Analysis of Factor Elasticity and Total Factor Productivity in Prefectural Economies in Japan

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Abstract—**General forms of models for the cross-prefectural production function in Japan are constructed. In addition, a set of procedures for parameter estimation based on Bayesian linear modeling and the Bayesian model average approach are developed. We also show the results of parameter estimation for analyzing the structure and performance of prefectural economies in Japan. Finally, based on the estimated results, similarities in prefectural economies in Japan are analyzed using a multi-dimensional scaling method.**

Index Terms—**Cross-prefectural production function models, Japanese regional economy, Bayesian linear models, Bayesian model averaging.**

I. Introduction

Conditions for the economic growth in a country vary across regions and change over time. For researchers and policy makers, analyzing the factors' influence on performance of economic growth is undoubtedly one of the more important issues in empirical studies.

In an empirical study of macroeconomics, there are generally two approaches for analyzing the sources of economic growth: one is a growth accounting approach and the other a regression approach. As for growth accounting, the most influential study is [1], while recent major research includes [2]-[4]. This approach supposes that the marginal productivity of each factor of production is equal to the cost of the relevant factor. Then the growth rate of total factor productivity (TFP) is obtained by deducting the contribution of each factor of production from the growth rate of the output. In other words, the conventional growth accounting approach regards the TFP growth rate as a residual. However, such equality between marginal productivity and the factor cost is not always satisfied in practice.

On the other hand, the regression approach examines the determinants of economic growth by estimating parameters for the production function or the growth regression model. This approach is applied in [5] - [7], for example. However, because it often happens that there is a high correlation among economic variables, the model is subject to multicollinearity and thus, it is difficult to obtain stable estimates. Additionally, it is usually assumed that the regression coefficients are constants over all regions. In practice, however, such parameters represent regional characteristics and the values may vary from region to region. Furthermore, a common problem in both traditional approaches is that TFP trends cannot be estimated very well.

In [8], we constructed a model for the cross-prefectural production function (CPPF) in Japan, and introduced a set of procedures for parameter estimation using Bayesian modeling methods. Features of the analysis in our previous paper can be summarized as follows. (1) The model has parameters that vary from region to region so that regional characteristics of economic growth can be expressed by their values. (2) The TFP trend can be successfully estimated by applying Bayesian analysis using a smoothness priors approach. (3) The explanatory variables include human capital, which is usually not considered in the literature on regional economies in Japan. [1] The basic concept and procedure for parameter estimation are expanded in [9] and [10]. However, a reflection on the modeling for CPPF is that some assumptions on the modeling for TFP are too hard. In this paper, we introduce the CPPF model in a more general form, and develop a procedure for parameter estimation based on Bayesian linear modeling (BLM) and the Bayesian model average (BMA) approach. Then, we present a set of results for analyzing similarity in the structure and performance of prefectural economies in Japan.

The rest of this paper is organized as follows. We construct the models for CPPF in Section 2, and introduce the set of procedures for parameter estimation in Section 3. Then, in Section 4, the main results are given for regional analysis of the Japanese economy. Finally, we present our conclusions in Section 5.

II. The Model

Consider prefecture i 's economy, which uses the physical capital in the private sector (hereafter referred to as private capital) $K_i(t)$, the physical capital in the public sector (hereafter referred to as public capital) $G_i(t)$, and labor $L_i(t)$ to produce output measured by the prefectural production $Q_i(t)$.

The production function for any prefecture is assumed to take a Cobb-Douglas form, which has the properties of the well-behaved production function in the neoclassical growth model. [2] Specifically, for each prefecture this is given by

$$Q_i(t) = A_i(t) K_i(t)^{\alpha_i} G_i(t)^{\beta_i} L_i(t)^{\gamma_i} \quad (i = 1, 2, \ldots, m), \qquad (1)$$

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[1] One of the exceptions is [6].
[2] See [11] for details of the neoclassical growth theory.

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where m is the total number of prefectures, $A_i(t)$ is the TFP, which is regarded as a time varying parameter, and α_i, β_i, and γ_i represent the elasticity of output with respect to each of the input factors, namely, private capital, public capital, and labor, respectively. Based on the economic meaning, we assume that

$$\alpha_i \ge 0, \quad \beta_i \ge 0, \quad \gamma_i \ge 0. \tag{2}$$

Under logarithmic transformation, the model in (1) is expressed as follows:

$$y_i(t) = a_i(t) + \alpha_i x_{1i}(t) + \beta_i x_{2i}(t) + \gamma_i x_{3i}(t), \tag{3}$$

where $y_i(t) = \ln Q_i(t)$, $a_i(t) = \ln A_i(t)$, $x_{1i}(t) = \ln K_i(t)$, $x_{2i}(t) = \ln G_i(t)$, and $x_{3i}(t) = \ln L_i(t)$. In (3), the parameters α_i, β_i, and γ_i represent the structure of the factors' influence on the economic growth of prefecture i, so they are called the structural parameters. The constrained conditions in (2) are called non-negative conditions for the structural parameters.

To simplify the model, in [8] it was assumed that $A_i(t) = C_i A(t)$ and $A(0) = 1$ with $A(t)$ and C_i being constants over time t and the prefectural number i, respectively. That is, it was assumed that

$$a_i(t) = \ln C_i + \ln A(t),$$

which implies that $a_i(t)$ and $a_j(t)$ are parallel to each other for $i \ne j$. We discontinue the above assumption owing to its lack of reality, and thus, the CPPF model can be constructed in a more general form.

When the model is fitted to a set of practical data, an error term has to be taken into account, i.e., for $t = 1,2,\ldots,n$, the model in (3) can be rewritten as

$$\begin{aligned} y_i(t) = a_i(t) + \alpha_i x_{1i}(t) + \beta_i x_{2i}(t) \\ + \gamma_i x_{3i}(t) + \varepsilon_i(t). \end{aligned} \tag{4}$$

Here, $\varepsilon_i(t)$ denotes the error term, which is regarded as a random variable with $\varepsilon_i(t) \sim \mathrm{N}(0, \sigma_i^2)$. We also assume that $\varepsilon_i(t_1)$ and $\varepsilon_j(t_2)$ are independent of each other for $i \ne j$ and $t_1 \ne t_2$.

In the model in (4) many parameters need to be estimated. These include the time varying parameters $a_i(t)$ $(i = 1,2,\ldots,m;\ t = 1,2,\ldots,n)$ and the structural parameters α_i, β_i, and γ_i $(i = 1,2,\ldots,m)$, excluding the variances σ_i^2 of the error term.

III. Procedures for Parameter Estimation

To obtain robust and meaningful estimates, in this section we develop a set of procedures for parameter estimation. It should be noted that the key problem in parameter estimation is how to estimate the structural parameters separately from the time varying ones.

Consider here the process of parameter estimation for the i-th prefecture. As a kind of prior information, the similarity in the structural parameters and the time varying parameters crossing the prefectures is taken into account. Concretely, for a prefecture with number $j \ne i$, we begin the process of parameter estimation based on the temporary assumption that

$$\alpha_i = \alpha_j = \alpha_{ij}, \quad \beta_i = \beta_j = \beta_{ij},$$
$$\gamma_i = \gamma_j = \gamma_{ij}, \quad a_i(t) - a_j(t) = \mu_{ij}$$

with μ_{ij} being a constant over time. Thus, from the model in (4) we have

$$u_{ij}(t) = \mu_{ij} + \alpha_{ij} z_{1ij} + \beta_{ij} z_{2ij} + \gamma_{ij} z_{3ij} + e_{ij}(t), \tag{5}$$

where

$$u_{ij} = y_i(t) - y_j(t), \quad z_{1ij} = x_{1i}(t) - x_{1j}(t),$$
$$z_{2ij} = x_{2i}(t) - x_{2j}(t), \quad z_{3ij} = x_{3i}(t) - x_{3j}(t),$$
$$e_{ij} = e_i(t) - e_j(t).$$

The model in (5) is a linear regression model, and thus, the parameters can be estimated easily by the least squares method. However, it is difficult to obtain robust and meaningful estimates owing to very high multicollinearities between the explanatory variables. To ameliorate this difficulty, we apply a combination of $\alpha_{ij} = 0$, $\beta_{ij} = 0$, and $\gamma_{ij} = 0$ to construct three simplified models as follows:

$$u_{ij}(t) = \mu_{ij} + \alpha_{ij} z_{1ij} + e_{1ij}(t), \ e_{1ij} \sim \mathrm{N}(0, \lambda_{1ij}^2), \tag{6}$$
$$u_{ij}(t) = \mu_{ij} + \beta_{ij} z_{2ij} + e_{2ij}(t), \ e_{2ij} \sim \mathrm{N}(0, \lambda_{2ij}^2), \tag{7}$$
$$u_{ij}(t) = \mu_{ij} + \gamma_{ij} z_{3ij} + e_{3ij}(t), \ e_{2ij} \sim \mathrm{N}(0, \lambda_{3ij}^2), \tag{8}$$

Thus, we can estimate the parameters for each independent model by using the least squares method subject to the non-negative conditions in (2).

Each model in (6)-(8) corresponds to a kind of estimate of $a_i(t)$. Let, $\tilde{\alpha}_{ij}$, $\tilde{\beta}_{ij}$, and $\tilde{\gamma}_{ij}$ denote the estimates of α_{ij}, β_{ij}, and γ_{ij}, respectively. Then, we consider the corresponding models as follows:

$$y_i(t) = a_i(t) + \tilde{\alpha}_{ij} x_{1i}(t) + \eta_{1ij}(t), \ \eta_{1ij} \sim \mathrm{N}(0, \tau_i^2), \tag{9}$$

$$y_i(t) = a_i(t) + \tilde{\beta}_{ij} x_{2i}(t) + \eta_{2ij}(t), \ \eta_{2ij} \sim \mathrm{N}(0, \tau_i^2), \tag{10}$$

$$y_i(t) = a_i(t) + \tilde{\gamma}_{ij} x_{3i}(t) + \eta_{3ij}(t), \ \eta_{3ij} \sim \mathrm{N}(0, \tau_i^2). \tag{11}$$

Based on the assumption that a change in TFP has continuity and smoothness, the smoothness priors approach introduced in [12] is applied to set up a prior distribution for $a_i(t)$ $(t = 1, 2, \ldots, n)$ Concretely, we use the following second order stochastic difference equation:

$$\begin{aligned} &a_i(t) - 2a_i(t-1) + a_i(t-2) = v_i(t), \\ &v_i(t) \sim N(0, \tau_i^2 / d_i^2)\ (t = 1, 2, \ldots, n). \end{aligned} \tag{12}$$

The following assumptions are required: (1) $v_i(t_1)$ and $v_i(t_2)$ are independent of each other for $t_1 \neq t_2$. (2) $\eta_{kij}(t)$ and $v_i(t)$ are independent of each other for any $k, j \neq i$, and t.

Thus, a set of Bayesian linear models for $a_i(t)$ $(t = 1, 2, \ldots, n)$ can be constructed based on (9) and (12). Similarly, the set of models in (10) and (12), and that in (11) and (12) are also considered. So, we can obtain three sets of estimates for $a_i(t)$ $(t = 1, 2, \ldots, n)$ based on every model set using the BLM method (see [13]). Below we only show a summary of the computation for the parameter estimation based on the model set in (9) and (12) using the BLM method. The computations for the other model sets are similar, and are omitted. Note that τ_i^2, $d_i > 0$, $a_i(-1)$, and $a_i(0)$ can be regarded as hyperparameters in this model set.

First, for given values of τ_i^2 and d_i we define $2n \times n$ matrix W, $2n \times (n+2)$ matrix V, and $2n \times 1$ vector g as

$$W = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ 0 & 1 & \ddots & & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & 1 \\ d_i & 0 & \cdots & \cdots & 0 \\ -2d_i & d_i & \ddots & & \vdots \\ d_i & -2d_i & d_i & \ddots & \vdots \\ & \ddots & \ddots & \ddots & 0 \\ 0 & & d_i & -2d_i & d_i \end{bmatrix},$$

$$V = \begin{bmatrix} O_1 & \\ H & W \\ O_2 & \end{bmatrix},$$

$$g = \begin{bmatrix} u_{ij}(1) - \tilde{\alpha}_{ij} z_{1ij}(1) \\ u_{ij}(2) - \tilde{\alpha}_{ij} z_{1ij}(2) \\ \vdots \\ \vdots \\ u_{ij}(n) - \tilde{\alpha}_{ij} z_{1ij}(n) \\ 0 \\ \vdots \\ \vdots \\ \vdots \\ 0 \end{bmatrix},$$

with $H = \begin{bmatrix} d_i & -2d_i \\ 0 & d_i \end{bmatrix}$, and O_1 and O_2 being $n \times 2$ and $(n-2) \times 2$ zero matrices, respectively. Furthermore, we set $\hat{\theta} = (b_i^T, a_i^T)^T$ based on the definitions $b_i = (a_i(-1), a_i(0))^T$, $a_i = (a_i(1), a_i(2), \ldots, a_i(n))^T$. Thus, the estimate for θ_i and the corresponding total square error are given by

$$\begin{aligned} \theta_{1ij} &= (\hat{\mathbf{b}}_{1ij}^T, \hat{\mathbf{a}}_{1ij}^T)^T = (V^T V)^{-1} V^T g, \\ S_{1ij}^2 &= (g - V\hat{\theta}_{1ij})^T (g - V\hat{\theta}_{1ij}). \end{aligned}$$

Thus, we can obtain the estimate $\hat{a}_{1ij}$ of a_i from $\hat{\theta}_{1ij}$. Then, the log-likelihood is calculated by (see [12])

$$\begin{aligned} l_{1ij}(\tau_i^2, d_i) = \frac{1}{2}\left(n \ln 2\pi\tau_i^2 + \frac{S_{1ij}^2}{\tau_i^2} \right) - \frac{1}{2} \ln \left| W^T W \right| \\ + \frac{n}{2} \ln d_i^2. \end{aligned}$$

Moreover, we can apply similar computations for the other model sets. Let $\hat{a}_{2ij}$ and $l_{2ij}(\tau_i^2, d_i)$ denote the estimate of a_i and the corresponding log-likelihood, respectively, for the model set in (10) and (12), and $\hat{a}_{3ij}$ and $l_{3ij}(\tau_i^2, d_i)$ denote the same for the model set in (11) and (12). So the average of likelihood for τ_i^2 and d_i is given by

$$F_i(\tau_i^2, d_i) = \frac{1}{3(m-1)} \sum_{j \neq i} \sum_{k=1}^{3} \exp(l_{kij}(\tau_i^2, d_i)).$$

Thus, the estimates $\hat{\tau}_i^2$ and $\hat{d}_i$ for τ_i^2 and d_i, respectively, can be obtained by maximizing $F_i(\tau_i^2, d_i)$ or equivalently maximizing $\ln F_i(\tau_i^2, d_i)$ numerically.

Based on the above results, we can obtain the estimates for the structural parameters and the time varying parameters using the BMA approach (see [14]). Concretely, here the BMA approach includes the following two steps. In the first step, individual estimates for parameters are obtained by averaging over the three model sets for a given j. That is, the individual estimates for the parameters α_i, β_i, γ_i, and a_i are respectively given by

$$\begin{aligned} &\hat{\alpha}_{ij} = w_{1ij}^* \tilde{\alpha}_{ij}, \ \hat{\beta}_{ij} = w_{2ij}^* \tilde{\beta}_{ij}, \\ &\hat{\gamma}_{ij} = w_{3ij}^* \tilde{\gamma}_{ij}, \ \hat{a}_{ij} = \sum_{k=1}^{3} w_{kij}^* \tilde{\alpha}_{kij}. \end{aligned} \tag{13}$$

In the second step, synthetic estimates for parameters are obtained by averaging over all values of $j \neq i$. That is, the synthetic estimates for the parameters α_i, β_i, γ_i, and a_i are given by

$$\hat{\alpha}_i = \sum_{j \neq i} w_{ij} \hat{\alpha}_{ij},\ \hat{\beta}_i = \sum_{j \neq i} w_{ij} \hat{\beta}_{ij},$$
$$\hat{\gamma}_i = \sum_{j \neq i} w_{ij} \hat{\gamma}_{ij},\ \hat{a}_i = \sum_{j \neq i} w_{ij} \hat{a}_{ij}. \tag{14}$$

In (13) and (14), weights w_{kij}^* and w_{ij} are defined by

$$w_{kij}^* = \frac{\exp(l_{lij}(\hat{\tau}_i^2, \hat{d}_i))}{\sum_{l=1}^{3} \exp(l_{lij}(\hat{\tau}_i^2, \hat{d}_i))},$$
$$w_{ij} = \frac{\sum_{k=1}^{3} \exp(l_{kil}(\hat{\tau}_i^2, \hat{d}_i))}{\sum_{l \neq i} \sum_{k=1}^{3} \exp(l_{kil}(\hat{\tau}_i^2, \hat{d}_i))}.$$

IV. Results and Analysis

The empirical analysis in this paper was performed using the Postwar Japan Regional Data developed for the analyses in [15]-[16].

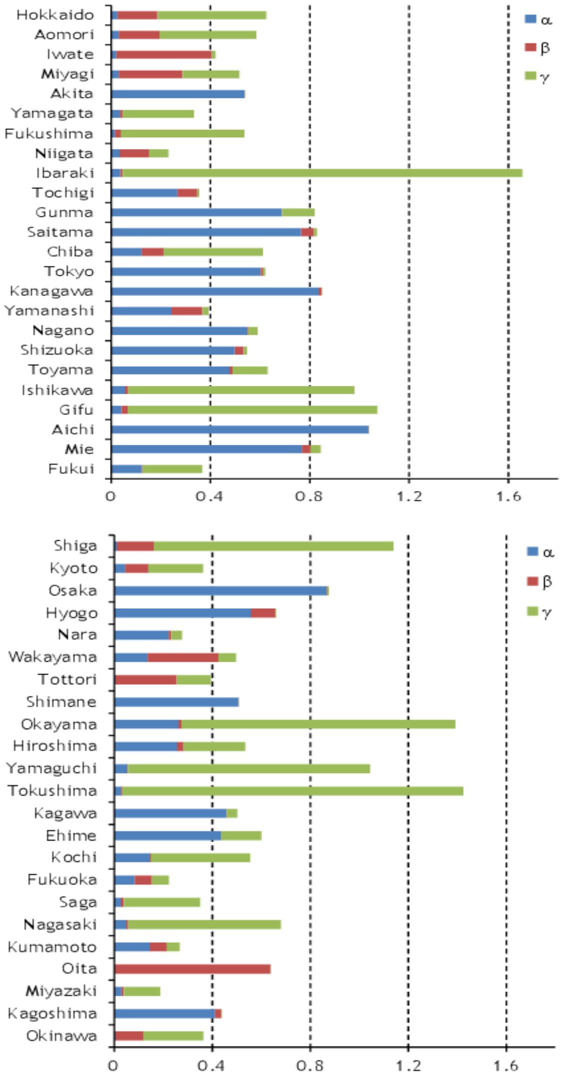

Fig. 1. Estimates for factor elasticity.

Fig. 1 shows the estimates of α_i, β_i, and γ_i for each prefecture.

Recall that α_i, β_i, and γ_i denote the elasticity of output with respect to private capital, public capital, and labor, respectively. The elasticity of output with respect to each factor means the percentage increase in output when the relevant factor increases by 1 percent, keeping other factors constant. For instance, the estimate of α_i for Tokyo is 0.602. This implies that if Tokyo's private capital increases by 1 percent, then Tokyo's output increases by 0.602 percent, with other factors kept constant. From Fig. 1, we see that the elasticity of each of the production factors takes various values among the prefectures. Regarding the variance of the elasticity among prefectures, the variance of private capital elasticity is 0.083, while that of public capital elasticity is 0.015, and that of labor elasticity is 0.161.

Next we examine the changes in the TFP during 1955-2005. Fig. 2 shows line graphs of the estimated trends for $a_i(t)$ in three typical prefectures, Tokyo, Osaka, and Aichi.

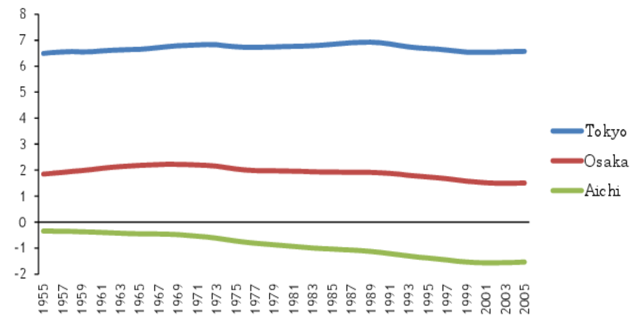

Fig. 2. Estimated trends for log-TFP.

The TFP trend appears to be roughly similar for Tokyo and Osaka. The TFP in Tokyo and Osaka increased slowly until the end of the 1960s; subsequently, however, it tended to either stagnate or decline. The TFP in Aichi revealed a decreasing trend throughout the period between the mid-1950s and the early 2000s.

The results for the estimated TFP by prefecture presented thus far suggest that the explanations for TFP movement given by models used in many preceding studies, in which the TFP growth rates of all regions are equal and increase at a constant rate, are inappropriate. Moreover, we have verified that the TFP behavior varies in different patterns. We have found some characteristics that are shared by the TFP trends in several prefectures.

To throw similarity in the factor elasticity of every prefecture into relief, we employ a multi-dimensional scaling (MDS) method. MDS is concerned with the problem of constructing a configuration of m points in Euclidean space using information about the distances between the m objects (prefectures). Here we regard $\hat{\alpha}_i, \hat{\beta}_i, \hat{\gamma}_i$ $(i = 1, 2, \ldots, m)$ as three-dimensional data and apply the Euclidean distance for the prefectures i and j as

$$d_{ij} = \sqrt{\left(\hat{\alpha}_i - \hat{\alpha}_j\right)^2 + \left(\hat{\beta}_i - \hat{\beta}_j\right)^2 + \left(\hat{\gamma}_i - \hat{\gamma}_j\right)^2}.$$

If two prefectures are adjoining in the figure, they have higher similarity in the factor. The MDS results for all prefectures based on factor elasticity are shown in Fig. 3.

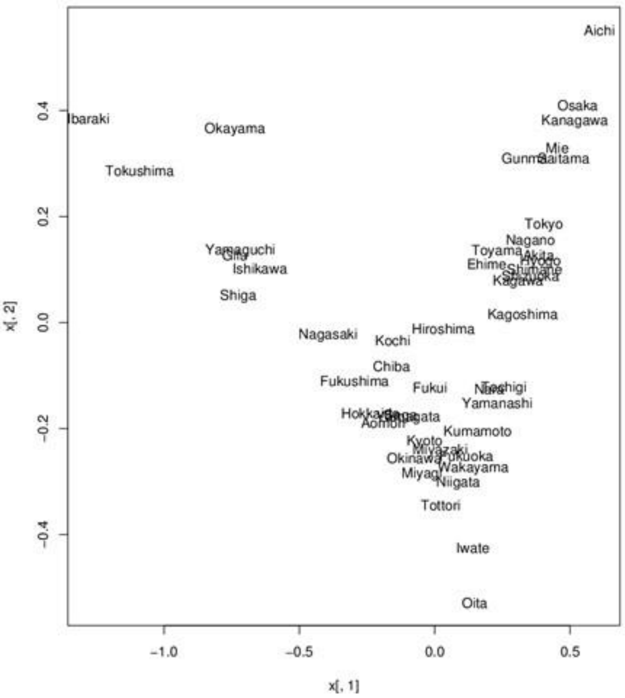

Fig. 3. Results of MDS based on factor elasticity.

According to the similarity in the prefectural economies obtained using factor elasticity, we can classify the prefectures into certain groups. For example, we consider that Akita, Hyogo, and Shimane belong to the same group. Moreover, we applied $\hat{a}_i(t)$ $(t = 1,2,\ldots,n;\ i = 1,2,\ldots,m)$ as n-dimensional data and also applied the Euclidean distance. The MDS results based on the estimates of the log-TFP are shown in Fig. 4.

From Fig. 4, for example, we can see that Gifu, Ishikawa, Yamaguchi, and Shiga have similarities in their log-TFP estimates.

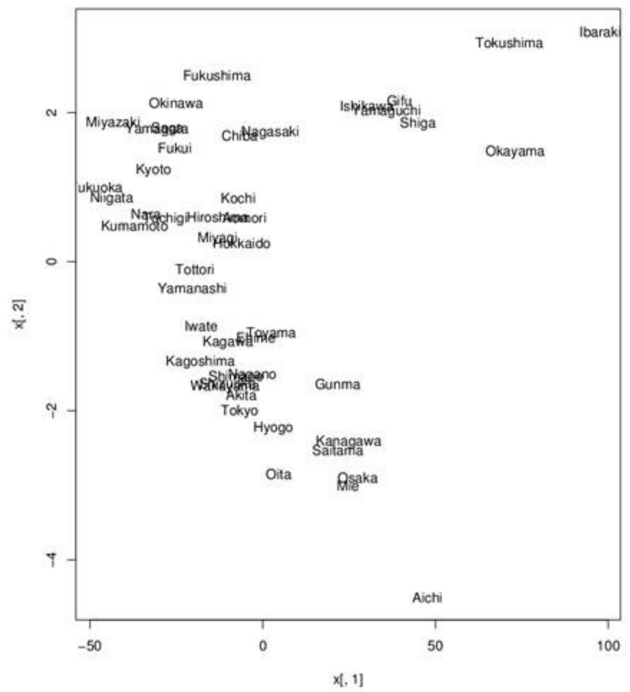

Fig. 4. Results of MDS based on log-TFP.

V. Conclusions

In the preceding sections, we examined the performance of Japan's prefectural economies using Bayesian modeling methods. Consequently, we confirmed that there is a sharp contrast among prefectures in terms of the elasticity of output with respect to the factors of production and TFP. According to our results, it can be considered that Japan's prefectural economies cannot necessarily be classified depending on geographical approachability. This suggests that a rigorous statistical analysis of the structural aspects of a regional economy is indispensable to the design of regional economic policies. The proposed approach is promising for this purpose.

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