doi:10.1111/j.1435-5957.2007.00148.x

Spatial data analysis of regional development in Greater Beijing, China, in a GIS environment*

Danlin Yu[1], **Yehua Dennis Wei**[2]

[1] Department of Earth and Environmental Studies, Montclair State University, Montclair, NJ, 07043, USA (e-mail: yud@mail.montclair.edu)
[2] Department of Geography & Institute of Public and International Affairs, University of Utah, Salt Lake City, UT, 84112-9155, USA (e-mail: wei@geog.utah.edu)

Received: 2 May 2005 / Accepted: 20 October 2006

Abstract. This study investigates spatial dependence and mechanisms of regional development in Greater Beijing, China by employing spatial statistical techniques. We have detected positive, strengthening global spatial autocorrelation from 1978 to 2001, and found such strengthening is the result of newly formed/extended clusters in the area. The local analysis recognizes local regimes of two-tier urban-rural spatial structure at the beginning of the reform period. While the urban-rural divide was lessening due to the reform, a north-south divide has emerged because of local natural conditions and development trajectories. Regarding mechanisms of regional development, ordinary least squares analysis is constrained by the existence of significant spatial autocorrelation among spatial units. Analytical results reveal that an error spatial regression model is a more appropriate alternative due to possible mismatch between boundaries of the underlying spatial process and the spatial units where data are organised. In 1995 and 2001, the signs of all the regression coefficients remained the same for both OLS and spatial models. However, their magnitude and significance change. Specifically, foreign direct investment and fixed-asset investment became less influential in the spatial model, while local government spending emerged as more influential.

JEL classification: O18, O53, P25, R11

Key words: Regional development, GIS, exploratory spatial data analysis, spatial regression, Greater Beijing

1 Introduction

Since the early 1990s, there has been a renewed multidisciplinary interest in regional convergence and divergence. This has been fuelled by concern over the effects of globalisation and

* An earlier version of this paper was presented at the Association of American Geographers West Lakes Division/ Wisconsin Geographical Society Meeting, Oshkosh, October 7–9. 2004. We'd like to thank the funding of the U.S. National Science Foundation (BCS–0552264) and the Natural Science Foundation of China (40428003).

liberalisation and research advances in new economic geography, endogenous growth theory, scalar perspective, and the emergence of regions (e.g., Barro and Sala-I-Martin 1995; Clark et al. 2000; Cheshire and Malecki 2004). There is also a growing body of literature on regional development in Asia, where substantial regional differences exist within countries (e.g., Hill 2002; Sjoholm 2002; Akita 2003), and in the former socialist countries, where scholars are debating intensely over the social and spatial effects of reforms and transition (e.g., Petrakos 2001; Bradshaw and Vartapetov 2003; Dienes 2005). While some maintain that globalisation and liberalisation have brought wealth to the poorer regions, others argue that regional inequality persists in many countries and new forms of uneven regional development are emerging.

Regional convergence and divergence in China has also attracted considerable scholarly interest, although largely escaping the attention of Western economic geographers. In the mid-1990s, newly released data disclosed a time-series picture of changing regional inequality in China (Fan 1995; Wei and Ma 1996; Zhao 1996) for the first time. This research challenged the conventional wisdom of regional convergence under Mao and regional divergence during the reform period, and underscored the dynamic and multiscalar nature of regional inequality and the significance of regional development trajectories in understanding regional development (Wei 1999). Since the mid-1990s, scholars have attempted to theorise and improve the understanding of the underlying forces of regional development, with the notions of triple transition, transitional institutions, multi-mechanisms, externally-driven development, place-based development, and development from below (e.g., Lin 1997; Wei 1999, 2000; Wei and Fan 2000; Ma and Cui 2002). The literature has also examined the effects of fiscal decentralisation, foreign investment, state investment, labour mobility, spillovers, and privatisation on regional development (Ma and Wei 1997; Wei 2000; Lu and Wang 2002; Wei and Kim 2002; Skinner et al. 2003; Ying 2003; Wei 2004; Groenewold 2007). More recently, scholars have further improved the understanding of regional development in China by uncovering recent developments, further scaling down, and particularly, using more vigorous geographical methods (e.g., Ying 2003; Yu and Wei 2003; Ye and Wei 2005; Yu 2006).

This work builds upon two of the most recent trends in the study of regional development and inequality in China. First, due largely to data limitation, most studies focus on China's regional development at the provincial level, while less attention has been paid to the county-level. Scholars have realised that regional development in China can be more thoroughly understood with studies of smaller scale spatial units (Wei and Fan 2000; Wei and Kim 2002). A series of publications has emerged to address such concerns, but because of data issues and scholarly interests, studies are usually limited to the southern coastal provinces, such as Jiangsu, Zhejiang and Guangdong (e.g., Wei 2000; Gu et al. 2001; Wei and Kim 2002; Huang and Leung 2002; Wei and Ye 2004; Ye and Wei 2005). Systematic research on other provinces or regions of China remains limited. As argued by Wei and Ye (2004), given the massive scale of China, geographical difference within provinces is as vast as across provinces. A better understanding of regional development in China requires more research in varied locales, including northern China, especially Greater Beijing, where the nation's capital is located and which has largely escaped the attention of Western researchers during the past decades.

Secondly, using recent developments in GIS and spatial analysis, research on China has uncovered the trend of spatial agglomeration in the reform period, despite convergence across the provinces in the 1980s, and dynamics of regional development shaped by the changing fortunes of regions. This challenges conventional 'global', 'black-box' approaches to study regional development (Yu and Wei 2003; Wei and Ye 2004). As mentioned earlier, most of the studies on China in the 1990s were at the provincial level, and at a high level of data aggregation. While this might provide an overall picture of regional development in China, it also obscures subtle spatial effects. The recent advances in GIS and spatial analysis, especially exploratory spatial data analysis (ESDA), visualisation, and spatial regression, have provided a great opportunity to further advance the study of regional development (Anselin 1996; Rey and Montouri 1999; Driffield et al. 2004; Goodchild and Janelle 2004), and can be used to provide an in-depth understanding of China's development.

As argued by Le Gallo and Ertur (2003), spatial effects become salient on finer scales. A number of factors, including the increasing intensity of trade between spatial units and more frequent technology and knowledge diffusion, etc., on a smaller scale, lead to geographically dependent spatial units. Those factors, if investigated on a provincial scale, may be unobservable or negligible due to their local characteristics. However, on a finer geographic scale, for example, at the county level in China, they may lead to significant spatial effects. Since spatial effects are inherent in geographic processes, ignoring finer scale data analysis might lead to misleading or even incorrect analytical results. Following the same rationale, in analyzing factors of regional development, the ordinary least squares (OLS) regression technique is employed widely in the literature (e.g., Barro and Sala-I-Martin 1995; Yu and Wei 2003). As argued by Anselin (1988), when the OLS estimator is used for cross-sectional data on geographic units, the existence of spatial autocorrelation could pose serious problems of model misspecification, and the Maximum Likelihood-based spatial regression estimator is usually deemed an effective alternative.

This paper employs the recent developments in GIS and spatial analysis, particularly exploratory spatial data analysis (ESDA) and spatial regression, to investigate regional development in Greater Beijing using county-level data. It intends to achieve two objectives. First, we explicitly investigate the spatial dependence and dynamic spatial processes in regional development at both the global and local levels. The greater attention to the local patterns of regional development through GIS techniques should reveal localised development characteristics that are significantly different from the southern provinces. Second, we employ the spatial regression method in order to understand mechanisms of regional development in China at the county level. Again, the explicit incorporation of spatial information in the modelling scheme might better capture spatial dimensions of regional development in this region. We contend that recent advances in GIS and spatial data analysis have empowered geographers in studying regional development by revealing complex socioeconomic structures and by identifying varied local development trajectories. The next section examines the development process and patterns of Greater Beijing. This is followed by the depiction of global spatial patterns and processes at the county level. We will then use the ESDA methods to analyse regional development patterns and processes, and present the methods and results of both OLS and spatial regression models. The last section concludes the paper.

2 Development process and regional patterns

Greater Beijing is located in northern coastal China and includes three provincial-level units: Beijing (with 11 county-level units,[1] or counties for simplification), Tianjin (with 8 counties), and Hebei (with 11 prefectures, 151 counties), which results in a total of 170 counties[2] (Figure 1). The region has an area of 216,420 square kilometres (approximately 2% of China's territory), and a total population of 91.6 million as of 2001. The region has also been called the Capital Region, or the (Bei)Jing-(Tian)Jin-Ji Region, reflecting the close socioeconomic linkages within the region and the efforts of local governments to promote regional growth and collaboration. The state has focused on transforming Greater Beijing (as well as the Yangtze

[1] 8 small districts in Beijing's city core, i.e., Haidian, Chaoyang, Fengtai, Shijingshan, Dongcheng, Xicheng, Xuanwu and Chongwen Districts, are considered as one county level spatial unit.

[2] Two of the counties are spatially separated due to historical administrative practices and are treated as four separated spatial units (but with identical socioeconomic indicators) in the analysis. They are Handan City and Luannan County.

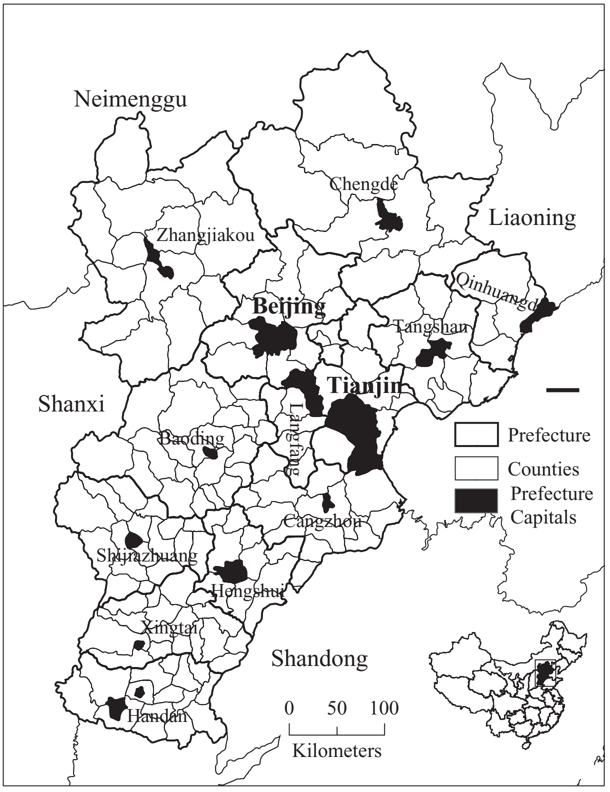

Fig. 1. The location of Greater Beijing

Delta and the Pearl River Delta) into one of China's emerging global city regions and the dragon's head of economic growth (e.g., Li 1999).

Beijing has been the most important ancient capital city of China, especially since the thirteenth century, making Greater Beijing China's most important political centre. This specific geopolitical position of Greater Beijing also favoured its economic development under Mao. For instance, shortly after the establishment of the new republic in 1949, massive state investment went to the capital in order to transform Beijing from a semi-feudal, semi-colonial city to a socialist, productive city. Benefiting from their geographic proximity to Beijing, Tianjin and Hebei also experienced rapid industrialisation. By the end of the first 'Five-Year-Plan' (1953), Greater Beijing had tremendous build-up in heavy industry. However, despite this economic growth under Mao, on the eve of economic reforms, Greater Beijing faced severe structural problems fundamental to its socialist economy. These problems were even more serious than those faced by many other Chinese regions under state socialism. First, the product structure, dominated by heavy, defence-oriented industry, and out-of-date technological equipment, mostly imported from the former Soviet Union in the 1950s, impeded industrial productivity. Second, industrialisation in the region was associated with urban industrialisation, while rural areas in Hebei remained less developed. Third, linkages among industries and regions in Greater Beijing were weak, leading to the waste of raw materials and duplication of similar industries (Lu 1997). Such an industrial structure, as well as the artificial barriers of the strict household registration system, created an imbalanced core-periphery spatial structure. The core region, represented by Beijing, Tianjin and the urban areas in Hebei province, was more developed than its rural peripheries. Such a spatial structure still holds in 2001 (Figure 2).

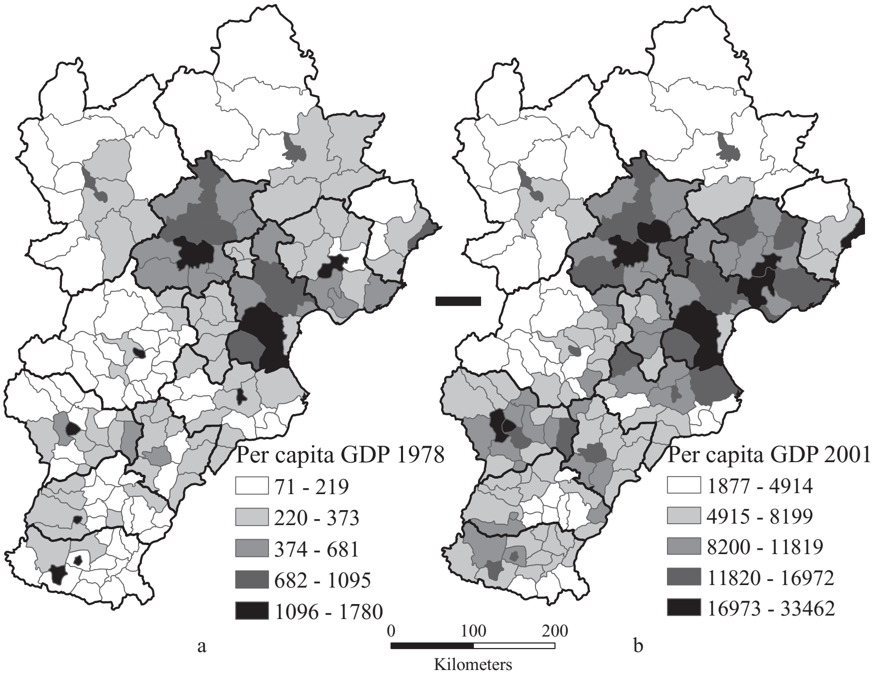

Fig. 2. Per capita GDP in 1978 (2a) and 2001 (2b) (Yuan)

China's post-Mao reform was a gradual, experimental, and spatially uneven process. Unlike southern regions such as Jiangsu, Zhejiang, and Guangdong, etc., the benefits of reform to this area were limited during the early stages of the reform, and the economic status of Greater Beijing was relatively stable (Yu and Wei 2003). This is due largely to the following two conditions. First, the spatially uneven reform policy was spearheaded by special economic zones in southern China and later by open coastal cities (OCCs). It allowed 'specific policies and flexible management' in Guangdong and Fujian provinces in 1979. These provinces are far away from Beijing. The central government treated the reform of the political centre, Beijing, as well as Tianjin, with caution. Even after the reform brought dramatic success in Guangdong and Fujian, cautious reform was still a dogma for the government. Tianjin and Qinhuangdao, two of the fourteen OCCs designated in 1984, were slow to reform and lagged behind other OCCs. Moreover, their trickle-down effects to other regions in Greater Beijing remained limited. Reform policy packages were not fully granted to Greater Beijing until after the early 1990s.

Second, the dominance of state-owned enterprises (SOEs) and heavy industry in the region limited the speed of economic growth. The long-established industrial and ownership structure in Greater Beijing was quite different from south-eastern coastal China, where rapid economic growth has been driven by foreign and non-state enterprises (Ma and Cui 2002; Wei 2004). This also indicates that the focus, processes, and results of the reform might be quite different from what was observed in the south-eastern provinces. A study of this area complements the research on south-eastern coastal provinces and improves our understanding of the process and effects of China's economic reforms.

As a result, the reform did not benefit Greater Beijing like it did with the southern provinces. From the development over time of the location quotients in Figure 3 it is clear that the overall economic status of the three provinces/municipalities in Greater Beijing decreased during the study period, while their southern peers (represented by Guangdong and Fujian provinces)

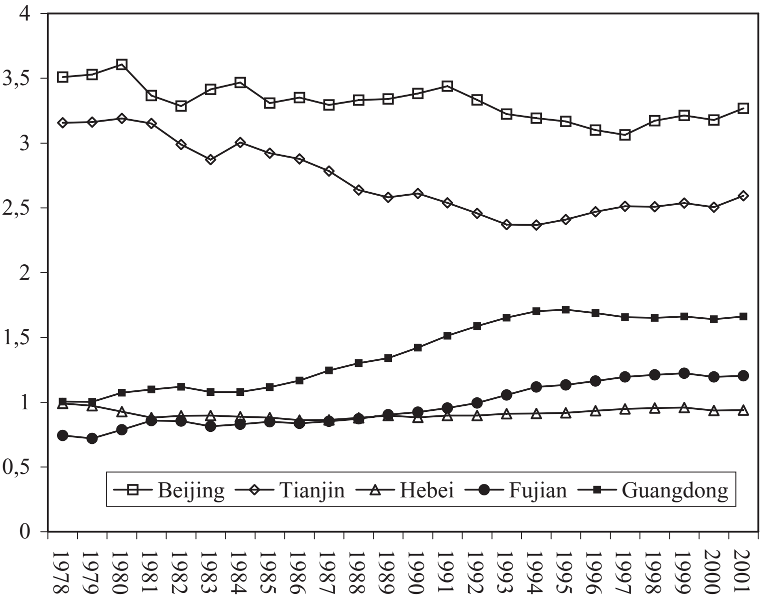

Fig. 3. LQs of the five provincial spatial units, 1978–2001

Note: The location quotient is calculated as: $LQ = \frac{GDP_i / \Sigma GDP_i}{Pop_i / \Sigma Pop_i}$, where GDP_i is the ith spatial unit's per capital GDP, and Pop_i its population. LQ is used to measure the economic status of a spatial unit in the study region.

gained substantially from the reform. Studies of Guangdong and Zhejiang have shown the emergence of new growth centres, such as Wenzhou and Dongguang, stimulated by the development of foreign and private enterprises (Lin 1997; Wei and Ye 2004). In Greater Beijing, the slow process of reform and heavy industrial structure have resulted in a lagging regional economy. This economy is different from the southern provinces, and will be analysed in the following sections.

3 Examining spatial patterns with global Moran's I

Two types of spatial effects are of particular interest as they have considerable influence in data analysis: spatial autocorrelation and spatial heterogeneity. The former indicates that regional development in neighbouring spatial units tends to be similar or dissimilar to one another (representing positive or negative autocorrelation, respectively); the latter refers to uneven development patterns across space with varied forms of spatial regimes, such as the core – a cluster of rich regions, and the periphery – a cluster of poor regions (Le Gallo and Ertur 2003). This study focuses on the spatial autocorrelation of regional development among counties in Greater Beijing. Following the literature (e.g., Wei 2000; Le Gallo and Ertur 2003; Yu and Wei 2003), we chose per capita GDP as an indicator for regional development. Several indices can be used to measure spatial autocorrelation (e.g., Cliff and Ord 1973; Anselin 1988; Getis and Ord 1992), and the most popular is the Moran's I (Anselin 1988, 1992; Yu and Wei 2003).

In general, the global Moran's I gives a formal indication of the degree of linear association between the spatial units and their neighbours. When compared with the expected value $E(I) = -1/(n-1)$, a larger I indicates positive spatial autocorrelation (spatial cluster), and a

Table 1. Characteristics of alternative spatial weight matrixes

Characteristics	BDSH*	Dist80	Dist160	Dist240	Dist320
Number of regions	170	170	170	170	170
Number of non-zero links	922	3,028	9,518	16,066	21,340
Percentage of non-zero weights	3.19	10.48	32.93	55.59	73.84
Average number of links	5.42	17.81	55.99	94.51	125.53

*: BDSH stands for border sharing; Dist80 stands for the 80 km weighting strategy, and so forth.

smaller I points to negative spatial autocorrelation (spatial dissimilarity). Since the global Moran's I does not follow a normal distribution, a significance test can be conducted using the saddlepoint approximation (Lieberman 1994; Tiefelsdorf 2000, 2002).

In calculating the Moran's I, the spatial weights matrix is of particular importance (Anselin 1988), because it represents the particular spatial linkage between spatial units. In the literature, different strategies of determining the weights are discussed (Anselin 1988, 1992; Rey and Montouri 1999; Ying 2003; Yu and Wei 2003). Two types of strategies to determine the spatial weights are often used, namely, spatial linkages based on border sharing and distance. Due to the complexity of interactions among geographic units (Anselin 1988), it is appropriate to examine alternative spatial weights strategies. This study constructs spatial weights matrices based on both border sharing and distance strategies. With regard to distance strategies, four alternatives are considered. In particular, geographic units within 80 km, 160 km, 240 km, and 320 km are deemed spatially linked neighbours for each alternative. The 80 km choice is based on our field experience. It is the distance for approximately an hour's drive on the expressways in this region. The characteristics of the five spatial weights matrices are reported in Table 1.

Our computation employs the SPDEP package (Bivand 2002, 2004) in R (R Development Core Team 2004), freely available through the R-project website.[3] While using different weighting strategies, we found that in Greater Beijing the spatial autocorrelation decreases at a farther distance in Greater Beijing, since the spatial relationship represented in the weights matrix becomes less specific as the distance increases. However, except for the 240 km and 320 km strategies before 1990, all strategies yield significant Moran's I at a 95% confidence level by saddlepoint approximation (Table 2).

For dynamic spatial autocorrelation, all weighting strategies yield very similar changing patterns from 1978 – 2001. We only depict the patterns of Moran's I (using the saddlepoint approximated standardised values) under the border-sharing strategy (county-level data for the years 1979, 1981–1984, 1986–1989, and 1991–1994 are not available) (Figure 4). The figure indicates a general trend of increasing spatial autocorrelation during the study period. This has two possible implications. On one hand, the increase could be due to the counties in each cluster[4] becoming more similar in per capita GDP. On the other hand, it might result from the emergence of newly formed clusters. Moran's I, as a global measure of spatial autocorrelation, does not allow us to distinguish between these possibilities. In addition, a global index tends to mask details by averaging information on atypical localisations or 'pockets of local non-stationarity' (Anselin 1995, 1996; Le Gallo and Ertur 2003). Thus, we turn to a disaggregated analysis of the structure of spatial autocorrelation of regional development in Greater Beijing.

[3] The North American mirror of the R-project website is http://cran.us.r-project.org.

[4] We define 'cluster' and 'hot spots' following the definition by Tiefelsdorf (2000). The definition treats positively autocorrelated regions as 'cluster', while regions with higher values in the negatively autocorrelated regions as 'hot spots'.

Table 2. Significance test (p-values) of Moran's *I* for different weighting strategies

Year	BDSH	Dist80	Dist160	Dist240	Dist320
1978	0.003*	0.015	0.006	0.080	0.201
1980	0.000	0.001	0.001	0.030	0.137
1985	0.001	0.002	0.004	0.543	0.978
1990	0.000	0.001	0.000	0.019	0.041
1995	0.000	0.000	0.000	0.000	0.001
1996	0.000	0.000	0.000	0.001	0.003
1997	0.000	0.000	0.000	0.003	0.006
1998	0.000	0.000	0.000	0.001	0.003
1999	0.000	0.000	0.000	0.001	0.004
2000	0.000	0.000	0.000	0.001	0.005
2001	0.000	0.000	0.000	0.000	0.003

* p-values are obtained through saddlepoint approximation (Tiefelsdorf 2000).

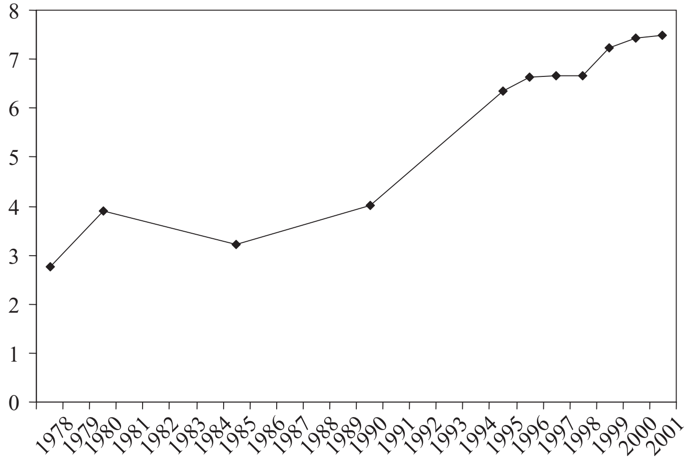

Fig. 4. Global Moran's I in Greater Beijing, 1978–2001

4 Investigating local patterns with the Moran scatterplot and local Moran's I

The Moran scatterplot is a graphic tool derived from the global Moran's *I*. When using a row-standardised weight matrix, the global Moran's *I* is formally equivalent to a regression coefficient in a regression of the spatial lag on the measuring variable, a scatterplot between these two would yield useful information on local non-stationarity (Anselin 1996). In the scatterplot, the outliers and/or leverages are represented as extreme points with respect to the central tendency reflected by the regression slope (the global Moran's *I*). The four quadrants divide positive and negative spatial autocorrelations into four types of local spatial autocorrelation. The positive autocorrelation is divided into quadrant I, HH, indicating high values surrounded by high values, and quadrant III, LL, indicating low values surrounded by low values. The negative autocorrelation includes quadrant II, LH, and quadrant IV, HL, indicating low values surrounded by high values, and high values surrounded by low values, respectively. This allows us to identify different types of similarity or dissimilarity in a neighbourhood environment, as well as potential local cluster centres (quadrant I) and 'hot spots' (quadrant IV).

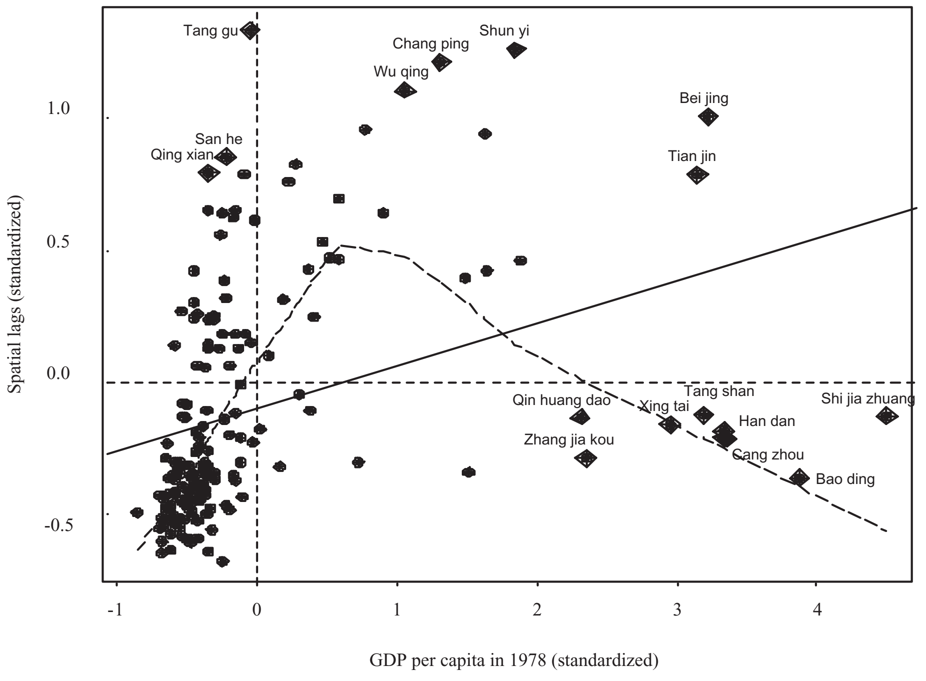

Fig. 5. Moran's scatterplot in 1978 with regression line and LOWESS curve (dotted line)

In addition, the four quadrants can be represented by different gray scales (or colours) in a map, which enables us to better identify local clusters.

In conjunction with Moran's scatterplot, the decomposed component of the Moran's I, the local Moran's I_i is used to assess significant 'local pockets' and is proportional to the global Moran's I (Anselin 1995). A positive value of I_i indicates spatial clustering of similar values (either high or low) around spatial unit i, and a negative value indicates gathering of dissimilar values between spatial unit i and its neighbours. Significance tests of local Moran's I_i are also conducted through the saddlepoint approximation (Tiefelsdorf 2000, 2002).

The following analyses present Moran scatterplots (Figures 5 and 6), corresponding Moran scatterplot maps (Figure 7), and significant local pocket maps (Figure 8). The scatterplots are created using R and its spatial package SPDEP. The border-sharing strategy is used in the computation again, but similar patterns are observed using different alternatives. The superimposed Locally Weighted Regression (LOWESS) curve lines use the standardised per capita GDP and its spatial lags (standardised as well) as inputting coordinates. A LOWESS curve in the Moran scatterplot gives an indication of local spatial structures (Anselin 1996): the closer the LOWESS curve to the fitted line in the scatterplot, the less heterogeneous the local spatial structures. Two thirds of the spatial units are used as the span for the local smoothing process (the trend could be detected using a span from 20% to 80% of the spatial units, see Cleveland 1979 for a detailed discussion). Points labelled by the SPDEP package represent either high-leverage spatial units or spatial units that impose relatively high influence on the overall spatial pattern. These influential spatial units are potential locations in determining the spatial structure of the region. All Moran scatterplot maps and local pocket maps are created in ArcGIS 9.0® in conjunction with R. In the local pocket maps, the hot spots are spatial units that have a p-value[5]

[5] A spatial unit's p-value is calculated through the saddlepoint approximation employing Barndorff-Nielsen formula (Tiefelsdorf 2002). $p = \Pr(I_i < I_{i0}|\Omega)$, where I_{i0} is the observed local Moran's I of spatial unit i, Ω is the level of global spatial process, it can be obtained through a slope-only spatial regression.

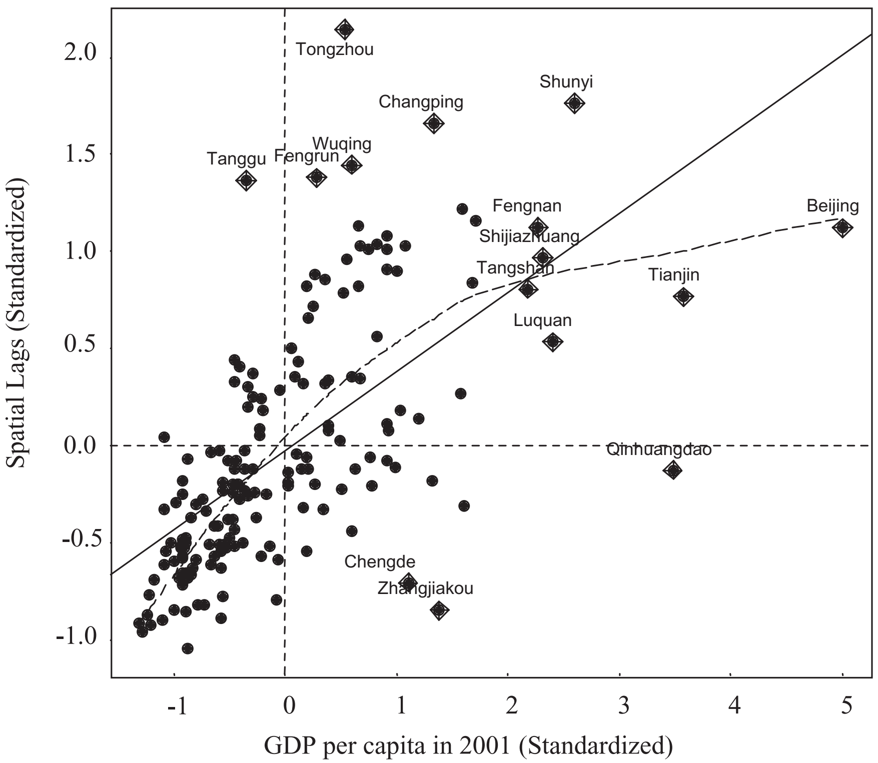

Fig. 6. Moran's scatterplot in 2001

less than 0.05 conditioned upon the corresponding year's global spatial process. They represent significant local pockets. The spatial units are significant local heterogeneities under the global spatial process. Clusters, on the other hand, are spatial units that have a p-value larger than 0.95, which represents positive local autocorrelation subject to an underlying global spatial process (Tiefelsdorf 2000, p. 134).

An investigation of the figures and maps leads to a series of findings. First, local patterns of spatial association reinforce the global trend of positive spatial autocorrelation reported earlier. More specifically, around three-quarters of the counties in the two years fall within either the first or the third quadrants in the Moran scatterplot, and the number continues to increase (1978 – 72.4%, 2001 – 78.2%, Figure 7). Moreover, low-value clusters dominate the process, although the number of high-value clusters is increasing. In 1978, among the counties representing negative spatial autocorrelation, spatial units in the second quadrant were more than twice that in the fourth quadrant. This suggests that at the beginning of the reform, although counties with similar per capita GDP tended to cluster together, the gap between rich and poor counties was large and widely distributed (Figure 7a), especially around the Beijing-Tianjin core. With reform, however, the counties surrounding the core regions seemed to have caught up. In 2001, counties in the second quadrant decreased to 14, while those in the fourth quadrant increased to 23 (Figure 7b). A comparison of the two Moran scatterplot maps (Figure 7) reveals a spreading trend from the core. The HH region extended from the traditional Beijing-Tianjin region to Beijing-Tianjin-Tangshan-Langfang, indicating that the strengthening of the global spatial autocorrelation is due to the newly formed cluster. In addition to this extension of the core region, a newly formed HH cluster around Shijiazhuang, Hebei's capital city, stands out in the 2001 Moran scatterplot map (Figure 7b).

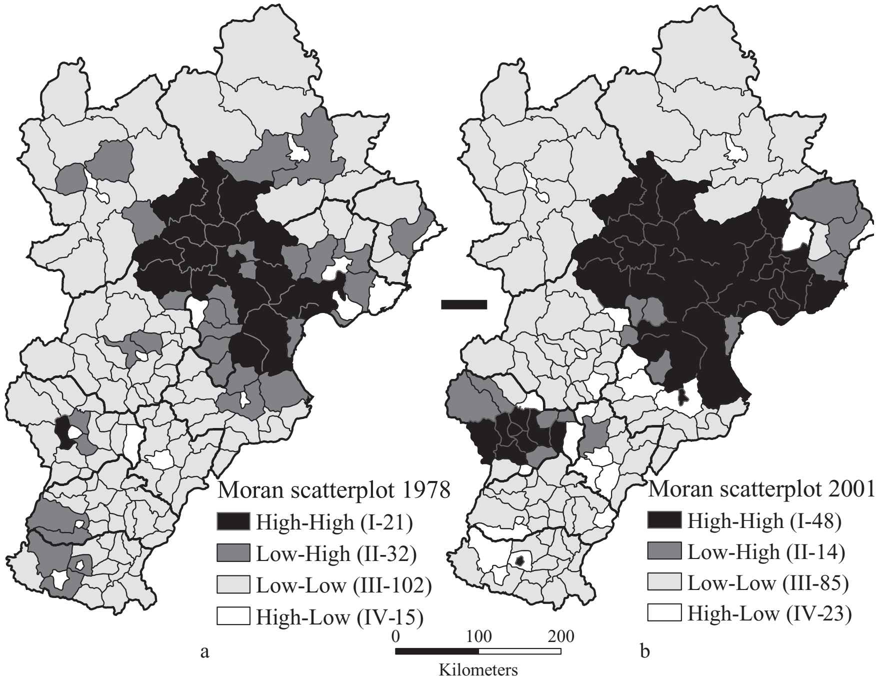

Fig. 7. Moran's scatterplot maps in 1978 (7a) and 2001 (7b)

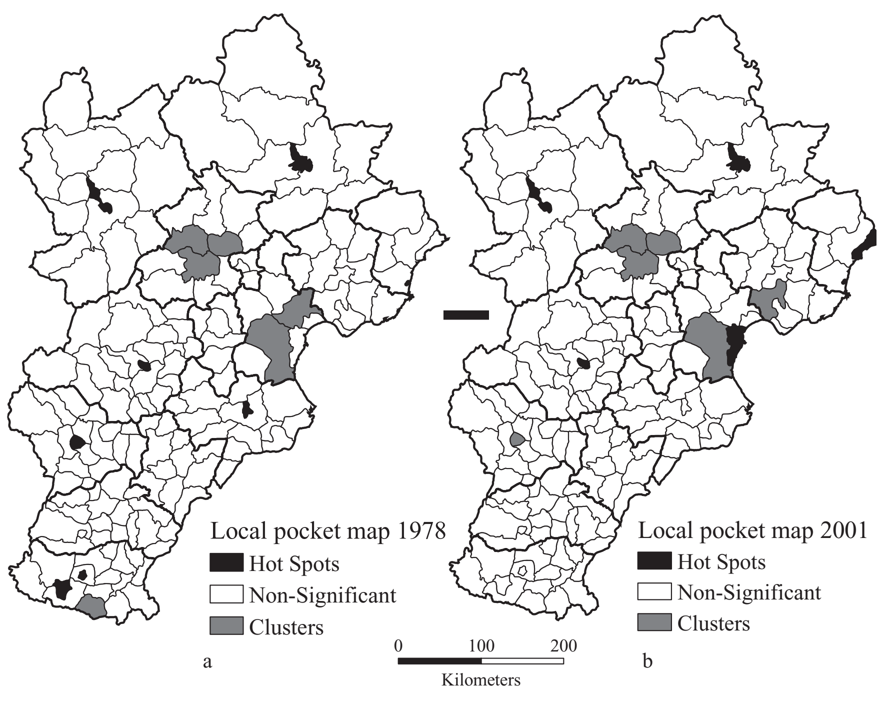

Fig. 8. Local spatial pattern in 1978 (8a) and 2001 (8b)

Second, the superimposed LOWESS curve line moves closer to the regression line from 1978 to 2001.[6] In 1978, a sudden dip in the LOWESS curve indicates a shift from positive to negative autocorrelation (Figure 5), which contributes to the lower value of the global Moran's *I* (Figure 4). This also shows that although globally Greater Beijing shows a positive spatial association, negative local spatial autocorrelation existed at the beginning of the reform, which is more salient in the local pocket map (Figure 8a). In Figure 8a, all counties in the fourth quadrant of the scatterplot (Figure 5) are significantly different from their neighbours and are marked as 'hot spots'. However, such local regimes disappear in 2001, and the LOWESS curve line becomes much smoother (Figure 6). The number of potential leverage and influential units in the fourth quadrant decreases as well. Indeed, some of the 1978 leverage 'fourth quadrant' spatial units move to the first quadrant, such as Shijiazhuang and Tangshan. In addition, the 2001 local pocket map shows fewer 'hot spots' (Figure 8b), indicating the decrease of local non-stationarity during the study period. This reinforces previous findings that the strengthening of the global spatial process was due to the newly formed/expanded clusters, and overall, the spatial structure of Greater Beijing became more uniform.

Third, in 1978, all the leverage points in the fourth quadrant, and also the 'hot spots' in the local pocket map (i.e., Shijiazhuang, Baoding, Cangzhou, Handan, Tangshan, Xintai, Zhangjiakou and Qinhuangdao) are prefecture capitals in Hebei (Figure 1). Although classified as counties, they are more urbanised than their county peers. Such local heterogeneity is the result of a development divide between urban and rural areas in the region existing in the pre-reform period. Mao's industrialisation was urban-centred, while rural areas focused on agriculture with little industry and were resource suppliers for the urban areas. Such a division of labour created a core-periphery structure between the more developed urban areas and less developed rural areas. Local heterogeneities of both the scatterplots and local pocket maps recognise such a two-tier structure. The two-tier structure was shattered due to problematic State-Owned-Enterprises in the cities, the development of rural areas through non-state enterprises, the reduction of urban-rural barriers to trade, and rural migration to urban areas. In the Moran scatterplot and the local pocket map for 2001, the significant differences between the prefecture capitals and their inland peers lessened in most regions (Figures 6 and 8b). Shijiazhuang even changed from a 'hot spot' to a 'cluster' centre (Figure 8b), although the metro areas (especially Beijing-Tianjin and Shijiazhuang areas) were still quite dominant in Greater Beijing's regional development.

Finally, while the urban-rural divide has decreased, a north-south divide however emerged. In 1978, the significant urban-rural divide is throughout Greater Beijing. In 2001, the divide in the southern regions (south of Beijing-Tianjin) become statistically insignificant, while such a divide remained significant in the northern regions (Figure 8b). In addition, the 1978 and 2001 Moran scatterplot maps show that counties around Shijiazhuang formed a new HH cluster in 2001, indicating that as the provincial capital of Hebei, Shijiazhuang and its vicinity had caught up with the traditional Beijing-Tianjin core (Figure 7). Some southern counties even moved from the initial LL cluster to the HL cluster, while the spatial structure of the northern region remained relatively stable. Moreover, the extension of the core was towards the east and the south, excluding the northern counties. Such a north-south divide can be attributed to both natural geography and the development trajectories of the counties. North Hebei, which includes the prefectures of Zhangjiakou and Chengde, is part of the Bashang plateau. The mountainous topography constrains the development of the economy and transportation, especially when compared with the southern prefectures belonging to the North China Plain. Although some military industries were moved to Zhangjiakou during Mao's era, policy failure and geographi-

[6] A series of Moran scatterplots with superimposed LOWESS curve were created but not reported here for the purpose of conciseness, and a trend of smoothing LOWESS curve was observed as well.

cal constraints limited the effectiveness of industrialisation. In addition, historically Zhangjiakou and Chengde were designated the northern gates of Beijing, both militarily and ecologically, which discouraged industrialisation. Meanwhile, Beijing took advantage of such a position by enjoying the external economy of its gates without much positive trickle-down effect, further limiting the development of the northern regions.

5 Analyzing regional development with spatial regression

The above sections use exploratory spatial data analysis techniques to investigate changing patterns of regional development in Greater Beijing. To better understand the spatial structure of regional development, this section analyses the mechanisms of regional development, using recently developed spatial regression techniques (Anselin 1988, 2003; Anselin and Rey 1991; Rey and Montouri 1999; Ying 2003).

5.1 Factors of regional development

In order to further the understanding of regional development during the reform period, we performed regular and spatial regression analyses. The former employed the ordinary least squares estimator, while the later relied on the Maximum Likelihood estimator. Following the production function, and considering the lack of growth rates in comparative prices, we treated the individual year's per capita GDP as the dependent variable indicating the output of Greater Beijing's economic system. The recent economic geography literature has introduced new spatial and institutional factors in determining uneven regional development, especially agglomeration, globalisation, and decentralisation, which were excluded in orthodox production functions (e.g., Krugman 1991; Clark et al. 2000; Scott and Storper 2003). Moreover, the research on China has examined the nature of transitional socialist economies by highlighting the role of institutions, as well as globalisation and decentralisation. Therefore, our review of the economic geography literature and studies on China lead us to include the following alternative as well as orthodox independent variables as potential development mechanisms:

1. per capita fixed asset investment (FIXINV) is selected as the primary factor of input in regional development. Regional allocation of fixed investment is considered a key instrument in China's industrialisation and regional development policy, and fixed assets are a major factor of growth in the literature and in the Chinese economy (Ma and Wei 1997; Wei and Kim 2002). FIXINV is expected to positively contribute to regional development;
2. an important aspect of China's economic reform is the open-door policy, which has resulted in the infusion of foreign direct investment (FDI) and the opening up of the domestic economy. The evidence suggests that FDI contributes to China's regional development, especially in coastal China (Wei 2000; Fujita and Hu 2001). Per capita FDI (FDIPC) is selected as a proxy to capture China's open door policy and the effects of globalisation, and is hypothesised to be positively related to regional development;
3. our fieldwork in Greater Beijing revealed that SOEs still play an important role in regional development in this area. This is very different from southern provinces like Jiangsu (Wei 2004) and Zhejiang (Wei and Ye 2004), where SOEs are no longer major agents of regional development, since the economic transition of China is spatially uneven, and the nature of SOEs is heterogeneous (Hu 2005). There is a consensus among scholars that SOEs generate negative influences on economic development (Lu 1997; Sun and Pannell

1999; Wei and Kim 2002; Yu and Wei 2003). The percentage of SOE's investment in total investment (SOEPCT) is utilised to examine the effects of SOEs on regional development;

4. decentralisation, particularly on the fiscal expenditure side, is instrumental in economic growth (Iimi 2005). Decentralisation is an essential component of China's economic reforms, and has provided local governments with increased financial power and more resources to support local development (Wei 2000). We include per capita local budgetary expenditure (FINEXP) to capture the role of decentralisation and local governments in regional development; and
5. in addition, spatial agglomeration has recently captured the attention of economic geographers. As noticed by scholars (Lu 1997; Yu and Mao 1999; Wei and Fan 2000, Yu and Wei 2003) and suggested by our previous analysis, spatial agglomeration, particularly the urban-rural divide, may have some influence on regional development in Greater Beijing. Urban areas tend to be more developed than their rural peers, and urbanisation stimulates regional development. Urbanisation (URB), represented by the percentage of urban population in the total population, is employed to investigate the effect of urbanisation on regional development.

5.2 *Specification of the OLS and spatial regressions*

We build our model based on the production function, which formally expresses the output of an economic system (per capita GDP in our models) as the product of its input factors: FIXINV, FDIPC, SOEPCT, FINEXP and URB, and all the input factors are hypothesised to be exogenous inputs. Hence, a production function-like regional development mechanism model can be specified as:

$$\mathrm{GDPPC} = \boldsymbol{A} * \mathrm{FIXINV}^{\beta 1} * \mathrm{FDIPC}^{\beta 2} * \mathrm{SOEPCT}^{\beta 3} * \mathrm{FINEXP}^{\beta 4} * \mathrm{URB}^{\beta 5} \tag{1}$$

The exponential form can be transformed into a linear form through logarithm transformation, which results in the familiar linear model:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{2}$$

where $\boldsymbol{y}$ is the logarithm transformed GDPPC; $\boldsymbol{X}$ is the matrix containing the five independent variables in their logarithm transformed forms and a constant term; $\boldsymbol{\beta}$ is the vector of model coefficients; and $\boldsymbol{\varepsilon}$ is the vector of unobservable noise. After the transformation, all the variables are asymptotically normally distributed. In the literature, model (2) is usually calibrated using the OLS estimator (Barro and Sala-I-Martin 1995; Wei and Kim 2002; Yu and Wei 2003). Under the linearity, normality, and homoscedasticity assumptions, the OLS is BLUE (best, least-squares, unbiased estimator). However, when dealing with cross-sectional data on geographic units, spatial dependence (either in the dependent variable or in the error term) could violate the basic OLS assumptions, which might lead to misspecified models (Anselin 1988; Anselin and Rey 1991; Ying 2003).

There are two types of alternatives that incorporate the spatial dependence in the model explicitly (see Anselin 1988; Anselin and Rey 1991). They represent two closely related but different spatial effects. The first is the dependence in the dependent variable, the spatial lag autoregressive model (akin to the time-series autocorrelation), which indicates significant spillover effects from neighbours. The second is the dependence in the regression's error terms, the spatial error autoregressive model, which represents a mismatch between the boundaries of the underlying spatial process and the geographic units where data are organised (Anselin and Rey 1991). The spatial lag autoregressive model can be expressed as:

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{\beta}\boldsymbol{X} + \boldsymbol{\varepsilon} \tag{3}$$

where $\boldsymbol{W}$ is a spatial weight matrix describing the spatial linkage among spatial units (we use the same $\boldsymbol{W}$ as in calculating the Moran's I); $\boldsymbol{Wy}$ is a spatially lagged dependent variable; ρ is the coefficient of $\boldsymbol{Wy}$. The spatial error autoregressive model reads:

$$\begin{aligned} \boldsymbol{y} &= \boldsymbol{\beta}\boldsymbol{X} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} &= \lambda \boldsymbol{W}\boldsymbol{\varepsilon} + \mu \end{aligned} \tag{4}$$

where the spatial dependence is in the error term, and μ is a well-behaved (i.i.d.) error. λ is the spatial autoregressive coefficient of the error, and all other symbols are defined as above.

In addition, Anselin (2003) provides a much broader taxonomy of specifications to address the spatial effects in regression analysis. The two alternatives discussed so far can be categorised to models incorporating spatial externalities in un-modelled effects. Other alternatives belonging to modelling spatial externalities in modelled effects are methodologically appealing. However, due to the following considerations, this study does not extend the model specification beyond the two alternatives already presented. First, in Greater Beijing, due to historically insular regional development practices (Lu 1997), development in one spatial unit is unlikely to have significant influence on neighbouring spatial units. That is to say, in our study region, spatial externalities are more likely incorporated in the un-modelled effects instead of the modelled ones. The second consideration is operational. The calibration means for the two discussed alternatives are readily available in various analytic environments, while relatively established procedures for other model specifications are still under development.

Following the above discussion, after calibration of the two spatial alternatives, we employ a 'specific to general' search procedure to determine the more appropriate model to fit the underlying spatial process. As discussed in Florax et al. (2003), the 'specific to general' search strategies usually dominate the 'general to specific' strategies, such as the Hendry strategy. Since following a Hendry search strategy requires estimation of both restricted and unrestricted spatial models, whilst a 'specific to general' strategy can rely on diagnostic statistics produced from residuals of the OLS estimator, computationally, the latter is preferred. To test spatial dependence in the models, Lagrange Multiplier (LM) robust diagnostics for both models can be calculated from the results of the OLS estimator. The robust LM tests are χ^2 distributed with one degree of freedom (Anselin and Rey 1991; Anselin 1992). As pointed out by Anselin and Rey (1991) and Florax et al. (2003), the comparison between the robust LM diagnostics can be used as guidance to choose the more appropriate alternative spatial model, the larger the significant LM statistic, the better the alternative.

In addition, the inclusion of a spatially-lagged dependent variable, or error term invalidates the use of OLS estimator to calibrate the spatial autoregressive models. Instead, the Maximum Likelihood estimator was suggested as an alternative (Anselin 1988). As a result, the OLS's goodness-of-fit measure, or R^2, is no longer applicable. Likelihood functions based goodness-of-fit statistics, mainly log-likelihood and Akaike Information Criterion (AIC), are used to measure the model's goodness-of-fit (Anselin 1992). Moreover, these statistics are directly comparable to their OLS estimators'. The model with the highest log likelihood or lowest AIC is considered the better fit for the data. Testing of the spatial autoregressive coefficients (either

ρ or λ) can be done through the likelihood ratio test as well, which is calculated as twice the difference between the log likelihood of the spatial autoregressive models and the linear model (in which the null hypothesis of no spatial dependence holds). The likelihood ratio is also χ^2 distributed with one degree of freedom (Anselin 1988; 1992).

5.3 Findings and interpretation

We first examine model (2) by means of the OLS estimator for data in 1995 and 2001 for temporal comparison (Table 3). Multicollinearity among the development mechanisms does not pose a serious problem due to the relatively low value of variance inflation factors (VIF) of the variables (Table 3). Based on the OLS estimation and the LM tests on spatial dependence, we present the results of the alternative spatial model. All model calibration and test statistics are carried out by means of the SPDEP package (Bivand 2004) in R (R Development Core Team 2004) or coded by the authors. The corresponding LM tests for both the lag and error spatial autoregressive models under the different weighting strategies are reported in Table 4.

As the LM tests suggest, the error models are more appropriate, indicating a mismatch between the underlying spatial process's boundaries and the county's boundaries (Anselin and Rey 1991; Florax et al. 2003). Table 4 also suggests that spatial dependence is the strongest when using the border-sharing spatial weighting strategy. Hence, our discussion focuses on the

Table 3. OLS results for 1995 and 2001

	1995			2001		
	Coefficients	t-values	VIF[a]	Coefficients	t-values	VIF[a]
Constant	5.291	14.128***		6.015	11.293***	
FDIPC	0.073	4.505***	1.543	0.066	5.139***	1.591
FINEXP	0.301	3.801***	4.380	0.099	1.335	3.873
FIXINV	0.218	4.827***	2.287	0.285	4.374***	2.476
SOEPCT	0.002	0.051	1.178	–0.090	–1.632	1.150
URB	–0.079	–1.178	4.392	0.113	1.672*	3.375
Model summary						
Adjust R^2:		0.594			0.607	
F statistics:		50.38 on 5 and 164 degrees of freedom, p = 0.00			53.14 on 5 and 164 degrees of freedom, p = 0.00	

Notes: *** significant at 1% level; * significant at 10% level; [a] Variance Inflation Factor.

Table 4. LM tests for the OLS models under different weighting strategies

	BDSH	Dist80	Dist160	Dist240	Dist320
LM_err 1995	79.710	29.172	16.175	8.330	0.793
	(2.19E-19)	(3.42E-08)	(3.05E-05)	(2.15E-03)	(0.301)
LM_lag 1995	63.120	27.188	25.794	5.805	1.924
	(9.87E-16)	(9.55E-08)	(1.97E-07)	(9.09E-03)	(0.110)
LM_err 2001	155.549	83.851	40.995	25.286	0.747
	(5.35E-36)	(2.70E-20)	(7.81E-11)	(2.56E-07)	(0.318)
LM_lag 2001	103.964	58.284	54.713	12.264	1.140
	(1.04E-24)	(1.15E-14)	(7.10E-14)	(2.47E-04)	(0.211)

Note: p-values are in parentheses.

Table 5. Spatial autoregressive error models based on border-sharing spatial weight matrices for 1995 and 2001

	1995		2001	
	Coefficients	z-values	Coefficients	z-values
Constant	5.507	16.343***	5.799	12.570***
FDIPC	0.049	3.402***	0.040	3.635***
FINEXP	0.365	5.047***	0.247	3.683***
FIXINV	0.122	3.068***	0.190	3.597***
SOEPCT	0.007	0.212	–0.029	–0.691
URB	–0.039	–0.687	0.051	0.987
λ	0.665	43.138***[a]	0.709	61.332***[a]
Model summary				
Breusch-Pagan test:	21.13 (OLS: 23.17)		12.94 (OLS: 6.76)	
Log likelihood:	–21.556 for error model (OLS: –43.13)		–28.728 for error model (OLS: –59.39)	
AIC:	59.112, (OLS: 100.25)		73.455, (OLS: 132.79)	

Notes: *** significant at 1% confident level; [a] for λ, this value is the likelihood ratio.

results of the two spatial error autoregressive models based on the border-sharing spatial weight matrix for both 1995 and 2001[7] (Table 5).

Based on the results (Tables 3–5), three interesting findings emerge. First, in agreement with the LM tests, the λ values in both years are highly significant. As a result, and also reflected by the log likelihood and AIC, the spatial error models are improved significantly from their OLS counterparts in both years (Table 5). This indicates that there exists strong spatial dependence in the regional development of Greater Beijing in both years. Furthermore, such spatial dependence mainly appears in the error terms, indicating a mismatch between the boundaries of regional development processes and administrative boundaries of counties for data collection. In order to obtain consistent data for the study, we treat the prefecture capitals in Hebei province and city cores of Beijing and Tianjin at the same geographic level as other counties. Regional development processes in these different geographical units vary dramatically. The city cores of Beijing and Tianjin (and even their surrounding counties) and the prefecture capitals in Hebei represent the urban areas, which are usually more developed and more attractive to FDI than their rural peers. On the other hand, the financial inputs from local governments are more important to local development in the periphery counties. Hence, when we treat these potentially very different geographic units as if they were the same, we witness spatial dependence in the errors. In addition, the Breusch-Pagan test for heteroscedasticity indicates that in both years, there still exists heteroscedasticity for the spatial error models, which reminds us to be cautious in interpreting the model parameters. Moreover, the existence of heteroscedasticity suggests a possible un-modelled parameter structural instability, which actually confirms the North-South divide we found earlier.

Second, the t (or z in spatial regression models) values of the coefficients for FDIPC and FIXINV decrease from the OLS to the spatial regression models, while the t/z value of coefficient for FINEXP increases (Table 5). More importantly, in 2001, the coefficient of FINEXP in the OLS model is not significant. However, once the spatial dependence is incorporated, it becomes highly significant. These findings could also be the result of our choice of the specific geographic units. As mentioned above, FDIPC and FIXINV are proxies for globalisation and the role of the inputs, whereas FINEXP is a proxy for decentralisation and

[7] An extensive set of model results based on other weighting strategies is available upon request, but not reported here to keep the paper concise.

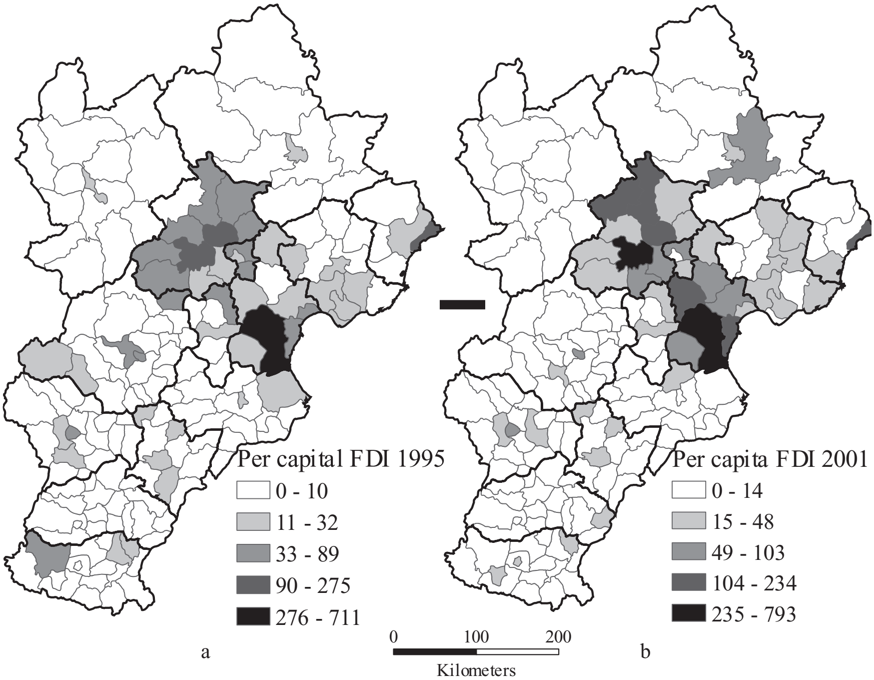

Fig. 9. Per capita FDI in Greater Beijing, 1995 (9a) and 2001 (9b) (US$)

local governments. In Greater Beijing, the impact of globalisation on regional development varies spatially, with more than 80% of the FDI concentrating in the city cores and suburban counties of Beijing and Tianjin and the prefecture capitals in Hebei (Fig. 9). This is because Beijing is the national capital, Tianjin is an open coastal city, and prefecture capitals tend to have better investment environments. FIXINV has a similar pattern, though less extreme than FDI. It also tends to concentrate on the more urbanised areas since cities are more industrialised than the countryside. The OLS models, due to the existence of significant nuisance spatial dependence, tend to exaggerate these effects. Once the spatial dependence is incorporated in the spatial error model, however, we obtain more appropriate values for their effects. A similar rationale applies to FINEXP. FINEXP is the least important factor in the OLS models, but once the nuisance spatial dependence is incorporated, it becomes the most important factor in both years (Table 5). This implies that although FDI and FIXINV have more influence on regional development in the core areas, decentralisation plays a more important role in the whole region.

Third, in both OLS and spatial error models, SOE and the urbanisation factor (URB) are not significant. A significant negative relationship between SOE and regional development, which has been identified for southern China (Wei and Fan 2000; Wei and Kim 2002), is not observed. This might be attributed to Greater Beijing's relatively long dominance of SOEs. Even in 2001, the gross industrial output of SOEs still accounted for 49.4% of the total output, considerably higher than in the southeastern provinces of Shanghai, Jiangsu, Zhejiang, Fujian and Guangdong (27.1%), and even higher than the national average (44.4%) (Table 6). Recent development in the rural areas is likely the reason for the insignificant relationship between urbanisation and regional development, confirming the findings that reform has boosted the development of non-state enterprises represented by rural industrialisation (Wei and Fan 2000; Lu and Wang 2002; Wei and Kim 2002).

Table 6. State-owned enterprises in Greater Beijing

	Gross Industrial output in 2001 (Billion Yuan)		
	All recorded[a]	State-owned	Percentage (%)
National average	9,544.90	4,240.85	44.43
Beijing	290.88	189.38	65.11
Tianjin	294.04	97.44	33.14
Hebei	376.69	188.07	49.93
Greater Beijing	961.61	474.89	49.39
Shanghai	700.39	340.97	48.68
Jiangsu	1,174.78	311.16	26.49
Zhejiang	788.25	119.47	15.16
Fujian	294.50	87.39	29.68
Guangdong	1,403.54	323.67	23.06
South-eastern China	4,361.46	1,182.67	27.12

Note: [a] All recorded enterprises include all state-owned enterprises and non-state-owned enterprises with annual sales revenue of more than 5 million Yuan (CSB 2002).

6 Conclusion

This study uses recent developments in GIS to analyse regional development in Greater Beijing and highlights the importance of spatial effects in regional studies. We demonstrate that GIS and spatial data analysis can reveal the fine spatial characteristics of regional development and present changing spatial patterns and dynamics of regional development in Greater Beijing. The analyses indicate significant positive global spatial autocorrelation, which is dominated by low value clusters with expanding high value clusters. The local analysis finds that the positive global spatial autocorrelation is strengthening, which is likely due to the extension of original clusters and the formation of new clusters. Moreover, the changing trajectories indicate that the reform has projected a positive influence on regional development, as the extended and newly formed clusters are high value clusters.

The analyses also recognises the two-tier, core-periphery structure of the urban and rural areas at the beginning of the reform. Such a structure has been gradually lessening with the deepening of the reform. The local analysis also reveals a north-south divide, which has emerged during the reform. Due to natural conditions and more importantly the development trajectories and geopolitical positions, northern areas have lagged behind their southern peers in development, indicating a unique regional pattern in Greater Beijing. Beijing, as the national capital, enjoys the strategic and ecological protections of its northern gates of Zhangjiakou and Chengde Prefectures, while overall offering only weak positive trickle-down effects. This finding is unfavourable for the latter's development.

To understand factors (mechanisms) of regional development, we construct OLS and spatial regression models using county data for 1995 and 2001. Specification tests indicate that the spatial error (nuisance) model is the more appropriate alternative, and we can draw three conclusions from the analysis. First, the spatial regression models incorporate spatial effects and identify a possible data collection unit (county) and process (development) mismatch due to the treatment of economically different geographic units at the same level. Second, the mismatch tends to exaggerate some location-specific development mechanisms. The importance of FDI and fixed-asset investment, which tend to be more concentrated in the core regions, is exaggerated, while the role of decentralisation, which projects a more uniform impact on the region, seems to be masked. Third, development in Greater Beijing has its own characteristics. Although they are a traditional industrial base, due to the reform, SOEs no longer have significant influence on recent regional development in Greater Beijing. Further, given the inefficiency and difficulty of economic transition, SOEs usually result in lagging regional development, as observed in the southern provinces and at the national level (Wei 2000; Wei and Fan 2000; Wei and Kim 2002; Yu and Wei 2003). This finding complements current literature on China's regional development.

References

Akita T (2003) Decomposing regional income inequality in China and Indonesia using two-stage nested Theil decomposition method. *Annual of Regional Science* 37: 55–77

Anselin L (1988) *Spatial economy: Methods and models*. Kluwer Academic Publisher, Dordrecht

Anselin L (1992) *SpaceStat: A program for the analysis of spatial data*. Tutorial National Center for Geographic Information and Analysis, University of California, Santa Barbara, CA

Anselin L (1995) Local indicators of spatial association-LISA. *Geographical Analysis* 27: 93–115

Anselin L (1996) The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In: Fisher M, Scholten HJ, Unwin D (eds) *Spatial analytical perspectives on GIS*. Taylor & Francis, London

Anselin L (2003) Spatial externalities, spatial multipliers and spatial econometrics. *International Regional Science Review* 26: 153–166

Anselin L, Rey S (1991) Properties of tests for spatial dependence in linear regression models. *Geographical Analysis* 23: 112–131

Barro R, Sala-I-Martin X (1995) *Economic growth*. McGraw-Hill, New York

Bivand RS (2002) Spatial econometrics functions in R: Classes and methods. *Journal of Geographical System* 4: 405–421

Bivand RS (2004) SPDEP: Spatial dependence: Weighting schemes, statistics and models URL: http://cran.r-project.org/src/contrib/spdep_0.2-14.tar.gz

Bradshaw MJ, Vartapetov K (2003) A new perspective on regional inequalities in Russia. *Eurasian Geography and Economics* 44: 403–442

Cheshire PC, Malecki EJ (2004) Growth, development, and innovation: A look backward and forward. *Papers in Regional Science* 83: 249–267

Clark GL, Feldman MP, Gertler MS (eds) (2000) *The Oxford handbook of economic geography*. Oxford University Press, Oxford

Cleveland WS (1979) Robust locally weighted regression and smoothing scatterplots. *Journal of American Statistical Association* 74: 829–836

Cliff A, Ord JK (1973) *Spatial autocorrelation*. Pion, London

CSB (Chinese Statistic Bureau) (2002) *Chinese statistical yearbook*. China Statistics Press, Beijing

Driffield N, Munday M, Roberts A (2004) Inward investment, transaction linkages and productivity spillovers. *Papers in Regional Sciences* 83: 699–722

Dienes L (2005) Observations on the Russian heartland. *Eurasian Geography and Economics* 46: 156–163

Fan CC (1995) Of belts and ladders: State policy and uneven regional development in post-Mao China. *Annals of the Association of American Geographers* 85: 421–449

Florax RJGM, Folmer H, Rey SJ (2003) Specification searches in spatial econometrics: The relevance of Hendry's methodology. *Regional Science and Urban Economics* 33: 557–529

Fujita M, Hu D (2001) Regional disparity in China 1985–1994: The effects of globalization and economic liberalization. *The Annals of Regional Science* 35: 3–37

Getis A, Ord JK (1992) The analysis of spatial association by use of distance statistics. *Geographical Analysis* 24: 189–206

Goodchild MF, Janelle DG (eds) (2004) *Spatially integrated social science*. Oxford University Press, Oxford

Groenewold N, Lee G, Chen A (2007) Regional output spillovers in China: Estimates from a VAR model. *Papers in Regional Science* 86: 101–122

Gu CL, Shen JF, Wong KY, Zhen F (2001) Regional polarization under the socialist-market system since 1978: A case study of Guangdong province in south China. *Environment and Planning A* 33: 97–119

Hill H (2002) Spatial disparities in developing East Asia: A survey. *Asian-Pacific Economic Literature* 16: 10–35

Hu FZY (2005) Deconstructing state-owned enterprises in socialist China under reform: A scalar examination. *Environment and Planning A* 37: 703–722

Huang Y, Leung Y (2002) Analysing regional industrialization in Jiangsu province using geographically weighted regression. *Journal of Geographical System* 4: 233–249

Iimi, A (2005) Decentralization and economic growth revisited. *Journal of Urban Economics* 57: 449–461
Krugman P (1991) *Geography and trade*. MIT Press, Cambridge, MA
Le Gallo J, Ertur C (2003) Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980–1995. *Papers in Regional Science* 82: 175–201
Li Y (1999) *Quyu Fazhan Xin Silu (New thoughts in regional development)*. Economy Daily Press, Beijing
Lieberman O (1994) Saddlepoint approximation for the distribution of a ratio of quadratic forms in normal variables. *Journal of the American Statistical Association* 89: 924–928
Lin GCS (1997) *Red capitalism in South China*. UBS Press, Vancouver
Lu D (1997) *Zhongguo Yanhai Diqu 21 Shiji Chixu Fazhan (Sustainable development of China's coastal regions in the 21st century)*. Hubei Science and Technology Press, Wuhan
Lu M, Wang E (2002) Forging ahead and falling behind: Changing regional inequalities in post-reform China. *Growth and Change* 33: 42–71
Ma LJC, Cui GH (2002) Economic transition at the local level: Diverse forms of town development in China. *Eurasian Geography and Economics* 43: 79–103
Ma LJC, Wei YH (1997) Ideology, national defense, and economic pragmatism: Determinants of state investment in China. *Tijdschrift voor Economische en Sociale Geografie* 88: 211–225
Petrakos G (2001) Patterns of regional inequality in transition economies. *European Planning Studies* 9: 359–383
R Development Core Team (2004) *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria URL http://www.R-project.org
Rey SJ, Montouri BD (1999) US regional income convergence: A spatial econometric perspective. *Regional Studies* 33: 143–156
Sjoholm F (2002) The challenge of combining FDI and regional development in Indonesia. *Journal of Contemporary Asia* 32: 381–393
Skinner MW, Joseph AE, Kuhn RG (2003) Social and environmental regulation in rural China: Bringing the changing role of local government into focus. *Geoforum* 34: 267–281
Scott AJ, Storper M (2003) Regions, globalization, development. *Regional Studies* 37: 579–593
Sun SH, Pannell CW (1999) The geography of privatization in China, 1978–1996. *Economic Geography* 75: 272–273
Tiefelsdorf M (2000) *Modeling spatial processes: The identification and analysis of spatial relationships in regression residuals by means of Moran's I*. Springer-Verlag, New York
Tiefelsdorf M (2002) The saddlepoint approximation of Moran's *I*'s and local Moran's Ii's reference distributions and their numerical evaluation. *Geographical Analysis* 34: 187–206
Wei YH, Ma LJC (1996) Changing patterns of spatial inequality in China, 1952–1990. *Third World Planning Review* 18: 177–191
Wei YHD (1999) Regional inequality in China. *Progress in Human Geography* 23: 48–58
Wei YHD (2000) *Regional development in China: States, globalization, and inequality*. Routledge, London
Wei YHD (2004) Trajectories of ownership transformation in China: Implications for uneven regional development. *Eurasian Geography and Economics* 45: 90–113
Wei YHD, Fan CC (2000) Regional inequality in China: A case study of Jiangsu. *Professional Geographer* 52: 455–469
Wei YHD, Kim S (2002) Widening inter-county inequality in Jiangsu province, China, 1950–95. *Journal of Development Studies* 38: 142–164
Wei YHD, Ye XY (2004) Regional inequality in China: A case study of Zhejiang province. *Tijdschrift voor economische en sociale geografie (Journal of Economic and Social Geography)* 95: 44–60
Ye XY, Wei YHD (2005) Geospatial analysis of regional development in China: The case of Zhejiang Province and the Wenzhou model. *Eurasian Geography and Economics* 46: 445–464
Ying LG (2003) Understanding China's recent growth experience: A spatial econometric perspective. *Annals of Regional Science* 37: 613–628
Yu DL (2006) Spatially varying development mechanisms in the Greater Beijing Area: A geographically weighted regression investigation. *Annals of Regional Science* 40: 173–190
Yu DL, Mao HY (1999) Economic development in China's costal regions. *Jingji Dili (Economic Geography)* 19: 25–30
Yu DL, Wei YHD (2003) Analyzing regional inequality in post-Mao China in a GIS Environment. *Eurasian Geography and Economics* 44: 514–534
Zhao XB (1996) Spatial disparities and economic development in China, 1953–92: A comparative study. *Development and Change* 27: 131–160

doi:10.1111/j.1435-5957.2008.00148.x

Análisis de datos espaciales de desarrollo regional en el Gran Beijing, China, en una plataforma SIG

Danlin Yu, Yehua Dennis Wei

Abstract. Este estudio investiga la dependencia especial y los mecanismos de desarrollo regional en el Gran Beijing, China, empleando técnicas estadísticas espaciales. Hemos detectado una autocorrelación espacial global en aumento y positiva desde 1978 al 2001, y hallado que dicho aumento es el resultado de clusters formados/ampliados recientemente en el área. El análisis local reconoce regimenes locales de estructura espacial urbana-rural de dos niveles al inicio del periodo de reforma. Mientras que la separación urbana-rural fue disminuyendo con la reforma, ha aparecido una separación norte-sur por condiciones naturales locales y trayectorias de desarrollo. Respecto de los mecanismos de desarrollo regional, el análisis de mínimos cuadrados ordinario (OLS) se ve restringido por la existencia de una autocorrelación espacial significativa entre unidades espaciales. Los resultados de análisis revelan que un modelo de regresión del error espacial es una alternativa más apropiada debido a una posible disparidad entre los límites del proceso espacial subyacente y las unidades espaciales donde están organizados los datos. En 1995 y en 2001, los signos de todos los coeficientes de regresión permanecieron iguales para OLS y modelos espaciales. Sin embargo, su magnitud y significancia cambian. En particular, la inversión extranjera directa y la inversión en activos fijos pasaron a ser menos influyentes en el modelo espacial, mientras que el gasto del gobierno local apareció más influyente.

JEL classification: O18, O53, P25, R11

Palabras clave: Desarrollo regional, SIG, análisis exploratorio de datos espaciales, regresión espacial, Gran Beijing

要旨： 本調査では、空間統計学的技術を用いて、中国の大北京地区における地域開発の空間依存性とメカニズムを検証する。我々は、1978年から2001年にかけて世界的な空間的自己相関の強化が明白に現われたことを検出し、また、この強化はこの地域において新たに形成された、あるいは、拡大したクラスターによる帰結であることを発見した。地域分析から、改革時代の初期、この地域は都市部と農村部という二層の空間構造を持つ社会体制であったことを確認している。改革により都市部と農村部の分裂は縮小する一方、地域の自然条件及び開発軌道により南北の分裂が浮上してきた。地域開発のメカニズムについては、空間単位間における有意な空間的自己相関の存在により普通最小二乗法分析（OLS）が抑制を受ける。基礎となる空間プロセスとデータが組成される空間単位の境界線との間に、不一致が起こる可能性があるため、解析結果は誤差空間回帰モデルがより適切な選択肢であることを明らかにしている。1995年及び2001年は、OLS及び空間モデルの双方について、すべての回帰係数が引き続き同じ兆候を示していた。しかし、各係数の重要性と有意性は変化している。特に、空間モデルにおいて外国直接投資及び固定資産投資の影響力が低下する一方、地方政府支出の影響力が浮上してきている。