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Economics Series

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Abstract

This paper models total factor productivity (TFP) in space and proposes an empirical model for TFP interdependence across spatial locations. The interdependence is assumed to occur due to age-structured human capital dynamics. A semi-parametric spatial vector autoregressive framework is suggested for modeling spatial TFP dynamics where the role of demographic state and technological change are explicitly incorporated in the model to influence their spatial TFP co-movements. Empirical scrutiny in case of Asian countries suggests that cross-country human capital differences in their accumulation and appropriation pattern significantly influenced TFP volatility interdependence. The finding of complementarity in TFP in spatial locations calls for joint policy program for improving aggregate and individual country welfare.

Keywords

Total factor productivity, spatial growth, non-linearity, human capital, age-structure, semi-parametric VAR

JEL Classifications

C14, C31, E61, N10, O30, O47

Contents

1 Introduction

The pioneering theoretical work of Solow (1956) established the idea that rising productivity can be defined as rising output with constant capital and labour inputs. Subsequent empirical applications have attempted to explain growth in total factor productivity (TFP) - that is the portion of output not explained by the amounts of inputs used in production - and its role in technology diffusion on country specific bases. For instance, in a recent concise survey of an international comparison of TFP differences, Islam (1999) evaluates various methodological approaches for explaining TFP growth across countries and shows that accounting for the quality of labour inputs renders the measurement of TFP more relevant. In the literature, TFP growth is often termed as the Solow residual, i.e., the part of growth not accounted for by capital accumulation (and that this residual is also pro-cyclical), inferring that labour input, broadly human capital with varying educational attainments, actually explains TFP growth. Given that the quality of human capital can be improved and the efficiency of labour enhanced, rising output can be directly associated with rising TFP, or more specifically, with rising human capital.

Comin and Gertler (2006) have shown that TFP growth can generate persistence in output at the national economy level. In the wake of globalisation, and shrinking national borders in favour of an increasingly integrated socio-economic and political world, it can be argued that no economy grows independently and that there is a high probability of spatial correlation of growth across countries, at least in the neibourhood. This feature of interdependence has been widely discussed in empirical and theoretical endogenous growth models in terms of spill-over effects of externalities (e.g., Romer, 1991 among others). Blackburn and Ravn (1993) and Tamura (1991) have devised theoretical growth models (frameworks) which suggest that co-operation in growth policies would lead to higher aggregate welfare, a feat that has been certified empirically by e.g., Crespo-Cuaresma and Mishra (2007). Since TFP depicts the unexplained part of output growth in terms of growing labour productivity, pro-cyclical growth features in one economy are most likely to be correlated with those of other economies through migration and other channels such as trade. However, productivity and knowledge spillovers can also take place between countries even without trade. This is facilitated mostly by migration in closely defined geographically clustered countries that share similar socio-economic characteristics.

In the current study we examine whether TFP growth is correlated across spatial locations and explore how human capital accumulation dynamics could possibly explain interdependence in TFP growth among countries. The investigation is carried out for a sample of 15 Asian countries for the period 1970-2000. We develop an interconnected model with feedback effects in a semi-parametric spatial Vector Autoregressive (VAR) setting (Chen and Conley, 2001) where we estimate dynamic spatial externalities among countries' TFP growth processes and their error terms with respect to human capital differences. The distance between countries is perceived as the human capital differences among them. Finally, we stress on the explicit role of demographic processes, i.e., the accumulation of age-structured human capital on TFP differences and complementarities across countries.

We argue that international technology spillovers from countries at the frontier to developing countries are facilitated by human capital stocks. Thus, the accumulation dynamics of this crucial input is likely to contribute to complementarities in TFP growth processes and their volatility. Thus, our idea is to shed light on a new explanation of cross-country TFP complementarity by utilizing the dynamics of age-structured human capital accumulation across countries. The latter exerts both productivity and scale effect on aggregate economic activity by explicitly underlining the dual role of demographic process and human capital-the two most important propellers of modern economic growth. The detection of such spillovers or externalities and their magnitudes are of great economic significance for the following reasons: First, many theoretical models of endogenous growth rely on externalities as a basic mechanism to generate growth endogenously. Second the importance of the interrelation between cross-country developments for aggregate fluctuations has not been well documented. Third, externalities can also be the source of indeterminacy and multiple equilibria. The study reveals that complementarities among Asian economies' TFPs with respect to age-structured human capital differences and that such complementarities call for joint policy programs in order to improve upon aggregate as well as individual welfare.

The plan of the paper is as follows: Section 2 highlights the nature of the relationship between human capital and TFP growth in spatial context. Section 3 presents the econometric analogue of the model developed in Section 2. In Section 4, we draw on key features of our data and construct the proposed distance matrix based on human capital. Section 5 presents empirical results and Section 5 concludes with main findings and expound their implications.

2 Spatial human capital and TFP growth

2.1 The context

The idea that countries growth processes and TFP can be correlated across space can be explained as follows: Space can be defined both in the relational and geographic sense. Usually, geographical proximity imposes/enhances certain relational patterns such that geographically clustered countries often display common socio-economic behaviour. Thus, a change in growth and its components in one location in the clustered region would impact on the others depending on their intensity of correlation. Human capital is one such factor that enhances interrelatedness among countries through growth momentum and knowledge spillovers.

Like the traditional factors of production such as capital and labour, the accumulation dynamics of human capital is the major driving force in an economy because it can easily be associated with either the efficiency unit of labour input (productivity parameter) or an embodied capital change where a higher stock of human capital generates higher physical capital. Thus, human capital defined on the basis of life cycle productivity is a major determinant of growth differentials within and/or without national boundaries. The characteristics of technical change, such as the adoption of new technology or more subtly innovative propensity in an economy, can all be defined in terms of the accumulation dynamics of human capital (see e.g., Benhabib and Spiegel, 2002; Mankiw et al., 1992).

Given that human capital is assumed to be an important input in the modern growth theory of production technology (Benhabib and Spiegel, op. cit.), it also substantially accounts for the generation of TFP. The growth of the latter is traditionally defined by output growth (adjusted for value added) less the growth of traditional factors of production such as labour and physical capital. Often conceptualized as the Solow residual, TFP is thought of as technological change in an economy. In this formulation, the growth of human capital does not appear as an input. Rather, it is netted out from output growth. However, some recent studies (e.g., Aiyar and Feyrer, 2002) have modelled TFP by explicitly, accounting for human capital as a factor of production. Indeed, TFP and human capital have a more discernible association than any other inputs of production. It adds efficiency to labour input and combined with productive labour, contributes directly to the generation of physical capital as well. Hence, the evidence on the contribution of human capital to TFP growth is mixed and needs an elaborate and comprehensive investigation at the cross-country level.

Cross-country spatial differences in TFP and the adoption of new technologies due to human capital accumulation differentials can be summarized by two conjectures: The first concerns the adaptive capability and learning which states that countries with greater human capital will obtain more private information and adopt more rapidly. The second concerns information-dissemination and learning which states that countries with neighbours which have already adopted, will have higher levels of cumulative information and adopt more rapidly. Aiyar and Feyrer (2002) have shown that human capital has a positive and significant effect on the long-run growth path of TFP in a sample of 86 heterogeneous countries, with countries converging to this growth path at a rate of three percent per annum. Their findings bear significance on the persistent debate over whether factor accumulation or TFP increases are more important for economic growth in the sense that while TFP differences explained most of the static variation in GDP across countries, human capital accumulation was a crucial determinant of the dynamic path of TFP.

Some recent studies (e.g., Ertur and Koch, 2007) have explicitly built empirically spatial growth and have devised ways to account for the contribution of human capital in TFP growth. However, very little has been researched on the nature and source of possible persistence in spatial TFP (growth) and/or output volatility and complementarity and their implications for countries' policies at the individual and collective levels. It is envisaged that correlation in cross-country growth can be linked to a common source of fluctuation such that possible growth volatility can be explicated by theoretical economic mechanisms viz., human capital and its recent extension, namely, demography led human capital growth (e.g., Boucekkine et al., 2002).

The relevance of the latter is quite pertinent in Asia where many economies are experiencing faster population growth and a surge in human capital growth, thus exerting enormous impact on long-run economic growth. Given that many Asian countries share common socio-economic and demographic dynamics, it is pertinent to address issues such as: complementarities in Asian countries TFP growth (at least in the neighborhood) with respect to levels of demographic change and (hence) human capital accumulation; possible co-movements caused by common aggregate shocks.

2.2 A spatial TFP growth model

Let us assume that there are N countries indexed by $i = 1, \dots, N$. Each country's production technology is assumed to follow a constant returns to scale Cobb-Douglas production function. Countries are assumed to be distributed over the Euclidean space, such that the distance among them can be described by inter-point locations which may be characterized by either geography or relation. It may be noted that the individual idiosyncrasies of production technology are preserved in the Euclidean space. However, while aggregated, the production function may exhibit patterns which are different from individual behavior. The production function is described by:

$$Y_i(t) = A_i(t) \left(H_i(t)^{\alpha} K_i(t)^{1-\alpha}\right)^{\gamma} \tag{1}$$

where A_i is TFP or the Solow residual, K_i is physical capital, and H_i is human capital adjusted labor input. γ measures the extent of returns to scale, whereas α delineates the importance of human capital in output. Constant returns to scale production technology would imply that in (1) $\gamma = 1$. Increasing or decreasing returns to scale are similarly characterized by $\gamma > 1$ or $\gamma < 1$. We suppose that the Solow residual is contaminated by human capital externalities through knowledge transmission or productivity effects and partly by learning by doing process where each country improves her production technology by gaining transmitted knowledge from other countries through tradeable or non-tradeable goods and services. The more a country would gain from knowledge spillover, the higher that country is proximus to other countries. The proximity could be geographic or relational or both. When the former is superimposed, that is, a defined geographical structure is supposed, relational proximity gets better (Tobler, 1970: "Everything is related to everything but closer things are more related than distant things"). From economic geography perspective, this is pertinent because physical proximity reduces transportation cost between countries which is one of the most important determinants of factor mobility. In this paper, we assume that countries are located in a defined geographical space (say Europe, Asia, Africa, etc.,) and then relational proximity is allowed to play a cohesive role. Now the Solow residual is written as:

$$A_i(t) = \Gamma(t) h_i(t)^{\delta} \prod_{j \neq i}^{N} A_j(t)^{\beta D_{ij}} \tag{2}$$

with $h_i(t) = H_i(t)/K_i(t)$, the human capital per unit of physical capital. Level of human capital externalities reflecting knowledge transmission and learning by doing is captured by $0 < \delta < 1$ in (2). Human capital interdependence (viewed as technological or productivity interdependence) is represented by the parameter $0 < \beta < 1$, where it is assumed that this interdependence is *not* perfect because of the presence of possible frictions between the home country i and foreign countries $j \neq i, j = 1, \ldots, N$, which is represented by D_{ij}. Elements of D_{ij} are assumed to be positive, such that $\sum_{j \neq i}^{N} D_{ij} = 1$. Now, Γ is the new residual or productivity parameter which is obtained after considering the above elements which model the relationships among countries. Values of D_{ij} higher (the limit being 1) or lower (the limit being 0) imply the strength of relationship or distance among countries. The greater is the strength the higher is the knowledge spillover. Moreover, the extent of profit in the home countries depends on the strength of this parameter. In other words, this parameter can be defined as an indicator of knowledge diffusion.

Equation (2) can be re-written by taking the natural logarithm on both sides:

$$A = \Gamma + \delta h + \beta D A \tag{3}$$

where A, γ, h, D and A without i subscripts refer to vectorial representation of countries. Eq. (3) describes a linear system can be solved for A, if $\beta \neq 0$ and if $1/\beta$ is not an eigenvalue of D. Mathematically, $(I - \beta D)^{-1}$ exists if and only if $|I - \beta D| \neq 0$. Now,

$$A = (I - \beta D)^{-1} \Gamma + \delta (I - \beta D)^{-1} h \tag{4}$$

which implies that the stock of knowledge contained in the Solow residual is a function of human capital accumulated over all countries. The balanced growth path properties of the economy with spatial human capital accumulation would then mean the similarity in the effect of human capital to the long-run growth of the economies. While this is a restrictive assumption in reality, this may be pertinent given that in the long-run growth pattern in some country blocks are more similar than others. Now assuming a constant returns to scale production (i.e., with $\gamma = 1$ in Eq. 1) and replacing Eq. 4 in the production function (Eq. 1) written in logarithms and matrix forms, $y = A + \delta h$, the following modified production function can be obtained:

$$y = (I - \beta D)^{-1} \gamma + \delta (I - \beta D)^{-1} h + \alpha h \tag{5}$$

Pre-multiplying both sides by $(I - \beta D)$, the spatial production function with human capital distance among countries is finally written as:

$$y = \Gamma + ((1 - \alpha) + \delta)h - \alpha\beta Dh + \beta Dy \tag{6}$$

The implication of Eq. 6 is that the level of development of a country depends positively (1) on the accumulation of its own production factors, and (2)on the same factors in foreign countries and on their level of development. Long-run growth of output will depend on the distance between countries' human capital as well as on the ratio of human and physical capital across country locations. Additionally, the spatial distribution of income influences the development captured by the last term in Eq. 6. The net effect of accumulated production factor depends on the extent of human capital externalities and by the spatial distribution of the factors. These in turn influence the total factor productivity. The spatial econometric representation of the above is discussed next which formulates a dynamic interaction among economies production (or income) with respect to human capital accumulation distribution.

3 Methodology and Estimation

3.1 Model specification

The dynamics of dependence of observations across time has been extensively documented in the statistical/econometric literature. Conceptualized in the form of long-memory time series, it says that when observations are correlated over time, the dependence structure displays some memory properties: the stronger is the dependence between current and remote past observations in time, the stronger is the memory and that this memory would determine the long-run evolutionary pattern of the variable as well as the correlated variables in the system. In spatial context, the strength of dependence is measured between two spatial locations and not by time differences. 'Space' can be both geographical and relational. The former has already found a meteoric development in the form of 'economic geography' literature (see, for instance, Fujita and Thisse, 2002, Krugman, 1992, and others), while the latter has been the baseline for innovation and diffusion literature (reference...). Although physical proximity enhances relational proximity, the scope, importance and effect of the latter has been enlarged in the wake of globalization. It is indeed the case as countries get more interdependent due to common economic agenda and increased volume of trade between them, their growth and/or productivity processes get also inter-connected consequently. The possibility of high degree of interdependence has called for growth complementarity theory which says that a marginal growth in one location increases as a function of growing economic activity in other locations. To illustrate assume that country locations are denoted as $i = 1, \ldots, n$, activity as A and their space of interaction as S. Notice that S is characterized by the strength of interdependence due to relational proximity. Countries growth or productivity processes (that is activity) can be said to be complementary to each other if a marginal increase in A at i is due to the increased activity at j. The complementarity is facilitated by spill-overs as well as by competition.

Our econometric specification concerns a panel vector autoregressive (VAR) model of TFP growth rates where the dynamical relationship in the model is upheld by correlation in the human capital accumulation and where the structure of the error term allows for a general type of spatial correlation across countries. This setting allows us to quantify the effect of *human capital distance* on the TFP comovement among countries in the sample. The econometric specification and the estimation method used are based on Chen and Conley (2001) and Conley and Dupor (2003). The model is characterized by spatio-temporal links in the process of economic growth, where the spatial dimension is based on a distance measure constructed using human capital data. In this model, the effect a country has on another country depends on the 'economic distance' between them. Although there is no naturally given distance between countries, plausible distances can be constructed from the appropriation or stock of human capital in each country. The modeling strategy is described below.

We describe economic growth in a semiparametric spatial VAR framework.[1] Let $\{Y_{i,t} : i = 1, \cdots, N; t = 1, \cdots, T\}$ denote the sample realizations of the TFP growth variable for N countries at locations $\{s_{i,t} : i = 1, \cdots, N; t = 1, \cdots, T\}$. Now, let $\mathbf{D}_t$ be a stacked vector of distances between the $\{s_{i,t}\}_{i=1}^{N}$ defined for two points i and j as $\mathbf{D}_t(i, j) = \|s_{i,t}, s_{j,t}\|$ with $\|.\|$ denoting the Euclidean norm. Then,

$$\mathbf{D}_t = [D_t(1, 2), \cdots, D_t(1, N), D_t(2, 3), \cdots, D_t(2, N), D_t(N-1, N)]' \in \mathbb{R}^{\frac{N(N-1)}{2}}$$

Moreover, the distances are assumed to have a common support $(0, \mathrm{d}_{\max}]$ for all t, $i \neq j$. We assume that the TFP growth of a given country denoted at $t+1$ denoted $Y_{i,t+1}$ will depend not only on its own past (home externalities), but also nonparametrically on the performance of its neighbors (spatial spillovers effects). Given the history $\{Y_{t-l}, D_{t-l}, l \geq 0\}$, our specification is given by

$$Y_{i,t+1} = \alpha_i Y_{i,t} + \sum_{j \neq i}^{N} f_i(\mathbf{D}_t(i, j)) Y_{j,t} \tag{7}$$

where the α_i parameters describe the *strength of externalities* generated by home growth, f_i are continuous functions of distances mapping from $(0, \infty)$ to $\mathbb{R}^l$. One interesting feature in this specification is that it does not assume an *a-priori* parametric specification of neighborhood structure as usually done in parametric spatial models.

[1] A spatial vector autoregressive model (SpVAR) is defined as a VAR which includes spatial as well as temporal lags among a vector of stationary state variables. SpVARs may contain disturbances that are spatially as well as temporally correlated. Although the structural parameters are not fully identified in SpVARS, contemporaneous spatial lag coefficients may be identified by weakly exogenous state variables.

Let us denote $\mathbf{Z}_t = (Y_{1,t}, Y_{2,t}, \cdots, Y_{N,t})' \in \mathbb{R}^N$ as a vector stacking $\{Y_{i,t}\}_{i=1}^N$. Following Chen and Conley (2001), we model the joint process $\{(\mathbf{Z}_t, \mathbf{D}_t) : t = 1, \cdots, T\}$ as a first order Markov process which designs the evolution of $\mathbf{Z}_t$ according to the following nonlinear Spatial Vector Autoregressive Model (SVAR):

$$\mathbf{Z}_{t+1} = A(\mathbf{D}_t)\mathbf{Z}_t + \boldsymbol{\varepsilon}_{t+1}, \quad \boldsymbol{\varepsilon}_{t+1} = Q(\mathbf{D}_t)\mathbf{u}_{t+1} \tag{8}$$

where $A(\mathbf{D}_t)$ is a $N \times N$ matrix whose elements are functions of human capital distances between countries. We assume that $\mathbf{u}_{t+1}$ is an i.i.d. sequence with $\mathbb{E}(\mathbf{u}_{t+1}) = 0$ and $\mathbb{V}(\mathbf{u}_{t+1}) = I_N$. It follows that the conditional covariance matrix of $\boldsymbol{\varepsilon}_{t+1}$ is $\mathbb{E}(\boldsymbol{\varepsilon}_{t+1}\boldsymbol{\varepsilon}'_{t+1}) = Q(\mathbf{D}_t)Q(\mathbf{D}_t)' := \Omega(\mathbf{D}_t)$ which is also a function of distances. In the specification (8), the conditional mean $A(\mathbf{D}_t)$ and the conditional covariance $\Omega(\mathbf{D}_t)$ are of importance and have to be estimated. More structure will be imposed on these objects in order to allow estimation.

1. *Structure on conditional means.*

   From (8), the conditional mean of $Y_{i,t+1}$ given $\{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\}$ is modeled as

$$\mathbb{E}\left[Y_{i,t+1} | \{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\right] = \alpha_i Y_{i,t} + \sum_{j \neq i}^{N} f_i(\mathbf{D}_t(i,j)) Y_{j,t} \tag{9}$$

   where as pointed out above, the f_i are continuous functions mapping from $(0, \infty)$ to $\mathbb{R}^l$. Notice that this conditional mean turns out to be relation (9). As a result, it follows that the conditional mean of $\mathbf{Z}_{t+1}$ given $\{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\}$ is $A(\mathbf{D}_t)\mathbf{Z}_t$

$$A(\mathbf{D}_t) = \begin{pmatrix} \alpha_1 & f_1(\mathbf{D}_t(1,2)) & \cdots & f_1(\mathbf{D}_t(1,N)) \\ f_2(\mathbf{D}_t(2,1)) & \alpha_2 & \cdots & f_2(\mathbf{D}_t(2,N)) \\ \vdots & \vdots & \vdots & \vdots \\ f_N(\mathbf{D}_t(N,1)) & f_N(\mathbf{D}_t(N,2)) & \cdots & \alpha_N \end{pmatrix} \tag{10}$$

   It can be interesting in practice to model the α_i parameters and the f_i functions as having features in common across i.

2. *Structure on conditional covariances.*

   The conditional covariance of $\mathbf{Z}_{t+1}$ given $\{\mathbf{Z}_{t-l}, \mathbf{D}_{t-l}, l \geq 0\}$ is modeled as

$$\Omega(\mathbf{D}_t) = \begin{pmatrix} \sigma_1^2 + \gamma(0) & \gamma(\mathbf{D}_t(1,2)) & \cdots & \gamma(\mathbf{D}_t(1,N)) \\ \gamma(\mathbf{D}_t(2,1)) & \sigma_2^2 + \gamma(0) & \cdots & \gamma(\mathbf{D}_t(2,N)) \\ \vdots & \vdots & \vdots & \vdots \\ \gamma(\mathbf{D}_t(N,1)) & \gamma(\mathbf{D}_t(N,2)) & \cdots & \sigma_N^2 + \gamma(0) \end{pmatrix} \tag{11}$$

   where $\gamma(.)$ is assumed to be continuous at zero and is k-dimensional isotropic covariance function.[2] The choice of γ ensures that $\Omega(\mathbf{D}_t)$ is positive definite for

[2] Isotropy means that the stationary random field (with indices in $\mathbb{R}^k$) that generates the process is directionally invariant.

any set of interpoint distance $\mathbf{D}_t$ and any values of the $\sigma_i^2 \geq 0$. Yaglom (1987: 353–354) showed that an isotropic covariance function has a representation as an integral of a generalized Bessel function. The representation of γ is analogous to the spectral representation of time-series covariance functions.

3.2 Estimation strategy

For simplicity, we assume that the distance function $\mathbf{D}_t$ is exogenous, i.e., determined outside the relation (8). We are interested in the shape of functions f_i and γ specified above. Chen and Conley (2001) propose a semiparametric approach based on the cardinal B-spline sieve method. This approach uses a flexible sequence of parametric families to approximate the true unknown functions. The cardinal B-spline of order m, B_m, on compact support $[0, m]$ is defined as

$$B_m = \frac{1}{(m-1)!} \sum_{k=0}^{m} (-1)^k \binom{m}{k} [\max(0, x-k)]^{m-1} \tag{12}$$

Hence, $B_m(x)$ is a piecewise polynomial of the highest degree $m-1$. Then, the functions of interest f_i and Φ can be approximated by

$$f_i(y) \approx \sum_{j=-\infty}^{\infty} a_j B_m(2^n y - j) \tag{13}$$

and

$$\Phi(y) \approx \sum_{j=-\infty}^{\infty} b_j B_m(2^n y - j) \tag{14}$$

where the index j is a translation and the index n provides a scale refinement. The coefficients a_j and b_j are allowed to differ across these approximations. As n gets larger more $B_m(2^n y - j)$ are allowed and this in turn improved the approximation. Moreover, since B_m is nonnegative, a nondecreasing and nonnegative approximation of Φ can be obtained by restricting the coefficients b_j to be nondecreasing and nonnegative.

The estimation is performed in two-steps sieve least squares. In the first step, LS estimation of α_i and f_i, $i = 1, \cdots, N$ is based on conditional mean (10) and sieve for f_i using the minimizations problem

$$\left(\hat{\alpha}_{i,T}, \hat{f}_{i,T}\right) = \underset{(\alpha_i, f_i) \in \mathbb{R} \times \mathcal{F}_{i,T}}{\arg\min} \frac{1}{T} \sum_{t=1}^{T} \left\{ Y_{i,t+1} - \left(\alpha_i Y_{i,t} + \sum_{j \neq i} f_i(\mathbf{D}_t(i,j)) Y_{j,t} \right) \right\}^2 \tag{15}$$

where $\mathcal{F}_{i,T}$ denotes the sieve for f_i (see Chen and Conley, 2001). Let us denote $\hat{\boldsymbol{\varepsilon}}_{t+1} = (\hat{\boldsymbol{\varepsilon}}_{1,t-1}, \cdots, \hat{\boldsymbol{\varepsilon}}_{N,t+1})$ the LS residuals following from the first stage:

$$\hat{\boldsymbol{\varepsilon}}_{t+1} = Y_{i,t+1} - \left(\hat{\alpha}_{i,T} Y_{i,t} + \sum_{j \neq i} \hat{f}_{i,T}(\mathbf{D}_t(i,j)) Y_{j,t} \right) \tag{16}$$

Then, in the second step, sieve estimation for σ^2 and $\gamma(.)$ based on the conditional variance (11), sieve for γ and fitted residuals $\hat{\varepsilon}_{i,t+1}$ is obtained as

$$\left(\hat{\sigma}_T^2, \hat{\gamma}_T\right) = \underset{(\sigma^2,\gamma)\in(0,\infty)^N\times\mathcal{G}_T}{\arg\min} \sum_{t=1}^{T-1} \left\{ \sum_i \left[\hat{\varepsilon}_{i,t+1}^2 - (\sigma_i^2 + \gamma(0))\right]^2 + \sum_i \sum_{i\neq j} \left[\hat{\varepsilon}_{i,t+1}\hat{\varepsilon}_{j,t+1} - \gamma(\mathbf{D}_t(i,j))\right]^2 \right\} \tag{17}$$

where $\mathcal{G}_T$ denotes the sieve for γ. Chen and Conley (2001) derived the $\sqrt{T}$ limiting normal distributions for the parametric components of the model. The authors also suggested a bootstrap method for inference as the pointwise distribution result for the nonparametric estimators $\hat{f}$ and $\hat{\gamma}$ is not provided. Moreover, the asymptotic covariances are computationally demanding.

The model proposed above is estimated using the estimated TFP growth as the Y_{it} variable and measures of the demographic distribution of human capital in order to specify the locations $s_{i,t}$. This allows us to assess and quantify the effect of (di)similarity in the demographic distribution of human capital on the transmission of productivity shocks across countries. It should be noticed that this nonparametric approach is a departure from typical spatial econometric models in which a parametric form of dependence is assumed (see, e.g., Anselin and Griffith 1988 or Case 1991). The spatial model as described above puts restrictions on co-movement across countries that are different from those of typical factor models. In this case, the covariance across variables is mediated by a relatively low dimensional set of factors as in, for example, Quah and Sargent (1993) and Forni and Reichlin (1998).

4 Data and Distance Definitions

4.1 Data

Our sample consists of 15 Asian countries[3] with data for the period 1970-2000. Physical capital stocks were calculated according to the method used in Klenow and Rodriguez-Clare (1997). Initial capital stocks are calculated according to the formula:

$$\frac{K}{Y_{1970}} = \frac{I/Y}{\gamma + \delta + \eta} \tag{18}$$

where (I/Y) is the average share of physical investment in output from 1970 through 2000, γ represents the average rate of growth of output per capita over that period, η represents the average rate of population growth over that period, and δ represents

[3]The list of countries are: Bangladesh, Cambodia, China, Hong Kong, India, Indonesia, Japan, Malaysia, Nepal, Pakistan, Philippines, Singapore, South Korea, Sri Lanka, and Thailand. The choice of countries are mainly guided by the data availability in human capital with explicit age dynamics.

the rate of depreciation, which is set equal to 0.03. Given initial capital stock estimates, the capital stock of country i in period t satisfies

$$K_{it} = \sum_{j=0}^{\infty}(1-\delta)^{t-j} I_{ij} + (1-\delta)^{t} K_{1970} \tag{19}$$

TFP growth is calculated by the standard definition of output growth minus the growth of labor and capital. The global share of labor and capital in the Cobb-Douglas production technology has been assumed to be approximately (1/3) and (2/3) respectively where a constant returns to scale is allowed in the aggregate growth of all inputs together.

$$TFP_{it} = y_{it} - \frac{1}{3}k_{it} - \frac{2}{3}l_{it} \tag{20}$$

where TFP_{it} represents the log of total factor productivity, y_{it} represents the log of real output, k_{it} represents the log of the physical capital stock, and l_{it} represents the log of the population.

Data on physical capital stock is available with the authors which we do not present in the paper to save space. The real GDP per capita series, measured in thousand constant dollars in 2001 international prices, are extracted from the *Penn World Table Version 6.1* (Summer and Heston, 2005), while the age-structured human capital data is sourced from IIASA-VID (see Lutz *et al.* 2007a, 2007b). The time frame is 1970-2000 with annual frequency in all cases. To study correlatedness among countries with respect to their volatility in TFP and output we have calculated the standard deviation of TFP and output growth for each country over our estimation sample period 1970-2000.

Some specific characteristics of the educational attainment data are in order. This human capital data set was produced in a joint effort by the International Institute for Applied Systems Analysis (IIASA) and the Vienna Institute of Demography (VID) and improves enormously on previously available data on education in several respects. In contrast to most earlier attempts to improve data quality, which were concentrated on raising more empirical information or using economic perpetual inventory methods and interpolation, such as the contributions of, for example, Barro and Lee (2001), de la Fuente and Domenech (2006) or Cohen and Soto (2001), this latest attempt is based on demographic back-projections and exploits for the first time differences in mortality across education levels.[4] Most importantly, this data set allows a cross-classification of education data by age groups (in age intervals of five years), and thus allows us to obtain estimates of the full demographic distribution of educational attainment.[5]

[4]The importance of these mortality differentials is highlighted by Cohen and Soto (2001), for instance. For a detailed description of the methodology used to reconstruct the data see Lutz *et al.* (2007a, 2007b).

[5]See Crespo Cuaresma and Lutz (2007) for evidence on the importance of the demographic dimension for explaining differences in income and income growth across countries.

As compared to the existing data sets by Barro and Lee, De la Fuente and Domenech as well as Cohen and Soto, the IIASA-VID data reflect explicitly the fact that mortality differs by level of education and have education categories that are consistent over time. The dataset also provides the full educational attainment distribution by five-year age groups. Indeed, most economic growth regressions so far approximated human capital by one variable giving the mean years of schooling of the population above age 25. This indicator includes all elderly people beyond retirement age and therefore shows a much slower pace of improving average human capital than age-specific indicators for younger adults. In addition, the full distribution of educational attainment categories by age allows for important empirical studies about the relative importance of primary education as compared to secondary and tertiary in the course of development.

4.2 Construction of distance

Two types of human capital distance measures have been used in this study: The first distance measure (D_1 is based on the secondary education attainment level of the age-structured population for males, females and total population. Distances are defined as the Euclidean distance between country locations which are in turn defined as vectors in $\mathbb{R}^3$ whose elements are the average proportions of population in an age group (three age groups are considered: 14-29, 30-49 and 50-64) with completed secondary education. Country locations $s_{i,t}$ are then identified with D_1. Thus, two countries are close in the sense of D_1 if the proportion of human capital in the age-structured population for two countries is same, distant, otherwise.

The second measure of economic distance (D_2) is based on country-specific elasticities of economic growth to human capital, which is calculated by estimating a standard Cobb-Douglas production function where human and physical capital are used as inputs. The estimates were obtained from a pooled data set of five-year averages by regressing the growth rate of GDP per capita on the average investment rate, the change in years of education for the adult population and the initial level of GDP per capita (the education data is sourced from IIASA-VID and the rest of the variables are from the *Penn World Table Version 6.2*). Country-specific estimates of the parameter attached to the human capital variable were then used as elasticities in the construction of the distance matrix. In this case, country locations $s_{i,t}$ are then identified with D_2. Two countries are close in the sense of D_2 if they utilize approximately same quantity of human capital in production. While the former induces productivity effects as the stock of human capital at each demographic level exerts varying productivity effects across country locations, the latter induces a scale effect in the economies (affecting production through knowledge creation). Time non-varying distance is assumed for simplicity, which could be reasonable, given the slow paced demographic changes.

Based on the contiguity matrix of economic distance, we estimate a SVAR model to infer on complementarities in TFP growth, their nature of interdependence and trace the source of fluctuations (in our case differences in the human capital accumulation in different countries). The number of countries comprising each group complies with our estimation requirement that the cross-section dimension is dominated by the time dimension.

5 Empirical results

As a preliminary descriptive statistics we present the kernel density plot of the first order autocorrelation coefficient of the TFP for Asian countries (Figure 1). Note that most of the mass of the density in Figure 1 is concentrated near 0.5, meaning that most of the autocorrelation coefficients are significantly different from zero. Still an important fraction of countries seem to show significant positive or negative serial correlation in their TFP. It is necessary thus to choose a specification which leaves the own coefficient of lagged TFP unrestricted.

Based on the model and data specifications described above, we explicate here the shapes of f (estimating the output co-movements) and γ (indicating residual covariance co-movements) with respect to the two distance metrics (in Figures 2 and 5). The solid line is our point estimate of f, plotted against the distances (in the X-axis). The crosses represent 95% non-symmetric bootstrap confidence interval. The discuss the results in two parts. First, we comment on the shape of the f function which reflects on the dynamic spatial autocorrelation structure of TFP. Two types of dependent variables are used for spatial VAR estimation, viz., TFP growth and TFP growth volatility. The latter is calculated by the standard deviation in TFP growth over the sample period. As stated before, we use two types of human capital distances to study TFP complementarity across Asian countries.

Figure 1: Plots of AR(1) Coefficients

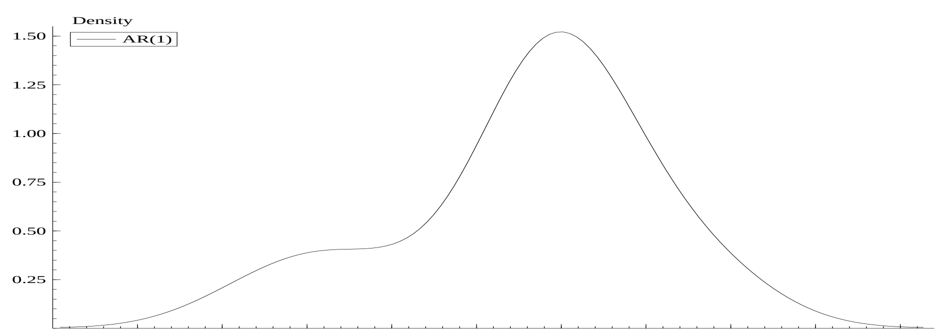


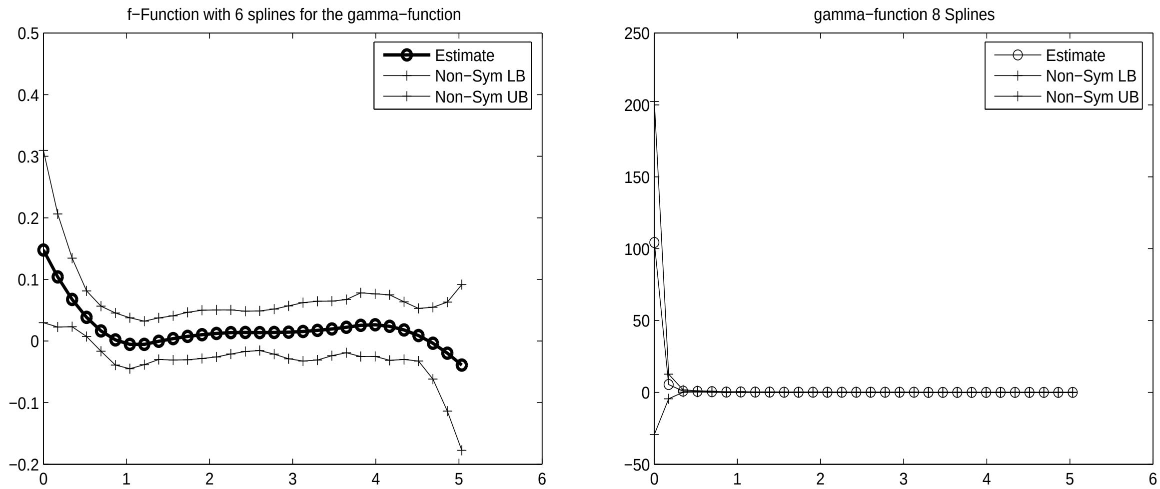
Figure 2 presents spatial VAR estimation results of output volatility across 15 Asian countries. Figure 3 to 5 presents results for TFP, TFP growth, and TFP growth volatility due to age-structured human capital differences among these countries. Once again, both D_1 - similarity in the stock of age-structured human capital and D_2 - the elasticity estimate of human capital, are used as the corresponding distance metrics for which spatial VAR is estimated. The left hand side of each Figure (2-5) presents f estimates indicating the pattern of dynamic spatial autocorrelation due to variability of the distance measure, whereas the left hand side of the figure represents response of residual covariance structure due to variation in human capital at country levels.

The purpose of estimating output volatility due to human capital accumulation dynamics is to gather first hand impression about the TFP volatility due to the proposed distance measure. Since TFP is a derived measure from output while accounting for factors of production, the nature of output volatility and its dependence structure in space can reflect on spatial dynamic autocorrelation structure of TFP (growth). In Figure 2, both f and γ functions are estimated using the D_1 measure of human capital distance. It is evident that output volatility in Asian countries show significant dynamic spatial autocorrelation, implying the co-movement of output volatility across Asian countries due to their differences in human capital stocks across age groups. As distance between countries increases the spatial autocorrelation steadily falls. However, the γ function shows that residual covariance while being a function of human capital distance tapers of quickly. A slow decline of residual covariance with respect to human capital distance would have indicated a slow convergence pattern of autocovariance function of the residuals. In any case, our theoretical expectation is that γ function should decline as human capital distances increase.

Figure 3-5 represent f and γ functions for TFP, TFP growth and their volatility with respect to measures of D_1 and D_2. The estimates of γ (indicating covariances of residuals) divided by the country variance estimates are presented in right panels of Fig. 2 to 5. Using the age-structured human capital distance, D_1 a significant positive dynamic spatial correlation at most distances is thus observed in Figure 3 and 5 for f functions. The average α, which reflects the extent of spatial spillover effects of human capital in TFP is 0.28 with an estimated standard error of 0.15. This indicates the presence of dynamic spatial correlation in TFP (growth) and volatility for most distances. Although f functions depict non-linear response to human capital distance variation, on the average it presents evidence of TFP growth and volatility co-movement among Asian economies.

The correlation of TFP growth at higher human capital distance is indicative of what we may call a 'spatial long-memory' effect in the sense that even at higher distance co-movement pattern of TFP cannot be ruled out. An equivalent expression of this feature can be found in time series where a random variable can be correlated with its past values over a long period of time. Irrespective of its existence in time and space, the long-memory property implies the presence of non-convergent and most possible non-stationary shock. In our case, it implies that a growth shock in the accumulation of human capital will have long-lasting impact on TFP co-movement. Notice that TFP growth volatility and level of TFP represent spatial co-movement with positive feedback effect while TFP growth (Figure 4) presents insignificant (although positive) effect of dynamic spatial correlation with respect to human capital differences. In this case the average α is 0.013 with a standard deviation of 0.163. For Figure 3 (with respect to the level of TFP), averaged $\alpha = 0.869$ with standard deviation 0.013 which indicates high significance of dynamic spatial autocorrelation structure in TFP for Asian countries.

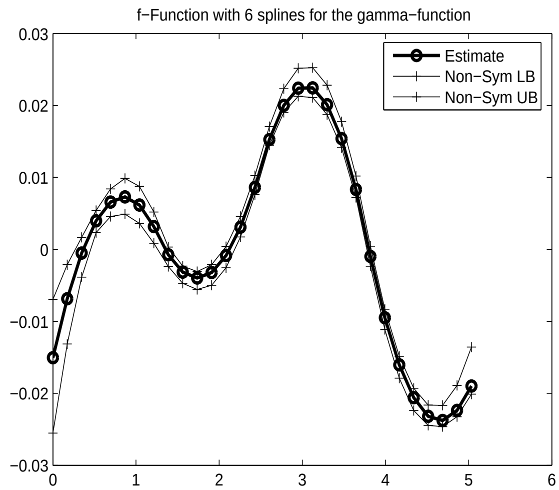
Figure 2: Conditional mean ($\hat{f}$ [left]) and covariance ($\hat{\gamma}$ [right]) functions based on age-structured human capital proportion and Output Volatility.



Putting together, this confirms that countries' TFP growth processes and their volatility are complementary and can be explained by the demography-led human capital accumulation, indicating the centrality of the latter in the generation of spatial TFP persistence. Since non-linear positive spatial correlation is observed for both distance metrics, we conjecture that both scale and productivity effects arising from the embedding of D_1 and D_2 in the regression (assuming feedback effect from demography to TFP growth via human capital accumulation) could be behind the non-linearity. The non-linear and positive dynamic spatial autocorrelation in TFP growth and volatility can also be interpreted as the possible presence of international business cycles.

To conclude, it is clear that TFP in Asian countries are dynamically and spatially correlated. That is the changes in TFP at location i and at time t will have significant bearing on location j with forward and/or backward time lag, i.e., at $t+1$ or $t-1$. We observed that the dynamic spatial autocorrelation of TFP across

Figure 3: Conditional mean ($\hat{f}$ [left]) and covariance ($\hat{\gamma}$ [right]) functions based on age-structured human capital proportion and TFP.



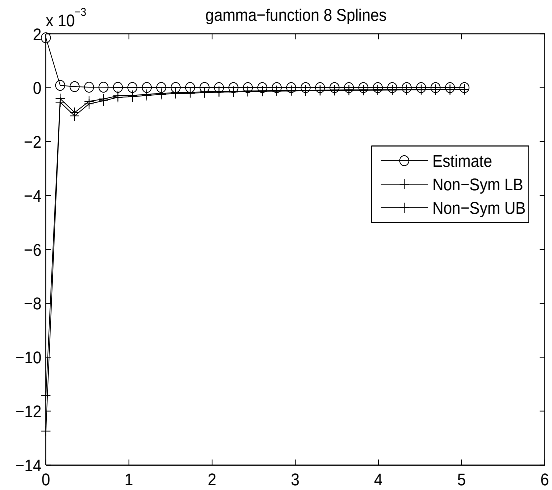


Figure 4: Conditional mean ($\hat{f}$ [left]) and covariance ($\hat{\gamma}$ [right]) functions based on age-structured human capital proportion and TFP growth.

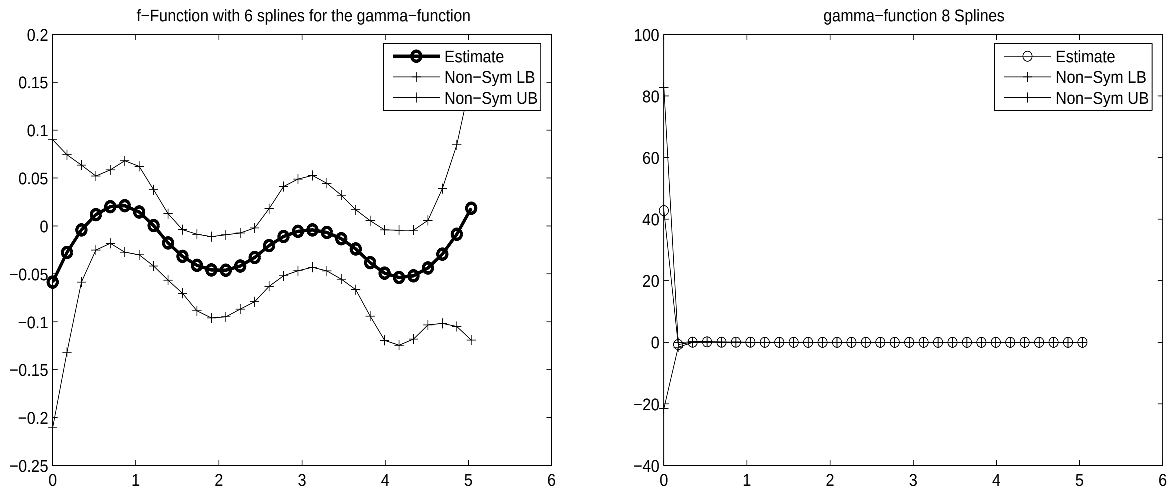
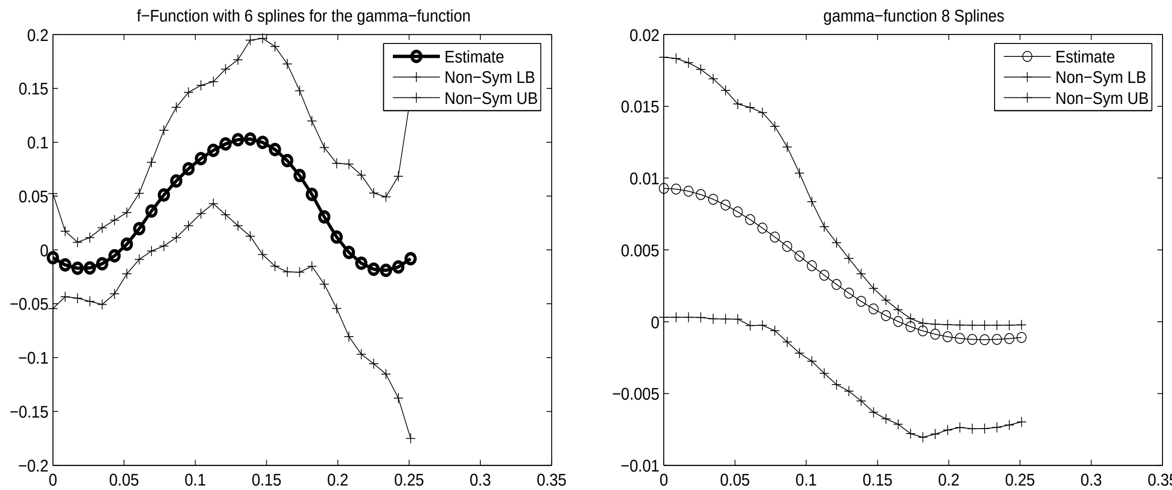


Figure 5: Conditional mean ($\hat{f}$ [left]) and covariance ($\hat{\gamma}$ [right]) functions based on Elasticity of Human Capital and TFP Growth Volatility.



Asian countries is a result of the rate of age-structured human capital accumulation which defines *prima facie* the extent of non-linearity (the neighborhood structure) on TFP and thus how such dynamic spatial correlations are going to shape up the growth momentum in Asian economies. These empirical evidence suggest that a cooperation in human capital policy and countering TFP growth volatility would prove beneficial for maximizing aggregate welfare. In the next section, we prove this point by providing a growth theoretic mechanism to establish how international policy coordination is a growth maximizer for many countries.

6 Conclusion

This paper had two broad objectives. First we wanted to show that TFP growth and volatility are co-moving in many country locations and that such interdependence and/or complementarity can be explained significantly and non-linearly with respect to human capital accumulation dynamics. Second, based on the empirical findings we aimed at providing a growth theoretic mechanism to explain if and how the cooperation in policy programs lead to higher social welfare.

This paper indeed underlined the role of human capital accumulation in the cross-country TFP (growth) complementarity. Following the tradition of Benhabib and Spiegel (2002), the paper assumed that the pattern of technology diffusion can be exponential, which would predict that nations would exhibit positive catch-up with the leader nation, or logistic, in which a country with a sufficiently small capital stock may exhibit slower total factor productivity growth than the leader nation. The correlatedness among countries total factor productivity, as the paper showed, can be gauged by the relative stock and dynamic accumulation feature of human capital over time.

The finding of spatial correlatedness in TFP and/or growth is significant in that differences in human capital across countries could explain the non-linear spatial correlation. We contended that adding human capital to the factors of production explained most of the variation in per capita incomes across Asian economies. This paper stressed that while TFP differences are important in accounting for variations in income, we also find that human capital plays a significant role in determining a country's potential TFP level. Depending on the closeness and distance human capital accumulation at varying age levels, we posit that conditional convergence in TFP could occur, and that human capital plays a crucial role in determining the dynamic path of TFP. It is important to define the channel whereby human capital affects productivity. In this paper, we argued that international technology spillovers from countries at the frontier to different countries are facilitated by human capital stocks. Therefore the stock of human capital at different age structure actually define the pace the economy is moving and is expected to move.

Moreover, the significant non-linear spatial autocorrelation structure it could be discerned that individual countries' own policy program to provide momentum to TFP and/or growth could be sub-optimum and that once a shock arises in one country location, it would, while migrate across country locations due to economies interdependence, continue to affect the long-run growth trajectory of the economy without a certain possibility that it would converge. The non-convergence of shocks across space and over time , as we have observed in the past, have given rise to chaotical economic pattern (e.g., East Asian crisis). Therefore, to achieve higher social optima it is necessary to devise joint policy program in human capital development and TFP growth. The evidence of spatial growth complementarity could also be generalized for other countries sets in a similar vein. Based on the evidence, it might be imperative to devise collective European policies to successfully check spatial growth volatility. A long term policy planning based on a greater co-ordination among individual countries with a common demographic/human capital management agenda could be useful in enhancing individual and collective social welfare. The theoretical description complemented our empirical finding that a policy cooperation is necessary to counter any spatial volatility which is most likely in TFP co-movement.

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