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« A Fresh Scrutiny on Openness and Per Capita Income Spillovers in Chinese Cities: A Spatial Econometric Perspective »

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A Fresh Scrutiny on Openness and Per Capita Income Spillovers in Chinese Cities: A Spatial Econometric Perspective

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Abstract

This paper investigates openness and per capita income spillovers over 367 Chinese cities in the year 2004. Per capita income is modelled as dependent on investment, physical and social infrastructure, human capital, governmental policies and openness to the world.

Our empirical analysis improves substantially the previous research in several respects: Firstly, by extending the data set to prefecture-level, it tackles the aggregation bias. Secondly, the introduction of recently developed explanatory spatial data analysis (ESDA) and spatial regression techniques allows to address misspecification issues due to spatial dependence. Thirdly, the endogeneity problem in the regression is taken into consideration through the use of generalised method of moments (GMM) estimator.

Our major findings are in Chinese cities, physical and social infrastructure development, human capital and investment could be recognised as major driving sources of per capita income (i), whereas, the government expenditure ratio exerts a negative impact on per capita GDP level (ii). Our empirical findings also yield evidence on the existence of FDI and foreign trade spillovers in China (iii). These findings are robust to a number of alternative spatial weighting matrix specifications.

Keywords: China, openness, spatial regression, spillovers, transition economies.

JEL Classification: O11, O18, P24, R10.

1. INTRODUCTION

Since the introduction of the economic reform policy in the early 1980's, China has been experiencing a continuous rapid economic growth. Alongside the implementation of market oriented policies, China has progressively emerged in the world economy as a major global economic partner. In 2002, China overtook the United States and became the largest recipient of foreign direct investment (FDI) in the world. Moreover, in 2006, it outpaced major trading countries and turned to be the world's 3rd largest trading partner.

In China, the transition from an autarchic to a market economy has been a gradual and spatially uneven process. Differences in regional resource endowments as well as opening up policies which favoured coastal regions lead to dramatic disparities in regional development paths.

The purpose of this study is to bring new insight to our understanding of China's recent economic performances. Based on a comprehensive data set, this study yields fresh empirical evidence to a number of questions: What are the driving forces behind China's recent economic development? What is the spatial pattern of China's per capita income distribution? To what extent the opening-up policies contribute to regional economic development of China? Are there any spillovers resulting from FDI and international trade?

This study improves substantially previous literature in several respects: First, in order to address any aggregation biases, it extends the cross-sectional basis to prefecture-level data. Due to data limitations, the existing literature on China's regional development is confined to province-level data. However, given the massive size of China, one can expect that using smaller scale spatial units would provide a better understanding of regional development patterns (Yu and Wei, 2008).

Second, the paper addresses spatial effects in the regression analysis by the explicit incorporation of spatial information in the modeling scheme. We consider that for a better understanding of regional development, the focus should be put on spatial patterns and interactions among geographical units. Moreover, ignoring spatial autocorrelation might lead to serious misspecification issues, inconsistent parameter estimates and statistical inferences (Anselin, 1988).

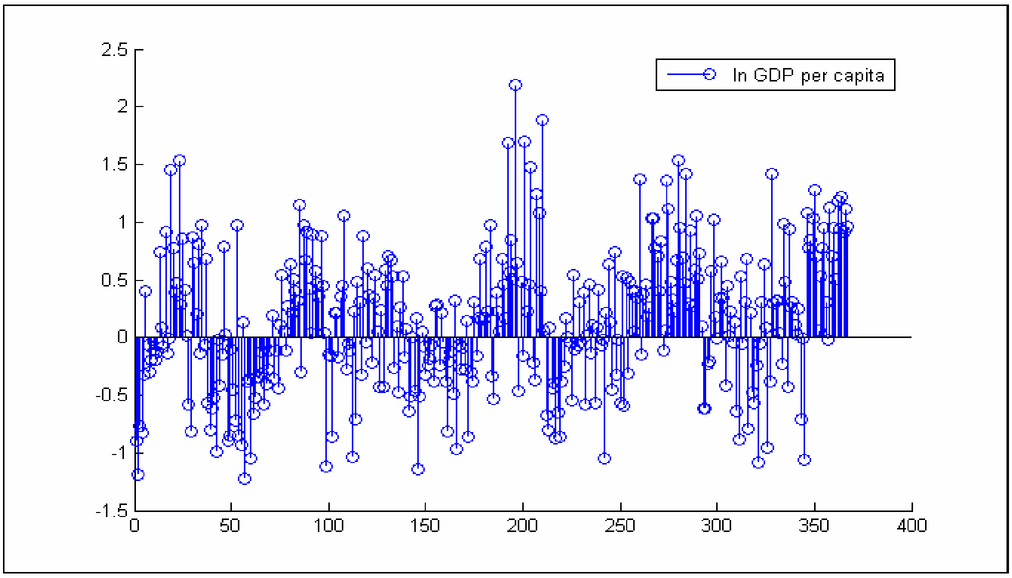
Third, previous studies generally overlook the endogeneity issue. However while investigating the contribution of openness to economic development, a potential inverse causality should also be taken into consideration. In this study, we tackle the endogeneity issue through the use of the GMM estimator.

The remainder of the paper proceeds as follows. The second section presents the underlying data set and methodology. Spatial effects are outlined and discussed in section 3. Section 4 presents the empirical outcomes. The last section concludes the paper.

2. METHODOLOGY

Our investigation of China's economic development is mainly inspired from the endogenous growth framework (Lucas, Romer). Following the empirical literature (Wei 2000; Yu and Wei 2008), we chose per capita GDP as an indicator of regional development. It can be clearly observed from Figure 1 that per capita income exhibits striking disparities among sample cities.

Figure 1: Distribution of GDP per capita in sample cities (2004).



2.1. Data

The underlying data is collected from *China Provincial Statistical Yearbook (2005)* from 31 provinces. The data set covers 364 county and prefecture-level cities and 3 super cities

(Beijing, Tianjin, Shanghai) spread over the entire Chinese territory. After excluding observations with missing values our final sample includes 367 cities for the year 2004 (see Appendix Table A1).

2.2. Model

The dependent we use, is the ratio of GDP to population at the year-end. The set of control variables is specified as follows: Physical capital accumulation is proxied by the ratio of completed investment in capital construction to population *(INV).* The ratio of number of beds in hospitals and sanitation agencies to population *(Bed)* proxies for social infrastructure. Physical infrastructure is quantified through the ratio of local telephone subscribers to population *(Phone).* The human capital variable is the ratio of student enrollment in regular secondary schools to population *(HK).* Openness is measured by the ratios of exports value to GDP (*EXP)* and foreign capital actually used to GDP (*FDI*). Political determinants are controlled by local government expenditure to GDP ratio (*GVT*). Table A2 summarizes a basic description of model series. After the log linear transformation, the model could be expressed as follows:

$$\begin{aligned} \ln GDP_i = \alpha_0 + \alpha_{1i} \ln Inv_i + \alpha_2 \ln Bed_i + \alpha_3 \ln HK_i + \alpha_4 \ln GVT_i + \alpha_5 \ln FDI_i + \\ \alpha_6 \ln Phone_i + \alpha_7 EXP_i + \varepsilon_i \end{aligned} \quad (1)$$

3. SPATIAL EFFECTS

Spatial econometrics takes its origins from Tobler's first law of geography (1970): « Everything is related to everything else, but near things are more related than distant things ». Spatial econometrics is dedicated to the study of spatial structure and spatial interactions between observation units. It is mainly inspired from the research issues of new economic geography and regional science (Anselin, 2001). The main distinguishing characteristic of spatial data analysis is taking into account the spatial arrangement of observations. That is to say, regions are not treated as isolated economies; the interactions between them are explicitly incorporated into the modelling scheme. Since the last decade, the increasing availability of geo-referenced socio-economic data sets made possible the extension of applied spatial econometrics studies to more traditional fields of economics (e.g. international economics, labour economics, public economics, agricultural and environmental economics). In addition, since few years, the time dimension has also started to be included in spatial modelling (see Ehorst 2001, Anselin and Le Gallo, 2008)

3.1. Spatial Dependence

Spatial dependence (or spatial autocorrelation) is one of the main issues introduced by the use of geographic data. It refers to absence of independence between geographic observations. In other words, spatial autocorrelation corresponds to the coincidence of value similarity and location similarity (Anselin, 2001).

Spatial dependence could arise from either theoretical or statistical issues. On one hand, it could be the outcome of the integration of geographical units due to labour migration, capital mobility, transfer payments and inter-regional trade. It can also arise from some institutional and political factors and externalities such as technology diffusion and knowledge spillovers (Buettner, 1999; Ying, 2003). On the other hand, spatial dependence could be related to some statistical issues such as measurement errors, varying aggregation rules, different sample designs and omission of some variables with spatial dimension (e.g. climate, topology and latitude) (Anselin and Florax, 1995).

3.2. Spatial weighting matrix

The spatial weighting matrix provides the structure of assumed spatial relationships and captures the strength of potential spatial interactions between observation units. Thereby, in spatial analysis, constructing appropriate spatial weighting matrices is of particular importance. The choice of the spatial matrix could affect both the performance of spatial diagnostic tests and estimated parameters. Given that the elements of the spatial weights matrix are expected to be exogenous to the model (otherwise the model would be highly non linear), in the literature, the weighting matrix is generally based on geographic contiguity based on border sharing or distance.

- **Simple contiguity**:

The binary contiguity matrix is widely used in the literature due to its simplicity of construction. It is based on the adjacency of locations of observations. Put w_{ij} to express the magnitude of the interaction between provinces i and j. Then, if two provinces share a common boundary w_{ij}=1 and w_{ij}=0 otherwise.

- **Distance based contiguity:**

In distance based contiguity matrices, spatial weights attributed to observations depend on geographic distance d_{ij} between locations *i* an *j*. Distance matrices differ in functional form used, distance function [$w_{ij}=d_{ij}$], inverse function of distance [$w_{ij} =1/d_{ij}$], inverse distance raised to some power [$w_{ij} =1/d_{ij}^N$] and negative exponential function [$w_{ij} =\exp(-\theta d_{ij})$] are mostly used in the literature. In distance decay functions, the strength of spatial interactions decline with geographic distance. d_{ij} corresponds to the cut-off point which maximizes the spatial association and beyond which spatial interactions between units are assumed to be non existent. In the literature, cut-off points are generally set up following some statistical or arbitrary criterions such as minimum or median distance between regions, the significance of spatial diagnostic statistics, and goodness of fit of the regression.

The weighting matrix is generally row standardised by dividing each weight of an observation by the corresponding row sum $w_{ij} / \Sigma_j w_{ij}$. Thereby, the elements of each row sum to unity[1] and each weight w_{ij} could be interpreted as the province's share in the weighted average of neighbouring observations. $w_{ij}=0$ indicates lack of spatial interactions between observations. By convention, distance matrix has zeros on the main diagonal, thus no observation predicts itself.

Given the complexity of interactions among geographic units, in this study, we explore the robustness of our results with respect to various specifications of distance weighting matrix. On this purpose, six spatial weights matrices are constructed based on either border sharing or distance based contiguity. The main characteristics of the Euclidian distance matrix for our sample are summarised in Table A3. We set the minimum upper distance band to 10 kilometres regarding the minimum allowable distance cut-off point (9.33 kilometers).

In spatial econometrics explanatory spatial data analysis (ESDA) techniques are used for univariate level analysis while, spatial regression techniques allow to explore spatial patterns for multivariate level. Recent literature (Anselin, 2001) provides taxonomy of spatial econometric models. In this study, our focus will be limited to two major spatial modeling schemes, namely spatial lag and spatial error models.

3.3. Spatial Regressions

- **Spatial Lag:**

[1] Whereas the original spatial weighting matrix is usually symmetric, the row-standardised one is not (Anselin and LeGallo, 2008). An asymmetric spatial weighting matrix implies that, region *i* could have a larger influence on the random variable of interest in region *j* and *vice-versa.*

The spatial lag model combines the standard regression model with a spatially lagged dependent variable introduced as an explanatory variable. Spatial lag operators refer to a weighting average of random variables in proximate regions. Spatial lag model could be expressed as below:

$$y = \rho Wy + X\beta + \varepsilon \qquad (2)$$

Using traditional notation, y is a (N x 1) vector of observations of dependent variable, X, a (N x K) matrix of K exogenous variables, β, a (K x 1) vector of explanatory variable coefficients and ε, a (N x 1) vector of stochastic disturbance terms. W corresponds to a (N x N) spatial weighting matrix which identifies the geographic relationship among spatial units. ρ refers to spatial autoregressive parameter that captures spatial interactions between observations. It measures the impact of surrounding regions (positive or negative) on the dependent variable in a reference region i. ρ is assumed to lie between -1 and 1. If $\rho \neq 0$, ignoring ρ have similar consequences to omitting a significant independent variable in the regression model. That is to say, the statistical inferences and estimated parameters would be questionable.

In spatial lag model, including a spatially lagged dependent variable in the right hand side introduces a simultaneity problem. By construction, the lagged dependent variable is correlated with the individual fixed effects in the error term. Consequently, the OLS estimator becomes inconsistent and biased. In the literature the endogeneity problem is corrected via instrumental variables, maximum likelihood (ML) estimator or generalised method of moments (GMM) estimator (see Kelejian and Prucha, 1999).

- **Spatial Error Model:**

In spatial error model, spatial autoregressive process is confined to the error term. Spatial error models can be represented in the following form:

$$y = X\beta + \varepsilon \qquad (3)$$

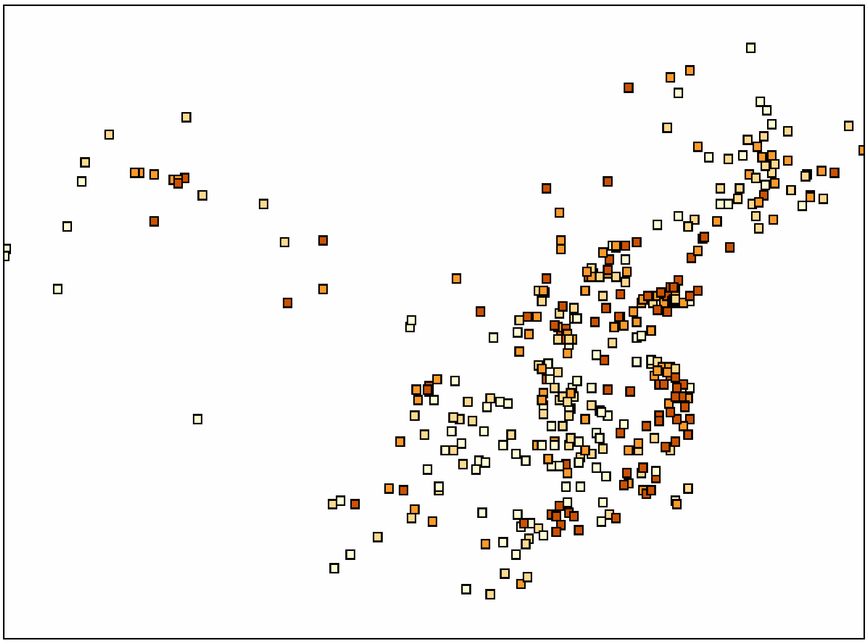
$$\varepsilon = \lambda W\varepsilon + \mu \text{ then } \varepsilon = (I - \lambda W)^{-1} \qquad (4)$$

Where ε, a (Nx1) element vector of error terms and λ the spatial autocorrelation coefficient which is assumed to lie between -1 and 1. The parameter λ captures how a random shock in a specific region is propagated to surrounding regions. By definition, the spatial lag term $W\varepsilon$ is clearly endogenous and correlated with the error term. Living out spatial correlation between error terms has similar consequences to ignoring heteroscedasticity. That is to say, the OLS estimator remains consistent but no longer efficient (it might lead to biased and inconsistent statistical inferences).

3.4. The diagnostic of spatial dependence

The distribution of GDP per capita among Chinese cities for the year 2004 is presented in the map below. The sample of Chinese cities is divided into quartiles with respect to their level of GDP per capita. We can observe from the map a clear spatial clustering pattern among Chinese cities. In other words, cities with high (low) level of per capita income are neighbours or proximate. The map also displays that high income cities are in particular located in the East coast. According to this visual information we strongly suspect the presence spatial autocorrelation in our sample. That is to say, Chinese cities are not isolated economies and are interacting with each other.

Figure 1 : Distribution of per capita income among Chinese cities (2004).



Note: The choropleth map is computed using Geoda 0.9.5-i software created by Luc Anselin.

- **Spatial Diagnostic tests**

In the literature, spatial autocorrelation diagnostic tests are mainly based on the pioneering work of Moran (1948) and Geary (1954). In sum, tests for spatial association investigate whether the value of an observation in one location is similar to those of observations in proximate regions. Moran's I is by far the most widely used test in by regional scientists (due to its simplicity). Moran's I is a univariate test which provides information on the degree of linear association between proximate observations. In general, spatial diagnostic tests are conducted under the null hypothesis of lack of model misspesification due to spatial dependency. The significance of the coefficient is based on z-values. Anselin (1995) has also developed a local indicator of spatial correlation (LISA) which provides a spatial association measure for a particular locality and identifies local clusters. Cliff and Ord (1981) adopted Moran's I test to regression residuals to detect spatial autocorrelation in multivariate level.

In order to detect a possible spatial dependence in the model, we perform Moran's I test for regression residuals. Table 1 reports the results of Moran's I statistic and associated probabilities with respect to six weighting matrices. Spatial diagnostic tests reveal a clear positive spatial autocorrelation process. Consequently, we reject the null hypothesis that in China economic development of cities is randomly distributed over space.

After identifying the presence of spatial dependence, we need to specify the adequate underlying structure of spatial dependence. On this purpose, we perform LM test which allows to distinguish between two alternative specifications of spatial models namely spatial error and spatial lag. The choice of the most adequate model is operated by the joint use of the LMERR and LMLAG statistics. According to the decision rule proposed by Anselin and Florax (1995) the model with the highest value (or lowest probability) should be chosen. In our case, according to the results of LM and robust LM tests presented in Table 1, spatial effects in the form of spatially lagged dependent variable (the SAR model) seems to fit better the underlying spatial structure.

Table 1: Diagnostic tests for spatial dependence

	Binary	D10	D25	D50	D75	D100
Morans's I	6.023	4.116	4.618	4.548	4.586	6.070
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LMSAR	79.420	49.239	49.263	48.111	48.768	82.579
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LMERR	32.536	14.978	18.730	18.054	18.328	32.514
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LMSAR	6.972	9.543	9.139	8.894	7.837	8.808
Robust	[0.008]	[0.002]	[0.002]	[0.002]	[0.005]	[0.002]
LMERR	5.760	0.317	0.882	0.815	1.114	3.766
Robust	[0.016]	[0.573]	[0.347]	[0.366]	[0.291]	[0.052]

Notes: Figures in brackets are probabilities. All spatial weights matrices are row-standardized: Binary is the first order contiguity; D10 refers to distance-based contiguity for a distance band of 0-10 km and so on. The tests are performed by using MATLAB program spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

4. Results

In this section, we augment Equation 1 by introducing a spatial lag component *WlnGDP*$_i$. Accordingly, we consider that due to spatial interactions and clustering phenomenon, per capita income in a given city could be affected by per capita income in neighbour or proximate cities. The spatial model we specify takes the following form:

$$\ln GDP_i = \alpha_0 + \alpha_1 W \ln GDP_i + \alpha_2 \ln Inv_i + \alpha_3 \ln Bed_i + \alpha_4 \ln HK_i + \alpha_5 \ln GVT_i + \alpha_6 \ln FDI_i + \alpha_7 \ln Phone_i + \alpha_8 EXP_i + \varepsilon_i \quad (5)$$

Before proceeding to the regressions, we first investigate a potential multicollinearity issue which arises from the presence of a linear relationship between some of the explanatory variables. The coefficients of correlation are presented in Table A4. First of all, we can observe from the correlation matrix that all of the explanatory variables are highly correlated with the dependent variable. This outcome hints at good explanatory power of the model. However we also detect some linear relationship between explanatory variables. For instance, the variables *FDI*, *EXP* and *GVT* are highly correlated with each other. Coefficient of correlation between the infrastructure variables *Bed* and *Phone* are also relatively high. The simultaneous inclusion of correlated variables to the right hand side could bias the empirical results. We therefore run several regressions to explore separately the specific effects of *FDI* and *EXP* on per capita income.

Table 2 displays estimation results of various specifications of Equation 4 by the OLS, ML and GMM estimators. As mentioned before, in the presence of spatial dependence the OLS estimator is no longer expected to achieve consistency. Thereby, the OLS results are only reported as a baseline for comparison. They should not be the basis of any substantive interpretation. Table 2 outlines that in 2004, infrastructure development, human capital and physical investment could be recognized as major sources of economic development in Chinese cites. The table also displays that while introduced separately in the model, FDI and foreign trade also exert a significant and positive effect on GDP per capita. Besides, from all of the specification we can observe a significantly negative impact (at the 1 per cent level) of the government expenditure ratio on per capita income. Table 2 also reveals that the coefficients associated with the spatial autocorrelation variable ρ have a positive sign and are always significant at the 1 percent confidence level. This confirms the positive pattern of spatial clustering among Chinese cities. That is to say, the more a city is surrounded by high-income cities the more its level of GDP is expected to be high. The magnitude of the coefficient associated with ρ ranges about 0.3. Accordingly in a given city, a 1% increase in per capita income leads to an increase of 0.3% of GDP per capita. It should be outlined that, even after allowing for spatially lagged dependent variables, we are still able to identify productivity spillovers from inward FDI and trade. This outcome strongly supports the argument that openness improves the regional economic development of China.

Table 2 : OLS, ML, GMM estimation results

Dependent variable : GDP/habitant	(1)	OLS (2)	(3)	(4)	(5)	ML (6)	(7)	(8)	(9)	GMM (10)	(11)	(12)
Constant	1.903	3.757	1.698	1.972	1.905	3.589	1.746	1.955	1.905	3.499	1.745	1.955
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Investment	0.030	0.044	0.030	0.030	0.025	0.036	0.025	0.025	0.025	0.032	0.025	0.025
Ratio	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.002]	[0.002]	[0.003]	[0.001]	[0.003]	[0.002]
Number of	0.416	0.260	0.402	0.427	0.397	0.249	0.385	0.404	0.397	0.243	0.386	0.404
beds ratio	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Human	0.256	0.528	0.246	0.263	0.290	0.548	0.283	0.296	0.289	0.558	0.282	0.297
capital	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Gvt	-0.687	-	-0.709	-0.692	-0.639	-	-0.655	-0.642	-0.641	-	-0.656	-0.641
expenditure	[0.000]		[0.000]	[0.000]	[0.000]		[0.000]	[0.000]	[0.000]		[0.000]	[0.000]
FDI	0.007	0.023	-	0.008	0.005	0.019	-	0.006	0.005	0.018	-	0.113
	[0.084]	[0.000]		[0.031]	[0.151]	[0.000]		[0.000]	[0.153]	[0.000]		[0.000]
Number of	0.136	0.196	0.146	0.134	0.115	0.163	0.122	0.113	0.116	0.145	0.123	0.006
phones	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exportations	0.016	0.021	0.018	-	0.011	0.015	0.013	-	0.012	0.012	0.013	-
	[0.000]	[0.023]	[0.013]		[0.100]	[0.076]	0.054		[0.099]	[0.163]	[0.005]	
Rho	-	-	-		0.293992	0.383	0.300	0.299	0.282	0.589	0.292	0.303
					[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.084]
Adjusted R^2	0.579	0.331	0.577	0.575	0.578	0.358	0.576	0.577	0.618	0.42	0.617	0.617
Log Likelihood					-32.038	-113.03	-33.068	-33.408				
Number of observations	367	367	367	367	367	367	367	367	367	367	367	367

Note: Figures in brackets are probabilities.

Robustness Check

In this section, we explore the robustness of the empirical results to alternative specifications of distance weighting matrix. For this purpose, five row standardised simple inverse distance matrices have been computed with the upper distance bands ranging from 10 to 100 km. Table 3 displays the estimations of Equation 5 with respect to various spatial weighting matrices.

Table 3 : ML and GMM estimates with respect to various distance weighting matrices

Dependent variable : GDP/habitant	D10	D25	ML D50	D75	D100	D10	D25	GMM D50	D75	D100
Constant	2.133	2.149	2.214	2.141	2.166	2.185	2.212	2.216	2.204	2.195
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Investment	0.027	0.027	0.026	0.026	0.025	0.025	0.025	0.023	0.023	0.024
Ratio	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.005]	[0.006]	[0.004]
Number of	0.423	0.425	0.427	0.428	0.419	0.417	0.418	0.421	0.423	0.415
beds ratio	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Human	0.309	0.309	0.307	0.306	0.319	0.329	0.330	0.330	0.328	0.330
capital	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Gvt	-0.637	-0.631	-0.634	-0.636	-0.626	-0.606	-0.595	-0.596	-0.601	-0.611
expenditure	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
FDI	0.003	0.003	0.003	0.003	0.002	0.003	0.002	0.002	0.002	0.002
	[0.596]	[0.465]	[0.478]	[0.478]	[0.558]	[0.455]	[0.538]	[0.487]	[0.581]	[0.615]
Number of	0.106	0.104	0.104	0.104	0.125	0.096	0.093	0.092	0.092	0.125
phones	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exportations	0.008	0.009	0.009	0.009	0.008	0.008	0.008	0.008	0.008	0.008
	[0.037]	[0.049]	[0.051]	[0.050]	[0.057]	[0.092]	[0.078]	[0.086]	[0.080]	[0.073]
Rho	0.246	0.279	0.283	0.287	0.332	0.373	0.418	0.453	0.454	0.402
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Adjusted R^2	0.586	0.587	0.586	0.585	0.585	0.613	0.613	0.612	0.611	0.624
Log Likelihood	-35.031	-34.565	-34.854	-35.342	-30.578	-	-	-	-	-
Number observations	367	367	367	367	367	367	367	367	367	367

Notes: Figures in brackets are probabilities. All spatial weights matrices are row-standardized: Binary is the first order contiguity; D10 refers to distance-based contiguity for a distance band of 0-10 km and so on.

From Table 3, we can clearly recognize that the ML and GMM estimations provides similar parameters to those based on simple binary contiguity matrix (Table 2 Columns 5 and 11). Besides, the spatial autoregressive parameter ρ is positive and significant at the 1 per cent level in all of the specifications. In sum, on the outcome of various specifications of W, the overall picture we obtain by various cut-off points is quite similar to those based on simple contiguity matrix. In other words, our results are not really sensitive to alternative specifications of spatial weights matrix[2].

5. Conclusion

In this study we direct attention to local patterns of regional development in China. We focus on prefecture level data and investigate the influence of several key economic and policy factors on regional development. By introducing spatial effects in the modelling scheme, we attempt to draw a clearer picture of regional income in China and regional dynamics between cities. Our empirical outcomes show that, consistent with theoretical framework, human capital, physical and social infrastructure development and investment could be recognised as major driving forces of per capita income. Besides, we also found evidence on the existence of positive spillovers from foreign trade and FDI.

Our study yields strong evidence on agglomeration pattern among Chinese cities. That is to say, the more a city is surrounded by high income cities, the more its level of economic development is expected to be high. This finding has serious policy implications: Policies that solely consist of opening up and developing some specific regions would not be efficient to improve the overall development. Development policies should rather focus on reinforcing complementarities and interactions across regions.

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[2] We also tested the robustness of spatial auto-regressive models which introduce separately *FDI* and *EXP*. We eventually obtained similar results to those in Table 2. In order to save space those results are not reported here but they are available from the author upon request.

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APPENDICES

Table A1 : List of sample cities (1/3)

Province	City	Province	City	Province	City	Province	City
Beijing	Beijing	Inner Mongolia	Feng Zhen	Jilin	Shuangliao	Jiangsu	Pizhou
Tianjin	Tianjin	Inner Mongolia	Gen He	Jilin	Shulan	Jiangsu	Qidong
Hebei	Anguo	Inner Mongolia	Man Zhou Li	Jilin	Taonan	Jiangsu	Rugao
Hebei	Bazhou	Inner Mongolia	Ulanhot	Jilin	Tumen	Jiangsu	Taicang
Hebei	Botou	Inner Mongolia	Xilinhot	Jilin	Yanji	Jiangsu	Taixing
Hebei	Dingzhou	Inner Mongolia	Ya Ke Shi	Jilin	Yushu	Jiangsu	Tongzhou
Hebei	Gaobeidian	Inner Mongolia	Zha Lan Tun	Heilongjiang	Acheng	Jiangsu	Wujiang
Hebei	Gaocheng	Liaoning	Beining	Heilongjiang	Anda	Jiangsu	Xinghua
Hebei	Hejian	Liaoning	Beipiao	Heilongjiang	Beian	Jiangsu	Xinyi
Hebei	Huanghua	Liaoning	Dengta	Heilongjiang	Fujin	Jiangsu	Yangzhong
Hebei	Jinzhou	Liaoning	Donggang	Heilongjiang	Hailin	Jiangsu	Yixing
Hebei	Jizhou	Liaoning	Fengcheng	Heilongjiang	Hailun	Jiangsu	Yizheng
Hebei	Luquan	Liaoning	Gaizhou	Heilongjiang	Hulin	Jiangsu	Zhangjiagang
Hebei	Nangong	Liaoning	Haicheng	Heilongjiang	Muleng	Zhejiang	Cixi
Hebei	Qian\'an	Liaoning	Kaiyuan	Heilongjiang	Ning\'an	Zhejiang	Dongyang
Hebei	Renqiu	Liaoning	Linghai	Heilongjiang	Shangzhi	Zhejiang	Fenghua
Hebei	Sanhe	Liaoning	Lingyuan	Heilongjiang	Shuangcheng	Zhejiang	Fuyang
Hebei	Shahe	Liaoning	Pulandian	Heilongjiang	Suifenhe	Zhejiang	Haining
Hebei	Shenzhou	Liaoning	Tiefa	Heilongjiang	Tieli	Zhejiang	Jiande
Hebei	Wu\'an	Liaoning	Wafangdian	Heilongjiang	Tongjiang	Zhejiang	Jiangshan
Hebei	Xinji	Liaoning	Xingcheng	Heilongjiang	Wuchang	Zhejiang	Lanxi
Hebei	Xinle	Liaoning	Xinmin	Heilongjiang	Wudalianchi	Zhejiang	Leqing
Hebei	Zhuozhou	Liaoning	Zhuanghe	Heilongjiang	Zhaodong	Zhejiang	Lin\'an
Hebei	Zunhua	Jilin	Daan	Heilongjiang	Zhaoyuan	Zhejiang	Linhai
Shanxi	Fenyang	Jilin	Dehui	Shanghai	Shanghai	Zhejiang	Longquan
Shanxi	Gaoping	Jilin	Dunhua	Jiangsu	Dafeng	Zhejiang	Pinghu
Shanxi	Gujiao	Jilin	Gongzhuling	Jiangsu	Dongtai	Zhejiang	Ruian
Shanxi	Hejin	Jilin	Helong	Jiangsu	Gaoyou	Zhejiang	Shangyu
Shanxi	Houma	Jilin	Huadian	Jiangsu	Haimen	Zhejiang	Shengzhou
Shanxi	Huozhou	Jilin	Huichun	Jiangsu	Jiangdu	Zhejiang	Tongxiang
Shanxi	Jiexiu	Jilin	Ji\'an	Jiangsu	Jiangyan	Zhejiang	Wenling
Shanxi	Lucheng	Jilin	Jiaohe	Jiangsu	Jiangyin	Zhejiang	Yiwu
Shanxi	Xiaoyi	Jilin	Jiutai	Jiangsu	Jingjiang	Zhejiang	Yongkang
Shanxi	Yongji	Jilin	Linjiang	Jiangsu	Jintan	Zhejiang	Yuyao
Inner Mongolia	Aershan	Jilin	Longjing	Jiangsu	Jurong	Zhejiang	Zhuji
Inner Mongolia	E Er Gu Na	Jilin	Meihekou	Jiangsu	Kunshan	Anhui	Jieshou
Inner Mongolia	Erenhot	Jilin	Panshi	Jiangsu	Liyang	Anhui	Mingguang

Table A1 : List of sample cities (2/3)

Province	City	Province	City	Province	City	Province	City
Anhui	Ningguo	Shandong	Laizhou	He'nan	Xinzheng	Hu'nan	Linxiang
Anhui	Tianchang	Shandong	Leling	He'nan	Yanshi	Hu'nan	Liuyang
Anhui	Tongcheng	Shandong	Linqing	He'nan	Yima	Hu'nan	Miluo
Fujian	Changle	Shandong	Longkou	He'nan	Yongcheng	Hu'nan	Shaoshan
Fujian	Fuan	Shandong	Penglai	He'nan	Yuzhou	Hu'nan	Wugang
Fujian	Fuding	Shandong	Pingdu	Hubei	Anlu	Hu'nan	Xiangxiang
Fujian	Fuqing	Shandong	Qingzhou	Hubei	Chibi	Hu'nan	Yuanjiang
Fujian	Jian\'ou	Shandong	Qixia	Hubei	Dangyang	Hu'nan	Zixing
Fujian	Jianyang	Shandong	Qufu	Hubei	Danjiangkou	Guangdong	Conghua
Fujian	Jinjiang	Shandong	Rongcheng	Hubei	Daye	Guangdong	Enping
Fujian	Longhai	Shandong	Rushan	Hubei	Enshi	Guangdong	Gaoyao
Fujian	Nan\'an	Shandong	Shouguang	Hubei	Guangshui	Guangdong	Gaozhou
Fujian	Shaowu	Shandong	Tengzhou	Hubei	Hanchuan	Guangdong	Heshan
Fujian	Shishi	Shandong	Wendeng	Hubei	Honghu	Guangdong	Huazhou
Fujian	Wuyishan	Shandong	Xintai	Hubei	Laohekou	Guangdong	Kaiping
Fujian	Yongan	Shandong	Yanzhou	Hubei	Lichuan	Guangdong	Lechang
Fujian	Zhangping	Shandong	Yucheng	Hubei	Macheng	Guangdong	Leizhou
Jiangxi	Dexing	Shandong	Zhangqiu	Hubei	Qianjiang	Guangdong	Lianjiang
Jiangxi	Fengcheng	Shandong	Zhaoyuan	Hubei	Shishou	Guangdong	Lianzhou
Jiangxi	Gaoan	Shandong	Zhucheng	Hubei	Songzi	Guangdong	Lufeng
Jiangxi	Guixi	Shandong	Zoucheng	Hubei	Tianmen	Guangdong	Luoding
Jiangxi	Jinggangshan	He'nan	Changge	Hubei	Wuxue	Guangdong	Nanxiong
Jiangxi	Leping	He'nan	Dengfeng	Hubei	Xiantao	Guangdong	Puning
Jiangxi	Nankang	He'nan	Dengzhou	Hubei	Yicheng	Guangdong	Sihui
Jiangxi	Ruichang	He'nan	Gongyi	Hubei	Yidu	Guangdong	Taishan
Jiangxi	Ruijin	He'nan	Huixian	Hubei	Yingcheng	Guangdong	Wuchuan
Jiangxi	Zhangshu	He'nan	Jiyuan	Hubei	Zaoyang	Guangdong	Xingning
Shandong	Anqiu	He'nan	Lingbao	Hubei	Zhijiang	Guangdong	Xinyi
Shandong	Changyi	He'nan	Linzhou	Hubei	Zhongxiang	Guangdong	Yangchun
Shandong	Feicheng	He'nan	Mengzhou	Hu'nan	Changning	Guangdong	Yingde
Shandong	Gaomi	He'nan	Qinyang	Hu'nan	Hongjiang	Guangdong	Zengcheng
Shandong	Haiyang	He'nan	Ruzhou	Hu'nan	Jinshi	Guangxi	Beiliu
Shandong	Jiaonan	He'nan	Weihui	Hu'nan	Jishou	Guangxi	Cenxi
Shandong	Jiaozhou	He'nan	Wugang	Hu'nan	Leiyang	Guangxi	Dongxing
Shandong	Jimo	He'nan	Xiangcheng	Hu'nan	Lengshuijiang	Guangxi	Guiping
Shandong	Laixi	He'nan	Xingyang	Hu'nan	Lianyuan	Guangxi	He Shan
Shandong	Laiyang	He'nan	Xinmi	Hu'nan	Liling	Guangxi	Ping Xiang

Table A1 : List of sample cities (3/3)

Province	City	Province	City	Province	City	Province	City
Hainan	Dan Zhou	Sichuan	Pengzhou	Yun'nan	Jinghong	Xinjiang	Atush
Hainan	Dong Fang	Sichuan	Qionglai	Yun'nan	Kaiyuan	Xinjiang	Bole
Hainan	Qiong Hai	Sichuan	Shifang	Yun'nan	Luxi	Xinjiang	Changji
Hainan	Wan Ning	Sichuan	Wanyuan	Yun'nan	Ruili	Xinjiang	Fukang
Hainan	Wen Chang	Sichuan	Xichang	Yun'nan	Xuanwei	Xinjiang	Hami
Hainan	Wu Zhi Shan	Guizhou	Bijie	Shannxi	Hancheng	Xinjiang	Hotan
Chongqing	Hechuan	Guizhou	Chishui	Shannxi	Huayin	Xinjiang	Kashi
Chongqing	Jiangjin	Guizhou	Duyun	Shannxi	Xingping	Xinjiang	Korla
Chongqing	Nanchuan	Guizhou	Fuquan	Gansu	Dun Huang	Xinjiang	Kui Tun
Chongqing	Yongchuan	Guizhou	Kaili	Gansu	Hezuo	Xinjiang	Miquan
Sichuan	Dujiangyan	Guizhou	Qingzhen	Gansu	Linxia	Xinjiang	Shihezi
Sichuan	Emeishan	Guizhou	Renhuai	Gansu	Yu Men	Xinjiang	Tacheng
Sichuan	Guanghan	Guizhou	Tongren	Qinghai	Delingha	Xinjiang	Turpan
Sichuan	Huaying	Guizhou	Xingyi	Qinghai	Golmud	Xinjiang	Urumqi
Sichuan	Jiangyou	Yun'nan	Anning	Ningxia	Ling Wu	Xinjiang	Usu
Sichuan	Jianyang	Yun'nan	Chuxiong	Ningxia	Qingtongxia	Xinjiang	Yi Ning
Sichuan	Langzhong	Yun'nan	Dali	Xinjiang	Aksu	Tibet	Xigaze
Sichuan	Mianzhu	Yun'nan	Gejiu	Xinjiang	Aletai		

Table A2 : Descriptive statistics

	BED	EDU	EX	FDI	GDPH	GVT	INV	PHONE
Mean	-6.094	-2.721	-4.825	-6.859	0.142	-2.653	-2.322	-1.534
Median	-6.136	-2.704	-3.302	-4.656	0.133	-2.723	-1.965	-1.507
Maximum	-4.269	-1.944	1.799	-0.613	2.194	-0.136	0.892	0.557
Minimum	-7.804	-4.993	-19.984	-19.984	-1.225	-3.729	-13.816	-5.066
Std. Dev.	0.513	0.299	4.930	5.513	0.606	0.499	2.372	0.561
Skewness	0.241	-3.135	-1.888	-1.226	0.202	1.088	-3.650	-0.597
Kurtosis	3.548	24.026	5.296	2.820	2.927	5.332	18.347	7.279
Jarque-Bera	8.128	7341.588	297.862	92.225	2.568	155.195	4404.705	300.984
Probability	0.017	0.000000	0.000	0.000	0.277	0.000	0.000	0.000
Sum	-2230.355	-995.932	-1765.990	-2510.431	52.170	-971.110	-850.023	-561.512
Sum Sq. Dev.	96.408	32.805	8872.445	11091.890	134.209	90.913	2052.414	114.9175

Note : All variabes are expressed in Ln.

Table A3: Euclidian distance matrix

Characteristics of distance matrix	
Dimension	367
Average distance between points:	14.284
Distance range:	57.234
Minimum distance between points:	0.080
<u>Quartiles:</u>	
First:	7.290
Median:	11.929
Third:	19.024
Maximum distance between points:	57.315
Min. allowable distance cut-off:	9.333

Note: The Euclidian distance matrix is computed using Anselin's SpaceStat – 1.8 version software package (1996).

Table A4: Correlation matrix

	BED	EDU	EX	FDI	GDPH	GVT	INV	PHONE
BED	1.000	-0.109	-0.124	-0.179	0.269	0.249	0.189	0.323
EDU	-0.109	1.000	-0.050	-0.003	0.212	-0.246	-0.034	-0.172
EX	-0.124	-0.050	1.000	0.519	0.191	-0.153	0.014	0.230
FDI	-0.179	-0.003	0.519	1.000	0.257	-0.342	0.038	0.224
GDPH	0.269	0.212	0.191	0.257	1.000	-0.577	0.258	0.527
GVT	0.249	-0.246	-0.153	-0.342	-0.577	1.000	-0.078	- 0.118
INV	0.189	-0.034	0.014	0.038	0.258	-0.078	1.000	0.169
PHONE	0.323	-0.172	0.230	0.224	0.527	-0.118	0.169	1.000

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