EXPLORING SPATIOTEMPORALLY VARYING REGRESSED RELATIONSHIPS: THE GEOGRAPHICALLY WEIGHTED PANEL REGRESSION ANALYSIS

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ABSTRACT:

Regression analysis with geographic information needs to take into consideration the inherent spatial autocorrelation and heterogeneity of the data. Due to such spatial effects, it is found that local regression such as the geographically weighted regression (GWR) tends to capture the relationships better. In addition, in panel data analysis, the variable coefficient panel regression can borrow such ideas of spatial autocorrelation and heterogeneity to develop models that would fit the data better and produce more accurate results than the pooled models. Despite the fact that both methods are well developed and utilized, models that take advantage of both methods simultaneously have eluded the research community. Combination of GWR and panel data analysis techniques has an obvious benefit: the added temporal dimension enlarges the sample size hence contains more degrees of freedom, adds more variability, renders less collinearity among the variables, and gives more efficiency for estimation. This research for the first time attempts such combination using a short regional development panel data from 1995 – 2001 of the Greater Beijing Area (GBA), China. A geographically weighted panel regression (GWPR) model is developed and compared with both cross-sectional GWR and panel regression. The study reveals very promising results that the GWPR indeed produced better and clearer results than both cross-sectional GWR and the panel data model. This indicates the new method would potentially produce substantial new patterns and new findings that cannot be revealed via pure cross-sectional or time-series analysis.

1. INTRODUCTION

Geographically weighted regression (GWR) and panel data analysis are well developed data analytical methodologies in geography and econometrics. Recognizing the fundamental question in social science that social processes are not likely governed by any universal "laws", but might vary depending on **where** the processes are investigated, Fotheringham and colleagues (2002) proposed the geographically weighted regression to address this "spatial non-stationarity" issue (Fotheringham et al. 2002, p 9). Panel data analysis, on the other hand, has received increasing interests in econometrics due to its obvious advantages over conventional cross-sectional or time-series data analysis techniques and increasingly available panel datasets (Hsiao 2003; Baltagi 2005). The enlarged sample size gives the researcher more degrees of freedom, reduces the collinearity among explanatory variables hence improves the efficiency of econometric estimates. Studies on both fields have yielded fantastic progresses, yet analysis that takes advantages of both methodologies eludes the research community. Two particular reasons would attribute to the lack of such combination.

First, geographically weighted regression, as its name suggests, focuses almost entirely on the ***spatial*** non-stationarity. The method recognizes that a set of universal coefficients in regression analysis might not be adequate to address the underlying data generating process of the observed geographic dataset. Instead, due either to intrinsic varying mechanisms or potential model misspecification, the regressed relationships are different from location to location. Relationships in regression analysis using geographic information, as evidenced in many a study (Fotheringham et al. 1998; Huang and Leung 2002; Yu and Wu 2004; Yu 2006; Yu et al. 2007), do vary in geographic space. It is only very recently, however, that scholars start to explore the possibility that relationships are potentially varying in not only geographic space, but also **temporal** space (Crespo et al. 2007; Demsar et al. 2008; Yu 2009).

Second, panel data analysis has long been regarded as an important analytical technique for econometric analysis. Although panel data analysis that utilizes geographic information is receiving increased attention in the mainstream econometric analysis (Anselin 1988, 2001; Elhorst 2001, 2003; Baltagi 2005; Anselin et al. 2008; Yu 2009; among others), such development focuses primarily on treating geography as an agent for dependence among cross-section observations. It is well known that the effects of geography are twofold – spatial autocorrelation and heterogeneity (Anselin 2001). Anselin et al. (2008) point out that the case of spatial heterogeneity can be handled by means of standard panel analysis methods. As detailed in Hsiao (2003), there is a full set of methods dealing with the so-called "**variable-coefficient models**" (Hsiao 2003, Ch. 6). While reviewing these well-developed methods, I found they indeed acknowledge the heterogeneous properties of the cross-sectional units. Such treatment, however, doesn't necessarily reflect the important characteristics of **spatial heterogeneity**.

As argued in Fotheringham et al. (2002), spatial heterogeneity is not like statistical heterogeneity that might follow certain distribution (Fotheringham et al. 2002). Instead, spatial heterogeneity is very much **determined** by **distances**. In GWR analysis, the spatial structure that follows the "First Law of Geography" (Tobler 1970) and generates spatial heterogeneity can be well simulated via the distance decaying Gaussian or Gauss-like kernel functions in which distance is the parameter. While in the "variable-coefficient" panel data analysis, **such important characteristics of geographic information are barely utilized**.

It is with this recognition that this proposed research attempts for the first time to combine research merits of both GWR and panel data analysis to produce new geo-panel data analysis methodology. In this particular study, I will utilize a set of regional development panel data from 1995 – 2001 of the Greater Beijing Area (GBA), China to develop such methodology. The results from this geo-panel analysis will be compared to the ones acquired from conventional methods. It is hoped with the new methods, we'll be able to discover new insights that was previously hidden in the dataset. Such new findings would potentially bring significant new understandings of regional studies in China.

The following section will give detailed reviews of the methodological development in spatiotemporal analysis from both geographic and econometric perspectives. This is followed by an introduction to the study region, GBA, China and the data. The fourth section extends the discussion of GWR and panel analysis and elaborates the development of the geographically weighted panel regression (GWPR) and its implementation. Results from applying the methods to the dataset will be reported in the fifth section. The study concludes with summary and future research foci.

2. BACKGROUND

2.1 Studies on spatiotemporal models and processes

Spatial data analysis techniques have borrowed many ideas from time series analysis. One of the most important aspect of spatial data, spatial autocorrelation, for instance, resembles the series autocorrelation, though differs in the way **lags** are defined (Anselin 1988; Anselin et al. 2008). The fundamental similarity between spatial data and time series data is that both follows a "*neighbors are similar*" Law. In spatial data, this is Tobler's (1970) "First Law of Geography", which resembles the common wisdom in time series analysis that observations close together in time will be more closely related than observations further apart. Another aspect of spatial data is the spatial heterogeneity, which constitutes the other aspect of Tobler's Law that "*non-neighbors are dissimilar*". It is the investigation of this spatial heterogeneity that leads to the development and implementation of the geographically weighted regression (Fotheringham et al. 2002). However, the current GWR analysis utilizes largely cross-sectional data instead of panel data. Though recent studies start to consider temporal information in GWR analysis (see Desmar et al. 2008; Yu 2009; Yu and Lv 2009), integrating time series data in GWR analysis is still under-developed.

Integrating time series into geographic analysis is termed **spatiotemporal analysis**. This spatiotemporal modeling technique has been applied to a wide range of scientific and engineering fields. Studies in the genre, however, focus mainly on the spatiotemporal clustering of observations and interpolation. For instance, Knox (1964) investigates the space-time interaction of epidemics and develops the Knox test to determine whether or not there are apparent spatiotemporal clusters. Bilonick (1985) and Kyriakidis and Journel (2001) apply the spatiotemporal models to determine space–time trends in the deposition of atmospheric pollutants. Bras and Rodrígues-Iturbe (1984), Armstrong et al. (1993) apply spatiotemporal kriging procedure to estimate rainfall in various regions. Hohn et al. (1993) develop spatiotemporal model to characterize population dynamics in ecology, to name but a few.

As pointed out by Kyriakidis and Journel (1999), joint analysis of space and time in a spatiotemporal framework mainly builds on the extension of established spatial analytical techniques that are widely applied in the fields of geology (Journel and Huijbregts 1978), forestry (Matérn 1980), and meteorology (Gandin 1963). Such extension usually treats time as an added spatial dimension, hence enlarges the two-dimensional geographic space to a three-dimensional **geographic-time** space. However, simple extension as such might not be all that plausible due to the fundamental differences between geographic space and time (or ***geographic*** space and ***temporal*** space). Geographic space represents a state of coexistence, in which there can be multiple directions. While temporal space represents a state of successive existence, a nonreversible ordering in only one direction is present (Snepvangers et al. 2003). Isotropy is well defined in **geographic** space, but has no meaning in a space-time context due to the ordering and nonreversibility of time.

The majority of the above mentioned studies are largely confined in the field of geostatistics (Kyriakidis and Journel 1999). The primary goals of these studies are fairly similar (Snepvangers et al. 2003): to predict an attribute $z = \{z(s,t) \quad s \in S, t \in T\}$ defined on a geographical domain $S \subset R^2$ and a time interval $T \subset R^1$, at a space–time point (s_0, t_0), where z was not measured. The prediction is to be based on n geographic measurements at t time intervals which constitute the nt points (s_i, t_i), with i=1, … , n. Seldom do the studies focus on relationships between regressed variables in the spatiotemporal framework. Just as in a pure cross-sectional scenario, regressed relationships tend to vary from geographic location to geographic location (the essence of the GWR method); it is very tenable that regressed relationships might vary from spatiotemporal location to spatiotemporal location.

2.2 The variable coefficient panel data analysis model

Panel data analysis has been well developed in econometrics for decades (Baltagi, 2005). It differs from pure cross-sectional or time-series analysis by incorporating both dimensions. Apparently, the added dimension enlarges the sample size hence contains more degrees of freedom, adds more variability, renders less collinearity among the variables, and gives more efficiency for estimation (Hsiao, 2003). Panel data analysis with geographic data has only recently attracted scholarly attention (Anselin 1988, 2001; Elhorst 2001, 2003; Anselin et al. 2008; Lv and Yu 2009). The focus of this trend of *spatial panel data analysis*, as termed in both Elhorst (2001, 2003) and Anselin et al. (2008), is primarily an extension of the spatial data analysis techniques with cross-sectional data. Estimations of the parameters focus on the pooled model that either incorporates a spatial lag term in the RHS of the equation or a spatial error term. The potential of heterogeneous parameters are usually overshadowed due to the less accurate prediction performance than the pooled model (Baltagi 2005; Baltagi et al. 2008) or a willingness to trade bias over a reduction in variance (Toro-Vizcarrondo and Wallace 1968).

Of course, this is not to say that panel data analysis can't deal with heterogeneous parameters. As a matter of fact, Hsiao (2003) indicates that "when data do not support the hypothesis of coefficients being the same, yet the specification of the relationships among variables appears proper or it is not feasible to include additional conditional variables, then it would seem reasonable to allow variations in parameters across cross-sectional units and/or over time as a means to take account of the interindividual and/or interperiod heterogeneity" (p.141). Many a study also indicates that pooling parameters over cross-sectional units might not be very tenable (Robertson and Symons 1992; Pesaran and Smith 1995; Pesaran et al. 1999). This is especially true when the cross-sectional units are samples from geographic space, as dictated by the "First Law of Geography" (Anselin 1988). However, if all the coefficients are treated as fixed and different for different cross-sectional units in different time periods, there will be more unknown parameters than available observations (N by K by T unknown parameters with only N by T observations). Apparently, we won't be able to estimate the unknowns from the data. To solve this dilemma, we need to search for approaches that allow the coefficients to differ, yet reduce the unknown parameters to be less than the available data. Hsiao (2003) introduced two potential approaches to solve the dilemma. First the coefficient is separated to three components including a trend, an individual variation and a temporal variation. Then either by treating the individual and temporal variations as fixed or random, we can impose restrictions (when fixed) or assume/estimate a distribution (when random) to drastically reduce the unknown parameters. It is found, however, such treatments are usually rather computationally prohibitive. Applications of those methods are rather limited (Hsiao, 2003).

Other than the computational consideration, the variable coefficient panel analysis is largely an **aspatial** approach in dealing with geographic information. No matter the fixed or the random approach, if the cross-section is on geographic space, it is apparent that the important characteristics of geographic information (governed by the "First Law of Geography) are not utilized. Apart from the above fixed with restriction, and random with distribution approaches, a third approach, in which the varying coefficients can be obtained via functions of the spatiotemporal locations, might seem to be rather tenable an alternative, yet studies are seldom extended in this direction.

3. STUDY AREA: THE GREATER BEIJING AREA, CHINA

The GBA is located in the Northern China Plain, includes Hebei province and Beijing, Tianjin provincial municipalities. The region is also often called the Capital Economic Circle, or Jing-Jin-Ji region. The area has in total 170 county level spatial units (Fig. 1). During the pre-reform era, due to the central location of Beijing as the national capital, GBA was one of the most developed heavy industry centers in China. As pointed out by Lu (1997), during the 1950s, 95% of the national and local investment went to heavy industries. Such massive investment brought tremendous economic gains for GBA under Mao's China (Yu and Wei 2008), and also formed the heavy industry-centered and government-sponsored economic structure.

During the reform era, however, as China gradually integrates its own economy to the global economic system, the changed global and regional geopolitical environment enables the southern provinces to achieve a rapid economic recovery. While in the mean time, the central government takes a very cautious attitude towards the reform in its heart regions, the GBA. Reform policies are experimented in the southern provinces and gradually extended to other parts of the nation as they are proven successful. Under such scenarios, many a scholar discovers an interesting trend in China's regional development dynamics during the first decade of reform that regional inequality converges (Yu and Wei 2003). Such convergence, however, reflects only a residual effect of China's economic distribution before the reform era. As a matter of fact, regional inequality in China resumes and deepens after the 1990s (Yu and Wei 2003). Yet this cautious attitude of the government again creates a fairly different regional development pattern in GBA than those often observed and studied in the southern provinces.

Recent research focus on the southern provinces for the reform China is well-justified as these regions spearhead China's economic dynamics during the reform era. Yet it is quite unrealistic to assume that development status and dynamics in these regions would be representative of China's regional development. As argued above and presented in Yu and Wei (2008), the patterns and status of the GBA's development might differ drastically from its southern peers. Hence an exploration to this particular region might shed light towards a more complete understanding of China's regional development.

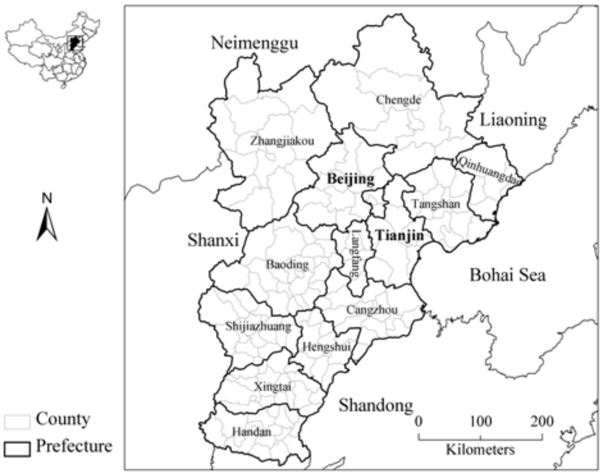

Figure 1: Location of GBA, China

Yu (2006) and Yu and Wei (2008) have pioneered the work in this direction. Their analyses of GBA indeed brought some fairly interesting results as different from the often studied southern provinces. For instance, they found that in contrast to the usually negative effect of investment in China's state-owned-enterprises (SOEs) in economic development, SOEs do not have significant impact in GBA (Yu and Wei 2008). Not surprisingly, they also identified that the governmental supports and investment dominate the performance of local economies. Agreeing with the results found in the southern provinces, attracting foreign direct investment seems to be an important factor to boost local economies as well. The increased urbanization, however, doesn't seem to be well associated with local economic performance.

Recent works in China's regional studies employ some rather recent development in GIS and spatial data analysis such as spatial regression and geographically weighted regression (Leung and Huang 2002; Yu 2006). These studies, however, resemble many others in that analyses are done from a cross-sectional aspect. Though data with time dimension are used, panel data analysis is left as an unexplored area. As argued by Baltagi (2005), cross-sectional analysis with relative stable distribution might hide a multitude of changes. Even with repeated cross-sectional analyses at different time periods, the dynamics of adjustment that are often of more interests will not be present. The current study hence intends provide better understanding of GBA's regional development via the application of advanced spatial and temporal analytical methodologies with a short panel from 1995 to 2001. In particular, to model the relationship between GBA's economic performance and a set of identified mechanisms, a geographically weighed panel regression analysis is developed and applied. The practice intends to capture the spatiotemporal dynamics of GBA's regional development from 1995 – 2001.

4. METHODOLOGY: GEOGRAPHICALLY WEIGHTED PANEL REGRESSION ANALYSIS

The central idea of geographically weighted panel regression (GWPR) analysis is fairly similar to the cross-sectional GWR analysis. In GWPR, however, it is assumed that the time series of observations at a particular geographic location is a realization of a smooth spatiotemporal process. Such spatiotemporal process follows a distribution that closer observations (either in geography or in time) are more related than distant observations. Depending on the panel analysis intends to pool over geographic (cross-sectional) or temporal observations, we can apply different models to simulate such process. In this particular study, since our panel data is a relatively short panel (7 years), but covers more cross-sectional units (170 counties), I will focus the discussion on developing models that simulate the spatiotemporal process over geographic space. The other scenario with more temporal observations can follow similar route of arguments.

If we only concern the regression coefficients vary over cross-sectional units (geographic space), the spatiotemporal process is effectively reduced to a spatial process just as in GWR analysis. Unlike GWR analysis, however, the spatial process is applicable to all the temporal observations simultaneously and is assumed to be temporally invariant (due to the short period). Based on such postulation, the GWPR on short panel can be seen as an expanded version of the cross-sectional GWR analysis to panel data. Following similar arguments as in GWR, a bandwidth (or bandwidths in adaptive kernel) can be obtained for each location to determine a set of local sampling locations. Observations within the local sampling locations will be weighted based on a kernel function just as in GWR (Fotheringham et al. 2002). Such weighting will be applied to all temporal periods. Within these local sampling locations, it is assumed that the panel is poolable over geographic space. A fixed or random effects model as detailed in Baltagi (2005) can be applied to obtain the coefficients of the explanatory variables at that specific location.

From the experiences of applying GWR with cross-sectional data, we found that Gaussian or Gaussian-like kernel density functions work rather well in simulating the spatial distance-decaying process (Fotheringham et al. 2002). Similar principles apply to the GWPR scenario. Specifically, a spatial kernel function will be established very much the same as the kernel functions in cross-sectional GWR analysis. The kernel function and its bandwidth will be used to determine the size of the subsample around any particular geographic location and assign weights to existing data points. Unlike the cross-sectional GWR model, this subsample will be a subsample of panel data that include both spatial and temporal observations. Weights generated from the spatial kernel function, however, will remain temporally invariant to keep the model simple. Temporally variant weights can certainly be generated by introducing a temporal scalar for each time period. The essence of the method would not change. After the sub-setting and weight-assigning, we can then apply a panel regression procedure for each location. Either a fixed effects or random effects panel analysis model will be applied to this subsample and obtain a unique coefficient for that particular location. The procedure can then be repeated for all the geographic locations to obtain the set of variable coefficients over geography.

One of the key components in applying locally weighted panel regression is the size of the local samples, per GWR terminology, the bandwidth of the (fixed) kernel function or the nearest neighbor of the (adaptive) kernel function. Two criteria are applied in cross-sectional GWR analysis. One is based on the cross-validation score (CV) and the other the Akaike Information Criterion (AIC) (see Fotheringham et al. 2002 for detail). At the current stage of development of GWPR, I focus only on utilizing the cross-validation score to determine the local sample size and the kernel weighting. Similar to how CV score is determined in cross-sectional GWR analysis, CV score is calculated based on the average of the dependent and independent variables over time:

$$CV = \sum_{i=1}^{n} [\bar{y}_i - \hat{\bar{y}}_{\neq i}(b)]^2 \tag{1}$$

where $\bar{y}_i$ is the average over time of the dependent variable at location *i*, $\hat{\bar{y}}_{\neq i}(b)$ is the estimated dependent variable with bandwidth *b* and excluding observation in location *i*.

Implementation of GWPR is done with R scripts (R Development Core Team, 2009). I have extended the cross-sectional GWR codes (SPGWR, Bivand and Yu, 2009) via incorporating panel analysis codes (PLM, Croissant, 2009). The codes are available upon request. At the current stage, estimation of the *geographically* variable coefficients, pseudo-significance t test for each coefficient are done.

5. RESULTS AND DISCUSSION

Based on previous studies in GBA, China (Yu, 2006; Yu and Wei 2008), five particular variables are identified for the exploration of regional development. Specifically, for each county, the per capita GDP (GDPPC) value is used as a proxy for regional development. Per capita fixed asset investment (FIXINVPC), per capita financial income (FININCPC), per capita foreign direct investment (FDIPC), and urbanization level (URB) are chosen as the development mechanisms. Among them, FIXINVPC represents the central government's support to local economic development. FININCPC indicates the local governments' financial capability. The financial capability of local governments would represent their potential possibility to support regional development. FDIPC is usually argued as the agent of globalization in China's regional development studies (Wei 2000, Fujita and Hu 2001). URB attempts to capture the co-movement between economic development and urbanization in China. The econometric relationship between development and mechanisms takes the form:

$$GDPPC = A \times FIXINVPC^{\beta_1} \times FININCPC^{\beta_2} \times FDIPC^{\beta_3} \times URB^{\beta_4} \tag{2}$$

A logarithm transformation of the above production-function alike equation yields a linear relationship between the logarithms of the above variables, and takes the usual form:

$$Y = X\boldsymbol{\beta} + \varepsilon \tag{3}$$

where *Y* is the logarithm transformed GDPPC; *X* is the matrix containing the four 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.

For short panel data such as the one we are using, it is rather hard to justify the application of a random effect model (Baltagi, 2005). A Hausman's test suggests just that. In addition, *F* test indicates that the dataset used has strong individual effects than time effects, which justify our pooling over cross-sectional units instead of time. The analysis hence discusses results generated from fixed effect panel analysis that has individual (cross-sectional) effect.

By using an adaptive kernel function, cross-validation for GWPR points out an optimal local sample (which minimizes the CV score) contains 26 geographic observations. Table 1 presents the results of an individual fixed effect panel regression analysis. Figure 2 gives the results generated by GWPR. Only coefficients that are pseudo-significant at 95% confidence level via the pseudo-t test are greyed. For comparison purposes, a cross-sectional GWR analysis using only data from the year 2001 is presented in Figure 3 as well.

From reading the tables and figures, a few observations emerge. First, resonating with previous findings (Yu and Wei 2008; Yu 2009), it seems no matter in aspatial panel analysis or cross-sectional GWR or GWPR, per capita foreign direct investment, which was usually deemed the agent of globalization, doesn't really play much of a role in the Greater Beijing Area. Such an observation would trigger a very interesting question: as GBA *is* one of China's economic centers, and GBA *is* progressively globalizing, why isn't globalization contributing to local regional development. As a matter of fact, according the GWPR analysis, FDIPC actually significantly (at 95% confidence level) works against regional development in Beijing and the inland Hebei counties that are adjacent to Beijing (Figure 2c). Possible answers would include the fact that FDIPC might not be a very good agent of globalization in this specific geography as it was originally identified in studying the southern China. In this regard, it might be more appropriate to identify a different agent of globalization in GBA, such as number of international visits. It might also attribute to the fact that, however, GBA's globalization process is also heavily involved with localization process, as Beijing is not only an economic center, but a cultural and political center as well. In addition, it is understandable that comparing with their southern peers such as Zhejiang and Jiangsu, regions in GBA, especially counties in inland Hebei province were not quite attractive during the period from 1995 – 2001 to FDI.

	Estimate	Std. Error	t-value	Pr(>|t|)
FININCPC	0.528	0.016	32.209	0.000
FDIPC	0.002	0.002	0.798	0.425
FIXINVPC	0.073	0.012	6.280	0.000
URB	0.287	0.044	6.527	0.000

Total Sum of Squares: 54.651
Residual Sum of Squares: 10.921
F-statistic: 1017.07 on 4 and 1016 DF, p-value: < 2.22e-16

Table 1. Panel regression analysis of GBA, China

Second, all the analyses point to the most important regional development mechanism in GBA is the local financial capability (figures 2b and 3b). This further supports the fact that decentralization in China, even at a location that is so centralized is working in favor to regional development. Although the two geographically weighted analysis captured the fact that Beijing, as the centralization center, benefits rather less from the local financial capability than its peers in Hebei and Tianjin. The difference between GWPR and cross-sectional GWR in 2001, however, remains quite interesting. With more information available for estimation, GWPR clearly picks out an urban area oriented trend that more urbanized regions benefit more than the less urbanized ones. This shall not come as a surprise, however, considering the administrative characteristics and fiscal distribution in China. Counties usually don't have their own fiscal revenue per se. The decentralization of fiscal power stops at the prefecture level. Within a specific prefecture, it is like a small regime of a centralized entity, in which the ones that are at the top tier enjoy more of the benefits than the ones that are below. This feature, however, is rather obscured in the cross-sectional GWR analysis in 2001. Similar conclusions can be drawn for per capita fixed asset investment, which is used to represent the central government's support for regional development. It seems that the central government's support is rather important mainly in the peripheral counties than in the more urbanized ones. From Figure 2a, support from the central government is not even significantly related with local development in Beijing and Tianjin.

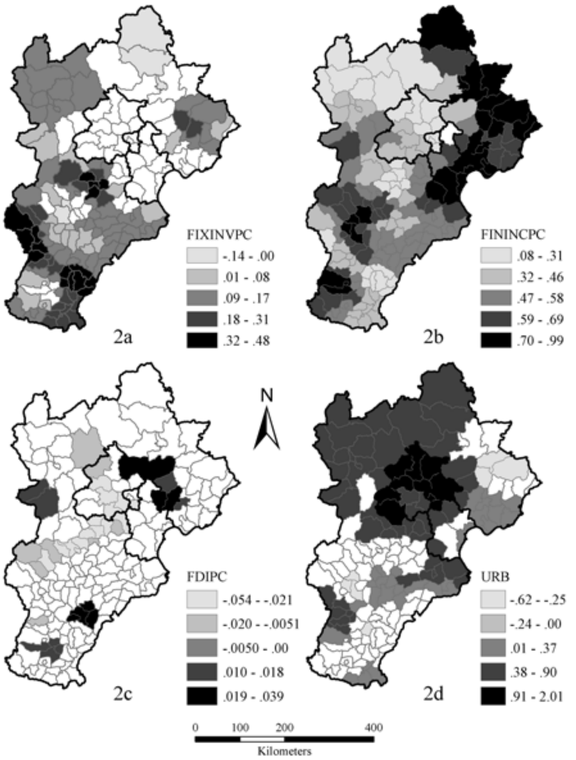

Figure 2. Coefficients surfaces generated from the GWPR, only locally pseudo-significant counties are greyed: 2a. coefficient surface for per capita fixed asset investment; 2b. coefficient surface for per capita financial income; 2c. coefficient surface for per capita foreign direct investment; 2d. coefficient surface for urbanization.

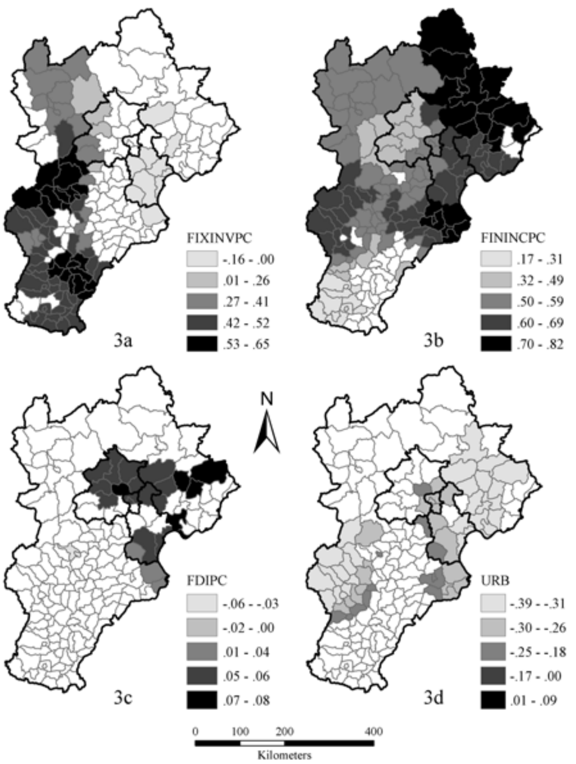

Figure 3. Coefficients surfaces generated from the cross-sectional GWR in 2001, only locally pseudo-significant counties are greyed: 3a. coefficient surface for per capita fixed asset investment; 3b. coefficient surface for per capita financial income; 3c. coefficient surface for per capita foreign direct investment; 3d. coefficient surface for urbanization.

Third, quite interestingly, when we are comparing Figures 2a and 2b, especially the shadings of the significant values, it is almost immediately clear that the two types of governments' supports, i.e., the central and local governments (represented by fixed asset investment and local financial income), are not only the strongest supportive mechanisms for regional development in GBA, but also complementary to each other across the region. Such mutual-complementing pattern is barely discernible in the cross-sectional GWR analysis with 2001 data (Figures 3a and 3b). It is, however, quite evident in the GWPR maps in which more information participated in the analysis. This mutual-complementing regional development mechanism is a significant discovery in the regional development studies in GBA, China. This result suggests a balanced investment strategy was on-going from 1995 – 2001 in GBA, in which the central government purposefully invested more on regions that had less financial self-dependence. Such an investment strategy reflects the developing history of GBA that it used to be one of the heavy industrial centers in China, and traditionally dependent heavily on government's supports for its economic development. Economic reform that started in 1978 changed the developing modes all across China drastically, yet the investment structure remains quite resistant. Such a pattern would not be immediately observable from cross-sectional analysis. With added dimension of temporal information, and the integration of geographic weighting techniques, the GWPR is able to make rather thorough discoveries.

Fourth, yet the most interesting conclusion drawn via applying GWPR is the relationship between urbanization and regional development in GBA. Our previous studies (Yu and Wei, 2008; Yu 2009) with cross-sectional analysis indicates urbanization is at best marginally contributing to regional economies. This is also reported via the cross-sectional GWR analysis (Figure 3d). The relationships between urbanization and per capita GDP are not only mostly negative, but also not significant at all in many counties. GWPR, however, suggests otherwise. As a matter of fact, via modeling with the added temporal information, it stands out immediately that more urbanized an area, higher the level of per capita GDP. This is especially true in Beijing, Tianjin and the capital city of Hebei, Shijiazhuang (figure 2d, place reference see figure 1). This finding supports the common wisdom in GBA, China that large cities tend to be more developed than less urbanized areas. More importantly, this finding solves a seemingly anti-intuitive dilemma that was usually obtained from cross-sectional analysis that urbanization is not significantly related with regional development. The advantage of modeling with more information speaks for itself again here.

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