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Beveridge Curve and Regional Mobilities of
Unemployed Job Seekers in Japan

by

Shigeki Kano and Makoto Ohta

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UNIVERSITY OF TSUKUBA
Tsukuba, Ibaraki 305-8573
JAPAN

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

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†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 this paper, we explore the implication of regional mobilities of unemployed job seekers on Beveridge curve. We extend a conventional stylized model of Beveridge curve based on the equilibrium unemployment theory so that regional dependencies can be explicitly addressed, and we estimate our Beveridge curve using Japanese 47 prefectural data in 2000. We apply spatial econometric methods to deal with underlying statistical problems in estimation. Holding other relevant variables of our model constant, we find negative relationships between unemployment in a region and its neighboring unemployment as well as between unemployment and vacancies. This finding is consistent with our model of Beveridge curve.

JEL classification: J61, J63, J64, C31.

Key words: Beveridge curve, Regional labor mobility, Japanese unemployment, Spatial econometrics.

1 Introduction

Beveridge curve is an empirically negative relationship among unemployment rate and vacancy rate, originally observed by Beveridge (1944) in pre- and mid-war UK This observational relationship have intrigued a number of economists and motivated them to depart from a Walrasian view of labor markets, since it means the co-existence of firms holding vacant positions and unemployed workers seeking their positions for a considerablly long time. One of possible explanations for this observation might be the existence of search frictions among workers and firms: It could take a non-negligible time and cost to find a desirable trading partner in the presence of a wide job types and worker talents. Based on this notion of frictional labor markets, the equilibrium unemployment theory by Blanchard and Diamond (1989) and Pissarides (2000), among others, proposes the determination mechanism of unemployment levels which models explicitly the inflow and outflow of unemployment.

From the standing point of the equilibrium unemployment theory, several authors have empirically addressed this negative relationship between unemployment and vacancies and the shift of its position over time. Here are the selected ones: Jackman and Nickell (1986) and Jackman et al. (1989) for UK; Abraham (1987) for USA; Brunello (1991) for Japan, all of which are time series estimation. Further, Börsch-Supan (1991) estimates the Beveridge curve using a German panel data.

This paper estimates the Beveridge curve with a quite different interest form aforementioned authors, using Japanese 47 prefectural data in 2000. Specifically, our focus is on regional mobilities of unemployed job seekers. The advantage of our approach over existing time series counterparts might be revealed by pointing out the latter's shortcomings and a room for extensions, as follows.

First, the time series observation of the Beveridge curve is often claimed to be less informative, since it shifts so frequently over time. Indeed, it is hard to visually distinguish between a "deviation" of a pair of unemployment and vacancies around a stable Beveridge curve and a "shift" of the curve. Second, like many other macroeconomic variables, unemployment is often characterized as $I(1)$ process, so there inevitably arise difficulties in dealing with non-stationary time series. However, previous studies rarely cope with this econometrically serious problem.[1]

Finally, and more importantly from our perspective, they view the national level of unemployment and vacancies as an outcome of a single labor market, neglecting possible interactions among local labor markets. Similar claims have already been made and empirically investigated by Coles and Smith (1996), Burda and Profit (1996), and Burgess and Profit (2001) in estimating the matching function, which is a closely related concept to the Beveridge curve and explained later. Particularly, in their panel data analysis of the regional matching function, Burda and Profit (1996) and Burgess and Profit (2001) take into account the effect of neighboring regions' unemployment on the hiring of a region in question. They find significant "spillover" effects of regional unemployment on hirings in the Czech republic and Britain, respectively.

These considerations make us pursue the following strategy for exploring the implication of regional mobilities of unemployed job seekers on the Beveridge curve. First, based on the regional matching function by Burda and Profit (1996) and Burgess and Profit (2001) in the

[1]Recently it is found that the non-stationary problem could occur even in a panel data setting. See, for example, Baltagi (2001, chap. 11).

equilibrium unemployment approach, we extend the conventional stylized model of Beveridge curve so that regional dependencies could be accounted for. Also we suggest an interesting correspondence between parameters of the Beveridge curve and of the matching function, which seems to be meaningful form the empirical standing point.

Next, in order to estimate regional dependencies in the Beveridge curve, we apply spatial econometric methods. Although they have been mainly developed in regional sciences and geology, e.g. Cliff and Ord (1981), recently such techniques seem to come to be familiar in the field of "mainstream" econometrics (Anselin and Bera 1998).[2]

Holding other relevant variables of our model constant, these techniques allow us to find negative relationships between unemployment in a region and neighboring unemployment as well as between unemployment and vacancies. This finding is consistent with our model of Beveridge curve in the presence of regional mobilities of unemployed job seekers. In addition, we find that some of demographic variables play significant roles for explaining regional differences in unemployment levels.

Another strand is well known to explain a negative relationship between unemployment and vacancies; disequilibrium foundation of labor market analysis (Hansen 1970, among others). However, it seems difficult to take regional mobilities of unemployed job seekers into account based on the disequilibrium foundation. In contrast, it is match easier to incorporate the regional mobilities into the equilibrium unemployment model by using the matching function. So we base our model on this approach.

[2]Now we can find their applications for a wide range of research fields: Growth convergence model by Moreno and Trehan (1997); expenditure patterns of US state governments by Case et al. (1993); international goods prices dependencies by Aten (1996); determinants of transaction price of land in residential use by Bell and Bockstael (2000). Notice that all of them are published in journals not specified to regional or urban economics.

The remainder of this paper is organized as follows. Section 2 proposes the model of Beveridge curve with regional mobilities of unemployed job seekers, and gives a brief description of the econometric methods used in our analysis. Section 3 reviews our data set. Section 4 presents our estimation results and discusses on them. Section 5 concludes the paper.

2 Model and Estimation Methods

2.1 Beveridge curve with regional mobilities of unemployed job seekers

Following previous empirical studies on Beveridge curves, we assume the labor market environment described by the equilibrium unemployment theory, e.g., Pissarides (2000). The only but crucial difference between the approach taken by us and by previous studies is that our model takes regional mobilities of unemployed job seekers into consideration while previous studies do not do so.

Let us assume that the labor market in a country consists of N local labor markets, and each labor market is characterized by costly search activities of job seekers and firms with vacant positions. At every point in time, existing jobs in each region are destroyed at exogenous constant rate s, and some of the unemployed job seekers are associated with some of the unfilled vacancies by means of a given matching function which is explained below. Therefore the net flow of unemployment in region i at time point t, $\dot{U}_i(t)$, is given by the inflow minus outflow, i.e.,

$$\dot{U}_i(t) = sE_i(t) - H_i(t), \tag{1}$$

where $E_i(t)$ and $H_i(t)$ denote employed workers and new hiring in region i at time point t, respectively. We assume that the employed job seekers does not participate in job search activities. Hereafter, we suppress t for visual simplicity.

A matching function positively relates the stock of unemployment and vacancies to new hiring, i.e., unemployment outflow. Of cause, this expression of a hiring mechanism is a great simplification of actually complex search and matching process thereby both parties meet their desirable partners. Following Burda and Profit (1996) and Burgess and Profit (2001), we specify the matching function with regional mobilities of unemployed job seekers as a Cobb-Douglas form;

$$H_i = A_i U_i^{\gamma_1} V_i^{\gamma_2} \tilde{U}_i^{\gamma_3}, \tag{2}$$

where U_i and V_i denote unemployment and vacancies in region i, respectively. $\tilde{U}_i$ captures the unemployed workers of neighboring regions who seek their positions in region i.[3] The presence of this regional effect constitutes a salient feature of our analysis. A_i denotes the degree of matching efficiency in local labor markets, which is analogous to the technological level in a production function. Parameters γ_1, γ_2, and γ_3 denote hiring elasticities with respect to unemployment, vacancies, and unemployment mobilities, respectively, so they are assumed to be positive.

We assume, following Burda and Profit (1996) and Burgess and Profit (2001) again, that mo-

[3] Burda and Profit (1996) and Burgess and Profit (2001) allow regional mobilities of vacancies as well as unemployment. However, we do not so because our data on vacancies already contains registrations of job applications from other regions.

bilities of unemployed job seekers $\tilde{U}_i$ is given by a geometric average of regional unemployment excluding region i,

$$\tilde{U}_i = \prod_{j=1,j\neq i}^{N} U_j^{\omega_{i,j}}, \tag{3}$$

where $\omega_{i,j}$, $i \neq j$ is a positive weight which we will explain later. We further assume that the degree of matching efficiency A_i is given by

$$A_i = \prod_{l=1}^{L} Z_{i,l}^{\phi_l}, \tag{4}$$

where $Z_{i,l}$ denotes possible factors affecting the degree of matching efficiencies in region i. Parameters ϕ_l, $l = 1, ..., L$ may or may not be positive, depending on the effect of a corresponding variable $Z_{i,l}$ on A_i.

Thus, in the steady state of unemployment flow (1), we obtain a fully parameterized relationship among unemployment, vacancies, and regional mobilities of unemployed job seekers in the following logarithmic form;

$$\ln(U_i) = \frac{1}{\gamma_1}\left[\ln(sE_i) - \sum_{l=1}^{L}\phi_l \ln(Z_{i,l})\right] - \frac{\gamma_2}{\gamma_1}\ln(V_i) - \frac{\gamma_3}{\gamma_1}\sum_{j=1,j\neq i}^{N}\omega_{i,j}\ln(U_j) + \varepsilon_i, \tag{5}$$

where ε_i denotes an i.i.d. error term with zero mean and constant variance σ. This is the Beveridge curve in our analysis. As pointed out before, our original point here is that we add the regional mobility term (i.e., the last term except the error term in the right hand side of the above equation) as one of the explanatory variables. If we ignore the effect of regional mobilities of unemployed job seekers, i.e., impose $\gamma_3 = 0$, equation (5) is reduced to a conventional Beveridge curve which illustrates a negative relationship between unemployment and vacancies.[4]

Notice that negative relationships between U_i and $\tilde{U}_i$ and between U_i and V_i in equation (5) stem from an implicit relationship among these variables in the matching function (2), holding output H_i fixed. This relationship holds as long as the matching function is increasing in these three arguments. Thus, we can view the Beveridge curve as an "isoquant" of the corresponding matching function. This property is also pointed out by some authors, e.g., Petrongolo and Pissarides (2001), for the case of conventional Beveridge curves.

Furthermore, equation (5) could make clear an interesting parametric relationship between the Beveridge curve and the matching function. It is obvious that the coefficient of $\ln(sE_i)$ is a reciprocal of the hiring elasticity with respect to unemployment, γ_1, and the coefficients of $\ln(V)$ and $\ln(\tilde{U}_i)$ are the ratios of hiring elasticities with respect to these variables, γ_2 and γ_3, to γ_1. So we can obtain estimates of matching function parameters γ_1, γ_2, and γ_3 by estimating the Beveridge curve. This equivalence is important in the situation where the data of new hiring is not available and so the matching function can not be estimated. The data of E_i seems to be more easily available and reliable than the data of H_i.

Additional variables that are possibly account for mismatch among job seekers and vacant

[4]More conventionally, neglecting regional mobilities of unemployed job seekers and assuming constant returns to scale of the matching function (2), (i.e., $\gamma_3 = 0$ and $\gamma_2 = 1 - \gamma_1$,) the Beveridge curve is given by

$$\ln(U/E) = (1/\gamma_1)(\ln(s) - A) - \{(1-\gamma_1)/\gamma_1)\}\ln(V/E) + \varepsilon.$$

This form is often estimated by a number of authors using time series data. However, we do not invoke the constant returns to scale assumption, since this assumption itself should be statistically tested. Indeed, some previous studies estimating the matching function report that this assumption cannot hold empirically. For example, in the panel cointegration analysis, Kano and Ohta (2002) find that constant returns to scale could not hold in the long-run matching relationship.

jobs can enter the estimation of the Beveridge curve (5) through $Z_{i,l}$'s. Particularly in our cross sectional study, it is interesting to introduce demographic variables into the estimation to assess difference in regional unemployment, because the apparent gap of unemployment levels between urban and rural areas is one of salient features in recent Japanese labor market. So we will try this extended regression at the end of the next section.

2.2 Econometric methods for regional dependencies

Our model of Beveridge curve with regional mobilities of unemployed job seekers, given by equation (5), can be re-written in the following matrix form,

$$y = X\beta + \rho W y + \varepsilon, \quad \varepsilon \sim \text{I.I.D.}(0, \sigma^2 I_N), \tag{6}$$

where y denotes a $N \times 1$ vector of dependent variable, and X denotes a $N \times K$ matrix of explanatory variables. A $N \times 1$ vector Wy denotes the regional effect, explained below. β and ρ denote a $K \times 1$ parameter vector and a scaler parameter to be estimated, respectively. This type of expression is called a *spatial lagged dependent variable model*, developed by Ord (1975), Cliff and Ord (1981), and Anselin (1988), among others. Notice that in our case, y corresponds to $\ln(U)$, and X contains a constant term and two variables $[\ln(V), \ln(E)]$, including the log of separation rate s into the constant term.[5]

W in the expression (6) denotes a $N \times N$ spatial weight matrix whose typical element is given by a parameter $\omega_{i,j}$. The element $\omega_{i,j}$ is determined by the distance between region i and j in

[5]Ministry of Health, Labour and Welfare reports the job separation rate. However, this statistic is not appropriate because it contains transfers within a firm.

the following way, before the estimation. So, notice that only the parameter ρ is estimated in the term ρWy. We specify W so that its i-j element $\omega_{i,j}$ is given by

$$\omega_{i,j} = \begin{cases} 0 & \text{if} \quad i = j \\ 1/d_{i,j}^2 & \text{if} \quad i \neq j, \end{cases} \tag{7}$$

where $d_{i,j}$ denotes the distance between region i and j. Further, these elements are row-standardized as follows;

$$\omega_{i,j}^* = \omega_{i,j} / \sum_{j=1}^{N} \omega_{i,j},$$

so that the regional effect in region i could be regarded as the weighted average of the dependent variable other than i.

This form of spatial weights obviously presumes that spatial dependence should be smoothly decay as the distance between individual units in question goes to large. This form is preferably used in the applications of spatial data analysis. In our model, the economic implication of this specification is straightforward: Unemployed job seekers will search their occupations more intensively in their home towns than in their neighboring areas, because cost of search is increasing in the distance between their home towns and targeted towns.[6]

It is not adequate to use OLS for estimating model (6) because of the endogeneity of the spatial lagged dependent variable Wy. However, Ord (1975) and Anselin (1988) show that this endogeneity problem could be solved by making use of maximum likelihood (ML) or instrumen-

[6]See Burda and Profit (1996) for the theoretical foundation of this notion.

tal variables (IV) methods, respectively. We can obtain the consistent estimators of $\{\beta,\rho\}$ by using these methods. Notice that for the ML estimation, the normality of the error term ε must be additionally assumed.

As a family of spatially dependent econometric models, the following is often estimated by existing applied literature;

$$\begin{aligned} y &= X\beta + e, \\ e &= \lambda We + \varepsilon. \end{aligned} \tag{8}$$

The above is called a *spatial autocorrelation model.* For our case of Beveridge curve, this expression provides a framework for investigating the regional propagation of shocks hitting unobservable part of matching technologies, A_i in (5). This expression also illustrates unobservable "similarity" of labor market conditions among neighboring regions.

The specification (8) involves a similar problem to the spatial lagged dependent model, and the parameters $\{\beta,\lambda\}$ can be estimated consistently by Ord's (1975) ML with an assumption of normally distributed errors. In addition, more recently, Kelejian and Prucha (1999) propose a generalized methods of moments (GMM) estimator for the spatial autocorrelation model. They show that their estimator is more efficient and computationally less burdensome than ML. However, we do ML in addition to GMM so that we can check the robustness of our findings with respect to regression methods.

Furthermore, although few applications have ever been found, the following is also possible;

$$\begin{aligned} y &= X\beta + \rho W y + e, \\ e &= \lambda W e + \varepsilon, \end{aligned} \tag{9}$$

which is a combination of the spatial lagged dependent variable model (6) and spatial autocorrelation model (8). The parameters, $\{\beta, \rho, \lambda\}$, of this most general form in the class of regional dependent models can be estimated consistently by Kelejian and Prucha's (1998) GMM estimator.[7]

3 Data description

`Figure 1 here`

We use 47 Japanese prefectural data on unemployment U, vacancies V, and employment E in 2000, so the number of observation N is equal to 47. The only reason for choosing the data set in 2000 is that it is the latest available one when our research started. The data on U and E are drawn from *Population Census 2000*, while V are from *Labour Market Annual 2000*. In order to construct the spatial weight matrix W, we use great circle distances among the seats of prefectural offices. This information comes from *Chronological Scientific Tables 1997*. See Appendix for more on the data.

Before proceeding, we must assess the reliability of our data on vacancies, V, since this

[7] Although Kelejian and Prucha (1998, 1999) originally named their estimators as a generalized two stage least squares estimator, here we call them as GMM in that they utilize over-identifying restrictions on moments.

statistic is based on the recorded figures of registrations at the prefectural unemployment referral offices. It is often suggested that the number of jobs registered at the offices could represent only a fraction of total vacancies in the Japanese labor market as a whole, and these occupational types might be biased toward low-skilled, low-wage jobs.[8] Nevertheless, we use such data because there exist no alternative data in Japan. In interpreting the following reports on our empirical results, therefore, it should be kept in mind that our V is a proxy variable for the true level of unfilled vacancies in each prefecture.

Figure 1 depicts a scatter plot of the prefectural unemployment rate (U/E) and vacancy rate (V/E) in 2000, in the same manner as previous time series studies. At first glance, we can observe a negative relationship among these two variables similar to its time series version. This figure also illustrates a great diversity of labor market conditions among prefectures in Japan. The unemployment rate widely distributed from 2.5% to 8% and the vacancy rate from 1% to 2.5%, respectively. An exceptionally high unemployment rate is found to be approximately 10% in Figure 1. This rate is that of *Okinawa* prefecture, the southern-west edge of the Japanese archipelago. We checked the effect of the exclusion of this outlier on the analysis, and confirmed that our main findings are unchanged by its presence or absence.

[8]For a detailed discussion, see Kano and Ohta (2002).

4 Estimation Results

4.1 Basic specifications

We estimate the following four alternative specifications, i.e.,

$$y = X\beta + \varepsilon, \tag{A}$$

$$y = X\beta + \rho Wy + \varepsilon, \tag{B}$$

$$y = X\beta + e, \quad e = \lambda We + \varepsilon, \tag{C}$$

$$y = X\beta + \rho Wy + e, \quad e = \lambda We + \varepsilon, \tag{D}$$

where the first is a Beveridge curve without regional mobilities of unemployed job seekers and it is used as a benchmark model, and the rest three are a reproduction of (6), (8), and (9) in Section 2. In all the cases the error term ε is assumed to be zero-mean, homoscedastic, and serially uncorrelated. Notice that the specification corresponding to our model of the Beveridge curve (5) is only (B). Nevertheless, we report the estimation results of the above four specifications for the purpose of demonstrating the robustness of our findings.

Table 1 here

Using the residual of OLS on (A), first we test the normality and homoscedasticity of the error term by Jarque-Bera and Breusch-Pagan tests, respectively. As shown in Table 1, both assumptions are not rejected. So it seems to be reasonable to employ the ML estimation and related test statistics based on the normally of the error term ε.

Table 2 here

Next we perform several tests for spatial dependencies, i.e., a normalized version of Moran's I test, and the set of Lagrange multiplier tests, LM_ρ, LM_λ, $LM_{\rho,\lambda}$, LM_ρ^*, and LM_λ^*.[9] Table 2 shows their results coupled with corresponding null hypotheses. The results of LM_ρ and LM_ρ^* suggest the presence of a significant spatial lagged dependent effect, ρ. In addition, in the presence of non-zero ρ, $H_0 : \lambda = 0$ is rejected by LM_λ^*. The rejections of $\rho = 0$ and $\lambda = 0$ are consistent with the result of $LM_{\rho,\lambda}$ test. These test results imply that all of the specifications (B), (C), and (D) should be investigated.

Table 3 here

Table 3 shows estimation results of specification (A) and (B), i.e., the Beveridge curve with and without regional mobilities of unemployed job seekers. For the specification (B), both ML and IV results are reported.[10] As shown in this table, all the estimates are statistically significant and exhibit theoretically expected signs. In particular, notice the significantly negative coefficient of the regional effect as well as of vacancies. This result is strongly in accordance with our aforementioned "isoquant" view of the Beveridge curve.

Estimated coefficients in (B) exhibit marked difference from those in (A). This difference is apparently due to the omission of regional dependencies existing in the true data generating

[9]See Anselin and Bera (1998) for their formal definitions and statistical properties.

[10]Technical notes are as follows. The ML estimators are obtained by numerically maximizing the likelihood function given by Ord (1975), via the Newton-Raphson algorithm. Reported asymptotic standard errors are based on numerical covariance matrix. For the analytical counterpart, see Anselin and Bera (1998). As for IV estimation, Kelejian and Prucha (1998) suggest that the weight matrix W times the subset of exogenous variables X, say $\tilde{X}$, should be used for the instruments. So we choose variables $[\ln(U), \ln(E)]$ as $\tilde{X}$. GAUSS code used here is available from the author upon request.

process. It is well known that ignoring a regional dependence term could cause omitted variables bias in estimates. (Anselin and Bera 1998.) Difference in the estimate of ρ by ML and by IV might be explained by difference in their finite sample performances and/or inappropriateness of normality assumption in ML estimation, though Jarque-Bera test supports the normality of the error term ε of our estimation equation.

In the study of estimating the matching function, its returns to scale is of special interest, since constant returns is often assumed in theory, and further increasing returns is consistent with the existence of multiple, Pareto-rankable equilibria. As illustrated in Section 2, there is a one-to-one relationship between the parameters of the Beveridge curve (5) and those of the matching function (2). So it is interesting to test the constant returns to scale of the matching function utilizing the estimates of the Beveridge curve. We can show easily that testing the following hypothesis

$$H_0 : \gamma_1 + \gamma_2 + \gamma_3 = 1, \qquad H_1 : \gamma_1 + \gamma_2 + \gamma_3 \neq 1,$$

namely, constant returns to scale of the matching function with regional dependencies in equation (2), is equivalent to testing

$$H_0 : \beta_E + \beta_V + \beta_{\tilde{U}} = 1, \qquad H_1 : \beta_E + \beta_V + \beta_{\tilde{U}} \neq 1,$$

where β_E, β_V, and $\beta_{\tilde{U}}$ denote coefficients of $\ln(E)$, $\ln(V)$, and $\ln(\tilde{U})$, respectively. Note that $\tilde{U}$ is given by equation (3). The p-values of corresponding two-sided Wald tests are reported in

Table 3. These results show that the constant returns assumption on the matching function (2) is accepted in both ML and IV. So the regional matching function in this period seems to exhibit constant returns to scale, as long as regional effects are taken into consideration in the estimation.

Table 4 here

Table 4 shows estimation results of specifications (C) and (D), i.e., the Beveridge curve with regional dependencies among error terms, and with mixture regional effects of (B) and (C), respectively. For the specification (C), both ML and GMM results are reported, while for the specification (D), GMM result is.[11]

In specification (C), all the estimates both by ML and GMM shows the expected signs. They are all significant by GMM, while they are all significant by ML except that $\hat{\lambda}$ has a larger variance than by GMM and so that it becomes insignificant. This different result is consistent with Kelejian and Prucha's (1999) study on the GMM approach for the estimation of spatial autocorrelation model, where they shows that their GMM estimator is more efficient than ML. So we should take GMM results as more reliable ones.

Positive $\hat{\lambda}$ means that positive shocks hitting the matching efficiencies in a region, such as changes in unemployment policies and workers' search intensities, could propagate to neighboring areas and give rise to a reduction of these unemployment levels. This effect might be interpreted as unobservable "copy cat" behaviors and resulting similarities of neighboring regional

[11] A technical note on ML exactly follows the previous footnote 10 on the ML of spatial lagged dependent model. Kelejian and Prucha's (1999) GMM procedure for (C) consists of the following three steps. First step; obtain OLS on (A) and corresponding residuals. Second step; construct sample moment conditions form the OLS residuals, and perform GMM. Third step; do the final OLS using appropriately transformed variables based on $\hat{\lambda}$, which is obtained at the second step. The estimation procedure for (D) follows these three steps exactly, replacing "OLS on (A)" with "IV on (B)". In the second step, we obtain GMM estimates using Gauss-Newton algorithm. Notice that these steps correspond to a conventional feasible GLS procedure. See Kelejian and Prucha (1998, 1999) for details.

units *à la* Case et al. (1993). The following might be one of the possible copy cat mechanisms for matching efficiencies among regions; if a local government strengthens job training policies for the unemployed in its region, then the neighboring regions' local governments cannot help imitating that policy due to the political pressure from their unemployed residents.

In the mixture specification (D), all estimates show theoretically expected signs and statistically significant. The obtained significances of $\hat{\rho}$ and $\hat{\lambda}$ are also consistent with the aforementioned $LM_{\rho,\lambda}$ test result. Thus, our "isoquant" view of the Beveridge curve was statistically verified by the most general form in the class of regionally dependent models.

4.2 Can demographic characteristics account for difference in regional unemployment?

As mentioned in the earlier section, it is quite legitimate that variables possibly affecting the level of matching efficiency are entered in the regression of the Beveridge curve. We re-estimate the Beveridge curve (5), adding logarithms of the following five variables to the vector of explanatory variables through $Z_{i,t}$'s in that curve; real wage (*WAGE*), unemployment benefit (*BENEFIT*), population density (*POP*), the ratio of older people (more than 60 years old) to the total (*OLD*), the ratio of higher-educated people (more than bachelor degree) to the total (*EDU*).[12]

Table 5 here

The estimation results are listed in Table 5. We report only specifications (A) and (B), since LM_λ and LM_λ^* cannot reject the null hypothesis $H_0 : \lambda = 0$ when adding additional explanatory

[12]The data sources are shown in Appendix A. We are forced to use data on *EDU* in 1990, because that data is the newest available one.

variables.[13] The result of this less parsimonious regression maintains our "isoquant" view of the Beveridge curve judging form the signs and sigificances of the estimates, though these estimates themselves differ greatly from previous ones. The estimated coefficient of $\ln(V)$ in specification (A) seems to be insignificant, but note that (A) should be considered as a mis-specified model in the presence of a significant regional effect.

Let us review the effects of additional variables on regional unemployment in turn. Table 5 shows that a higher wage (*WAGE*) seems to reduce regional unemployment. This result might be due to the fact that higher wage raises unemployed worker's search intensity. However, this result cannot be expected *a priori*, because higher wage also means higher labor cost, resulting in a reduction in job vacancies that might increase unemployment.

An interesting result is a positive and significant effect of population density (*POP*) on unemployment. This finding is not consistent with Coles and Smith's (1996) estimation result of regional matching function. They argue that the matching will be better in a more population-dense region, because the distance between job seekers and firms is smaller and they can easily find their desirable trading partners in such a region. However, in our case, both parties seem to have more difficulties in finding partners in more population-dense regions. This result may be due to a wider diversity of workers' skills and firms' skill requirements in more dense, urbanized regions, which makes the matching between the unemployed and the vacancies more difficult.

Well-educated labor force (*EDU*) seems to be helpful for successful matching, because firms in a region with a plenty of highly educated residents hardly draw an inappropriate labor force from the pool of unemployment in their region. However, this finding is not so robust in that the

[13]Full test results are available upon request.

estimated coefficient of *EDU* by ML is not significant. The effects of *BENEFIT* and *OLD* on regional unemployment level are statistically rejected in all the three cases.

Thus, through this section, we have demonstrated that our findings discussed in Section 2 are robust against a wide variety of specifications. Particularly, the significant effect of regional unemployment mobilities might strengthen the empirical validity of the equilibrium unemployment theory which uses the matching function; in an alternative theoretical background of the Beveridge curve, e.g., the disequilibrium approach initiated by Hansen (1970), it is difficult to take regional effects empirically into account.

5 Concluding Remarks

In this paper, we estimate the Beveridge curve taking regional mobilities of unemployed job seekers into account. The Japanese 47 prefectural data in 2000 is used. We find negative relationships between unemployment in a region and its neighboring unemployment as well as between unemployment and vacancies. This finding is consistent with our model of Beveridge curve with regional mobilities of unemployed job seekers. In addition, some of demographic variables play significant roles for explaining regional differences in unemployment levels.

Our regional approach for investigating the Beveridge curve might be applicable to the case of multi-country data, where labor forces can migrate from their home countries to the neighbors, such as EU regions. This application is interesting in that our view of the Beveridge curve is examined in an environment where heterogeneity among regional units will be stronger than that in one country cases.

A remaining but considerable question is whether regional mobilities of unemployed job seekers would vary over time or not in the Beveridge curve; in other words, the cyclical behavior of cross sectional dependencies in the curve, in contrast to Burgess and Profit (2001) in the matching function. In order to do so, we will have to use a panel data structure. However, unfortunately, we were unable to find appropriate econometric techniques which could explicitly inference the time series variation of cross sectional dependencies.

Appendix A: Data Source

1. U_i, E_i, POP_i and OLD_i: *Population Census (Kokusei Chōsa) 2000*, Statistics Bureau, Ministry of Public Management, Home Affairs, Posts and Telecommunications.

2. V_i: *Labour Market Annual (Rodō Shijyō Nenpō) 2000*, Employment Security Bureau, Ministry of Health, Labour and Welfare.

3. $WAGE_i$: *Basic Survey on Wage Structure (Chingin Kōzō Kihon Chōsa) 2000*, Employment Security Bureau, Ministry of Health, Labour and Welfare.

4. $BENEFIT_i$: *Report on Employment Insurance Services (Koyō Hoken Chyōsa Hōkoku) 2000*, Employment Security Bureau, Ministry of Health, Labour and Welfare.

5. EDU_i: *Population Census (Kokusei Chōsa) 1990*, Statistics Bureau, Ministry of Public Management, Home Affairs, Posts and Telecommunications.

6. $d_{i,j}$: *Chronological Scientific Tables (Rika Nenpyō) 1997*, National Astronomical Observatory (in CD-ROM).

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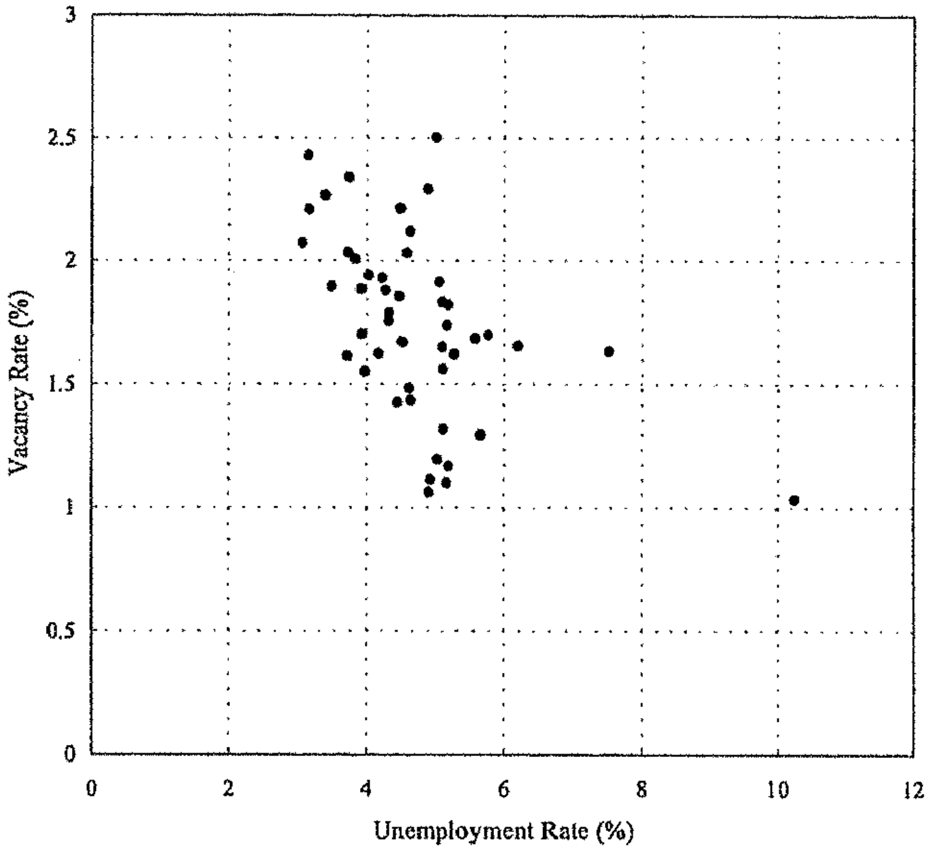
Figure 1: U-V plot of Japanese 47 prefectures in 2000



Note: Unemployment rate and vacancy rate are defined by U/E and V/E, respectively.

Table 1: Preliminary test results

Statistic	Null hypothesis	Value	(p-value)
Jarque-Bera	$H_0 : E(\varepsilon^3) = E(\varepsilon^4) = 0$	0.834	(0.659)
Breusch-Pagan	$H_0 : \sigma_i^2 = \sigma^2 \; \forall \, i$	3.113	(0.375)

Note: The sample size $N = 47$. All statistics are based on the OLS residual, reported in Table 3.

Table 2: Tests for spatial dependencies

Statistic	Null hypothesis	Value	(p-value)
Moran's I	$H_0 : \lambda = 0$	52.309	(0.000)
LM_ρ	$H_0 : \rho = 0$	7.901	(0.005)
LM_λ	$H_0 : \lambda = 0$	1.879	(0.170)
$LM_{\rho,\lambda}$	$H_0 : \rho = \lambda = 0$	12.812	(0.002)
LM_ρ^*	$H_0 : \rho = 0, \lambda \neq 0$	10.933	(0.001)
LM_λ^*	$H_0 : \lambda = 0, \rho \neq 0$	4.911	(0.027)

Note: The sample size $N = 47$. All statistics are based on the OLS residual, reported in Table 3.

Table 3: Estimation results (1)

	Dependent variable: $\ln(U)$		
Model	(A)	(B)	(B)
Estimation method	OLS	ML	IV
Constant	-5.595^{**}	-4.713^{**}	-3.471^{**}
	(0.634)	(0.818)	(0.926)
$\ln(V)$	-0.503^{**}	-0.687^{**}	-0.698^{**}
	(0.123)	(0.106)	(0.125)
$\ln(E)$	1.537^{**}	1.777^{**}	1.792^{**}
	(0.120)	(0.116)	(0.132)
$\hat{\rho}$	-	-0.222^{**}	-0.346^{**}
	-	(0.080)	(0.089)
$H_0 : \gamma_1 + \gamma_2 + \gamma_3 = 1$	-	0.045^{a}	0.003^{a}
Adjusted R^2	0.950	-	0.955
Log-likelihood	-	5203.205	-

Note: The sample size $N = 47$. Values in parentheses denote (asymptotic) standard errors. Asterisk (*) and double asterisk (**) denote that the estimate is significant at 5% and 1% level, respectively.

a: The p-value is shown.

Table 4: Estimation results (2)

	Dependent variable: ln(U)		
Model	(C)	(C)	(D)
Estimation method	ML	GMM	GMM
Constant	−6.220**	−6.074**	−2.075
	(0.862)	(0.731)	(1.784)
ln(V)	−0.453**	−0.458**	−0.642**
	(0.123)	(0.126)	(0.150)
ln(E)	1.549**	1.541**	1.709**
	(0.120)	(0.130)	(0.152)
$\hat{\rho}$	-	-	−0.420**
	-	-	(0.154)
$\hat{\lambda}$	0.543	0.428**	0.560**
	(0.506)	(0.159)	(0.136)
Adjusted R^2	-	0.948	0.942
Log-likelihood	5037.516	-	-

Note: The sample size $N = 47$. Values in parentheses denote (asymptotic) standard errors. Asterisk (*) and double asterisk (**) denote that the estimate is significant at 5% and 1% level, respectively.

Table 5: Estimation results (3)

	Dependent variable: ln(U)		
Model	(A)	(B)	(B)
Estimation method	OLS	ML	IV
Constant	3.773	0.923	4.524
	(7.094)	(9.682)	(7.588)
ln(V)	−0.245	−0.349*	−0.355*
	(0.159)	(0.170)	(0.165)
ln(E)	1.240**	1.373**	1.383**
	(0.178)	(0.184)	(0.187)
ln($WAGE$)	−1.249*	−1.225*	−1.236*
	(0.593)	(0.513)	(0.593)
ln($BENEFIT$)	0.357	0.605	0.406
	(0.639)	(0.588)	(0.661)
ln(POP)	0.462**	0.443**	0.422**
	(0.156)	(0.174)	(0.156)
ln(OLD)	−0.194	−0.171	−0.299
	(0.378)	(0.304)	(0.388)
ln(EDU)	−0.154*	−0.127	−0.113*
	(0.066)	(0.182)	(0.067)
$\hat{\rho}$	-	−0.167**	−0.180**
	-	(0.061)	(0.069)
Adjusted R^2	0.964	-	0.969
Log-likelihood	-	5640.652	-

Note: The sample size $N = 47$. Values in parentheses denote (asymptotic) standard errors. Asterisk (*) and double asterisk (**) denote that the estimate is significant at 5% and 1% level, respectively.