No. 997

Estimating A Matching Function and Regional Matching Efficiencies: Japanese Panel Data for 1973-1999

by

Shigeki Kano and Makoto Ohta

July 2002

Estimating A Matching Function and Regional Matching Efficiencies: Japanese Panel Data for 1973-1999

Shigeki Kano
Doctoral Program in Policy and Planning Sciences
University of Tsukuba†
and
Makoto Ohta
Institute of Policy and Planning Sciences
University of Tsukuba

July 2002

†Correspondence: Shigeki Kano, Doctoral Program in Policy and Planning Sciences, University of Tsukuba, Tsukuba, Ibaraki 305-8573, Japan (e-mail address; skano@sk.tsukuba.ac.jp). The data set and GAUSS programming code used in this paper are available upon request.

Abstract

In estimating matching functions by using aggregate time series data, an implicit assumption is imposed that search efficiencies are common to all regions in a country. This paper estimates the matching function using annual panel data covering 47 Japanese prefectures from 1972 to 1999, which allows variation of matching efficiencies over regions. We find that the matching function exhibits mildly but statistically significantly decreasing returns to scale regardless of whether unobservable regional heterogeneity be controlled or not. Further, we find a statistical evidence that estimated matching efficiency is negatively correlated with population density and per capita income. This contradicts previous finding that, *ceteris paribus*, matching is better for higher population density area. We give a verbal interpretation of this finding.

JEL Classification Number: C23, E24, J41, J60.

1 Introduction

The matching function relates the number of new hirings to the number of unemployed and job vacancies, and it plays a central role in the theory of equilibrium unemployment, one of predominant strands in macroeconomics and labor economics. By now, like aggregate production function, the matching function has been widely used as a modeling device for frictional labor market: Frictions in the job search by workers and the employee search by firms[1].

Although the theoretical derivation of the matching function has not been studied enough, dozens of authors attest empirically to the existence of a well-behaved and constant returns to scale matching function during the last decade[2].

Since Blanchard and Diamond (1989), early studies on empirical matching functions were conducted on aggregate data, partly because equilibrium unemployment theory aims at describing macroeconomic behavior of unemployment, and mainly because it is harder to obtain disaggregate data set on hirings, unemployment, and vacancies[3]. Because of this aggregation, they may impose strong and presumably counter-factual assumption on the form of the matching function, i.e., one that search frictions are homogeneous across regions in a country.

Coles and Smith (1996)'s cross sectional analysis on England and Wales shows

---

[1] See Pissarides (2000).

[2] See Petrongolo and Pissarides (2001)'s excellent survey for recent development of matching function. However, previous studies are exclusively concentrated on US and Europe, while they are few on Asian countries including Japan. To our best knowledge, there are no such studies except for Kano and Ohta (2002) as for Japan.

[3] See Kano and Ohta (2002) for an aggregate study on the Japanese matching function.

the importance of underlying demographic factors in estimating the matching function such as population density and age structures, and claims that the population density of the “market place”, not its size, matters for explaining search frictions. Their study cautions researchers for the existence of regional heterogeneity, which is entirely neglected by aggregate time series studies. In addition, they find that the matching function exhibits constant returns to scale in their cross sectional study as in the previous time series studies.

In order to control such observable and unobservable heterogenieties among regions and correct possible aggregation bias, recently some authors have shifted their foci from aggregate time series to regional panel data analysis: Anderson and Burgess (2000) for 4 US states and 20 industries; Burgess and Profit (2001) for 303 “travel to work” areas in UK; Burda and Profit (1996) and Boeri and Burda (1996) for 76 districts of Czehc Republic; and van Ours (1995) for 8 regions of Netherlands. They estimate matching functions with panel data, and some of these panel data analyses show sharp differences in estimated returns to scales from aggregate studies.

In this paper, we estimate the matching function in Japanese labor market using annual panel data which covers 47 prefectures from 1972 to 1999, and find that the matching function exhibits mildly but statistically significantly decreasing returns to scale. Although it is not pointed out by aforementioned previous studies of the panel data, their extension toward panel data analysis is analogous to that of estimating production function by using disaggregate data sets, known as the "stochastic frontier" production function and applied to various industries of various countries[4]. We specify the matching function following them, i.e., regarding regional difference in matching efficiencies as departures from a common level or grand mean. Here we say that matching efficiency is high (low) when the number of matching is high (low) for the given numbers of the unemployed and the job vacancies[5].

Previous studies, for instance Coles and Smith (1996), put their emphasis on the spatial aspect of matching efficiency, mainly arguing that denser local labor market could absorb unemployed and unfilled vacancies more successfully. It is a natural argument, because at a given level of unemployment and vacancies, both parties would be "close" and easily communicate each other with lower efforts in a denser space. In terms of equilibrium unemployment theory, they enjoy lower search cost. However, there may be another plausible cause of regional variation in matching efficiencies, i.e., regional variation due to the difference in the distribution of heterogeneous labor force and firms, which we will explain below.

Firms have different hiring standards and payable wages because their production technologies are different. Unemployed workers have different skill levels and correspondingly different reservation wages. The distributions of hiring standards and skill levels and of payable wages and reservation wages are decisive to the achievement of the matching.

[4]Schmidt and Sickles (1984) and Cornwell, Schmidt, and Sickles (1990) might be representative empirical studies on stochastic production frontier with panel data.

[5]So, matching efficiency depends on the search frictions in the labor market.

Consider region A where firm distribution is concentrated to lower hiring standard and worker distribution is also concentrated to lower skill level. Little conflicts would come about in the region, so they do well in matching.

On the other hand, consider, say, region B where the firm is distributed over the wide range from lower to higher hiring standards, and also worker distribution spreads over the wide range from lower to higher skill levels. In this region, at the same levels of the unemployed and the job vacancies as region A, the matching will be more difficult because it will be highly possible that firms with higher hiring standard might draw workers with lower skill levels from the pool of unemployment in this region and *vice versa*. In the Japanese case, region A might correspond to less urbanized prefectures such as *Iwate* while region B to highly urbanized prefectures such as *Tokyo*.

If this hypothesis is true, it results in opposite prediction to the previous view of Coles and Smith (1996) mentioned before, since skill requirements and skill endowments will distribute more widely in more urbanized regions. In other words the matching may be more difficult in higher population density regions. By investigating our estimated regional matching efficiencies, we find that the previous view of Coles and Smith is not applicable to Japan; our estimation shows that matching efficiencies are lower in more urbanized prefectures which exhibit higher population density and per capita income. This result of Japan supports our hypothesis, not of Coles and Smith.

Technically, we pay special attentions to the problems particular to spatial panel data analysis. Unlike non-regional panel data set such as Panel Study of Income Dynamics (often referred to as PSID) in USA, regional panels are by nature not randomly sampled from the large population, which means that each sample presumably incurs common disturbances. Hence, *spatial correlation* could arise in error terms. Spatial correlation matters because the covariance matrix estimator of parameter estimates obtained by the usual manner is inconsistent, and any tests based on it, such as *t* test and Hausman's specification test, are no longer valid. Indeed, Driscoll and Kraay (1998)'s Monte Carlo study shows that only small spatial correlation among errors could cause non-negligible bias in the estimate of the covariance matrix against true value, especially as the cross sectional dimension is large.

Therefore, in making use of regional panels, diagnostic tests are required in three ways to perform correct inference; heteroskedasticity, autocorrelation, and spatial correlation. We implement them, specifically following Anselin and Hudak (1992), and find that error terms are spatially correlated. So we apply the remedy for this problem devised by Driscoll and Kraay (1998), namely, heteroscedasticity, autocorrelation, and spatial correlation consistent covariance matrix estimator. This statistical elaboration would make up our technical advantage over past works estimating matching functions by using regional panels.

The rest of this paper is organized as follows. Section 2 introduces and specifies the matching function with region-specific matching efficiencies *a la* stochastic production frontier. Section 3 describes the data we used. Section 4 provides our estimation results. Section 5 shows and discusses the regional difference in matching efficiencies. Section 6 concludes the paper.

2 Specification of a matching function with regional difference in matching efficiencies

Matching function summarizes underlying search frictions and matching process in a labor market. In the literature of equilibrium unemployment theory, its general form is given by

$$H = M(U, V),$$

where H denotes new hiring, U unemployment, and V unfilled vacancies. The following is natural and testable set of assumptions on properties of the matching function; $H_U(U, V) > 0$, $H_V(U, V) > 0$, $H(0, V) = H(U, 0) = 0$, namely, it is an increasing function with respect to both arguments, and both arguments are essential for the achievement of positive amount of matching. Further it is assumed to be homogeneous of degree one (i.e., constant returns to scale) in the equilibrium unemployment theory, which has been also the hypothesis tested often in previous empirical studies.

As mentioned earlier, it might be a misleading assumption that the degree of search frictions is the same for every regional labor market. In order to add regional differences to the matching function, we extend the above expression as follows, following the stochastic production frontier literature and assuming the Cobb-Douglas form for the matching function. For cross sectional dimension $i = 1, ..., N$ and time series dimension $t = 1, ..., T$,

$$H_{i,t} = M_{i,t}(U_{i,t-1}, V_{i,t-1}) = A_{i,t} U_{i,t-1}^{\beta_u} V_{i,t-1}^{\beta_v}, \tag{1}$$

where $H_{i,t}$ denotes the flow of new hiring during a period t, while $U_{i,t-1}$ and $V_{i,t-1}$ denote the stock of unemployment and vacancies at the beginning of t, respectively. $A_{i,t}$ denotes region-specific and time-varying matching efficiency which depends on various factors hindering or promoting matching among unemployed workers and firms.

Let us further specify $A_{i,t}$ as

$$A_{i,t} = Ae^{(\mu_i + \lambda_t + \varepsilon_{i,t})}, \tag{2}$$

where μ_i denotes time-invariant regional attribute for i, λ_t region-invariant time attribute for t, and $\varepsilon_{i,t} \sim i.i.d.(0, \sigma^2)$ a pure random shock for region i at time period t.

Taking a log of equation (1), we have

$$h_{i,t} = a + \beta_u u_{i,t-1} + \beta_v v_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{i,t}, \tag{3}$$

where variables in lower case denote the logarithms of the corresponding variables in upper case. This is a typical two-way error components model, and the following basic panel data techniques are applicable for its estimation.

If we treat individual effect μ_i and time effect λ_t as nuisance parameters, and impose additional assumptions that

$$\sum_{i=1}^{N} \mu_i = \sum_{t=1}^{T} \lambda_t = 0 \tag{4}$$

for avoiding perfect multicolinearity, equation (3) is the fixed effect model that can be estimated by the Least Squares Dummy Variable (LSDV) or equivalently within estimator.

On the other hand, assume that μ_i and λ_t are random variables as $\mu_i \sim i.i.d.(0, \sigma_\mu^2)$ and $\lambda_i \sim i.i.d.(0, \sigma_\lambda^2)$. Further assume that the moment condition

$$E(e|X) = 0, \tag{5}$$

holds, where e is the vector of composite error terms whose typical element is $e_{i,t} = \mu_i + \lambda_t + \varepsilon_{i,t}$ and X denotes the pooled right hand side variables. Then (3) is the random effect model that can be estimated by GLS[6].

3 Data description

The data used in our analysis comes form "Referentials and Placements by Prefecture, Employment Referral Statistics" in *Year Book of Labour Statistics*, issued by The Ministry of Labour, Japan[7]. Our variables correspond to the published data as follows; $H_{i,t}$ = *Placements*, $U_{i,t}$ = *Active Applicants*, and $V_{i,t}$ = *Active Openings*, all of which are based on reports from Employment Referral Services (*Syokugyo-Antei-zyo* in Japanese) all over the country, and aggregated on the prefectural level. For the definitions of variables, see Appendix A.

[6] See Baltagi (2001), Chapter 3, for details.
[7] Currently, Ministry of Health, Labour, and Welfare.

Figure 1:

attach here

Our sample period is 1973-1999 (i.e., T=27), but our estimation equation uses variables with lag one, so the actual data collection starts form 1972. This is the sample period of the maximum length available at the start of our analysis, because the data on *Okinawa* prefecture is available only after 1972, and 1999 was the latest year for which the data was available at the start of our research. The number of prefectures, N, is 47, so the sample size is $NT = 1269$. The data are monthly averages. For all the variables new school leavers and casual labors are excluded. Part-timers were excluded before 1991 but have been included since then. We checked the effect of this different treatment of part-timers by plotting three variables H, U, and V for each prefecture, and could not find any unnatural breaking points around 1990 for all cases. So we believe that the change of the treatment of part-timers is a minor problem[8].

Before presenting our estimation results, let us review aggregate behaviors of the three variables. Figure 1 plots new hiring (H), unemployment (U), and vacancies (V) from 1972 to 1999. At least for our sample period, they seem to be consistent with the stylized facts commonly observed by previous studies on various countries, i.e., new hiring and unemployment are counter-cyclical while

[8]We also checked the variation of estimated time effects, and no evidence on such "structural changes" was found.

Table 1: Summary statistics on aggregate variables, in thousands.

	New Hiring	Unemployment	Vacancies
mean	126	1648	1284
standard deviation	13	333	293
variation coefficient	0.10	0.20	0.22
max	157	2530	1963
min	107	1113	845
correlation with ΔGDP	-0.20	-0.77	0.32

vacancies are pro-cyclical. For instance, since 1992, which is the beginning of the "lost decade" of Japanese economy, new hiring and unemployment have grown at increasing rates, while the number of vacancies shows steady decline.

Table 1 provides summary statistics on these variables. Though vacancies are as volatile as unemployment, the latter is more cyclical than the former since unemployment is more strongly correlated with the first difference of real GDP, denoted by ΔGDP. This asymmetric response of both variables to business cycles is itself interesting and might open the room for further investigation.

For a candidate for U, *Complete Unemployment* by Statistics Bureau, Ministry of Public Management, Home Affairs, Posts and Telecommunications is also available. It might be pointed out that the data on job seekers reported by Employment Referral Office is more cyclical than unemployment series by other sources such as the above *Complete Unemployment*, since the use of the referral service itself would increase in recessional periods. Indeed, for the same sample period, the correlation of *Complete Unemployment* with ΔGDP is -0.68, slightly lower

Table 2: Estimation results

	OLS	LSDV
Constant	-0.548	-
($s.e._{NW}$)	(0.088)	-
($s.e._{DK}$)	(0.044)	-
Unemployment	0.588	0.560
($s.e._{NW}$)	(0.023)	(0.039)
($s.e._{DK}$)	(0.037)	(0.067)
Vacancies	0.290	0.302
($s.e._{NW}$)	(0.015)	(0.032)
($s.e._{DK}$)	(0.035)	(0.036)
R^2	0.788	0.968
DW	0.100	0.048
LM_{KB}	81.605	9.073
(*p-value*, H_0: homoscedasticity)	(0.000)	(0.011)
RTS	0.878	0.862
(*p-value*, H_0*: constant RTS*)	(0.000)	(0.009)

Note: Standard errors by the Newey-West covariance matrix estimator ($s.e._{NW}$) and by the Driscoll-Kraay's one ($s.e._{DK}$) are in the first and the second parentheses, respectively.

than that of *Active Applicants*, -0.77. However we preferably use *Active Applicants* because, as noted in the Appendix A, *Placements* are defined as the outflow from *Active Applicants*. Virtually, this selection problem of the definition of the unemployed job seekers would not matter in our analysis because the correlation between these two candidates are high (0.94) enough.

4 Estimation results

4.1 Results ignoring spatial correlation

Table 2 presents our estimation results of equation (3). The column OLS of the table shows pooled OLS estimates (i.e., ignoring individual and time effects), and the column LSDV shows LSDV (within) estimates. The number in the first parenthesis below the estimate is the estimated standard error based on Newey-West consistent covariance matrix estimator, while that in the second parenthesis is the one based on Driscoll and Kraay (1998)'s one, which is to be explained in subsection 4.2.

The Hausman's test statistic for fixed versus random effects specification is 21.676 (with p-value = 0.000), which suggests that the latter is rejected in our case[9]. So we do not report the estimation result of feasible GLS for equation (3). We also do not report between estimates, because we employ two-way error components model.

The F test statistic for the joint significance of fixed effects, i.e., $H_0 : \mu_1 = \mu_2 = ... = \mu_{N-1} = 0$ and $\lambda_1 = \lambda_2 = ... = \lambda_{T-1} = 0$, is 91.604 and its p-value is 0.00[10]. Hence we could reject the null hypothesis. We also test $H_0 : \mu_1 = \mu_2 = ... = \mu_N = 0$ given that $\lambda_t \neq 0, t = 1, ..., T - 1$ by $F = 3.935$ (with p-value = 0.00), and $H_0 : \lambda_1 = \lambda_2 = ... = \lambda_T = 0$ given that $\mu_i \neq 0, i = 1, .., N - 1$ by $F = 136.202$

[9]For the Hausman test, we implement Swamy-Arola's two-stage feasible GLS. See Baltagi (2001) for the recipe of feasible GLSs.

[10]Note that the μ_N and λ_T are dropped out due to restrictions (4).

(with p-value = 0.00), so both sets of effects are separately significant.

All estimates exhibit correct signs and are statistically significant for both pooled OLS and LSDV estimates. Although fixed effects specification is not rejected, there are no major differences between OLS and LSDV. Therefore, unlike previous studies, biases due to ignorance of unobservable regional heterogeneity could not be found, and the difference between the result of OLS and that of LSDV is mainly attributed to the variation of the constant term, i.e., the matching efficiency. For LSDV, the estimated coefficient of unemployment, $\hat{\beta}_u$, is 0.560 and of vacancies, $\hat{\beta}_v$, is 0.302, so its estimated returns to scale (RTS) is $\hat{\beta}_u + \hat{\beta}_v = 0.862$, which seems to be slightly less than unity. Formally, the t-value for two-sided test of the null hypothesis that $H_0 : \beta_u + \beta_v = 1$ is -2.357 with p-value = 0.009, so we reject constant RTS.

Koenker-Bassett Lagrange multiplier test statistic (LM_{KB}) and the panel Durbin-Watson (DW) test statistic (by Bhargava, Franzini, and Narendranathan, 1982) in Table 2 suggest that there would exist both heteroscedasticity and first order autocorrelation in the error term, so standard errors based on the usual covariance matrix estimator are improper. Therefore standard errors based on Newey-West's consistent covariance matrix estimator are reported in the table.

4.2 Test of and remedy for spatial correlation.

As suggested by Driscoll and Kraay (1998) and others, spatial correlation in the error term should be tested since ignoring it makes the covariance matrix esti-

Figure 2:

`attach here`

mator inconsistent. We check it by Burridge (1980)'s *LM* test statistic, which is distributed as χ^2_1 under the null hypothesis of no spatial correlation, for each period[11]. In Figure 2 we plot the series of the *LM* as well as its 5% critical value. The *LM* exceeds the critical value for 18 out of 27 years, so we conclude that the error term suffers from spatial correlation.

In order to avoid this problem, we employ Driscoll and Kraay (1998)'s "wild card" covariance matrix estimator which is consistent for heteroscedasiticity, autocorrelation, and spatial correlation. Its attractive features are as follows: First, since it is consistent for general form of spatial correlation, we need not specify the exact form of its correlation structure parametrically. It is well known that detecting the form of spatial correlation is difficult because, unlike autocorrelation in the case of time series data, there is no natural order of spatial dependence[12]. Second, its asymptotic property relies only on time dimension T, free from the order of cross sectional dimension N. See Appendix B.2 for its construction.

In Table 2, numbers in the second parentheses are estimated standard errors based on Driscoll and Kraay's consistent covariance matrix estimator. It turns out

[11] For details, see Burridge (1980) and Anselin and Hudak (1992) as well as Appendix B.1 in this paper. We did not employ presumably more popular Moran's I test (also called as Criff-Ord test) because it requires extra burdensome computation for inference. On the other hand, Burridge's *LM* can be easily implemented with residuals and given spatial weighting matrix.

[12] See Anselin (1988) and Anselin and Hudak (1992).

that standard errors based on the Newey-West covariance matrix estimator might be under-estimated for the estimated coefficients of unemployment and vacancies. For instance, the standard error of unemployment's estimated coefficient based on the Driscoll-Kraay's consistent covariance matrix estimator is 0.067, greater than that based on the Newey-West's one (0.039) by approximately 72%.

The modification of covariance matrix estimator of estimated coefficients might alter not only estimated standard errors but also results of the Hausman and the constant RTS test[13]. We re-examined them using Driscoll and Kraay's covariance matrix estimator, but obtained the same results as before. Thus it turns out that our test results are robust against the existence of spatial correlation.

5 Search frictions across prefectures

Although we eliminated individual and time effects, μ_i and λ_t, in equation(3) by the within transformation, they can be recovered by

$$\hat{\mu}_i = (\overline{y}_{i.} - \overline{y}_{..}) + \hat{\beta}(\overline{x}_{i.} - \overline{x}_{..}),$$

$$\hat{\lambda}_t = (\overline{y}_{.t} - \overline{y}_{..}) + \hat{\beta}(\overline{x}_{.t} - \overline{x}_{..}),$$

where $\hat{\beta}$ denotes the within estimate, $\overline{z}_{i.} = T^{-1}\sum_{t=1}^{T} z_{i,t}$, $\overline{z}_{.t} = N^{-1}\sum_{i=1}^{N} z_{i,t}$, $\overline{z}_{..} = (NT)^{-1}\sum_{i=1}^{N}\sum_{i=1}^{T} z_{i,t}$, $z = x, y$, and x is the set of explanatory variables and y is the dependent variable[14]. Figures 3 and 4 show the estimated regional difference in

[13] Note that the values of other test statistics are unchanged, because they are constructed by the residuals.

[14] See Baltagi (2001), Chapter 3.

Figure 3:

attach here

Figure 4:

attach here

matching efficiencies, $\hat{\mu}_i$, normalized in the following way,

$$\mu_i^* = \hat{\mu}_i - \min(\hat{\mu}_j), \quad i, j = 1, ..., N, \tag{6}$$

which is often done in the literature of stochastic production frontiers[15]. Observing the figure, we immediately notice a remarkable pattern in the variation in matching efficiencies, i.e., the more the prefecture in question is urbanized, the more severe is its search friction. For example, μ_i^* of *Hokkaido* and *Aomori* are 0.57 and 0.31, while those of *Tokyo* and *Osaka* are 0.07 and 0.16, respectively. This is obviously inconsistent with the previous view that the region with higher population density would more efficiently absorb unemployed labor forces and unfilled vacancies.

In order to check our visual inspection statistically, we try to regress the estimated degree of matching efficiency, $\hat{\mu}_i$, on the log of *% of Densely Inhabited Districts to Whole Area* in 1986, $\log D_i$, and get the following result;

$$\hat{\mu}_i = \underset{(0.047)}{0.021} - \underset{(0.035)}{0.119} \log D_i, \quad i = 1, ..., N,$$
$$R^2 = 0.187,$$

[15]In our case, $\min(\hat{\mu}_j)$ corresponds to *Kyoto*'s one.

where standard errors are in parentheses[16]. Thus an increase in population density significantly decreases matching efficiency in a prefecture. This result is in favor of our hypothesis that the region characterized by more dispersed distribution of firms' hiring standards and of workers' skill levels would exhibit lower matching efficiency due to higher possibility of conflicts between requirements from both parties, because hiring standards and skill levels are expected to show more dispersion in more urbanized prefectures.

The direct and desirable way to test our finding is to regress regional efficiencies on the measure of worker and/or firm heterogeneity such as the variance of wage levels in a prefecture. However, such data are not available. Therefore we instead regress regional efficiencies on the log of par capita income, $\log pGDP_i$, be assuming that the variance of per capita income becomes greater as the per capita income is higher, and the variance of per capita income reflects the heterogeneieties of hiring standards and skills. The regression result is as follows;

$$\hat{\mu}_i = \underset{(0.9041)}{2.239} - \underset{(0.2740)}{0.679} \log pGDP_i, \quad i = 1, ..., N,$$
$$R^2 = 0.100,$$

where standard errors are in parentheses[17]. Therefore, though $pGDP_i$ might be

[16]The data is drawn from "Statistical Yearbook 1989", by Bureau of Statistics. The Density Inhabited Districts is defined as a area which is composed of a group of contiguous census-enumeration districts with high population density (4000 inhabitants or more per km^2) within the boundary of city, ward, town, or village, and constitutes an agglomeration of 5000 inhabitants or more as of the census-taking. We did not collect the data for all the sample years, since it is less frequently (every five years) recorded and almost unchanged during our sample period.

[17]The data is drawn form "Statistical Yearbook 1989", by Bureau of Statistics. Again, we did not collect the data for all the sample years, since prefectural income and unemployment is highly correlated.

an insufficient proxy variable for the variety of the hiring standards and the labor skills, its rise significantly reduces matching efficiency.

So our finding of the regional difference in the matching efficiency of Japan contradicts the claim of Coles and Smith (1996) that the matching efficiency is positively related to the population density. We conclude that our finding is consistent with our claim that the matching efficiency is negatively correlated with the degree of conflicts among firms' hiring standards and workers' skill levels.

6 Concluding remarks

In this paper we estimated the matching function in Japanese labor market using annual prefectural panel data, and showed that the matching function exhibits mildly but statistically significantly decreasing returns to scale. Further, we found that more urbanized prefectures with higher population density and higher per capita income exhibit poorer matching efficiencies. This result supports our hypothesis that the matching efficiency is negatively correlated with the degree of conflicts among firms' hiring standards and workers' skill levels.

Our data is limited to the one registered at the Employment Referral Office. This means that unemployment (U) and the job (V) in our paper are those who use the office, and that the new hiring (H) are recorded only when the unemployed matches the job vacancies registered at the office: The new hirings are not recorded even if the unemployed at the office match the vacancies by the routes other than the office. The unemployed might use various routes for their job seeking activities, such as private referral services, advertisements in magazines, and visiting firms directly.

Because of these routes of job seeking other than using the Employment Referral Office, the total new hirings occurred actually are higher than those recorded by the office for the unemployed registered at the office. When we consider the difference of the total new hirings occurred actually from the new hirings used in this paper, there can be the following two cases: (1) The relative difference between these two new hirings is higher in the urban area than in the rural area, and (2) the opposite case to (1).

Thus these other routes of job seeking may weaken or strengthen our claim that the matching efficiency is lower in more urbanized area with higher population density and higher per capita income, when we use the total new hirings instead of our new hirings data. Since we do not have the data about the total new hirings occurred actually for the unemployed registered at the Employment Referral Office, we cannot answer which is the case empirically.

A Definitions of the variables

Following definitions are based on *Labor Market Annual*, issued by Bureau of Employment Security, Ministry of Labour (currently, Ministry of Health, Labour, and Welfare), Japan.

1. *Placements (corresponding to H)*; The number of active applicants registered at an Employment referral service who matched job openings mediated by the service.

2. *Active applicants (corresponding to U)*; The number of job seekers whose registrations have been made before and still been valid and who have not found their jobs, plus newly registered job applicants in this month.

3. *Active openings (corresponding to V)*; The number of job vacancies whose registrations have been made before and still been valid and which have not been filled, plus newly registered job openings in this month.

B Test of no spatial correlation and consistent covariance matrix estimator

In our analysis we used the test statistic of no spatial correlation and consistent covariance matrix estimator under spatial correlation, which might not be well-known. This appendix is devoted to give the overview of them.

B.1 Burridge (1980)'s *LM* test of no spatial correlation

Burridge (1980) proposes a Lagrange multiplier (*LM*) test for spatial correlation, which is defined by

$$LM_t = (\frac{e_t' W e_t}{\sigma_t^2})^2 / tr[W'W + W^2],$$

where e_t denotes the column vector of the residuals over regions $i = 1, ..., N$ in a period t, W spatial weighting matrix (explained below) whose typical element is $\omega_{i,j}, i, j = 1, ...N$, and diagonal elements are zero, and $\sigma_t = e_t' e_t / N$. It distributes as χ_1^2 under the null hypothesis of no spatial correlation. For the relation between the *LM* and the well-known but burdensome Moran's *I* test statistic, see Burridge (1980) and Anselin and Hudak (1992).

We compute LM_t and test the null hypothesis of no spatial correlation for each period $t = 1, ..., T$. Although Burridge's test is devised for cross sectional studies, we apply it to the residual in the same year t where the residuals themselves are estimated by the panel. This procedure of ours follows previous panel data analysis that used Moran's *I* test in the same manner (e.g., Holtz-Eakin, 1994 and Burgess and Profit, 2001).

For the spatial weighting matrix W, we employ the simplest, the first order binomial contiguity matrix, i.e., the one whose elements are $\omega_{i,j} = 1$ if a region i is neighboring to a region j, and $\omega_{i,j} = 0$ otherwise. We need not specify any further complex weighting matrix for Driscoll and Kraay (1998)'s covariance matrix estimator, because it is consistent for the general form of spatial correlation structure. For extensive discussions on the specification problem of spatially dependent econometric models, see Anselin (1988), though it is not for panel data but for cross sectional study. (To our best knowledge, there does not seem to be a test statistic for spatial correlation in the panel data.)

B.2 Driscoll-Kraay (1998)'s consistent covariance matrix estimator

Consider a panel data whose cross sectional dimension is $i = 1, ..., N$ and time series dimension is $t = 1, ..., T$. The number of parameters to be estimated is k. For a $NT \times k$ matrix $h(\hat{\beta})$, we define the following matrix of sample moments $\overline{h}_{.}$ evaluated at estimates. The matrix $\overline{h}_{.}$ is $T \times k$ and its typical element is give by

$$\overline{h}_{.,t}(\hat{\beta}) = \frac{1}{N} \sum_{i=1}^{N} h_{i,t}(\hat{\beta}), \qquad t = 1, ..., T, \tag{7}$$

that is, $\overline{h}_{.,t}(\hat{\beta})$ is the k dimensional vector of the sample moments over the *region i* for each period t. For instance, in this paper $h(\hat{\beta}) = Xe(\hat{\beta})$, where X is the matrix of explanatory variables and $e(\hat{\beta}) = y - X\hat{\beta}$ is residual.

Next, with lag length $l = 1, ..., L$, define

$$\hat{\Omega}_l = \sum_{t=1+l}^{T} \overline{h}_{.,t}(\hat{\beta})' \overline{h}_{.,t-l}(\hat{\beta}) \tag{8}$$

and

$$\hat{S} = \hat{S}_0 + \frac{1}{T} \sum_{l=1}^{L} \omega(l)[\hat{\Omega}_l + \hat{\Omega}_l'], \tag{9}$$

where $\hat{S}_0 = T^{-1}\hat{\Omega}_0 = T^{-1}\sum_{t=1}^{T}\overline{h}_{\cdot,t}(\hat{\beta})'\overline{h}_{\cdot,t}(\hat{\beta})$, and $\omega(l) = 1 - \frac{l}{L+1}$ denotes a Bartlett kernel. We thus have the covariance matrix estimator of $\hat{\beta}$,

$$C\hat{o}v(\hat{\beta}) = \frac{1}{T}\left(\frac{1}{NT}X'X\right)^{-1}\hat{S}\left(\frac{1}{NT}X'X\right)^{-1},$$

which is consistent for heteroscedasticity, autocorrelation, and spatial correlation in error term as $T \to \infty$. See Driscoll and Kraay (1998) for its proof. Note that as in the case of Newey-West's one, the Bartlett kernel $\omega(l)$ here could be replaced by alternatives such as truncated or quadratic spectral.

In short, in order to get the Driscoll-Kraay's consistent covariance matrix estimator, we need only to (i) compute sample moments over i for each period t, and then (ii) calculate Newey-West's consistent covariance matrix estimator based on them.

References

ANDERSON, P. M., AND S. M. BURGESS (2000): "Empirical Matching Functions: Estimation and Interpretation Using State-Level Data," *Review of Economics and Statistics*, 82(1), 93–102.

ANSELIN, L. (1988): "Model Validation in Spatial Econometrics: A Review and Evaluation of Alternative Approaches," *International Regional Science Review*, 11(3), 279–316.

ANSELIN, L., AND S. HUDAK (1992): "Spatial Econometrics in Practice: A Review of Software Options," *Regional Science and Urban Economics*, 22, 509–536.

BALTAGI, B. H. (2001): *Econometric Analysis of Panel Data*. John Wiley and Son's, Chichester, England, second edn.

BHARGAVA, A., L. FRANZINI, AND W. NARENDRANATHAN (1982): "Serial Correlation and Fixed Effect Model," *Review of Economic Studies*, 49, 533–549.

BLANCHARD, O. J., AND P. DIAMOND (1989): "The Beveridge Curve," *Brooking Papers on Economic Activity*, 1, 1–76.

BOERI, T., AND M. BURDA (1996): "Active Labor Market Policies, Job Matching and The Czech Miracle," *Europian Economic Review*, 40, 805–817.

BURDA, M. C., AND S. PROFIT (1996): "Matching across Space: Evidence on Mobility in The Czech Republic," *Labour Economics*, 3, 255–278.

Burgess, S., and S. Profit (2001): “Externalities in The Matching of Workers and Firms in Britain,” *Labour Economics*, 8, 313–333.

Burridge, P. (1980): “On The Cliff-Ord Test for Spatial Correlation,” *Journal of The Royal Statistical Society B*, 42(1), 107–108.

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

Cornwell, C., P. Schmidt, and R. C. Sickles (1990): “Production Frontiers with Cross-Sectional and Time-Series Variation in Efficiency Levels,” *Journal of Econometrics*, 46, 185–200.

Driscoll, J. C., and A. C. Kraay (1998): “Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data,” *Review of Economics and Statistics*, 80(4), 549–60.

Holtz-Eakin, D. (1994): “Public-Sector Capital and The Productivity Puzzle,” *Review of Economics and Statistics*, 76, 12–21.

Kano, S., and M. Ohta (2002): “An Empirical Matching Function with Regime Switching: The Japanese Case,” Discussion Paper Number 967, Institute of Policy and Planning Sciences, University of Tsukuba, Japan.

Petrongolo, B., and C. A. Pissarides (2001): "Looking into The Black Box: A Survey of The Matching Function," *Journal of Economic Literature*, 36, 390–431.

Pissarides, C. A. (2000): *Equilibrium Unemployment Theory*. The MIT Press, Cambridge, MA, second edn.

Schmidt, P., and R. C. Sickles (1984): "Production Frontiers and Panel Data," *Journal of Business and Economic Statistics*, 2(4), 367–374.

van Ours, J. C. (1995): "An Empirical Note on Employed and Unemployed Job Search," *Economics Letters*, 49, 447–452.