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Determinants of Land-Price Movements in Japan

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DETERMINANTS OF LAND-PRICE MOVEMENTS IN JAPAN*

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【Abstract】

The purpose of this paper is to apply spatial econometrics, a new statistical tool that has recently attracted much attention, to Japanese land-price data and investigate how land-price movements are determined in Japan. A strong emphasis is put on measuring the degree of *spatial correlation of land prices*, the phenomenon whereby one area's land prices are correlated with another area's land prices just because the two areas are adjacent to each other. To explore this issue, we compile regional data on land prices in the 47 prefectures in Japan and in the 23 wards in Tokyo. Japanese land prices are shown to display a high degree of spatial correlation not only at the ward level, but also at the prefecture level. We also investigate the plausibility of the claim that price formation in the Japanese land market has become more dependent on economic fundamentals since the asset bubble burst in the early 1990s. We show that although this claim may hold in commercial areas in Tokyo, there is no robust evidence that it holds for the rest of Japan.

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【Non-technical Summary】

Trends in land prices should be carefully analyzed by the central bank, since they can have a substantial impact on the stability of the financial system as well as the behavior of output and prices. Usually, land-price movements are considered to be influenced by the following five factors: (i) economic fundamentals, such as population and income; (ii) financial factors like amounts of bank lending and interest rates on bank loans; (iii) the price movements of financial substitutes like stock prices; (iv) the *spatial correlation of land prices*, namely the phenomenon whereby one area's land prices are correlated with another area's just because the two areas are adjacent to each other; (v) price bubbles in land markets. The relative importance of each of these determinants depends on the country and period under examination.[1]

The purpose of this paper is twofold. First, we apply spatial econometrics, a new statistical tool which has recently attracted much attention, to Japanese land-price data and investigate how strong the spatial correlation is in the Japanese land market. To explore this issue, we compile regional data on land prices in the 47 prefectures in Japan and in the 23 wards in Tokyo. Our empirical analysis shows that Japanese land prices display a high degree of spatial correlation not only at the ward level, but also at the prefecture level. The correlation is strong, although it has decreased a little since the 1990s. These results do not depend on land usage (i.e., whether it is used for commercial or residential purposes). We also find that economic interdependence is as important as geographical propinquity for commercial areas.

Second, we investigate the plausibility of the claim that land prices have become more sensitive to economic fundamentals since the asset bubble burst in the early 1990s. According to official data, land prices have almost bottomed out in Japan and are rising steeply in the central areas of Tokyo, Osaka, Nagoya, and Fukuoka. Some experts in the real-estate business say that the rises in land prices reflect improved economic fundamentals in Japan, while others are worried about the resurgence of a land-price bubble. In this paper, we use regional data to analyze the determinants of

[1] It should be pointed out that accounting and tax schemes related to land transactions and holdings may also influence the formation of land prices.

land prices in Japan and whether economic fundamentals now play a more influential role in price formation in the Japanese land market than hitherto.

Our empirical studies show that, basically, land prices have always been determined by economic fundamentals, such as population growth and income *per capita*, and the availability of funds, such as amounts of bank lending. However, we find no robust evidence to support the opinion that the sensitivity of Japanese land prices to economic fundamentals has increased since the 1990s. We also apply the same method to land-price data for the 23 wards in Tokyo. One notable result is that land prices in residential areas are clearly correlated with stock prices, although the correlation has weakened since the 1990s. Another interesting result is that the argument that land prices have become more sensitive to economic fundamentals since the 1990s may hold in Tokyo commercial areas, although an extensive robustness check is required before this can be stated with any conviction.

I. INTRODUCTION

In general, movements in land prices are considered to depend on the following five factors. First, land prices are thought to depend on economic fundamentals, such as population and income. Second, financial factors, such as bank lending rates and amounts of bank lending, are likely to influence trends in land prices. Third, land prices may be correlated with the prices of financial substitutes like stocks. Fourth, rises in one area's land prices may be correlated with those in another area, just because the two areas are adjacent. Below, we refer to this phenomenon as the *spatial correlation of land prices*. Fifth, bubbles may occur in land markets, such as Japan experienced in the 1980s. The relative importance of each determinant depends on the country and period under examination. Since land-price movements have a significant influence on the stability of the financial system and the outlook for economic activity and prices, the central bank needs to pay careful attention to the factors that affect them.

The first purpose of this paper is to investigate which factors have driven movements in Japanese land prices since the 1980s. We put a particular emphasis on the fourth factor mentioned above, i.e., the spatial correlation of land prices. For instance, the skyrocketing land prices during the asset bubble period were triggered by sharp rises in the price of commercial land, which reflected strong demand for office space in metropolitan areas like Tokyo, and which then spread across neighboring areas. Figures 1 and 2 depict annual changes in land prices across Japan from fiscal year 1986 to 1989 in residential and commercial areas, respectively. The figures clearly illustrate the importance of spatial correlation in determining movements in land-prices.[2] No one can deny *a priori* the possibility of spatial correlation playing a role during periods not plagued by asset bubbles. One of our goals in this paper is to

[2] In the post-war era, the Japanese economy experienced sharp rises in land prices on two occasions in addition to the *asset-price bubble* period in the late 1980s (Yoshikawa, 2002). In the *Iwato boom*, land prices rose sharply, reflecting high economic growth in Japan, spreading from industrial sites to residential and commercial areas. The next land-price bubble was triggered by the Tanaka administration's *Plan to Remodel the Japanese Archipelago;* it boosted prices across all types of land simultaneously, all over Japan.

measure the degree of this spatial correlation in the Japanese land market.

In this paper, we apply *spatial econometrics*, a new statistical method which has recently attracted much attention as a tool for investigating the spatial aspects of various phenomena, to Japanese land-price data and investigate how movements in land prices are determined in Japan. Since the seminal work by Anselin (1988), the theory of spatial econometrics has been developed rapidly and its empirical applicability has become widely recognized. Ignoring spatial correlation, should it exist, would result in the emergence of misspecification biases when estimating economic models. Our analysis of panel data on land prices in neighboring areas suggests that such biases are likely to be substantial. Spatial econometrics is a tool particularly useful to resolve this problem.

The second purpose of this paper is to identify whether or not the determinants of land-price movements have changed in the Japanese land market. The *published land prices* (official land prices reported by the Ministry of Land, Infrastructure and Transport) in fiscal year 2005 indicate some returning strength in land prices in Japan: average land prices across Japan are bottoming out; in some big cities they have been rising; in Tokyo, Osaka, Nagoya, and Fukuoka they are rising rapidly. Looking at these improvements in land markets, some experts in the real-estate business argue that land prices in Japan have become more sensitive to economic fundamentals since the bursting of the asset bubble. We, however, can find no satisfactory evidence to prove that the sharp land price rises in big cities reflect enhanced profitability due to the recent recovery of the Japanese economy. Indeed, there are other real-estate experts issuing warnings about the possible resurgence of a land-price bubble. Evidently, the issue of whether or not there have been any changes in the mechanisms affecting price formation in Japanese land markets since the 1990s is a crucial one for the central bank.

The remainder of this paper is constructed as follows. In section II, we present our basic econometric model and the Bayesian method for estimating it. In section III, we report the results of our model estimation, based on the official land-price data compiled for the 47 prefectures in Japan. In section IV, we extend our basic model in two directions, as well as discussing the robustness of the result obtained in the previous section. In section V, we report the results of the model estimation, based on the official land-price data compiled for the 23 wards in Tokyo. In section VI, we summarize our main results and offer some concluding remarks.

II. THE BASIC MODEL

In this section, we present the basic model used in this paper, known as a *spatial autoregressive model* in the literature. We estimate the model using the Bayesian econometric method of *Markov chain Monte Carlo* (MCMC). Another notable feature of the paper is its application of panel data within the context of a spatial autoregressive model. Since the above require the use of some cutting-edge econometric techniques, we provide a detailed introduction to the model structure and estimation methodology.[3]

(1) A Spatial Autoregressive Model

In this paper, we first compile panel data on annual land-price changes in the 47 Japanese prefectures from fiscal year 1977 to 2005.[4] The annual land-price change in prefecture i ($i = 1, \cdots, N$) in year t ($t = 1, \cdots, T$) is denoted by $y_{i,t}$. Here, we have a sample of 1,363 data with $N = 47$ and $T = 29$.

We apply this panel data to a spatial autoregressive model in order to investigate the determinants of land-price movements in Japan. Our basic model is given by the following equation.

$$y_{i,t} = \rho \Sigma_{j \neq i} w_{i,j} y_{j,t} + \alpha_i + x_{i,t} \beta + \varepsilon_{i,t}, \qquad (2\text{-}1)$$

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[3] The explanation in this section is based on Wago and Kakamu (2005) and Wago (2005), whose treatments have been extended by the authors.

[4] The *published land prices,* released by the Ministry of Land, Infrastructure and Transport, start from January 1st, 1970. Thus, we can construct data on annual changes from fiscal year 1970. However, we choose to start our analysis from 1977, because of the limited availability of data for use as explanatory variables for land-price movements.

where $w_{i,j}$ is a weight that indicates how strongly prefecture i is related to j, one of the most important parameters used in spatial autoregressive models. There is more than one way to determine this so-called 'linkage' weight. We employ two alternative methods both of which are used frequently in the literature: *geographical weight* and *economic weight*.[5]

The geographical weight is defined as follows. Suppose that a total of M_i prefectures are adjacent to prefecture i. Then $w_{i,j} = 1/M_i$ if prefecture j is adjacent to prefecture i; otherwise, $w_{i,j} = 0$. Note that $\Sigma_{j \neq i} w_{i,j} y_{j,t}$ thus describes the average land-price change in the neighborhood of prefecture i. This is what allows us to interpret parameter ρ as a measurement of the spatial correlation of land prices. If ρ is significantly positive, then land prices are spatially correlated; if it is close to zero, there is no spatial correlation.

The economic weight is based on the flow of commodities between prefectures.[6] We define $w_{i,j}$ to be the share of commodity flow observed between prefectures i and j. Note that the value of $w_{i,j}$ is zero if there is no transportation between the two prefectures, even if they are adjacent. On the other hand, when goods flow between them, $w_{i,j}$ is positive even if the two prefectures are located far apart. As a result, economic weights involving metropolitan areas like Tokyo, Osaka, and Aichi tend to be greater than their equivalent geographical weights. Here, $\Sigma_{j \neq i} w_{i,j} y_{j,t}$ represents the average land-price change in areas that display strong economic interdependence with prefecture i.

In equation (2-1), $\alpha = (\alpha_1, \cdots, \alpha_N)'$ is a column vector consisting of 47 elements, where α_i indicates a *fixed effect* specific to prefecture i. $x_{i,t} = (x_{1,i,t}, \cdots, x_{K,i,t})$ is a row vector consisting of K elements that we consider determine land-price

[5] Two prefectures, separated by an ocean, can be thought of as being connected if there is a bridge between them: Hokkaido to Aomori, Hyogo to Tokushima, Okayama to Kagawa, Hiroshima to Ehime, and Yamaguchi to Fukuoka. We do not report the results obtained when connection by bridges is considered, since they are almost the same as those obtained when it is ignored.

[6] We use the *National Survey on Cargo Transportations*, published by the Ministry of Land, Infrastructure and Transport, to provide commodity flow data.

movements. An element $x_{k,i,t}$ can be common across all prefectures (e.g., stock prices) or specific to an individual prefecture (e.g., population growth in each prefecture). The coefficient β is a column vector consisting of K elements and governs the extent to which the K determinants explain land-price movements. We consider the value of each β_k to be common across all prefectures.

An error term, $\varepsilon_{i,t}$, is assumed to be i.i.d. with mean zero and variance σ_i^2. Below, Σ is a diagonal matrix whose elements are given by $(\sigma_1^2,\cdots,\sigma_N^2)$. We allow σ_i^2 to vary across prefectures. The $\varepsilon_{i,t}$ summarize prefecture-specific behavior that is not captured by α_i and $x_{i,t}$. Consider, for example, the implications of a large number of redevelopment projects being carried out in the Tokyo metropolitan area. In such a case, it is highly probable that the area would be hit by greater land-price shocks than elsewhere. If σ_i^2 were prohibited from varying across prefectures, the model estimation would become inefficient.

In this section, we assume that the $\varepsilon_{i,t}$ display no serial correlation. It is likely, however, that the $\varepsilon_{i,t}$ are in fact serially correlated, especially when we remember the continuous decline in land prices observed since the asset bubble burst. If this is indeed the case, then the model estimation will suffer from bias. We therefore relax this no serial correlation assumption in a later section.

We can rewrite equation (2-1) in matrix form as follows:

$$Y = \rho W_T Y + D_T\alpha + X\beta + \varepsilon, \tag{2-2}$$

where $Y = (y_{1,1},\cdots,y_{N,1},\cdots,y_{i,t},\cdots,y_{1,T},\cdots,y_{N,T})'$,

$$W = \begin{pmatrix} w_{1,1} & \cdots & w_{1,N} \\ \vdots & \ddots & \vdots \\ w_{N,1} & \cdots & w_{N,N} \end{pmatrix},\ W_T = I_T \otimes W,$$

$$D_T = (\underbrace{I_N,\cdots,I_N}_{T})',\ \alpha = (\alpha_1,\cdots,\alpha_N)',$$

$$X = (x'_{1,1},\cdots,x'_{N,1},\cdots,x'_{i,t},\cdots x'_{1,T},\cdots,x'_{N,T})',$$

$$\varepsilon = (\varepsilon_{1,1},\cdots,\varepsilon_{N,1},\cdots,\varepsilon_{i,t},\cdots\varepsilon_{1,T},\cdots,\varepsilon_{N,T})'.$$

(2) Bayes Theorem and Markov Chain Monte Carlo

We estimate the parameters in equation (2-1) using Bayesian methods. Bayesian econometrics is based around three key concepts: a prior distribution, a posterior distribution, and a likelihood function. The prior distribution is the subjective probability distribution of parameters which the investigator has in mind before looking at the data. The likelihood function indicates the probability of the observed data actually occurring conditional on a particular set of parameters. The posterior distribution is obtained by updating the prior distribution, based on the observed data. Our purpose is to derive a posterior distribution for ρ, α, β, and Σ in equation (2-2).

We assume the following prior distribution:

$$\pi(\rho,\alpha,\alpha_0,\xi^2,\beta,\Sigma) = \pi(\rho)\pi(\beta)\pi(\Sigma)\pi(\alpha,\alpha_0,\xi^2), \quad (2\text{-}3)$$

$$\text{where } \pi(\alpha,\alpha_0,\xi^2) = \Pi_{i=1}^{N}\pi(\alpha_i \mid \alpha_0,\xi^2)\pi(\alpha_0 \mid \xi^2)\pi(\xi^2). \quad (2\text{-}4)$$

As is clear in equation (2-4), the probability distribution assumed in this paper imposes a hierarchical structure. We use α_0 as a mean of α_i: α_i deviates randomly from a particular realization of α_0. We make the following specific assumptions:

$$\pi(\beta) \sim N(\beta^*,\Sigma_\beta),$$

$$\pi(\alpha_i \mid \alpha_0,\xi^2) \sim N(\alpha_0,\xi^2),$$

$$\pi(\alpha_0 \mid \xi^2) \sim N(\mu^*,\xi^2 / N^*),$$

$$\pi(\xi^2) \sim Gamma^{-1}(\nu^* / 2,\lambda^* / 2),$$

$$\pi(\sigma_i^2) \sim Gamma^{-1}(\kappa^* / 2,\tau^* / 2),$$

$$\pi(\rho) \sim U(1/\lambda_{\min},1/\lambda_{\max}).$$

The prior distribution is characterized by the hyper-parameters β^*, Σ_β, μ^*, N^*, ν^*, λ^*, κ^*, and τ^*, which summarize the information the investigator has in mind before looking at the data.[7] We assume that the investigator has no *ex ante*

[7] We set the hyper-parameters as $\beta^* = 0$, $\Sigma_\beta = 100 \times I_k$, $\mu^* = 0$, $\nu^* = 0.01$, $\lambda^* = 0.01$, $N^* = 0.01$, $\kappa^* = 0.01$, and $\tau^* = 0.01$.

information about ρ; thus its prior distribution is given by a uniform distribution. As shown by Sun *et al.* (1999), however, ρ is necessarily located in between $1/\lambda_{\min}$ and $1/\lambda_{\max}$ in a spatial autoregressive model like equation (2-1), where $\lambda_{\max}$ and $\lambda_{\min}$ are, respectively, the maximum and the minimum of the characteristic values of matrix W. We incorporate this result in the following investigation.

Suppose that we observe data, Y and X. The associated likelihood function is given by $\pi(X,Y \mid \rho,\alpha,\alpha_0,\xi^2,\beta,\Sigma)$. According to Bayes Theorem, we combine the likelihood function with the prior distribution assumed above to obtain the posterior distribution as follows:

$$\underset{\text{(posterior)}}{\pi(\rho,\alpha,\alpha_0,\xi^2,\beta,\Sigma \mid Y,X)} \propto \underset{\text{(prior)}}{\pi(\rho,\alpha,\alpha_0,\xi^2,\beta,\Sigma)}\ \underset{\text{(likelihood function)}}{\pi(X,Y \mid \rho,\alpha,\alpha_0,\xi^2,\beta,\Sigma)}$$

If the posterior distribution is given by some well-known probability distribution, we can derive characteristics, such as the means and variances of the model parameters, ρ, α, α_0, ξ^2, β, and Σ, algebraically. Unfortunately, our posterior distribution is so complicated that we can obtain no explicit form for the means and variances.

Even in the above case, however, it is possible to derive key characteristics of the posterior distribution by using the estimation method known as Markov chain Monte Carlo (MCMC). Two sampling strategies are used frequently: the *Gibbs sampler* and *Metropolis-Hastings* (MH) algorithm. In the literature, the posterior distribution of a certain parameter conditional on all other parameters is called a *full conditional posterior distribution*. The *Gibbs sampler* is used when the full conditional posterior distribution is well-known; the *Metropolis-Hastings* algorithm is used when the full conditional posterior distribution is not well-known. The Markov chain Monte Carlo starts with initial values for all the parameters set arbitrarily. We generate a value for ξ^2 randomly, given α_0, β, α_i, ρ, and σ_i^2, and update ξ^2 with the realization. Next, we generate a value for α_0 randomly, given ξ^2, β, α_i, ρ, and σ_i^2, and update α_0 with the realization. We generate values for β, α_i, ρ, and σ_i^2 randomly in a similar fashion and update these parameters with the realizations. Iterating this process many times, we can generate a massive sample, consisting of a huge number of parameter values, and use it as a sample analogue of the true posterior distribution.[8]

(3) Full Conditional Distributions

The following is a list of the full conditional distributions for the model parameters:

$$\beta \mid \rho,\alpha,\Sigma,Y,X \sim N(\tilde{\beta},\tilde{\Sigma}_\beta), \tag{2-5}$$

where $\tilde{\Sigma}_\beta = (X'\Sigma_T^{-1}X + \Sigma_\beta^{-1})^{-1}$, $\Sigma_T = I_T \otimes \Sigma$,

$\tilde{\beta} = \tilde{\Sigma}_\beta (X'\Sigma_T^{-1}U + \Sigma_\beta^{-1}\beta^*)$, $U = Y - \rho W_T Y - D_T \alpha$.

$$\alpha_i \mid \rho,\alpha_0,\beta,\xi^2,\Sigma,Y,X \sim N(\tilde{\alpha}_i,\tilde{\xi}^2), \tag{2-6}$$

where $\tilde{\xi}^{-2} = \xi^{-2} + T\sigma_i^{-2}$, $\tilde{\alpha}_i = \tilde{\xi}^2(\alpha_0\xi^{-2} + \Sigma_{t-1}^T c_{i,t}\sigma_i^{-2})$,

$c_{i,t} = y_{i,t} - \rho\Sigma_{j\neq i} w_{i,j} y_{j,t} - x_{i,t}\beta$.

$$\xi^2 \mid \alpha \sim Gamma^{-1}(\tilde{\nu}/2,\tilde{\lambda}/2), \tag{2-7}$$

$$\alpha_0 \mid \alpha,\xi^2 \sim N(\tilde{\mu},\xi^2/\tilde{N}), \tag{2-8}$$

where $\tilde{\nu} = \nu^* + N$, $\tilde{\lambda} = \lambda^* + \Sigma_{i=1}^N(\alpha_i - \overline{\alpha})^2 + N^*N(\mu^* - \overline{\alpha})^2/\tilde{N}$,

$\tilde{N} = N^* + N$, $\overline{\alpha} = \Sigma_{i=1}^N \alpha_i / N$, $\tilde{\mu} = (N^*\mu^* + N\overline{\alpha})/\tilde{N}$.

$$\sigma_i^2 \mid \rho,\alpha,\beta,Y,X \sim Gamma^{-1}(\tilde{\kappa}/2,\tilde{\tau}/2), \tag{2-9}$$

where $\tilde{\kappa} = \kappa^* + T$, $\tilde{\tau} = \tau^* + \Sigma_{t=1}^T e_{i,t}^2$, $e_{i,t} = y_{i,t} - \rho\Sigma_{j\neq i} w_{i,j} y_{j,t} - \alpha_i - x_{i,t}\beta$.

$$\rho \mid \alpha,\beta,\Sigma,Y,X\ , \quad \propto |I_N - \rho W|^T \exp\{-\tfrac{1}{2}(\rho-\tilde{\rho})'(W_TY)'\Sigma_T^{-1}(W_TY)(\rho-\tilde{\rho})\}, \tag{2-10}$$

where $\tilde{\rho} = \{(W_TY)'\Sigma_T^{-1}(W_TY)\}^{-1}(W_TY)'\Sigma_T^{-1}(Y - D_T\alpha - X\beta)$,

$1/\lambda_{\min} < \rho < 1/\lambda_{\max}$.

We can use the Gibbs sampler for the sampling of α , α_0 , ξ^2 , β , and Σ , since their full conditional distributions are given by well-known distributions, such as the normal and gamma distributions, as in equations (2-5) to (2-9). As observed in

[8] Since sample values generated in the early stages are likely to depend on the initial values, we throw away the first 2,000 values (called *burn-in*) and keep the remaining 8,000 values.

equation (2-10), the full conditional distribution of ρ resembles the normal distribution, but deviates from it by the term $|I_N - \rho W|^T$. Therefore, sampling ρ directly from this equation is hard to implement.

(4) The Metropolis-Hastings Algorithm for ρ

Although the full conditional distribution of ρ does not have a well-known shape, the MH algorithm enables us to generate a sample for it. The MH algorithm proceeds in the following two steps: (i) sample generation from a *proposal distribution*, which resembles the target distribution closely and (ii) sample selection, according to a prescribed rule.

Appropriate construction of a proposal distribution is the key for successful sampling through the MH algorithm. If the proposal distribution fails to approximate the true distribution, many values generated from the proposal distribution are discarded in the next sample-selection step, and thus it takes a huge amount of time to obtain a sufficient number of sample values. A typical way of constructing a proposal distribution is to approximate the true distribution by a normal distribution. Denote the right hand side of equation (2-10) by $G(\rho)$ and its logarithmic transformation by $g(\rho)$. Let ρ^m be the maximizer of $g(\rho)$, satisfying $g'(\rho^m) = 0$. Second order Taylor-expansion of $g(\rho)$ around ρ^m gives us $h(\rho)$, as follows.

$$
\begin{aligned}
h(\rho) &= g(\rho^m) + (\rho - \rho^m) g'(\rho^m) + \tfrac{1}{2}(\rho - \rho^m)^2 g''(\rho^m) \\
&= g(\rho^m) + \tfrac{1}{2}(\rho - \rho^m)^2 g''(\rho^m).
\end{aligned}
$$

Transforming this back exponentially, we obtain the following normal distribution.

$$H(\rho) \propto \exp\{-\tfrac{1}{2}(\rho - \rho^m)^2 / v\},$$

where $v = -g''(\rho^m)^{-1}$.

That is, a plausible proposal distribution for ρ is given by $N(\rho^m, v)$.

The second step of the MH algorithm is to choose values from a sample generated from the proposal distribution. Let ρ^{old} be a value chosen in the previous round and ρ^{new} be a value generated in the current round. We adopt ρ^{new} with the following probability; otherwise, we keep ρ^{old}.

$$P(\rho^{old}, \rho^{new}) = \min\left[\frac{G(\rho^{new})/H(\rho^{new})}{G(\rho^{old})/H(\rho^{old})}, 1\right].$$

The probability of ρ^{new} being chosen is called the *acceptance rate*. When we use $H(\rho)$ as defined above, we often run into the problem that the acceptance rate is extremely low. An effective way to resolve this is to enlarge the variance of the proposal distribution. We use $c \times v$ as the variance of the proposal distribution instead of v and adjust the tuning parameter, c, to prevent the emergence of an extremely low acceptance rate.

(5) Convergence to Posterior Distributions

Finally, we should check how successful the MCMC sampling is. A particular concern is whether or not a sampled distribution achieves convergence satisfactorily, starting from initial values chosen arbitrarily. If the convergence is unsatisfactory, we should try an alternative proposal distribution or increase the number of MCMC iterations.

There are two standard methods for checking the convergence of a sample distribution. First, Geweke (1992) proposes comparing data generated in the early iteration rounds with those in the later rounds. Sub-sample 1 consists of 10 percent of the sample generated in the early iteration rounds; sub-sample 2 consists of 50 percent of the sample generated in the later iteration rounds. Denote their sample means by m_1 and m_2, respectively. We construct the following statistic called GWK:

$$GWK = \frac{m_1 - m_2}{\sqrt{s_1^2 + s_2^2}},$$

where s_i^2 is the estimated variance of sub-sample i.[9] It is known that GWK follows a standard normal distribution when the sample size is sufficiently large. Hence, when the absolute value of GWK is small or its p-value, called *Geweke's p-value,* is large, we can judge convergence to have been achieved. An alternative and simpler method for

[9] In the definition of GWK, s_i^2 is given by $2\pi \hat{f}_i(0)/n_i$, where $\hat{f}_i(0)$ is the estimate of spectral density at zero frequency and n_i is the sample size.

judging the convergence of a posterior distribution is to check whether the extent of autocorrelation in the sample is sufficiently small. Below, each time we change a model specification or a sample period, we look at both Geweke's p-value and the extent of autocorrelation, although they are not presented.

III. Determinants of Land-Price Movements in the 47 Prefectures in Japan

In this section, we investigate the determinants of land-price movements in the 47 Japanese prefectures, looking in particular at the degree of spatial correlation of land prices in Japan. We first explain the compilation of the panel data used in the estimation and then report estimation results of the spatial autoregressive model for Japanese land prices.

(1) Data

In this paper, we use the *published land prices*, or official land prices, issued by the Ministry of Land, Infrastructure and Transport. Japan has 47 prefectures. We aggregate the micro-level data to construct 47 time series for average land prices in those prefectures (see figures 3 and 4).[10] Since observed sites included in the released statistics change over time, we are unable to keep track of land prices at fixed sites for any substantial length of time.[11] Hence, we follow the method proposed by Nagahata *et al*. (2004): every year observed sites where land prices are compiled for two consecutive years are picked up and their growth rates averaged using transaction values as weights.

To see whether price formation in the Japanese land market has changed since

[10] When calculating prefecture-level land prices, the Ministry of Land, Infrastructure and Transport uses a simple mean of annual changes in each prefecture's land prices with equal weights, irrespective of the size of land values. Nagahata *et al*. (2004) claim that the prefecture-level land prices that they obtain using their method describe more precisely the trend asset value of the land in each prefecture.

[11] In order to narrow the gaps between official prices and actual transaction prices, observed sites are subject to partial replacement every year.

the 1990s, we estimate the model with two samples: (i) the *long sample*, spanning the period from fiscal year 1997 through 2005; and (ii) the post-bubble sample, spanning fiscal years 1991 through 2005. Note that the published land prices are prices as of January 1st every year. Below, the published land prices, say, as of January 1st, 2006, are called the land prices for fiscal year 2005 (i.e., for the period April 1, 2005, to March 31, 2006).

As explanatory variables for land-price movements, we assume population growth (figure 5), *per capita* income growth (figure 6), increases in bank lending (figure 7), rises in lending rates (figure 8), and rises in stock prices (figure 9). See Nagahata *et al*. (2004) for details regarding data construction. Note that since the data on *per capita* income in individual prefectures are published with a substantial delay, we extend them, based on the data on industrial production in each prefecture and on corporate goods prices.

(2) Baseline Results

Table 1 presents the estimation results of the basic model for the 47 prefectures in Japan. The first column shows the results for residential areas using the geographical weight, based on the long sample; the fifth column gives the equivalent results for commercial areas. In both, spatial correlation, ρ, is seen to be 0.6, indicating that land prices in Japan are correlated between adjacent prefectures (significant at the 2.5% level in a one-sided test). Note that the basic model captures only the short-run spatial correlation observed within one year. It is likely that long-run correlation of land prices among prefectures is larger than the correlation reported in the table.

Both in residential areas and in commercial areas, land-price movements are influenced by population, income, and bank lending (significant at the 2.5 % level in a one-sided test). That is, economic fundamentals and financial conditions have influenced the formation of land prices in the long run, in the direction anticipated. In contrast, capital costs and stock prices are insignificant or fail to satisfy expected sign restrictions. We discuss the significance of stock prices again in later sections.

In the table, we also list the prefectures that display the largest error-term variances. In residential areas, the top 5 prefectures are Kanagawa, Tokyo, Chiba, Saitama, and Kyoto. In commercial areas, they are Kanagawa, Chiba, Aichi, Hokkaido, and Saitama. Clearly, error-term variances are larger in metropolitan areas than in local areas. Recall that the asset bubble originated in certain metropolitan areas and then spread to their surroundings. Therefore, it is reasonable to postulate that these estimates for error-term variances are strongly affected by the land-price bubbles in the late 1980s.

(3) Effects of the Choice of Linkage Weight

Replacing the linkage weight allows us to assess the relative importance of geographical vis-à-vis economic connection in the determination of land prices. The third column of table 1 presents the results for residential areas using the economic weight, based on the long sample. Unsurprisingly, the spatial correlation is reduced by half. While it is perfectly natural for land prices in adjacent areas to be strongly correlated, it is not especially plausible for residential land prices in Hokkaido to be correlated with those in Tokyo, even if commodity flows are large between the two prefectures.

We present the results for commercial areas with the economic weight, based on the long sample, in the seventh column. It should be noted that the spatial correlation is as large as that obtained with the geographical weight. This implies that in commercial areas, economic interdependence is as important a factor as geographic connection in determining the trend of land prices. This contrasts with the results for residential areas, where economic interdependence is seen to be less important than geographical connection.

(4) Effects of Sample Changes

By changing the sample period, we can see whether or not price formation in the Japanese land market has changed since the asset bubble burst in the early 1990s. The second column of Table 1 gives the results for residential areas using the geographical weight, but now based on the post-bubble sample (fiscal 1991 through 2005); the sixth column gives equivalent results for commercial areas. In both, spatial correlation, ρ, falls from 0.6 to 0.5. Nonetheless, the spatial correlation is still more than adequate (significant at the 2.5% level in a one-sided test) to conclude that land price movements among the 47 prefectures in Japan are correlated according to their propinquity.

Bank lending remains a significant factor affecting land-price movements during the post-bubble period. Note, however, that the influence of population and income has weakened during the post-bubble period. In residential areas, we find that income has lost its significance. In commercial areas, although the influence of population has increased when we employ the economic weight, it has become insignificant with the geographical weight. These results suggest that Japanese land prices have become less sensitive to economic fundamentals than during the pre-bubble period.

In Japan, balance sheet adjustment continued for a long time after the bursting of the asset bubble. Recall that in the 1990s, many companies, especially private banks, disposed of their real-estate property, selling company-owned flats and holiday cottages. It is highly likely that this balance sheet problem weakened the Japanese land market and kept land prices below fundamental values. Therefore, the argument that economic fundamentals have become more influential in the formation of land prices can be applicable, if at all, for at most the few years since the recent resolution of these balance sheet problems.

IV. EXTENDED MODELS

The results obtained in the preceding sections match our experience since the bursting of the asset bubble very well, suggesting the effectiveness of a spatial autoregressive model in the analysis of the Japanese land-price market. In this section, we check the robustness of these results by extending the basic model in two directions. First, we take into consideration serial correlation in error terms; then we consider extension to a dynamic setting. In the appendix, we discuss the effectiveness of a probit model.

(1) Serial Correlation in Error Terms

Clearly, annual land-price changes in the 1990s were less volatile than the growth rates of income *per capita* during the same period. One interpretation is that the behavior of other determinants of land prices is sticky enough to offset the effects of income growth. Another interpretation is that the error terms in equation (2-1), $\varepsilon_{i,t}$, are serially correlated. If the latter is the case, theory states the econometric consequence: OLS estimators will be biased if the serial correlation in error terms is ignored. Here, to deal with this problem, we take into consideration serial correlation in the error terms in equation (2-1). We assume that the $\varepsilon_{i,t}$ can be described by an AR(1) model (first order autoregressive model) as follows.

$$\varepsilon_{i,t} = \theta\varepsilon_{i,t-1} + \eta_{i,t}, \tag{4-1}$$

where $\eta_{i,t}$ is i.i.d. with zero mean and variance denoted by σ_i^2.

A convenient way of estimating equation (2-1) when the error term is serially correlated as described by equation (4-1) is to transform the data using a quasi-differencing operator $(1-\theta L)$, where L is a lag operator. Transform the data such that $\hat{y}_{i,t} \equiv (1-\theta L)y_{i,t}$, $\hat{x}_{i,t} \equiv (1-\theta L)x_{i,t}$, and $\hat{\alpha}_{i,t} \equiv (1-\theta)\alpha_i$ for $t > 1$. Equation (2-1) can then be rewritten as

$$\hat{y}_{i,t} = \rho\Sigma_{j\neq i} w_{i,j}\hat{y}_{j,t} + \hat{\alpha}_{i,t} + \hat{x}_{i,t}\beta + \eta_{i,t}. \tag{4-2}$$

For $t = 1$, we have no preceding data ($t = 0,-1,\cdots$); thus quasi-differencing is impossible. By successive substitution in equation (4-1), however, we find that the error terms in the first period are given by

$$\varepsilon_{i,1} = \eta_{i,1} + \theta\eta_{i,0} + \theta^2\eta_{i,-1} + \cdots. \tag{4-3}$$

Thus, ε_{i1} follows a normal distribution with mean zero and variance $\sigma_i^2/(1-\theta^2)$. Now we transform the data such that $\hat{y}_{i,1} \equiv \sqrt{1-\theta^2}\,y_{i,1}$, $\hat{x}_{i,1} \equiv \sqrt{1-\theta^2}\,x_{i,1}$, and $\hat{\alpha}_{i,1} \equiv \sqrt{1-\theta^2}\,\alpha_i$. Then, equation (4-2) is applicable for all $t \geq 1$, and the means and variances of the error terms are given by zero and σ_i^2, respectively.

We can rewrite equation (4-2) in matrix form as follows.

$$\hat{Y} = \rho W_T\hat{Y} + \hat{D}_T\alpha + \hat{X}\beta + \eta. \tag{4-4}$$

where $\hat{Y} = (\hat{y}_{1,1}, \cdots, \hat{y}_{N,1}, \cdots, \hat{y}_{1,T}, \cdots, \hat{y}_{N,T})'$,

$$\hat{D}_T' = \begin{pmatrix} \sqrt{1-\theta^2} & \cdots & 0 & 1-\theta & \cdots & 0 & \cdots & 1-\theta & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{1-\theta^2} & 0 & \cdots & 1-\theta & \cdots & 0 & \cdots & 1-\theta \end{pmatrix},$$

$\hat{X} = (\hat{x}_{1,1}, \cdots, \hat{x}_{N,1}, \cdots, \hat{x}_{1,T}, \cdots, \hat{x}_{N,T})'$,

$\eta = (\eta_{1,1}, \cdots, \eta_{N,1}, \cdots, \eta_{1,T}, \cdots, \eta_{N,T})'$.

Compared with the basic model, we are faced with two new features. First, we need the full conditional posterior distribution of θ, the AR parameter governing the error term. Second, we have to make appropriate changes to the full conditional posterior distribution of α_i. For the other distributions, it is enough to replace Y with $\hat{Y}$ and X with $\hat{X}$.

$$\beta \mid \rho, \alpha, \Sigma, Y, X \sim N(\hat{\beta}, \hat{\Sigma}_\beta), \tag{4-5}$$

where $\hat{\Sigma}_\beta = (\hat{X}'\Sigma_T^{-1}\hat{X} + \Sigma_\beta^{-1})^{-1}$, $\hat{\beta} = \hat{\Sigma}_\beta(\hat{X}'\Sigma_T^{-1}\hat{U} + \Sigma_\beta^{-1}\beta^*)$,

$\hat{U} = \hat{Y} - \rho W_T \hat{Y} - \hat{D}_T \alpha$.

$$\alpha_i \mid \rho, \alpha_0, \beta, \Sigma, Y, X \sim N(\hat{\alpha}_i, \hat{\xi}^2), \tag{4-6}$$

where $\hat{\xi}^{-2} = \xi^{-2} + \{(1-\theta^2) + (1-\theta)^2(T-1)\}\sigma_i^{-2}$,

$\hat{\alpha}_i = \hat{\xi}^2[\alpha_0\xi^{-2} + \{\sqrt{1-\theta^2}\,\hat{c}_{i,1} + (1-\theta)\Sigma_{t=2}^T \hat{c}_{i,t}\}\sigma_i^{-2}]$,

$\hat{c}_{i,t} = \hat{y}_{i,t} - \rho\Sigma_{j\neq i} w_{i,j}\hat{y}_{j,t} - \hat{x}_{i,t}\beta$.

$$\xi^2 \mid \alpha \sim Gamma^{-1}(\tilde{\nu}/2, \tilde{\lambda}/2). \quad \text{(the same as equation (2-7))} \tag{4-7}$$

$$\alpha_0 \mid \alpha, \xi^2 \sim N(\tilde{\mu}, \xi^2/\tilde{N}). \quad \text{(the same as equation (2-8))} \tag{4-8}$$

$$\sigma_i^2 \mid \rho, \alpha, \beta, Y, X \sim Gamma^{-1}(\hat{\kappa}/2, \hat{\tau}/2), \tag{4-9}$$

where $\hat{\kappa} = \kappa^* + T$, $\hat{\tau} = \tau^* + \Sigma_{t=1}^T \hat{e}_{i,t}^2$, $\hat{e}_{i,t} = \hat{y}_{i,t} - \rho\Sigma_{j\neq i} w_{i,j}\hat{y}_{j,t} - \hat{\alpha}_{i,t} - \hat{x}_{i,t}\beta$.

$\rho \mid \alpha, \beta, \Sigma, Y, X$,

$$\propto |I_N - \rho W|^T \exp\{-\tfrac{1}{2}(\rho - \hat{\rho})'(W_T Y)'\Sigma_T^{-1}(W_T Y)(\rho - \hat{\rho})\}, \tag{4-10}$$

where $\hat{\rho} = \{(W_T Y)'\Sigma_T^{-1}(W_T Y)\}^{-1}(W_T Y)'\Sigma_T^{-1}(\hat{Y} - \hat{D}_T\alpha - \hat{X}\beta)$,

$1/\lambda_{\min} < \rho < 1/\lambda_{\max}$.

$$\theta \mid \rho,\alpha,\beta,\Sigma,Y,X \propto A(\theta)\exp\{-\tfrac{1}{2}(\theta-\hat{\theta})^2/\hat{\sigma}_\theta^2\}, \qquad (4\text{-}11)^{12}$$

where $A(\theta) = (1-\theta^2)^{N/2}\exp\{-\tfrac{1}{2}(1-\theta^2)e_1'\Sigma^{-1}e_1\}$,

$$\hat{\theta} = \hat{\sigma}_\theta^2(\sigma_\theta^{-2}\theta^* + e_-'\Sigma_{T-1}^{-1}e_+),\ \hat{\sigma}_\theta^{-2} = \sigma_\theta^{-2} + e_-'\Sigma_{T-1}^{-1}e_-,$$

$$e_t = y_t - \rho W y_t - \alpha - x_t\beta,\ e_+ = (e_2',\cdots,e_T')',\ e_- = (e_1',\cdots,e_{T-1}')'.$$

As apparent in equation (4-11), a standard form for the full conditional posterior distribution of θ is impossible due to presence of the term $A(\theta)$. Therefore, we use the MH algorithm to sample θ via a proposal distribution approximating equation (4-11), just as we did for sampling ρ in section II.[13]

Table 2 presents estimation results for equation (4-2), taking into consideration serial correlation in the error terms. The first column shows the results for residential areas using the geographical weight, based on the long sample; the fifth column gives equivalent results for commercial areas. In both, serial correlation in the error terms, θ, is more than 0.6, implying a strong degree of serial correlation (significant at the 2.5% level in a one-sided test).

When we use the economic weight instead of the geographical weight, we still find strong serial correlation of around 0.7 in both residential and commercial areas (see the third and seventh columns). Confining ourselves to the post-bubble sub-sample, we see the estimates of θ increase to around 0.9 (see the second, fourth, sixth, and eighth columns). Note that the long sample includes the period of the land-price bubble, during which a sharp one-off fluctuation of land prices occurred. Thus, the estimated serial correlation is smaller than it would be if the asset bubble period were excluded.

This serial correlation in the error terms suggests that the estimation results reported in the previous section may be biased. Three points are worth noting about

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[12] For the new hyper-parameters, we set $\theta^* = 0$ and $\sigma_\theta^2 = 100$.

[13] An alternative proposal distribution is $\theta \sim N(\hat{\theta},\hat{\sigma}_\theta^2)$ (see Wago (ed.), 2005, for instance).

the results given in Table 2. First, when we use the long sample, bank lending loses significance as a determinant of land-price movements in residential areas (see the first and third columns). This contrasts with the basic model where bank lending was always a significant determinant of land prices. Second, for the post-bubble sub-sample, stock prices become a significant land-price determinant in commercial areas (see the sixth and eighth columns). Third, the existence of serial correlation in the error terms does not affect the estimate of ρ and thus is a minor problem, if our primary interest is in the measurement of spatial correlation.

(2) A Dynamic Model

As has already been mentioned, the basic model captures only the short-run effects of spatial correlation that occur within one year and thus underestimates its long-run effects on the land market. Below, we assume that it takes one year for spatial correlation to reveal itself. Under this assumption, land-price movements in one prefecture are explained by the lag of average land-price changes in adjacent prefectures.

Equation (2-1) now becomes

$$y_{i,t} = \rho \Sigma_{j \neq i} w_{i,j} y_{j,t-1} + \alpha_i + x_{i,t}\beta + \varepsilon_{i,t} . \tag{4-12}$$

We can rewrite this in matrix form as follows.

$$Y_+ = \rho W_{T-1} Y_- + D_{T-1}\alpha + X_+\beta + \varepsilon_+ , \tag{4-13}$$

where $Y_+ = (y_{1,2}, \cdots, y_{N,2}, \cdots, y_{1,T}, \cdots, y_{N,T})'$,

$Y_- = (y_{1,1}, \cdots, y_{N,1}, \cdots, y_{1,T-1}, \cdots, y_{N,T-1})'$,

$X_+ = (x'_{1,2}, \cdots, x'_{N,2}, \cdots, x'_{1,T}, \cdots, x'_{N,T})'$,

$\varepsilon_+ = (\varepsilon_{1,2}, \cdots, \varepsilon_{N,2}, \cdots, \varepsilon_{1,T}, \cdots, \varepsilon_{N,T})'$.

The full conditional posterior distributions of α_0 and ξ^2 are exactly the same as those derived in the previous section. The full conditional posterior distributions of α, β, and Σ are obtained by replacing Y with its lag. For the sake of precision, we provide a complete list of full conditional posterior distributions.

$$\beta \mid \rho, \alpha, \Sigma, Y, X \sim N(\beta^d, \Sigma_\beta^d), \quad (4\text{-}14)$$

where $\Sigma_\beta^d = (X_+{}'\Sigma_{T-1}^{-1}X_+ + \Sigma_\beta^{-1})^{-1}$, $\beta^d = \Sigma^d(X_+{}'\Sigma_{T-1}^{-1}U^d + \Sigma_\beta^{-1}\beta^*)$,

$U^d = Y_+ - \rho W_{T-1}Y_- - D_{T-1}\alpha$.

$$\xi^2 \mid \alpha \sim Gamma^{-1}(\tilde{\nu}/2, \tilde{\lambda}/2). \quad \text{(the same as equation (2-7))} \quad (4\text{-}15)$$

$$\alpha_0 \mid \alpha, \xi^2 \sim N(\tilde{\mu}, \xi^2/\tilde{N}). \quad \text{(the same as equation (2-8))} \quad (4\text{-}16)$$

$$\alpha_i \mid \rho, \alpha_0, \beta, \Sigma, Y, X \sim N(\alpha_i^d, \xi^{d^2}), \quad (4\text{-}17)$$

where $\xi^{d^{-2}} = \xi^{-2} + (T-1)\sigma_i^{-2}$,

$\alpha_i^d = \xi^{d^2}(\alpha_0\xi^{-2} + \Sigma_{t=1}^{T-1}c_{i,t}^d\sigma_i^{-2})$,

$c_{i,t}^d = y_{i,t} - \rho\Sigma_{j\neq i}w_{i,j}y_{j,t-1} - x_{i,t}\beta$.

$$\sigma_i^2 \mid \rho, \alpha, \beta, Y, X \sim Gamma^{-1}(\kappa^d/2, \tau^d/2), \quad (4\text{-}18)$$

where $\kappa^d = \kappa^* + T - 1$, $\tau^d = \tau^* + \Sigma_{t=1}^{T-1}e^{d}{}_{i,t}^{2}$, $e_{i,t}^d = y_{i,t} - \rho W y_{i,t-1} - \alpha_i - x_{i,t}\beta$.

Recall that, in the basic model, dependent variable Y also appeared as an explanatory variable on the right-hand side. For this reason, the full conditional posterior distribution of ρ had a very complex shape, as was apparent in equation (2-10). Since the dynamic model (4-12) suffers from no such simultaneity, the full conditional posterior distribution of ρ is greatly simplified. However, since we need a distribution for land-price movements in the first year, i.e., $y_1 = (y_{1,1}, \cdots, y_{N,1})'$, the full conditional posterior distribution of ρ remains somewhat complex. Successive substitution in equation (4-12) gives us the following model.

$$\begin{aligned} y_1 &= \rho W y_0 + \alpha + x_1\beta + \varepsilon_1. \\ &= (\alpha + x_1\beta) + \rho W(\alpha + x_0\beta) + \rho^2 W^2(\alpha + x_{-1}\beta) + \cdots \\ &\quad + \varepsilon_1 + \rho W\varepsilon_0 + \rho^2 W^2\varepsilon_{-1} + \cdots. \end{aligned}$$

Now suppose that the steady state value of x_t is given by $\bar{x}$.[14] Denote the mean of y_1 by $\bar{y}_1$ and the variance of y_1 by Σ_{y_1}. Then we have

[14] One question is how to define $\bar{x}$. In this paper, we assume $y_1 = \bar{y}_1$. $\bar{x}$ is defined implicitly to be consistent with this assumption.

$$\bar{y}_1 = (I - \rho W)^{-1}(\alpha + \bar{x}\beta).$$

$$\Sigma_{y_1} = \Sigma + \rho^2 W\Sigma W' + \rho^4 W^2 \Sigma W^{2}{}' + \cdots.$$

(We can redefine Σ_{y_1} as the matrix $\Sigma_{y_1} = \Sigma + \rho^2 W\Sigma_{y_1} W'$). Using these, we have

$$\rho \mid \alpha, \beta, \Sigma, Y, X$$

$$\propto B(\rho)\exp\{-\tfrac{1}{2}(\rho - \rho_{y_1})'(W_{T-1}Y_-)'\Sigma_{T-1}^{-1}(W_{T-1}Y_-)(\rho - \rho_{y_1})\}, \qquad (4\text{-}19)$$

where $B(\rho) = \left|\Sigma_{y_1}\right|^{-1/2} \exp\{-\tfrac{1}{2}(y_1 - \bar{y}_1)'\Sigma_{y_1}^{-1}(y_1 - \bar{y}_1)\}$,

$$\rho_{y_1} = \{(W_{T-1}Y_-)'\Sigma_{T-1}^{-1}(W_{T-1}Y_-)\}^{-1}(W_{T-1}Y_-)'\Sigma_{T-1}^{-1}(Y_+ - D_{T-1}\alpha - X_+\beta),$$

$$-1 < \rho < 1.$$

Note that $\bar{y}_1$ and Σ_{y_1} are both functions of ρ, as is $B(\rho)$. Therefore, the full conditional posterior distribution of ρ does not fall nicely into the shape of any well-known distribution, due to $B(\rho)$. Hence, we use the MH algorithm for sampling ρ. A plausible proposal distribution is constructed by approximating the right-hand side of equation (4-19), as suggested in section II.

Table 3 presents estimation results for equation (4-12), which as we have seen introduces a one-year lag into the spatial autoregressive model. The first column shows the results for residential areas using the geographical weight, based on the long sample; the fifth column gives those for commercial areas. In both, spatial correlation, ρ, is measured to be 0.5, demonstrating mutual Granger-causality of land prices among prefectures (significant at the 2.5 % level in a one-sided test). The results suggest that we should assume a one-year lag to avoid underestimating spatial correlation among prefecture-level land prices.

Our estimation of the dynamic model uncovers the following two interesting facts. First, when we confine ourselves to the post-bubble sub-sample, stock prices become a significant land-price determinant in both residential and commercial areas, irrespective of the linkage weight adopted (see the second, fourth, sixth, and eighth columns). This contrasts with the basic model where stock prices were not a significant determinant of land prices. One interpretation is that stock prices influenced the behavior of land prices, but their influence was mixed up with that of spatial correlation in the estimation.

Second, recall that in the basic model there were very small falls observed in spatial correlation when we switched from the long sample to the post-bubble sample. This contrasts with the dynamic model where, comparing the fifth and sixth columns (also the seventh and eighth) in Table 3, we find substantial falls in spatial correlation in commercial areas when we switch to the post-bubble sub-sample. This is an interesting finding, since it implies that the transmission of land-price shocks has become short-lived in commercial areas.

V. Determinants of Land-Price Movements in the 23 Wards in Tokyo

Land-price rises in Tokyo peaked out in 1986, earlier than in other prefectures. Figures 10 and 11 show the annual land-price changes in the 23 Tokyo wards during the period from 1984 through 1987.[15] We can see how land-price rises in Tokyo start in central areas, such as Chiyoda, Chuo, and Minato, and then spread rapidly toward the periphery.

(1) Data

In this section, we explore the determinants of land-price movements in the 23 Tokyo wards and discuss the city's peculiarities compared to the rest of Japan. We have a sample of 713 data with $N = 23$ and $T = 31$. We estimate the basic model, i.e., equation (2-1). We measure the interrelatedness of wards via the geographical weight. Candidate land-price determinants include population growth, *per capita* income

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[15] The data does not necessarily offer, for all wards all of the time, observations for sites where land prices are reported for two consecutive years. In particular, we are missing some data for residential land prices in certain wards located in the central area of Tokyo before the asset-bubble period. To compensate for the missing data, we adopt the following imputation strategy. Annual changes for Chiyoda, Chuo, Bunkyo, and Taito residential land prices in fiscal 1982 are given by the average of annual changes in the previous and following years in the respective wards. Annual changes for Chuo and Sumida residential land prices during the period from fiscal 1975 through 1980 are approximated by those observed for these years in Minato and Koto, respectively, since land-price behavior has been very close between these wards since fiscal 1980.

growth, increases in bank lending, rises in lending rates, rises in stock prices, and of course spatial correlation – just as assumed in the prefecture-level analysis. In order to gauge the importance of financial intermediaries in determining land-price trends, we estimate the model with and without the financial-condition variables, bank lending and capital costs. Since we have data on population growth in each ward, we make use of this in the estimation. Unfortunately, however, there is no such ward-level data available for the other determinants, so we have to be satisfied with employing the same data as in the prefecture-level analysis.

(2) Results

Table 4 presents the basic model estimation results for the 23 wards in Tokyo. In the first column, we show the results for residential areas with financial variables included, based on the long sample; in the fifth column, those for commercial areas. In both, spatial correlation, ρ, is estimated at 0.9 (significant at the 2.5% level in a one-sided test). The same results obtain even if we drop the financial variables (see the third and seventh columns). In the post-bubble sample, spatial correlation declines, but only marginally (see the second and sixth columns). Note that the spatial correlation among the Tokyo wards is larger than among the prefectures (estimated at 0.6). The high spatial correlation may simply be thought to reflect the fact that the average distance between the Tokyo wards is shorter than that between the prefectures.

One notable result is that only stock prices have a positive influence on the behavior of land prices in residential areas (significant at the 2.5 % level in a one-sided test; see the first and second columns). In section IV (2), we pointed out the possibility that stock prices act as determinants of land-price movements during the post-bubble period. Here, in the analysis of Tokyo, we can identify the effects of stock prices on the behavior of land prices clearly even in the basic model. Furthermore, the influence of stock prices on land prices was greater during the pre-bubble period than during the post-bubble period. These results suggest that land may be more consciously considered an investment asset in Tokyo than in the rest of Japan.

In commercial areas, population and bank lending are seen to affect the trend of land prices (significant at the 2.5 % level in a one-sided test). It is worth noting that population is always a determinant of commercial land-price movements in Tokyo whatever the sample or specification (see the fifth to eighth columns) is. The suggestion is that land values in Tokyo commercial areas are determined by population, which affects business conditions such as ability to pull in customers. Furthermore, the influence of population on land prices has increased during the post-bubble period. Hence, in Tokyo commercial areas, the argument that land prices have become more sensitive to economic fundamentals since the bursting of the asset bubble may hold.

Lastly, let us examine the estimates of error-term variances. As expected, central wards, such as Chiyoda, Chuo, and Shibuya, have been hit by relatively large shocks. Yet it is interesting that some peripheral wards, such as Nerima and Sumida, have also experienced large shocks. One notable finding, although not reported in the table, is that inequality in error-term variances has expanded during the post-bubble period. When we use the full sample, the maximum variance (Taito ward) is five times as large as the minimum (Kita ward). In contrast, when we use the post-bubble sub-sample, the maximum variance (Chuo ward) is ten times as large as the minimum (Kita ward). That is, land-prices shocks are concentrated in the central areas of Tokyo during the post-bubble period. This suggests that local factors have played a more important role in the formation of land prices than macro-economic factors in commercial areas of post-bubble Tokyo.

VI. CONCLUSION

In this paper, we compile prefecture-level panel data on official land prices for the period from fiscal year 1977 through 2005 to investigate how important spatial correlation is among the 47 prefectures in Japan and what economic factors determine the movements of Japanese land prices from a Bayesian econometric point of view. The main conclusions in this paper can be summarized as follows:

- There is spatial correlation among the 47 prefecture in Japan.
- Spatial correlation in residential areas is likely to arise as a result of geographical propinquity, while in commercial areas as a result of economic links as well as

geographical propinquity.

・Basically, trends in land prices have been determined by economic fundamentals, such as population and income, as well as financial conditions, such as bank lending.

・No firm evidence is obtained to support the argument that price formation in the Japanese land market has become more sensitive to economic fundamentals since the bursting of the asset bubble.

Furthermore, we explore the determinants of land-price movements in the 23 wards in Tokyo and discuss Tokyo's peculiarities. The main findings are as follows.

・The spatial correlation among the 23 wards in Tokyo is higher than that among the 47 prefectures in Japan. This is thought to reflect the fact that the average distance between the Tokyo wards is shorter than that between the prefectures.

・In Tokyo, price movements of financial substitutes have a relatively clear influence on the behavior of land prices.

・The argument that land prices have become more sensitive to economic fundamentals since the 1990s may hold in Tokyo commercial areas, although an extensive robustness check is required before this conclusion can be stated with any conviction.

Since the bursting of the asset bubble, the Japanese economy has been undergoing a long period of structural adjustment during which the problem of non-performing loans has been gradually settled. In addition, the Japanese economy has returned to a path of steady growth. The rises in land prices observed recently in metropolitan areas are thought to reflect these improvements in economic fundamentals in Japan. Particularly, it is often pointed out that the recent boom in the Tokyo land market has been supported in part by the diversification of financial technology, as demonstrated in the increased popularity of non-recourse loans and real-estate investment funds (REIT).

Some say, however, that this mini land-price boom is a local phenomenon, triggered by foreign funds aimed at the redevelopment projects currently underway in central Tokyo. Others suggest that the boom is a temporary phenomenon, reflecting strong demand for condominiums by the second-generation of baby boomers. These arguments all cast suspicion onto the idea that the boom in the central Tokyo land market will spread all across Japan. Moreover, looking at the long-run perspective, demand for residential land will decrease as the number of households declines due to low birthrates. Therefore, it is highly likely that the Japanese land market will shrink over time.

Finally, it should be noted that polarization in land-price movements between metropolitan areas and local areas may be expected to worsen. Polarization will occur if local economies recover more slowly than Tokyo, although it will be partially alleviated by spatial correlation. Even if the economy expands at the same pace across Japan, the population is likely to concentrate in the Tokyo metropolitan area, as was observed in the 1980s. Differences in market conditions between local areas and metropolitan areas need to be carefully monitored in order to achieve stability in the financial system and the behavior of output and prices across Japan.

APPENDIX. A PROBIT MODEL

As pointed out by Nishimura and Shimizu (2002, 2006) and Saita (2003), the land prices published by the Ministry of Land, Infrastructure and Transport are appraisal values and thus may not reflect actual transaction prices. If these published land prices deviate from true prices, inference based on them will be misleading. Two points in particular need to be considered concerning the reliability of this data set: first, how reliable are the observed magnitudes of price movements; second, how reliable is the timing of any changes in the trend of price movements. Nishimura and Shimizu (2002, 2006) point out that the reliability of the published land prices is weak in both these senses. If this is indeed the case, there is no way forward other than to create a reliable set of land prices with which to replace the published land prices. In this appendix, however, we assume that at least the timing of changes in the trend of price movements is reliable. This enables us to alleviate the measurement error problem by focusing on shifts in the direction of price changes.

We use a spatial panel probit model, as introduced by Wago and Kakamu (2005). Denote the true transaction price of land in the i th prefecture in period t by $z_{i,t}$. A price change is then given by $\Delta z_{i,t}$ and driven by the following model.

$$\Delta z_{i,t} = \rho \Sigma_{j \neq i} w_{i,j} \Delta z_{j,t} + \alpha_i + \Delta x_{i,t} \beta + \varepsilon_{i,t} . \qquad \text{(A-1)}$$

In matrix form, we have

$$\Delta Z = \rho W_{T-1} \Delta Z + D_{T-1} \alpha + \Delta X \beta + \varepsilon . \qquad \text{(A-2)}$$

where $\Delta Z = (\Delta z_{1,2}, \cdots, \Delta z_{N,2}, \cdots, \Delta z_{i,t}, \cdots, \Delta z_{1,T}, \cdots, \Delta z_{N,T})'$,

$\Delta X = (\Delta x'_{1,2}, \cdots, \Delta x'_{N,2}, \cdots, \Delta x'_{i,t}, \cdots \Delta x'_{1,T}, \cdots, \Delta x'_{N,T})'$.

This equation is obtained by replacing the dependent and independent variables with their first differences in equation (2-1) or (2-2).[16]

Next, we define binominal random variable $q_{i,t}$, an indicator for whether the

[16] Note that fixed effects, α_i, disappear when differencing equation (2-1). In equation (A-1), however, we reintroduce this term.

change in the land price represents an increase or a decrease.

$$q_{i,t} = \begin{cases} 1, & if \quad \Delta z_{i,t} \geq 0. \\ 0, & if \quad \Delta z_{i,t} < 0. \end{cases}$$

The estimation method is almost the same as that employed when estimating the basic model. Note, however, that we cannot identify the variance of the error term, $\varepsilon_{i,t}$, nor of the other parameters. For this reason, it is usual to assume that the variance of the error term is 1. In this case, we have $\Sigma = I_N$. Having dealt with this point, we can derive the full conditional posterior distributions as follows.

$$\beta \mid \rho, \alpha, \Sigma, Y, X \sim N(\beta^p, \Sigma_\beta^p), \tag{A-3}$$

where $\Sigma_\beta^p = (\Delta X' \Sigma_{T-1}^{-1} \Delta X + \Sigma_\beta^{-1})^{-1}$, $\beta^p = \Sigma_\beta^p (\Delta X' \Sigma_{T-1}^{-1} U^p + \Sigma_\beta^{-1} \beta^*)$,

$U^p = \Delta Z - \rho W_{T-1} \Delta Z - D_{T-1} \alpha$.

$$\alpha_i \mid \rho, \alpha_0, \beta, \Sigma, Y, X \sim N(\alpha_i^p, \xi^{p^2}), \tag{A-4}$$

where $\xi^{p^{-2}} = \xi^{-2} + T - 1$, $\alpha_i^p = \xi^{p^2}(\alpha_0 \xi^{-2} + \Sigma_{t=1}^{T-1} e_{i,t}^p)$,

$e_{i,t}^p = \Delta z_{i,t} - \rho \Sigma_{j \neq i} w_{i,j} \Delta z_{j,t} - \Delta x_{i,t} \beta$.

$$\xi^2 \mid \alpha \sim Gamma^{-1}(\tilde{\nu}/2, \tilde{\lambda}^2/2). \quad \text{(the same as equation (2-7))} \tag{A-5}$$

$$\alpha_0 \mid \alpha, \xi^2 \sim N(\tilde{\mu}, \xi^2/\hat{N}). \quad \text{(the same as equation (2-8))} \tag{A-6}$$

$$\rho \mid \alpha, \beta, Y, X$$
$$\propto \mid I_N - \rho W \mid^T \exp\{-\tfrac{1}{2}(\rho - \rho^p)'(W_{T-1}\Delta Z)'(W_{T-1}\Delta Z)(\rho - \rho^p)\}, \tag{A-7}$$

where $\rho^p = \{(W_{T-1}\Delta Z)'(W_{T-1}\Delta Z)\}^{-1}(W_{T-1}\Delta Z)'(\Delta Z - D_{T-1}\alpha - \Delta X \beta)$,

$1/\lambda_{\min} < \rho < 1/\lambda_{\max}$.

The distinguishing feature of this model is that although we know whether changes in land prices, $\Delta z_{i,t}$, are positive or negative, we do not know their magnitude. Therefore, we need to sample the values of $\Delta z_{i,t}$, in addition to sampling the model parameters. To do so, we need the full conditional posterior distribution for $\Delta z_{i,t}$. Another thing to bear in mind is that each $\Delta z_{i,t}$ needs to be sampled from the positive domain for $q_{i,t}$ = 1, but from the negative domain for $q_{i,t}$ = 0. In other words, we have to implement the sampling of $\Delta z_{i,t}$ from a truncated normal distribution. The problem is more complicated, since the $\Delta z_{i,t}$ are not independent simultaneously.

We utilize Geweke's (1991) method for the sampling of $\Delta z_{i,t}$. Note that each $\Delta z_{i,t}$ is serially independent. Then we have

$$\Delta z_t \sim N(\mu_{\Delta z_t}, \Sigma_{\Delta z_t}),$$

$$\text{where} \quad \mu_{\Delta z_t} = (I_N - \rho W)^{-1}(D\alpha + \Delta x_t \beta),$$

$$\Sigma_{\Delta z_t} = \{(I_N - \rho W)'(I_N - \rho W)\}^{-1}.$$

Define a new variable $\varsigma_t = \Delta z_t - \mu_{\Delta z_t}$. Construct a new vector by dropping the i th element from ς_t and denote it by ς_t^{-i}. Then we can implement the sampling of $\varsigma_{i,t}$, given an arbitrary realization of ς_t^{-i}.

$$\varsigma_{i,t} = \gamma^{-i}\varsigma_t^{-i} + \psi_i \nu_i,$$

$$\text{where} \ \gamma^{-i} = -\phi_i^{-i}/\phi_{i,i}, \ \psi_i^2 = \phi_{i,i}^{-1},$$

$$\nu_i \sim N(0,1) \ \text{ for } \ (\underline{b}_{i,t} - \gamma^{-i}\varsigma_t^{-i})/\psi_{i,t} < \nu_{i,t} < (\overline{b}_{i,t} - \gamma^{-i}\varsigma_t^{-i})/\psi_{i,t}.$$

Note that $\phi_{i,i}$ is the element in the i th row and i th column of $\Sigma_{\Delta z_t}^{-1}$; ϕ_i^{-i} is the i th row of $\Sigma_{\Delta z_t}^{-1}$ with its i th element dropped. We also define boundaries $\underline{b}_{i,t}$ and $\overline{b}_{i,t}$ as follows:

$$\begin{cases} \underline{b}_{i,t} = -\mu_{\Delta z_t, i} & \text{and} \quad \overline{b}_{i,t} = +\infty \quad \text{for} \quad q_{i,t} = 1. \\ \underline{b}_{i,t} = -\infty & \text{and} \quad \overline{b}_{i,t} = -\mu_{\Delta z_t} \quad \text{for} \quad q_{i,t} = 0. \end{cases}$$

Once we complete the generation of $\varsigma_{i,t}$ for $i = 1, \cdots, N$, we can obtain $\Delta z_{i,t}$ through the relationship $\Delta z_t = \varsigma_t + \mu_{\Delta z_t}$.

Table A1 presents the estimation results of the probit model for the 47 prefectures in Japan. The first thing to note is that the estimates of spatial correlation, ρ, in the probit models are larger than those obtained in the basic model, irrespective of land use, selected sample, and choice of linkage weight. This tells us that the peaks and troughs of annual changes in land prices are synchronized among the 47 prefectures in Japan, although their heights and depths differ.

When we use the full sample, we find that land prices in residential areas are affected significantly by population growth and bank lending, while they are determined by stock prices and bank lending when we use the post-bubble sub-sample. As for commercial areas, land prices are affected significantly by bank lending and stock prices, whichever sample we use. These results all suggest that financial conditions, such as bank lending, and the price movements of financial substitutes, such as stock prices, have played an important role in determining the turning points of land-price movements.

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Table 1. Estimation Results for the Basic Model (47 prefectures)

Land Use	Residential				Commercial			
Linkage weight	Geographical		Economic		Geographical		Economic	
Sample	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble
spatial correlation	0.607 **	0.517 **	0.305 **	0.252 **	0.599 **	0.520 **	0.450 **	0.449 **
population	1.985 **	0.763 **	4.256 **	2.408 **	0.662 **	▲ 0.405	0.907 **	2.737 **
income	0.120 **	0.018	0.187 **	0.143 **	0.285 **	0.137 **	0.429 **	0.230 **
bank lending	0.025 **	0.091 **	0.051 **	0.159 **	0.167 **	0.278 **	0.249 **	0.427 **
lending rates	0.417 **	0.157 *	0.729 **	0.040	1.186 **	0.253	1.509 **	0.388 **
stock prices	▲ 0.013 **	0.001	▲ 0.055 **	▲ 0.009 **	▲ 0.001	0.005	▲ 0.085 **	0.004
Top 5 error-term variances	Kanagawa	Kyoto	Kanagawa	Kyoto	Kanagawa	Aichi	Chiba	Aichi
	Tokyo	Tokyo	Tokyo	Tokyo	Chiba	Tokyo	Kanagawa	Osaka
	Chiba	Hyogo	Chiba	Osaka	Aichi	Osaka	Kyoto	Tokyo
	Saitama	Osaka	Kyoto	Hyogo	Hokkaido	Hokkaido	Tokyo	Kyoto
	Kyoto	Chiba	Osaka	Chiba	Saitama	Kyoto	Saitama	Akita

Note: ** significant at the 2.5 % level in a one-sided test; * significant at the 5 % level in a one-sided test.

Table 2. Estimation Results for the Serially-Correlated Error-Term Model (47 prefectures)

Land use	Residential				Commercial			
Linkage weight	Geographical		Economic		Geographical		Economic	
Sample	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble
spatial correlation	0.549 **	0.566 **	0.257 **	0.339 **	0.535 **	0.535 **	0.470 **	0.514 **
population	1.673 **	0.181	2.338 **	0.494 *	1.263 **	0.174	1.912 **	2.150 **
income	0.041 **	0.021	0.068 **	0.048 **	0.119 **	0.051 *	0.150 **	0.064 **
bank lending	▲ 0.004	0.034 **	▲ 0.015 **	0.048 **	0.065 **	0.106 **	0.050 **	0.125 **
lending rates	0.283 **	0.180 **	0.493 **	0.172 **	0.879 **	0.583 **	0.960 **	0.563 **
stock prices	▲ 0.003	0.003	▲ 0.016 **	0.000	0.004	0.014 **	▲ 0.033 **	0.016 **
serial	0.667 **	0.923 **	0.722 **	0.944 **	0.644 **	0.853 **	0.672 **	0.895 **
Top 5 error-term variances	Kanagawa Chiba Tokyo Saitama Kyoto	Kyoto Tokyo Hyogo Chiba Osaka	Kanagawa Chiba Saitama Tokyo Kyoto	Kyoto Osaka Tokyo Hyogo Chiba	Kanagawa Chiba Saitama Tokyo Kyoto	Aichi Osaka Tokyo Saga Hokkaido	Chiba Saitama Kanagawa Kyoto Tokyo	Aichi Osaka Tokyo Saga Toyama

Note: ** significant at the 2.5 ％ level in a one-sided test; * significant at the 5 ％ level in a one-sided test.

Table 3. Estimation Results for the Dynamic Model (47 prefectures)

Land use	Residential				Commercial			
Linkage weight	Geographical		Economic		Geographical		Economic	
Sample	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble
spatial correlation	0.500 **	0.465 **	0.297 **	0.205 **	0.516 **	0.297 **	0.403 **	0.171 **
population	2.546 **	1.179 **	5.073 **	3.252 **	0.646 *	▲ 1.645 **	1.792 **	▲ 1.025
income	0.154 **	0.013	0.119 **	0.037	0.309 **	0.039	0.335 **	0.043
bank lending	0.090 **	0.129 **	0.095 **	0.181 **	0.253 **	0.275 **	0.303 **	0.368 **
lending rates	0.724 **	0.387 **	0.421 **	0.023	1.724 **	0.374 *	1.695 **	0.271
stock prices	0.001	0.020 **	▲ 0.021 **	0.014 **	0.056 **	0.041 **	▲ 0.005	0.035 **
Top 5 error-term variances	Tokyo Kanagawa Chiba Kyoto Osaka	Tokyo Hyogo Kyoto Chiba Aichi	Kanagawa Tokyo Chiba Kyoto Osaka	Tokyo Hyogo Kyoto Chiba Osaka	Chiba Tokyo Kanagawa Kyoto Aichi	Tokyo Aichi Osaka Kyoto Hokkaido	Chiba Kanagawa Kyoto Tokyo Osaka	Tokyo Aichi Osaka Kyoto Chiba

Note: ** significant at the 2.5 % level in a one-sided test; * significant at the 5 % in a one-sided test.

Table 4. Estimation Results for the Basic Model (23 Tokyo Wards)

Land use	Residential				Commercial			
Financial variables	Included		Excluded		Included		Excluded	
Sample	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble
spatial correlation	0.881 **	0.782 **	0.884 **	0.807 **	0.892 **	0.807 **	0.902 **	0.806 **
population	0.162	0.214	0.112	0.216	0.394 **	0.956 **	0.281 *	0.962 **
income	0.053	0.088	0.081 *	0.077	0.048	0.085	0.095 **	0.084
bank lending	0.045	▲ 0.154 **			0.082 **	▲ 0.026		
lending rates	▲ 0.050	0.166 **			▲ 0.098	0.149		
stock prices	0.023 **	0.011 *	0.028 **	0.009	0.005	0.001	0.013	0.001
5 largest error-term variances	Taito	Chuo	Taito	Chuo	Bunkyo	Shibuya	Bunkyo	Shibuya
	Chiyoda	Chiyoda	Chiyoda	Chiyoda	Nerima	Chuo	Nerima	Chuo
	Bunkyo	Minato	Bunkyo	Minato	Sumida	Edogawa	Sumida	Edogawa
	Shinjuku	Shibuya	Shinjuku	Shibuya	Chuo	Setagaya	Chuo	Setagaya
	Sumida	Toshima	Sumida	Toshima	Setagaya	Shinjuku	Setagaya	Shinjuku

Note: ** significant at the 2.5 % level in a one-sided test; * significant at the 5 % level in a one-sided test.

Table A1. Estimation Results for the Probit Model (47 prefectures)

Land use	Residential				Commercial			
Linkage weight	Geographical		Economic		Geographical		Economic	
Sample	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble	Long	Post-bubble
spatial correlation	0.802 **	0.698 **	0.874 **	0.773 **	0.660 **	0.562 **	0.824 **	0.793 **
population	0.462 *	0.017	1.040 **	0.848 **	▲ 0.447 *	▲ 0.734 **	0.029	0.017
income	0.010	0.015	0.004	0.004	0.009	0.024	0.006	0.018
bank lending	0.006 *	0.033 *	▲ 0.005	0.024	0.008 **	0.045 **	0.003	0.033 *
lending rates	0.181 **	0.211 **	0.086 **	0.110 **	0.155 **	0.170 **	0.081 **	0.102 **
stock prices	0.002	0.006 **	▲ 0.001	0.004 **	0.003 *	0.003 *	▲ 0.001	0.002

Note: ** significance at the 2.5 ％ level in a one-sided test; * significant at the 5 ％ level in a one-sided test.

Figure 1. Spatial Correlation (47 prefectures, residential use)

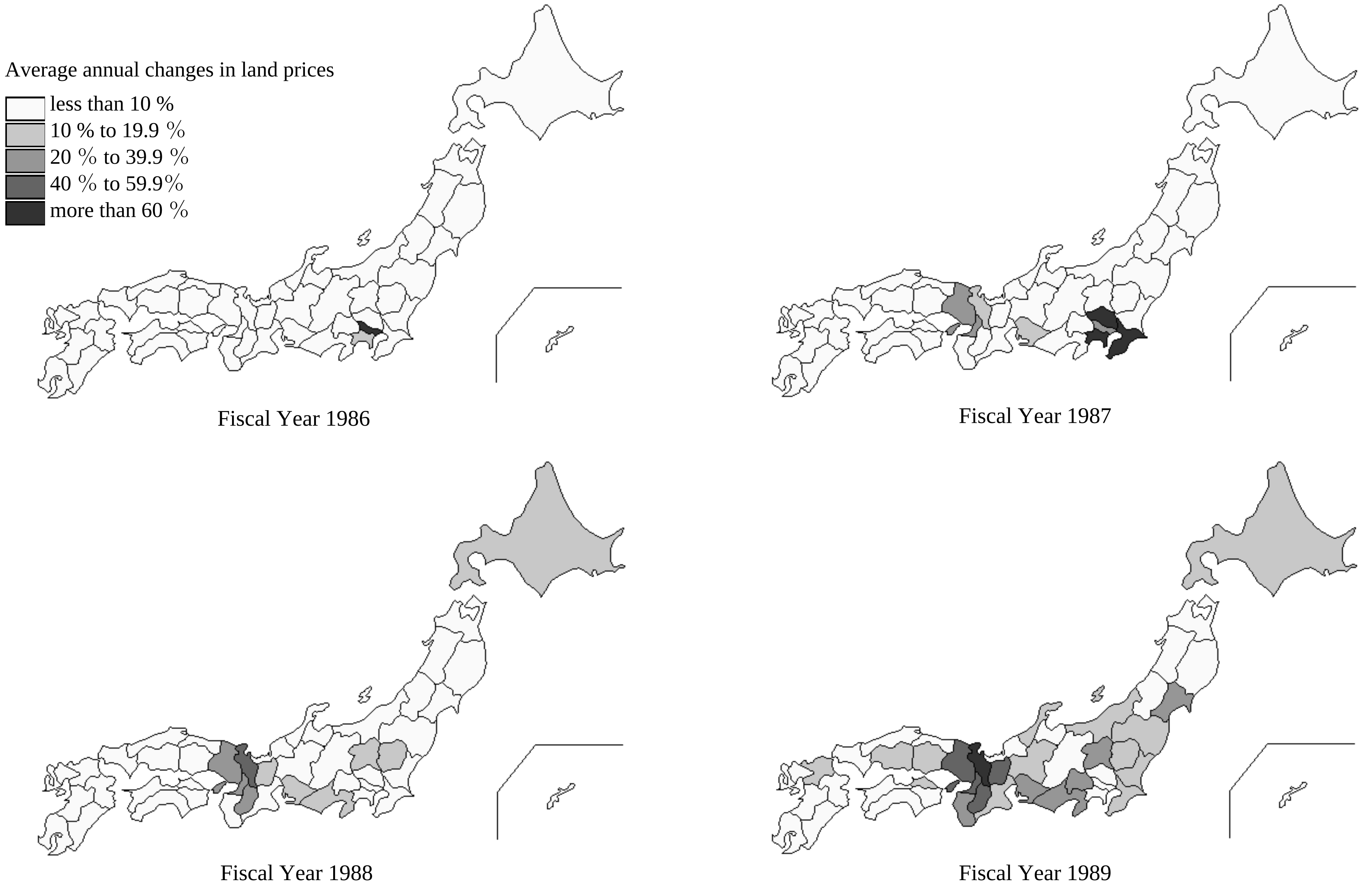

Figure 2. Spatial Correlation (47 prefectures, commercial use)

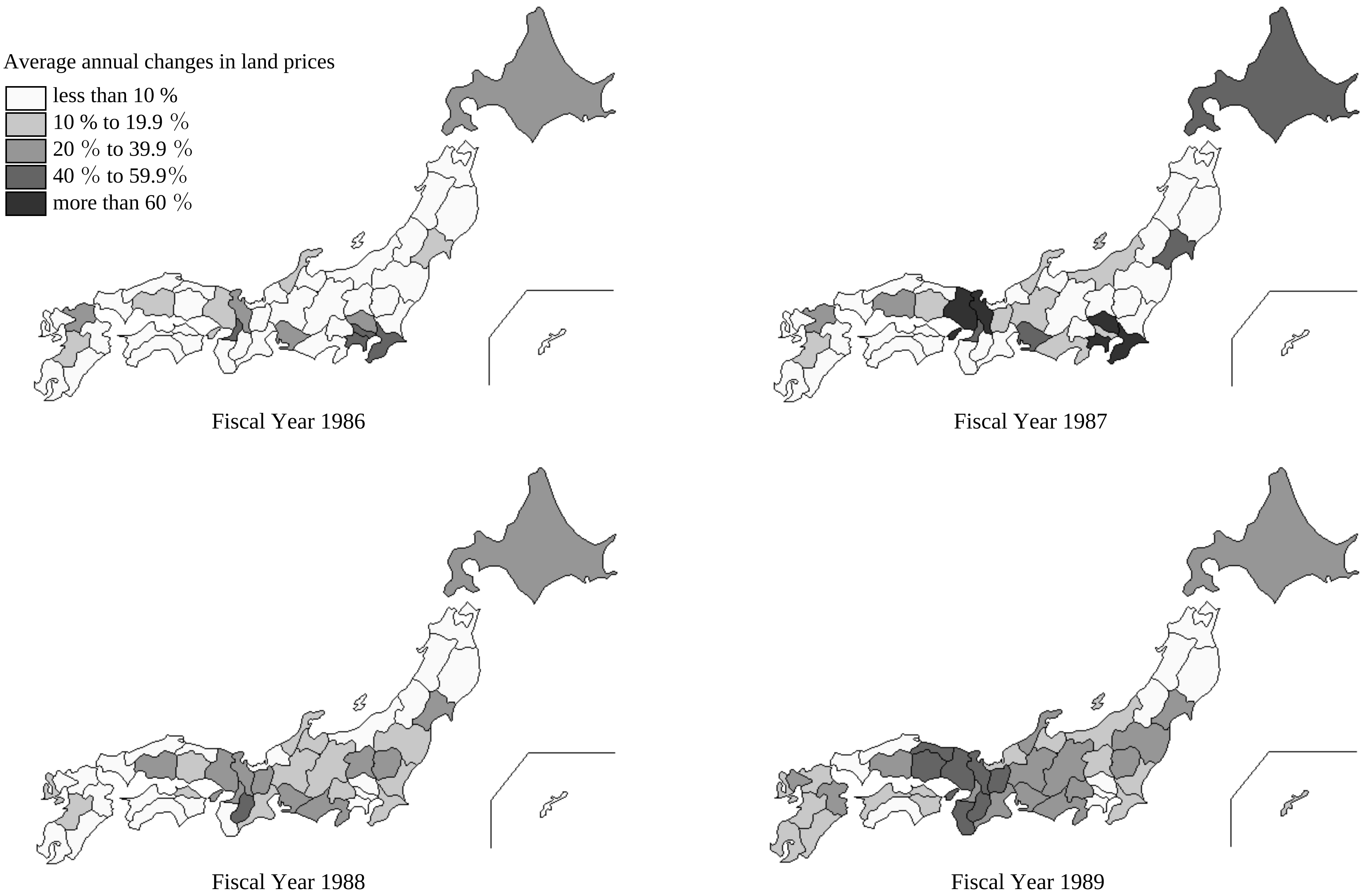

Figure 3. Residential Land Prices (47 prefectures)

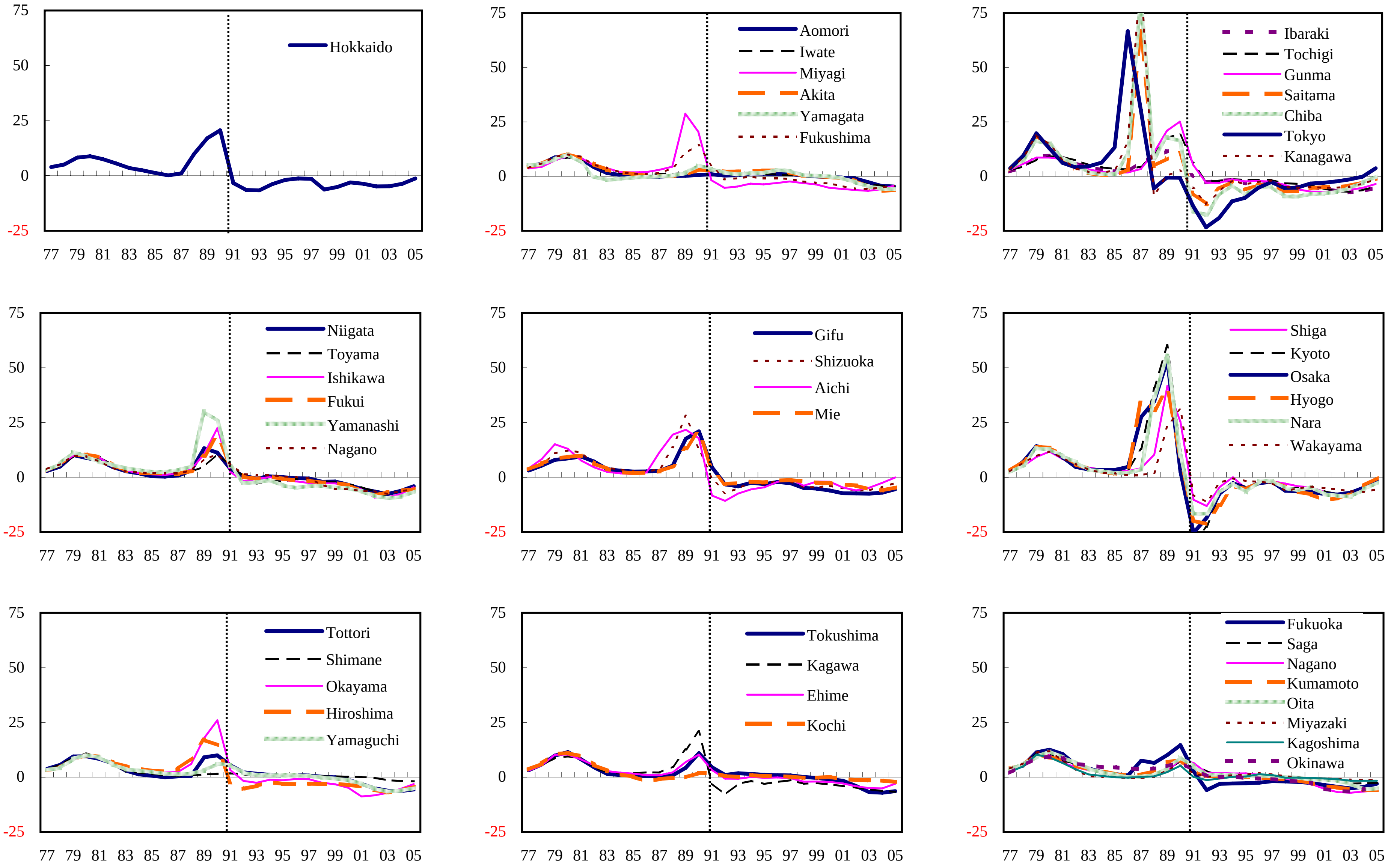

Figure 4. Commercial Land Prices (47 prefectures)

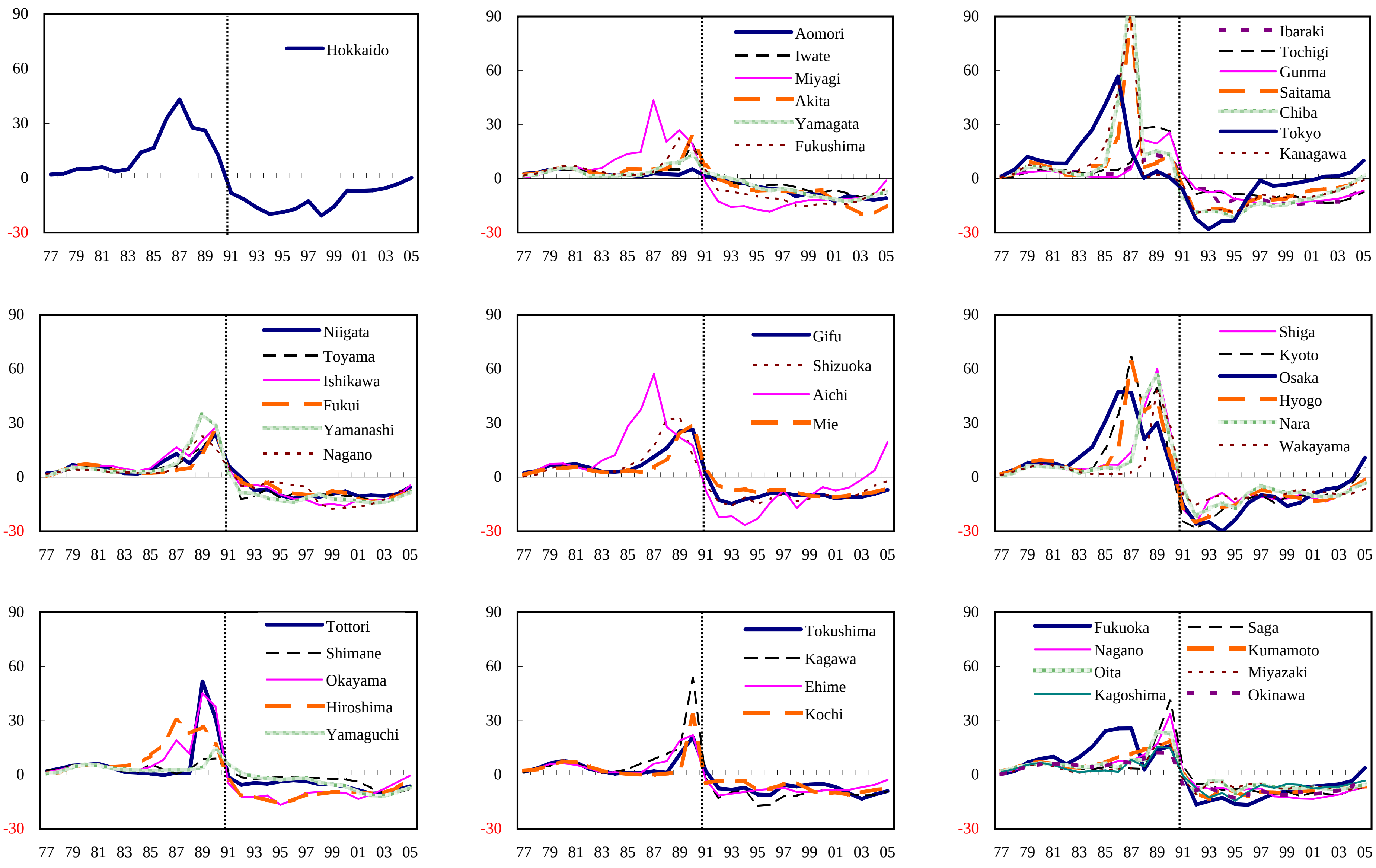

Figure 5. Population Growth (47 prefectures)

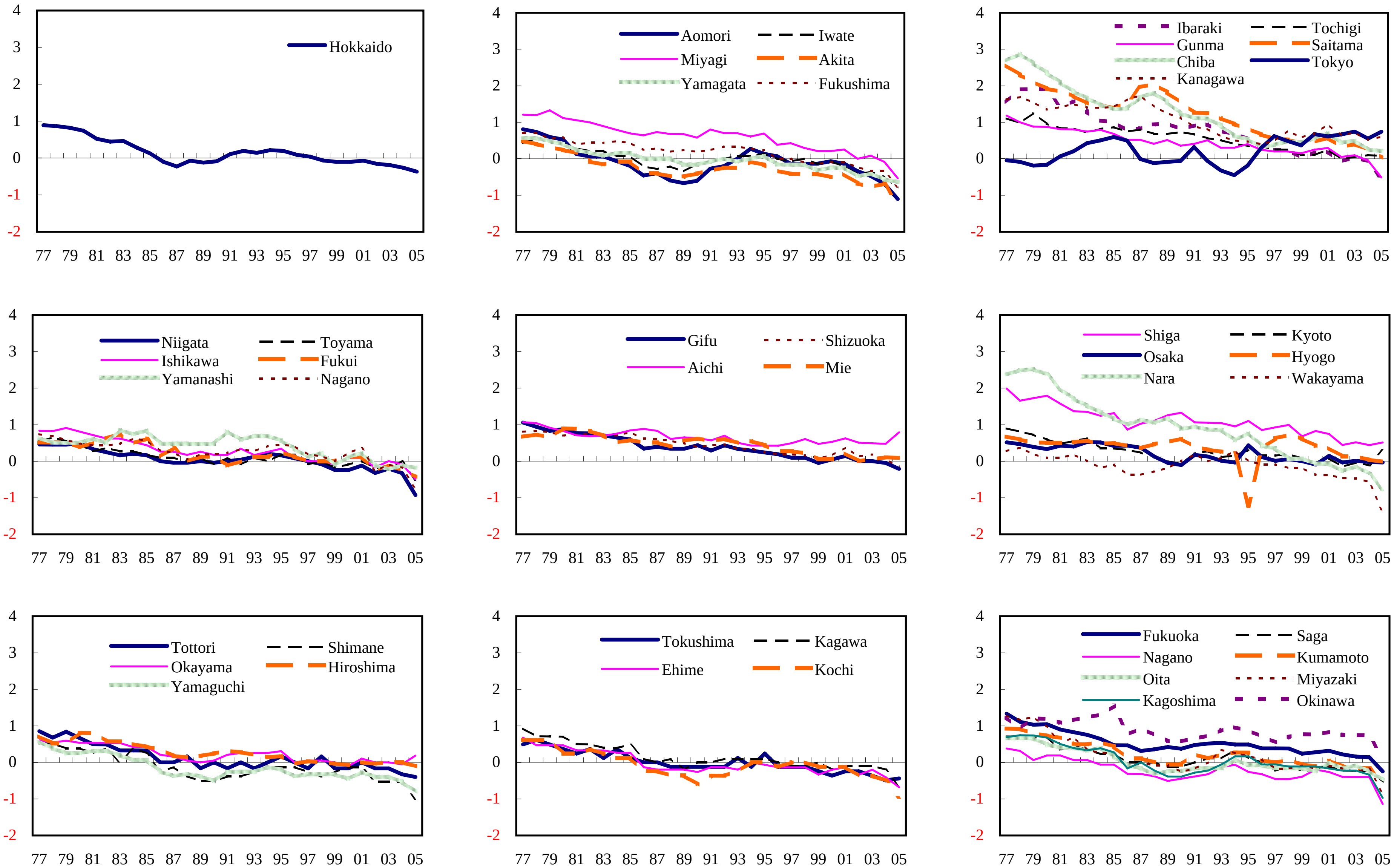

Figure 6. Per-Capita Income Growth (47 prefectures)

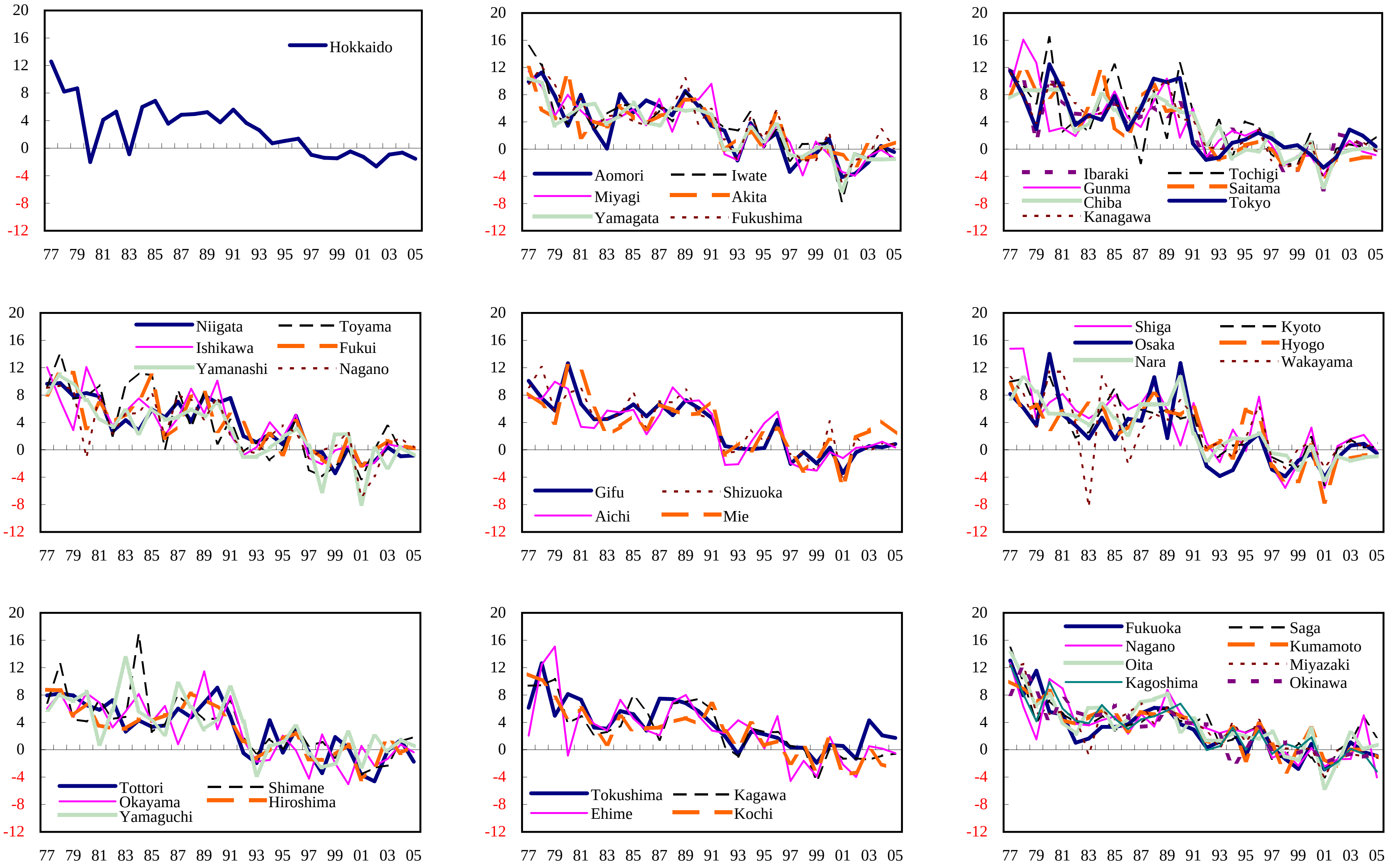

Figure 7. Increases in Bank Lending (47 prefectures)

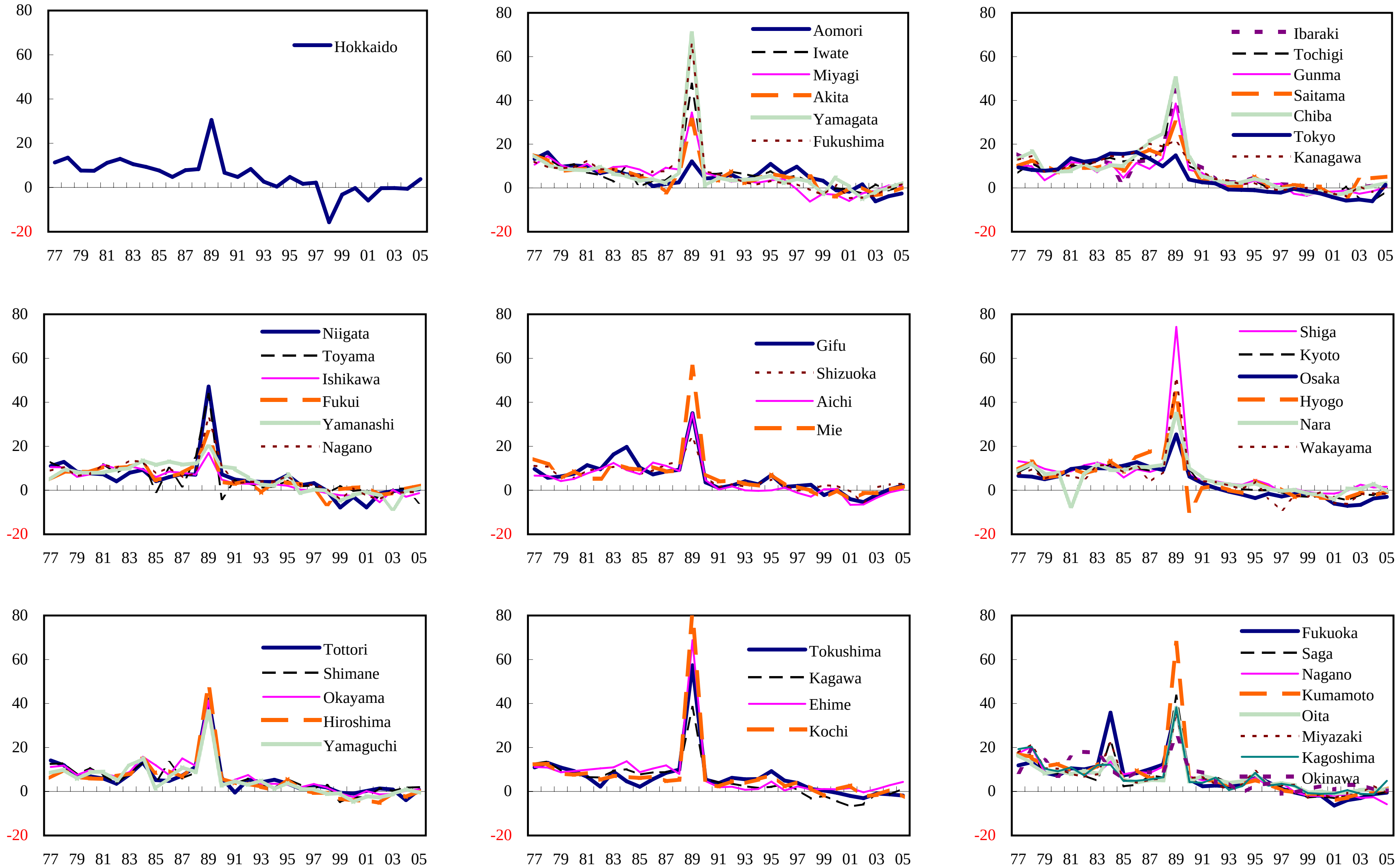

Figure 8. Capital Costs (47 Prefectures)

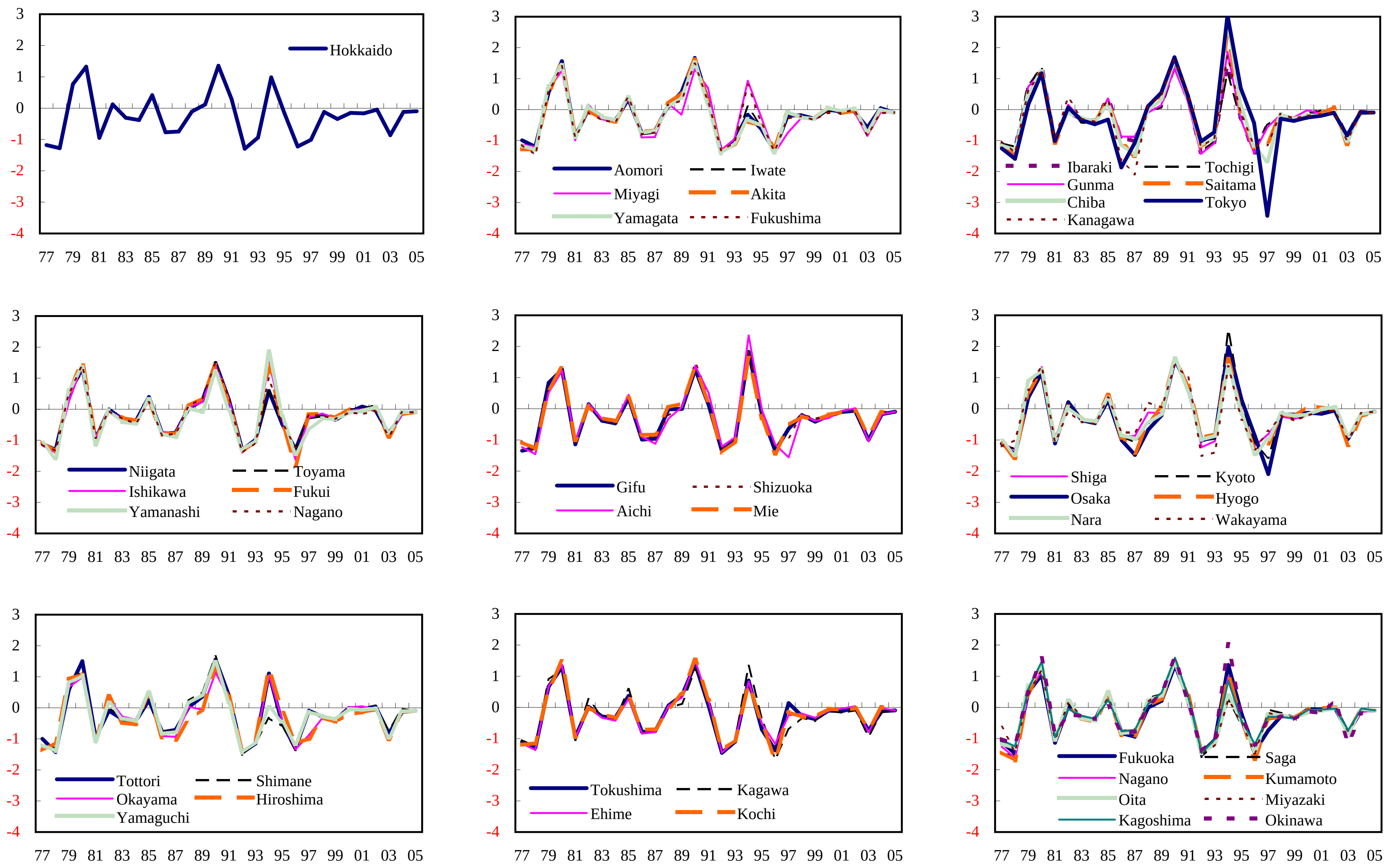

Figure 9. Changes in Stock Prices in Japan

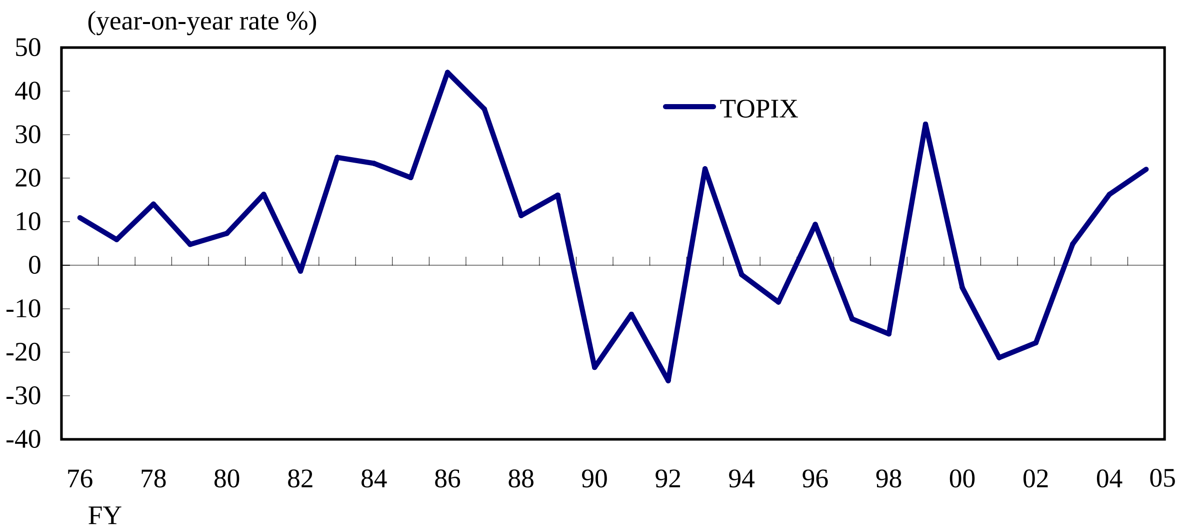

Figure 10. Spatial Correlation (23 Tokyo wards, residendial use)

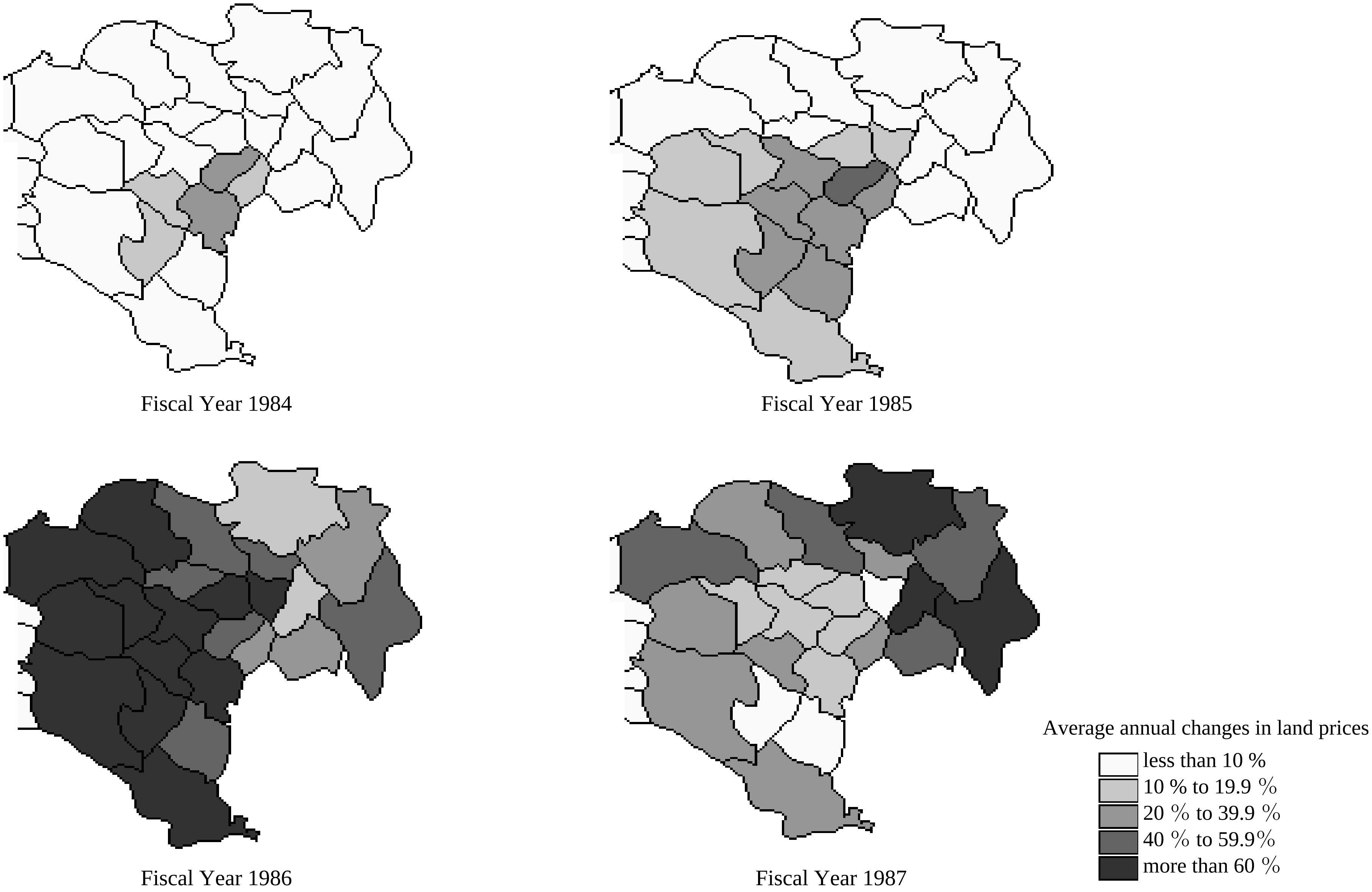

Figure 11. Spatial Correlation (23 Tokyo wards, commercial use)