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Are Geese Flying by Themselves inside China?

An LSTR-SEM Approach to Income Convergence of Chinese Counties

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German Institute for Economic Research
Mohrenstr. 58
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Are geese flying by themselves inside China? An LSTR-SEM approach to income convergence of Chinese counties

Konstantin A. Kholodilin* Eric Girardin**

Abstract

In this paper, we examine β-convergence of real per-capita income of Chinese counties. We account for both the spatial dependences between counties and the possibility of different convergence regimes. The first feature is captured by the spatial error term, whereas the second one is modeled using the spatial logit smooth transition approach. Two groups of counties can be identified: 1) counties, which have relatively poor neighbors and tend to grow faster and converge, and 2) counties, which have relatively rich neighbors and tend to grow slower and hence fail to converge. The counties belonging to the first group are concentrated mainly in western interior provinces, such as Qinghai, Sichuan, Yunnan, western part of Xinjiang Uygur. The counties of the second group are located mainly in coastal regions. Whereas in the benchmark model the estimated convergence rate is 0.8% for unconditional regression and 1.7% for condtional regression, the alternative models produce the convergence rate of 1.3-1.5% for unconditional regressions and 2.3-2.6% for conditional regressions, which is quite close to the estimates reported typically in the literature.

Keywords: Chinese counties; income convergence; LSTR; spatial effects.

JEL classification: C21; O47; R11.

*DIW Berlin, Mohrenstrasse 58, 10117 Berlin, Germany, e-mail: kkholodilin@diw.de

**GREQAM, Faculty of Economics, Université de la Méditerranée, 14 Avenue Jules Ferry, 13621 Aix en Provence, France, e-mail: eric.girardin@univmed.fr

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1 Introduction

The aim of this paper is to investigate the β-convergence of real per-capita income between Chinese counties. This is important, given the fast growth of the Chinese economy and reportedly increasing gap between the coastal and interior provinces.

It is not surprising, therefore, that the growing disparities are increasingly attracting the attention of the country's leadership. As Kwan (2009) points out "The administration of Hu Jintao, which took office in 2002, has consequently pursued policies to redress the regional disparity — including a program of developing China's western reaches, encouraging the rise of the central region, and spurring growth in the northeast — with the aim of creating a harmonious society." As an example of such policy a project called "10,000 Businesses Going West" can be cited, which is encouraging about 10,000 foreign firms and Chinese companies based in eastern areas to invest in the interior regions of China.

The shift of some industries from developed countries to developing ones that took place in Post-War Asia is known as the "flying geese" model. This unusual name is an allusion to a flock of geese flying in V-shaped formation headed by the leading goose. Historically, Japan was such a leading goose, whereas South Corea, Malaysia, Thailand were the geese following the leader. Currently, China is trying to implement a domestic version of this model — see Kwan (2009). In the Chinese version it is the Coastal regions that play the role of a leading goose, which is expected to be followed by the Central and Western regions of the country. The question is, whether these regions can catch up on their own or do they need an impetus from the central government in order to fly.

There are quite a few papers examining the income convergence between Chinese provinces, among them Wei and Liu (2004), Aroca et al. (2006), and Sha et al. (2007). Very few of these papers, such as Sandberg (2004), focus their attention on the spatial dimension of the income convergence. It should be noted, however, that many Chinese provinces are comparable to the large European states. For example, in 2007, the population of Guandong was 94.5 million persons compared to 82.3 million persons in Germany. The income data aggregated at such a high level may "conceal substantial heterogeneity or smooth over the impacts of important economic developments" at the county level, to use the words of Curran et al. (2007).

To the best of our knowledge, there is only one paper investigating the convergence of per-capita income of Chinese counties, namely Curran et al. (2007). Their study covers 2199 observations at county and city level over the period 1997-2005 and uses the Gross Regional Product (GRP) per capita as the dependent variable. Another interesting paper is that of Ho and Li (2007), which analyzes income convergence among Chinese cities during the period 1984-2003 accounting for spatial dependence by the means of the so-called spatial clustering index.

In this paper, we examine both unconditional and conditional β-convergence of the real per-capita income of Chinese counties. We account for both the spatial dependences between the counties and the possibility of different convergence regimes, or clubs of convergence. The first feature is captured by the spatial error term, whereas the second one is modelled using the Spatial Logistic Smooth Transition Regression (SpLSTR) approach. We show that two groups of counties can be identified: those having poor neighbors and growing fast and those having rich neighbors and growing slow. As a result, a much stronger convergence at county level can be observed than that at the province level. Thus, given that the government's "flying geese" policies have been implemented since just a few years, the observed income convergence between counties can be attributed mainly to the effects of the market forces. Hence, one can conclude that the "geese are flying by themselves" inside China.

The paper is organized as follows. Section 2 introduces the econometric models used to investigate the convergence process. Section 3 describes the data used in this study. Section 4 reports the estimation results. Finally, section 5 concludes.

2 Model

As the benchmark a simple model of the unconditional β-convergence is used:

$$\Delta^{\tau} y_{i,t+\tau} = \alpha + \beta y_{i,t} + \varepsilon_i, \tag{1}$$

where $y_{i,t}$ is the log of real per-capita GRP of county i in year t; τ is the time span over which convergence is being assessed, $\Delta^{\tau} y_{i,t+\tau} = y_{i,t+\tau} - y_{i,t}$.

The existence of spatial dependencies between Chinese counties — the fact that the economies of the regions located next to each other might be related stronger than the economies of the regions located far from each other — requires a special treatment. Not accounting for this leads to the omitted variable bias and hence to the incorrect estimates of the convergence rate. Therefore, we examine also the models that account for the spatial dependence by allowing for spatial correlation of errors. We refer to this model as spatial error model (SEM) and formulate it below:

$$\begin{aligned} \Delta^{\tau} y_{i,t+\tau} &= \alpha + \beta y_{i,t} + u_i \\ u_i &= \lambda W u_i + \varepsilon_i, \end{aligned} \tag{2}$$

where λ is the spatial autoregressive coefficient related to the error term; W is the spatial weights matrix[1]. The typical element of this matrix, w_{ij}, is defined as follows:

$$w_{ij} = \frac{1}{d_{ij}^2}, \tag{3}$$

where d_{ij} is the great circle distance between the centroid of county i and that of county j. All the elements on the main diagonal of matrix W are equal to zero. In addition, all the distances exceeding the median distance were set to zero. Finally, the constructed weights matrix is normalized such that all the elements in each row sum up to one.

Spatial Logistic Smooth Transition Regression (SpLSTR) model was suggested in Pede et al. (2008). Unlike the typical LSTR model introduced first in Teräsvirta and Anderson (1992)[2], which identifies the regimes in time (e.g., expansionary and recessionary periods of business cycle), SpLSTR distinguishes between regimes in space. An example relevant for this context might be two regimes: slow (or no) convergence and relatively quick convergence. The simplest form of the model can be formulated as:

$$\Delta^{\tau} y_{i,t+\tau} = \alpha_1 G_i + \alpha_2 (1 - G_i) + \beta_1 G_i y_{i,t} + \beta_2 (1 - G_i) y_{i,t} + \varepsilon_i, \tag{4}$$

where G_i is the logistic transition function defined as follows:

$$G_i = \frac{1}{1 + exp(-\gamma(z_{i,t} - c))} \tag{5}$$

where γ is the smoothness parameter; c is the threshold. The advantage of a logistic function is that it has two distinct regimes that are associated

[1] The use of a matrix of spatial weights based on the contiguity between the regions is precluded by the existence of the island provinces and counties.

[2] For more details on smooth transition regression models in general and LSTR models in particular see an excellent, albeit a bit outdated, survey in van Dijk et al. (2002).

with small and large values of the transition variable relative to the threshold c. When the transition variable for region i is lower than c, G_i is low and the region is classified as belonging to regime 2. Otherwise G_i is high and the region is classified as belonging to regime 1. As in Pede et al. (2008), we choose the transition variable, $z_{i,t}$, to be the spatial lag of the initial per-capita GRP: $z_{i,t} = Wy_{i,1997}$.

Finally, the fourth model includes both SpLSTR specification and spatially correlated errors and will be denoted as SpLSTR-SEM:

$$\begin{aligned} \Delta^{\tau} y_{i,t+\tau} = \alpha_1 G_i + \alpha_2(1 - G_i) + \beta_1 G_i y_{i,t} + \beta_2(1 - G_i) y_{i,t} + u_i \\ u_i = \lambda W u_i + \varepsilon_i, \end{aligned} \tag{6}$$

The β coefficient is an important measure of convergence. However, it is not easy to interpret. Therefore, based on this coefficient we compute additional indicators that are more intuitive. The first of them is the convergence rate, or speed of convergence, which measures by how much a region is approaching its steady state each period and is calculated as:

$$CR = -\frac{ln(1 + \hat{\beta})}{\tau}, \tag{7}$$

where τ is the number of periods, and $\hat{\beta}$ is the coefficient of the initial observation, $\hat{\beta} = \beta$ in models without spatial regimes and $\hat{\beta} = \beta_{kj}$ in the models with spatial regimes where $k, j = \{1, 2\}$. Here, 1 and 2 denote two different regimes. The time necessary for the economies to fill half of the gap, which separates them from their steady state, is called the half-life and is computed as:

$$HL = \frac{ln(2)}{CR}. \tag{8}$$

For the case of conditional β-convergence all the above four models can be re-written as follows:

The benchmark model accounting neither for nonlinearity nor for spatial autocorrelation:

$$\Delta^{\tau} y_{i,t+\tau} = \alpha + \beta y_{i,t} + X_i' \delta + \varepsilon_i \tag{9}$$

where X_i is the set of conditioning variables. The spatial error model:

$$\begin{aligned} \Delta^{\tau} y_{i,t+\tau} = \alpha + \beta y_{i,t} + X_i' \delta + u_i \\ u_i = \lambda W u_i + \varepsilon_i, \end{aligned} \tag{10}$$

Te SpLSTR model:

$$\Delta^\tau y_{i,t+\tau} = \alpha_1 G_i + \alpha_2(1 - G_i) + \beta_1 G_i y_{i,t} + \beta_2(1 - G_i)y_{i,t} + \\ X_i'\delta_1 G_i + X_i'\delta_2(1 - G_i) + \varepsilon_i, \tag{11}$$

The SpLSTR model with spatially autocorrelated errors:

$$\Delta^\tau y_{i,t+\tau} = \alpha_1 G_i + \alpha_2(1 - G_i) + \beta_1 G_i y_{i,t} + \beta_2(1 - G_i)y_{i,t} + \\ X_i'\delta_1 G_i + X_i'\delta_2(1 - G_i) + u_i \\ u_i = \lambda W u_i + \varepsilon_i \tag{12}$$

3 Data

The data used in the study are briefly described in Table 1. The principal variable is the real per-capita GRP of 1890 Chinese counties and cities in 1997 and 2007. The number of counties is determined by the availability of both economic and geographical data. The nominal GRP and population data were obtained from the China Data Center of Michigan University (CDC), see http://chinadatacenter.org/newcdc/. The nominal GRP series were deflated using the 31 provincial deflators, because no GRP deflators or consumer price indices are available at the county level. The provincial deflators were computed by dividing the change in the nominal provincial GRP over the provincial GRP volume indices borrowed from the National Bureau of Statistics of China (NBS), see the last column of Table 2. Although the assumption of identical price changes in the counties of the same province is a bit too strong, it is better than not deflating the data at all as it is done in Banerjee et al. (2009).

An additional word of caution must be said. Since we do not dispose of the county price levels, we cannot adjust the GRP data for price differentials between counties, which potentially might be large. Given that the prices are generally higher in the richer regions, we can assume that the price-level unadjusted data somewhat overestimates the income discrepancy between counties. Moreover, as Kwan (2002) indicates, the intercounty per-capita income inequality may be exaggerated to some extent due to 1) the use of registered, instead of actual, population figures in the per-capita calculations and 2) the failure to account for the remittances that the workers stemming from poorer regions and working in the richer regions send to their families staying home. Unfortunately, such adjustments are a tremendous task requiring too much effort, whereas the degree of overestimation remains unknown.

Table 2 reports the availability of data as well as correspondence between the county- and province-level data. As it shows, there exist quite large inconsistencies between the provincial data published by the NBS and provincial data aggregated from the county-level data provided by the CDC. This discrepancy was also noted by Curran et al. (2007). Thus, as columns under heading "Counties\provinces, %" show, the share of county-level data aggregated to the provincial data in the province-level data of the NBS is quite low and variable. On average, the county-level nominal GRP data cover only 52.6% of the province-level nominal GRP data in 1997 and 50.0% in 2007. The situation is a bit better for the nominal per-capita GRP: on average, the county-level data cover 73.6% of the province-level GRP data in 1997 and 66.8% in 2007. However, these average figures mask the situation at the level of individual provinces. The lowest coverage of the GRP data is even as small as 5.7% (Beijing and Shanghai), whereas that of the per-capita GRP data is 29-32% (Guandong and Tibet).

The geographical distribution of per-capita GRP in 1997 is shown in Figure 1. It can be seen that the clusters of relatively rich counties (darker areas) are predominantly located in the coastal areas as well as in Inner Mongolia and Xinjiang Uygur. This resembles quite closely Figures 3 and 4 in Curran et al. (2007).

4 Estimation results

The estimation results of models of unconditional β-convergence, defined in equations (1), (2), (4), and (6), are reported in Table 3. The lower three rows contain the Lagrange multiplier (LM) tests for nonlinearity and spatial autocorrelation elaborated for data with possible spatial autocorrelation by Pede et al. (2008). Thus, $LM_{\lambda=0}$ is the test for spatially autoregressive errors; $LM_{\phi=0}$ is the test for nonlinearity, whereas $LM_{\lambda=\phi=0}$ is the joint test for nonlinearity and spatially autoregressive errors. Notice that the first two tests reported under the heading of Benchmark are based on the assumption of linearity or no spatial autocorrelation, correspondingly. In contrast, the respective tests reported under the headings of SEM and SpLSTR are based on the assumption of possible nonlinearity or presence of spatial autocorrelation, correspondingly. In order to save space we do not reproduce the formulae of these tests here and refer the interested readers for more details to Pede et al. (2008). As can be seen, all the tests reject the null hypotheses of linearity or absence of spatial autocorrelation or a joint null implying both of them simultaneously. Thus, the use of spatial models accounting for spatial effects can be seen as justified.

In the linear, or benchmark, model without spatial effects, the estimate of β-coefficient is negative and significant. However, it implies a very low convergence rate of 0.7%, which corresponds to a half-life of more than 90 years. In the SEM, the estimated coefficient $\widehat{\beta}$ is much larger than in the benchmark case. The corresponding convergence rate is 1.4% and the half-life is almost twice as low — about 50 years. SpLSTR model produces two estimates of the coefficient β: the first one corresponding to the slower growing counties (the estimated unconditional mean of the growth rate of real per-capita GRP is $\frac{\widehat{\alpha_1}}{1-\widehat{\beta_1}} = 1.16$), whilst the second one corresponding to the faster growing counties, since the respective unconditional mean growth rate is 1.69. Moreover, only $\widehat{\beta_2}$ is significant. The respective convergence rate is 1.3%, very similar to the SEM, and the half-life is 52 years. Finally, in the SpLSTR-SEM, $\widehat{\beta_1}$ is positive and not significant, whereas $\widehat{\beta_2}$ is both negative and significant. The latter corresponds to a convergence rate of 1.5% and half-life of about 45 years.

In addition, the threshold value estimated for SpLSTR, $\widehat{c} = 8.68$, is somewhat lower than that for SpLSTR-SEM, $\widehat{c} = 8.84$. It implies that, when surrounded by poorer counties (the distance-weighted real per-capita GRP of neighbors in 1997 lower than $5860.6 (= exp(8.68))$ yuan, according to SpLSTR, and 6891.2 yuan, according to SpLSTR-SEM), the county tends to grow faster and converge. By contrast, when the county has rich neighbors, the probability of it growing slower and failing to converge is higher.

The transition from one convergence regime to another is in SpLSTR smoother than in SpLSTR-SEM, for its smoothness parameter is smaller, $\widehat{\gamma} = 3.45$, whereas in case of SpLSTR-SEM $\widehat{\gamma} = 22.96$, see Table 3. This can also been seen in panel (a) of Figure 2, which shows the empirical transition functions of SpLSTR (black circles) and SpLSTR-SEM (gray squares) models. The inflexion point of both curves is located near the estimated threshold value of c.

The geographical distribution of counties belonging to different convergence regimes can be inspected in Figure 3. This figure shows a map of

Chinese counties painted in different degrees of gray, depending on the convergence rate. The darker is the color the higher is the convergence rate. The white areas on the map correspond to the missing values. It can be seen that the counties belonging to the first group are concentrated mainly in the western interior provinces, such as Qinghai, Sichuan, Yunnan, western part of Xinjiang Uygur. As Figure 1 shows, these counties are themselves poor. However, the growth experience of the counties is rather variable. The counties of the second group are located mainly in the coastal regions. These are relatively rich counties neighboring with other rich counties, which had probably already reached some kind of steady state.

The results of estimation of the conditional β-convergence equations (9)-(12) are presented in Table 4. Two conditioning variables have been included into regressions: 1) population growth over the 1997-2007 period, *DPop*, and 2) the share of primary sector production (value added) in the GRP in 1997, *Primary*. In the Chinese statistics, the primary sector is defined as agriculture including farming, forestry, animal husbandry, and fishery. The population growth variable, along with the initial GRP per capita, is typically included into the growth and convergence regressions, see, for example, the seminal paper of Levine and Renelt (1992). Additional typical variables, such as the investment share of GDP used as a proxy for physical capital and the primary/secondary school enrollment used as a proxy for human capital were excluded from the regressions, since they turned out to be statistically insignificant. The variable *Primary* can be relevant for our analysis, since as Pääkkönen (2009) has shown, there is a clear division in terms of convergence between the predominantly agricultural and predominantly industrial Chinese regions at least at the provincial level. Unfortunately, the indicator of the degree of industrialization introduced in Pääkkönen (2009) as well as the share of the secondary sector in the GRP turned out to be insignificant and hence we had to use the share of the primary sector. Moreover, in the literature, the share of agriculture is often used as a proxy for the economic backwardness of a region, which might be an important factor of convergence.

As in the case of unconditional convergence, the LM tests point out to a clear presence of both nonlinearity and spatial autocorrelation of errors.

Comparing the unconditional and conditional β-convergence results, one comes to the following conclusions. Firstly, transitions become smoother because the estimate of smoothness parameter, $\widehat{\gamma}$, is smaller in the conditional regression, see also the panel (b) of Figure 2. The reason for this might be the fact that the conditioning variables, especially *Primary*, capture some of the nonlinearity present in the data, e.g, agricultural vs. industrial convergence clubs. Secondly, the estimate of the threshold, $\widehat{c}$, remains virtually unchanged: $\widehat{c}_{SpLSTR} = 8.883$ and $\widehat{c}_{SpLSTR-SEM} = 8.806$. Thirdly, the estimate of the overall β coefficient in the benchmark model and SEM as well as in the regime 2 of the SpLSTR and SpLSTR-SEM models becomes larger implying almost twice as shorter half-life varying between 27-30 years for all models and 42 years for the benchmark model. The corresponding convergence rate is 2.3-2.6% and 1.7%. For regime 1, the β coefficient turned out to be insignificant. Fourthly, both the population growth and share of primary sector in county's GRP are negative and significant only in the regime 2.

The convergence rates estimated in this study are quite close to the typical convergence rate of 2% documented in many studies, see Abreu et al. (2005). In particular, convergence rates obtained in our regressions of conditional β-convergence. The estimated values correspond also quite closely to those of Curran et al. (2007): their estimates of β-coefficient vary between -0.015 and -0.024 (on the left-hand side of their convergence equations they have an average growth rate and not the growth over the entire period), which correspond to convergence rates (half-lives) between 1.5% and 2.4% (46 and 29 years).

The convergence rate estimated for the counties is very different from that we estimated for for the sake of comparison for the provinces: in the linear model, which does not account for spatial depence, the convergence rate (half-life) is 0.4% (170 years) and in the linear model accounting for the spatial dependence, the convergence rate (half-life) is even lower (higher) 0.2% (290 years).

5 Conclusion

In this paper, we investigated unconditional and conditional β-convergence of the real per-capita income of Chinese counties. In our analysis, we took into account both the existence of spatial dependences between the counties and the possibility of different convergence regimes, or clubs of convergence. The first feature was captured by the spatial error term, whereas the second one was modeled using the spatial LSTR approach.

Two groups of counties could be identified: 1) counties, which have relatively poor neighbors and tend to grow faster and converge, and 2) counties, which have relatively rich neighbors and tend to grow slower and hence fail to converge. The counties belonging to the first group are concentrated mainly in the western interior provinces, such as Qinghai, Sichuan, Yunnan, western part of Xinjiang Uygur. The counties of the second group are located mainly in the coastal regions.

In addition, the analysis of conditional convergence shows that two variables contribute to the convergence process of the counties belonging to the first group: population growth and share of primary sector. Both of them exert a negative impact upon the income convergence.

To summarize, a much stronger convergence at county level than that at the province level can be observed in China. Thus, given that the government's "flying geese" policies have been implemented since just a few years, the observed income convergence between counties can be attributed mainly to the effects of the market forces. Hence, one can conclude that the "geese are flying by themselves" inside China, which will eventually allow to fill the gap existing between the rich coastal regions and the poor interior regions.

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Appendix

Table 1: Data used in the study

Variable	Unit	Period	Source
Nominal GRP at county level	10^8 yuan	1997 & 2007	CDC
Nominal GRP at provincial level	10^8 yuan	1997-2007	NBS
Real GRP at provincial level	%, previous year=100	1997-2007	NBS
Population at county level	10^4 persons	1997 & 2007	CDC
Population growth rate at county level	%, 1997=100	1997-2007	own calculations
Value-added of primary industry	10^8 yuan	1997	CDC
Share of primary industry in GRP	%	1997	own calculations

CDC — China Data Center; NBS — National Bureau of Statistics of China.

Table 2: Consistency between county- and province-level GRP data

Province name	No. of counties	Provincial data aggregated over counties: GRP (10^8 yuan) 1997	GRP (10^8 yuan) 2007	GRP per capita (yuan) 1997	GRP per capita (yuan) 2007	Provincial data: GRP (10^8 yuan) 1997	GRP (10^8 yuan) 2007	GRP per capita (yuan) 1997	GRP per capita (yuan) 2007	Counties\provinces, %: GRP 1997	GRP 2007	GRP per capita 1997	GRP per capita 2007	Provincial GRP deflator, 1997-2007
Beijing	5	136.9	533.6	7321.4	21692.3	1810.1	9353.3	16735	58204	7.6	5.7	43.7	37.3	1.689
Tianjin	4	222.3	470.8	9792.1	19699.2	1240.4	5050.4	13796	46122	17.9	9.3	71.0	42.7	1.209
Hebei	138	3200.2	9803.6	5752.6	15644.2	3953.8	13709.5	6079	19877	80.9	71.5	94.6	78.7	1.204
Shanxi	97	762.6	3326.8	3458.4	13483.4	1480.1	5733.4	4736	16945	51.5	58.0	73.0	79.6	1.304
Inner Mongolia	84	696.8	4242.4	3788.8	19716.3	1094.5	6091.1	4691	25393	63.7	69.6	80.8	77.6	1.358
Liaoning	44	1279.7	4077.0	5556.6	17170.7	3490.1	11023.5	8525	25729	36.7	37.0	65.2	66.7	1.091
Jilin	41	784.9	2653.6	4310.0	14231.3	1446.9	5284.7	5504	19383	54.2	50.2	78.3	73.4	1.282
Heilongjiang	66	1096.8	2425.7	4911.9	10149.8	2708.5	7065.0	7243	18478	40.5	34.3	67.8	54.9	0.997
Shanghai	3	191.9	881.1	10317.7	45182.1	3360.2	12188.9	25750	66367	5.7	7.2	40.1	68.1	1.201
Jiangsu	58	3662.2	13322.4	7729.4	25662.9	6680.3	25741.2	9344	33928	54.8	51.8	82.7	75.6	1.175
Zhejiang	62	3189.4	9858.4	10134.7	28060.1	4638.2	18780.4	10515	37411	68.8	52.5	96.4	75.0	1.250
Anhui	61	1707.0	3491.3	3745.8	7348.0	2670.0	7364.2	4390	12045	63.9	47.4	85.3	61.0	1.024
Fujian	59	1828.4	5003.7	7911.6	19503.1	3000.4	9249.1	9258	25908	60.9	54.1	85.5	75.3	1.044
Jiangxi	81	893.7	3235.0	2943.6	8844.0	1715.2	5500.3	4155	12633	52.1	58.8	70.8	70.0	1.156
Shandong	92	3798.2	15203.6	6042.2	22648.6	6650.0	25965.9	7590	27807	57.1	58.6	79.6	81.4	1.194
Henan	110	2913.4	10682.3	3769.0	12625.2	4079.3	15012.5	4430	16012	71.4	71.2	85.1	78.8	1.273
Hubei	66	2517.1	3484.7	6046.4	8134.6	3450.2	9230.7	5899	16206	73.0	37.8	102.5	50.2	0.978
Hunan	88	1860.8	5411.7	3543.7	9726.1	2993.0	9200.0	4643	14492	62.2	58.8	76.3	67.1	1.140
Guangdong	77	3246.2	5522.1	7060.1	9650.3	7315.5	31084.4	10428	33151	44.4	17.8	67.7	29.1	1.290
Guangxi	85	1475.9	3019.6	3885.0	7367.5	2015.2	5955.7	4356	12555	73.2	50.7	89.2	58.7	1.183
Hainan	18	241.5	620.9	3785.3	8780.0	409.9	1223.3	5698	14555	58.9	50.8	66.4	60.3	1.117
Chongqing	26	662.6	1917.6	3059.2	8421.6	1350.1	4122.5	4452	14660	49.1	46.5	68.7	57.4	1.110
Sichuan	140	1938.9	5777.3	3216.5	8767.4	3320.1	10505.3	4029	12893	58.4	55.0	79.8	68.0	1.152
Guizhou	78	583.4	1903.0	1802.8	5339.8	793.0	2741.9	2215	6915	73.6	69.4	81.4	77.2	1.317
Yunnan	120	928.9	3021.6	2638.2	7688.0	1644.2	4741.3	4042	10540	56.5	63.7	65.3	72.9	1.198
Tibet	72	21.5	223.8	1025.2	8592.6	77.0	342.2	3194	12109	28.0	65.4	32.1	71.0	1.441
Shaanxi	87	611.2	2679.5	2371.9	9682.1	1326.0	5465.8	3707	14607	46.1	49.0	64.0	66.3	1.437
Gansu	76	386.2	1086.6	1838.0	4950.5	781.3	2702.4	3137	10346	49.4	40.2	58.6	47.8	1.279
Qinghai	39	101.8	459.2	2571.5	10689.2	202.1	783.6	4066	14257	50.4	58.6	63.2	75.0	1.355
Ningxia	19	75.4	407.7	2733.3	9864.0	210.9	889.2	4025	14649	35.8	45.9	67.9	67.3	1.514
Xinjiang Uygur	90	875.2	3657.6	5763.7	17979.6	1050.1	3523.2	5904	16999	83.3	103.8	97.6	105.8	1.336

Sources: 1) county-level data — China Data Center; 2) province-level data — National Bureau of Statistics of China.

Table 3: Estimation results: unconditional β-convergence

	Benchmark		SEM		SpLSTR		SpLSTR-SEM	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
γ					3.474	0.689	22.964	0.365
c					8.677	54.881	8.839	166.160
α	1.500	12.054	2.190	9.186				
α_1					1.176	0.750	-1.429	-0.646
α_2					1.904	6.446	2.283	3.731
β	-0.072	-4.713	-0.131	-6.974				
β_1					-0.011	-0.063	0.287	1.184
β_2					-0.124	-3.288	-0.143	-3.811
λ			0.939	31.656			0.937	7.931
CR	0.007		0.014					
Half-life	93.084		49.568					
CR_1					0.001		-0.025	
Half-life$_1$					626.662		-27.472	
CR_2					0.013		0.015	
Half-life$_2$					52.357		44.917	
	Statistic	p-value	Statistic	p-value	Statistic	p-value		
$LM_{\lambda=0}$	764.72	0.000			722.85	0.000		
$LM_{\phi=0}$	22.713	0.000	20.158	0.000				
$LM_{\lambda=\phi=0}$	787.43	0.000						

Table 4: Estimation results: conditional β-convergence

	Benchmark		SEM		SpLSTR		SpLSTR-SEM	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
γ					1.692	1.007	3.943	0.772
c					8.883	20.198	8.806	46.523
α	2.377	13.760	3.035	11.003				
α_1					-1.731	-0.298	-1.850	-0.416
α_2					2.989	5.634	3.178	3.791
β	-0.154	-8.147	-0.208	-9.380				
β_1					0.284	0.473	0.332	0.714
β_2					-0.226	-3.761	-0.219	-4.233
DPop	-0.027	-2.344	-0.023	-2.569				
DPop_1					-0.014	-0.337	-0.007	-0.290
DPop_2					-0.150	-3.247	-0.164	-3.710
Primary	-0.519	-7.211	-0.469	-6.209				
Primary_1					1.742	0.545	0.733	0.424
Primary_2					-0.625	-3.054	-0.497	-2.940
λ			0.937	30.801			0.942	7.398
CR	0.017		0.023					
Half-life	41.594		29.724					
CR_1					-0.025		-0.029	
Half-life_1					-27.728		-24.178	
CR_2					0.026		0.025	
Half-life_2					27.057		28.042	
	Statistic	p-value	Statistic	p-value	Statistic	p-value		
$LM_{\lambda=0}$	710.33	0.000			701.91	0.000		
$LM_{\phi=0}$	41.31	0.000	51.91	0.000				
$LM_{\lambda=\phi=0}$	751.64	0.000						

Figure 1: GRP per capita, 1997

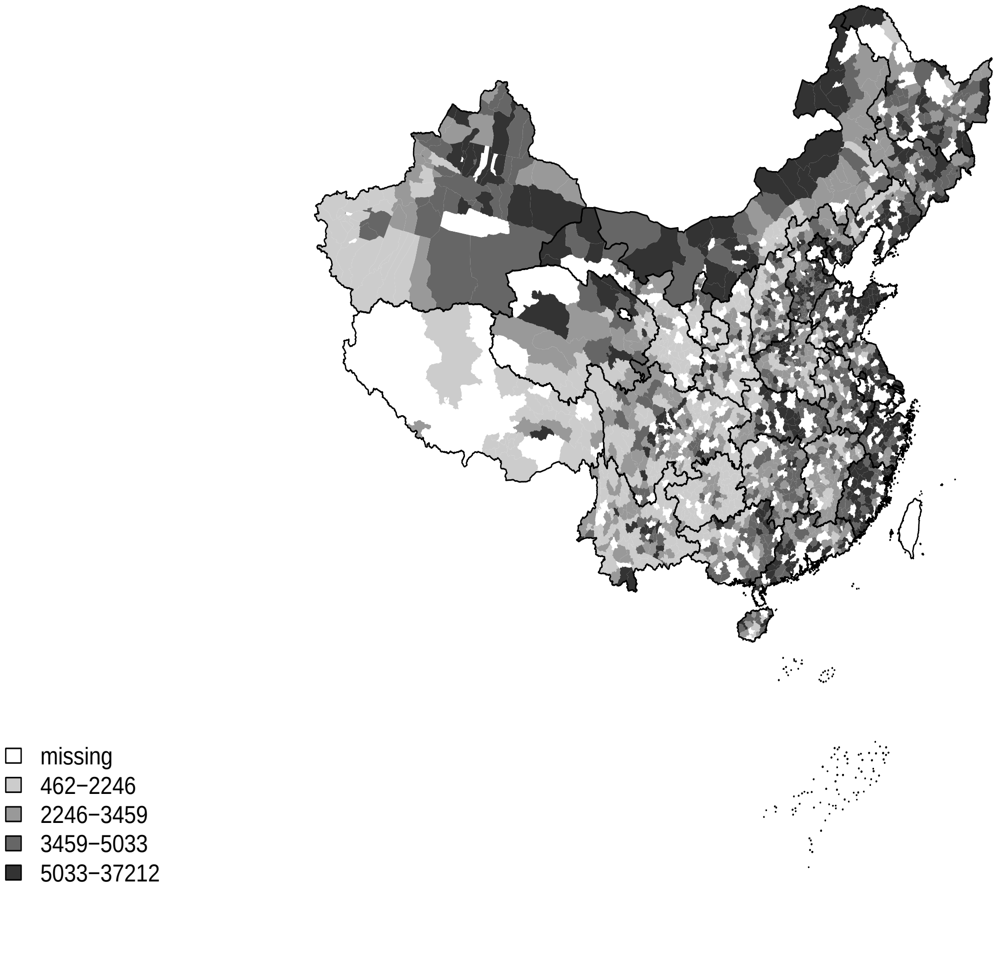
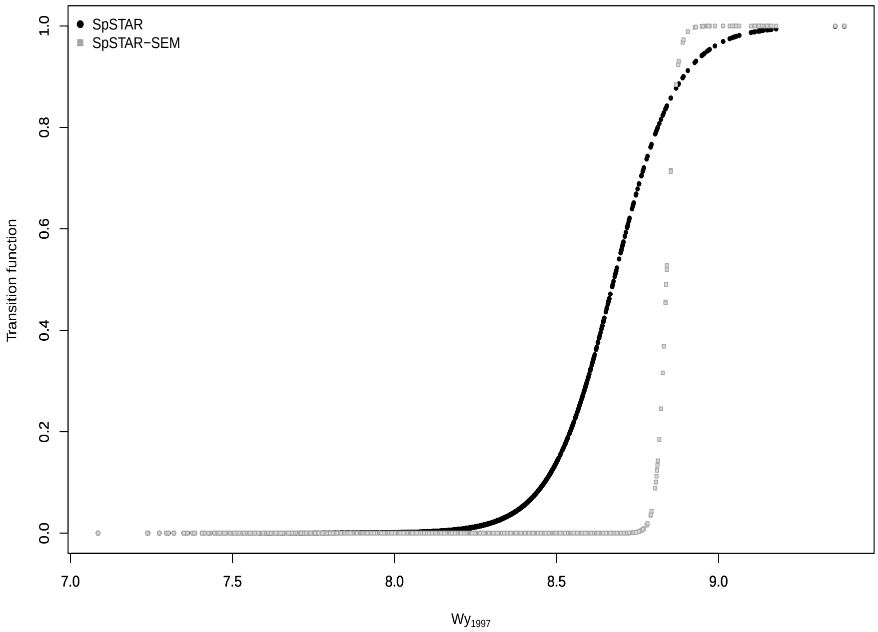


Figure 2: Empirical transition functions

(a) Unconditional β-convergence



(b) Conditional β-convergence

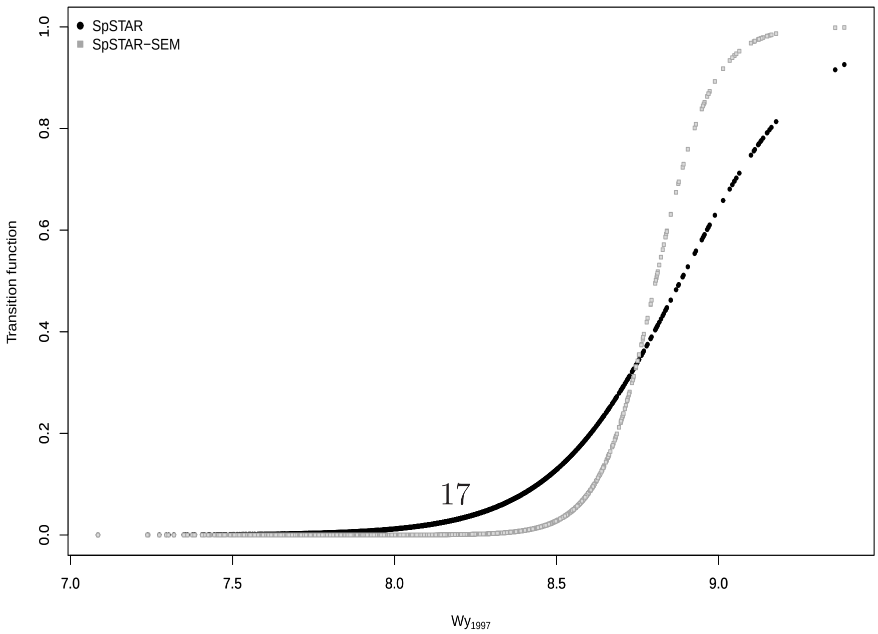


Figure 3: Convergence rate (%) across counties (SpLSTR model), 1997-2007