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Vacancy Market Structure and Matching Efficiency

by

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Abstract

This paper analyzes labor market frictions, caused by heterogeneity among traders on the demand side (firms). Vacancy numbers per firm created at once can vary, and this heterogeneity affects the application rate by job seekers. On the aggregate level, theory predicts that vacancy distribution would affect matching efficiency as a whole. Following this theory, we formulated a matching function that reflects market concentration level into its efficiency parameter, and verified by panel data estimation that a more concentrated market has better matching efficiency for the latter half of 90s in the Japanese labor market. Since the number of vacancies per establishment has been increasing again from the end of the 90s, this would be expected to lead to a more concentrated market structure, which could enhance matching efficiency in regional labor markets.

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1 Introduction

There have been many empirical studies on aggregate matching function to capture the influence of friction on equilibrium in the labor market. Even though the trading process among agents is complicated, it could be summarized as well-behaved matching functions at an aggregated level. At the same time, some of the previous studies provide a micro foundation for the behavior of aggregate matching functions by controlling the individual characteristics of agents. These micro studies usually discuss relations between unemployed characteristics and their hazard rates, and their impact on aggregate-level matching. On the other hand, only a few studies have taken individual employer's factors into account (Petrogolo and Pissarides (2001), Lindeboom, van Ours, and Renes (1994)).

While not much attention has been paid to demand-side factors empirically, their importance should not be overlooked. There are several theoretical studies of research that point out the importance of demand-side factors, including Burdett, Shi, Wright (BSW) (2001) and Lagos (2000). The former focuses on demand-side heterogeneity in terms of their "capacity." Usually, firms post multiple vacancies at the same time. If firms choose applicants randomly when they have more than one applicant per vacancy, the employability of an applicant depends on the ratio of vacancies to applicants, which varies among firms. This could affect the probability with which job seekers apply to each firm. Intuitively, vacancy-size distribution matters for aggregate-level of matching. Job seekers are more likely to apply for the firm with more vacancies, given that wages are at the same level and that they do not have any prior information on other workers' behavior. This is because the expected utility level to apply for the firm with more vacancies would be higher than those with less vacancies. As a result, the aggregated level of matching probability would be higher.

Therefore, it might be insightful to examine the impact of market structure on regional matching efficiency¹ by using labor market data. Usually, vacancy distribution varies both among regional markets and through time-periods, so we could examine their impact on matching efficiency. We find that our estimation results are consistent with the expectation on the positive impact of market concentration level on aggregate matching efficiency. However, even if we do not take concentration into account, matching efficiency differs among regional markets. One previous study shows that matching efficiency is decreasing in population density and income per workers of the regional market in Japan (Kano and Ohta (2005)).

In addition, there is another motivation to focus on the heterogeneity in vacancies in the market. A few of the studies adopt the model of non-random matching by emphasizing a systematic element of search, such as Coles and Smith (1998) and Gregg and Petrongolo (2004). They assume that every vacancy and unemployed worker who has gone through sampling within one matching period would not match later with a pre-existing worker or vacancy. Such search has been characterized by stock-flow matching. I construct time-aggregated matching functions which include this type of heterogeneity among agents. We again find

¹ Alternative definitions of labor markets (by sector or occupation) are not used in this work, since the concepts of sectoral or occupational unemployment are not clearly defined or available by data (Petrongolo (2001)).

that our estimation is in line with the predictions of stock-flow matching, at least in term that job seekers distinguish between stock vacancies and flow ones. In contrast, there are some differences from the results derived in previous studies, which we consider to have been caused by the particular characteristics of Japan's labor market.

When we include this heterogeneity into the estimation, we regarded it as an exogenous factor that firms in each regional markets are facing. However, we need to be careful since vacancy numbers would be determined endogenously by firms, and they would lead to form vacancy distribution in the end. About the possible estimation bias from such an assumption, we will discuss later how that assumption does not lead to serious estimation bias in our results.

The paper is organized as follows. In Section 2, we discuss the model used in the estimation. Section 3 describes the data and their basic trends during the latter half of the 1990s. In Section 4 we examine the estimation results and their interpretations. Section 5 presents some discussion related to the possible bias of estimation results, and Section 6 concludes.

2 Model

Assuming the existence of submarkets $j=1 \dots N$ in the market, estimation of matching functions in each submarket takes the following form:

$$M_{jt} = M(U_{jt}, V_{jt}, X_{jt})$$

For short period $[t, t+dt>$, M_{jt} corresponds to the number of new matching in the submarket j . U_{jt} is the number of job-seekers, V_{jt} is that of vacancies, and X_{jt} s are market characters at the beginning of period t . Function $M(\cdot)$ is increasing in both U_{jt} and V_{jt} , and requires $V_{jt}>0$ and $U_{jt}>0$ to be $M_{jt}>0$ for all j . For simplicity, assume the matching function takes the usual Cobb-Douglass form. In addition, since we expect matching speed to be affected by market structure of the demand side as discussed in Section 1, the matching function could be formulated as follows:

$$M_{jt} = A_{jt} [s(H_{jt})]^{\alpha_3} V_{jt}^{\alpha_2} U_{jt}^{\alpha_1}$$

s is some function of market structure index (H_{jt}). Let $s(H)$ linear function of H (i.e. $s(H)=s*H$), and A_{jt} describes innovation in matching technology, which could be specified as $A_{jt}=A*\exp(\beta_j+\delta_j t+\varepsilon_{jt})$. Then the aggregate matching function (reduced form) for each region $j=1, 2 \dots N$, and for period $t=1, 2 \dots T$ could be expressed as follows;

$$\ln M_{jt} = \alpha_0 + \alpha_1 \ln U_{jt} + \alpha_2 \ln V_{jt} + s * \alpha_3 H_{jt} + \delta_j t + \beta_j + \varepsilon_{jt}$$

When

$$\varepsilon_{jt} \sim iid(0, \sigma_\varepsilon^2) \quad \text{AND} \quad \sum_{j=1}^N \beta_j = 0,$$

we could apply the usual OLS estimation method to estimate aggregate matching functions. In this formulation, β_j captures all market-specific factors, which are time invariant within every region. We could think of many demand-side factors that might affect the regional matching efficiency at the aggregate level, such as composition of job types (for example, jobs that require special skills are more difficult to be filled than unskilled jobs). To keep our discussion simple, and to focus on the impact of market structure on aggregated matching technology, we treat all other demand-side factors (and also supply-side factors) as unobserved heterogeneity in the panel-data estimation.

3. Basic Description of Data

1) Data

We have employed “Basic Statistics on Labor Market” (Ministry of Health, Labor and Welfare, government of Japan) for the basic trend of labor market and “Survey on Employment Trends” (Ministry of Health, Labor and Welfare, government of Japan) for the details on vacancy creation.

a) “Basic Statistics on Labor Market”

This dataset, which was collected through local job centers, contains “active vacancies” V_A (number of vacancies active during a certain period, which corresponds to the sum of vacancy stock at the beginning and new vacancy flow during that period), “new vacancies” V_f (inflow of vacancies), “active unemployment” U_A (number of workers who are actually in search of vacancies during a certain period), “new unemployment” U_f (inflow into unemployment pool), and “matching” M (placements). All these statistics are non-seasonally adjusted data and available monthly by region (47 prefectures), from January 1996 to December 2003. From now on, we will call V_A Stock Vacancy, U_A Stock Unemployment, V_f Flow Vacancy, U_f Flow Unemployment.

Three points are noted about this data. First, these are only available at the prefectural level, so that we cannot infer market structure from this dataset. Second, here we assume that prefectures correspond to regional labor markets. While prefectures might be too large for the corresponding concept of travel-to-work areas (TTWAs²) in the UK, which are the usual approximation of self-contained labor markets, further breakdown of data is not possible in the case of Japanese data. However, since this data source is the most reliable one on labor market conditions in Japan, it has been usual to employ this dataset to estimate aggregate matching functions as in previous studies. Third, vacancies, unemployed, and placements registered at job centers may not be representative of the entire labor market. In fact, from the result of “Worker Survey,”³ we know that roughly 30 percent of all successful placements have been arranged

² TTWAs are areas that meet the following criteria: they have a minimum working population of 3,500; 2.75 percent of those living in the area work there, and 3.75 percent of those working in the area live there.

³ “Worker Survey” is worker sample survey conducted annually by the government. Workers surveyed reply which search method they have employed to obtain their current jobs.

through public job centers, while others are arranged by informational sources, such as classifieds, friends, and so on. We would discuss this in the part of estimation result (Section 4).

b) “Survey on Employment Trends”

Because we do not know about vacancy market structure from “Basic Statistics,” we use “Survey on Employment Trends” as well. This survey describes employment trends from both stock and flow base, based on a fairly large national cross-sectional survey on vacancies of establishments. Each survey contains information of around 10,000 establishments with more than five employees, and all establishments with more than 500 employees are surveyed. Same establishments are surveyed twice a year (at the end of June and December), and they report the employee numbers at the point of survey, and also vacancy numbers they created, filled vacancy numbers, job-separations, etc., during the six months preceding the survey point.

Attention is required if the interpretation of the number of “created vacancy”. We could only count the vacancy number ex post facto, by adding the total number of workers who joined the establishment through the preceding 6 months and the total number of unsatisfied vacancies. Data that fit our model are actually the number of posted vacancies at each recruiting point, and we cannot tell if this coincides with the number we derived in the above-mentioned method. However, since this is the best approximation we could make due to data limitation, we employ these numbers as an approximation⁴. Data are available for 1991-2001, thus we used 1996-2001 data to combine them with “Basic Statistics on Labor Market.” Since this survey includes geographical location of establishments, we can derive the index of vacancy market structure by prefecture.

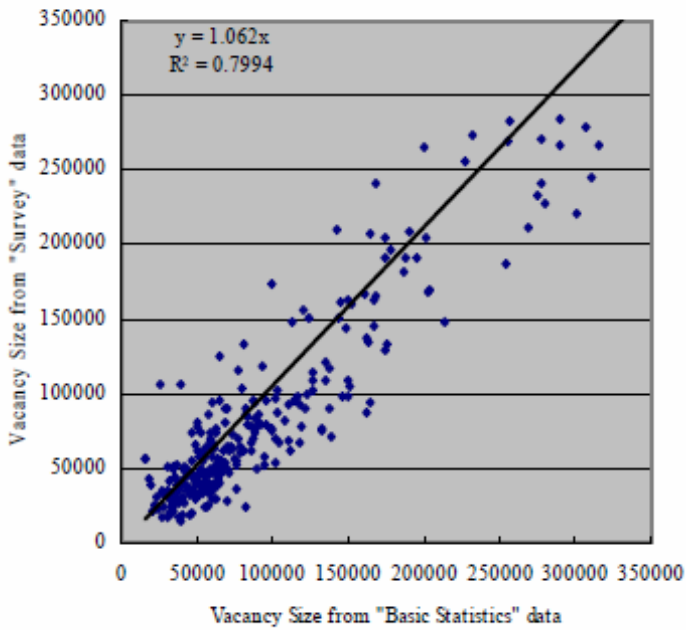
c) Consistency Between Two Statistics

To estimate the aggregate matching function using market structure index, we need to combine two different datasets. Since we are using two data sources for vacancy information to estimate aggregate matching functions (i.e. vacancy size for “Basic Statistics on Labor Market” and vacancy market structure for “Survey on Employment Trends”), we would like to discuss the consistency between these two data sources.

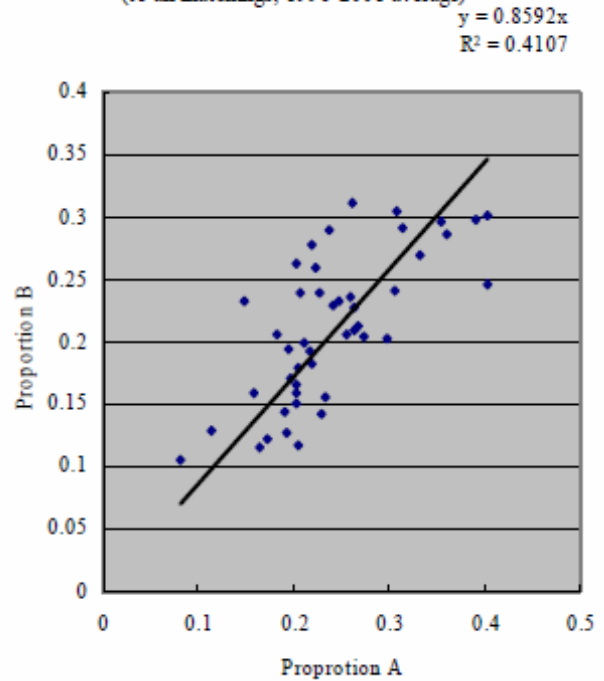
As discussed above, the former statistics are compiled from public job center information, which covers only part of labor market. Discrepancy might exist if firms inproportionally register all of their vacancies at job centers. On the other side, Survey does not include vacancies created by small establishments with fewer than five employees. If we assume that vacancy sizes by such establishments are rather small on average, the concentration index from the Survey might have been calculated with an upward bias.

⁴ As explained in Section 5, the entire vacancy market size could be regarded to be consistent with the sum of the vacancy sizes for each establishment, assuming the proportion of vacancies that used public channels is stable among regions. In addition, it would be hard to infer that establishments would either inflate or deflate their vacancy sizes when they actually are posting them. Therefore, we assume that estimation bias would not be caused when we have employed the estimated vacancy sizes as alternatives.

Graph A Vacancy Number (by Prefecture, 1996-2001)



Graph B Proportion of Public Search Channel Usage (to all matchings, 1996-2001 average)



To check those discrepancies or inconsistencies between two datasets, we depict Graph A, which presents the relations between estimated vacancy sizes from these two datasets for 47 prefectures by using 1996-2001 data. The horizontal axis corresponds to vacancy size derived from “Basic Statistics,” and the vertical axis corresponds to that from “Survey.” In sum, they seem to coincide, or at least we could see there are not any consistent gaps between them. Graph B in turn presents the relations between proportions of public search channel dependence among successful matching numbers by using additional data sources. The proportions show regional variation from our dataset, so that we first derived the proportion of matching to the total by using both Survey and Basic Statistics for each region (Proportion A). Then we calculated the proportion of the usage of public channel among all search methods by region, using data from “Basic Survey of Workers⁵”, year 1997-2002 (Proportion B). The data scatters with more variation around the 45 degree line than Graph A, while there are not any consistent biases shown in this result. From these results, we would conclude that my assumption on the consistency between “Survey” data and “Basic Statistics” would not yield any significant bias in our estimation.

2) Index of Vacancy Market Structure

Assured the consistency of two datasets, we then construct an index that stands for the level of vacancy market concentration, which depicts the distributional characteristics of vacancies in the regional market. According to the discussion of BSW (2001), this index should become larger, the greater the proportion of

⁵ This survey asks workers who were hired during the preceding one year from the survey point the actual search method they used to find their current jobs. By combing through this data and regional information, we could derive the dependence rate on public search method for each region.

“high-type” establishments in the market. That is, the proportion of establishments that create multiple vacancies would increase relative to that of “low-type” establishments (i.e. with single vacancy, given that all establishments in the market would create at least one vacancy). In case there are more than two types (i.e. high-type and low-type), the greater the market share of establishments with many vacancies, the greater this concentration index should be. Tirole discusses in his textbook that a market concentration index in an industrial organization context should have the characteristics described in the following two points:

1. To treat all establishments symmetrically (establishments are recognized only by vacancy numbers).
2. To satisfy the Lorenz condition (increasing when the distribution changes in the sense of increasing in mean preserving spread).

In addition, we would add the following condition 3, so that our index should not be affected when establishment numbers have increased by the same numbers at each vacancy level without changing the distributional form of vacancies.

3. To remain unchanged if the number of establishments changes without changing the shape of CDF of vacancies (for example, when distribution follows uniform distribution, number of establishments would not affect the shape of CDF).

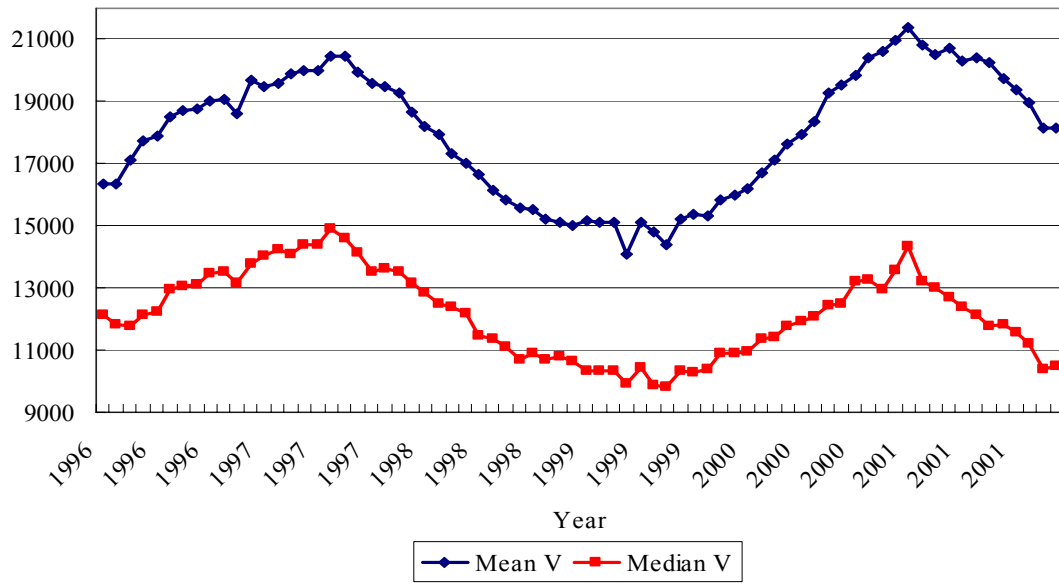
Therefore, we applied here the market share of vacancies created by the largest 10 percent of establishments in terms of vacancy size as an alternative indicator. In other words, if there are 100 establishments in the vacancy market, we calculate the sum of market share from the largest to the 10th-largest number of vacancies. To confirm the robustness of the discussion, we also calculate the market share of vacancies created by the largest 5 percent and 25 percent establishments, as well as the largest 10 percent of establishments in terms of establishment size (i.e. employee number). If large establishments are creating more vacancies than small ones, all of these indicators should have similar impacts on matching efficiency.

3) Overview of Labor Market

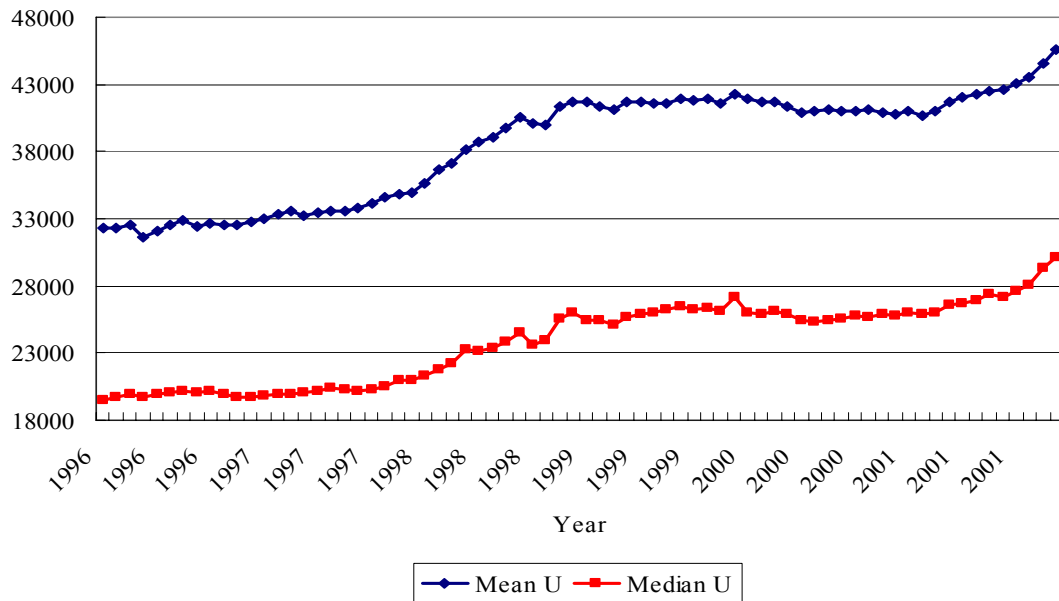
a) Overview

Now, let us overview the Japanese labor market by Basic Statistics. Graph 1 shows the trend of average and median level of regional V_A , and Graph 2 shows that of U_A .

Graph1 Regional V(Seasonally adjusted, Mean & Median of 47 regions)



Graph2 Regional U (Mean & Median of 47 regions, seasonally adjusted)



Both show seasonally-adjusted series, while they have seasonal patterns, and peaking around March and April, and October. V declined around the mid 1990s, then recovered toward the end of the 90s. U shows a modest increase throughout the period. Thus the number of vacancies per unemployed declined around 1998 and 1999, then increased again at an aggregate level (Figure3). Note that unemployment is countercyclical, while vacancies are procyclical, so that the v-u ratio is mostly procyclical and rather volatile.

Figure3 Monthly Job-Finding Probability and Vacancy-Unemployment Ratio(1996-2001)

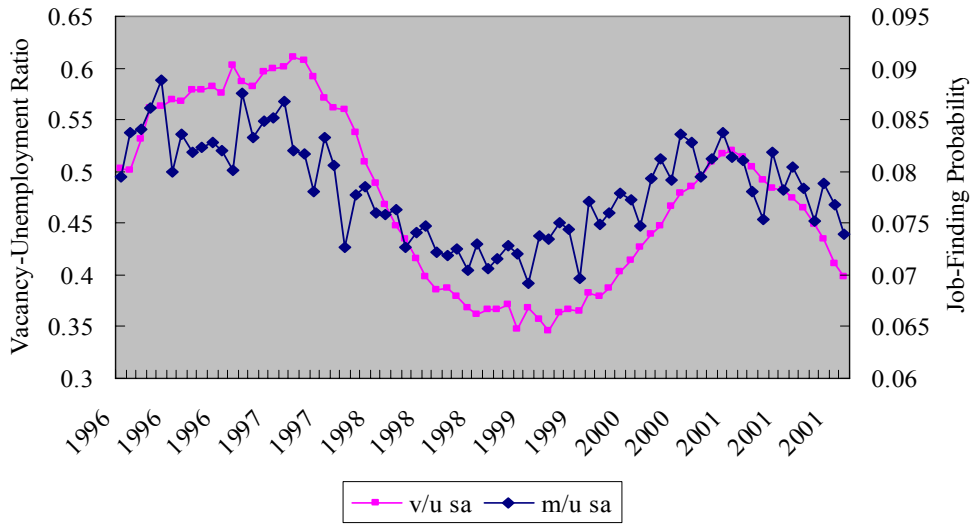
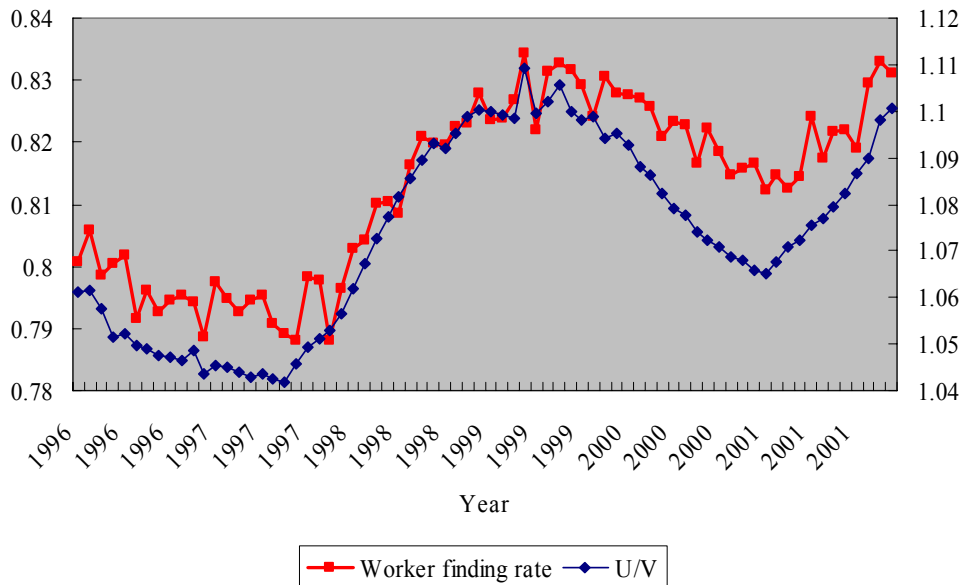


Figure 3 shows time-series relations between vacancy-unemployment ratio (θ) and job-finding probability (f) by using seasonally adjusted data. As theory predicts, they are positively correlated and seem to reflect the form of the constant-return-to-scale aggregate matching function $m(u,v)$. In fact, original (seasonally-unadjusted) series show a positive correlation (0.4) between market tightness and workers' job finding rate. Figure 4, in turn, shows the relationship between worker finding rate for vacancies and unemployment-vacancy ratio. Again one could see they are closely correlated through the period.

Figure4 Worker Finding Rate for Vacancy and U/V



Over the period, unemployment obviously shows an increasing trend. We therefore would like to focus on the cyclical behaviour of unemployment and vacancy. To highlight business-cycle-frequency fluctuations, we take the difference between the log of the unemployment level and an extremely low frequency trend (a HP filter with smoothing parameter 10^4 using monthly data).

Figures 5-1 and 5-2 show a scatter plot of the relationship between the cyclical component of unemployment and vacancies a la Beveridge curve⁶. The correlation of the percentage deviation of unemployment and vacancies from trend is -0.68 between 1996 and 2001.

Figure5-1 UV (Less Concentrated Regional Market)

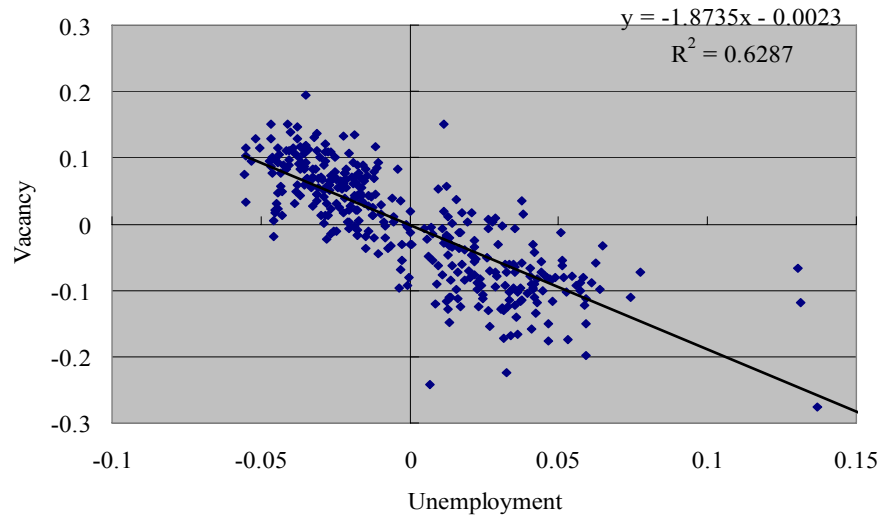
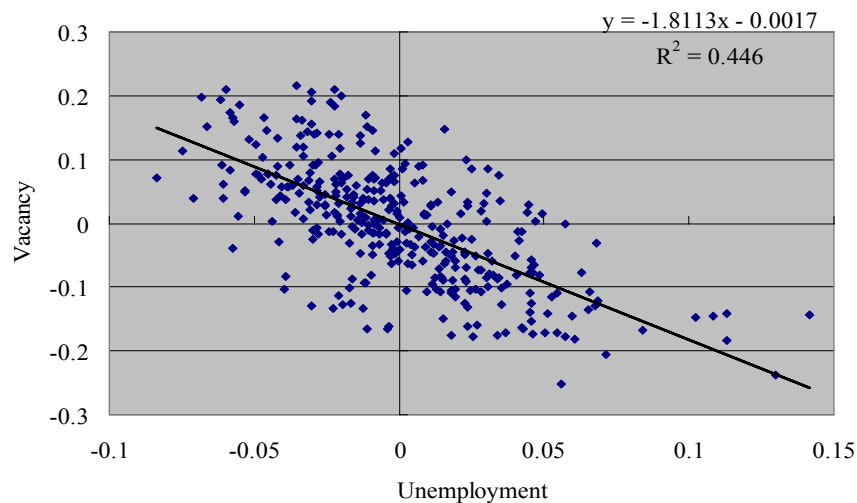


Figure5-2 UV(Concentrated regional Market)



The interesting point observed from these figures is that standard deviation with unemployment difference is as small as 0.03, while that of vacancy difference is as relatively large as 0.08-0.09. This means, on the one hand, that unemployment moves as much as 6 percent above or below the trend. On the other hand, vacancy moves as much as 16-18 percent above or below the trend. In addition, the standard deviation with vacancy differs among regional markets, and it tends to be greater when the vacancy market has a concentrated structure.

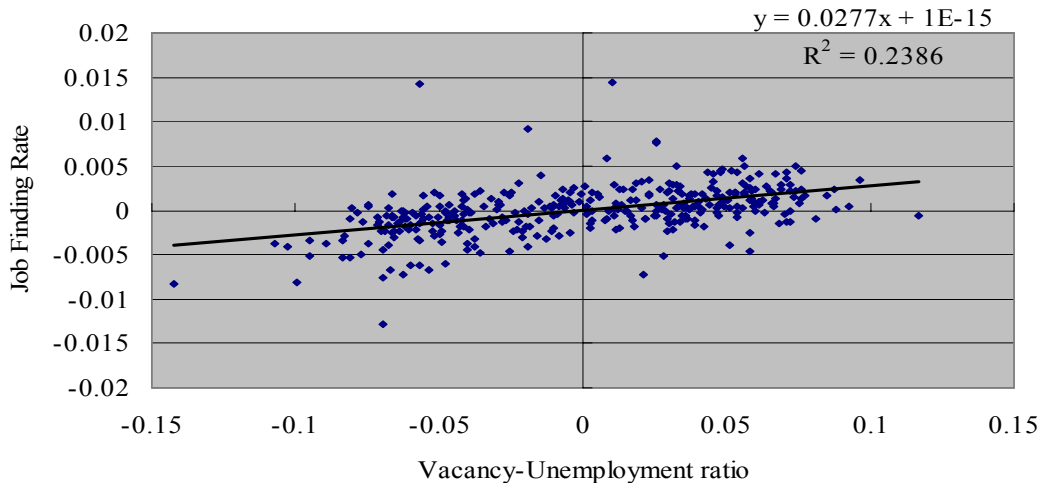
⁶ We use the level of unemployment rather than the rates to keep units comparable to those of vacancies. We could refer to the unsatisfied vacancy rates instead of vacancy levels, while these are available only once a month, which is not sufficient for the analysis. A similar method is employed in Shimer (2005), and he argues there are not any significant differences that would affect conclusions.

Therefore, it might be possible that some variation or changes among regional vacancy markets have affected matching efficiency during this period.

Moreover, after detrending with the low-frequency HP filter, the correlation between f and θ is 0.3, which is not high but is statistically significant. The standard deviation of f is around 15 percent that of θ . Therefore, one can use the measured job-finding rate and market tightness (v - u ratio) to estimate $m(u,v)$ in the form of $f_t = F(\theta_t)$ as well. Because unemployment and vacancies are rather strongly negatively correlated in the detrended series, it is difficult to predict whether $m(u,v)$ exhibits either constant, increasing, or decreasing returns to scale. However, in their literature survey, Petrogolo and Pissarides (2001) conclude that most estimates of the matching function cannot reject the null hypothesis of constant returns. Their findings support the idea of estimating $f_t = F(\theta_t)$, consistent with a constant returns to scale matching function. Actually, as Figures 6-1 and 6-2 show, the raw data for f_t and θ_t are in a nearly linear relationship when both variables are expressed as deviations from the log trend, and when they are expressed by regional market⁷.

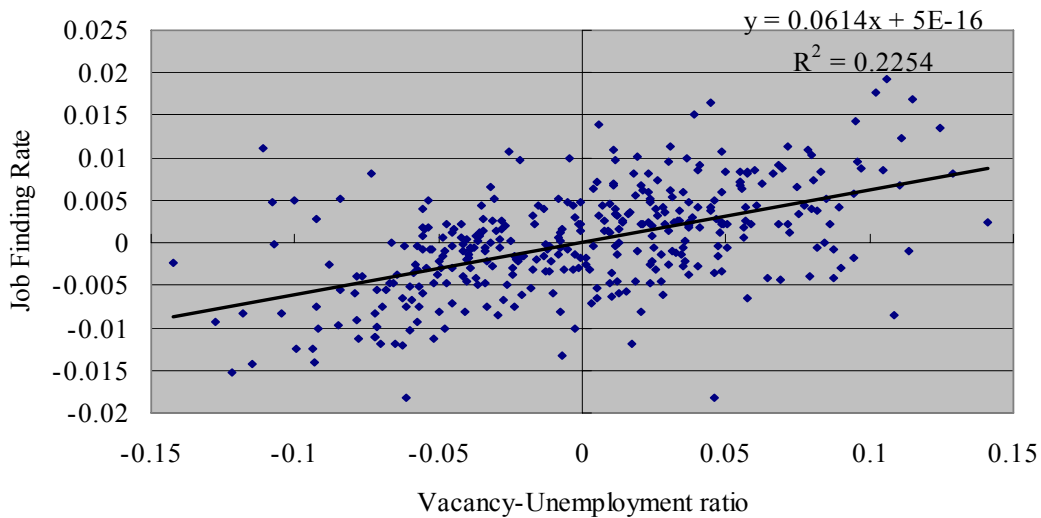
When the vacancy market is less concentrated, vacancy shows smaller variation. Figure 6 shows regional markets' performance in matching, and Figure 6-1 shows the case with the smallest vacancy market concentration, and Figure 6-2 shows that of greatest vacancy market concentration. Note also the coefficient of market tightness on job-finding rates is around 0.04 on average, 0.03 in less-concentrated markets, and 0.06 in the most concentrated markets. We would like to discuss this market structure in greater detail in the following section.

Figure6-1 Monthly Matching Function (Less Concentrated Regions)



⁷ When we divide the sample into five regional categories by market concentration level, the correlations between f and θ increased around 0.5 on average.

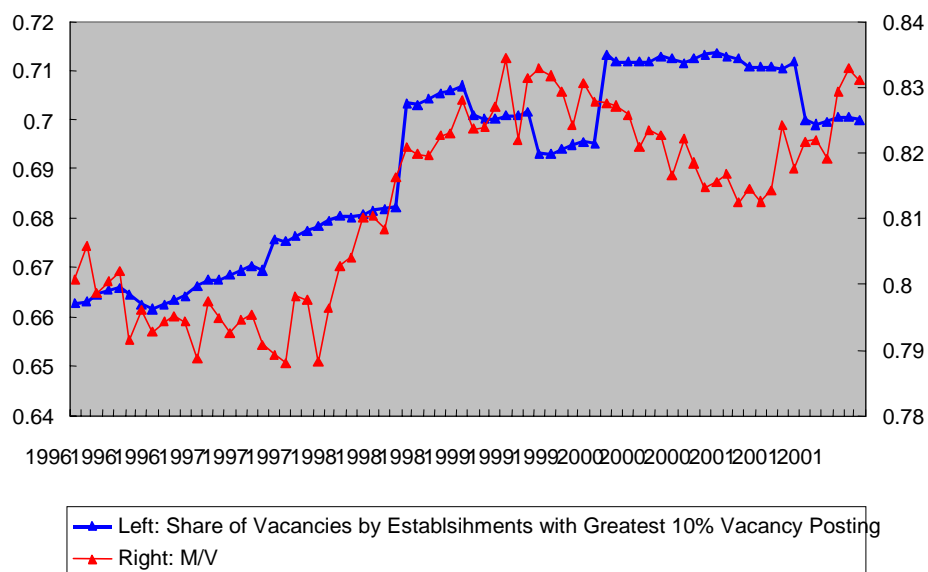
Figure6-2 Monthly Matching Function (Concentrated Regions)



b) Vacancy Market Structure

Figure 7 shows the trend of vacancy market structure and matching efficiency for vacancy through the latter half of the 1990s. The indicator for market structure stands for market share of largest 10 percent establishments in terms of their vacancy size. Correlation between this indicator and worker-finding probability for each vacancy is fairly high (0.80), and statistically significant. However, note this indicator is available biannually so that we simply interpolated for the months for which exact data are not available. If durations of vacancies are much shorter than six months, the indicator might fluctuate at monthly level. While exact data are not available, we consider this is not the usual case, especially for regular workers in the Japanese labor market.

Figure 7 Share of Vacancies by High Type Establishments



Among 47 prefectural regions, the above-mentioned vacancy indicator records a particularly small level in metropolitan areas with large market sizes, and high

in rural areas with small market sizes. As explained in 3) a), Figure 6-2 shows the matching function observed among areas of greatest concentration, which corresponds to rural areas. Figure 6-1 shows matching function observed among areas of smallest concentration, which basically correspond to metropolitan areas⁸.

As for composition of vacancies by establishment size, nearly 30 percent of vacancies are created by establishments larger than 100 employees in 1991, while that number declined around 22 percent in the mid- 90s, and recovered again to the same level (28 percent) in 2001 (Appendix Table 2). This is reflected in the fact that the mean level of vacancies per establishment was quite high at the beginning of the 1990s, decreased once, and rebounded again (Appendix Graph 1). On the other hand, median vacancy stayed at the same level throughout the period. This indicates that the increase in mean number was mainly caused by the small number of establishments, which created many vacancies at once.

Appendix Graph 3 shows the change in median vacancy size in the 1990s by establishment size. The trend shows a similar pattern irrespective of establishment size. For example, the median vacancy size at one time for large establishments (with more than 500 employees) was around 130 at the beginning of the 90s, while it declined to almost the half of that level in the mid-90s, and recovered to almost the 70 percent level at the end of the decade. Appendix Graph 3 describes the trend of vacancy satisfaction rates over six-month periods for each year. Surprisingly, they show a decreasing trend all through the 90s for all establishment sizes. From this, we could see that firms' recruiting behavior changed through the 90s, both in terms of the way of posting vacancies and that of filling vacancies.

Figure 8 shows regional vacancy market structures by their concentration level. Figure 8-1 compares the distribution of vacancies among the most concentrated markets and the least concentrated markets in the year 1991. Vacancy market structure has generally been changing through the 1990s—it has become more concentrated (Figure 8-2). Although the individual vacancy size started to recover around 1999, the market structure has not changed; it has slightly increased in concentration up to 2001.

⁸ We derived the highest/lowest concentration regions by taking average of vacancy market share of the period 1996-2001. The greatest regions are Aomori, Iwate, Shiga, Nara, and Ehime, and the lowest regions are Tokyo, Saitama, Chiba, Osaka, and Kobe.

Figure8-1 Vacancy Distribution per Establishment by Region (1991, Comparison between regions of greatest and lowest concentration level)

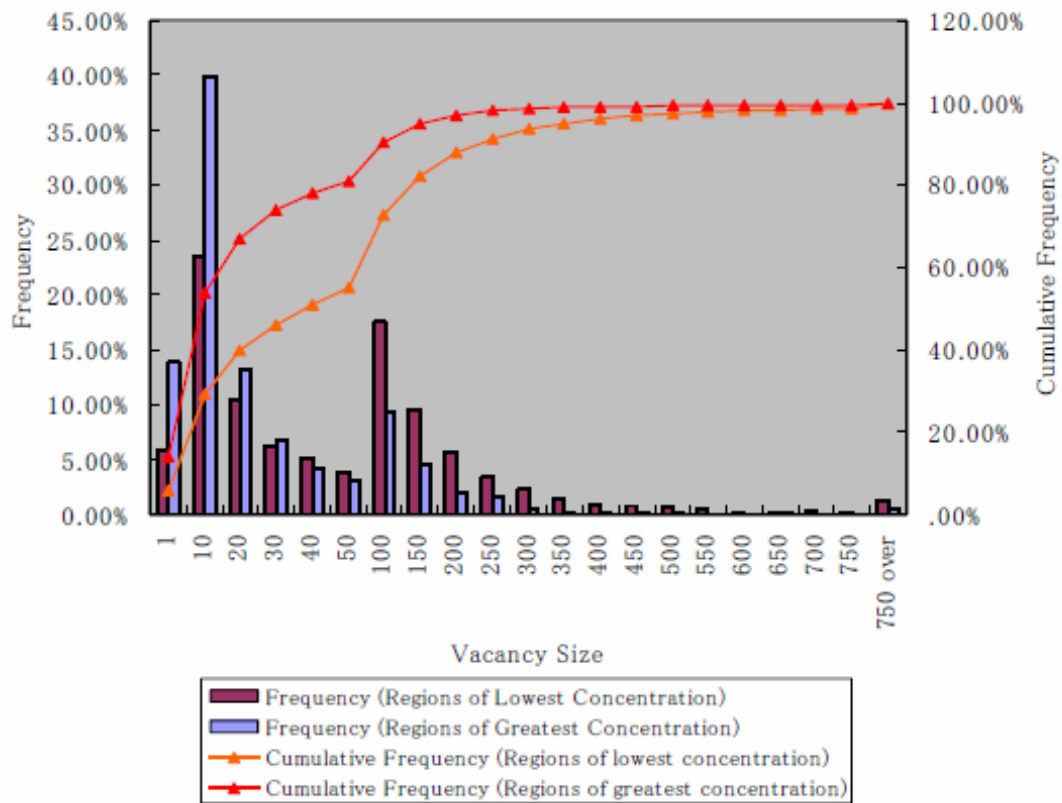
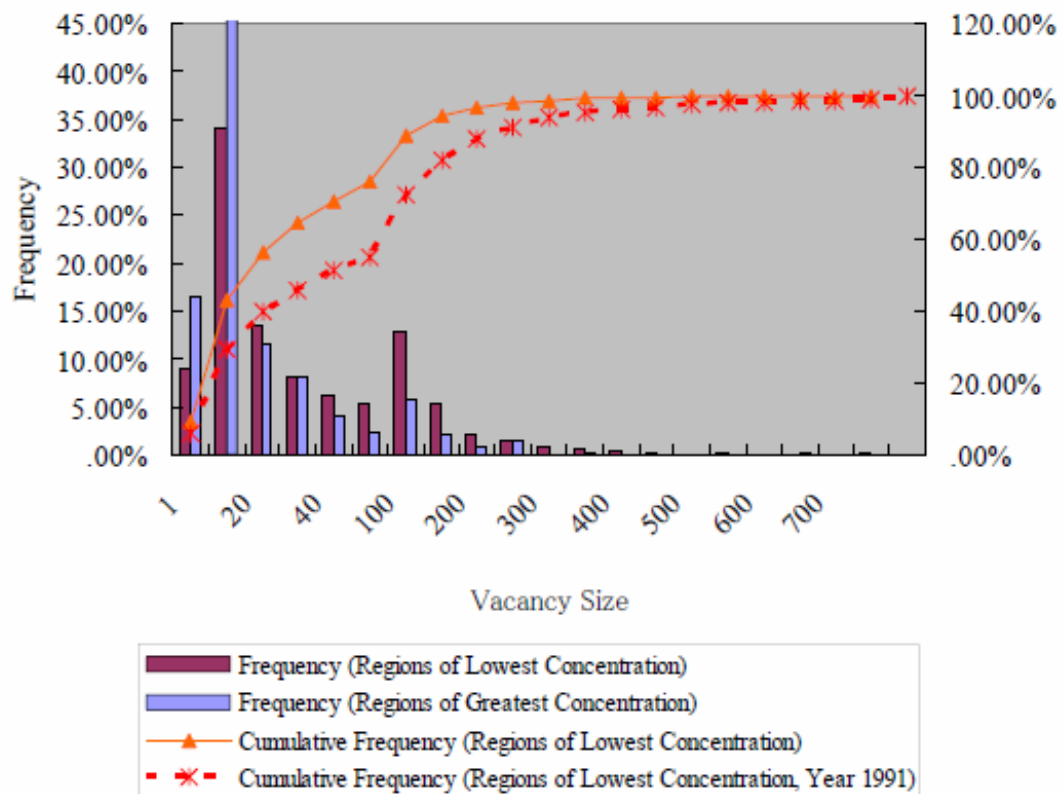


Figure8-2 Vacancy Distribution per Establishment by Region (2001, Comparison between Regions of Greatest and Lowest Concentration Level)



At the same time, it should be noted that the mean vacancy creation rate has dropped from 0.261 in 1991 to 0.215 in 2001, and the mean number of vacancies per establishment has decreased for all sizes. The largest establishments experienced the greatest reduction rate through this period.

3) Data Smoothing and Tests for Stationarity

Since we employed a monthly dataset for matching, vacancies, and unemployed, we need to look into the stationarity of series before analysis. By checking autocorrelations and partial autocorrelations of data series, they are pretty high, around 12, 13, and 24 months lags for most regions. This implies the existence of seasonality in dataset for every year. Such seasonality differs among regions, and more precisely, it could be assumed to be dependent on their regional industry structure. For example, if a regional economy of a certain area relies heavily on public spending, it sometimes happens that most vacancies and matchings are formed around spring because public works usually start around that time (i.e. at the beginning of fiscal year).

A correlogram shows yearly patterns; they are also correlated with sufficiently long time-lags (for example, more than two years). Therefore, we need to look into the existence of unit roots after we take away seasonal pattern from the data series.

With regards to market concentration index, we can only use data every six months. For most regions, market concentration is higher in the latter half of the year than in the former half, mainly because most firms post a very limited number of vacancies (even zero) in the latter half of the year, which is not their usual recruiting period. Such firms would leave vacancies unfilled if some employees quit in the middle of the year, and wait for new recruiting season arrives. Therefore, first we need to interpolate market concentration at a monthly basis, and then adjust seasonality if necessary.

There are several ways to interpolate data series over one year. Among them, we tried the following three methods for seasonal adjustment: moving average, exponential smoothing, and the ARIMA process. The details are provided in Appendix 1.

4 Estimation Results

As we discussed in Section 2, we use a log-linear functional form of matching function. Empirically, we used the number of stocks for vacancy (V) and unemployed (U) at the beginning of every period, by subtracting V_f from V_A (U_f from U_A) so that we could avoid simultaneity bias with matching numbers.

In practice, we first estimate pooled OLS assuming no regional specific factors μ_j , then estimate random effects and fixed effects models, with tests for their validities. Pooled OLS estimations are executed so that we could compare the estimated coefficients for U and V with those when we took regional factors into account. We do not estimate between effects models because there is a difference of data frequency among explanatory variables. In this estimation, we expect

market structure index (H) for regional markets as time-variant. In addition, there are unobservable fixed-effects components that are time-invariant. We also expect that regional matching is affected by aggregate factors such as trends and seasonal (monthly) patterns, which affect all regions equally. Thus we use monthly dummies and time trends.

However, it is easy to see that the seasonal patterns for the original series (M, V, U, H) differ by region. Thus, it might not be adequate to use dummy variables in the above formulation to extract seasonal factors. We estimated the above matching functions by using seasonal adjusted series of (M, V, U, H) as well, and checked the existence of any significant changes in the estimated coefficients.

Table 1 summarizes the result of matching function estimation with seasonally-adjusted series. Hausman test results support fixed-effects model against random-effects in all cases. Results with both monthly dummies and trend dummy are shown in Appendix Table 3.

Table 1 Regression results for matching function (Fixed-effects model, 6 months average)

	Coefficient	Std. err	p-value	Coefficient	Std. err	p-value	Coefficient	Std. err	p-value
Stock V	0.295	0.018	0.000	0.153	0.022	0.000	0.296	0.018	0.000
Stock U	0.812	0.022	0.000	0.248	0.061	0.000	0.806	0.023	0.000
Vacancy share (Greatest 10%)	0.151	0.052	0.004	0.094	0.048	0.052			
Vacancy share (Greatest 25%)							0.253	0.115	0.028
month dummy (June-December=1)				-0.001	0.001	0.060			
Time Trend				0.003	0.000	0.000			
Constant	-3.473	0.315	0.000	3.567	0.777	0.000	-3.552	0.316	0.000
R-sq: within		0.763			0.802			0.762	
between		0.890			0.888			0.890	
overall		0.884			0.863			0.885	
corr(ui, Xb)		-0.713			0.780			-0.707	

The estimation result is stable even when we changed the index of vacancy market structure (vacancy distribution). The returns to scale are 1.5 in all cases. These are rather high for previous Japanese studies. For example, Kano and Ohta (2005) report their returns to scale to be 0.862, and they reject the CRS hypothesis. However, even though they employ the same dataset and implement within an effects model as well, their estimation period is from 1973 to 1999, and they use annual data. We thus cannot simply compare their results to ours⁹.

The coefficients of the vacancy market-structure index are always positive and significant. The Hausman test statistics of fixed effects model versus random effects model are large enough to mean we could reject the latter model. Positive signs for vacancy share imply that market concentration level has positive effects on matching efficiency. From these facts, we could tell matching speed increase both as market size gains, and as the market becomes more concentrated.

If proportions of vacancy registration, unemployed registration, and placements at job centers are different among regions, this would cause bias in estimation results. In other words, let ϕ_j^M (ϕ_j^V , ϕ_j^U) denote the ratio of the measured placements (vacancies, unemployed) to the true number of placements (vacancies, unemployed) in region j . If this ratio ϕ_j^M (ϕ_j^V , ϕ_j^U) is constant across j , the OLS estimate of returns to matching is not biased, since the matching function is assumed to have a log-linear functional form. Unfortunately, we do not have

⁹ Our result using annual data from 1991 to 2001 shows almost constant returns to scale.

information on whether ϕ_j^V is constant across region j without any systematic variance. With regards to ϕ_j^M and ϕ_j^U , we can see they are not so different for the same region j , although both have some variance among regions (Appendix Graph 2). Though such variance is not so distinct as the ratios of classifieds, this might cause some bias on the coefficients of V and U . However, following the same way as Coles and Smith (1996), when we drop the regions with the highest and/or lowest dependence of job centers (i.e. highest/lowest ϕ_j^M), the estimated coefficients were almost the same¹⁰ both for U and V , so we assume the above proportions are almost similar among regions.

So far, we have been trying the estimation by using interpolated data for market concentration. However, given the fact that we do not have information on vacancy duration, the interpretation of interpolated vacancy market concentration would be difficult. In order to deal with this problem, we estimate the same form of matching functions by using 6-month average data for matching, vacancy, and unemployment. This time since we only have 12 samples in time-series direction, we would not use time trend as an explanatory variable. The estimation result is described in the following Table 2.

Table 2 Regression results for matching function (Fixed-effects model, 6 months average)

	Coefficient	Std. err	p-value	Coefficient	Std. err	p-value
Stock V	0.295	0.018	0.000	0.296	0.018	0.000
Stock U	0.812	0.022	0.000	0.806	0.023	0.000
Vacancy share (Greatest 10%)	0.151	0.052	0.004			
Vacancy share (Greatest 25%)				0.253	0.115	0.028
Constant	-3.473	0.315	0.000	-3.552	0.316	0.000
N		564			564	
R-sq: within		0.763			0.762	
between		0.890			0.890	
overall		0.884			0.885	
corr(ui, Xb)		-0.713			-0.707	

This is the result of fixed-effects estimation. Random effects estimation results are almost the same, while coefficients for vacancy market share are bigger than the above, and Hausman tests support fixed-effects estimation results again. By comparing Tables 4-1 and 4-2, the coefficients of stock vacancy are much smaller in Table 4-2 than in Table 4-1. In fact, the results of Table 4-2 are much closer to the previous estimation results of Japanese matching functions (Kano and Ohta (2005) for example), while the coefficients of unemployment are still a bit larger than them. In any case, coefficients of the vacancy concentration index are significantly positive, so that we could conclude that the vacancy market concentration level would affect matching efficiency in a positive way.

5 Discussion

1) Stock-flow bias

¹⁰ Without the sample of the five-highest dependence regions and/or five-lowest dependence regions, the estimated homogeneity degrees are around 1.3-1.4 and stay at almost the same level. Coefficients for market concentration rate are also similar, and quite significant as well.

It has been pointed out that placements are rather dependent on new inflow of partners than on stock volume of one's partners. If the speed of search in the market is large enough, people are not interested in the stock of their partners, after they have once searched among them and decided not to match with them. Therefore, it is natural to assume placements are mostly dependent on the volume of new inflows, instead of the volume of old stocks. Actually, several papers have empirically shown that placements are increasing in flow unemployment and flow vacancies.

To see if this is an important factor in the Japanese labor market as well, we tried to see the relationship between the employment probability within one month (conditional on being unemployed at the beginning of a particular month), and stock vacancy, stock unemployment, flow vacancy, and flow unemployment. We have also added some variables that depict the average characteristics of market participants, to control the impact from them. Unfortunately, the vacancy characteristics are not available, so I only controlled the attributes of unemployment side.

To be precise, the estimation we tried is expressed as follows;

$$P_{it} = \alpha + \beta_1 * SV_{it} + \beta_2 * SU_{it} + \beta_3 * FV_{it} + \beta_4 * FU_{it} + \gamma_1 * SX_{it} + \gamma_2 * FX_{it} + \delta * Timedummy + \varepsilon_{it}$$

P_{it} is employment probability of the unemployed within one month at period t in area i . SV is stock of vacancies, SU is stock of unemployment, FV is flow of vacancies, and FU is flow of unemployment. SX is stock average attributes, and FX is flow average attributes. In this estimation, we used original series and controlled any seasonality, trend, etc. by adding time dummies (year dummies, month dummies, cross-dummies of year and month).

It is expected that vacancy coefficients are positive, while unemployment coefficients are negative. If market participants are discerning the differences between stock and flow in Japan's labor market as well, both β_1 and β_3 are expected to be negative, as are both β_2 and β_4 .

Employment probabilities show strong seasonality, which is mostly correlated with the increase in the flow of unemployment at an aggregated level. After seasonal adjustment, short-term employment probability for workers seems to be positively correlated with UV ratio. Graph 9-2 shows the relations between employment probability within one month and stock V/U level, and Graph 10-2 shows those with flow V/U level. In both cases, the correlations are not so high, but significant at the 1 percent level. Moreover, the correlation is slightly higher with flow ratio. Therefore, it makes sense to consider the possible impact of flow variables on matching efficiency in Japanese labor markets as well. Table 1 describes the correlations between employment probabilities within varied periods and both stock and flow variables. From this table, again we could see flow variables are likely to affect employment probabilities rather than stock variables. In addition, vacancies seem to have more impacts on employment probabilities than unemployment.

Table3 Correlations between U,V and Job Finding Rate (p-values in parentheses)

	Stock Vacancy	Stock Unemployment	Flow Vacancy	Flow Unemployment
Job Finding Rate within 1 month	0.3179 (0.059)	-0.041 (0.812)	0.4251 (0.010)	-0.7435 (0.000)
Job Finding Rate within 3 month	0.4356 (0.008)	0.078 (0.651)	0.5108 (0.002)	-0.4505 (0.006)
Job Finding Rate within 6 month	0.4668 (0.004)	0.2337 (0.170)	0.4577 (0.005)	-0.2315 (0.174)

Note: 1 Shadowed numbers are significant at least 10% level.

2 The result is for the data 1999-2001, prefectural level.

The estimation results are summarized as follows:

Table4 Estimation result of Stock-Flow Matching-1(1999-2001)

	Fixed Effects Model			Random Effects Model		
	Non-seasonally adjusted series			Non-seasonally adjusted series		
	Coefficient	Std. err.	p	Coefficient	Std. err.	p
Stock V	0.17	0.17	0.311	0.17	0.14	0.019
Stock U	-0.34	0.21	0.112	-0.57	0.13	0.000
Flow v	0.42	0.16	0.009	0.45	0.16	0.192
Flow u	-0.06	0.10	0.542	-0.10	0.10	0.904
Stock Age	/			/		
Stock Sex						
Stock Education						
Stock Married						
Flow Age	/			/		
Flow Sex						
Flow Education						
Flow Married						
Year		yes			yes	
Month		yes			yes	
Month*Year		yes			yes	
Constant	0.22	0.09	0.928	2.73	0.58	0.000
R-sq: within	0.846			0.8458		
between	0.0831			0.3655		
overall	0.7924			0.8127		
corr(u _i , Xb)	-0.024			0		

Correlation between error terms and explanatory variables is quite low (-0.02), and the Hausman test for fixed effects model against random effects model does not support fixed effects model at a statistically significant level. The estimation result of random effects model suits previous expectations in terms of coefficients signs, while they are not statistically significant with respect to flow variables. When we add the average characteristics of unemployed people, the estimation results have changed as follows;

Table 5 Estimation Result of Stock-Flow Matching-2 (1999-2001)

	Fixed Effects Model			Random Effects Model		
	Non-seasonally adjusted series			Non-seasonally adjusted series		
	Coefficient	Std. err.	p	Coefficient	Std. err.	p
Stock V	-0.20	0.17	0.218	-0.04	0.14	0.218
Stock U	0.20	0.22	0.361	-0.22	0.14	0.361
Flow v	0.08	0.16	0.626	0.22	0.15	0.626
Flow u	0.04	0.11	0.706	-0.02	0.10	0.706
Stock Age	0.01	0.04	0.782	0.05	0.03	0.064
Stock Sex	-1.11	0.91	0.225	-0.34	0.82	0.681
Stock Education	-0.31	0.49	0.536	-0.27	0.26	0.308
Stock Married	-1.83	0.99	0.064	1.00	0.74	0.177
Flow Age	0.00	0.01	0.436	0.00	0.01	0.606
Flow Sex	0.16	0.12	0.207	0.17	0.12	0.180
Flow Education	0.04	0.07	0.558	0.04	0.07	0.508
Flow Married	-0.05	0.13	0.712	0.04	0.13	0.751
Year		yes			yes	
Month		yes			yes	
Month*Year		no			no	
Constant	3.02	3.90	0.439	-0.36	2.16	0.868
R-sq: within		0.8144			0.8111	
between		0.417			0.4352	
overall		0.7101			0.7818	
corr(u _i , X _b)		-0.1047			0	

As average attributes variables, we employed age (average age of the unemployed), sex (proportion of female among unemployed), education (average educational level), marital status (proportion of married people among unemployed).

Most variables do not have statistically significant explanatory powers against employment probabilities once we added characteristics variables. In this estimation, the result of the Hausman test of fixed effects model against random effects model is significant at the 10 percent level, but not significant at the 5 percent level. In any case, the correlation between error terms and average unemployment attributes is not so high for any of them (greatest one is 0.33), so we would assume average attributes of unemployed do not have strong explanatory power on employment probabilities.

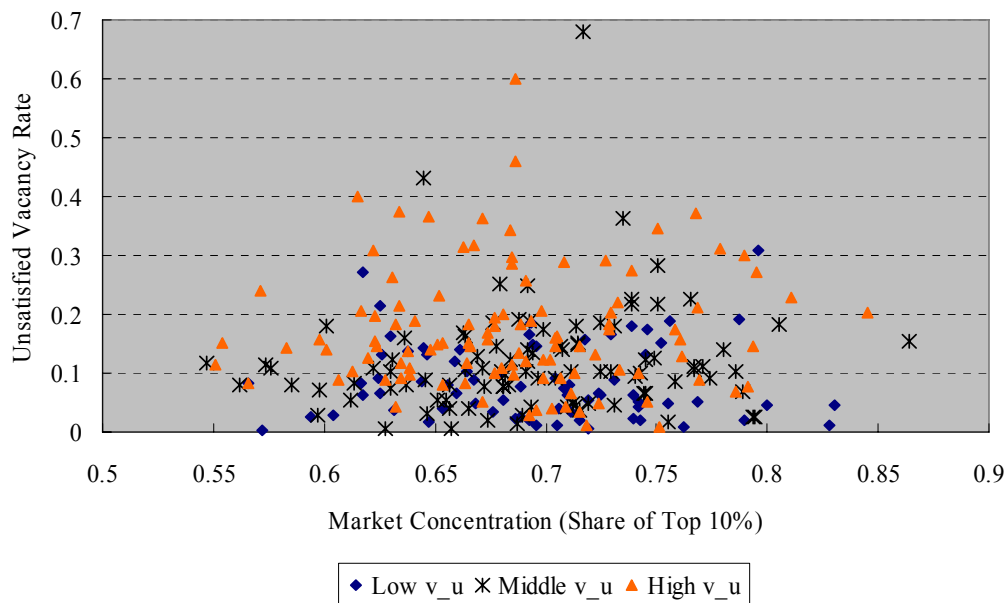
To conclude, the greater the stock amount of vacancies, the more likely for the unemployed to get out of unemployment within a very short period. At the same time, the greater the stock amount of unemployed, the less likely for them to get out of unemployment because competition over a vacancy would become severer. Flow variables for both vacancy and unemployment do not have special impact on employment probabilities, which implies that market participants do not distinguish stock and flow in our labor markets. Average characters on the side of unemployment do not affect employment probabilities as well, so placements might be created in a quite simple and rather random way at least on the side of unemployed.

2) Vacancy Creation and Reservation on Productivity

When we discuss vacancy market structure, we should consider the relations between vacancy size posted at once and productivity reservation set by firms. Our estimation assumes vacancy concentration level has been decided exogenously for regional markets, so that we plugged in vacancy concentration index as one of the explanatory variables. However, vacancy sizes per firms could be correlated with reservations for firms. For instance, in the case of rapidly growing industries, firms often create large vacancies, especially when they are setting up new establishments one after another. In such cases, firms might put weight on filling in all vacancies rather than on matching with workers of sufficiently high skill levels. Thus, vacancy sizes could be correlated with reservation productivity for firms. If large part of vacancies in some regional markets is consisted of such vacancies, market structure could be related with matching speed at an aggregate level for regions. As a result, we are just picking up the positive effect of firms' reservation of productivity on matching efficiency, by adding concentration level as an explanatory variable into matching function.

Although the level of reservation productivity for firms is not directly observable, we could get some clues to see if the above really matters matching efficiency by using an average unsatisfied vacancy ratio¹¹ as a proxy for reservation. Graph 11 shows relations between average unsatisfied vacancy ratio and vacancy market concentration level by region through 1996-2001. Market tightness might matter for both factors, so we divided the entire sample into three categories by the level of market tightness (i.e. high, middle, and low) and plotted them separately in the same graph.

Graph11 Market Concentration & Unsatisfied Vacancy Rate (1996-2001 Region)



Obviously, correlations between market concentration level and unsatisfied vacancy rate are not statistically significant. The result is the same when I used market concentration index as the share of the top 25 percent establishments'

¹¹ Unsatisfied ratio has been derived as the ratio of unsatisfied vacancies to total vacancies per establishment. We calculated the weighted average of these ratios by region and by year.

vacancies. Therefore, we would assume that the reservation level on the vacancy side is not correlated with the vacancy market structure in a consistent way, so that adding a market structural index as an exogenous explanatory variable into our matching function would not induce bias in estimation.

6 Conclusion

In this paper, we discussed matching efficiency in Japan's labor market for the latter half of the 1990s. We have taken into account the micro-structure of demand-side in labor market, and examined the impact on aggregate matching efficiency.

We focused on the difference in vacancy-size distribution among distinct regional markets, and showed that a more concentrated market has higher matching efficiency, which is consistent with the theory. This implies that more densely-populated (by firms) areas tend to get negative impact from dispersed-market structure, since usually in such areas market concentration rate is relatively low. We applied two formulations in our panel estimation, and found that the market concentration rate makes matching function shift positively, either in a structural way or in a stochastic way. At the same time, aggregate matching function shows increasing returns to scale, and such returns to scale are not affected by the existence of a market concentration index.

The data show that Japanese firms were more cautious in creating vacancies through the 1990s, because of the decline in their profitability. This would raise market concentration of vacancy markets, which could lead to less friction in the market. Further research, in particular extensions of analysis in time-series, would make our discussion clearer on the relationship between matching efficiency and market concentration. On the other hand, it is necessary to improve the concentration index accompanied with the research which would verify individual recruitment behavior of Japanese employers.

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