Hi-Stat

Discussion Paper Series

No.179

Vacancy Size and Offered Wage
A Source of Search Friction in the Japanese Labor Market

Ryo Kambayashi
Yuko Ueno

August 2006

**Hitotsubashi University Research Unit
for Statistical Analysis in Social Sciences**
A 21st-Century COE Program

Institute of Economic Research
Hitotsubashi University
Kunitachi, Tokyo, 186-8603 Japan
http://hi-stat.ier.hit-u.ac.jp/

Vacancy Size and Offered Wage

A Source of Search Friction in the Japanese Labor Market[1]

Ryo KAMBAYASHI

Institute of Economic Research, Hitotsubashi University

Yuko UENO

Economic and Policy Analysis Bureau, Cabinet Office, Government of Japan

[1] An earlier version of this paper was prepared as an Economic and Social Research Institute, Cabinet Office, Government of Japan (ESRI) discussion paper series. We thank to ESRI and Ministry of Health, Labor and Welfare for providing us micro-level data. We thank comments from the participants in seminars held at Tohkeikenkyukai, Hitotsubashi University, and ESRI.

Abstract

Behind rising natural rate of unemployment, they often point out the decline in matching efficiency of the labor market. We empirically examine the cause of matching friction based on the theory of directed search model such as Burdett, Shi and Wright (2001). From rich micro data on vacancy size and wage variation of job changers in Japanese labor market, we observe the negative relationship between vacancy size and offered wage, which show the existence of search friction, not in the whole labor market but in some particular unskilled markets, especially those of clerks and production workers.

Key Words:
Search friction, matching, directed search, vacancy, wage offer, Japan.

JEL Classification Code:
J63, J31, J42.

1. INTRODUCTION

As in many countries, the natural unemployment rate of Japan has rapidly risen through the 1990s due to the decline in matching efficiency of the labor market. For example, UV analysis shows the shift of the aggregate matching function during this period; in other words, fewer jobs were formed even with the same number of vacancies and job seekers as before. In effect, newly created employment dropped and unemployed people remained longer in the market.[2]

Such recognition naturally induces us to try to improve the matching efficiency in the labor market, which would lead to a recovery in market performance as well. Under the presupposition that the key to improving matching efficiency is the speed of information transmission, we have spent much time and money in changing the relevant institutions. Accordingly, in 1998 new information technology was introduced by public agencies; this contained a searchable database on vacancy information that could be shared through networks, made a part of the vacancy information available on the internet, and shared the above information with private employment agencies. In 1999, the public monopoly of the job placement service was abandoned for the first time in 61 years.

Unfortunately, the effects of these efforts are not so obvious. For instance, job matching achieved by private employment agencies has been about 300,000 a year, or less than 20% of matching by the public agencies, and the trend for the total number shows no increase from 1998FY.[3] In addition, the proportion of new employees hired thorough private employment

[2] Sasaki (2004) and Kondou and Genda (2003) discuss in detail the Japanese empirical references.

[3] Actual numbers of matching recorded at public job centers are 1,667,986 in 1998FY, 1,762,950 in 1999FY, 1,868,742 in 2000FY, 1,902,981 in 2001FY, 2,048,300 in 2002FY, and 2,153,796 in 2003FY for regular workers (i.e., except new graduates and including part-time workers).

agencies only amounts to 1–2% to the total.[4] Public service through the Internet remains low, the matching number being as little as 1,360 per month on average during 2003 FY. These facts suggest that a simple increase in the variety of search methods or in the speed of information transmission would not necessarily improve matching efficiency in the labor market.

These policies have been based on a fundamental assumption that economic agents match together under some specific technology. In other words, it is considered that matching is technologically determined in the same way that production is determined by a production function. Therefore, matching productivity should be enhanced if new methods are introduced or if IT investments are executed for the matching process, just as the introduction of new technology or IT investment on a production line would improve productivity. However, the failure of these policies suggests that such a simple technology-determined idea for the matching process should be abandoned.

In this research, we utilize the discussion on endogeneity of matching functions, which argues that matching efficiency in labor markets depends not only on exogenous technological conditions (for example, speed of information transmission among agents), but also on interdependency among individual agents in the market. In particular, our main theme is to confirm empirically that the abovementioned mechanism is actually working in the Japanese labor market.

The sections below are organized as follows. In Section 2, we present our empirical hypothesis by showing that there could exist negative relations between the size of vacancies posted at each firm and the offered wage levels, applying directed search models that provide

[4] The proportion amounts to 0.9% in 2000FY, 1.2% in 2001FY, 1.7% in 2002FY, and 1.6% in 2003FY ("Employment Trend Survey" by the Ministry of Health, Labor and Welfare).

a theoretical base for most endogenous matching functions. Section 3 briefly explains the dataset created from the "Employment Trend Survey". In Section 4, we present our empirical model based on the hypothesis derived in Section 2. The estimation results are summarized in Section 5, and Section 6 concludes.

2. HYPOTHESIS: VACANCY SIZE AND POSTED WAGE LEVEL

In this section, we first introduce the discussion on endogenous matching function, and then show how the empirical proposition that "there exists a negative correlation between posted wage level and vacancy size" could be derived from the discussion.

The usual discussion on matching efficiency in the labor market focuses on how many matchings would be generated from a certain number of vacancies and job seekers. Many theoretical researchers assume some specific functions among these three variables, precisely functions of homogeneous degree one. At the same time, such functions that are homogeneous of degree one, which had simply been theoretically assumed at first, have been observed in various pieces of empirical research. Therefore, researchers have come to share a common understanding that matching functions have the shape of an "aggregate matching function" (AMF) that is homogeneous of degree one (Petrongolo and Pissarides, 2001).

Of course, many questions have been raised from an empirical viewpoint in estimating such AMF, such as that the estimation bias might exist only when stock variables are used in estimation, or when estimation results are unstable by region and by phases of business cycle (Coles and Smith (1996, 1998)).[5] There have been some theoretical attempts to solve these questions. As a result, instead of assuming ad hoc functional relations for vacancies, job

[5] Nakamura (2002) also observe the downward shift of matching functions during recessions in Japan. Kano and Ohta (2005) point out the existence of regional discrepancy of matching efficiency in the Japanese labor market by estimating the regional UV curve.

seekers and matching at an aggregated level, a new analytical approach has been proposed that formulates individual behavior as well as matching rules in the market, and leading to an ex-post aggregate AMF. In this context, AMF is not a technological device, but is generated endogenously through each agent's behavior. Research has revealed that the assumption of random search without any interdependency among agents would play an essential role in deriving a stable AMF that is homogeneous degree one.[6]

In other words, if we drop the assumption of random search and/or independence of agents, AMF would not necessarily be homogeneous degree one and would change its shape depending on phases of the business cycle.

For example, employers would send signals to the labor market based on the predicted responses of other employers and of job seekers. Usually, this signal is interpreted as job conditions attached to each vacancy, such as wages or working hours. As a result, various vacancies with various conditions might appear in the job market at the same time, and each vacancy could receive applications from job seekers. In this situation, employers would try to control other agents' strategy by changing working conditions.

Many researchers discuss posted wage levels at recruitment as a working condition.[7] Montgomery (1991) and Moen (1997) define the equilibrium condition as job seekers obtaining a certain amount of expected utility, whichever vacancy they applied for. In their theory, the expected utility, which is equal to the product of posted wage and hiring probability, would be determined by the exogenous outside option. Intuitively, high posted wages would attract more applicants and thus lead to lower hiring probability, while low

[6] The derivation of AMF is discussed in Albrecht, Tan, Gautier and Vroman (2004).

[7] Most research uses wage levels as signals. Offered wages play an important role in actual classifieds, and such theoretical approximation is acceptable. However, we must always be aware that wage levels are not the only factors attached to vacancies.

wages would lead to fewer applicants and higher hiring probability. The aim of the theoretical work is to consider which combination of posted wage and application probability would hold in equilibrium.

Within this, what becomes important is the "large market assumption." This assumption considers it difficult for posted wages to coordinate thoroughly when the sizes of both vacancies and job seekers are large enough. Take an example of n homogeneous vacancies and n homogeneous job seekers in the market. When the market can coordinate perfectly in this case, n homogeneous job seekers could decide where to apply *without any multiplication* with each other. Namely, even if they are completely homogeneous, we describe the situation as a "perfectly coordinated market" if job seekers could cooperate with each other by using some tools (such as ex-ante meetings). However, when n is large enough, or when it is difficult for agents to communicate with each other, it is rather realistic to assume ideal coordination does not hold, and an overlap of job seekers would be generated for certain vacancies. The assumption of large labor markets would directly lead to the implication of "coordination failure" in the market, which leads to inefficient resource allocation. In other words, the labor market friction studied in search theory could be interpreted to be dependent on the assumption mentioned above of coordination failure.

Montgomery (1991) assumes large markets and that an expected utility level guaranteed to job seekers is determined by market conditions as a whole, which is taken as given to each agent. He proved there exists a unique symmetric equilibrium such that every firm would post the same wage without ex-ante heterogeneity of employers.

On the other hand, Burdett, Shi and Wright (2001) discuss how the change in posted wage levels would affect the expected utility level to be guaranteed to a job seeker even in large markets. Under this framework they examine the equilibrium implied by introducing ex-post heterogeneity on the vacancy side, assuming that firms could choose the size of vacancy, and prove that all vacancies do not necessarily select identical size and wage levels, but vacancy sizes and wage levels distribute endogenously with negative correlations, even though they have an identical vacancy cost function. To put this in a different way, if one firm could post more than two vacancies at once, the assumptions conventionally regarded as standard would be insufficient to derive the true shape of matching functions (Burdett, Shi and Wright (2001) p. 1080.)[8] Intuitively, employers could place much weight on ex-post heterogeneity to job seekers by selecting the size of vacancies they post at one time. Greater vacancy size would allow employers to hold wages at a low level, since they could offer higher hiring probability for job seekers (given that other things are equal). This would lead to the situation in which employers with larger vacancies and smaller vacancies coexist ex post when they determine vacancy size, although they are identical with the same profit opportunities ex ante.

Therefore, when there are frictions in the market in the sense that perfect coordination is not achievable, vacancy sizes and wage levels may have negative relations.

3. DATA

In this research, we use microdata of the Employment Trend Survey (hereafter ETS) by the Ministry of Health, Labor and Welfare for the years 1993–1995, in order to investigate if the negative relationship between offered wages and vacancy sizes discussed in the previous section actually holds in the Japanese labor market.

[8] Albrecht, Tan, Gautier and Vroman (2004) relax the limitation on simultaneous applications by job seekers in a standard matching model. In addition, Burdett, Shi and Wright (2001) assume vacancy numbers are controllable for employers who move first, while Albrecht, Tan, Gautier and Vroman (2004) increase the number of possible applications sent by job seekers, and these differences have led to variant conclusions.

ETS surveys worker flow at establishment level for the preceding six months twice a year (first half: January 1–June 30, second half: July 1–December 31). The establishments surveyed are those with more then five regular workers of nine major industries. Sample size would be around 10,000 establishments each year with around 70,000 to 100,000 outflow and inflow workers. In addition, all establishments over 500 employees are surveyed.

This survey covers establishment, inflow worker, outflow worker, and additional information. The establishment questionnaire asks the basic attributes such as industry classification, employee size, and location, as well as the flow of regular workers during the period surveyed. In other words, the number of regular workers at the end of the last period, the number of inflow and outflow workers during the period, and the number of regular workers at the end of this period are inquired by sex and by job category. The inflow worker questionnaire randomly asks the inflow workers about their attributes. Although the detailed questions vary year by year, they generally contain age, sex, education and occupation, as well as previous industry where employed, previous occupation, job-search route, unemployment period, and wage change for job changers. On the other hand the outflow questionnaire is sent to the personnel office to ask the characteristics and reason of quitters. The additional questionnaire is distributed only at the end of the first half of each year and surveys the stock numbers of regular workers by sex, age category, and occupation as at June 30, as well as the number of unsatisfied vacancies.[9]

In this research, we estimate wage levels at recruitment for inflow workers by utilizing wage changes of job changers from inflow worker questionnaires. At the same time, we also assess the vacancy size posted by the particular establishment during that period, and see their relations statistically. However, these estimation results are heavily dependent on the

[9] From the first half of 1998 the additional questionnaire was absorbed into the establishment questionnaire.

technology owned by the establishment. In order to control for these effects, we constructed a panel dataset of establishments through 1993–1995, which depicts the history of outflow and inflow of workers by each establishment, so that we could see the unobservable individual effects for each establishment on wage change. In addition, since unsatisfied vacancies are observable only at the first half of each year, we need to confine our sample to data for the first half year and consider the relationship between vacancy sizes and wage changes for the first half.

The establishment questionnaire tabulated as many as 11,155 establishments for the first half of 1993, 11,148 for 1994 and 11,233 for 1995, but we drop from the sample those without consistency with the additional questionnaire, those that miss the target variables, those that disappeared during the three years, and government establishments.[10] Finally, we obtained a panel database of 4,687 establishments. With regard to inflow workers, we select samples of job changers whose wage change is known, but eliminate workers newly employed by the government. For our estimation, we cannot use samples of either new graduates, the previously self-employed, or those unemployed for longer than one year, as we do not have any information on wage changes.

Appendix Table 1.1 and 1.2 describe the summary statistics for those samples, and summarize the derivation method of variables used in our estimation.

4. ECONOMETRIC MODEL

Let the wage posted to jobseeker *i* who later earned after joining the establishment *j* denote w_{ij}^{offer}. Following Burdett, Shi and Wright (2001), w_{ij}^{offer} is dependent on worker *i*'s

[10] In the case of government establishments, wage levels are determined by laws or regulations, so that they have no connection to the number of applications received by them.

attributes at matching ($X_i^{present}$) and establishment *j*'s vacancy size (v_j), and could be expressed as the following (1). In this formulation, β_1^0 is expected to be negative.

(1) $$w_{ij}^{offer} = \alpha^o + \beta_1^o v_j + \beta_2^o X_i^{present} + e_{ij}^{offer} .$$

Regarding the demand shocks that establishments face that are dependent on industry, size, and location, it is quite natural to consider the posted wage levels w_{jk}^{offer} as dependent on establishment *j*'s industry, size, and location. We introduce such demand-side variables as Y_j. Therefore, (1) could be rewritten as (2).

(2) $$w_{ij}^{offer} = \alpha^o + \beta_1^o v_j + \beta_2^o X_i^{present} + \beta_3^o Y_j + u_j + e_{ij}^{offer} .$$

As for Y_j, we employ the establishment's industry, size, and turnover rate resulting from private reasons. As Brown and Medoff (1989) point out, it has been usually observed that (average) wage levels vary by industry or by establishment size. Burdett and Mortensen (1998) propose that the wage level would affect density of on-the-job search among current workers and thus they would have some effect on the turnover rate caused by employees' private reasons. To be precise, workers at establishments with high wages do not put much effort into on-the-job search activities, since they find it more difficult to find better job opportunities even though they keep on searching good job offers. As a result, the turnover rate at such establishments would be smaller. If the establishments offer relatively low wages, then the reverse will be the case, so that they face higher turnover rates. In this paper, we estimate turnover rates resulting from private reasons from the questionnaire on displaced workers, and use that as one of the explanatory variables.[11] In addition to Y_j, we can use establishment fixed effects u_j as well to control the unobservable technological shock to offered wage.

Let recruitment activities be planned at the beginning of each year for the coming six months, and be unchanged through that period. v_j is actually derived by summing the number of inflow workers during that term and unsatisfied vacancies left at the end of June.

As explained above, if the directed search model discussed in section 2 actually holds, our goal for the estimation is to examine empirically if this sign is actually negative in formulation (2). In other words, if we consider that we could control firm-specific factors by Y_j and fixed effects u_j, then our main concern would be to test the hypothesis empirically that vacancy size and wage level are indeed negatively correlated.

While we could observe v_j directly from the questionnaire to establishments, we unfortunately could not see w_{ij}^{offer} directly from the questionnaire to incoming workers, but could only observe the wage change level (relative to previous wages) by five categories. We can decompose the wage change level into two parts, i.e., wages at displacement and posted wages at job change. We can then construct an estimation method as follows.

At the first stage, we simulate worker *i*'s wage level at displacement w_i^{past} by a Mincer-type wage function using workers' attributes when s/he left the job. In other words, if we

[11] In the ETS, the outflow questionnaire asks the reason for leaving work from among 11 reasons, such as "expiration of contract term", "management decision", etc. We assume displaced workers as the result of job-seeking activities while at previous work are those whose reason corresponds to "other private reasons", so that we derived the voluntary turnover rate for each establishment by multiplying overall turnover rate and the proportion of workers who chose "other private reasons".

denote worker i's attributes at the time of displacement X_i^{past}, we could write estimation formula (3) to estimate w_i^{past}.

(3) $$w_i^{past} = \alpha^p + \beta^p X_i^{past} + e_i^{past} .$$

Here, e_i^{past} is unobservable factors for econometrician and α^p is constant. We use the questionnaire of incoming workers for X_i^{past} variables, such as age, education, sex, previous job, previous firm size, and previous industry. In total, we summarize the result by denoting wage change as w_{ij}^{offer}-w_{ij}^{past} at job change in the following way:

(4) $$\begin{aligned} w_{ij}^{offer} - w_{ij}^{past} &= \left(\alpha^o + \beta_1^o v_j + \beta_2^o X_i^{present} + \beta_3^o Y_j + u_j + e_{ij}^{offer}\right) - \left(\alpha^p + \beta^p X_i^{past} + e_i^{past}\right) \\ &= \left(\alpha^o - \alpha^p\right) + \beta_1^o v_j + \left(\beta_2^o X_i^{present} - \beta^p X_i^{past}\right) + \beta_3^o Y_j + u_j + e_{ij}^{offer} - e_i^{past} \end{aligned} .$$

Of course, it is possible that wages at survey and offered wages are different because of wage increases. However, there is only six months' difference between the surveyed timing and offered point, so that we do not need to believe there might exist either large or systematic difference between these two wages ($w_{ij}^{offer} = w_{ij}^{present}$). Similarly, we assume that basic attributes of job seekers do not change at displacement and at recruitment, thus we rewrite the estimation equation as follows:

(5) $$w_{ij}^{present} - w_i^{past} = \alpha + \beta^v v_j + \beta_1 X_i + \beta_2 Y_j + u_j + e_{ij} .$$

$\beta_1^{\,0}$ in (1), the major theme of this estimation, could be derived as β_v from panel estimation of (5) with establishments' fixed effects u_j. We could determine that market friction, arising from search activities, actually exists in labor markets as directed search models predict, if β_v is estimated to be negative.

β_1, the estimated coefficients, includes effects on both offered wage (2) and previous wage (3), so their signs are not ex-ante obvious. Previous studies have shown that the older the worker or the greater the size of previous firm (Nakamura, 2002, Table 7), the greater the wage decrease experienced by that worker would be, as is the case with workers with lower educational levels (Kodama, Higuchi, Abe, Matsuura and Sunada, 2004). Therefore, we assume the depreciation level of human capital at job change by such workers is rather higher than for other workers.[12]

5. ESTIMATION RESULTS

5.1. Basic results

Table 1 shows the estimation result of (5), using the sampled experienced full-time job changers during the first half of each year from 1993 to 1995. As the vacancy variable, we used permanent full-time vacancies for each establishment and the turnover rate caused by private reasons among full-time workers. The detailed derivation of these variables from row data is discussed in the appendix.

(1a) shows that both worker attributes and turnover rates of full-time workers at each establishment have significant coefficients with expected signs, so we could consider that the model itself has explanatory power to some extent. On the contrary, the coefficient of full-

[12] Nakamura (2002) reports that there are no statistically significant relationships between UV ratio and wage increase at job change, and suggests that individual attributes rather than market conditions are relevant in the Japanese labor market.

time vacancy size on which we have been focusing is estimated to be positive (0.0005), and we cannot reject the null hypothesis that coefficients are equal to zero in a statistical sense (p-value 0.105). Therefore, we cannot empirically confirm that β_1^{0} in estimation formula (1a) is negative, so that there does not exist negative relations between vacancy sizes and offered wage levels.

5.2. Measurement of vacancy size

We now discuss the measurement method of vacancy, which might have affected the estimation result of Section 5.1's conclusion. In theory, the vacancy should be conceived as such that a job applicant would compete with other job seekers. For example, when experienced job seekers think new graduates are not their rivals, it may not be appropriate to include such *different* job postings into a vacancy variable. Because we cannot classify which job posting is different from others for an experienced job applicant in our data, we use various vacancy variables to confirm the estimation results in Table (1a).

In estimation (1a), we assumed full-time new graduates and full-time job changers are not in the same labor market due to Japanese labor market customs, and used the latter numbers for estimation. In estimation (1b) in Table1, we assume both job applicants, i.e., job changers and new graduates, are in the same labor market, so add vacancy numbers for both and use the total number as the vacancy size that job seekers face and estimated formula (5). The result is almost the same as (1b), and the coefficient we are interested in is positive (0.0002) with insignificant p-value (0.476). Again, we cannot reject the null hypothesis that the coefficient is equal to zero.

Other than new graduates, the job changers of the ETS include job seekers who do not have any work experience after graduation as well as those who have found jobs after a period of long-term unemployment (longer than one year). Among these are females who left the labor market in mid career.[13] An experienced job changer might not pay much attention to such job seekers who have some blank periods in their careers. Accordingly, we tried another estimation by using the number of vacancies only for direct job changers as a proxy for full-time vacancies. This is depicted in (1c) in Table1 and shows quite similar results to (1a) and (1b). While the coefficient of vacancy size is negative, it is not statistically significant (p-value 0.647).

As stated above, we should use vacancy size at the beginning of the year as the explanatory variable if possible, but we need to substitute that number by an estimation on some assumptions because of the limitations of the dataset. In order to confirm if such estimation has influenced the estimation result, we employed the unsatisfied vacancy numbers at the end of the first half that could be directly observed as a proxy for vacancy size. The result is shown in (1d) in Table1. Here again we cannot see any particular difference between results (1a) and (1c), i.e., the coefficient of full-time unsatisfied vacancies is positive (0.0013), and neither can we reject the null hypothesis (p-value 0.397).

In conclusion, the difference in vacancy measurement, for example whether new graduates are included or not, or whether we could regard vacancies through the period as a whole or not, does not affect the conclusion derived in Section 5.1. We accordingly use full-time vacancies as vacancy size in the following estimations, except for the cases we noted.

[13] Actually, among inflow workers during Jan–June of 1993–1995, male workers account for 58.4% and young workers below 25 account for 25.5% of job changers, while these proportions are 35.9% and 43.3% correspondingly with respect to entering workers.

5.3. Establishments and worker attributes

The most important process for the empirical framework above is to control particular demand shocks for each establishment by using establishments' attributes Y_j and fixed effects u_j. In order to check the robustness of the conclusion derived in the estimation in Section 5.1, we need to check if such demand shocks have sufficiently been controlled by establishments' attributes (industry, size, turnover rate, location) and fixed effects. For this purpose, the estimation results of (5) with various combinations of fixed effects and observable establishments' attributes have been derived, and are shown in Table 2.

At first, the result without any establishment attributes is the case (2a). Without any control for establishment attributes, vacancy size would have a positive impact on offered wage level. If we assume that we could control supply shocks on the worker side by using worker attributes, location, and trend as a control, estimation (2a) suggests the combination of wages and new employment under various levels of labor demand. Therefore, the positive sign mentioned above could be interpreted as the labor supply curve that each establishment faces has a positive slope.

Next, (2b) describes the case with only fixed effects of establishments, and (2c) shows the case with only observable establishment attributes. On the one hand, when we control only fixed effects, a seemingly positive correlation has been maintained. On the other hand, when we control only observable establishments' attributes, such as industry or size, the impact of vacancy size on offered wages declines relative to the results of (2a) or (2b), and becomes statistically insignificant. This suggests that establishment attributes are more effective in controlling the demand shocks that each firm faces. In addition, results (2d) and (2e) suggest establishment size and industries' locations are more effective in controlling demand shock than are turnover rates. In any case, we deduce that demand shocks for establishments could have been fairly removed by fixed effects and establishment attributes.

On the other side, when we interpret estimation (2a) as the explanation of wage change at job transfer, it becomes important for workers how to choose new industry, new job, and new establishment size. Precisely, when workers are moving between different jobs or industries, or diminishing establishment size, they would be more likely to earn smaller wages than before (Nakamura, 2002). Therefore, estimation (2f) and (2g) in Table 2 focus on whether workers have changed jobs, industries, or sizes from their previous employment.

In estimation (2f), after including current industry, job, and size in the estimation, we add the dummy variables as explanatory variables to indicate if such attributes of the previous job are different from current ones. Therefore, previous industry, job, and size are excluded from the estimation. We created different dummies for upward and downward movements of establishment size to distinguish the impact from each case. The estimation result indicates that with job alternation or with downward movement of size, wages tend to decrease. With industry change, wages tend to decline as well, although this is not significant. On the contrary, the upward movement of size would lead to an increase in the wage after a job change; in general, these results fit the results from previous studies. In these cases, the vacancy size affect offered wages positively in a significant way, compared with case (1a). In estimation (2g), we used previous industry, job, and size as well as dummies for the changes between positions as explanatory variables, and excluded present industry, job, and size. The result of (2g) is almost the same as (2f), and the coefficient of vacancy on offered wage is also positive.

5.4. Estimation by occupation

It is possible that job seekers regard vacancies in different jobs even at the same firm as different vacancies. If this holds, vacancy size as the sum of vacancies of all jobs at one establishment always exceeds vacancy size of one job, thus the coefficient for vacancy might have been overestimated. Therefore, we divide the data by eight jobs, and re-estimate (5) for each job. The results are shown in Table (3a)–(3h). In these estimations, we used vacancy size for each job as an explanatory variable, as well as turnover rate for each job. Care must be taken with interpreting the result, however, since we cannot separate full-time vacancies from part-time vacancies because of data reliability. In addition, turnover rate by job is not available solely for full-time workers or for reason.[14]

In general, the estimation result is not stable. There are no cases in which all worker attributes have significant coefficients as predicted, and turnover rate by job also shows unstable coefficients. However, there are no cases for vacancy size by job in which positive coefficients have been derived; in fact, they are significantly negative for clerks and sales jobs and negative for security, communication and transportation, and production, although in these cases they are insignificant. This might suggest the existence of different sources of friction by job, given that labor markets are divided by job. We could assume from the above result that, in the case of technology or management jobs, which require more skill than others, matchings are taking place similar to the random search case, or coordination has

[14] The number of inflow workers is around six on average per establishment in our dataset. By using such information, a relatively large number of samples correspond to zero when we calculate proportions of workers by job and by displacement reason. As a result, we cannot maintain sufficient variation in explanatory variables and cannot obtain stable estimation results. For instance, we employed only managers for our samples in estimation 13; simple turnover rate for managers by establishment was equal to zero with 251 out of 829 samples (30.1%), while managers turnover rate by private reason was equal to zero with 343 samples (41.4%).

already been formed from the beginning, while in the case of clerks or sales jobs, which do not require many specific skills, the failure of coordination caused by interdependence between employers and job seekers might lead to mismatch.

Of course, we need to be very careful about the above interpretation as the estimation results do not seem to be robust. For example, since we divide samples by job, there might have been serious sample selection bias with regard to workers' attributes. Nonetheless, it is not ex-ante clear how much such sample bias might have affected the result. Therefore, we could at least assume it might be possible that different frictional sources exist for each job caused by coordination failure.

5.5. Endogeneity

In order to derive a consistent estimator of β^v by fixed-effects estimator, the interested explanatory variable v_j should be independent of error term e_{ij}.

e_{ij} is the difference between e_{ij}^{offer} derived from (2) and e_i^{past} derived from (3). From the assumption of (2), e_{ij}^{offer} is independent of v_j. On the other side, e_i^{past} describes the unobservable ability of a displaced worker, which is reflected in wage level at displacement. If there exists some mechanism with which larger vacancies would attract workers with better skills, then v_j and e_{ij} are positively correlated, yielding negative bias in the estimation of β^v.

Although this might be the case, the conclusion derived from (1a) is such that there are no negative relations between vacancy and posted wage, given that β^v is positive. Thus, the abovementioned bias would not affect our discussion in a serious way. On the contrary, discussion on the case in Section 5.3 in which the relevant variables sometimes have negative coefficients makes clear that we must be more careful about the interpretation of the results.

5.6. Sample selection bias[15]

In the discussion on endogeneity in Section 5.5, we discuss the possibility that e_{ij} might be correlated to v_j when the distribution of e_{ij} reflects the population as a whole. In this section, we consider the possibility that e_{ij}'s distribution does not reflect the entire population, caused by the fact that samples are limited to experienced job changers.

Whether a worker decides to change jobs is originally a choice variable, and we can assume a worker would make that decision after observing the vacancy size distribution of this period. Moreover, let e_{ij} from (5) be interpreted as profits at job change, which is unobservable by econometricians. In this case, if the true relationship between vacancy size and offered wage is negative, then a greater vacancy size would suggest a lower probability of wage increase at job change on average for workers who are considering the opportunity of job change. Under these circumstances, if some workers have actually changed their jobs with large vacancies, they could be expecting large e_{ij}. This leads to a positive correlation between v_j and e_{ij}, and yields a positive bias on β^v estimation. Conversely, if true relations between vacancy and offered wage are negative, then similar reasoning expects negative correlations between v_j and e_{ij}, yielding negative bias on the β^v estimation. Overall, the discussion on selection bias caused by endogeneity of job change decision by workers suggests that the β^v estimation result could be distorted to zero whichever the direction of correlations, which suggests a possible lack in the statistical power of the test of the null hypothesis that β^v is equal to zero.

This might be problematic in our estimation, because e_{ij} includes e_i^{past}. As we discussed above, e_i^{past} itself corresponds to workers' abilities at displacement. Once they have observed (distribution of) vacancy size, workers might decide whether they should change jobs taking

[15] Discussion in this section depends on remarks from Daiji Kawaguchi. We appreciate his comments.

into account their individual abilities. Let the true relations between vacancy size and offered wage be positive. Under this assumption, workers who have held large e_i^{past} in the sense that their abilities were highly evaluated at displacement might change jobs with relatively large vacancy sizes. In this case, v_j and e_i^{past} have positive relations, thus v_j and e_{ij} are negatively correlated, and negative bias is caused in estimating β^v. Similarly, if we assume the true relationship would be negative, then v_j and e_{ij} have a positive correlation, and positive bias is caused in estimating β^v. In these cases, no matter what the true relations are, the β^v estimation result could be distorted to zero in any case, which suggests a possible lack in the effectiveness of the test of the null hypothesis that β^v is equal to zero.

In order to examine the plausibility of the above discussion we re-estimate (5), limiting the sample to workers who have left their jobs because of "mandatory retirement, dismissal, or end of contract." In case of dismissal, the decision whether a worker changes her/his job is determined exogenously, thus the decision of job change and e_i^{past} is not so strongly correlated compared with the case when workers choose to change their jobs by themselves. The estimation result is (4a) in Table 4 for all occupations, providing significant and greater positive coefficients for vacancy size. Results (4b) and (4c) describe the case for service workers and production workers, respectively. Comparing these results with the previous ones ((3e) and (3h), respectively), the absolute value of vacancy coefficients has become greater with higher significance levels. These results suggest there might be sample selection bias as discussed in this section.

In any case, we could at least presume that the coefficient of vacancy size takes the value from (1a) and (4c), although selection bias of both kinds has actually taken place. In other words, it is not negative, and this implies friction from coordination failure is not necessarily important in the Japanese labor market. Furthermore, it sometimes has negative value with service workers or production workers, thus the pattern of friction by job evidently varies in each labor market.

6. DISCUSSION AND CONCLUSION

As far as is implied by the estimation results, we should not overestimate the importance of interdependence among job seekers and employers in the Japanese labor market. In that sense, recent policies that try to improve matching efficiency from a technical viewpoint are reasonable and have some rationale.

On the other hand, in cases such as clerks and production workers, who are generally regarded as relatively low-skilled workers, the wage variations actually observed are significantly explained by the variation in vacancies, and moreover, that sign is not contradictory to the existence of search friction arising from interdependence between job seekers and employers. In such instances, the relative size of vacancies might affect applicants' behavior or other employers' recruitment, and play the role of public signals. Therefore, matching of unskilled workers possibly may not lead to the improvement of matching technology in a direct way, so that it is more important to control the interdependence between job seekers and employers and to take the direction with fewer market frictions.

With regard to skilled workers such as engineers or managers, the wage variation cannot be explained by vacancy size. This primarily suggests that the model of Burdett, Shi and Wright (2001) does not hold with these occupations, and the discussion might be roughly amplified to the following three possibilities.

The first case is that the part of vacancy size unexplainable by demand or supply factors does not make much sense to either workers or employers, and they bargain with each other by using other information. The second case might be that search frictions caused by these skilled occupations are mainly caused by random search. The third case is that frictions do not exist with these skilled jobs, as they are perfectly coordinated via job centers and private referrals. In fact, around 62% of engineers and 90% of managers find new jobs within two weeks of displacement, numbers vastly different from those for production workers (37%) and service workers (20%). If they are directed by another indicator instead of vacancy size, or if they are in a random match situation, such quick matching speed is not achievable, compared with the case with production or service workers.

Of course, we could think of various interesting issues, including that search frictions from different sources by occupation have come to be apparent from the 1990s, or the level to which they have contributed to the background of the rapid rise in unemployment rates in the overall market. While this paper does not provide direct answers to such questions, it does aim to raise the importance on different sides from the technical issues that have been traditionally discussed. In particular, if there is much bargaining going on among job seekers instead of random search, it would be unrealistic to expect to clear this mismatch simply by IT investment. In this case, what is more important would be to control the bargaining between workers and employers, and to enhance the coordination function in the market.

Table 1： Estimation Results (1) : Full Sample

		(1a)	(1b)	(1c)	(1d)
Estimation Method		Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect
Vacancy for Fulltime Job-changers		0.0005	—	—	—
		(0.0003)			
Vacancy for Fulltime inclusing New Graduates		—	0.0002	—	—
			(0.0002)		
Vacancy for Fulltime Experienced Job changers		—	—	-0.0002	—
				(0.0004)	
Vacancy for Fulltime at the end of period		—	—	—	0.0013
					(0.0015)
Worker Attributes	Graduate	-0.0295 ‡	-0.0296 ‡	-0.0297 ‡	-0.0297 ‡
		(0.0109)	(0.0109)	(0.0109)	(0.0109)
	Age	-0.0395 ‡	-0.0396 ‡	-0.0396 ‡	-0.0396 ‡
		(0.0037)	(0.0037)	(0.0037)	(0.0037)
	Female Dummy	0.1092 ‡	0.1098 ‡	0.1097 ‡	0.1095 ‡
		(0.0224)	(0.0224)	(0.0224)	(0.0224)
	Previous Firmsize	0.0865 ‡	0.0867 ‡	0.0867 ‡	0.0866 ‡
		(0.0067)	(0.0067)	(0.0067)	(0.0067)
	previous parttime dummy	0.6008 ‡	0.5998 ‡	0.5999 ‡	0.5997 ‡
		(0.0324)	(0.0323)	(0.0324)	(0.0323)
	previous industry dummy	YES	YES	YES	YES
	previous occupation dummy	YES	YES	YES	YES
	present occupation dummy	YES	YES	YES	YES
	year dummy	YES	YES	YES	YES
	present occupation * year dummy	YES	YES	YES	YES
Establishment Attributes	turnover rate	-0.6623 ‡	-0.6432 ‡	-0.6128 ‡	-0.6438 ‡
		(0.2488)	(0.2488)	(0.2500)	(0.2486)
	firmsize dummy	YES	YES	YES	YES
	firmsize * year dummy	YES	YES	YES	YES
	industry dummy	YES	YES	YES	YES
	industry * year dummy	YES	YES	YES	YES
	prefecture dummy	YES	YES	YES	YES
	prefecture * year dummy	YES	YES	YES	YES
Constant		-4.0110 ‡	-3.8331 ‡	-3.8195 ‡	-3.8254 ‡
		(0.3288)	(0.3031)	(0.3031)	(0.3029)
Sample Size		11257	11257	11257	11257
# of establishment		1834	1834	1834	1834
F Statistics		7.92	7.91	7.91	7.91
R square (within)		0.125	0.125	0.125	0.125
R square (between)		0.046	0.022	0.021	0.022
R square (overall)		0.062	0.042	0.040	0.042

Notes)
standard erros are in parenthesis
† means 10% statistically significant, and ‡ means 5% as well.
the expalanation of variables is in Appendix

Table 2： Estimation Results (2) Full Sample

		(1a)	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)
	Estimation Method	Fixed Effect	OLS	Fixed Effect	OLS	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect
	Vacancy for Fulltime Job-changers	0.0005	0.0004 ‡	0.0005 †	0.0001	0.0006 †	0.0004	0.0006 †	0.0006 †
		(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Worker Attributes	Graduate	-0.0295 ‡	-0.0109	-0.0280 ‡	-0.0228 ‡	-0.0283 ‡	-0.0292 ‡	-0.0422 ‡	-0.0235 ‡
		(0.0109)	(0.0103)	(0.0108)	(0.0105)	(0.0109)	(0.0109)	(0.0108)	(0.0108)
	Age	-0.0395 ‡	-0.0490 ‡	-0.0402 ‡	-0.0483 ‡	-0.0402 ‡	-0.0396 ‡	-0.0446 ‡	-0.0396 ‡
		(0.0037)	(0.0033)	(0.0037)	(0.0033)	(0.0037)	(0.0037)	(0.0037)	(0.0037)
	Female Dummy	0.1092 ‡	0.0170	0.1027 ‡	0.0600 ‡	0.1040 ‡	0.1082 ‡	0.1169 ‡	0.0836 ‡
		(0.0224)	(0.0198)	(0.0223)	(0.0201)	(0.0223)	(0.0224)	(0.0222)	(0.0220)
	Previous Firmsize	0.0865 ‡	0.0702 ‡	0.0859 ‡	0.0864 ‡	0.0857 ‡	0.0867 ‡	NO	0.0720 ‡
		(0.0067)	(0.0059)	(0.0067)	(0.0062)	(0.0067)	(0.0067)		(0.0122)
	Upward on Firmsize dummy	NO	NO	NO	NO	NO	NO	0.1360 ‡ (0.0206)	0.0655 † (0.0384)
	upward on Firmsize * year dummy	NO	NO	NO	NO	NO	NO	NO	YES
	downward on Firmsize dummy	NO	NO	NO	NO	NO	NO	-0.1800 ‡ (0.0269)	-0.0979 ‡ (0.0451)
	downward on Firmsize * year dummy	NO	NO	NO	NO	NO	NO	NO	YES
	previous parttime dummy	0.6008 ‡	0.5404 ‡	0.6002 ‡	0.5470 ‡	0.6002 ‡	0.6005 ‡	0.6300 ‡	0.6140 ‡
		(0.0324)	(0.0316)	(0.0322)	(0.0317)	(0.0322)	(0.0324)	(0.0324)	(0.0324)
	previous industry dummy	YES	YES	YES	YES	YES	YES	NO	YES
	industry change dummy	NO	NO	NO	NO	NO	NO	-0.0120 (0.0199)	0.0067 (0.0327)
	industry change * year dummy	NO	NO	NO	NO	NO	NO	NO	YES
	previous occupation dummy	YES	YES	YES	YES	YES	YES	NO	YES
	occupation change dummy	NO	NO	NO	NO	NO	NO	-0.0529 ‡ (0.0196)	-0.0781 ‡ (0.0314)
	occupation change * year dummy	NO	NO	NO	NO	NO	NO	NO	YES
	present occupation dummy	YES	YES	YES	YES	YES	YES	YES	NO
	year dummy	YES	YES	YES	YES	YES	YES	YES	YES
	present occupation * year dummy	YES	YES	YES	YES	YES	YES	YES	NO

Establishment Attributes	turnover rate	-0.6623 ‡ (0.2488)	NO	NO	-0.3283 ‡ (0.1293)	-0.5574 ‡ (0.2313)	NO	-0.6615 ‡ (0.2504)	-0.6821 ‡ (0.2428)
	firmsize dummy	YES	NO	NO	YES	NO	YES	YES	NO
	firmsize * year dummy	YES	NO	NO	YES	NO	YES	YES	NO
	industry dummy	YES	NO	NO	YES	NO	YES	YES	NO
	industry * year dummy	YES	NO	NO	YES	NO	YES	YES	NO
	prefecture dummy	YES	NO	NO	YES	NO	YES	YES	YES
	prefecture * year dummy	YES	NO	NO	YES	NO	YES	YES	YES
Constant		-4.0110 ‡ (0.3288)	-3.5582 ‡ (0.1339)	-3.8811 ‡ (0.1369)	-2.7859 ‡ (0.2125)	-3.8564 ‡ (0.1373)	-3.8883 ‡ (0.2100)	-3.3978 ‡ (0.2802)	-3.8394 ‡ (0.1401)
Sample Size		11257	11265	11265	11257	11257	11265	11257	11257
# of establishment		1834	—	1835	—	1834	1835	1834	1834
F Statistics		7.92	25.38	23.32	8.14	22.97	7.93	7.53	9.35
Adjusted R square		—	0.0941	—	0.124	—	—	—	—
R square (within)		0.1251	—	0.107	—	0.107	0.124	0.1111	0.1149
R square (between)		0.0456	—	0.112	—	0.113	0.057	0.0249	0.0794
R square (overall)		0.0617	—	0.085	—	0.086	0.072	0.042	0.0783

Notes)
standard erros are in parenthesis
† means 10% statistically significant, and ‡ means 5％ as well.
the expalanation of variables is in Appendix

Table 3： Estimation Results (3) Occupation

		(3a)	(3b)	(3c)	(3d)	(3e)	(3f)	(3g)	(3h)
Sample		Tech	Manager	Clerk	Sales	Service	Security Guard	Transportation	Production
Estimation Method		Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect
Vacancy for Fulltime Job-changers		0.0000	0.0004	-0.0019 †	0.0099	-0.0044 †	-0.0124	-0.0042	-0.0010
		(0.0013)	(0.0011)	(0.0011)	(0.0097)	(0.0025)	(0.0112)	(0.0029)	(0.0014)
Worker Attributes	Graduate	-0.0095	-0.0356	-0.0837 ‡	-0.1737 ‡	-0.0328	0.2080 †	-0.0090	-0.0082
		(0.0294)	(0.0344)	(0.0409)	(0.0738)	(0.0312)	(0.1160)	(0.0525)	(0.0234)
	Age	-0.0320 ‡	-0.0784 ‡	-0.0264	-0.1028 ‡	-0.0126	0.0535	-0.0111	-0.0441 ‡
		(0.0136)	(0.0250)	(0.0179)	(0.0336)	(0.0092)	(0.0373)	(0.0197)	(0.0061)
	Female Dummy	-0.0396	0.8268 †	0.0240	0.2838	0.2144 ‡	0.5114	-0.1183	0.1537 ‡
		(0.0713)	(0.4880)	(0.0848)	(0.1744)	(0.0499)	(0.7056)	(0.2155)	(0.0414)
	Previous Firmsize	0.0194	0.0479	0.0850 ‡	0.0938 ‡	0.0927 ‡	0.1108	0.0062	0.1175 ‡
		(0.0217)	(0.0364)	(0.0234)	(0.0429)	(0.0212)	(0.0769)	(0.0325)	(0.0119)
	previous parttime dummy	0.6995 ‡	—	0.9747 ‡	0.5058 ‡	0.4783 ‡	0.7531 ‡	0.8973 ‡	0.5194 ‡
		(0.1235)		(0.1148)	(0.2360)	(0.0658)	(0.3768)	(0.2525)	(0.0550)
	previous industry dummy	YES	YES	YES	YES	YES	YES	YES	YES
	previous occupation dummy	YES	YES	YES	YES	YES	YES	YES	YES
	present occupation dummy	NO	NO	NO	NO	NO	NO	NO	NO
	year dummy	YES	YES	YES	YES	YES	YES	YES	YES
	present occupation * year dummy	NO	NO	NO	NO	NO	NO	NO	NO
Establishment Attributes	turnover rate	-0.1351	-0.5964 †	-0.0756	1.6329 ‡	-0.1196	2.0624	-0.6540 ‡	-0.0777
		(0.2026)	(0.3299)	(0.2037)	(0.5020)	(0.1969)	(2.1421)	(0.3074)	(0.0867)
	firmsize dummy	YES	YES	YES	YES	YES	YES	YES	YES
	firmsize * year dummy	YES	YES	YES	YES	YES	YES	YES	YES
	industry dummy	YES	YES	YES	YES	YES	YES	YES	YES
	industry * year dummy	YES	YES	YES	YES	YES	YES	YES	YES
	prefecture dummy	YES	YES	YES	YES	YES	YES	YES	YES
	prefecture * year dummy	YES	YES	YES	YES	YES	YES	YES	YES
Constant		-4.3318 ‡	-3.4617 ‡	-3.7331 ‡	-3.2034 ‡	-4.0235 ‡	-7.7020 ‡	-4.2446 ‡	-4.2041 ‡
		(0.6186)	(0.6127)	(0.7822)	(1.1057)	(0.5459)	(1.9355)	(0.8535)	(0.2334)
Sample Size		1625	829	1513	481	1516	194	574	4002
# of establishment		624	383	743	226	229	67	171	869
F Statistics		1.53	1.07	2.55	1.59	3.48	2.63	2.89	4.21
R square (within)		0.172	0.206	0.320	0.490	0.253	0.607	0.440	0.158
R square (between)		0.003	0.000	0.041	0.024	0.004	0.002	0.010	0.034
R square (overall)		0.016	0.013	0.052	0.044	0.063	0.023	0.065	0.056

Notes)

standard erros are in parenthesis

† means 10% statistically significant, and ‡ means 5％ as well.

the expalanation of variables is in Appendix

Table 4： Estimation Results (4) Quit Reason

		(4a)	(1a) (re)	(4b)	(3e) (re)	(4c)	(3h) (re)
Sample		All Occupation Dissmissed	All Occupation All Sample	Service Dissmissed	Service All Sample	Production Dissmissed	Production All Sample
Estimation Method		Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect
Vacancy for Fulltime Job-changers		0.0041 ‡	0.0005	-0.3519 ‡	-0.0044 †	-0.0064 †	-0.0010
		(0.0009)	(0.0003)	(0.1132)	(0.0025)	(0.0035)	(0.0014)
Worker Attributes	Graduate	-0.0170	-0.0295 ‡	0.0136	-0.0328	-0.0201	-0.0082
		(0.0224)	(0.0109)	(0.0154)	(0.0312)	(0.0445)	(0.0234)
	Age	-0.0246 ‡	-0.0395 ‡	0.0061	-0.0126	-0.0076	-0.0441 ‡
		(0.0071)	(0.0037)	(0.0045)	(0.0092)	(0.0109)	(0.0061)
	Female Dummy	0.1664 ‡	0.1092 ‡	0.1411 ‡	0.2144 ‡	0.0791	0.1537 ‡
		(0.0512)	(0.0224)	(0.0324)	(0.0499)	(0.0775)	(0.0414)
	Previous Firmsize	0.0687 ‡	0.0865 ‡	-0.0518	0.0927 ‡	0.1851 ‡	0.1175 ‡
		(0.0210)	(0.0067)	(0.0400)	(0.0212)	(0.0309)	(0.0119)
	previous parttime dummy	0.5570 ‡	0.6008 ‡	-0.1155	0.4783 ‡	0.3206 †	0.5194 ‡
		(0.1052)	(0.0324)	(0.1523)	(0.0658)	(0.1650)	(0.0550)
	previous industry dummy	YES	YES	YES	YES	YES	YES
	previous occupation dummy	YES	YES	YES	YES	YES	YES
	present occupation dummy	YES	YES	NO	NO	NO	NO
	year dummy	YES	YES	YES	YES	YES	YES
	present occupation * year dummy	YES	YES	NO	NO	NO	NO
Establishment Attributes	turnover rate	0.9217	-0.6623 ‡	—	-0.1196	1.3020 ‡	-0.0777
		(1.1459)	(0.2488)		(0.1969)	(0.5286)	(0.0867)
	firmsize dummy	YES	YES	YES	YES	YES	YES
	firmsize * year dummy	YES	YES	YES	YES	YES	YES
	industry dummy	YES	YES	YES	YES	YES	YES
	industry * year dummy	YES	YES	YES	YES	YES	YES
	prefecture dummy	YES	YES	YES	YES	YES	YES
	prefecture * year dummy	YES	YES	YES	YES	YES	YES
Constant		-3.5357 ‡	-4.0110 ‡	0.1862	-4.0235 ‡	-3.7982 ‡	-4.2041 ‡
		(0.4038)	(0.3288)	(1.1706)	(0.5459)	(1.0751)	(0.2334)
Sample Size		1763	11257	466	1516	697	4002
# of establishment		544	1834	64	229	227	869
F Statistics		5.05	7.92	17.63	3.48	4.21	4.21
R square (within)		0.384	0.125	0.684	0.253	0.425	0.158
R square (between)		0.028	0.046	0.031	0.004	0.000	0.034
R square (overall)		0.077	0.062	0.094	0.063	0.002	0.056

Notes)

standard erros are in parenthesis

† means 10% statistically significant, and ‡ means 5％ as well.

the expalanation of variables is in Appendix

Appendix A: Explanatory Variables

Some of the explanatory variables in the estimation have been created as follows.

<Proportion of Occupation among Inflow and Outflow Workers>

The “Employment Trend Survey” asks both the numbers of inflow workers during Jan–June and the proportion of occupation among workers within each establishment at the end of June, while this survey does not ask the proportion of occupation among inflow workers during these six months. However, the inflow worker questionnaire surveys occupation for each worker, so that we recover the occupational structure among inflow workers by using inflow questionnaires (including part-time workers) and derive inflow worker rates by occupation at establishment level. Similar methods have been applied in the case of occupational structure of outflow workers.

<Vacancy Size by Occupation>

By using the above occupational structure, we derived the numbers of inflow workers by occupation as a result of multiplication of proportion and total number of inflow workers (including part-time workers, Jan–June). Then we added unsatisfied vacancy numbers to these inflow numbers by occupation, giving vacancy size by occupation during the first half of each year. As for the numbers of displaced workers by occupation during the same period, we multiplied the total number of outflow workers for each occupation by occupational ratio derived in a similar way as the inflow workers’ case.

<Proportion of New Graduates>

Following the same method as for occupational ratio, we calculated the rates of new graduates from the inflow worker questionnaire by establishment, and then obtained the number of inflow workers who were new graduates by multiplying these with total inflow workers' numbers (full-time workers). There were very few workers who got part-time jobs as new graduates. In addition, the number of workers remaining after subtracting the number of new graduates from the number of full-time workers we classify as mid-career workers.

Appendix B-1: Summary Statistics (Worker Attribute)

		sample size	average	s. d.	min.	max.	
Worker Attribute	Industry	11265	42.53	27.96	5	94	2 digit
	Establishment Size	11265	2.00	0.81	1	4	over 500=1, 100-499=2, 30-99=3, 5-29=4
	Firm Size	11265	2.45	1.19	1	5	over 1000=1, 300-999=2, 100-299=3, 30-99=4, 5-29=5
	Sex	11265	1.30	0.46	1	2	male=1, female=2
	Age	11265	5.09	2.63	1	11	under 19=1, ･･･, over 65=11
	Graduates	11265	2.28	0.95	1	4	junior high=1, high=2, junior college=3, university=4
	Recruit Route	11265	4.79	2.33	1	8	public job center=1, school=2, previous employer=3, shukko=4, return from shukko=5, private network=6, advertisement=7, others=8
	Occupation	11265	5.26	2.77	1	9	tech=1, manager=2, clerk=3, sales=4, service=5, sequrity guard=6, transportation=7, production=8, others=9
	Previous Industry	11265	5.79	2.12	1	9	1 digit: agriculture=1, mining=2, construction=3, manufacture=4, transportation=5, retail/wholesale/restaurant=6, finance=7, service=8,
	Previous Occupation	11265	5.00	2.74	1	9	tech=1, manager=2, clerk=3, sales=4, service=5, sequrity guard=6, transportation=7, production=8,
	Working Status	11265	1.07	0.25	1	2	fulltime=1, parttime=2
	Unemployment Period	11236	2.35	1.39	1	5	under 15days=1, 15-30days=2, 1-3month=3, 3-6month=4, 6-12month=5
	Previous Firm Size	11265	3.13	1.48	1	6	over 1000=1, 300-999=2, 100-299=3, 30-99=4, 5-29=5, under 4=6
	Wage Variation	11265	2.95	0.85	5	1	under -30%=1、-30% to -10%=2, -10% to +10%=3, +10% to +30%=4, over +30%=5

Appendix B-2: Summary Statistics (Establishment Attribute)

			sample size	average	s. d.	min.	max.
establishment attribute	stocks at the beggining of periods	over all	11265	601.92	1124.28	8	21623
		fulltime	11265	565.75	1104.98	0	21346
		parttime	11265	25.84	88.83	0	1113
	# of inflows	overall	11265	56.15	111.08	0	1801
		fulltime	11265	51.27	107.11	0	1801
		parttime	11265	4.88	23.23	0	410
	occupational composition of inflows	technitian	11265	0.15	0.26	0	1
		manger	11265	0.04	0.11	0	1
		clerk	11265	0.17	0.25	0	1
		sales	11265	0.04	0.14	0	1
		service	11265	0.14	0.30	0	1
		sequrity guard	11265	0.01	0.08	0	1
		transportation	11265	0.05	0.18	0	1
		production	11265	0.35	0.40	0	1
		others	11265	0.05	0.15	0	1
	# of outflows	over all	11265	42.68	81.11	0	1364
		fulltime	11265	38.20	75.83	0	1286
		parttime	11265	4.48	18.94	0	315
	occupational composition of outflows	technitian	11265	0.12	0.25	0	1
		manger	11265	0.07	0.15	0	1
		clerk	11265	0.17	0.25	0	1
		sales	11265	0.04	0.13	0	1
		service	11265	0.13	0.30	0	1
		sequrity guard	11265	0.02	0.08	0	1
		transportation	11265	0.05	0.19	0	1
		production	11265	0.35	0.41	0	1
		others	11265	0.05	0.17	0	1
	composition of separation reason	end of contract term	11265	0.12	0.25	0	1
		restructuring	11265	0.02	0.10	0	1
		shukko	11265	0.05	0.15	0	1
		return from shukko	11265	0.03	0.11	0	1
		mandatory retirement	11265	0.10	0.19	0	1
		dismissal	11265	0.02	0.11	0	1
		personal reason	11265	0.53	0.36	0	1
		marriage	11265	0.05	0.12	0	1
		child birth	11265	0.03	0.09	0	1
		family health care	11265	0.01	0.04	0	1
		death	11265	0.03	0.08	0	1
	unsatisfied vacancy at the end of June	over all	11265	3.22	9.86	0	150
		fulltime	11265	2.87	9.09	0	150
		parttime	11265	0.35	2.91	0	150
	# of vacancy	overall	11265	59.37	113.32	0	1801
		technitian	11265	43.87	87.39	0	1222
		manger	11265	54.37	108.91	0	1765.686
		clerk	11265	47.16	100.70	0	1341.922
		sales	11265	54.53	110.03	0	1801
		service	11265	47.26	107.15	0	1801
		sequrity guard	11265	55.39	109.96	0	1801
		transportation	11265	54.54	110.11	0	1801
		production	11265	40.93	84.62	0	1765.686
		other occupation	11265	54.35	109.23	0	1553.804
		fulltime	11265	54.14	109.06	0	1801
		parttime	11265	5.23	24.24	0	425
		new graduates	11265	0.25	0.27	0	0.9821429

References

Albrecht, J., S. Tan, P. Gautier and S. Vroman, "Matching with Multiple Applications Revisited," *Economics Letters* 84(3) (2004), 311–14.

Brown, C. and J. Medoff, "Employer Size–Wage Effect," *The Journal of Political Economy* 97(5) (1989), 1027–59.

Burdett, K. and D.T. Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review* 39(2) (1998), 257–73.

Burdett, K., S. Shi and R. Wright, "Pricing and Matching with Frictions," *Journal of Political Economy* 109(5) (2001), 1060–85.

Coles, M.G. and E. Smith, "Cross-Section Estimation of the Matching Function: Evidence from England and Wales," *Economica* 63(252) (1996), 589–97.

Coles, M.G. and E. Smith, "Marketplaces and Matching," *International Economic Review* 39(1) (1998), 239–54.

Genda, Y. and A. Kondoh, "On Structural Unemployment", *The Japanese Journal of Labour Studies* 516 (2003), 4-15. (in Japanese).

Kano, S. and M. Ohta, "Estimating a Matching Function and Regional Matching Efficiencies: Japanese Panel Data for 1973–1999," *Japan and the World Economy* 17(1) (2005), 25–41.

Kodama, T., Y. Higuchi, M. Abe, T. Matsuura and A. Sunada, "Effect of Search Method Selection on Job Changes", RIETI Discussion Paper 04-J-035, RIETI, 2004 April (in Japanese).

Moen, E.R., "Competitive Search Equilibrium," *Journal of Political Economy* 105(2) (1997), 385–411.

Montgomery, J.D., “Equilibrium Wage Dispersion and Interindustry Wage Differentials,” *Quarterly Journal of Economics* 106(1) (1991), 163–79.

Nakamura, J., “Public Referral Functions as Supporting System for Job-Changers,” *The Japanese Journal of Labour Studies* 503 (2002), 26-37. (in Japanese).

Petrongolo, B. and C.A. Pissarides, “Looking into the Black Box: A Survey of the Matching Function,” *Journal of Economic Literature* 39(2) (2001) 390–431.

Sasaki, M., “Shift of UV Curve and Unemployment Caused by Mismatch between Age Cohorts,” *The Japanese Journal of Labour Studies* 524 (2004), 57-71. (in Japanese).

Shinozaki, T., “On Long-Term Unemployed in Japan – Changes over Periods, Attributes, and Areas,” *The Japanese Journal of Labour Studies* 528 (2004), 4-18. (in Japanese).