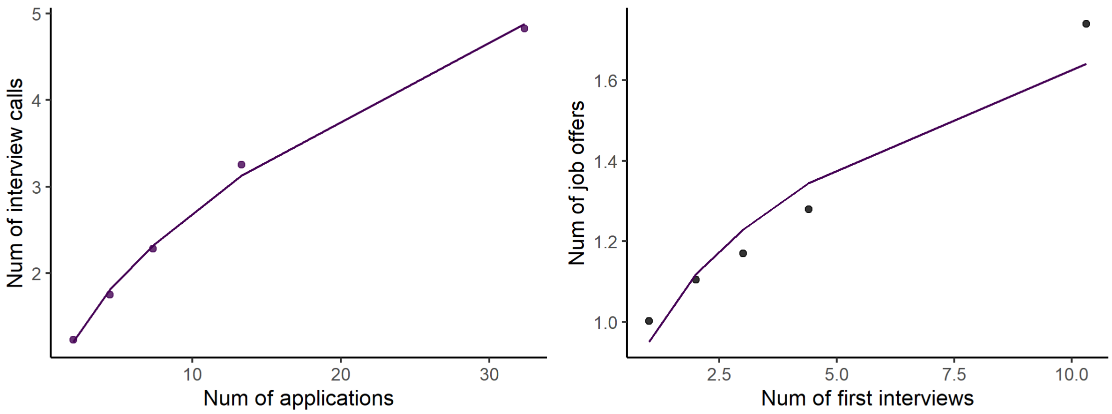
Stage	Proceed
Application	0.118
Receiving an interview call	0.527
Inteview attendance	0.863
Receiving an offer	0.489
Offer acceptance	0.777

Note: The average transition probability of proceeding to the next stage is computed by dividing the size of the worker-level choice set at the next stage by the size of the worker-level choice set at the current stage for each worker and taking its average over active workers at the current stage. We omit the worker-vacancy pairs that skip the stage (1.2 % of all realized worker-vacancy pairs) as outliers.

newly hired full-time mid-career workers in the ESS. This is because the intermediate targets at the university graduate white collar with relatively high-wage jobs.

5.3 Selection in the Job Matching Process

The selection of workers and vacancies in the job matching process is the key to our analysis. Therefore, we describe their selections and evaluate the competitive pressure of peers. Table 6 summarizes the average probability that a worker proceeds to the next stage. For example, for the probability of application, we first divide the number of applications by the number of information collected for each worker and take the average of them between workers. For the probability of interview calls, we first divide the number of interview calls by the number of applications of each worker and take the average of them between workers. We omit the worker-vacancy pairs that skip the initial information collection stage because only 1.2% of



(a) $c_1 n_1^{\tau_1}$ (dots) and $\hat{c}_1 n_1^{\hat{\tau}_1}$ (solid line) (b) $c_2 n_2^{\tau_2}$ (dots) and $\hat{c}_2 n_2^{\hat{\tau}_2}$ (solid line)

Figure 2: The vacancy-level number of applications, interview calls, interview attendances, and job offers

Note: We drop outlier vacancies which have top 1% of the number of interviews and top 0.05% of the number of applications for illustration. We also drop vacancies that have zero interview call or zero job offer to avoid log(0) in the following regression. The dots show the average $c_1 n_1^{\tau_1}$ and $c_2 n_2^{\tau_2}$ of quantile-spaced bins of n_1 and n_2. The solid lines are the fitted values of a regression of the log binned averages on the log midpoints of the bin.

Table 7: The estimation results of c_1, c_2, τ_1 and τ_2.

	Interview calls		Offers
c_1	0.891	c_2	0.969
	(0.004)		(0.003)
τ_1	0.407	τ_2	0.173
	(0.002)		(0.003)
Obs	59552	Obs	15765
R2 Adj	0.358	R2 Adj	0.189

Note: The regression results correspond with Figure 2. The standard errors are in the parentheses. We drop outlier vacancies which have top 1% of the number of interviews and top 0.05% of the number of applications for illustration. We also drop vacancies that have zero interview call or zero job offer to avoid log(0) in the following regression. The estimated coefficients and standard errors of c_1 and c_2 are converted from these of $\log(c_1)$ and $\log(c_2)$ through the delta method.

the applications are initiated by the CA without the worker's information collection.

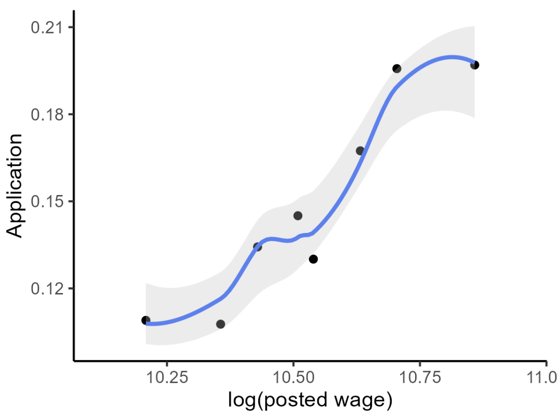
After collecting information on the vacancies, the worker applies to 13.7% of them. After applying for vacancies, the worker receives an interview call from 50% of them. The worker attends 85% of the interviews called. Therefore, workers are more selective in interview attendance than in application decisions. Only 16.5% of the interviews lead to an offer of a job. Thus, the vacancy is more selective after the interview than after the application. Upon receiving a job offer, the worker accepts with a probability of 78%.

We also document the marginal change in the selection probability when the number of applications and interviews increases, that is, the elasticity of interview calls to the number of applications, and the elasticity of offers to the number of interviews. This elasticity is determined by the flexibility of the vacancy's capacity and determines the competitive pressure from other applicants faced by an applicant. For example, at the application stage, if the selection is elastic, the competitive pressure from other workers is mild because the number of workers who can proceed to the next step flexibly increases as the number of peers increases in responding to the higher posted wage. On the contrary, if the selection is inelastic, the competitive pressure from other workers is strong because the number of workers who can proceed to the next step does not increase as the number of peers increases in responding to the higher posted wage. This elasticity of interview calls to applications corresponds to τ_1 and the elasticity of offers to interviews to τ_2 in the model.

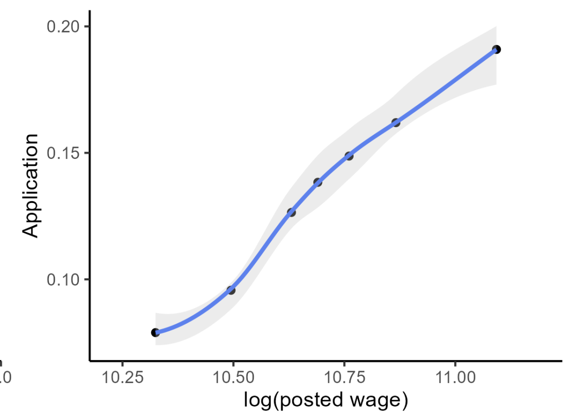
To visualize the elasticity of selection by vacancy, we divide the vacancies into five quantile-spaced bins of the number of applications and the number of workers attending the interview and plot the bin averages of the number of interview calls and the number of job offers in Figure 2. The left panel shows the relationship between the number of applications and the number of interview calls, and the right panel shows the relationship between the number of interview attendances and the number of offers. The binned scatter plots show diminishingly increasing curves. Table 7 reports that $\hat{\tau}_1 = 0.407$ and $\hat{\tau}_2 = 0.173$ with $\hat{c}_1 = 0.891$ and $\hat{c}_2 = 0.969$ when we fit the model to the data.

5.4 Wage Elasticity in the Job Matching Process

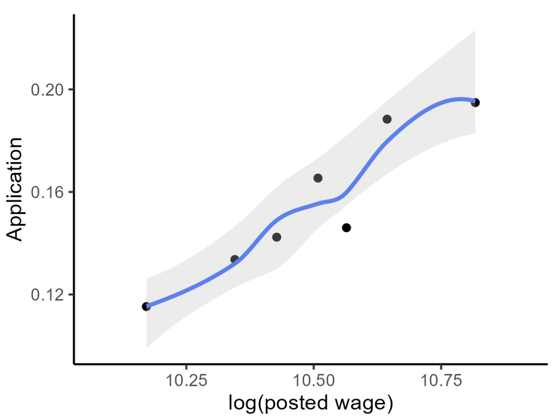
We next visualize how the workers' decisions change according to the posted wage of the vacancy. We investigate this at each stage of application, interview attendance, and offer acceptance because the cost of taking action and the perceived competitive pressure for a worker are deemed different across stages. To capture the difference in the wage elasticity according to the economic conditions, we also split the worker sample into two groups: employed and unemployed. We also categorize them by previous wage level: above- and



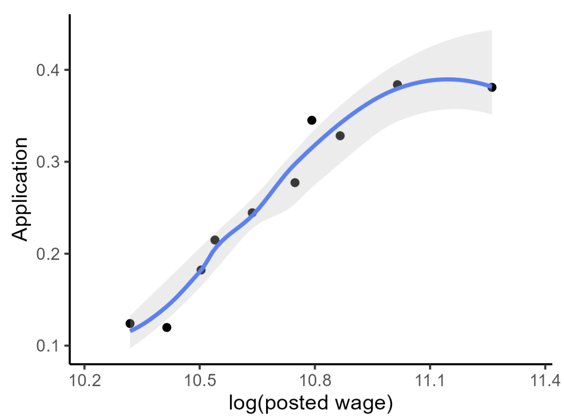
(a) Employed/Lower Income



(b) Employed/Upper Income



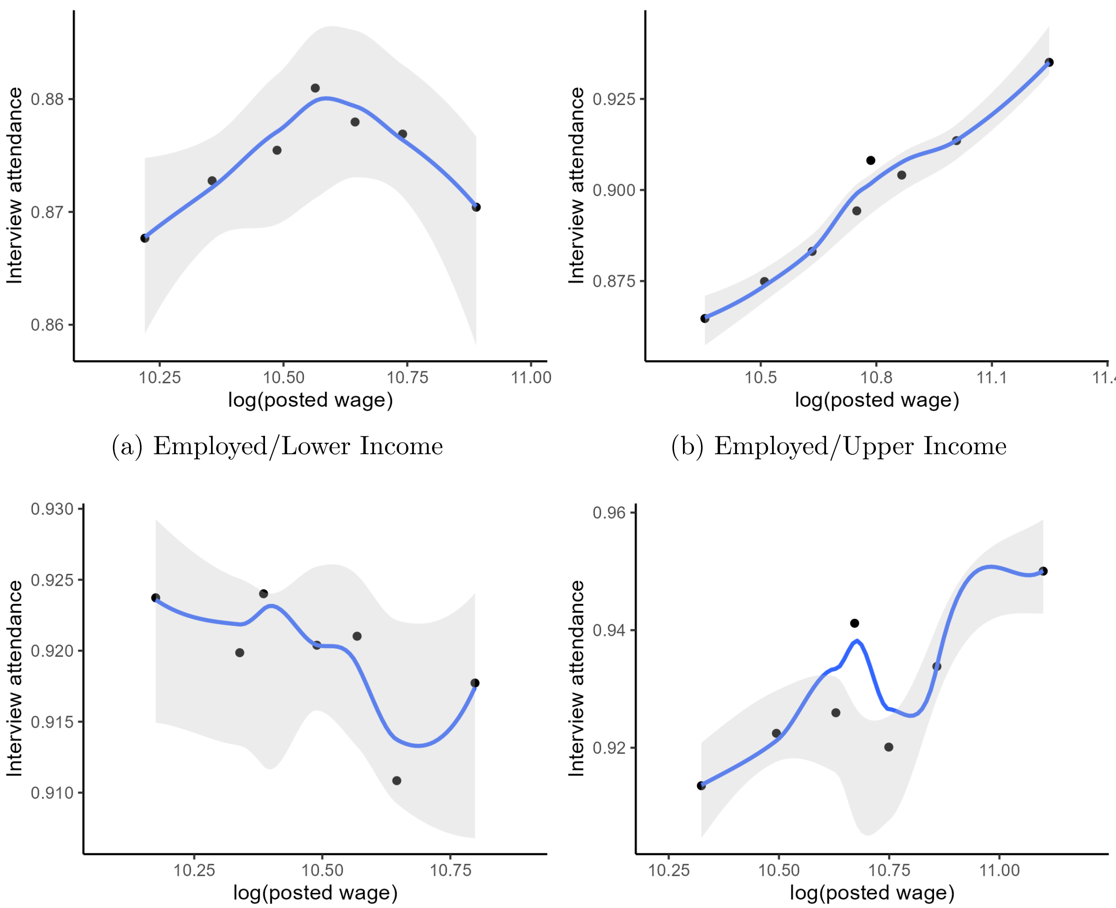
(c) Unemployed/Lower Income



(d) Unemployed/Upper Income

Figure 3: The application probability conditional on the posted wage

Note: We calculate the application probability at each bin and its 95% confidence interval. The y-axis is relative to the value at the bottom posted wage group.



(a) Employed/Lower Income

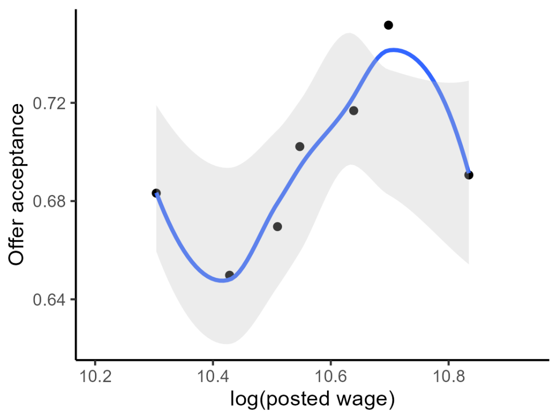
(b) Employed/Upper Income

(c) Unemployed/Lower Income

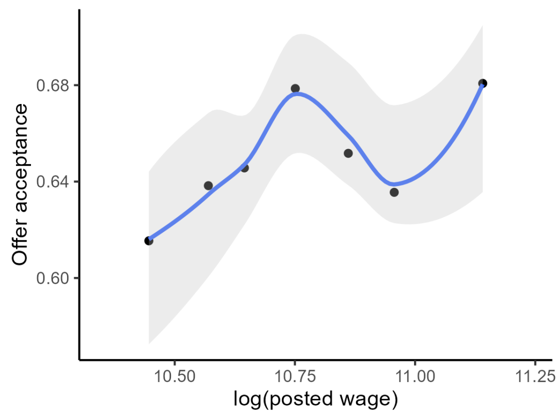
(d) Unemployed/Upper Income

Figure 4: The interview attendance probability conditional on the posted wage

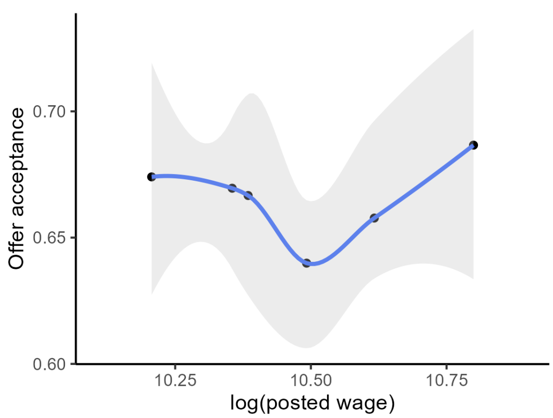
Note: We calculate the interview attendance probability at each bin and its 95% confidence interval. The y-axis is relative to the value at the bottom posted wage group.



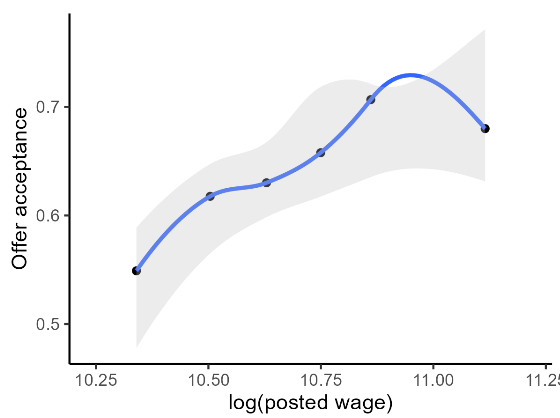
(a) Employed/Lower Income



(b) Employed/Upper Income



(c) Unemployed/Lower Income



(d) Unemployed/Upper Income

Figure 5: The offer acceptance probability conditional on the posted wage

Note: We calculate the offer acceptance probability at each bin and its 95% confidence interval. The y-axis is relative to the value at the bottom posted wage group.

below-median wage.

Figure 3 shows the application probability as a function of the posted wage of the vacancy. The x-axis is the log of posted wage of the vacancy and the y-axis is the probability of application. The error bar represents the 95% confidence interval from a fitted line. At this stage, the application probability is increasing in the posted wage for both employed and unemployed, and above- and below-median wage workers. Thus. the workers are elastic to the posted wage at the application stage. This will be because the cost of application is low, and the elasticity of interview calls to applications is higher than in the later stage. It is reasonable for a worker to just apply when they find a high-wage vacancy. Nevertheless, the wage elasticity implied from the slope is no greater than 1 except for the above-median wage unemployed workers. The workers are elastic to the posted wage, but not strongly.

Figure 4 shows the interview attendance probability as a function of the posted wage of the vacancy. The y-axis is the probability of interview attendance. It shows that the interview attendance probability is increasing in the posted wage only for the above-median wage workers and it is insensitive to the posted wage for the below-median wage workers. This will be because the cost of attending an interview is high and the elasticity of offers to interviews is lower than the elasticity of interview calls to applications. Even if the posted wage is high, a worker may not attend the interview if they anticipate higher competitive pressure from other workers, especially if the worker is not competitive enough.

Figure 5 shows the offer acceptance probability as a function of the posted wage of the vacancy. The y-axis is the probability of offer acceptance. It shows that the offer acceptance rate is increasing in the posted wage for the above-median wage workers, regardless of current employment. The offer acceptance rate of the below-median wage workers is less sensitive to the posted wage for the below-median wage workers. Thus, the offer acceptance rate is less elastic to the posted wage for the below-median wage workers than for the above-median wage workers.

In summary, the wage elasticity is different across each stage of the job-matching process and by the economic conditions and the competitiveness of the worker. The findings are consistent with the view that the offers are more selective than interviews and the workers anticipate the different competitive pressure and the different cost of taking action at each stage of the job-matching process. In the subsequent section, we confirm these findings by regressions.

Table 8: First stage results

	(1)	(2)	(3)	(4)	(5)
Log(rivals' vacancies)	0.004			0.004	0.001
	(0.001)			(0.001)	(0.001)
Log(rivals' employees)		0.000		0.000	0.000
		(0.000)		(0.000)	(0.000)
Log(other markets' mean wage)			0.455		0.455
			(0.003)		(0.003)
Num.Obs.	156144	156144	156144	156144	156144
R2	0.461	0.461	0.541	0.461	0.541
R2 Adj.	0.457	0.457	0.538	0.457	0.538

Note: The dependent variable is the log of the posted wage (the lower bound of the range). We omit the coefficients of control variables from the table. We control for a log of the number of employees, the required second language level, the required number of experiences, and vacancy-specific dummies for job rank, eligible education level, job category, workplace prefecture, and registered week. The standard errors are in parentheses.

6 Estimation Results

6.1 First Stage Results

Table 8 reports the first-stage regression results. The wage instruments z_j are i) the log of the number of vacancies posted by a vacancy's competitors in the preceding two weeks in the same job category and the prefecture (BLP-type instruments), ii) the log of the sum of the number of employees of competitors who posted a vacancy in the preceding two weeks in the same job category and the prefecture, and iii) the log of mean wages posted by the same firm in other markets (Hausman-type instruments). For the third instrumental variable, if a firm does not post in other markets, the variable is replaced with the log of mean wages of all vacancies. We control for a log of the number of employees, the required second language level, the required number of experiences, and vacancy-specific dummies for job rank, eligible education level, job category, workplace prefecture, and registered week.

Columns (1), (2), and (3) show the results when each instrumental variable is used separately. It shows that the number of rivals' vacancies and the mean wage in other markets is statistically significant, but the number of the rivals' employees is not. The magnitude of the number of rivals' vacancies is small. Columns (4) and (5) show the results when both BLP-type instrumental variables are used and all instrumental variables are used. It shows that the numbers of rivals' vacancies and employees are no longer statistically significant, and only the mean wage in the other markets is statistically and economically significant. This makes sense because firms tend to set a uniform wage across markets. Moreover, it is likely

Table 9: Estimation results for offer acceptance decision: Employed

(a) Employed/Upper Income

	(1)	(2)	(3)	(4)	(5)	(6)
Log(posted wage)	0.120	0.478	0.482	0.120	0.764	0.771
	(0.003)	(1.164)	(0.365)	(0.003)	(1.163)	(0.373)
Log(posted wage) × previous wage				-0.005	-0.013	-0.013
				(0.003)	(0.003)	(0.003)
Num.Obs.	6708	6708	6708	6708	6708	6708
Covariates	No	Yes	Yes	No	Yes	Yes
IV	No	B	H	No	B	H

(b) Employed/Lower Income

	(1)	(2)	(3)	(4)	(5)	(6)
Log(posted wage)	0.143	-1.652	0.040	0.144	-1.442	0.232
	(0.003)	(1.367)	(0.474)	(0.003)	(1.376)	(0.496)
Log(posted wage) × previous wage				-0.005	-0.007	-0.007
				(0.004)	(0.005)	(0.005)
Num.Obs.	5429	5429	5429	5429	5429	5429
Covariates	No	Yes	Yes	No	Yes	Yes
IV	No	B	H	No	B	H

Note: The dependent variable is the offer acceptance decision by a worker. We omit the coefficients of control variables from the table. In addition to the characteristics of the vacancy used in the first stage, we control for the elapsed weeks from the date the vacancy is posted to the date when the worker applies for the vacancy. It also includes the inside option dummy times the worker's employed dummy to capture the level difference between employed and unemployed workers for the offer acceptance and the difference in the skill vector of the vacancy's job category and the worker's current (for employed) or previous (for unemployed) job category. The standard errors are in the parenthesis.

that the uniform wage is set independently of the local labor supply shocks. Therefore, in the following estimation of the offer acceptance decision, we use the Hausman-type instrumental variable as the favorite instruments.

6.2 Offer Acceptance Decision

We first examine the estimation results of the offer acceptance decision. The choice set for a worker $\mathcal{J}_{i3}$ is the offer set.

Tables 9 and 10 report the estimation results for the worker's offer acceptance decision. Columns (1) to (3) estimate the model without heterogeneity in the wage coefficient. Columns (4) to (6) estimate by interacting the standardized previous wage of the worker

Table 10: Estimation results for offer acceptance decision: Unemployed

(a) Unemployed/Upper Income

	(1)	(2)	(3)	(4)	(5)	(6)
Log(posted wage)	0.137	0.281	2.444	0.137	0.123	2.309
	(0.006)	(2.312)	(0.787)	(0.006)	(2.318)	(0.801)
Log(posted wage) $\times$ previous wage				0.015	0.008	0.008
				(0.007)	(0.008)	(0.008)
Num.Obs.	1862	1862	1862	1862	1862	1862
Covariates	No	Yes	Yes	No	Yes	Yes
IV	No	B	H	No	B	H

(b) Unemployed/Lower Income

	(1)	(2)	(3)	(4)	(5)	(6)
Log(posted wage)	0.140	2.275	0.414	0.140	2.639	0.719
	(0.005)	(1.774)	(0.619)	(0.005)	(1.796)	(0.644)
Log(posted wage) $\times$ previous wage				-0.006	-0.012	-0.012
				(0.005)	(0.007)	(0.007)
Num.Obs.	2986	2986	2986	2986	2986	2986
Covariates	No	Yes	Yes	No	Yes	Yes
IV	No	B	H	No	B	H

Note: The dependent variable is the offer acceptance decision by a worker. We omit the coefficients of control variables from the table. In addition to the characteristics of the vacancy used in the first stage, we control for the elapsed weeks from the date the vacancy is posted to the date when the worker applies for the vacancy. It also includes the inside option dummy times the worker's employed dummy to capture the level difference between employed and unemployed workers for the offer acceptance and the difference in the skill vector of the vacancy's job category and the worker's current (for employed) or previous (for unemployed) job category. The standard errors are in the parenthesis.

Table 11: Offer acceptance elasticity

(a) Employed/Upper Income

(1)	(2)	(3)	(4)	(5)	(6)
0.0423	0.169	0.17	0.0407	0.265	0.267
[0.0403, 0.0442]	[-0.635, 0.972]	[-0.0824, 0.422]	[0.0369, 0.0445]	[-0.541, 1.07]	[0.00757, 0.527]

(b) Employed/Lower Income

(1)	(2)	(3)	(4)	(5)	(6)
0.0447	-0.515	0.0124	0.043	-0.452	0.0703
[0.0426, 0.0468]	[-1.35, 0.32]	[-0.277, 0.302]	[0.0388, 0.0473]	[-1.3, 0.392]	[-0.236, 0.376]

(c) Unemployed/Upper Income

(1)	(2)	(3)	(4)	(5)	(6)
0.0507	0.104	0.906	0.0561	0.0485	0.858
[0.0464, 0.0549]	[-1.57, 1.78]	[0.334, 1.48]	[0.0471, 0.0652]	[-1.64, 1.74]	[0.271, 1.45]

(d) Unemployed/Lower Income

(1)	(2)	(3)	(4)	(5)	(6)
0.0476	0.773	0.141	0.0454	0.893	0.24
[0.0445, 0.0507]	[-0.408, 1.95]	[-0.272, 0.553]	[0.0391, 0.0517]	[-0.308, 2.09]	[-0.193, 0.674]

Note: This calculates the average wage elasticity of each type of worker. The parenthesis shows the 95% confidence interval.

to the log wage. Columns (1) and (4) estimate models without any covariates and instruments. Columns (2) and (5) use the BLP-type instruments and Columns (3) and (6) use the Hausman-type instruments. In addition to the characteristics of the vacancy used in the first stage, covariates x_{ij} include the elapsed weeks from the date the vacancy is posted to the date when the worker applies for the vacancy. It also includes the inside option dummy times the worker's employed dummy to capture the level difference between employed and unemployed workers for the offer acceptance and the difference in the skill vector of the vacancy's job category and the worker's current (for employed) or previous (for unemployed) job category. The implied average wage elasticity is summarized in Table 11. Each column of the table corresponds to the specification of the same column in Tables 9 and 10.

We ignore the models with BLP-type instruments because the standard errors are substantially high as we expected. The results in Column (1) correspond to the findings in Figure 5. The coefficients are positive and statistically significant. However, the implied elasticities are around 0.05, which is small. Further considering the heterogeneity in the coefficient by the previous wage within the worker segments does not change the results as in Column (4). When controlling for unobserved fixed effects by the Hausman-type instruments, the estimated coefficients get larger but are statistically significant only for above-median unemployed workers in Columns (4) and (6) and for above-median employed workers in Column (6). Their implied elasticities are no greater than 1.

6.3 Interview Attendance Decision

Next, we discuss the estimation results for the worker's interview attendance decision. In addition to the covariates in the offer acceptance decision model, we control for the state variables, s, n_{i2}, $n_{i2}(s)$, and e_r.

Table 12 shows the estimation results. We do not consider unobserved fixed effects because this is a decision before the worker and the vacancy meet in the interview. Columns (1) and (2) do not consider the heterogeneity in the wage coefficient while Columns (3) and (4) do. Columns (1) and (3) do not control for the covariates while Columns (2) and (4) do. The results show that the wage coefficients are positive and statistically significant for above-median workers, regardless of employed or unemployed, and of the specification. These results are consistent with the findings in Figure 4. Even for above-median wage workers, the implied wage elasticities are substantially low. Table 13 shows that the wage elasticities are less than 0.01 for above-median wage workers.

Table 12: Estimation results for interview attendance decision

(a) Employed/Upper Income

	(1)	(2)	(3)	(4)
Log(posted wage)	0.080	0.064	0.052	0.059
	(0.004)	(0.006)	(0.005)	(0.007)
Log(posted wage*previous wage)			0.001	0.000
			(0.000)	(0.000)
Num.Obs.	110969	110969	110969	110969
Covariates	No	Yes	No	Yes

(b) Employed/Lower Income

	(1)	(2)	(3)	(4)
Log(posted wage)	0.010	-0.013	0.018	0.010
	(0.006)	(0.009)	(0.006)	(0.010)
Log(posted wage*previous wage)			-0.001	-0.001
			(0.000)	(0.000)
Num.Obs.	78494	78494	78494	78494
Covariates	No	Yes	No	Yes

(c) Unemployed/Upper Income

	(1)	(2)	(3)	(4)
Log(posted wage)	0.043	0.028	0.029	0.028
	(0.006)	(0.009)	(0.007)	(0.010)
Log(posted wage*previous wage)			0.001	0.000
			(0.000)	(0.000)
Num.Obs.	36327	36327	36327	36327
Covariates	No	Yes	No	Yes

(d) Unemployed/Lower Income

	(1)	(2)	(3)	(4)
Log(posted wage)	-0.013	-0.021	-0.011	-0.011
	(0.007)	(0.009)	(0.007)	(0.010)
Log(posted wage*previous wage)			0.000	0.000
			(0.000)	(0.000)
Num.Obs.	50981	50981	50981	50981
Covariates	No	Yes	No	Yes

Note: The dependent variable is the interview attendance decision by a worker. We omit the coefficients of control variables from the table. In addition to the covariates in the offer acceptance decision model, we control for the state variables, s, n_{i2}, $n_{i2}(s)$, and e_r. The standard errors are in the parenthesis.

Table 13: Interview attendance elasticity

(a) Employed/Upper Income

(1)	(2)	(3)	(4)
0.00875	0.00697	0.00583	0.00645
[0.00786, 0.00965]	[0.00569, 0.00826]	[0.0048, 0.00686]	[0.00501, 0.0079]

(b) Employed/Lower Income

(1)	(2)	(3)	(4)
0.00127	-0.00162	0.00214	0.0011
[-0.000269, 0.00281]	[-0.00383, 0.000582]	[0.000518, 0.00377]	[-0.00135, 0.00356]

(c) Unemployed/Upper Income

(1)	(2)	(3)	(4)
0.0032	0.00204	0.00219	0.00204
[0.00232, 0.00407]	[0.000737, 0.00335]	[0.00119, 0.00319]	[0.00063, 0.00345]

(d) Unemployed/Lower Income

(1)	(2)	(3)	(4)
-0.00104	-0.00173	-0.000926	-0.000961
[-0.00209, 9.76e-06]	[-0.00321, -0.000248]	[-0.00202, 0.000165]	[-0.00258, 0.000654]

Note: This calculates the average wage elasticity of each type of worker. The parenthesis shows the 95% confidence interval. The specification of each column is the same as Table 12.

Table 14: Estimation results for application decision

(a) Employed/Upper Income

	(1)	(2)	(3)	(4)
Log(posted wage)	0.153	0.106	0.172	0.119
	(0.006)	(0.008)	(0.006)	(0.008)
Log(posted wage*previous wage)			-0.001	-0.001
			(0.000)	(0.000)
Num.Obs.	55500	55500	55500	55500
Covariates	No	Yes	No	Yes

(b) Employed/Lower Income

	(1)	(2)	(3)	(4)
Log(posted wage)	0.160	0.125	0.160	0.127
	(0.010)	(0.013)	(0.010)	(0.013)
Log(posted wage*previous wage)			0.000	0.000
			(0.000)	(0.000)
Num.Obs.	31966	31966	31966	31966
Covariates	No	Yes	No	Yes

(c) Unemployed/Upper Income

	(1)	(2)	(3)	(4)
Log(posted wage)	0.338	0.274	0.373	0.279
	(0.015)	(0.019)	(0.016)	(0.019)
Log(posted wage*previous wage)			-0.002	0.000
			(0.000)	(0.000)
Num.Obs.	14141	14141	14141	14141
Covariates	No	Yes	No	Yes

(d) Unemployed/Lower Income

	(1)	(2)	(3)	(4)
Log(posted wage)	0.136	0.045	0.145	0.057
	(0.014)	(0.017)	(0.014)	(0.018)
Log(posted wage*previous wage)			-0.001	-0.001
			(0.000)	(0.000)
Num.Obs.	18143	18143	18143	18143
Covariates	No	Yes	No	Yes

Note: The dependent variable is the application decision by a worker. We omit the coefficients of control variables from the table. In addition to the covariates in the offer acceptance decision model, we control for the state variables, s, $n_{i1}(s)$, and e_r. The standard errors are in the parenthesis. To reduce the computational burden, we use worker-vacancy-level observations of workers randomly sampled by 1% from the full sample without replacement.

Table 15: Application elasticity

(a) Employed/Upper Income

(1)	(2)	(3)	(4)
0.134 [0.123, 0.144]	0.093 [0.0794, 0.107]	0.149 [0.138, 0.16]	0.103 [0.0885, 0.118]

(b) Employed/Lower Income

(1)	(2)	(3)	(4)
0.137 [0.121, 0.154]	0.107 [0.0859, 0.129]	0.137 [0.12, 0.154]	0.109 [0.0862, 0.132]

(c) Unemployed/Upper Income

(1)	(2)	(3)	(4)
0.26 [0.237, 0.282]	0.21 [0.182, 0.239]	0.284 [0.26, 0.309]	0.213 [0.183, 0.243]

(d) Unemployed/Lower Income

(1)	(2)	(3)	(4)
0.115 [0.0918, 0.139]	0.0386 [0.00948, 0.0677]	0.122 [0.0977, 0.146]	0.0474 [0.0166, 0.0783]

Note: This calculates the average wage elasticity of each type of worker. The parenthesis shows the 95% confidence interval. The specification of each column is the same as Table 14.

Table 16: Calibration results of the mean recruitment elasticity

Type	Estimate	Min	Max
Lower income × Unemployed	0.186	0.183	0.229
Lower income × Employed	0.125	0.118	0.228
Higher income × Unemployed	0.39	0.374	0.59
Higher income × Employed	0.241	0.233	0.342

Note: Column "Estimate" uses $\widehat{\tau}_1$ and $\widehat{\tau}_2$ to calculate the recruitment elasticity based on equation (22). Column "Min" sets $\tau_1 = \tau_2 = 0$ and Column "Max" sets $\tau_1 = \tau_2 = 1$.

6.4 Application Decision

Finally, we discuss the estimation results of the worker's application decision. The choice set for a worker $\mathcal{J}_{i1}$ is the set of vacancies for which the worker has checked information. To reduce the computational burden, we use worker-vacancy-level observations of workers randomly sampled by 1% from the full sample without replacement. In addition to the covariates in the offer acceptance decision model, we control for the state variables, s, $n_{i1}(s)$, and e_r.

Table 14 shows the estimation results. We do not consider unobserved fixed effects because this is a decision before the worker and the vacancy meet in the interview. Columns (1) and (2) do not consider the heterogeneity in the wage coefficient while Columns (3) and (4) do. Columns (1) and (3) do not control for the covariates while Columns (2) and (4) do. The results show that the wage coefficients are positive and statistically significant for all segments and specifications. Table 15 shows that the implied wage elasticities are also positive and relatively higher than the elasticities in other stages. If we focus on the results in Column (4), the wage elasticities at the application stage are 0.103 for above-median employed workers, 0109 for below-median employed workers, 0.213 for above-median unemployed workers, and 0.0474 for below-median unemployed workers. Thus, except for below-median unemployed workers, who are less competitive and in urgent need of a job, the wage elasticities are larger than 0.1.

7 Discussion

7.1 Recruitment Elasticity

We evaluate the recruitment elasticity, that is, the elasticity of employment with respect to the 1% change in the posted wage. We can calculate this by simulation under the assumption that workers and other vacancies do not strategically change the behavior to this hypothetical change in the posted wage by a vacancy.

Before calculating it by a simulation, develop the intuition about the role of wage elasticities at each stage and the elasticity of vacancy's selection to applications and interviews in a simplified setting. Suppose that there are n workers and 1 vacancy. As we discussed in Section 5, suppose that $c_1 n_1^{\tau_1}$ workers are called for interviews when n_1 workers apply to the vacancy and $c_2 n_2^{\tau_2}$ workers receive offers when n_2 workers attend the vacancy interview. Let $p_t(w)$ for $t = 1, 2, 3$ be the probability that a worker applies to the vacancy, attends the interview, and accepts the offer. Consequently, the number of recruited workers is

$$r(w) = p_3(w) c_2 \{p_2(w) c_1 [p_1(w) n]^{\tau_1}\}^{\tau_2}. \tag{20}$$

Then, the logarithm of (20) is

$$\ln r(w) = \ln p_3(w) + \tau_2 \ln p_2(w) + \tau_2 \tau_1 \ln p_1(w) + constant. \tag{21}$$

Therefore, the recruitment elasticity is

$$\frac{\partial \ln r(w)}{\partial \ln w} = \frac{\partial \ln p_3(w)}{\partial \ln w} + \tau_2 \frac{\partial \ln p_2(w)}{\partial \ln w} + \tau_2 \tau_1 \frac{\partial \ln p_1(w)}{\partial \ln w}. \tag{22}$$

Under the assumptions, we can calibrate the values of τ_1 and τ_2 by comparing the number of applications and interview calls and the number of interview attendance and offers. We can also state that the sum of the wage elasticities is the upper bound of the recruitment elasticity. If there is no employer selection, then $\tau_1 = \tau_2 = 1$, and the recruitment elasticity is equal to the upper bound. The lower bound is obtained when $\tau_1 = \tau_2 = 0$, which happens when the employer regards the workers as homogeneous and sets a hard constraint on the number of interview calls and offers.

Table 16 shows the implied recruitment wage elasticities. Because the results using the control function approach are unstable and not statistically significant, we use the results without controlling for unobserved fixed effects (Column 4). The Column of Estimate shows the number when the elasticities of vacancies' decisions are considered. The estimated recruitment elasticities are 0.186 for below-median wage unemployed, 0.125 for below-median employed, 0.390 for above-median unemployed, and 0.241 for above-median employed. The Column of Min only gives the offer acceptance elasticity and the Column of Max gives the sum of application, interview attendance, and offer acceptance elasticities. It shows that i) the recruitment elasticity tends to be higher for above-median wage workers, but the difference between employed and unemployed workers is not substantial, and ii) the recruitment elasticity is no greater than 1 even if we ignore the elasticities of vacancies' decisions.

8 Conclusion

In this paper, we used data from one of the largest job-matching intermediaries in Japan to evaluate the market power of employers in job matching. The data allowed us to estimate three wage elasticities in the job matching process and to evaluate the employer selection in the interview and offers. We found that the application elasticity was the largest, interview attendance elasticity was not statistically significantly different from zero, and the offer acceptance elasticity was positive but low. The paper highlighted the importance of considering employer selection and the resulting competitive pressure on the worker's decision in job matching and provided the basic estimates for analyzing the decentralized job matching process.

There are several limitations to be addressed in future research. First, we did not fully characterize the equilibrium of the decentralized job-matching process. This prevented us from obtaining the exact recruitment elasticity that incorporates the strategic response of workers and vacancies when a vacancy changes the posted wage. Second, we did not explicitly model the wage negotiation between a worker and a vacancy after the offer is made. Analyzing this feature will be important to evaluate the ex-post welfare of workers. Third, the analysis lacked detailed information on the firms posting the vacancy. Obtaining the firm names and associating their behavior in the labor market with their behavior in the product market should be important for designing antitrust policies focusing on both input and output markets.

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