# Incorporating Technology Diffusion, Factor Mobility and Structural Change into cross-region Growth Regression: An Application to China*

Laixiang SUN [a, b], Eunsuk HONG [c] and Tao LI [d]

[a] Department of Financial & Management Studies, SOAS, University of London, Thornhaugh Street, Russell Square, London WC1H 0XG, UK. Email: LS28@soas.ac.uk

[b] Institute of Geographic Sciences & Natural Resources Research (IGSNRR), Chinese Academy of Sciences, Beijing, China

[c] Management School, Queen's University Belfast, M112, 25 University Square, Belfast BT7 1NN, Northern Ireland, UK. Email: e.hong@qub.ac.uk

[d] School of Economics, Central University of Finance and Economics, 39 South College Road, Haidian District, Beijing 100081, P. R. China. Email: econlitao@gmail.com

**Abstract**

This paper advocates a spatial dynamic model that introduces technology diffusion, factor mobility, and structural change into the cross-region growth regression. The spatial setting is derived from theory rather than spatial statistical tests. An application of this model to the study of cross-province growth in China over the period 1980-2005 indicates that incomes are spatially correlated, which highlights the significance of technology diffusion and factor mobility. Furthermore, the integration of neoclassical growth empirics and the structural change perspective of development economics provides a much improved account of inter-provincial variations in income levels and economic growth.

Key words: Growth convergence; Spatial dynamic panel; Structural change; China.

JEL classifications: C23; J61; O40; R11.

---

* We gratefully acknowledge the support of the Sixth Framework Programme of the European Commission (contract number: 044255, the CATSEI project) and the 'Human Activities and Ecological Environment' Project of Chinese Academy of Sciences. We are especially grateful to Mark Partridge, the Editor in Chief, and an anonymous referee of this journal for detailed and very constructive comments and suggestions. Also, we have benefited from the comments of the seminar participants at Queen's University Belfast, SOAS of the University of London, and the participants at the International Conference on 'Microeconomic Drivers of Growth in China' in Oxford, 29-30 September 2008.

## 1. INTRODUCTION

The issue of cross-regional (or -country) convergence in per capita income levels has been a major concern in recent literature on economic growth. Since the seminal work of Barro (1991), two important extensions can be distinguished. The first one is strongly linked to economic growth theory and its empirics have been based on standard panel data econometrics. In contrast, the second extension tends to be weakly linked to theory, but applies relatively sophisticated spatial econometrics to capture the impact of spatial dependencies across regions on income convergence. In other words, the choice of empirical model in the second tradition is largely based on statistical diagnostic tests carried out on the data rather than derivations from a theory.[1] Both extensions make important contributions to the literature. However, there has been a shortage of interaction between them (Abreu et al., 2005a; Rey and Janikas, 2005; Ertur and Koch, 2007).

This paper intends to promote interactions between these two lines of developments. Yu's (2007) introduction of technological spillover and factor mobility into a labour-augmenting Cobb-Douglas production function leads to an estimate equation with both spatial and serial lags of the dependent variable (i.e., per capita income level). Nevertheless, Yu's specification follows the long-standing tradition of interpreting the assumption of exogenous technology as technology or total factor productivity (TFP) grows at the same exogenous rate in all regions. While this interpretation serves as a helpful simplification for model derivation and a reasonable approximation for studying growth convergence in the US economy, it may introduce considerable inaccuracies when we apply his specification to the case of a large developing economy like China.

In the case of China, industrialization has proceeded unevenly across regions and the marginal product of labour is much lower in the agricultural sector. The reallocation of agricultural workers to non-agricultural sectors where the marginal product is much higher (World Bank, 2005; Zhang and Tan, 2007) will raise total output and thus aggregate productivity. This implies that the aggregate TFP will grow faster in regions where the pace of labour reallocation to the non-agricultural activities is faster. To account for this obvious variation in TFP growth across regions, we further augment Yu's spatial dynamic growth model. This augmentation allows us to introduce structural change in a similar manner to Temple and Wößmann (2006), who incorporate structural change into a conventional cross-country regression model.

We apply this augmented spatial dynamic model to the panel data on Chinese provinces over the period of 1980-2005. We estimate the model using the most representative estimators adopted in the literature, including the pooling regression with OLS, fixed effects estimator, spatial panel regression with maximum likelihood (ML) estimator, and the combined spatial and dynamic panel regression with system generalized method of moments (GMM) estimator. The system GMM is capable of dealing with the joint endogeneity problem of the serially and spatially lagged dependent variable, corrects for the potential endogeneity of other explanatory variables, and allows for unobserved region-specific effects and measurement errors. We find that the introduction of technological spillover, factor mobility, and structural changes provides a much improved account of interregional variations in income levels and economic growth. The incomes are spatially correlated mainly due to technological spillover and factor mobility. The speed of convergence becomes higher when spatial dependence and structural change are taken into account. Furthermore, the findings suggest that capital investments, changes in the structure of employment, force of conditional convergence, and population growth are the main sources of the income and growth difference across Chinese provinces.[2] These findings shed new light on the growth empirics in the world's biggest developing and transitional economy, China, during the vital stage of its economic take off.

The rest of the paper is organized as follows. Section 2 derives a spatial dynamic growth model from the neoclassical growth theory and further augments the model so as to incorporate structural change. Section 3 reviews the growth empirics in, and provides justification for the applicability of our model specification to, the context of China. Sections 4 and 5 apply the augmented spatial dynamic model to the case of China. Section 4 introduces data and variables and discusses estimation issues. Section 5 reports the empirical results and discusses how China's story is either different or similar to that of others. Section 6 concludes.

## 2. A SPATIAL DYNAMIC PANEL DATA APPROACH

In this section we modify and extend the spatial dynamic growth model of Yu (2007) with the aim of incorporating structural change. Following the modern empirical growth literature, the production function takes the labour-augmenting Cobb-Douglas form:

$$Y_{it} = K_{it}^{\alpha}\left(A_{it}L_{it}\right)^{1-\alpha}, \qquad 0 < \alpha < 1, \tag{1}$$

where $Y$ is output, $K$ is capital, $L$ is labour, and $A$ is labour augmenting technological progress. The subscript $i$ stands for provinces and $t$ for years. For notational convenience, define output and capital per unit of effective labour as $\hat{y} = Y / AL$ and $\hat{k} = K / AL$ respectively and let bold letter denote a vector such as $\mathbf{A}_t = (A_{1t}, A_{2t}, \cdots, A_{Nt})'$ and $\mathbf{1}_N = (1, 1, \cdots, 1)'$ with $N$ indicating the number of elements in the vector.

Both technology spillovers and factor mobility contribute to spatial interaction of economic activities across provinces. Technology spillovers can be specified as

$$A_{it} = A_{i0} e^{g_i t} \prod_{j \neq i}^{N} A_{jt}^{\rho w_{ij}}, \qquad 0 \leq \rho < 1. \tag{2}$$

The expression (2) says that the technology level in province $i$, $A_{it}$, depends on not only its own initial level $A_{i0}$ and progress rate $g_i$, but also on a Cobb-Douglas combination of the levels of its neighbours' $A_{jt}$. Technology levels in other provinces spill over to the province $i$ with an elasticity of $\rho \cdot w_{ij}$, where $w_{ij}$ depends on the distance between province $i$ and $j$. Such a specification allows the spillover effect of $A_{jt}$ on $A_{it}$ to be different across $j$, depending on the distance between $j$ and $i$. In fact, existing empirical evidence does suggest that the technology spillovers tend to be geographically bounded and decay rapidly across geographic space (e.g., Adams and Jaffe, 1996; Bottazi and Peri, 2003).

The expression (2) can be transformed into $\ln \mathbf{A}_t = \ln \mathbf{A}_0 + \mathbf{g}t + \rho \mathbf{W} \ln \mathbf{A}_t$, where $\mathbf{g} = (g_1, g_2, \cdots, g_N)'$ and $\mathbf{W} = (w_{ij})$ is a row-normalized $N \times N$ matrix of inverse distance between province $i$ and $j$. This $\mathbf{W}$ is called the spatial lag weighting matrix in spatial econometrics and we will specify it in details in the next section. Let $\bar{g}$ denote the mean of $\mathbf{g}$ vector. Noting that $(\mathbf{I}_N - \rho \mathbf{W})^{-1} \bar{g} \mathbf{1}_N = \frac{1}{1-\rho} \bar{g} \mathbf{1}_N$ as $\mathbf{W}$ is row-normalized and assuming that $(\mathbf{I}_N - \rho \mathbf{W})'(\mathbf{g} - \bar{g}\mathbf{1}_N)$ is dominated by $(\mathbf{I}_N - \rho \mathbf{W})' \bar{g} \mathbf{1}_N$ , i.e., $(\mathbf{I}_N - \rho \mathbf{W})^{-1} (\mathbf{g} - \bar{g}\mathbf{1}_N) \approx \frac{1}{1-\rho} (\mathbf{g} - \bar{g}\mathbf{1}_N)$, we obtain

$$\ln \mathbf{A}_t = (\mathbf{I}_N - \rho \mathbf{W})^{-1} \ln \mathbf{A}_0 + \frac{t}{1-\rho} \mathbf{g}, \tag{3}$$

and

$$\frac{\dot{\mathbf{A}}_t}{\mathbf{A}_t} = \frac{1}{1-\rho} \mathbf{g}. \tag{4}$$

To incorporate factor mobility we recognize that the mobility of labour and capital is typically a ‘gravity-driven’ flow, moving from economies with low return rates to those with high return rates. Denote capital per effective labourer as $\hat{\mathbf{k}}_t = (\hat{k}_{1t}, \hat{k}_{2t}, \cdots, \hat{k}_{Nt})'$. We postulate a labour migration function $m_i^L(\mathbf{k}_t) = b^L(\ln \hat{k}_{it} - \sum_{j\neq i}^N m_{ij} \ln \hat{k}_{jt})$ for province $i$, with $b^L > 0$ to indicate that labour moves from an economy with lower capital-labour ratio to one with higher capital-labour ratio, where, $m_{ij}$ is the ($i$, $j$) entry of a spatial weights matrix $\mathbf{M}_N$ and $\sum_{j\neq i}^N m_{ij} \ln \hat{k}_{jt}$ is the weighted average of $\ln \hat{k}_{jt}$, which can be regarded as a proxy for wage rate, across neighbouring provinces. Thus we have

$$\frac{\dot{L}_{it}}{L_{it}} = n_i + m_i^L(\mathbf{k}_t). \tag{5}$$

Eq. (5) indicates that the change in labour supply in province $i$ comes from two sources: the exogenous growth rate of population $n_i$ and migration from (to) other provinces as specified by $m_i^L(\mathbf{k}_t)$.[3]

We postulate a capital movement function $m_i^K(\mathbf{k}_t) = b^K(\ln \hat{k}_{it} - \sum_{j\neq i}^N m_{ij} \ln \hat{k}_{jt})$ in a parallel fashion. The change in capital stock is then given by

$$\dot{K}_{it} = s_i Y_{it} - \delta_i K_{it} + m_i^K(\hat{\mathbf{k}}_t) \cdot K_{it}, \tag{6}$$

where $s_i$ is the saving rate and $\delta_i$ the depreciation rate. Eq. (6) adds a capital movement term $m_i^K(\hat{\mathbf{k}}_t) \cdot K_{it}$ to the otherwise standard Solow-Swan capital formation model.

The dynamics of $\hat{k}_{it}$ can be derived from Eq. (6) as follows.

$$\dot{\hat{k}}_{it} = s_i \hat{y}_{it} + m_i^K(\mathbf{k}_t) \cdot \hat{k}_{it} - (\frac{\dot{L}_{it}}{L_{it}} + \frac{\dot{A}_{it}}{A_{it}} + \delta_i) \cdot \hat{k}_{it} = s_i \hat{k}_{it}^{\alpha} - \hat{k}_{it}(n_i + \frac{g_i}{1-\rho} + \delta_i + m_i^L(\mathbf{k}_t) - m_i^K(\mathbf{k}_t)). \tag{7}$$

In the steady state, $\dot{\hat{k}}_{it} = 0$ and $m_i^L(\mathbf{k}_t) = m_i^K(\mathbf{k}_t) = 0$, which implies that

$$\hat{k}_i^* = \left(\frac{s_i}{n_i + g_i/(1-\rho) + \delta_i}\right)^{1/(1-\alpha)} \text{ and thus } \hat{y}_i^* = \left(\frac{s_i}{n_i + g_i/(1-\rho) + \delta_i}\right)^{\alpha/(1-\alpha)}. \tag{8}$$

Using $\dot{\hat{k}}_{it} / \hat{k}_{it} = \frac{d}{dt}(\ln \hat{k}_{it} - \ln \hat{k}_i^*)$ and approximating around the steady state based on Eq. (7), the speed of convergence is given by

$$\frac{d}{dt}(\ln \hat{k}_{it} - \ln \hat{k}_i^*) = -\lambda_i(\ln \hat{k}_{it} - \ln \hat{k}_i^*), \tag{9}$$

where $\lambda_i$ is the rate of convergence and given by

$$\lambda_i = (1-\alpha)(n_i + g_i/(1-\rho) + \delta_i) + b^L - b^K . \tag{10}$$

Eq. (10) indicates that if 0 < (1 − ρ) < 1, i.e., the technology spillovers are present, and $b^L - b^K > 0$, e.g., in the case that labour moves from an economy with lower capital-labour ratio to one with higher capital-labour ratio and capital moves in the opposite direction, the convergence rate will be greater than the standard rate of $(1-\alpha)(n_i + g_i + \delta_i)$ as suggested in the convergence literature (Barro and Sala-i-Martin, 1992; Islam, 1995). Nevertheless, if $b^L - b^K < 0$, e.g., in the case that both labour and capital move towards higher capital-labour ratio to pursue economies of agglomeration, and ρ is sufficiently small, the convergence rate could become less than the standard rate of $(1-\alpha)(n_i + g_i + \delta_i)$. For the feasibility of empirical estimation, we assume that $\lambda_i$ is same for all *i* and denoted by $\lambda$.

Solving the first-order differential equation (9) and noting that the path of $\ln \hat{k}_{it}$ is the same as that of $\ln \hat{y}_{it}$ because $\hat{y}_{it} = \hat{k}_{it}^{\alpha}$, we obtain

$$\ln \hat{y}_{it_2} = e^{-\lambda\tau} \ln \hat{y}_{it_1} + (1-e^{-\lambda\tau}) \ln \hat{y}_i^* , \tag{11}$$

where $\hat{y}_i^*$ is given by (8) and $\tau = t_2 - t_1$. Placing $\ln y_{it} = \ln \hat{y}_{it} + \ln A_{it}$ into (11) and using vector form we have the following equation

$$\ln \mathbf{y}_{t_2} = e^{-\lambda\tau} \ln \mathbf{y}_{t_1} + \ln \mathbf{A}_{t_2} - e^{-\lambda\tau} \ln \mathbf{A}_{t_1} + (1-e^{-\lambda\tau}) \ln \hat{\mathbf{y}}^* . \tag{12}$$

A combination of (12) and (3) gives

$$\begin{aligned}(\mathbf{I}_N - \rho\mathbf{W}) \ln \mathbf{y}_{t_2} &= (\mathbf{I}_N - \rho\mathbf{W}) e^{-\lambda\tau} \ln \mathbf{y}_{t_1} + (1-e^{-\lambda\tau}) \ln \mathbf{A}_0 \\ &\quad + (1-e^{-\lambda t})(t_2 - e^{-\lambda\tau} t_1)\, \mathbf{g} + (\mathbf{I}_N - \rho\mathbf{W})(1-e^{-\lambda\tau}) \ln \hat{\mathbf{y}}^* .\end{aligned} \tag{13}$$

Eqs. (13) and (8) lead to our basic estimation equation as follows.

$$\begin{aligned}\ln \mathbf{y}_{t_2} &= \rho\mathbf{W} \ln \mathbf{y}_{t_2} + e^{-\lambda\tau} \ln \mathbf{y}_{t_1} - \rho e^{-\lambda\tau} \mathbf{W} \ln \mathbf{y}_{t_1} + (1-e^{-\lambda\tau})(t_2 - e^{-\lambda\tau} t_1)\, \mathbf{g} \\ &\quad + (1-e^{-\lambda\tau}) \ln \mathbf{A}_0 + \frac{\alpha(1-e^{-\lambda\tau})}{1-\alpha} (\mathbf{I}_N - \rho\mathbf{W}) \ln \mathbf{x_t} + \mathbf{v}_t .\end{aligned} \tag{14}$$

where $\mathbf{x} = \left(\frac{s_1}{n_1 + g_1/(1-\rho) + \delta_1}, \frac{s_2}{n_2 + g_2/(1-\rho) + \delta_2}, \cdots, \frac{s_N}{n_N + g_N/(1-\rho) + \delta_N}\right)'$ and $\mathbf{v}_t = (v_{1t}, v_{2t}, \cdots, v_{Nt})'$ is the transitory error terms that are assumed to be *i.i.d.* across *i* and *t*. It can be seen that the spillover effect ρ is crucial in the derivation of Eq. (14). If ρ = 0, Eq. (14) will be reduced to Eq. (11) in Islam (1995), with different convergence rate due to the presence of factor mobility as indicated in Eq. (10).

What distinguishes Eq. (13) from Yu's (2007) formulation is that the growth rate of a province's own technology or total factor productivity (TFP), $g_i$, varies across provinces and is free for a further augmentation. While it is difficult to have a complete account for $g_i$, Temple and Wößmann (2006) suggest a partial account which quantifies the direct contribution of labour reallocation to aggregate TFP growth in economies with sizeable differentials in the marginal product of labour across different sectors. The intuition is that if the marginal product of labour is lower in agriculture, the movement of agricultural workers to sectors where the marginal product is higher will raise the total output. Because this additional output is produced without additional input of capital and labour, the reallocation of labour raises aggregate productivity. In a large developing economy like China where regional differentials on industrialization has been substantial (World Bank, 2005; Zhang and Tan, 2007; Section 3), their account is particularly relevant and would be able to capture a substantial part of aggregate TFP growth. Their final regression specification of the relationship between the aggregate TFP growth and structural change is as follows.

$$\frac{\dot{z}}{z} = \beta'\mathbf{V} + (\kappa - 1)\phi MGRORTH + \kappa\phi\frac{1}{\psi}DISEQ\,, \tag{15}$$

where $z$ is the aggregate TFP, $\mathbf{V}$ is a vector of determinants of aggregate TFP growth including regional dummies and $ln\mathbf{A}_0$, and the structural change terms are

$$MGROWTH = (1-a)\frac{\dot{m}}{m} \approx \Delta m\,, \tag{16a}$$

$$DISEQ = \frac{p}{1-p}(1-a)\frac{\dot{m}}{m} \approx \frac{p}{1-p}\Delta m\,. \tag{16b}$$

where $a$ is the share of agricultural employment in total employment, $m = 1 - a$ is the share of non-agricultural employment in the total employment, $\Delta m = m_{t_2} - m_{t_1}$ , $p = -\Delta a / a$ ($\Delta a = a_{t_2} - a_{t_1}$) is the migration propensity, $\phi$ is proximately equal to the labour share in total output, and the parameters $\kappa$ and $\psi$ capture the intersectoral wage ratio at and the speed of adjustment to the long-run migration equilibrium respectively.

Intuitively speaking, *MGROWTH* captures the effect of labour reallocation on TFP growth for a fixed marginal product ratio. This effect is essentially that examined in Kuznets (1961) and Denison (1967). *DISEQ* implies that the growth impact of a given extent of structural change will be greater in those regions experiencing more rapid structural change, because at least on average the intersectoral differential in those regions is greater. Because of this distinction, the former is termed as the 'linear' effect and the latter 'nonlinear' effect.

Given the Cobb-Douglas production technique in Eq. (1), TFP growth is proximately equal to $g_i$ times the exponent on the efficiency index $(1 - \alpha)$ if we ignore the secondary impact of neighbour's $A_j$. In the presence of wage differentials, TFP growth is a function of structural change terms as specified in Eq. (15). A combination of Eqs (14) and (15) give the final estimation equation.

$$\begin{aligned}\ln \mathbf{y}_{t_2} &= \rho \mathbf{W} \ln \mathbf{y}_{t_2} + e^{-\lambda\tau} \ln \mathbf{y}_{t_1} - \rho e^{-\lambda\tau} \mathbf{W} \ln \mathbf{y}_{t_1} + \frac{(1-e^{-\lambda\tau})(1-\alpha)+1}{1-\alpha} \ln \mathbf{A}_0 \\ &+ (1-e^{-\lambda\tau})(t_2 - e^{-\lambda\tau} t_1)\phi\left(\frac{\kappa-1}{1-\alpha} MGROWTH + \frac{\kappa}{(1-\alpha)\psi} DISEQ\right) \\ &+ \frac{\alpha(1-e^{-\lambda\tau})}{1-\alpha} (\mathbf{I}_N - \rho \mathbf{W}) \ln \mathbf{x_t} + \mathbf{v}_t \ .\end{aligned} \tag{17}$$

A complete mechanical adoption of Eq. (17) for real regression would be problematic due to nonlinear parameter restrictions and high correlation between some variables. Our first estimation will not impose parameter restrictions and the second one will impose the linear restrictions only. We will exclude some variables that are of secondary importance and highly correlated with key variables. Another pragmatic approximation is necessary for $\ln(n_i + g_i/(1-\rho) + \delta_i)$ because it contains the spatial effect parameter $\rho$. We will focus on the variation of population growth $n_i$ and take the average value of technological progress and depreciation for $g_i/(1-\rho) + \delta_i$. This is to assume that variations in $g_i/(1-\rho) + \delta_i$ is likely to be modest in relation to the inter-provincial variations in population growth in a large developing country like China.

## 3. GROWTH EMPIRICS IN THE CONTEXT OF CHINA

*Literature on Convergence Regression*

China's remarkable growth record over the last 30 years has reinforced the concern about how to cope with continued growth while maintaining balanced regional income inequality. This concern, in combination with the persistent academic interest in economic growth, has led to a growing number of studies that focus on cross-regional convergence regressions for China. These studies, dependent on sample periods and the estimate methods adopted, have suggested the tendency towards either convergence or divergence across Chinese provinces or cities. For example, Chen and Fleisher (1996) report the evidence of conditional convergence of per capita production across 25 provinces during the period 1978-1993 after controlling for a province's coastal location, physical investment, employment growth, foreign direct investment, and human capital investment. Jian et al. (1996) indicate a tendency towards convergence across 28 provinces over 1952-1965 and 1978-1990 and a tendency towards divergence over 1965-1978. For 1990-1993, they suggest that although convergence continued within coastal provinces, regional incomes started to diverge once again for the country as a whole.

Yao and Zhang (2001) propose an augmented Solow growth model to examine club divergence among Chinese provinces based on real per capita GDP data over 1952-1997. Their parametric and nonparametric estimates indicate that the divergence of regional income per capita between three predetermined clubs of the east, central and west became more apparent during the reform period (1978-1997). Employing the system GMM estimator and allowing for the possible difference in technological progress rate between the coastal and interior provinces and endogeneity of some explanatory variables, Weeks and Yao (2003) confirmed a tendency towards convergence among provinces during the pre-reform period (1953-1977) while a tendency towards divergence between two distinct convergence clubs of the coastal and interior provinces during the reform period (1978-1997).

Some recent studies employ city-level data. For example, Jones et al. (2003) estimate growth equation using panel data on 200 largest Chinese cities over 1989-1999 and report conditional convergence after additionally controlling for Chinese preferential openness policies. Using panel data on 180 cities over 1990-2002, Madariaga and Poncet (2007) report several important findings. First, their system GMM estimations confirm conditional convergence after adding FDI, spatially lagged per capita GDP, and spatially lagged FDI to traditional Solow growth model. Second, the coefficient on initial income level (serially lagged per capita GDP) decreases when spatially lagged variables (e.g., spatially lagged per capita GDP and spatially lagged FDI) are accounted for. This suggests that controlling for spatial interdependence in terms of income and FDI would produce a convergence rate faster than the standard one without such control. However, their incorporation of spatial lagged variables is based on statistical diagnostic tests for spatial dependence rather than on derivations from the growth theory.

*The Presence of Technology Spillovers*

Technology spillovers across regions (firms) occur when the productivity of R&D in a region (firm) is affected by the processes and outcomes of innovative activities in other regions (firms) in spatial proximity (Botazi and Peri, 2003). Vertical, pecuniary, or rent spillovers flow in two directions of suppliers and buyers, i.e., forward and backward linkages, respectively. For example, in the forward linkage, a cost-reducing innovation of a seller firm lowers the cost for a buyer firm and thereby increases the level of the buyer's producer surplus. In the backward linkage, a quality-improving innovation of a buyer firm may lead to higher requirements for input quality and on-time delivery which confer incentives on suppliers to upgrade their production technology and management.

Horizontal, non-pecuniary, or knowledge spillovers result from the nature of knowledge as a local or partial public good. The codified part of an invention (innovation) is likely to be a fully public good. The embodied and tacit part of the inventive (innovative) knowledge is linked to the experiences of the inventors (innovators) and attached to people. This stock of knowledge grows in a region as local inventors and innovators discover new ideas. It diffuses mostly via personal interactions and labour mobility. It is local public good because it mainly benefits inventors and innovators within the region or its neighbourhoods but fades farther away as interactions and labour mobility decrease (Botazi and Peri, 2003). On the other hand, although borrowing an idea from someone else's research will not reduce the available knowledge stock for the original inventors or innovator, it may erode the returns from an invention or innovation if the leaked knowledge helps competitors imitate and therefore may confer a disincentive for a firm to perform its own R&D  (Koo, 2005).

Numerous empirical studies have shown positive economic impact of technology diffusion in terms of output or productivity. For example, Keller (2002) estimates the spatial distribution of productivity effects of G-5 country R&D spending in other OECD countries. His evidence suggests that the productivity effects of R&D are significantly positive and decline with the geographic distance between sender and recipient countries. The half-life distance of technology ranges from a low of 162 km to an average of about 1,200 km. Adams and Jaffe (1996) focus on manufacturing establishments in the US and examine the extent to which their productivity is affected by R&D performed in formal research labs. They show that the productivity enhancing effects of R&D spillovers are strong but diminish as both geographic and technological distance increase. In more details, R&D performed out the state or, alternatively, more than 100 miles away, is roughly 10% to 30% as effective as R&D performed in the same state and within 100 miles. Bottazzi and Peri (2003) use R&D and patent data for European Regions in 1977-1995 and estimate an 'innovation generation' function for Europe. They find that the effects of R&D spillovers in generating innovations are significantly positive but most of the benefits accrue to regions within 300 km from it.

Empirical evidence in the context of China is limited but emerging. Wei and Liu (2006) assess the productivity enhancing effects of technology spillovers across firms from R&D, exports and the very presence of FDI in China's manufacturing sector. Their estimations based on a panel of more than 10,000 indigenous and foreign-invested firms for 1998–2001 indicate strong productivity enhancing effects of inter-industrial spillovers from R&D and exports, and of both intra- and inter-industrial spillovers from foreign presence to indigenous Chinese firms. While their study is confined to the impact of knowledge spillovers on the productivity of indigenous Chinese firms only and does not pay attention to the geographical scale of proximity, Wei et al. (2008), using the same panel dataset, show that the diffusion of indigenous technology and local knowledge helps the productivity enhancement of multinationals' operations in China. Their evidence further indicates that mutual productivity spillovers between foreign and local firms are significantly positive and both national and regional in scale.

*Evidence on Factor Mobility and Structural Change*

With the progress in economic reform, institutional barriers to labour mobility have been gradually removed. Increasing labour movement has been observed across different regions and sectors and mainly from rural to urban areas. The latest sampling data of the 2000 census indicates that there were 131 million migrants during 1995-2000, of which 33.92 million were inter-provincial and 97.24 million intra-provincial.[4] It is estimated that 78% of inter-provincial migrants and 52% of intra-provincial migrants were from rural to urban areas. This means that the total number of rural-to-urban migrants is about 76 million during 1995-2000 (World Bank, 2005). Furthermore, much of the inter-provincial migration was interregional. According to the calculation of Lin et al. (2004) based on the same census data, inland-to-coast migration accounted for 60.1% of all inter-provincial migration of the working-age population and thus dominated the whole migration scene. In contrast, the corresponding shares for coast-to-inland, within-coast, and within-inland migration were 6.1%, 18.6% and 15.2%, respectively.[5]

Labour mobility across sectors has been even more substantial due to the rise of rural township and village enterprises (TVEs) and the growth of urban services sector. Sun et al. (2008) present the patterns of labour allocation across four major sectors at the national level and for four large regions. At the national level, the most remarkable labour movement is from agriculture to rural non-farming activities. The rapid expansion of the rural non-farming sector created additional jobs for 20.1% of China's total labour force during 1980-2001, and about 95% of these new jobs, which was at a scale of 120 million, were taken by those moving away from agriculture. The dominant part of this huge scale labour reallocation took place within the same township or county ('left farmland but didn't leave the local community') and therefore cannot be accounted for by inter-provincial migration. This provides a strong motivation for our structural change accounting. In the urban areas, the urban services sector created additional jobs for 4.5% of China's total labour force during the same period, which were took by those urban workers who left the urban industry and by migrants from the countryside.[6]

At the regional level, there exists large variation in the extent of cross-sectoral labour reallocation. The eastern region had experienced the most rapid structural changes in terms of labour reallocation. The share of agricultural labourers in the total decreased by 25.1 percentage points from 67.3% in 1980 to 42.2% in 2001, whereas the TVE sector created new jobs for 53 million workers, which is equivalent to 23.9% of total employment in the region in 2001. During the same period, the total employment in the region increased by an incredible 78.3 million. In sharp contrast, the share of the agricultural labour force in the northeast region had remained unchanged and labour reallocation was largely from the urban industry to the TVE sector. Although the central and western regions had experienced impressive labour reallocation from agriculture to other sectors, by 2001 they were still much less industrialized in comparison with the northeast region.

With regard to capital mobility, on the one hand, World Bank (2005) acknowledges that the patterns of capital flows within China remain closer to that of international capital movement across OECD countries as opposed to intra-national capital mobility observed in countries with no internal barriers (such as Japan). On the other hand, its statistical analysis based on provincial data does suggest that when investment is motivated mostly by profit maximization, it tends to go where it is most productive. In particular, foreign direct investment and investment by domestic firms based on selfraised funds do respond positively to local GDP growth, after controlling for the initial level of income and provincial specific effects.

The extent to which labour reallocation across sectors and regions can contribute to the enhancement of aggregate productivity depends on the gaps of labour productivity, or more accurately the marginal product of labour, between sectors and between regions. In the case of China during the reform era, sectoral and regional differences in labour productivity are large and increasing. Sun et al. (2008) also present labour productivity by sector and region for the period of 1980-2001. Despite the large scale reallocation of labour from the agricultural to non-agricultural sectors and migration from rural to urban areas, the productivity disparity between the urban industry and the agricultural sector is large and increasing. At the national level, the ratio had risen from 9.2 in 1980 to 18.8 by 2001 due to the relatively slow growth rate of labour productivity in the agricultural sector (4.8% vs. 8.45% per annum). This rising disparity is most severe in the western region, with the ratio standing at 23.7 by 2001, whereas the northeast appears to show the least degree of disparity and its increase. It is also worth noting that the labour productivity in the urban industry in the poorest western region had improved faster than that of agriculture in the booming eastern region. Another sharp contrast is that the rural non-farming sector had the fastest growth in labour productivity while the traditional agricultural sector has the lowest labour productivity and slowest growth.

A comparison at the regional level indicates that initially the northeast region had the highest labour productivity but it fell behind the eastern region by 2001. The growth rate of labour productivity in the eastern region was the highest at 9.88% per annum, followed by the central at 8.33%, the western at 7.44% and the northeast at 7.14%. As a result of these differences, regional disparity in labour productivity between the coastal and inland regions had worsened over this period.

Because marginal product of labour equals to labour productivity (*Y/L*) times the output elasticity of labour and labour elasticity in traditional labour intensive sectors like agriculture is typically much lower than that in the modern capital intensive sectors like industry, the above disparity between the agricultural and non-agricultural sectors will be further extended when we move to examining marginal product of labour. The above severe disparity in marginal return of labour across sectors and regions not only explains a large part of growth in aggregate productivity but also indicates future opportunities for achieving productivity gains by reallocating labour across sectors and regions.

## 4. DATA, VARIABLES, AND ESTIMATION METHODS

Data used in our estimations is a panel of 29 provinces and municipalities for the period 1980-2005. Among all 31 provinces and municipalities in China, Tibet is excluded mainly because of lack of data. For data consistency Chongqing is included in Sichuan, since Chongqing became a central municipality out of Sichuan province in 1997. We collected data from SSB (1999) for the period 1980-1998 and SSB (2000-2006) for the period 1999-2005, respectively. All the value variables are deflated using 1980 prices.

Following the tradition of growth empirics (Islam, 1995), we opt for five-year time intervals in order to reduce the influence of business cycle fluctuations and to alleviate the problem of parameter heterogeneity. For the period 1980-2005 we have five data point for each province: 2005, 2000, 1995, 1990, and 1985. When $t = t_2 = 1985$, $t - 1 = t_1 = 1980$, saving and population growth variables are averages over 1980-1985, and the structural change is the change between 1980 and 1985. The analogy holds for other intervals.

Because $\mathbf{W}\ln\mathbf{y}_{t-1}$, $\mathbf{W}\ln\mathbf{s}_t$ and $\mathbf{W}\ln(\mathbf{n}_t + \bar{g}/(1-\bar{\rho}) + \bar{\delta})$ are highly correlated with $\mathbf{W}\ln\mathbf{y}_t$ ($r$ = 0.99, 0.96, and 0.79 respectively), in our first set of regressions, which focuses on the endogenous impact of $\mathbf{W}\ln\mathbf{y}_t$, we remove them from the regression equation. Following the conventional notion of the panel data literature and noting that $\ln\mathbf{A}_0$ is time invariant, we can reformulate Eq. (17) as follows.

$$\begin{aligned}\ln y_{it} &= \gamma \ln y_{i,t-1} + \rho(\mathbf{W}\ln\mathbf{y})_{it} + \beta_1 \ln s_{it} + \beta_2 \ln(n_{it} + \bar{g}/(1-\bar{\rho}) + \bar{\delta}) \\ &\quad + (\beta_3 + \beta_4 t)\cdot MGROWTH_{it} + (\beta_5 + \beta_6 t)\cdot DISEQ_{it} + \eta_i + \mu_t + \varepsilon_{it}\,,\end{aligned} \tag{18}$$

where $t = t_2$, $t - 1 = t_1$, $\gamma = e^{-\lambda\tau}$, and $\tau = t_2 - t_1$. In the unrestricted setting, we expect that $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3$ to $\beta_6$ are nonnegative, $\beta_3$ or $\beta_4 > 0$, and $\beta_5$ or $\beta_6 > 0$. In the restricted setting, we expect $\beta_1 = -\beta_2$ in addition. Moreover, because *MGROWTH* is highly correlated with $t \cdot MGROWTH$ and *DISEQ* is highly correlated with $t \cdot DISEQ$ ($r > 0.99$ in both case), we have to drop one of the paired two variables and examine the effect of the other.

It is worth noting that the omission of $\mathbf{W}\ln\mathbf{x}_t$ may result in spurious significance of the $\mathbf{W}\ln\mathbf{y}_t$ term in Eq. (18) because $\mathbf{W}\ln\mathbf{x}_t$ and $\mathbf{W}\ln\mathbf{y}_t$ are likely to be statistically substitutive. To check this, we conduct second set of regressions based on Eq. (19):

$$\begin{aligned}\ln y_{it} &= \gamma \ln y_{i,t-1} + \rho(\mathbf{W}\ln \mathbf{y})_{it} + \beta_{1a}\ln s_{it} + \beta_{2a}\ln(n_{it} + \overline{g}/(1-\overline{\rho}) + \overline{\delta}) \\ &+ \beta_{1b}(\mathbf{W}\ln s)_{it} + \beta_{2b}(\mathbf{W}\ln(n + \overline{g}/(1-\overline{\rho}) + \overline{\delta}))_{it} \\ &+ (\beta_3 + \beta_4 t)\cdot MGROWTH_{it} + (\beta_5 + \beta_6 t)\cdot DISEQ_{it} + \eta_i + \mu_t + \varepsilon_{it}\,,\end{aligned} \tag{19}$$

In the unrestricted setting, we expect that $\beta_{1a} > 0$ , $\beta_{2a} < 0$ , $\beta_{1b} < 0$ , and $\beta_{2b} > 0$ . Expectations on others are same as in Eq. (18). In the restricted setting, we expect $\beta_{1a} = -\beta_{2a}$ and $\beta_{1b} = -\beta_{2b}$ in addition. Given that Eq. (19) mainly serves the purpose of robustness check, unless specially mentioned we will focus on Eq. (18) in the following.[7]

Table 1 presents the definition of the variables in Eq. (18) and the corresponding summary statistics. The disturbance term consists of the unobserved provincial fixed effect that is constant over time $(\eta_i)$, the unobserved time effect that is common across provinces $(\mu_t)$ and the transitory errors $(\varepsilon_{it})$ that varies across provinces and time periods and has mean equal to zero.

The spatial weight matrix **W** describes the spatial arrangement of the *N* regions concerned. Let $w_{jk}$ denote the $(j, k)$-th element of **W**, where $j$ and $k = 1, \cdots, N$. It is assumed that all $w_{jk}$ are known constants, all diagonal elements of **W** are zero, and the characteristic roots of **W** are known. The first assumption excludes the possibility that the spatial weight matrix is parametric. The second one implies that no region can be viewed as its own neighbour. The third presupposes that the characteristic roots of **W** can be computed accurately using the computing technology typically available to empirical researchers and ensures that the log-likelihood function of the spatial regression models we distinguish can be computed (Elhorst, 2003). In this research the off-diagonal elements of **W** are first defined as $w_{jk} = 1/d_{jk}$ where $d_{jk}$ is the distance between the capital city of province $j$ and that of province $k$, with $k \neq j$.[8] This **W** is then row-normalized so that each row sums to unity. This row-normalized **W** being multiplied by the vector of $\ln \mathbf{y_t}$ leads to the vector of the spatial lagged dependent variable.

There is a host of methods to estimate Eq. (18). The most representative ones include pooling regression with OLS, fixed effects estimator, spatial panel regression with maximum likelihood (ML) estimator, and the combined spatial and dynamic panel regression with system GMM. In the literature on growth empirics which does not use spatial econometric technique it is well-known that the simple pooled OLS estimate of the coefficient on the initial income term, $\hat{\gamma}$, is likely to be inconsistent and biased upwards due to the positive correlation between $\ln y_{i,t-1}$ and $\eta_i$ (Hsiao, 2003). The fixed effects estimator, although the within groups transformation wipes out the time-invariant province-specific effects $(\eta_i)$, produces the opposite, a downward bias with the extent of attenuation increasing when exogenous covariates are added (Nickell, 1981). Bond et al. (2001) and Caselli et al. (1996) suggest a bound for $\hat{\gamma}$: the observed biases in the OLS and within group estimators are used as references to define upper and lower bounds for this serial autoregressive parameter.

The inclusion of a spatially lagged dependent variable $(\mathbf{W}\ln\mathbf{y})_{it}$ on the right-hand side of Eq. (18) further causes a simultaneity problem and renders both OLS and fixed effects estimators inconsistent. Although this simultaneity problem can be solved by employing ML estimator established in spatial econometrics, the existing spatial ML estimators are not designed to solve the endogeneity problem caused by the inclusion of a serially lagged dependent variable $\ln y_{i,t-1}$ (Abreu et al., 2005a; Elhorst, 2003). An exception is Elhorst (2005) who uses a first-differenced model to eliminate fixed effects and then derives an unconditional likelihood function. However, his ML method does not allow for instrumental treatment to control the potential endogeneity of other explanatory variables than the serially and spatially lagged dependent variable, which is very likely in our case.

Badinger et al. (2004) propose a two-step procedure to take care of spatial interdependence in the estimation of a dynamic panel-data model. The variables are first filtered to remove spatial autocorrelation and then a standard GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) is applied to the filtered data. Although this procedure avoids addressing the joint problem of serial and spatial endogeneity in one equation, it is incapable of making explicit inference for spatially lagged variables and removes some of the variation that could potentially explain differences in growth rates. In addition, the two-step procedure implies that the coefficients of the spatial filtering and the other coefficients in the model are not determined jointly but sequentially, and the properties of such a sequential estimator are not known (Abreu et al., 2005a).

In comparison, a direct application of the system GMM to Eq. (18) appears to be the best estimator available as it deals with the joint problem of serial and spatial endogeneity and corrects for the potential endogeneity of other explanatory variables. The basic idea of the system GMM is to estimate Eq. (18) as a system of two equations. One is in first difference, which allows the removal of the fixed effects, and the other is in levels, which brings in the technical gains of additional level moment conditions and increased efficiency. Lagged first differences and lagged levels are used as instruments for equations in levels and for equations in first differences, respectively. The use of instrumental variables allows consistent estimation of parameters even in the presence of measurement error and endogenous right-hand-side variables.

Considering that the consistency of the system GMM estimator depends on whether a selected set of lagged level and first-differenced values of the explanatory variables are valid instruments in the regression, three sets of specification tests are employed. First, the overall validity of the instruments is tested by the standard Hansen's *J* test of over-identifying restrictions, which analyses the sample analogue of the moment conditions used in the estimation process. Second, following the recommendations in Roodman (2009), Difference-in-Hansen tests for the full set of instruments for the levels equation as well as for the subset based on the dependent variable are conducted. The number of instruments generated for the regressions are reported. Third, because significant second-order serial correlation of the first-differenced residuals indicates serial correlation in the original error terms and therefore misspecification of the instruments, we also test for first-order and second-order serial correlation in the first-differenced residuals. If the original error terms are not serially correlated, there should be evidence of a significant negative first-order serial correlation in differenced residuals and no evidence of second-order serial correlation in the first-differenced residual. In addition to the validity tests, a finite-sample correction to the two-step covariance matrix as suggested in Windmeijer (2005) is implemented.

(Tables 1-3 about here)

## 5. EMPIRICAL RESULTS

In Table 2, three unrestricted models are estimated and different estimators are applied to each model. The 'Solow Model' is in line with the standard specification in the literature (e.g., Islam, 1995; Bond et al., 2001) and does not incorporate structural change and spatial dependence caused by technology diffusion and factor mobility. The 'Solow Model + Structural Change' incorporates two structural change variables, *MGROWTH* and *DISEQ*, derived from labour reallocation from agriculture to the non-agricultural sector. The third model is the full specification as presented in Eq. (18). For the second and third models, the results reported correspond to the inclusion of $t \cdot MGROWTH$ and $t \cdot DISEQ$

only. Alternative results with the inclusion of *MGROWTH* and *DISEQ* are qualitatively unchanged and quantitatively similar.

Let us first look at the results for the standard Solow Model. The OLS regression produces a significantly positive coefficient larger than unity on serially lagged income, which suggests divergence rather than conditional convergence across provinces. This is, however, not surprising as we discuss above that the OLS coefficient of the lagged dependent variable is upward biased in the presence of individual-specific effects. In contrast, this serial autoregressive parameter, $\hat{\gamma}$, decreases to 0.712 with the fixed effects (within groups) estimator and is 0.975 with the system GMM estimator, which suggest conditional convergence. It is clear that $\hat{\gamma}$ with the system GMM does fall between the upper bound of 1.007 given by OLS and the lower bound of 0.712 by the within group estimate. The system GMM estimator is expected to address the inconsistency of both OLS and within-groups estimators caused by endogeneity and measurement errors. The standard Hansen's *J* test, two tests of Difference-in-Hansen, AR(1) and AR(2) tests suggest that the instruments used in the system GMM regression are valid and the original error terms are not serially correlated. Thus the system GMM estimator is well-behaved and should be the preferred one in comparison with the other two estimators. The GMM estimation suggests that the conditional convergence of provincial incomes across China does exist and the annual convergence rate implied in a standard Solow model is 0.51% during 1980-2005. Nevertheless, that capital investment loses the significance in the system GMM regression is not in line with the theoretical expectation. This unexpected result may be due to the omitted variable problem associated with structural change and spatial dependence, which will be addressed by the other two models.

The incorporation of structural change into the standard Solow model reduces the size of the coefficient on serially lagged income consistently in corresponding to each of the three estimators and hence exerts a significant impact on convergence. With OLS the $\hat{\gamma}$ estimation is now below 1, which supports the existence of conditional convergence. With the fixed effects $\hat{\gamma}$ decreases to 0.696, which is heavily downward-biased. With the system GMM $\hat{\gamma}$ is 0.958, which lies within the bound given by the fixed effects and OLS estimations. The better behaved system GMM estimator further shows that the coefficients on both capital investment and population growth are significant now and their signs are as expected, i.e., capital investment promotes per capita income growth while population growth plays the opposite role. The coefficient on $t \cdot MGROWTH$ is significantly positive, while that on $t \cdot DISEQ$ is not significant, which suggests a strong linear effect of labour reallocation on TFP growth.

Eq. (18) is estimated by the OLS, fixed effects, spatial ML and system GMM estimator, respectively. In comparison with the Solow Model and the Solow Model plus Structural Change, the incorporation of technology diffusion and factor mobility reduces the size of the coefficient on serially lagged income with respect to each of the OLS, fixed effects, and system GMM estimator.[9] This reduction leads to a higher convergence rate. With OLS the $\hat{\gamma}$ estimation decreases to 0.968 now, implying an annual convergence rate, $\lambda$, of 0.65%. With the fixed effects $\hat{\gamma}$ falls to 0.669, implying a $\lambda$ of 8.04%, which is heavily upward- biased. With the system GMM $\hat{\gamma}$ is 0.902, which suggests a $\lambda$ of 2.06%. Surprisingly, the spatial ML produces an estimation of $\hat{\gamma}$ smaller than the estimation given by the fixed effects, which is widely regarded as the lower bound for a plausible estimation of $\hat{\gamma}$. This result suggests that in the presence of the joint endogeneity of both serially and spatially lagged dependent variable, a control for the spatial endogeneity alone may enhance rather than reduce the downward bias on $\hat{\gamma}$ in comparison with the fixed effects panel estimation.

Let us shed more light on estimates of spatially lagged per capita income. The coefficient estimates for this variable are significantly positive for the estimators of OLS, spatial ML, and system GMM, respectively. Furthermore, this spatial autoregressive parameter lies between 0 and 1, as assumed in Eq. (2). These results clearly provide evidence in favour of our theoretical specification, which introduce technology spillovers and factor mobility into standard Solow model. From the perspective of pure empirics, these results also signal the importance of including spatially lagged income in growth regressions.

We now focus on the results of system GMM estimator, which addresses the joint endogeneity of serially and spatially lagged income, possible endogeneity of other explanatory variables, and possible measurement errors, and passes the specification tests of Hansen's *J*, Difference-in-Hansen, AR(1) and AR(2). It can be seen that all coefficients are statistically significant and have the expected sign. In addition to the implied convergence rate of about 2% per annum, the results indicate that capital investment and both the linear and nonlinear components of structural change make significantly positive contribution to the growth of per capita income. On the contrary, population growth plays a significantly negative role. The significantly positive coefficient on spatially lagged income per capita indicates the strong presence of technological diffusion and factor mobility across Chinese provinces and suggests that this presence has generated a complementary effect between a given province and its neighbours although the effect decays in distance.

Table 3 reports that the imposition of the linear parameter restriction of $\beta_1 = -\beta_2$ on all above regressions generates qualitatively unchanged and quantitatively similar results to those presented in Table 2. Most importantly, the restricted regressions confirm that in comparison with the Solow Model and the Solow Model plus Structural Change, the incorporation of the $\mathbf{W}\ln\mathbf{y}_t$ term reduces the size of the coefficient on serially lagged income with respect to each of the OLS, fixed effects, and system GMM estimator, thus leading to a higher convergence rate. In addition, the restricted regression by system GMM increases both the significant level and magnitude of the coefficient on spatially lagged income per capita (Table 3).

To test the possible spurious significance of the coefficient on the spatial autoregressive term, we estimate Eq. (19) and the results from the unrestricted regressions are presented in Table 4.[10] The results indicate that the incorporation of $\mathbf{W}\ln\mathbf{x}_t$ into the regressions does not crowd out the significance of $\mathbf{W}\ln\mathbf{y}_t$. In comparison with Table 2, the significance of $\mathbf{W}\ln\mathbf{y}_t$ is in fact strengthened. Moreover, with the well-behaved system GMM estimator, the coefficients of both $\mathbf{W}\cdot\ln s_{it}$ and $\mathbf{W}\cdot\ln(n_{it} + g + \delta)$ become statistically insignificant. These findings suggest that the significance of the coefficient on the spatial autoregressive term is very unlikely to be spurious.

In order to shed light on how China's convergence story is either different or similar to others, it helps highlight two key findings in the literature. First, based on 619 estimates in 48 publications, which are taken from a random sample of empirical growth studies published in peer-reviewed journals, Abreu et al. (2005b) conduct a meta-analysis of β-convergence literature. They find that 'a substantial number of observations is clustered around a convergence rate of 2%; the proportion of estimates that lies between a convergence rate of 1 and 3% is close to one-third' (p. 399). Second, in the literature on convergence across EU-regions, it is found that the estimations with spatial dependence typically yield considerably lower convergence rates than those without spatial dependence (Eckey and Türck, 2007; Paas and Schlitte, 2008).

In line with the habitual 2% convergence rate, the system GMM estimations of our well-specified spatial dynamic model suggest a rate of convergence between 1.37 and 2.06% (Tables 2 and 3). While our findings indicate that the convergence rate across Chinese provinces is not an outlier in comparison to that across EU-regions or OECD countries, it is worth noting that the existing literature on growth empirics of China has been dominated by divergence or weak convergence arguments (Section 3.1). A further contrast is that the incorporation of spatial dependence in the context of China leads to considerably higher convergence rates rather than lower ones as being the case in the context of EU-regions. The implications of the above contrasts are twofold. First, the divergence or weak convergence arguments presented in the existing literature on growth empirics of China can be largely attributed to the problem of model-misspecification since mechanisms and variables representing the effects of technology diffusion, factor mobility, and structural changes, which significantly enhance the convergence force in China, are omitted. Second, the opposite effects of spatial dependence on convergence rate between the Chinese and EU contexts are surprising and deserve further investigation. Because the presence of technological spillover, i.e., $0 < (1 - \rho) < 1$, is confirmed for both China and the EU, the above opposition would lie on $b^L - b^K \geq 0$ for China versus $b^L - b^K < 0$ for the EU according to Eq. (10).

Given the significant presence of interprovincial migration in China since the early 1980s (Section 3.3), $b^L - b^K \geq 0$ for China can be attributed to two possibilities. First, factor movements across provinces have been dominated by labour mobility and the mobility of capital has been limited (World Bank, 2005). Second, while labour moves on average from a province with lower capital-labour ratio to one with higher capital-labour ratio, capital may move in the opposite direction (i.e., $b^K < 0$) to pursue higher return on capital (Zhang, 2009). These two possibilities are clearly not mutually exclusive and can be interwoven. In contrast, $b^L - b^K < 0$ for the EU might imply that both labour and capital move in the same direction on average and factor mobility across EU-regions is dominated by capital mobility.

(Table 4 about here)

## 6. CONCLUDING REMARKS

This study augments Yu's (2007) theoretical specification and introduces technology diffusion, factor mobility, and structural change into cross-region growth regression. The process of derivation naturally leads to a spatial dynamic model prior to a diagnostic test for spatial interdependence and thus provides a strong link between empirical spatial econometrics in growth regression and the economic growth literature. The demand for this link is compellingly highlighted in Abreu et al. (2005a) and Ertur and Koch (2007). To justify the emphasis on technology diffusion, factor mobility, and structural change, the study conducts a literature review on technology spillovers and a preliminary data analysis with regard to the scale and variation of factor (mainly, labour) mobility across regions and sectors in the context of China's reform era. The data analysis shows that the continuing labour reallocation in huge scale from agriculture to rural non-farming and urban activities, in combination with the persistent severe disparity in inter-sectoral and inter-regional marginal return of labour, would explain a large part of growth in aggregate productivity at the regional level. In addition, the persistent severe disparity in inter-sectoral and inter-regional marginal return of labour is highly indicative of future opportunities for achieving productivity gains by reallocating labour across sectors and regions.

We apply our spatial dynamic model to the study of cross-province growth in China over the period of 1980-2005. The estimations have to address the joint endogeneity problem of the serially and spatially lagged dependent variable, as indicated in the theoretical model. We employ system GMM estimator to deal with this join endogeneity problem. For robustness, we also make use of alternative estimators and model structures. The estimations show that incomes are spatially interdependent, which, from growth theory's point of view, highlights the significance of technology diffusion and factor mobility. By taking into account spatial dependence and structural change, the speed of conditional convergence becomes faster and much closer to the legendary 2% (Abreu et al., 2005b). This result departs from the existing literature on growth empirics of China, which has been dominated by divergence or weak convergence arguments. This departure highlights the essential importance of technology diffusion, factor mobility and structural change in shaping the pattern and dynamics of cross-region growth in China. The result is also in sharp contrast to the negative impact of spatial dependence on convergence speed across EU-regions as presented in Paas and Schlitte (2008). An initial assessment of this contrast based on our theoretical model suggests that factor movements across Chinese provinces may have been dominated by labour mobility and capital and labour may move in the opposite direction, whereas in the case of EU-regions, both labour and capital may move in the same direction on average and factor mobility may be dominated by capital flows.

From the perspective of driving forces accounting, our results suggest that capital investment, changes in structure of employment, population growth, and the force of conditional convergence are the determinants of the income and growth difference across Chinese provinces. With the understanding of a convergence force as one that the province with lower initial level of per capita income will have a faster growth rate than those regions with higher initial level of per capita income, our fuller model advocates a stronger convergence force in the context of China. In terms of policy implications, this study points to a richer possibility for policy actions in raising the long-run income levels of regions and in accelerating the pace of reaching them. It suggests that policy and regulatory efforts which reduce barriers to and promote technology diffusion and movement of labour and capital across sectors and regions will not only contribute to individual regions' TFP and income growth in the long-run, but also have the potential to enhance convergence force across regions, thus leading to reduction in regional income disparity.

## Note

[1] For a comprehensive survey on the first extension, see Islam (2003). For two representative surveys on the second extension, see Abreu et al. (2005a) and Rey and Janikas (2005). Two important exceptions are López-Bazo et al. (2004) and Ertur and Koch (2007), in which technology in a region is modelled to depend on the technological level of the neighbours, which in turn is related to their stock of physical and human capital per unit of labour.

[2] Despite the tension in the interpretation of convergence parameter, it is safe to say that conditional convergence means the region with lower initial level of per capita income still having on average a faster growth rate than those regions with higher initial level of per capita income after conditioning on a set of variables which underlie a region's own steady state of economic growth (Islam, 2003).

[3] What we need is a postulation of a migration function and thus the optimization problem for migrants is not considered here.

[4] In the 2000 population census of China, migration is defined as the movement of residence within the last 5 years. If a change in *hukou* registration occurs along with the change in residence, the movement is recorded as *hukou* migration in the census. If a person has left the place of *hukou* registration for more than 6 months, the movement is recorded as non-*hukou* migration. The census does not consider the movement of residence for shorter than 6 months as migration, which is called 'floating population' in Chinese media.

[5] For the sake of comparability, Lin et al. (2004) adopts the definition of non-*hukou* migration in the 1990 census, that is, the person concerned has left the place of *hukou* registration for more than 1 year. After reconciling the differences in definitions of two censuses and discount the 2000 migration figures, they come to a figure of 27.53 million inter-provincial migrants during 1995-2000.

[6] It is worth noting that the aggressive economic restructuring started in the mid-1990s led to the layoffs of 43.28 million workers in the urban industrial and services sectors during 1995-2001. Many millions of them with no expectation of reemployment were either involuntarily retired early or did not register with local governments for unemployment benefits. The estimations based on 2000 population census put China's urban unemployment rate at 10-12.7% in 2000 (Giles et al., 2005), indicating that the urban unemployed was equivalent to 2.3-2.9% of China's total employment.

[7] Please note that the number of observation in our database is small only 145, which makes it infeasible to include nonlinear parametric constraints in the regressions. Once this inclusion becomes feasible, it would lead to more accurate estimations of the structural parameters. We leave this for the attention of future work.

[8] We experimented with alternative weighting schemes such as the binary contiguity matrix and got broadly similar results to those reported in this paper.

[9] If $W \ln \mathbf{y}_t$ is introduced in the absence of theoretical reasoning, we would not be in a position to make this direct comparison because $(\mathbf{I}_N - \rho\mathbf{W})y = X\gamma + \mathbf{W}X\beta + \varepsilon$ means $y = (\mathbf{I}_N - \rho\mathbf{W})^{-1}(X\gamma + \mathbf{W}X\beta + \varepsilon)$ . Fortunately, in our case Eq. (13) indicates that the marginal impact of $\ln \mathbf{y}_{t-1}$ is $\gamma = e^{-\lambda\tau}$ .

[10] The corresponding results for the restricted regressions are qualitatively unchanged and quantitatively similar. These and other results on robustness tests are available upon request.

## Reference


Abreu, Maria, Henri L F de Groot, and Raymond J G M Florax. 2005a. "Space and Growth: A Survey of Empirical Evidence and Methods," *Région et Développement*, 21, 13-44.

Abreu, Maria, Henri L F de Groot, and Raymond J G M Florax. 2005b. "A Meta-analysis of *β*-convergence: The Legendary 2%," *Journal of Economic Surveys*, 19 (3), 389-420.

Adams, James D. and Adam B. Jaffe. 1996. "Bounding the Effects of R&D: An Investigation Using Matched Establishment-firm Data," *RAND Journal of Economics*, 27(4), 700-721.

Arellano, Manuel and Olympia Bover. 1995. "Another Look at Instrumental Variable Estimation of Error-Component Models," *Journal of Econometrics*, 68(1), 29-52.

Badinger, Harald, Werner G Muller, and Gabriele Tondl. 2004. "Regional Convergence in the European Union, 1985-1999: A Spatial Dynamic Panel Analysis," *Regional Studies*, 38(3), 241-253.

Barro, Robert J. 1991. "Economic Growth in a Cross-Section of Countries," *Quarterly Journal of Economics*, 106(2), 407-443.

Barro, Robert J. and Xavier Sala-i-Martin. 1992. "Convergence," *Journal of Political Economy*, 100 (2), 223-251.

Blundell, Richard and Stephen Bond R. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87(1), 115-143.

Bond, Stephen R., Anke Hoeffler, and Jonathan Temple. 2001. "GMM Estimation of Empirical Growth Models," CEPR Discussion Paper No. 3048, London: Centre for Economic Policy Research.

Bottazzi, Laura and Giovanni Peri. 2003. "Innovation and Spillovers in Regions: Evidence from European Patent Data," *European Economic Review*, 47(4), 687-710.

Caselli, Francesco, Gerardo Esquivel and Fernando Lefort. 1996. "Reopening the Convergence Debate: A New Look at Cross-Country Growth Empirics," *Journal of Economic Growth*, 1(3), 363-389.

Chen, Jian and Belton M. Fleisher. 1996. "Regional Income Inequality and Economic Growth in China," *Journal of Comparative Economics*, 22(2), 141-164.

Denison, Edward F. 1967. *Why Growth Rates Differ: Postwar Experiences in Nine Western Countries*. Washington, D.C.: Brookings Institution.

Eckey, Hans-Friedrich and Matthias Türck. 2007. "Convergence of EU-Regions: A Literature Report," *Investigaciones Regionales*, 10, 5-32.

Elhorst, J. Paul. 2003. "Specification and Estimation of Spatial Panel Data Models," *International Regional Science Review*, 26(3), 244-268.

Elhorst, J. Paul. 2005. "Unconditional Maximum Likelihood Estimation of Dynamic Models for Spatial Models," *Geographical Analysis*, 37(1), 85-106.

Ertur, Cem and Wilfried Koch. 2007. "Growth, Technological Interdependence and Spatial Externalities: Theory and Evidence," *Journal of Applied Econometrics*, 22(6), 1033-1062.

Giles, John, Albert Park, and Juwei Zhang. 2005. "What is China's True Unemployment Rate?," *China Economic Review*, 16(2), 149-170.

Hsiao, Cheng. 2003. *Analysis of Panel Data*. 2nd edition. Cambridge: Cambridge University Press.

Islam, Nazrul. 1995. "Growth Empirics: A Panel Data Approach," *Quarterly Journal of Economics*, 110(4), 1127-1170.

Islam, Nasrul. 2003. "What Have We Learnt from the Convergence Debate?," *Journal of Economic Survey*, 17(3), 309-362.

Jian, Tianlun, Jeffrey D. Sachs, and Andrew M. Warner. 1996. "Trends in Regional Inequality in China," *China Economic Review*, 7(1), 1-21.

Jones, Derek C., Cheng Li, and Ann L. Owen. 2003. "Growth and Regional Inequality in China During the Reform Era," *China Economic Review*, 14(2), 186-200.

Keller, Wolfgang. 2002. "Geographic Localization of International Technology Diffusion," *American Economic Review*, 92(1), 120-142.

Koo, Jun. 2005. "Technology Spillovers, Agglomeration, and Regional Economic Development," *Journal of Planning Literature*, 20 (2), 99-115.

Kuznets, Simon. 1961. "Economic Growth and the Contribution of Agriculture: Notes on Measurement," *International Journal of Agrarian Affairs*, 3 (1), 56-75.

Lin, Justin Y., Gewei Wang, and Yaohui Zhao. 2004. "Regional Inequality and Labor Transfers in China," *Economic Development and Cultural Change*, 52(3), 587-603.

López-Bazo, Enrique, Esther Vayá, and Manuel Artís. 2004. "Regional Externalities and Growth: Evidence from European Regions," *Journal of Regional Science*, 44(1), 43-73.

Madariaga, Nicole and Sandra Poncet. 2007. "FDI in Chinese Cities: Spillovers and Impact on Growth," *World Economy*, 30(5), 837-862.

Nickell, Stephen J. 1981. "Biases in Dynamic Models with Fixed Effects," *Econometrica*, 49(6), 1417-1426.

Paas, Tiiu and Friso Schlitte. 2008. "Regional Income Inequality and Convergence Processes in the EU-25," *Italian Journal of Regional Science*, 7(2), 29-49.

Rey, Sergio J. and Mark V. Janikas. 2005. "Regional Convergence, Inequality and Space," *Journal of Economic Geography*, 5(2), 155-176.

Roodman, David. 2009. "A Note on the Theme of Too Many Instruments," *Oxford Bulletin of Economics and Statistics*, 71(1), 135-158.

State Statistical Bureau (SSB). 2000-2006. *China Statistical Yearbook.* Beijing: China Statistical Publishing House.

State Statistical Bureau (SSB). 1999. *Statistical Data on 50 Years of New China, 1949-1998*. Beijing: China Statistical Publishing House.

Sun, Laixiang, W. ven Veen, X. Zhang, J. Huang, and H. Qiu. 2008. "China's Economic Growth outside the Farm Sector: Plausible Trends towards 2030," EU-FP6-CATSEI Project Deliverable D4, School of Oriental and African Studies (SOAS), University of London. http://www.catsei.org/catseiweb/upload/2009/320093512113891.pdf.

Temple, Jonathan and Ludger Wößmann. 2006. "Dualism and Cross-Country Growth Regressions," *Journal of Economic Growth*, 11(3), 187-228.

Weeks, Melvyn and James Yudong Yao. 2003. "Provincial Conditional Income Convergence in China, 1953-1997: A Panel Data Approach," *Econometric Reviews*, 22(1), 59-77.

Wei, Yingqi and Xiaming Liu. 2006. "Productivity Spillovers from R&D, Exports and FDI in China's Manufacturing Sector," *Journal of International Business Studies*, 37(4), 544-557.

Wei, Yingqi, Xiaming Liu and Chengang Wang. 2008. "Mutual Productivity Spillovers between Foreign and Local Firms in China," *Cambridge Journal of Economics*, 32(4), 609-631.

Windmeijer, Frank. 2005. "A Finite Sample Correction for the Variance of Linear Efficient Two-Step GMM Estimators," *Journal of Econometrics*, 126(1), 25-51.

World Bank. 2005. *China: Integration of National Product and Factor Markets – Economic Benefits and Policy Recommendations*. Washington, D. C.: World Bank.

Yao, Shujie and Zongyi Zhang. 2001. "On Regional Inequality and Diverging Clubs: A Case Study of Contemporary China," *Journal of Comparative Economics*, 29(3), 466-484.

Yu, Jihai. 2007. "Essays on Spatial Dynamic Panel Data Model: Theories and Applications," Ph.D. dissertation, Department of Economcis, The Ohio State University.

Zhang, Xiaobo and Kong-Yam Tan. 2007. "Incremental Reform and Distortions in China's Product and Factor Markets," *World Bank Economic Review*, 21(2), 279-299.

Zhang, Xiaobo. 2009. "Have Geese Flown to the Inland?" Manuscript, Washington DC: International Food Policy Research Institute (IFPRI).

TABLE 1. Definition of Variables and Summary Statistics

| Variable | Label | Definition | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|---|
| Income level | $\ln y_{it}$ | Logarithm of real GDP per capita in 1985, 1990, 1995, 2000, and 2005. | 145 | 7.393 | 0.829 | 5.900 | 9.874 |
| Initial income level | $\ln y_{i,t-1}$ | Logarithm of real GDP per capita in 1980, 1985, 1990, 1995, and 2000. | 145 | 6.956 | 0.804 | 5.380 | 9.625 |
| Saving rate | $\ln s_{it}$ | Logarithm of the average share of fixed asset investment in real GDP. The 6-year average is over 1980-85, 1985-90, 1990-95, 1995-2000, and 2000-05, respectively. | 145 | -1.136 | 0.281 | -1.860 | -0.322 |
| Population growth rate | $\ln(n_{it} + \bar{g}/(1-\bar{\rho}) + \bar{\delta})$ | Logarithm of the sum of average population growth rate ($n$), technological progress rate ($g$) and capital depreciation rate ($\delta$), where $\bar{g}/(1-\bar{\rho})+\bar{\delta}$ = 0.07. The 6-year average of population growth is over 1980-85, 1985-90, 1990-95, 1995-2000, and 2000-05, respectively. | 145 | -2.498 | 0.097 | -2.791 | -2.054 |
| Structural change (linear part) | *MGROWTH* | The change in the share of non-agricultural population in total population over each of the five-year intervals of 1980-85, 1985-90, 1990-95, 1995-2000, and 2000-05. | 145 | 0.049 | 0.062 | -0.016 | 0.339 |
| Structural change (non-linear part) | *DISEQ* | $DISEQ = \Delta MGROTH \cdot p / (1 - p)$, where $p$ is the migration propensity, defined by $p = -\Delta a / a$, where $a$ is the share of agricultural population in total population. | 145 | 0.035 | 0.200 | -0.588 | 1.797 |
| Income level of neighbouring provinces | $(W \cdot \ln \mathbf{y})_{it}$ | Spatially lagged dependent variable | 145 | 7.420 | 0.642 | 6.448 | 8.582 |

Note: The inconsistence of data on employment by sector and province is well-known and the use of them, in fact, generates many negative values for *MGROWTH* and *DISEQ*, which are in contradiction to observed structural changes. In comparison, data on agricultural versus non-agricultural population at the provincial level, although under-representing the extent of rural non-farming activities, are regarded as basically consistent and the measurements of *MGROWTH* and *DISEQ* based on these data are largely in line with the observed structural changes.

TABLE 2. Estimation Results (unrestricted regression, number of observation = 145)

| | Solow Model | | | Solow Model + Structural Change | | | Solow Model + Structural Change + Spatial Dependence | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | Within Groups | System GMM | OLS | Within Groups | System GMM | OLS | Within Groups | Spatial ML | System GMM |
| $\ln y_{i,t-1}$ | 1.007*** | 0.712*** | 0.975*** | 0.989*** | 0.696*** | 0.958*** | 0.968*** | 0.669*** | 0.440*** | 0.902*** |
| | [0.016] | [0.056] | [0.028] | [0.018] | [0.063] | [0.041] | [0.022] | [0.064] | [0.019] | [0.035] |
| $\ln s_{it}$ | 0.041 | 0.202*** | 0.067 | 0.023 | 0.200*** | 0.135* | -0.002 | 0.170*** | 0.127** | 0.092** |
| | [0.046] | [0.059] | [0.058] | [0.046] | [0.059] | [0.075] | [0.049] | [0.062] | [0.065] | [0.040] |
| $\ln(n_{it} + g + \delta)$ | -0.485*** | -0.332*** | -0.284*** | -0.456*** | -0.348*** | -0.357*** | -0.380*** | -0.365*** | -0.279*** | -0.326*** |
| | [0.108] | [0.090] | [0.100] | [0.113] | [0.092] | [0.112] | [0.122] | [0.092] | [0.093] | [0.076] |
| $t \cdot MGROWTH_{it}$ | | | | 0.079* | 0.030 | 0.109*** | 0.044 | 0.033 | 0.048* | 0.119*** |
| | | | | [0.046] | [0.064] | [0.037] | [0.051] | [0.064] | [0.029] | [0.040] |
| $t \cdot DISEQ_{it}$ | | | | -0.008 | 0.005 | 0.005 | 0.009 | 0.005 | 0.003 | 0.009** |
| | | | | [0.012] | [0.009] | [0.004] | [0.012] | [0.009] | [0.009] | [0.004] |
| $(W \cdot \ln \mathbf{y})_{it}$ | | | | | | | 0.055 | 0.520 | 0.528*** | 0.291* |
| | | | | | | | [0.035] | [0.324] | [0.015] | [0.170] |
| Constant | -0.778*** | 2.078*** | 0.036 | -0.619** | 2.136*** | -0.054 | -0.709** | -2.066 | | -2.014 |
| | [0.294] | [0.558] | [0.441] | [0.312] | [0.582] | [0.605] | [0.316] | [2.684] | | [1.353] |
| $R^2$ / Log likelihood | 0.978 | 0.960 | | 0.979 | 0.990 | | 0.980 | 0.990 | 0.990 | |
| Number of Instruments | | | 27 | | | 25 | | | | 30 |
| Hansen J test (*p*-value) | | | (0.243) | | | (0.152) | | | | (0.418) |
| Difference-Hansen tests (*p*-value) | | | | | | | | | | |
| All system GMM instrument | | | (0.600) | | | (0.305) | | | | (0.454) |
| Those based on lagged income only | | | (0.212) | | | (0.240) | | | | (0.373) |
| AR(1) test in differences (*p*-value) | | | (0.003) | | | (0.004) | | | | (0.004) |
| AR(2) test in differences (*p*-value) | | | (0.849) | | | (0.559) | | | | (0.370) |
| Implied $\lambda$ | -0.0014 | 0.0679 | 0.0051 | 0.0022 | 0.0725 | 0.0086 | 0.0065 | 0.0804 | 0.1642 | 0.0206 |

Notes. Numbers in [ ] and ( ) are standardized errors and *p*-values respectively. *, ** and *** denotes significance at the 10%, 5% and 1% level respectively. Province dummy in Spatial ML and Period dummy in the Within Groups and System GMM are not reported.

TABLE 3. Estimation Results (Restricted regressions, number of observation = 145)

| | Solow Model | | | Solow Model + Structural Change | | | Solow Model + Structural Change + Spatial Dependence | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | Within Groups | System GMM | OLS | Within Groups | System GMM | OLS | Within Groups | Spatial ML | System GMM |
| $\ln y_{i,t-1}$ | 0.997*** | 0.695*** | 0.984*** | 0.977*** | 0.679*** | 0.944*** | 0.947*** | 0.655*** | 0.429*** | 0.934*** |
| | [0.017] | [0.054] | [0.028] | [0.018] | [0.061] | [0.015] | [0.022] | [0.064] | [0.017] | [0.063] |
| $\ln s_{it} - \ln(n_{it} + g + \delta)$ | 0.097** | 0.245*** | 0.170** | 0.068 | 0.248*** | 0.179*** | 0.022 | 0.237*** | 0.182*** | 0.130** |
| | [0.046] | [0.044] | [0.067] | [0.047] | [0.045] | [0.056] | [0.050] | [0.046] | [0.047] | [0.057] |
| $t \cdot MGROWTH_{it}$ | | | | 0.116** | 0.027 | 0.089* | 0.055 | 0.028 | 0.047* | 0.101** |
| | | | | [0.047] | [0.064] | [0.046] | [0.052] | [0.064] | [0.029] | [0.048] |
| $t \cdot DISEQ_{it}$ | | | | -0.003 | 0.004 | 0.009*** | 0.001 | 0.004 | -0.004 | 0.006 |
| | | | | [0.013] | [0.009] | [0.003] | [0.012] | [0.009] | [0.009] | [0.007] |
| $(W \cdot \ln \mathbf{y})_{it}$ | | | | | | | 0.085** | 0.395 | 0.528*** | 0.456** |
| | | | | | | | [0.034] | [0.317] | [0.015] | [0.223] |
| Constant | 0.323*** | 2.470*** | 0.341 | 0.480*** | 2.565*** | 0.561*** | 0.139 | -0.523 | | -3.099* |
| | [0.096] | [0.433] | [0.224] | [0.111] | [0.469] | [0.165] | [0.176] | [2.523] | | [1.613] |
| $R^2$ / Log likelihood | 0.975 | 0.989 | | 0.976 | 0.989 | | 0.977 | 0.990 | 0.990 | |
| Number of Instruments | | | 27 | | | 24 | | | | 22 |
| Hansen J test ($p$-value) | | | (0.253) | | | (0.252) | | | | (0.341) |
| Difference-Hansen tests ($p$-value) | | | | | | | | | | |
| All system GMM instrument | | | (0.790) | | | (0.648) | | | | (0.246) |
| Those based on lagged income only | | | (0.808) | | | (0.311) | | | | (0.268) |
| AR(1) test in differences ($p$-value) | | | (0.002) | | | (0.003) | | | | (0.006) |
| AR(2) test in differences ($p$-value) | | | (0.883) | | | (0.601) | | | | (0.663) |
| Implied $\lambda$ | 0.0006 | 0.0728 | 0.0032 | 0.0047 | 0.0774 | 0.0115 | 0.0109 | 0.0846 | 0.1693 | 0.0137 |

Notes. The same as in Table 2.

TABLE 4. Robustness of the Results on the Spatial Autoregressive Term (unrestricted regressions, number of observation = 145)

| | OLS | Within Groups | Spatial ML | System GMM |
|---|---|---|---|---|
| $\ln y_{i,t-1}$ | 0.938*** | 0.676*** | 0.500*** | 0.917*** |
| | [0.022] | [0.062] | [0.050] | [0.048] |
| $\ln s_{it}$ | 0.099** | 0.188*** | 0.154** | 0.098 |
| | [0.050] | [0.059] | [0.064] | [0.062] |
| $\ln(n_{it}+g+\delta)$ | -0.353*** | -0.327*** | -0.298*** | -0.378*** |
| | [0.113] | [0.089] | [0.095] | [0.098] |
| $t \cdot MGROWTH_{it}$ | 0.080 | -0.036 | 0.074** | 0.045 |
| | [0.050] | [0.065] | [0.031] | [0.086] |
| $t \cdot DISEQ_{it}$ | 0.003 | 0.006 | -0.006 | 0.006* |
| | [0.012] | [0.008] | [0.009] | [0.003] |
| $W \cdot \ln s_{it}$ | -1.012*** | 0.775* | -0.510*** | -0.356 |
| | [0.212] | [0.403] | [0.185] | [0.439] |
| $W \cdot \ln(n_{it}+g+\delta)$ | -0.087 | 2.061*** | 0.117 | 0.535 |
| | [0.494] | [0.685] | [0.255] | [1.346] |
| $(W \cdot \ln \mathbf{y})_{it}$ | 0.322*** | 0.268 | 0.604*** | 0.553** |
| | [0.073] | [0.357] | [0.015] | [0.261] |
| Constant | -3.680*** | 6.067 | | -3.335*** |
| | [1.069] | [3.677] | | [2.998] |
| $R^2$ | 0.982 | 0.991 | 0.991 | |
| Instruments | | | | 23 |
| Hansen J test (*p*-value) | | | | (0.223) |
| Difference-Hansen tests (*p*-value) | | | | |
| All system GMM instrument | | | | (0.119) |
| Those based on lagged income only | | | | (0.232) |
| AR(1) test in differences (*p*-value) | | | | (0.007) |
| AR(2) test in differences (*p*-value) | | | | (0.547) |
| Implied λ | 0.0128 | 0.0783 | 0.1386 | 0.0173 |

Notes. The same as in Table 2.