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IZA DP No. 17613

Decomposing Recruitment Elasticity in Job Matching

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ABSTRACT

Decomposing Recruitment Elasticity in Job Matching*

This study estimates and decomposes recruitment elasticity, a key measure of employer market power, across job-matching stages using data from Japan's largest job-matching intermediary. On average, recruitment elasticity is negative but not statistically significantly different from zero. However, this masks heterogeneity across stages. The negative elasticity arises from lower-wage workers avoiding higher-wage vacancies during inquiry. Posted wages positively influence application, interview attendance, and offer acceptance decisions, with elasticity decreasing in that order. Other important patterns are also examined.

JEL Classification: J20, J30, J42, J64, L13, L40

Keywords: market power of employers, monopsony, job matching intermediary, recruitment elasticity, inquiry, application, interview, offer, control function approach

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1 Introduction

The growing recognition of non-competitive labor markets (Manning, 2003), declining labor share (Karabarbounis and Neiman, 2014), and renewed focus on antitrust enforcement (Department of Justice and Commission, 2016; **?**; Azar and Marinescu, 2024) has driven a research agenda centered on estimating employer market power, with recruitment elasticity —a measure of wage elasticity of labor supply at the firm level—playing a pivotal role (Naidu and Posner, 2022). While traditional labor economics assumes perfectly competitive markets where recruitment elasticity is infinite, recent insights into imperfectly competitive markets highlight its finite nature, necessitating alternative methodologies to estimate wage elasticity beyond market-level approaches reliant on household panel data such as Chetty (2012).

At the same time, data limitations have hindered researchers from directly estimating recruitment elasticity at the firm level in a potentially imperfectly competitive labor market. Therefore, the literature has assumed the identity between recruitment elasticity and other identifiable elasticities in a specific model, including the inverse of separation elasticity using establishment/firm-level flow data (Dube et al., 2020; Horton et al., 2011; Yin et al., 2018; Langella and Manning, 2021; Sokolova and Sorensen, 2021), job change elasticity using employer-employee matched data (Hirsch et al., 2022; Bassier et al., 2022), and application elasticity using data from job advertising platforms (Dal Bó et al., 2013; Dube et al., 2020; Pörtner and Hassairi, 2018; Belot et al., 2022; Azar et al., 2019b; Banfi and Villena-Roldán, 2019; Azar et al., 2022).

Although these estimates should align if their identification assumptions hold, the restrictive nature of these assumptions often renders the estimates incomparable, as they focus on different components of worker's decisions: The inverse separation elasticity assumes a steady state; the job change elasticity focuses on on-the-job changers, ignores off-the-job seekers, and does not control for the posted wage of unmatched vacancies; and the application elasticity focuses on the application decisions and ignores the following decisions including offer and offer acceptance before recruitment. The only exceptions are Dal Bó et al. (2013) that randomly posted low and high wages for Mexican public service and estimated the application elasticity as well as the offer and offer acceptance elasticity. Even so, their analysis is limited in the variety of jobs considered.

In this study, we address the limitations of previous research by utilizing data from one of the largest private job-matching intermediaries in Japan, which encompasses all decisions involved in the job-matching process from applications to offer acceptances for a year in 2014. Taking advantage of this rich data set, we uncover how the decisions at each stage of the job-matching process determine the overall recruitment elasticity. We study and decompose the recruitment elasticity of both employed and unemployed workers and how they differ in the worker's competitiveness represented by their current or previous wage.

Our data offer several additional advantages: i) coverage of both on-the-job and off-the-job searches; ii) inclusion of employed workers' current wage and unemployed workers' previous wage; and iii) availability of the posted wage range for all vacancies without any missing values. Despite partial coverages of the labor market, the distribution of posted wages on this private intermediary resembles the wage distribution of the newly hired full-time mid-career workers found in the representative governmental survey[1]. The role of private intermediaries in job matching was both quantitatively and qualitatively important already in the middle of 2000s and has become even more important since then[2].

Our analysis reveals that the average recruitment elasticity is negative but not statistically different from zero. We demonstrate that the zero recruitment elasticity mainly stems from the fact that lower-wage workers avoid inquiring about vacancies that post higher wages[3]. Inquiring about a vacancy is the first step in the job-matching platform, which involves getting advice from consultants and initiating an application. We divide employed into the upper- and lower-current wage workers and unemployed into upper-and lower-preivous wage workers and examine the heterogeneity in the elasticity. This inquiry elasticity is 0.971 and 0.106 for employed upper-wage workers and -1.33 and -1.19 for employed and unemployed lower-wage workers, hindering their chance to be recruited for well-paid jobs from the very beginning of the job-matching process.

Workers react positively to the posted wages when making application decisions, conditional on inquiring about the vacancies and discussing with the consultants at the job-matching platform. The application elasticity to the posted wage is 1.74 and 0.763 for employed and unemployed upper-wage workers, and 0.662 and 0.55 for employed and unemployed lower-wage workers. After applying, workers wait for interview calls and decide whether to attend. This decision is not sensitive to the posted wage. Once workers receive an offer from the vacancy, they decide whether to accept it. This decision mildly increases with the posted wage, with elasticities of 0.189 and 0.982 for employed and unemployed upper-wage workers, and 0.148 and 0.115 for employed and unemployed lower-wage workers.

The findings that the average recruitment elasticity is not statistically significantly dif-

[1]The distribution of posted wages in our dataset is similar to the wage distribution of newly hired (full-time mid-career) workers in the Employment Status Survey (ESS) in 2012.

[2]In 2014, approximately 4.2% of job changers through institutions used private job-matching intermediaries and the share increased to 9.9% in 2023 according to the Employment Trend Survey of the Ministry of Health, Labour and Welfare. The matching efficiency of private intermediaries is substantially higher than the public service (Otani, 2024a; **?**) whose efficiency has steadily declined over time (Otani, 2024b)

[3]As pointed out in (Marinescu and Wolthoff, 2019), zero elasticity is possible from the negative bias due to lack of detailed job description.

ferent from zero and can be negative for lower-wage workers are consistent with the existing literature that used alternative elasticities. Sokolova and Sorensen (2021) calculated that the median inverse separation elasticity was 0.865 by a meta-analysis, Hirsch et al. (2022) found that the job change elasticity was 1.4, and application elasticity was negative (Marinescu and Hovenkamp, 2019), 0.1 to 0.25 (Banfi and Villena-Roldán, 2019), 0.43 (Azar et al., 2019a), and 0.7 (Belot et al., 2022). The relatively high recruitment elasticity of 2.15 found by Dal Bó et al. (2013) could be specific to the Mexican public service.

In addition to these main results, we find several interesting patterns in the data. First, we find that workers prefer vacancies of the same job category and in the same location when they inquire about and apply for vacancies. This indicates that vacancies are horizontally differentiated from the worker's perspective. Manning (2020) distinguishes between monopsony models based on search friction, referred to as modern monopsony models, and those based on workers' taste heterogeneity, known as neoclassical monopsony models. Because search friction is deemed small inside the platform, the differentiation of vacancies would be the main source of market power for employers, embodied in the low recruitment elasticity in this job-matching process.

Second, we find that the matched wages are, on average, close to but slightly smaller than the lower bound of the posted wage range. Moreover, the matched wage is not affected by the endogenous state of the workers in the job-matching process, including the number of interview calls and offers, conditional on observed characteristics. Thus, the vacancies largely commit to the lower bound of the posted wage, though not perfectly. This is consistent with the directed search literature combined with the fact that workers select themselves into vacancies at the early stage based on wages and other characteristics. (Burdett and Mortensen, 1998; Burdett et al., 2001).

2 Institutional Background

2.1 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.[4] A job matching intermediary is required to have a license (Article 33), and it can charge fees only to the employer with very few exceptions (Article 32-3(2)).[5] 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 results after matching, such as the retention rate.

In 2022, there existed 28.1 thousand for-profit job-matching intermediaries in Japan. They handled 10.7 million vacancies and 28.7 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. According to the Employment Trend Survey, 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.[6]

Since the beginning of industrialization, the job matching intermediary has been under regulation. ILO conventions have prohibited for-profit job-matching intermediaries to rule 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 had been mitigated because of the improvement of labor laws and regulations and the diffusion of Internet technology. Thus, the ratification of the Convention on Private Employment Agencies in 1997 (C181) automatically overruled C096, and finally R001 was withdrawn in 2002. 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

[4] "[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)

[5] "[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)

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

from this wave of deregulation.

2.2 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 vacancy-side consultants for vacancies and worker-side consultants for workers. When a vacancy is registered, the vacancy-side consultant communicates with the corresponding employer to gather unwritten job details, adjusts the advertisement as necessary, and verifies the qualifications of potential candidates. Meanwhile, the worker-side consultant meets with registered workers to discuss their goals, job-search scope, and assess their experience and qualifications. The consultants maintain a close relationship to share information, enabling the worker-side consultant to recommend suitable vacancies to workers. When a worker applies for a vacancy, the vacancy-side consultant 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 worker-side consultant interviews them and provides a recommendation. Applications without a worker-side consultant's recommendation are automatically rejected, so the worker-side consultant's recommendation essentially determines the worker's choice set at the application stage. If the application passes the vacancy-side consultant'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.

3 Data

We use proprietary data from a job matching intermediary in Japan, covering the period from the 1st to the 40th week of 2014. The dataset encompasses all 47 prefectures in Japan and includes 39 job categories as defined by the intermediary. It records not only the observed characteristics of registered firms, workers, and vacancies but also details the decision-making process of workers and vacancies. This includes applications, interview attendance, offer acceptance for workers, and interview invitations and offers for vacancies. We refer to the data detailing the workers' decision processes as the worker event data. All monetary values, like posted and prior wages, are expressed in US dollars utilizing the average exchange rate in 2014 of 105 Japanese yen (JPY) to the dollar.

3.1 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 worker-side consultant's recommendation, the data indicates that a worker almost exclusively applies to a vacancy if, and only if, the worker-side consultant 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 worker-side consultant's preference during their meeting. If this is the case, the application data only reveals the worker's preference after their meeting with the worker-side consultant.

First, we can think that the estimand can be the preference after the meeting with the worker-side consultant. Although this raises concerns about the external validity of the estimated application elasticity in other setups, 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 worker-side consultant, we could argue that the bias in the estimated application elasticity is negligible. The worker-side consultant's recommendation accommodates the worker's interest: only 1.2% of the applications recommended by the worker-side consultant are about vacancies for which the worker did not collect information by themselves, and the worker complies with almost all the worker-side consultant's recommendations above. Thus, if the worker-side consultant 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 worker-side consultant has little reason to reject the application because it is the vacancy-side consultant's job to reject it. Therefore, it would be plausible to assume that the worker-side consultant serves workers as perfect agents rather than strategic agents.

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

(a) Inquiry and Application stage

	N	mean	sd	min	max
Number of information collection	44545	174.95	153.72	1.00	1034.00
Number of applications	44545	21.30	27.42	0.00	699.00
Current wage (U.S. dollars)	44545	49666.27	22048.81	105.00	315000.00
Number of jobs experienced	44545	1.93	1.27	0.00	34.00
Worker rank	44545	3.93	2.21	1.00	9.00
Second language level	44545	0.92	1.08	0.00	3.00
Full-time dummy	44545	0.86	0.34	0.00	1.00
University graduate dummy	44545	0.83	0.37	0.00	1.00
Male dummy	44545	0.75	0.44	0.00	1.00
Young cohort dummy	44545	0.64	0.48	0.00	1.00

(b) Interview attendance stage

	N	mean	sd	min	max
Number of interview calls	29385	5.95	5.07	1.00	90.00
Number of interview attendance	29385	5.23	4.54	0.00	78.00
Current wage (U.S. dollars)	29385	48437.86	19795.41	420.00	304500.00
Number of jobs experienced	29385	1.84	1.18	0.00	25.00
Worker rank	29385	3.74	2.10	1.00	9.00
Second language level	29385	0.90	1.05	0.00	3.00
Full-time dummy	29385	0.87	0.34	0.00	1.00
University graduate dummy	29385	0.85	0.36	0.00	1.00
Male dummy	29385	0.75	0.43	0.00	1.00
Young cohort dummy	29385	0.69	0.46	0.00	1.00

(c) Offer acceptance stage

	N	mean	sd	min	max
Number of offers	10248	1.23	0.62	1.00	12.00
Number of offer acceptance	10248	0.81	0.40	0.00	2.00
Current wage (U.S. dollars)	10248	48822.76	18405.38	2520.00	304500.00
Number of jobs experienced	10248	1.77	1.12	0.00	23.00
Worker rank	10248	3.72	2.01	1.00	9.00
Second language level	10248	0.87	1.04	0.00	3.00
Full-time dummy	10248	0.88	0.33	0.00	1.00
University graduate dummy	10248	0.85	0.35	0.00	1.00
Male dummy	10248	0.77	0.42	0.00	1.00
Young cohort dummy	10248	0.70	0.46	0.00	1.00

Note: The data includes 39 job category dummies and 47 prefecture dummies for workers. Previous wages for employed workers are not available (NAs), therefore, this variable is omitted from the table. Definitions of the variables can be found in the main text.

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

(a) Inquiry and Application stage

	N	mean	sd	min	max
Number of information collection	18445	164.47	149.06	1.00	936.00
Number of applications	18445	27.08	35.61	0.00	616.00
Previous wage	18445	43245.91	22225.30	105.00	367500.00
Number of jobs experienced	18445	1.97	1.37	0.00	31.00
Worker rank	18445	3.56	2.28	1.00	9.00
Second language level	18445	0.83	1.05	0.00	3.00
Full-time dummy	18445	0.79	0.41	0.00	1.00
University graduate dummy	18445	0.79	0.40	0.00	1.00
Male dummy	18445	0.67	0.47	0.00	1.00
Young cohort dummy	18445	0.69	0.46	0.00	1.00

(b) Interview attendance stage

	N	mean	sd	min	max
Number of interview calls	12468	7.05	6.64	1.00	89.00
Number of interview attendance	12468	6.49	6.24	0.00	88.00
Previous wage	12468	42040.02	19398.19	420.00	267645.00
Number of jobs experienced	12468	1.87	1.17	0.00	24.00
Worker rank	12468	3.32	2.13	1.00	9.00
Second language level	12468	0.81	1.04	0.00	3.00
Full-time dummy	12468	0.81	0.39	0.00	1.00
University graduate dummy	12468	0.82	0.38	0.00	1.00
Male dummy	12468	0.68	0.47	0.00	1.00
Young cohort dummy	12468	0.74	0.44	0.00	1.00

(c) Offer acceptance stage

	N	mean	sd	min	max
Number of offers	4108	1.29	0.73	1.00	9.00
Number of offer acceptance	4108	0.82	0.39	0.00	2.00
Previous wage	4108	43018.54	18553.33	630.00	262500.00
Number of jobs experienced	4108	1.77	1.07	0.00	10.00
Worker rank	4108	3.27	2.03	1.00	9.00
Second language level	4108	0.81	1.04	0.00	3.00
Full-time dummy	4108	0.84	0.37	0.00	1.00
University graduate dummy	4108	0.84	0.37	0.00	1.00
Male dummy	4108	0.69	0.46	0.00	1.00
Young cohort dummy	4108	0.76	0.43	0.00	1.00

Note: The data include 39 job category dummies and 47 prefecture dummies for workers. Since the log of current wages for unemployed workers is mechanically zero (with current wages set to one), this variable is omitted from the table. Definitions of the variables are provided in the main text.

Table 3: Summary statistics of vacancy's variables

	N	mean	sd	min	max
Mean posted wage (U.S. dollars)	154488	55832.83	17596.15	13125.00	304500.00
Lower bound of posted wage	154488	43938.21	12936.99	3675.00	210000.00
Upper bound of posted wage	154488	67727.44	24474.54	13650.00	420000.00
Required number of jobs experienced	154488	1.46	1.40	0.00	10.00
Job rank	154488	5.94	1.80	1.00	9.00
Required second language level	154488	0.25	0.69	0.00	3.00
Eligible education (high)	154488	0.42	0.49	0.00	1.00
Eligible education (vocational)	154488	0.50	0.50	0.00	1.00
Eligible education (college)	154488	0.51	0.50	0.00	1.00
Eligible education (technical)	154488	0.58	0.49	0.00	1.00
Eligible education (undergraduate)	154488	1.00	0.05	0.00	1.00
Eligible education (postgraduate)	154488	0.98	0.13	0.00	1.00
Number of employees	154488	3254.42	14744.76	1.00	344109.00

Note: The data also includes 39 job category dummies and 47 prefecture dummies for the vacancies. The definitions of these variables are provided in the main text.

Table 4: Summary statistics of pairwise-level variables for inquired pairs

	N	mean	sd	min	max
Duration (week)	10161572	9.82	9.08	0.00	52.00
Log(1 + distance (km))	10161572	2.37	2.20	0.00	7.72
1(posted wage > previous wage)	10161572	0.64	0.48	0.00	1.00
1(job rank > worker rank)	10161572	0.80	0.40	0.00	1.00
Same skill	10161572	0.56	0.50	0.00	1.00
Same location	10161572	0.42	0.49	0.00	1.00

Note: The definitions of these variables are provided in the main text.

3.2 Summary Statistics

We compile data for variables at the worker, vacancy, and pairwise levels. This section outlines the summary statistics, focusing on workers and vacancies registered within the first 40 weeks of 2014 to avoid right-censoring.

The worker-level data 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 levels from 0: No knowledge to 3: Very fluent. The second language required 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. Workers who make inquiries that exceed the highest 10% in the application stage, as well as those that exceed the highest 10% in interview attendance, are excluded, as they do not appear to seriously assess individual job vacancies.

Table 1 reports the summary statistics of the employed workers. At the application stage, on average, a worker collects information on 175.0 vacancies and applies to 21.3 vacancies. In the interview attendance stage, which means that among workers who receive at least one call back, a worker receives 5.95 interview calls and attends 5.23 interviews on average. At the offer acceptance stage, on average, a worker receives 1.23 offers if he receives at least one offer and accepts 0.81 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 stage.

In the application stage, the average current wage is $49,666, the number of jobs experienced is 1.93, and the rank of the job is 3.93 (between the player and the senior player). 86% are full-time, 83% are university graduates, 75% are male, and 64% are under 35 years of age. The averages of these variables are similar in the interview attendance and offer acceptance stages. Hence, there appears to be no evident selection based on the observed characteristics during the job matching process.

Table 2 reports the summary statistics of the unemployed. The number of unemployed workers is 18,445 at the application stage, 12,468 at the interview attendance stage, and 4,108 at the offer acceptance stage. The current wage for unemployed workers is mechanically zero. The average wage for their previous jobs is \$43,245 in the application stage. The number of jobs experienced is 1.97 and the worker rank is 3.56. 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 the employed workers. 79% are full-time, 79% are university graduates, 67% are male, and 69% are under 35 years of age. 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-level data 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. The job rank and language level are defined in the same way as the worker data.

The average lower and upper bounds of the posted wage are \$43,938 and \$67,727. 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 5.94, which is between the junior leader and the leader. The required rank of the vacancies is higher than the average rank of the jobs of registered workers. The required second language level is 0.25 on average, which means that about 75% of the vacancies do not require a 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 3,254 on average, which means that vacancies in this intermediary are mainly posted by large companies.

The pairwise-level data The pairwise-level data at the application stage includes variables that assess several key aspects of pairs of workers and vacancies that workers inquired about: the time interval from when a job is posted to when a worker applies, the geographic proximity between the worker and vacancy, as well as current or previous wages and job ranks compared to those posted. Since locations are recorded only at the prefecture level, geographic distance is measured between the capital cities of the prefectures where the current or previous job (if unemployed) is located and where the vacancy is posted.

Additionally, to account for the transition cost across different job categories, a skill distance metric is used, indicating whether the job category of the vacancy matches that of the worker's previous job.

Table 4 presents a summary of the pairwise variables for the worker-vacancy pairs during the application stage. The average duration is 9.82 weeks, with a standard deviation of 9.08 weeks. The average logarithm of the geographic distance (in km) plus one is 2.37, indicating that many recommended vacancies are located in different prefectures. Additionally, 64% of the recommended vacancies offer a lower bound wage higher than workers' current or previous wages, and 80% are of a higher rank. The skill distance standard deviation exceeds 0.50, suggesting that some vacancies pertain to different job categories than those of the workers' previous roles.

3.3 Building Choice Sets at Each Stage

We define each week as a round and analyze the interactions between workers and vacancies within this period. Our focus is on workers' actions such as inquiries, applications, interview attendance, and offer acceptance for vacancies within the same round, disregarding actions for other vacancies.

In the inquiry stage, a worker's choice set includes vacancies available for inquiry during that round. Due to the overwhelming number of vacancies, those not directly inquired about are sampled, with the sample receiving an inverse sampling ratio as its weight in analysis. Specifically, a worker's choice set comprises vacancies they inquired about and a 5% random sample of those they did not. In the application stage, the choice set includes vacancies recommended by the worker-side consultant. During the interview stage, based on actual interview attendance data, the choice set is defined by vacancies with interview calls at each time state, allowing workers to decide on attendance. In the offer stage, the offer set encompasses all offers received by the worker after all rounds are completed.

4 Descriptive Analysis

We analyze the data to guide the specifications for the estimation models. Initially, we decide if the lower, middle, or upper bounds of the posted wage are most suitable for evaluation. Next, we examine the selectivity of job vacancies. Finally, we visually display the relationship between posted wages and workers' decisions at each stage, with formal estimations provided in subsequent sections.

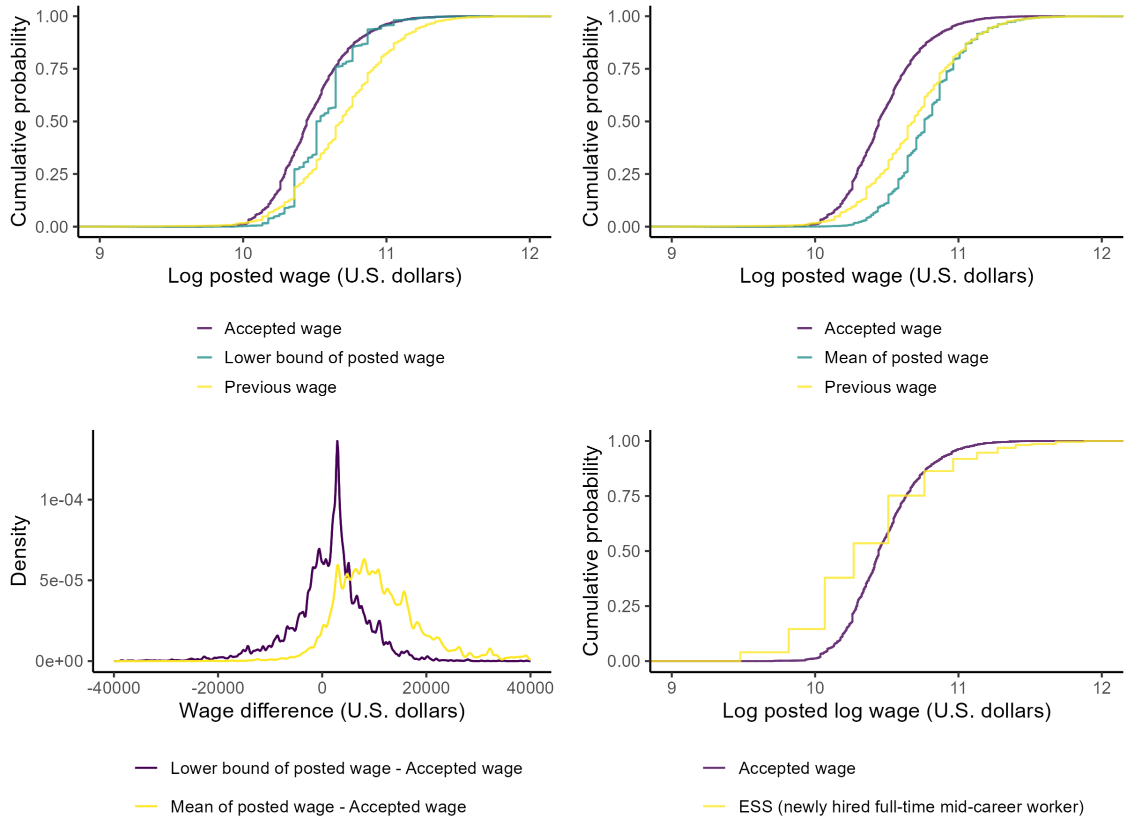


Figure 1: The empirical cumulative distribution of wages

Note: In the upper panels, posted wages pertain to all job vacancies, while current and previous wages are relevant to all workers. Accepted wages are specific to matched worker-vacancy pairs. In the bottom-left panel, data is presented for all matched worker-vacancy pairs. In the bottom-right panel, the distribution of accepted wages is compared with a representative wage distribution in Japan, specifically focusing on the income of newly hired full-time mid-career workers as reported in the 2012 Employment Status Survey (ESS).

4.1 Which Wage to Use in the Analysis?

A job posting specifies a wage range. For each worker-job match, we observe both the offered wage in addition to the posted wage range. While previous studies have used the midpoint of the posted wage range for analysis, we opt to use the lower bound of the posted wage based on our analysis. We also argue that the offered wage aligns closely with the lower bound of the posted wages.

To determine whether the lower bound or the mean of the posted wage is more relevant, the upper left panel of Figure 1 illustrates the distribution of lower bounds for posted wages, accepted wages, and current or previous wages. This comparison considers posted wages from all vacancies and accepted wages from all matched worker-vacancy pairs, along with current or previous wages for all workers.

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

	Accepted wage	Accepted wage	Accepted wage	Accepted wage
Lower bound of the posted wage	0.899	0.613	0.613	0.613
	(0.006)	(0.006)	(0.006)	(0.006)
Num.Obs.	16907	16907	16907	16907
R2	0.542	0.687	0.687	0.687
R2 Adj.	0.542	0.685	0.685	0.685
RMSE	8803.92	7283.81	7277.14	7283.21
Worker characteristics		Yes	Yes	Yes
Application state variables			Yes	
Interview state variables				Yes

Note: Each observation corresponds to a matched pair of workers and vacancies. The characteristics of workers considered include second language proficiency, rank, number of job experiences, education level, gender, age group, employment status, prefecture, and job category. Standard errors are presented in parentheses.

The lower bounds of the posted wages are slightly below the current or previous wages. Similarly, the accepted wages are marginally lower than these lower bounds but not significantly different. 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, indicating that the average posted wages are considerably higher than those of other categories. Therefore, the lower bound more accurately reflects the nature of the vacancy than the average or upper wage bounds.

The lower left panel of Figure 1 illustrates the distribution of differences for matched worker-vacancy pairs: between the lower bound of the posted wage and the accepted wage, and between the mean posted wage and the accepted wage. It reveals that the difference is, on average, close to 0 for the lower bound but positive for the mean. Therefore, the lower bound of the posted wage is a less biased predictor of the accepted wage compared to the mean.

The figures suggest that the accepted wage is not as tightly bound by the posted wage range as the directed search literature posits, yet it's not completely independent of it as the random search literature suggests. This observation prompts several questions: first, how accurately can we predict accepted wages based on posted wages? Second, when there is a discrepancy between the accepted and posted wages, does it indicate the bargaining power of the worker or the employer?

Table 5 shows the results of regressing the accepted wage on the lower bound of the posted wage for the matched worker-vacancy pairs. The second column controls for the

Table 6: The average transition probability conditional on the current stage outcome

Stage	Proceed
Application	0.115
Receiving an interview call	0.524
Inteview attendance	0.864
Receiving an offer	0.485
Offer acceptance	0.779

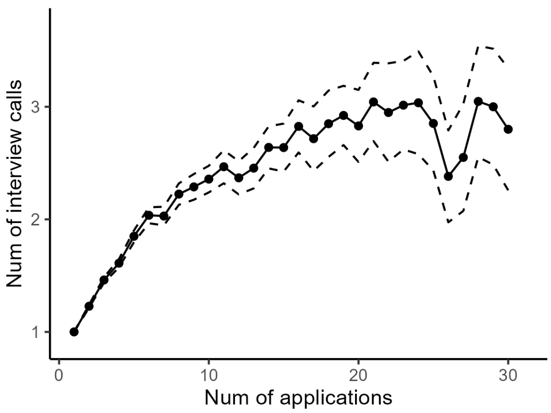
Note: The average transition probability of proceeding to the next stage is calculated by dividing the size of the worker-level choice set at the next stage by the size of the worker-level choice set at the current stage for each worker, and then taking the average over active workers at the current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

worker's characteristics. Additionally, the third column controls for the state of the worker at the application stage, measured by the number of vacancies the worker has applied for each type of vacancy. The fourth column controls the state of the worker at the interview stage, measured by the number of vacancies for which the worker has received interview calls for each type of vacancy.

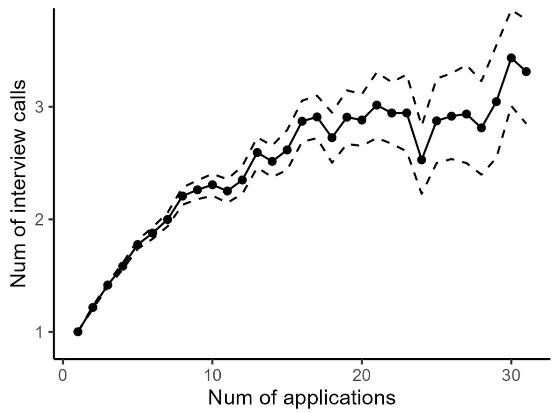
Without controlling for any variables, the coefficient for the lower bound of the posted wage is 0.899 and statistically significant, with an adjusted R-squared of 0.542. When controlling for worker characteristics, the coefficient decreases to 0.613, and the adjusted R-squared increases to 0.685. This indicates that while the lower bound of the posted wage is not a perfect predictor, it is highly indicative of the accepted wage. Notably, including worker state variables at the application and interview stages does not improve the model's fit. Thus, although worker characteristics do influence the accepted wage, the worker's state, endogenously formed during the job-matching process, does not have an impact.

For these reasons, in the following analysis, we use the lower bound of the posted wage in the model and consider the difference between the accepted and posted wages as exogenous shocks.

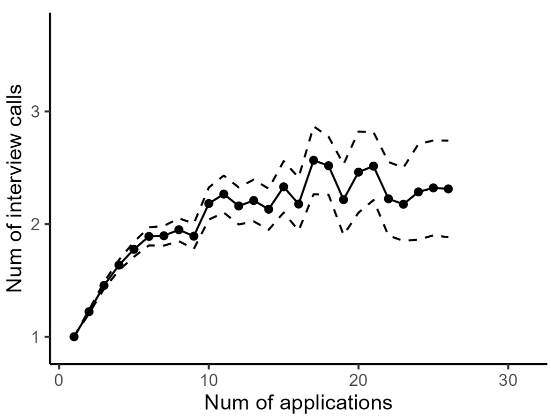
The lower right panel of Figure 1 compares the distribution of accepted wages with a representative wage distribution in Japan. We specifically compare it with the income of newly hired full-time mid-career workers from the 2012 Employment Status Survey (ESS). The results show that accepted wages in the intermediary are higher than the average wages of these workers. This is because the intermediary targets university graduates in white-collar, relatively high-wage jobs.



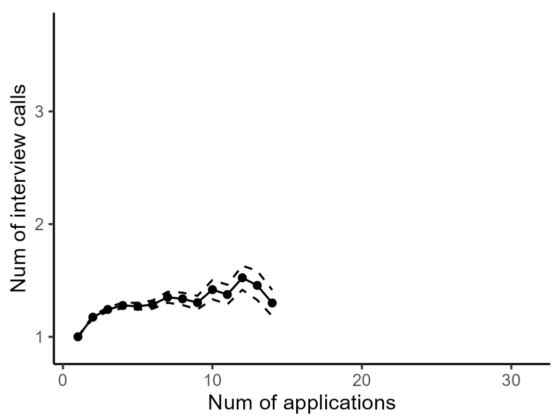
(a) Employed/Lower Wage



(b) Employed/Upper Wage



(c) Unemployed/Lower Wage



(d) Unemployed/Upper Wage

Figure 2: The vacancy-level number of applications and interview calls

Note: We calculate the number of interview calls and applications for each bin, along with their 95% confidence interval. The y-axis represents the number of interview calls, and the x-axis shows the number of applications for each employment and wage group.

(a) Employed/Lower Wage

(b) Employed/Upper Wage

(c) Unemployed/Lower Wage

(d) Unemployed/Upper Wage

Figure 3: The vacancy-level number of interview attendances and job offers

Note: We calculate the number of interview attendances and job offers for each bin along with its 95% confidence interval. The y-axis represents the number of job offers, while the x-axis shows the number of interview attendances for each employment and wage group.

4.2 How Selective Are Vacancies?

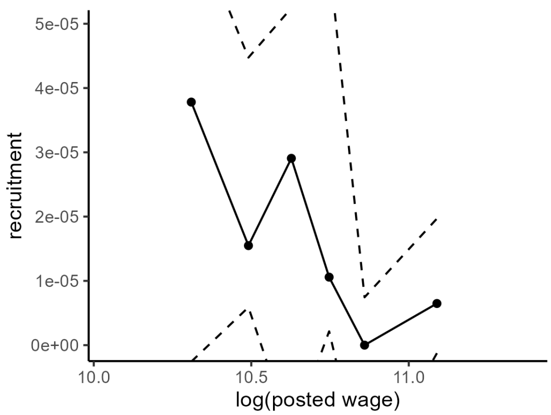
We first examine how selective the vacancies are. Initially, we assess the average likelihood that a vacancy will result in an interview call and a subsequent offer to a worker. Next, we analyze how an increase in the number of applications and interviews affects the number of interview calls and offers made. This sensitivity is crucial for workers' decisions as it affects the competitiveness of the vacancy. If a vacancy proportionally increases interview calls and offers with more applications and interviews, there is no increased competition among workers. In contrast, if the numbers grow less rapidly than the applications and interviews, workers can anticipate higher competition for vacancies with favorable terms.

Table 6 summarizes the conditional probabilities that a worker progresses to the next stage after having completed all previous stages. For example, the conditional probability of an application is calculated by dividing the number of applications by the information collected, averaging this ratio between workers. Similarly, for interview calls, the probability is determined by dividing the number of interview calls by the applications submitted, then averaging across all workers.

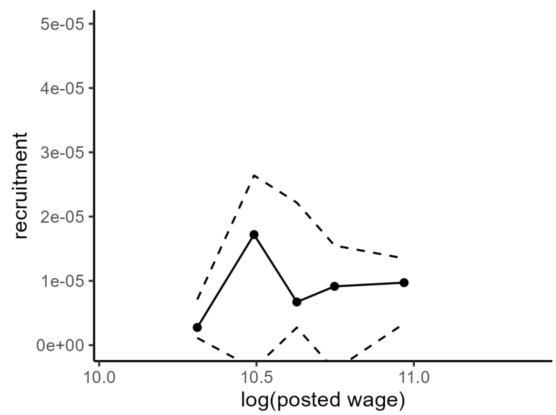
After inquiring about vacancies, the worker applies to 11.5% of them. From these applications, the worker receives an interview call from 52.4%. The worker attends 86.4% of the interviews. Of the interviews attended, 48.5% result in a job offer. This shows that the selection process becomes more rigorous after the interview stage compared to the application stage. Upon receiving a job offer, the worker accepts it 77.9% of the time.

What matters more for a worker's decision is the elasticity of selectivity to the number of applications and interviews. To illustrate the elasticity of selection per vacancy, we present a binned scatter plot that depicts the relationship between interview calls and job applications, as well as job offers relative to initial interviews. These plots are categorized by employment status (employed vs. unemployed) and further segmented by income levels (current income for employed and previous income for unemployed).

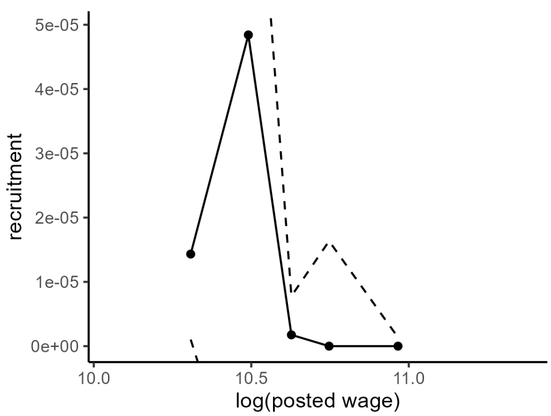
Figure 2 shows the relationship between the number of applications and the number of first interview calls, and Figure 3 shows the relationship between the number of interview attendances and the number of offers. The graph is increasing in both figures, but the slope is flatter for the graphs between the number of offers and the number of first interview calls, suggesting that the capacity of offers is less elastic. There is little difference in shape between worker types except for unemployed lower-wage workers, whose sample size is smaller compared to other types.



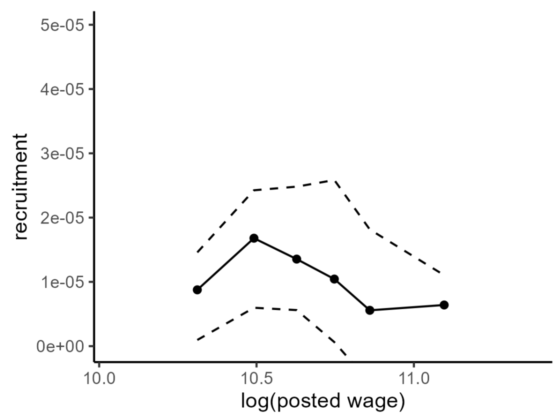
(a) Employed/Lower Wage



(b) Employed/Upper Wage



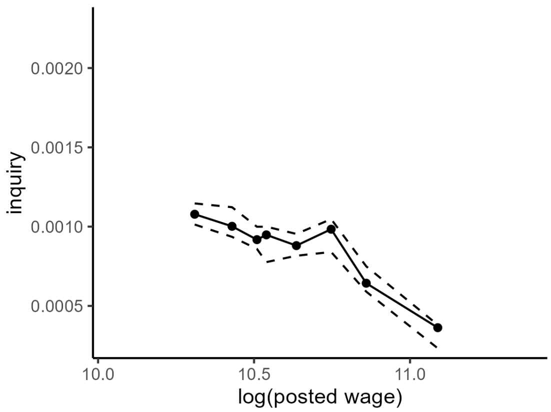
(c) Unemployed/Lower Wage



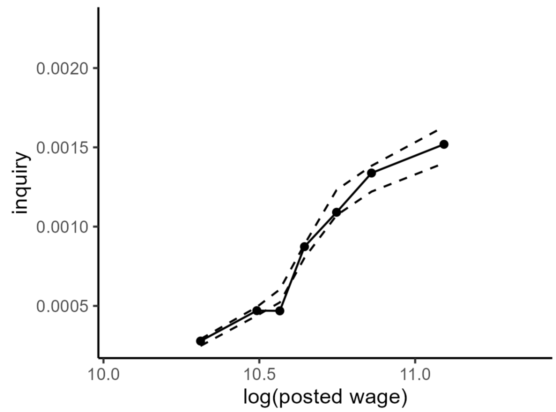
(d) Unemployed/Upper Wage

Figure 4: The recruitment probability conditional on the posted wage

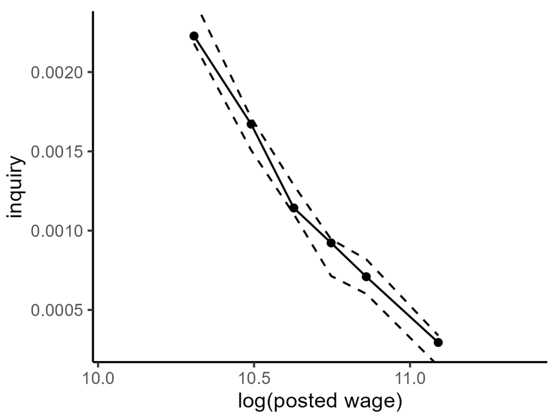
Note: We calculate the recruitment probability for each bin, along with its 95% confidence interval. The y-axis is anchored to the value of the lowest posted wage group. We utilize the same sub-sample of workers as used in the application stage estimation. Each worker's vacancy set is constructed by randomly selecting a 1/100 sample of vacancies that the worker did not inquire about but could have theoretically considered. The recruitment probability is adjusted according to the sampling ratio.



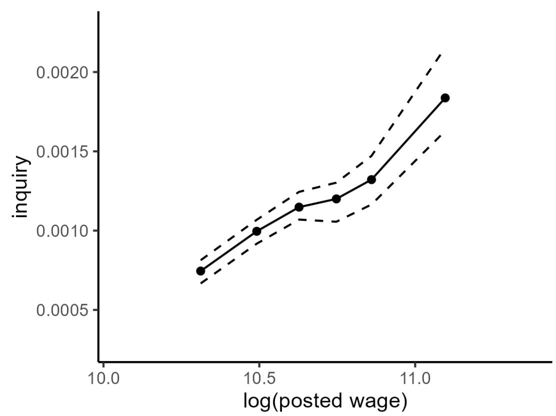
(a) Employed/Lower Wage



(b) Employed/Upper Wage



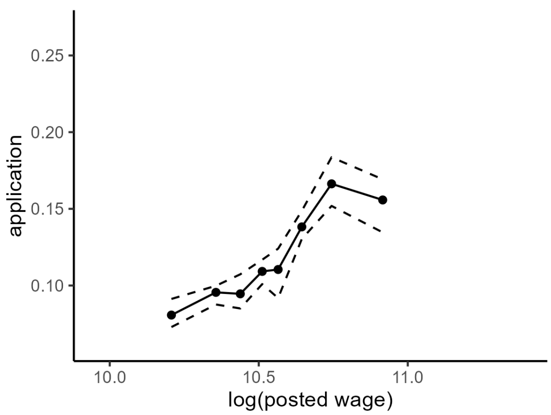
(c) Unemployed/Lower Wage



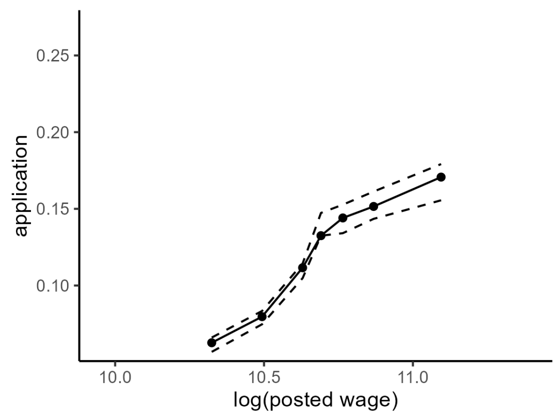
(d) Unemployed/Upper Wage

Figure 5: The inquiry probability conditional on the posted wage

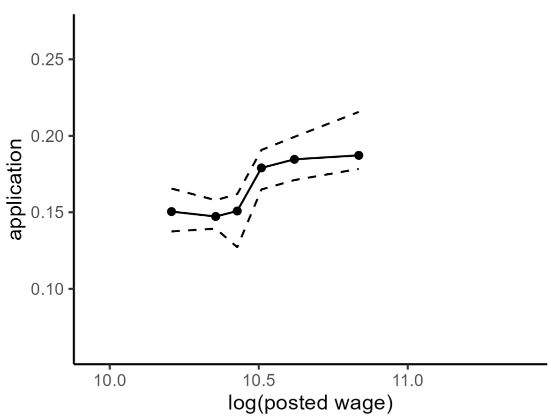
Note: We calculate the inquiry probability for each bin, along with its 95% confidence interval. The y-axis is anchored to the value of the lowest posted wage group. We utilize the same sub-sample of workers as used in the application stage estimation. Each worker's vacancy set is constructed by randomly selecting a 1/100 sample of vacancies that the worker did not inquire about but could have theoretically considered. The inquiry probability is adjusted according to the sampling ratio.



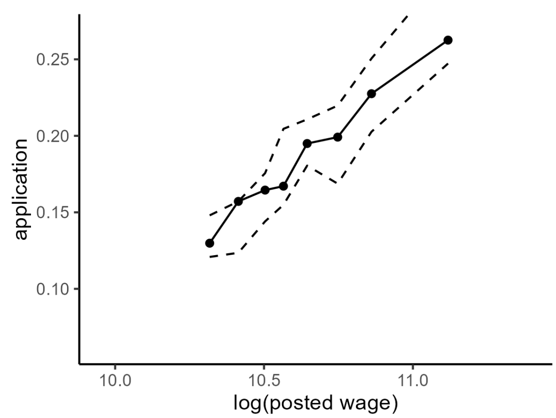
(a) Employed/Lower Wage



(b) Employed/Upper Wage



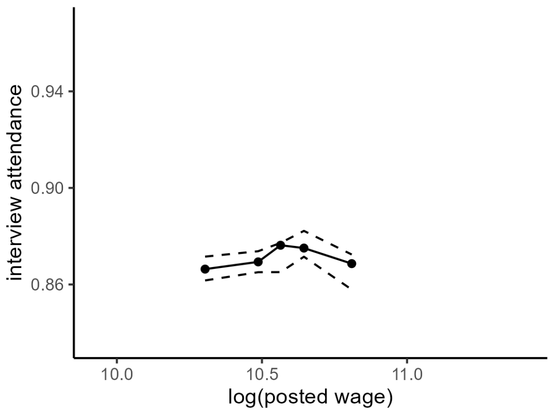
(c) Unemployed/Lower Wage



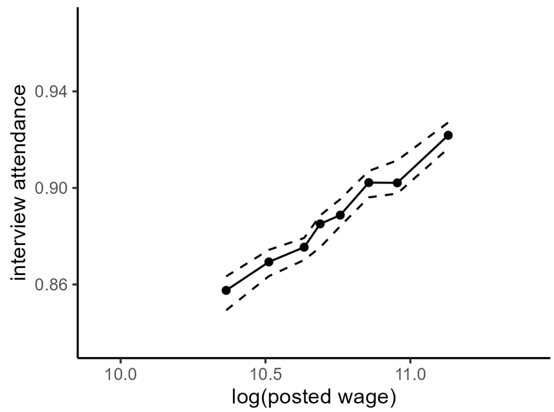
(d) Unemployed/Upper Wage

Figure 6: The application probability conditional on the posted wage

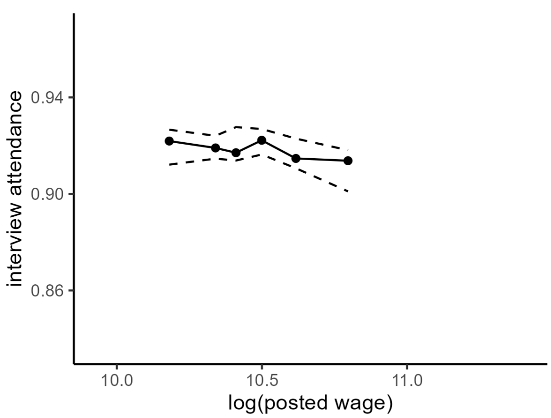
Note: We calculate the application probability for each bin, along with its 95% confidence interval. The y-axis is anchored to the value of the lowest posted wage group.



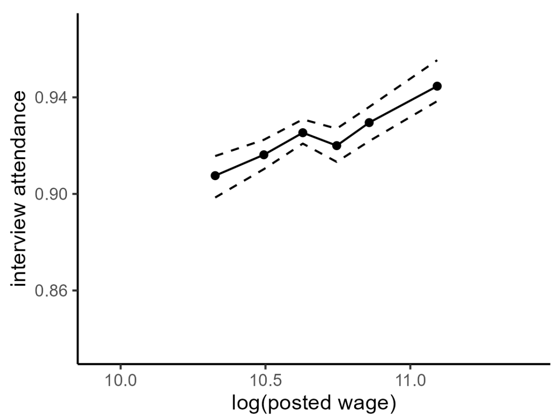
(a) Employed/Lower Wage



(b) Employed/Upper Wage



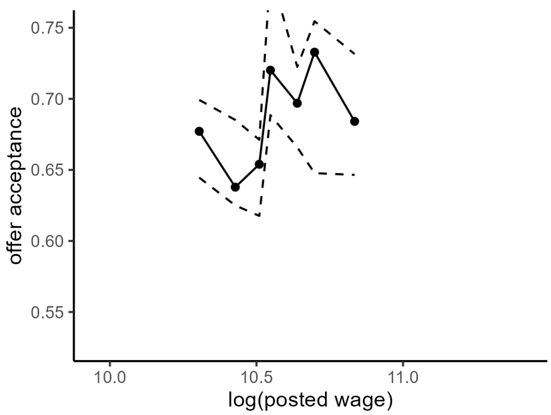
(c) Unemployed/Lower Wage



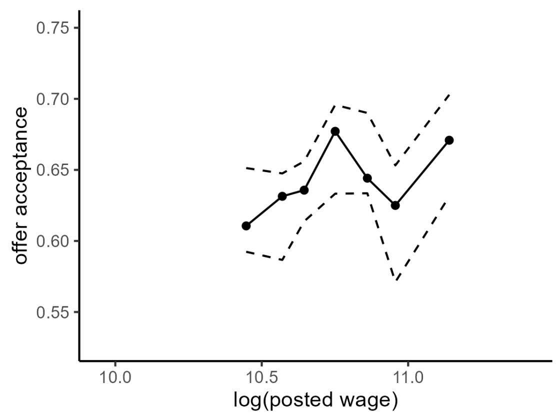
(d) Unemployed/Upper Wage

Figure 7: The interview attendance probability conditional on the posted wage

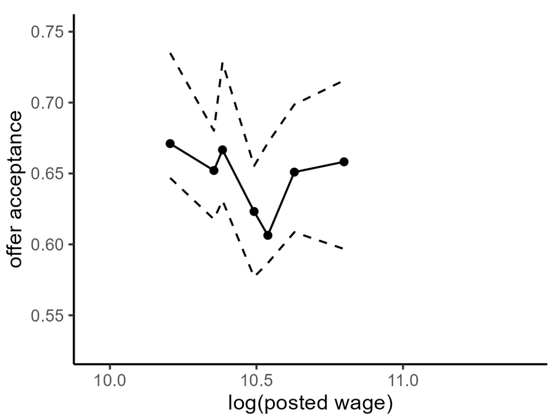
Note: We calculate the interview attendance probability for each bin, along with its 95% confidence interval. The y-axis is anchored to the value of the lowest posted wage group.



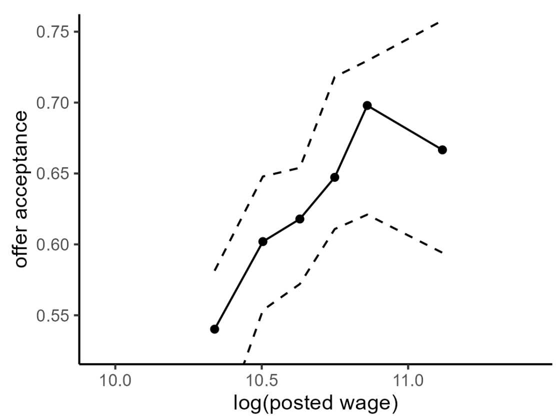
(a) Employed/Lower Wage



(b) Employed/Upper Wage



(c) Unemployed/Lower Wage



(d) Unemployed/Upper Wage

Figure 8: The offer acceptance probability conditional on the posted wage

Note: We calculate the offer acceptance probability for each bin, along with its 95% confidence interval. The y-axis is anchored to the value of the lowest posted wage group.

4.3 How Elastic Are Workers' Decisions to Posted Wages?

Next, we visualize how sensitive the recruitment of a worker by a vacancy and the workers' decisions at each stage are to the wage (the lower bound of the posted wage) of the vacancy.

Figure 4 presents the recruitment probability as a function of the posted wage for vacancies. The x-axis represents the logarithm of the posted wage, while the y-axis indicates the recruitment probability. The error bars depict the 95% confidence interval of the fitted line. It suggests that the relationship between posted wage and recruitment probability is unclear, as the recruitment probability is nearly constant and close to zero for all worker types.

We further investigate the workers' decisions at each stage of inquiry, application, interview attendance, and offer acceptance.

Figure 5 shows the probability of inquiry as a function of the posted wages for vacancies. The x-axis represents the logarithm of the posted wage, and the y-axis represents the probability of inquiry. The inquiry probability increases with posted wages for higher-wage workers, but decreases for lower-wage workers. There is little difference in this pattern between employed and unemployed workers. This indicates that lower-wage workers are likely to give up on well-paying vacancies at the inquiry stage. Therefore, increasing the posted wage may not increase the number of inquiries but may change the composition of the applicants.

Figure 6 illustrates the application probability as a function of the posted wage for a vacancy. The x-axis represents the logarithm of the posted wage, and the y-axis shows the application probability. At this stage, the application probability increases with the posted wage for both employed and unemployed individuals, as well as for both upper- and lower-wage workers. Therefore, workers are responsive to the posted wage during the application stage. It is important to note that elasticity at the application stage may not be representative of decisions made at other stages.

Figure 7 illustrates the probability of interview attendance as a function of the wage posted for a vacancy. The y-axis represents the interview attendance probability. It indicates that this probability increases with the posted wage primarily for workers in higher wage brackets, irrespective of their current employment status, while it remains unchanged for other workers. This is likely because the cost of attending an interview is substantial, and the competition following interviews is more intense than that following application submissions. Even when the posted wage is high, a worker might refrain from attending an interview if they foresee significant competitive pressure from other applicants, especially if they feel they are less competitive.

Figure 8 illustrates the probability of offer acceptance as a function of the posted wage for

Table 7: Choice Probability Based on Skills and Location

(a) Inquiry

	Same Location	Different Location
Same Skill	0.07761	0.03561
Different Skill	0.01958	0.00639

(b) Application

	Same Location	Different Location
Same Skill	0.149	0.124
Different Skill	0.144	0.125

(c) Interview

	Same Location	Different Location
Same Skill	0.901	0.880
Different Skill	0.905	0.886

(d) Offer

	Same Location	Different Location
Same Skill	0.646	0.651
Different Skill	0.666	0.265

Note: The observations involve pairs of workers and vacancies. At each stage, we calculate the ratio of the number of choices in skill/location combinations relative to the size of the choice set for each skill/location.

a vacancy. The y-axis represents the probability of offer acceptance. The figure indicates that the offer acceptance rate slightly increases with the posted wage for higher-wage workers, regardless of their current employment status. In contrast, the offer acceptance rate for lower-wage workers is less sensitive to the posted wage.

4.4 Do Workers Prefer Similar Jobs in the Same Area?

We show the types of jobs workers select regarding skills and location at each stage of inquiry, application, interview, and offer. At each stage, we calculate the choice probability of a vacancy with the same skill set and in the same location as the worker's main previous occupation. Table 7 presents the results.

During the inquiry stage, job vacancies with the same location and skill set are inquired about with a probability of 7.7%. The inquiry probability drops to less than half if either the location or skill differs. When both the skill and location are different, the inquiry probability is only 0.6%. This indicates a strong preference among workers for similar jobs at the inquiry stage. On the other hand, the probabilities for applying to jobs and attending interviews remain consistent, regardless of differences in skill or location. The offer acceptance probability is lower only for jobs that require both different skills and are in different locations; otherwise, it remains similar.

5 Model

To support our empirical analysis, we present a conceptual framework for the job-matching process, which involves applications, interviews, offers, and inquiries. We streamline the employer's decision model and concentrate on the decisions of registered workers regarding inquiries, applications, interview participation, and offer acceptance. To simplify the dynamic model's description, we discretize the characteristics of workers and registrants. Since we do not estimate the model's structural parameters, the formal definition of the equilibrium is provided in Appendix A.

Consider a round of job matching processes indexed by t. 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 public and private characteristics and posted wage of vacancy j. For the outside option, $x_0 = \xi_0 = w_0 = 0$. Thus, the characteristics of the current job of the worker are captured by z_i. We call z_i the type of worker and (x_l, ξ_m, w_n) the type of a vacancy. Let $\{F(z_k)\}_{k=1}^K$ and $\{\{\{G(l, m, n)\}_{l=1}^L\}_{m=1}^M\}_{n=1}^N$ be the masses of each type. We consider a symmetric equilibrium for each type. Let H_t summarize the distribution of types in round t.

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

The inquiry stage lasts for a unit of time. A job vacancy's posting randomly arrives to the worker according to an arrival rate, and the worker decides whether to inquire about the job description. The application stage also lasts for a unit of time. Job descriptions the worker has inquired about randomly arrive to the worker at an arrival rate, and the worker decides whether to apply to the vacancy. As the application stage concludes, a vacancy determines the rate at which interview calls are made for each worker type based on the number of applications accumulated during the application stage. Thus, the vacancy does not categorize workers by their characteristics when deciding on interview calls.

The interview stage also includes a unit-time period following the application stage. An interview call for a vacancy randomly arrives to the worker according to its arrival rate, and the worker decides whether to attend the interview. At the end of the interview stage, interviews are conducted, and workers learn about the vacancies' unobserved characteristics.

The offer stage follows the interview stage. At the beginning of the offer stage, the employer decides the number of job offers for each type of worker based on the number of interviews accumulated during the interview attendance stage for each type of worker, and then randomly makes offers to fill these positions. Thus, the employer distinguishes workers only by characteristics relevant to the offer decision. A worker chooses one of the offered and current jobs by comparing the posted wage, as well as the public and private characteristics of the jobs. As offer decisions are made, matches are realized, and both workers and employers receive the surplus.

6 Estimating Recruitment Elasticity

6.1 Reduced-form Model

First, we estimate the equilibrium recruitment elasticity by considering a reduced-form model of recruitment at the vacancy level. The probability that worker i is recruited by vacancy j is

$$p_{ij} = \frac{e^{\delta_{ij}}}{\sum_{j'=0}^{J} e^{\delta_{ij'}}}, \tag{1}$$

where δ_{ij} is specified as

$$\delta_{ij} = \alpha \ln(w_j) + \beta_i' x_j, \tag{2}$$

and

$$\beta_i = \Pi z_i + \Sigma \nu_i. \tag{3}$$

Note that δ_{ij} does not have an interpretation as direct utility, because the recruitment is a consequence of the bilateral decisions of workers and vacancies. We consider this as a predictive model of recruitment.

We add controls related to vacancies and workers. For vacancies, this includes the number of employees in the job, the job's rank, the language used in the job, the level of education required, the number of required experiences, the job's location, and the field of the job. Regarding workers, this includes the age group and gender of the worker. Additionally, for these combinations of workers and vacancies, we controlled for whether the field was the same as the previous job (skill distance), whether the region was the same as the previous job (location distance), whether the salary was higher than in the previous job, whether the rank was higher than in the previous job, and the time it took from the worker's registration to matching with the vacancy. In our baseline specification, we allow that the coefficient of skill and location distance variables can differ across workers.

We construct a random sample of the data because the original data is too large to handle with our computer. First, we sample 1% of workers who have made any application. Second, for each worker, we select all vacancies the worker has inquired about and randomly sample 1% of vacancies of each type that were not inquired about but were in their choice set, making it a sample of vacancies $\widetilde{J}$. To adjust the sampling weight, the likelihood is approximated by

$$p_{ij} = \frac{e^{\delta_{ij}}}{\sum_{j'=0}^{\widetilde{J}} n_{ij'} e^{\delta_{ij'}}}, \tag{4}$$

with $n_{ij'} = 1$ if worker i inquired about vacancy j' and $n_{ij'} = 100$ if worker i did not inquire about vacancy j'.

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

$$w_j = \delta' x_j + \kappa d(x_j, H_t) + \nu_j, \tag{5}$$

where $d(x_j, H_t)$ is a measure of the distance in the characteristics space of the vacancy from other registered vacancies. H_t represents the market structure, that is, the vector of number of vacancies of type at the registration week of the worker, t. ν_j is the function of the private characteristics ξ_j and assumed to be linear: $\nu_j = \rho^{-1}\xi_j$. 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 (5). Then, we obtain the residual estimate of

$$\hat{\nu_j} = w_j - \hat{\delta}' x_j - \hat{\kappa} d(x_j, H_t). \tag{6}$$

Table 8: First-stage results

	(1)	(2)	(3)	(4)	(5)
Log(rivals' vacancies)	0.004			0.004	-0.002
	(0.002)			(0.002)	(0.002)
Log(rivals' employees)		0.001		0.000	0.000
		(0.000)		(0.001)	(0.000)
Posting in other markets			-4.806		-4.808
			(0.168)		(0.167)
Posting in other markets $\times$ Log(other markets' mean wage)			0.452		0.452
			(0.016)		(0.016)
Num.Obs.	154488	154488	154488	154488	154488
R2	0.461	0.461	0.540	0.461	0.540
R2 Adj.	0.456	0.456	0.536	0.456	0.536
AIC	-72623.9	-72608.6	-97266.3	-72622.1	-97266.0
RMSE	0.19	0.19	0.18	0.19	0.18

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

We insert this into equation (8) to obtain

$$\hat{\delta}_{ij} \coloneqq \alpha \ln(w_j) + \beta_i' x_j + \rho \hat{\nu}_j. \tag{7}$$

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

Following Azar et al. (2022), the instruments for wage w_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 (BLP-type instruments), 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.

Table 9: Average recruitment results

(a) Estimation results

	(1)	(2)	(3)
Log(posted wage)	-0.677	-5.321	-1.082
	(0.253)	(2.887)	(0.821)
Num.Obs.	904145	904145	904145
Covariates	No	Yes	Yes
IV	No	B	H

(b) Recruitment elasticity

(1)	(2)	(3)
-0.677	-5.32	-1.08
[-1.17, -0.181]	[-11, 0.338]	[-2.69, 0.528]

Note: The dependent variable is the worker's decision to accept the offer. We omit the coefficients of control variables from the table. We control for the logarithm of the number of employees, the required level of a second language, the required amount of experience, and vacancy-specific dummies for job rank, eligible education level, job category, workplace prefecture, and registered week. Additionally, we control for the number of weeks elapsed from when the vacancy is posted to when the worker applies for the vacancy. It also includes the age and gender of the worker, and the difference in the skill vector between the vacancy's job category and the worker's current (if employed) or previous (if unemployed) job category. The standard errors are in parentheses. The parentheses of the elasticity show the 95% confidence interval.

6.2 First-Stage Results

Table 8 reports the first-stage regression results for the posted wage. 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 are statistically significant, but the number of 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, as well as when 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 other markets is statistically and economically significant. This makes sense because firms tend to set a uniform wage across markets. Moreover, it is likely that the uniform wage is set independently of local labor supply shocks. Therefore, in the following estimation of the offer acceptance decision, we use the Hausman-type instrumental variable as the preferred instrument.

Table 10: Recruitment results and elasticity

(a) Estimation results

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Log(posted wage)	-2.768	-4.620	-0.447	-1.919
	(2.277)	(5.166)	(1.417)	(1.554)
Num.Obs.	109941	123839	445391	224974
Covariates	Yes	Yes	Yes	Yes

(b) Recruitement elasticity

(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
-2.77	-4.62	-0.447	-1.92
[-7.23, 1.7]	[-14.7, 5.51]	[-3.22, 2.33]	[-4.97, 1.13]

Note: See the note of Table 9. The results are based on Hausman instruments.

6.3 Second-Stage Results

Table 9a and 9b shows the estimation results for the reduced-form model of recruitment. Column (1) estimates the model without any covariates and instruments. Column (2) uses the BLP-type instruments, and Column (3) uses the Hausman-type instruments. It shows that the coefficients on the posted wage are negative and not statistically significant. The unclear results are consistent with the descriptive analysis.

Table 10a reports the estimation results using Hausman-tyep instruments for each type of worker, employed or unemployed, and upper wage or lower wage. The implied recruitment elasticity is summarized in Table Table 10b. As we focus on estimation results with instruments, the coefficients of posted wage are negative and not statistically significant.

7 Decomposing Recruitment Elasticity

The analysis in Section 6 showed that the recruitment elasticity is negative and not statistically significant, confirming the findings in the descriptive analysis. In this section, we decompose the recruitment elasticity by estimating the conditional choice probability of workers at each stage.

7.1 Econometric Models

To construct state variables for estimating inquiry, application, and interview attendance conditional choice probabilities, we fix the numbers of distinct characteristic points to three, i.e., set $K = L = M = N = 3$. We construct discretized markets using three groups based on the quantile of: (1) the number of employees groups (x), (2) posted wage groups (w), (3) three geographical groups (East, Middle, and West), and (4) two job category groups (blue and white collar). Specifically, each worker-date observation can have state variables for at most 54 ($= 3 \times 3 \times 3 \times 2$) discretized markets. These segments are used to build state variables at each stage.

To explicitly differentiate the parameters across stages, we assign the subscript "3" to the offer acceptance stage, "2" to the interview attendance stage, "1" to the application stage, and "0" to the inquiry stage. Following the model described in Appendix A, we formulate a worker's offer-acceptance decision as a multinomial logit model over their offer set and their interview-attendance, application, and inquiry decisions as a binary logit model for each vacancy available at each stage for the worker.

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

$$u_3(z_i, w_j, x_j, \xi_j) = \alpha_{i3} \ln(w_j) + \beta_{i3}' x_j + \xi_j, \tag{8}$$

and that of the current job by

$$u_3(z_i, 0, 0, 0) = 0, \tag{9}$$

where w_{0i} is the wage of the current job. The coefficient β_{i3} can be different across workers due to the observed worker characteristics as

$$\beta_{i3} \coloneqq \Pi_3 z_i. \tag{10}$$

We use the control function approach to address the private type ξ_j. We add controls related to vacancies and workers. For vacancies, this includes the number of employees in the position, the rank of the job, the language used in the job, the level of education required, the amount of experience required, the job location, and the field of the job. For workers, this includes age group and gender. Additionally, for these combinations of workers and vacancies, we control for whether the category is the same as in the previous job, whether the region is the same as in the previous job, whether the salary is higher than in the previous job, whether the rank is higher than in the previous job, and the time taken from the worker's registration to matching with the vacancy.

Interview attendance The choice-specific value function for a worker to attend an interview of vacancy j is formulated as

$$V_2[z_i, w_j, x_j, s, q_{i2}, q_{i2}(s), H_t] = \alpha_{i2}\ln(w_j) + \beta'_{i2}x_j + \lambda_{2s}s + \lambda'_{2n}q_{i2} + \lambda'_{2ns}q_{i2}(s) + \lambda'_{2e}H_t, \quad (11)$$

and

$$V_2[z_i, 0, 0, 0, 0, 0, H_t] = 0. \quad (12)$$

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 $q_{i2} := q_i(\mathcal{J}_{i2})$, the number of vacancies that the worker has received interview calls $q_{i2}(s) := n_i[\mathcal{J}_{i2}(s)] \in \mathbb{Q}^{LMN}$, and the industry environment H_t. The industry environment H_t 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.

We specify state variables, s, q_{i2}, $q_{i2}(s)$, and H_t to approximate the value function. First, we specify s as elapsed days at the event decision timing since i's registration. Second, we construct q_{i2} and $q_{i2}(s)$ for each discretized market. Finally, we construct H_t as the number of applications and interviews in a round r in the 54 $(= 3 \times 3 \times 3 \times 2)$ discretized markets. In addition to this, we control for the variables as in the offer stage model. For the combinations of vacancy and worker characteristics, we control for the time from the worker's registration to the interview call by the vacancy.

Application and inquiry The choice-specific value function for a worker to apply to and inquire about a vacancy j is formulated similarly to that of the interview attendance decision. In the application decision, we replace the number of applications q_{i2} with the number of inquiries q_{i1}, the number of vacancies that the worker has received interview calls $q_{i2}(s)$ with the number of applications that the worker has applied $q_{i1}(s)$, the time from the worker's registration to the interview call with the time to the application to the vacancy. In the inquiry decision, we replace the number of applications that the worker has applied $q_{i1}(s)$ with the number of inquired the worker has made.

7.2 Estimation Results

Table 11 reports the estimation results for each type of worker, employed or unemployed, and upper wage or lower wage. Table 12 decomposes recruitment elasticity into each stage elasticity.

Table 11: Wage coefficients in each stage

(a) Offer acceptance

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Log(posted wage)	2.648	0.350	0.569	0.493
	(1.057)	(0.855)	(0.463)	(0.651)
Num.Obs.	1577	2492	5595	4513
Covariates	Yes	Yes	Yes	Yes

(b) Interview attendance

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Log(posted wage)	0.500	-0.073	0.553	0.222
	(0.147)	(0.143)	(0.078)	(0.100)
Num.Obs.	37424	50489	102149	72771
Covariates	Yes	Yes	Yes	Yes

(c) Application

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Log(posted wage)	0.950	0.634	1.981	0.740
	(0.205)	(0.188)	(0.111)	(0.163)
Num.Obs.	11927	17847	51924	30586
Covariates	Yes	Yes	Yes	Yes

(d) Inquiry

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Log(posted wage)	1.180	-1.373	1.134	-1.544
	(0.093)	(0.085)	(0.041)	(0.062)
Num.Obs.	109941	123839	445391	224974
Covariates	Yes	Yes	Yes	Yes

Note: Note: The dependent variable is the worker's decision to accept an offer, attend interview, apply, and inquire about the vacancy. The coefficients of control variables are omitted from the table. We control for the logarithm of the number of employees, the required second language level, the required years of experience, and vacancy-specific dummies for job rank, eligible education level, job category, workplace prefecture, and registration week. Additionally, we control for the elapsed weeks from when the vacancy is posted to when the worker makes the decision. Also included are the worker's age and gender, as well as the difference in skill vectors between the vacancy's job category and the worker's current (for employed) or previous (for unemployed) job category. We standardize the previous wage variable to have a mean of 0 and a variance of 1. Standard errors are in parentheses.

Table 12: Wage elasticity in each stage

(a) Offer acceptance

(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
0.982	0.115	0.189	0.148
[0.204, 1.76]	[-0.469, 0.699]	[-0.127, 0.504]	[-0.255, 0.551]

(b) Interview attendance

(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
0.0389	-0.00646	0.0641	0.0281
[0.016, 0.0618]	[-0.0296, 0.0167]	[0.0462, 0.0821]	[0.00218, 0.054]

(c) Application

(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
0.763	0.55	1.74	0.662
[0.42, 1.11]	[0.234, 0.867]	[1.54, 1.93]	[0.372, 0.953]

(d) Inquiry

(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
1.06	-1.19	0.971	-1.33
[0.892, 1.23]	[-1.33, -1.04]	[0.898, 1.04]	[-1.44, -1.22]

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

Table 13: Same skill and location coefficients in each stage

(a) Offer acceptance

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Same Skill	0.213	0.167	0.061	-0.165
	(0.221)	(0.173)	(0.111)	(0.131)
Same Location	0.629	-0.110	-0.040	0.280
	(0.285)	(0.198)	(0.139)	(0.149)
Num.Obs.	1577	2492	5595	4513
Covariates	Yes	Yes	Yes	Yes

(b) Interview attendance

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Same Skill	0.075	0.045	-0.030	0.021
	(0.066)	(0.053)	(0.035)	(0.037)
Same Location	0.354	0.387	0.202	0.318
	(0.084)	(0.064)	(0.044)	(0.044)
Num.Obs.	37424	50489	102149	72771
Covariates	Yes	Yes	Yes	Yes

(c) Application

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Same Skill	0.025	0.132	-0.074	0.047
	(0.115)	(0.092)	(0.056)	(0.068)
Same Location	0.915	0.265	0.346	0.712
	(0.140)	(0.097)	(0.071)	(0.082)
Num.Obs.	11927	17847	51924	30586
Covariates	Yes	Yes	Yes	Yes

(d) Inquiry

	(Unemp/Upper)	(Unemp/Lower)	(Emp/Upper)	(Emp/Lower)
Same Skill	2.856	1.862	3.262	2.262
	(0.045)	(0.037)	(0.019)	(0.025)
Same Location	2.052	2.069	1.675	1.861
	(0.054)	(0.042)	(0.024)	(0.029)
Num.Obs.	109941	123839	445391	224974
Covariates	Yes	Yes	Yes	Yes

Note: These tables show the estimated coefficients on the same skill and same location dummies of the regression models in Table 11. The standard errors are in the parentheses.

For offer-acceptance decision, the coefficients of posted wages are 0.553 and 0.222 for employed upper-wage and lower-wage workers and 0.500 and -0.073 for unemployed upper-wage and lower-wage workers. The estimates are statistically significant except for unemployed lower-wage workers. The elasticities are positive and statistically significant except for unemployed lower-wage workers, but the magnitudes are small and no greater than 0.1.

For interveiw-attendance decision, the coefficients of posted wages are 0.553 and 0.222 for employed upper-wage and lower-wage workers and 0.500 and -0.073 for unemployed upper-wage and lower-wage workers. The estimates are statistically significant except for unemployed lower-wage workers. The elasticities are positive and statistically significant except for unemployed lower-wage workers, but the magnitudes are small and no greater than 0.1.

For application decision, the coefficients of posted wages are 1.981 and 0.740 for employed upper-wage and lower-wage workers, and 0.950 and 0.634 for unemployed upper-wage and lower-wage workers. The estimates are all positive and statistically significant. These numbers correspond to 1.74 and 0.662 for employed upper-wage and lower-wage workers, and 0.763 and 0.55 for unemployed upper-wage and lower-wage workers. They are all positive and statistically significant. Thus, the application decisions are sensitive and increasing in posted wages.

For inquiry decision, the coefficients of posted wages are 1.134 and -1.544 for employed upper-wage and lower-wage workers, and 1.180 and -1.373 for unemployed upper-wage and lower-wage workers, respectively. All estimates are statistically significant; they are positive for upper-wage workers and negative for lower-wage workers. The elasticities are 0.971 and -1.33 for employed upper-wage and lower-wage workers, and 1.06 and -1.19 for unemployed upper-wage and lower-wage workers. They are all statistically significantly different from zero.

Lastly, we study whether workers prefer vacancies in the same job category and/or in the same location. If that is the case, vacancies are horizontally differentiated. Table 13 shows the coefficients on the dummy of the same job category and the same location in the estimated models in the previous section. Table 13 shows that workers strongly prefer vacancies in the same job category and location at the inquiry stage. However, these factors become less relevant in the later stage of the job-matching process. Also, being in the same location still matters but being in the same job category becomes less relevant at the application stage. Finally, we show that being in the same location is no longer relevant at the offer acceptance stage.

8 Conclusion

In this paper, we utilized data from one of Japan's largest job-matching intermediaries to assess employers' recruitment elasticity in the job-matching process. Our initial findings indicate that this elasticity is not statistically significantly different from zero. We then broke down the overall elasticity into components at various stages: inquiry, application, interview attendance, and offer acceptance. Our analysis revealed that application elasticity was the highest, while interview attendance elasticity was not statistically significant, and offer acceptance elasticity, although positive, was relatively low. Additionally, our findings indicate that workers earning above-median wages are more likely to inquire about high-wage vacancies, whereas those earning below the median tend to avoid them. The estimation results further showed that workers perceive job vacancies differently regarding skill and location fit during the inquiry stage.

There are several limitations to address in future research. First, our study did not fully characterize the equilibrium of the decentralized job-matching process, hindering our ability to precisely calculate recruitment elasticity by considering the strategic responses of workers and vacancies to changes in posted wages. Second, the wage negotiation between a worker and a vacancy, post-offer, was not explicitly modeled. Investigating this aspect is crucial for assessing the ex-post welfare of workers. Third, unlike Marinescu and Wolthoff (2019), our analysis lacked detailed data on the firms posting the vacancies and their job descriptions. Identifying these firms and correlating their labor market behavior with their product market actions is vital for developing antitrust policies addressing both input and output markets.

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Appendix

A Conceptual Formal Model

A.1 Offer Stage

Consider a worker who has the job *offer set* $\mathcal{J}_{i3}$. The worker observes the private characteristics ξ_j through interviews and idiosyncratic preference shock ϵ_{ij3} for $j \in \mathcal{J}_{i3} \cup \{0\}$ which are drawn from an i.i.d. type-I extreme value distribution. Let $q_{ilmn3} = q_{lmn}(\mathcal{J}_{i3})$ be the number of vacancies of type (x_l, ξ_m, w_n) in offer set $\mathcal{J}_{i3}$ and let $\boldsymbol{q}_{i3} = \{\{\{q_{ilmn3}\}_{l=1}^{L}\}_{m=1}^{M}\}_{n=1}^{N} = \boldsymbol{q}(\mathcal{J}_{i3})$ be its vector. We refer to $\boldsymbol{q}_{i3}$ as the *offer vector* of worker i.

The worker chooses the alternative that maximizes the utility. The utility for worker i of type z_k to be recruited by a vacancy of type (x_l, ξ_m, w_n) is

$$u_{ij} \coloneqq u_3(z_k, x_l, \xi_m, w_n) + \epsilon_{ij3}, \tag{13}$$

for vacancy $j \in \mathcal{J}_{i3}$ of type (x_l, ξ_m, w_n) and

$$u_{i0} \coloneqq u_3(z_k, 0, 0, 0) + \epsilon_{i03} \tag{14}$$

for the current job or being unemployed. This implies the choice probability of

$$p_{klmn3}(\boldsymbol{q}_{i3}) \coloneqq \frac{e^{u_3(z_k, x_l, \xi_m, w_n)}}{e^{u(z_k,0,0,0)} + \sum_{l=1}^{L} \sum_{m=1}^{M} q_{ilmn3} \sum_{n=1}^{N} e^{u_3(z_k, x_l, \xi_m, w_n)}}, \tag{15}$$

and the value function of the worker of type z_k of having an offer vector $\boldsymbol{q}_{i3}$

$$v_{k3}(\boldsymbol{q}_{i3}) \coloneqq \ln\left(e^{u_3(z_k,0,0,0)} + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{n=1}^{N} q_{ilmn3} \sum_{n=1}^{N} e^{u_3(z_k, x_l, \xi_m, w_n)}\right) + const. \tag{16}$$

At the beginning of the offer stage, the vacancies make job offers. Consider a vacancy that has the *interview set* $\mathcal{I}_{j2}$. Let $q_{jk2} = n_k(\mathcal{I}_{j2})$ be the number of interviews with workers of type z_k in interview set $\mathcal{I}_{j2}$ and let $\boldsymbol{q}_{j2} = \{q_{jk2}\}_{k=1}^{K} = \boldsymbol{q}(\mathcal{I}_{j2})$ be its vector.

We assume that the vacancy randomly makes an offer to $c_{k2} q_{jk2}^{\tau_{k2}}$ interviewed workers of each type. Therefore, the probability for a worker of type z_k of getting an offer after the interview is $c_{k2} q_{jk2}^{\tau_{k2}-1}$.

Moreover, we assume that in equilibrium the interview vectors are symmetric across vacancies of the same type. Let q^*_{Jklmn2} be the equilibrium number of interviews q_{jklmn2},

$\boldsymbol{q}^*_{Jlmn2} = \{q^*_{Jklmn2}\}_{k=1}^K$ be its vector, and $\boldsymbol{Q}^*_{J2} = \{\{\{\boldsymbol{q}^*_{Jlmn2}\}_{l=1}^L\}_{m=1}^M\}_{n=1}^N$ be its matrix. Under this assumption, vacancies of the same type are ex-ante homogeneous from workers.

Similarly, consider a worker that has the *interview set* $\mathcal{I}_{i2}$. Let $q_{ilmn2} = n_{lmn}(\mathcal{I}_{i2})$ be the number of interviews with vacancies of type (x_l, ξ_m, w_n) in interview set $\mathcal{I}_{i2}$ and let $\boldsymbol{q}_{i2} = \{\{\{q_{ilmn2}\}_{l=1}^L\}_{m=1}^M\}\}_{n=1}^N = \boldsymbol{q}(\mathcal{I}_{i2})$ be its vector.

Then, the probability that a worker of type z_k with interview vector $\boldsymbol{q}_{i2}$ at the end of the interview stage receives an offer vector $\boldsymbol{q}_{i3}$ is

$$g_{k3}(\boldsymbol{q}_{i3}|\boldsymbol{q}_{i2}, \boldsymbol{Q}^*_{J2}) \coloneqq \prod_{l=1}^L \prod_{m=1}^M \prod_{n=1}^N \binom{q_{ilmn2}}{q_{ilmn3}} (c_{k2} q^{*\tau_{k2}-1}_{Jklmn2})^{q_{ilmn3}} (1 - c_{k2} q^{*\tau_{k2}-1}_{Jklmn2})^{q_{ilmn2}-q_{ilmn3}}. \quad (17)$$

A.2 Interview Stage

Consider a vacancy that has the *application set* $\mathcal{J}_{j1}$ at the beginning of the interview stage. Let $q_{jk1} = q_{jk}(\mathcal{J}_{j1})$ be the number of workers of type z_k in $\mathcal{J}_{j1}$ and $\boldsymbol{q}_{j1} = \{q_{jk1}\}_{k=1}^K = \boldsymbol{q}(\mathcal{J}_{j1})$ be its vector. We refer to $\boldsymbol{q}_{j1}$ as the vacancy's *application vector*.

We assume that the vacancy randomly makes interview calls to workers of type z_k according to a Poisson process of rate $c_{1k} q_{jk1}^{\tau_{1k}-1}$.

Moreover, we assume that in equilibrium the application vectors are symmetric across vacancies of the same type. Let q^*_{Jklmn1} be the equilibrium number of applications for vacancies of type (x_l, ξ_m, w_n), $\boldsymbol{q}^*_{Jlmn1} = \{q^*_{Jklmn1}\}_{k=1}^K$ be its vector, and $\boldsymbol{Q}^*_{J1} = \{\{\{\boldsymbol{q}^*_{Jlmn1}\}_{l=1}^L\}_{m=1}^M\}_{n=1}^N$ be its matrix.

Consider a worker who has the *application set* $\mathcal{J}_{i1}$ at the beginning of the interview stage. Let $q_{iln1} = q_{ln}(\mathcal{J}_{i1})$ be the number of vacancies taking the value of (x_l, w_n) in $\mathcal{J}_{i1}$. ξ is unknown at this stage. Let $\boldsymbol{q}_{i1} = \{\{q_{ilkn1}\}_{l=1}^L\}_{n=1}^N = \boldsymbol{q}(\mathcal{J}_{i1})$ be its vector and $\boldsymbol{Q}_{I1} = \{\boldsymbol{q}_{i1}\}_{i=1}^I$ be its matrix (with some abuse of name because i is continuous). We refer to $\boldsymbol{q}_{i1}$ as the worker's *application vector*.

Moreover, let $\mathcal{J}_{i2}(s)$ be the set of vacancies that the worker has received the interview call and decided to attend the interview up to time $s \in [0, 1]$. Let $q_{iln2}(s) = q_{ln}(\mathcal{J}_{i2}(s))$ be the number of vacancies taking the value of (x_l, w_n) in $\mathcal{J}_{i2}(s)$. ξ is unknown at this stage. Let $\boldsymbol{q}_{i2}(s) = \{\{q_{iln2}(s)\}_{l=1}^L\}_{n=1}^N = \boldsymbol{q}(\mathcal{J}_{i2}, s)$ be its vector. We refer to $\boldsymbol{q}_{i2}(s)$ be the worker's *interview vector* at time s. At the end of the interview stage, workers attend interviews and find the vacancies' unobserved types are revealed. Therefore, $\boldsymbol{q}_{i2}$ is drawn from

$$q_{k2}[\boldsymbol{q}_{i2}|\boldsymbol{q}_{i2}(1)] \coloneqq \prod_{l=1}^L \prod_{n=1}^N \frac{q_{iln2}(1)!}{\prod_{m=1}^M q_{ilmn2}!} \prod_{m=1}^M G(m|l, n)^{q_{ilmn2}}, \quad (18)$$

because the vacancies are symmetric for the observed type. Let $\mathcal{Q}_{k2}[q_{k2}(1)]$ is a partition of

$q_{k2}(1)$.

At time $s \in [0,1]$, suppose that the worker received an interview call from a vacancy in $\mathcal{J}_{i1}$. Let j denote the vacancy's index and (x_l, w_n) be its observed type. The worker observes the idiosyncratic preference shocks ϵ_{dij2} for $d = 0, 1$, which are drawn from an i.i.d. extreme value distribution. The idiosyncratic preference shocks are only relevant for the interview attendance decision on the vacancy and are independent of everything else. The state of the worker is summarized by the time s, the application vector $\boldsymbol{q}_{i2}$, the interview vector at time s $\boldsymbol{n}_{i2}(s)$, given the expected vacancy's interview matrix $\boldsymbol{Q}^*_{J2}$. Letting e_{ln} be the vector taking the value of 1 at the element corresponding to type (l, n) and 0 otherwise.

Let $v_{k2}[s, \Delta\boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}^*_{J1}, \boldsymbol{Q}^*_{J2}]$ be the value function for worker i of type k at time s with the remaining applications $\Delta\boldsymbol{q}_{i2}(s) \coloneqq \boldsymbol{q}_{i1} - \boldsymbol{q}_{i2}(s)$, interview vector $\boldsymbol{q}_{i2}(s)$, and the vacancies' application matrix $\boldsymbol{Q}^*_{J1}$ and interview matrix $\boldsymbol{Q}^*_{j2}$.

The terminal condition is

$$\begin{aligned} &v_{k2}[1, \Delta\boldsymbol{q}_{i2}(1), \boldsymbol{q}_{i2}(1), \boldsymbol{Q}^*_{J1}, \boldsymbol{Q}^*_{J2}] \\ &= \sum_{q_{k2} \in \mathcal{Q}_{k2}[q_{k2}(1)]} \sum_{\boldsymbol{q}_{i3} \leq \boldsymbol{q}_{i2}} q_{k2}[\boldsymbol{q}_{i2} | \boldsymbol{q}_{i2}(1)] g_{k3}(\boldsymbol{q}_{i3} | \boldsymbol{q}_{i2}, \boldsymbol{Q}^*_{J2}) v_{k3}(\boldsymbol{q}_{i3}), \end{aligned} \tag{19}$$

where the summation is over the set of offer vectors that can be generated from the interview vector weighted by the probability of the offer vector.

Then, if the worker of type z_k decides to attend the interview of vacancy j of observed type (x_l, w_n) at time s, the state evolves as

$$\Delta\boldsymbol{q}_{i2}(1)' = \Delta\boldsymbol{q}_{i2}(s) - e_{ln}, \tag{20}$$

and

$$\boldsymbol{q}_{i2}(s)' = \boldsymbol{q}_{i2}(s) + e_{ln}, \tag{21}$$

and the mean choice-specific value function is

$$\begin{aligned} &v_{kln2}[1, s, \Delta\boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}^*_{J1}, \boldsymbol{Q}^*_{J2}] \\ &\coloneqq u_2(z_k, x_l, w_n) + v_{k2}[s, \Delta\boldsymbol{q}_{i2}(s) - e_{ln}, \boldsymbol{q}_{k2}(s) + e_{ln}, \boldsymbol{Q}^*_{J1}, \boldsymbol{Q}^*_{J2}], \end{aligned} \tag{22}$$

where $u_2(z_k, x_l, w_n)$ is the instantaneous payoff relevant to attending the interview, such as the transportation costs. If the worker decides not to, the state evolves as

$$\Delta\boldsymbol{q}_{i2}(1)' = \Delta\boldsymbol{q}_{i2}(s) - e_{ln}, \tag{23}$$

and

$$\boldsymbol{q}_{i2}(s)' = \boldsymbol{q}_{i2}(s), \tag{24}$$

and the mean choice-specific value function is

$$v_{kln2}[0, s, \Delta \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}, \boldsymbol{Q}_{J2}^{*}] \coloneqq v_{k2}[s, \Delta \boldsymbol{q}_{i2}(s) - e_{ln}, \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}, \boldsymbol{Q}_{J2}^{*}]. \tag{25}$$

The probability for worker i of type z_k of deciding to attend the interview at this state is

$$\begin{aligned} &p_{kln2}[s, \Delta \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}, \boldsymbol{Q}_{J2}^{*}] \\ &\coloneqq \frac{e^{v_{kln2}[1, s, \boldsymbol{q}_{i2} - \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}, \boldsymbol{Q}_{J2}^{*}]}}{e^{v_{kln2}[0, s, \boldsymbol{q}_{i2} - \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J2}^{*}]} + e^{v_{kln2}[1, s, \boldsymbol{q}_{i2} - \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}, \boldsymbol{Q}_{J2}^{*}]}}. \end{aligned} \tag{26}$$

The probability that an interview call arrives at the worker of type z_k and the vacancy is of type (x_l, w_n) is

$$\omega_{kln2}[\Delta \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}] \coloneqq \Delta q_{iln2}(s) \sum_{m=1}^{M} G(m|l,n) c_{k1} q_{Jklmn1}^{*\tau_{k1}-1}. \tag{27}$$

Therefore, the Bellman equation for the worker of type z_k at time s is

$$\begin{aligned} &v_{k2}[s, \Delta \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}, \boldsymbol{Q}_{J2}^{*}] \\ &= \frac{\sum_{l=1}^{L} \sum_{n=1}^{N} \omega_{kln2}[\Delta \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}] \ln \left(1 + e^{v_{kln2}[s, \boldsymbol{q}_{i2} - \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J2}^{*}]}\right)}{\sum_{l=1}^{L} \sum_{n=1}^{N} \omega_{kln2}[\Delta \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}]} + const. \end{aligned} \tag{28}$$

The number of interview calls to workers of type z_k by a vacancy of type (x_l, w_n) is

$$c_{k1} q_{Jklmn1}^{*\tau_{k1}}, \tag{29}$$

and the number of interviews attended by workers of type z_k for a vacancy of type (x_l, ξ_m, w_n) is

$$q_{Jklmn2}^{*} = c_{k1} q_{Jklmn1}^{*\tau_{k1}} \int_0^1 \mathbb{E}\{p_{kln2}[s, \Delta \boldsymbol{q}_{i2}(s), \boldsymbol{q}_{i2}(s), \boldsymbol{Q}_{J1}^{*}, \boldsymbol{Q}_{J2}^{*}]\} ds. \tag{30}$$

The equilibrium of the interview subgame starting with application matrix of workers $\boldsymbol{Q}_{I1}$ and vacancies $\boldsymbol{Q}_{J1}^{*}$ is i) the value function of having an offer vector $\{v_{k3}(\cdot)\}_{k=1}^{K}$ satisfying equation (16), ii) the value function $\{v_{k2}[\cdot, \cdot, \cdot, \boldsymbol{Q}_{j2}^{*}]\}_{k=1}^{K}$ satisfying equations (19) and (28) for a given vacancy's interview matrix $\boldsymbol{Q}_{J2}^{*}$, and the vacancy's interview matrix $\boldsymbol{Q}_{j2}^{*}$ satisfying equation (30).

The equilibrium of the application subgame and that of the original game starting from the inquiry stage are defined similarly.