A Spatial Econometric Examination of China's Economic Growth

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Abstract
It is universally acknowledged that China's recent economic growth involves distinct spatial patterns across the 30 provinces. Despite this, most studies analyze provincial economic growth patterns using cross-sectional methods that average over all provinces. This study analyzes China's recent economic growth at a provincial level using non-parametric and Bayesian spatial econometric methods that allow for locally linear spatial variation in the relationships being analyzed.

I. INTRODUCTION

There is a large literature on China's recent economic growth during the first and second phases of economic reform covering the periods 1978 to 1984 and 1985 to the present, respectively. Many of these papers point to the geographic pattern of economic growth in post-reform China (see Chen and Fleisher, 1996; Howes and Hussain, 1994; Khan, Griffin and Risken, 1999; Knight and Song, 1993; Liu,1992; Raiser, 1998; Rozelle, 1994; Rozelle, Taylor and DeBrauw, 1999; Sachs, Woo, Chang and Bao, 1999; Tsui, 1991.) Some studies examine convergence of regional income aggregates, (Chen and Fleisher, 1996; Raiser, 1998), others focus on reform policies that target coastal regions for development with the hope that these areas will serve as an engine of growth to pull the entire economy along the path of economic development (Liu, 1992), some study explicit geographical determinants of economic growth (Sachs, Woo Chang, and Bao 1999), others look at regional income inequality (Khan, Griffin and Risken, 1999) or migration of labor from rural to urban areas (Rozelle, Taylor and DeBrauw, 1999).

Despite the fact that all of these issues under study involve a spatial distribution of sample data, none of these studies employ spatial econometric methods to analyze the data. In fact, to this author's knowledge, there are no published studies involving Chinese provincial data that rely on spatial econometric methods. This is disturbing because the relationships analyzed in these studies seem likely to vary over space. Important influences in one region of the country may be less important in other regions. Ideally, statistical methods used in these studies should allow for variation in the relationships under study across provinces.

In this study we examine a model set forth in Sacks, Woo, Chang and Bao (1999) to explain provincial variation in GDP growth rates over the period 1978-1997 as a function of geographic factors. This model was estimated using least-squares regression methods that provide a global or average summary of important influences on provincial growth. A similar relationship is studied here using spatial econometric methods that allow for variation in the influences at work over the cross-section of provinces. Aside from the specific example provided in this study, a broader point is that researchers interested in essentially spatial phenomena involving China's development at the provincial level can employ spatial econometric methods that allow inferences at the provincial level.

Non-parametric and Bayesian methods are introduced in Section 2 of the paper that produce locally linear regression estimates. These methods are used in Section 3 to produce estimates for a regression relationship analyzed by Sacks, Woo, Chang and Bao (1999). The locally linear estimates allow us to examine the impact of geographic and economic factors in post-reform economic growth at the provincial level. Inferences based on these estimates that allow for spatial variation in the influences across the provinces lead to different conclusions than those from a global analysis based on estimates that reflect sample averages.

II. GEOGRAPHICALLY WEIGHTED REGRESSION

In this section we introduce the geographically weighted regression model (GWR) that will be used to examine a regression relationship set forth in Sacks, Woo, Chang and Bao (1999) (SWCB hereafter). This spatial econometric method uses distance weighted sub-samples of the data to produce locally linear regression estimates for every province. Each set of

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parameter estimates is based on a distance-weighted sub-sample of "neighboring observations", which has a great deal of intuitive appeal in this application. While this approach has a definite appeal, it also presents some problems that plague non-parametric estimation methods when they encounter outliers. A Bayesian variant of the method introduced in LeSage (1999) is used to produce robust/heteroscedastic GWR estimates. Estimation results are presented in the next section.

SWCB set forth a theoretical growth model that incorporates geographical and reform factors in a production function for the GDP of each province:

$$Q_i = A(K,R)F(K,L) \quad (1)$$

Where Q_i denotes the GDP of province *i*, *K* and *L* represent capital and labor used in the constant returns production process *F*, and *A* is the productivity factor that models efficiency and productivity gains during the reform and development process. This is modeled as a function of both capital and reform factors *R*. The motivation for including capital is a learning-by-doing argument.

Their model centers on the fact that the major differences among provinces are initial income levels and natural geography. A host of geography factors such as distance to world markets, transport costs, elevation and terrain, coastline length and population near the coasts are explored as potentially important explanatory variables.

They use this endogenous growth model to suggest that the economic reform factors could lead to a take-off for provinces that have natural geographical advantages. This they argue results in domestic and foreign capital investments that spur labor migration and more capital flow into provinces with advantageous geography. This model is consistent with the observed fact that coastal provinces have exhibited higher economic growth than interior provinces during the second phase of economic reform covering the period from 1985 to the present.

An empirical implementation of the model involves using regression to assess the relative importance of geographical factors in explaining cumulative economic growth (GDP growth rates) over the period 1978 to 1997. The theoretical model suggests implementing the following regression relationship:

$$\hat{Q}_i = \beta_0 + \beta_1(1+s_i)^{-1} + \beta_2 T_i + \beta_3 K_{i0} + \beta_4 L_{i0} + \varepsilon_i \quad (2)$$

Where $\hat{Q}_i$ represents the time rate of change in GDP for province *i*, S_i is the distance of province *i* from world markets, T_i is a set of geographical characteristics of province *i* and K_i, L_{i0} denote initial period capital and labor endowments of province *i*.

In moving to empirically implement the regression expression in (2), SWCB replace capital with GDP per capita as a proxy. They argue that labor is proportional to capital and determined by the amount of capital, eliminating this argument from the relationship. The ultimate model that is estimated using least-squares is:

$$\hat{Q}_i = \gamma_0 + \gamma_1(GDP/POP)_{i0} + \gamma_2(1+s_i)^{-1} + \gamma_3 T_i + \varepsilon_i \quad (3)$$

Where *s* is the distance from the geographic center of the province to the nearest coastline measured in kilometers, and T denotes a host of alternative geographic explanatory variables that were tested for significance. The variable $(GDP/POP)_{i0}$ represents GDP per capita in 1978, the initial period.

From the least-squares results, SWCB conclude that coastline length and proportion of the population within 100 kilometers of the coastline or ocean-navigable waterway were statistically significant geographical explanatory variables. The distance variable s_i had the correct sign but was insignificant in three of the best fitting models. Model fits were between *R*-squared of .55 and .75, depending on the particular configuration of geographical explanatory variables used. The coefficient estimates also showed that initial capital and labor endowments were negatively related to GDP growth rates across the provinces, suggesting convergence in the growth rates over time. This was also interpreted as consistent with the model hypothesis that abundant labor supply led to high rates of return for capital thereby attracting a flow of foreign investment that fostered economic growth.

The following four conclusions are drawn by SWCB.

1. All provinces grew rapidly by international standards during the reform period from 1978-1997. They draw this inference from the fact that the intercept term in the regression model was by far the most significant explanatory variable.
2. The initial income level was not the reason for divergence in GDP levels among the provinces. They state that this is in contrast to other studies that argue for the importance of initial capital endowments. Their conclusion is that initially low income levels can work to produce a high labor-to-capital ratio, leading to a higher rate of return for capital that attracts more capital resulting in economic growth. This inference is drawn from the negative coefficient on the (GDP/POP) variable in the regression.
3. Geographic factors are important in explaining growth across the spatial sample of provinces. They draw this inference from the fact that their model excludes exogenous economic variables

such as investment and labor input, forcing these variables to exert impacts through endogenous geographical factors.

4. The important geographic factors were coastline length and proportion of the population near the coasts. Distance and elevation variables were found to be less important.

Most of these conclusions regard comparisons across the provinces, so the ability of the GWR model to produce estimates of the regression relationship for each of the 30 provinces is appealing. It is interesting to note that official Chinese economic development strategies may be aimed at targeting coastal provinces for investment in the hope that spatial spillover provide the impetus for a takeoff in neighboring provinces (see Zhao, 1981).

Spatial heterogeneity also seems likely in provincial data samples. Much of the literature on China has heterogeneity as its theme. The existence of outlying or aberrant observations for a handful of provinces will not come as a surprise to those that have studied provincial data. Despite this intuitive and commonly accepted knowledge, investigators have often relied on estimation methods that assume constant variance (e.g., Raiser, 1998; Rozelle, Taylor and DeBrauw, 1999; Sacks, Woo, Chang, and Bao 1999).

Given that spatial heterogeneity implies variation in the regression relationship over space, we might expect to draw different inferences regarding the relationship between economic growth and geographic factors for the various provinces. This is in stark contrast to a single cross-sectional regression that produces a set of estimates that reflect an average relationship between economic growth and the explanatory variables over all 30 provinces.

The distance-based weights used in GWR for data at observation i take the form of a vector W_i which can be determined based on a vector of distances d_i between observation i and all other observations in the sample. This distance vector along with a distance decay parameter are used to construct a weighting function that places relatively more weight on neighboring observations in the spatial data sample. A host of alternative approaches have been suggested for constructing the weight function, but we will rely on one suggested by Brunsdon et al (1996) shown in (4).

$$W_i = \sqrt{\exp(-d_i/\theta)} \tag{4}$$

The parameter θ is a decay or "bandwidth" parameter. Changing the bandwidth results in a different exponential decay profile, which in turn produces estimates that vary more or less rapidly over space. A single value of the bandwidth parameter θ is determined with a cross-validation procedure often used in locally linear regression methods. A score function taking the form:

$$\sum_{i=1}^{n}[y_i - \hat{y}_{\neq i}(\theta)]^2 \tag{3}$$

is minimized with respect to θ, where $\hat{y}_{\neq i}(\theta)$ denotes the fitted value of y_i with the observations for point i omitted from the calibration process.

The non-parametric GWR model relies on a sequence of locally linear regressions to produce estimates for every point in space using a sub-sample of data information from nearby observations. Let y denote an nx1 vector of dependent variable observations collected at n points in space, X an nxk matrix of explanatory variables, and ε an nx1 vector of normally distributed, constant variance disturbances. Letting W_i represent an nxn diagonal matrix containing the vector W_i of distance-based weights for observation i that reflect the distance between observation i and other observations, we can write the GWR model as:

$$W_i y = W_i X\beta_i + \varepsilon_i \tag{6}$$

The subscript i on β_i indicates that this kx1 parameter vector is associated with observation i. The GWR model produces n such vectors of parameter estimates, one for each observation. These estimates are produced using:

$$\hat{\beta}_i = (X'W_i^2X)^{-1}(X'W_i^2y) \tag{7}$$

The Bayesian approach, which we label BGWR is best described using matrix expressions shown in (8) and (9). First, note that (8) is the same as the GWR relationship, but the addition of (9) provides an explicit statement of the parameter smoothing that takes place across space. Parameter smoothing in (9) relies on a locally linear combination of neighboring areas, where neighbors are defined in terms of first-order contiguity.

$$W_i y = W_i X\beta_i + \varepsilon_i \tag{8}$$

$$\beta_i = (c_{i1} \otimes I_k \cdots c_{in} \otimes I_k)\begin{pmatrix}\beta_1\\ \vdots \\ \beta_n\end{pmatrix} + u_i \tag{9}$$

The terms c_{ij} in (2) represent row i from a standardized first-order spatial contiguity matrix. This means that the row-vector (c_{i1}, c_{in}) sums to unity, and we set $c_{ii}=0$. This will act as a stochastic restriction on the parameter estimates for each province requiring them to take on values similar to those from neighboring provinces. Intuitively, it seems reasonable to assume that variation in the regression relationship over space should be fairly smooth. Of course, this stochastic prior restriction will be evaluated in light of the sample data to produce posterior parameter estimates that reflect a combination of the data and prior information. If the data is in stark disagreement with our prior smoothing relationship, the posterior estimates will not adhere to the smoothing relationship.

To complete our model specification, we add distributions for the terms ε_i and u_i:

$$\varepsilon_i \sim N[0,\sigma^2 V_i],\quad V_i = diag(v_1, v_2, \ldots, v_n) \tag{10}$$

$$u_i \sim N[0,\sigma^2\delta^2(X'W_i^2X)^{-1}] \tag{11}$$

The $V_i = diag(v_1, v_2, \ldots, v_n)$, represent a set of n variance scaling parameters (to be estimated) that allow for non-constant variance as we move across space. Of course, the idea of estimating n terms v_j, $j=1,\ldots,n$ at each observation i for a total of n^2 parameters (and nk regression parameters β_i) with only n sample data observations may seem truly problematical! The way around this is to assign a prior distribution for the n^2 terms V_i, $i=1,\ldots,n$ that depend on a single *hyperparameter*. The V_i parameters are assumed to be i.i.d. $x^2(r)$ distributed, where r is a hyperparameter that controls the amount of dispersion in the V_i estimates across observations. This allows us to introduce a single hyperparameter r to the estimation problem and receive in return n^2 parameter estimates, (see LeSage, 1999 for details).

The distribution for the stochastic parameter u_i in the parameter smoothing relationship is normal with mean zero and a variance based on Zellner's (1971) *g*-prior. This prior variance is proportional to the least-squares variance-covariance matrix, $\sigma^2(X'W_i^2X)^{-1}$, with δ^2 acting as the scale factor. The use of this prior specification allows individual parameters to vary by different amounts depending on their magnitude.

The parameter δ^2 acts as a scale factor to impose tight or loose adherence to the parameter smoothing specification. LeSage (1999) shows that as δ becomes very small the smoothing restriction forces β_i to look like a distance-weighted linear combination of other β_i from neighboring observations. On the other hand, as $\delta \rightarrow \infty$ (and $V_i = I_n$) we produce the GWR estimates. There is a trade-off between the increased precision and insensitivity to outliers that result from imposing Bayesian prior information and bias. In this study, our aim is to provide robust estimates that are not subject to influence from aberrant observations by introducing only a small amount of bias. Since the non-Bayesian GWR estimates are unbiased, a comparison with the Bayesian estimates can be used to judge our success in meeting this goal.

Details concerning Markov chain, Monte Carlo estimation of this model can be found in LeSage (1999).[1]

In conclusion, the simple regression relationship from SWCB will be examined using the GWR and BGWR methodology to provide locally linear estimates of the relationship between provincial economic growth and geographic factors for every province. This allows us to overcome spatial heterogeneity due to variation in the relationship over space.

III. A SPATIAL EXAMINATION OF THE SWCB MODEL

The SWCB model was estimated using one set of geographic explanatory variables, plus the 1985 level of investment in total fixed capital assets. This includes foreign direct investment as well as domestic. This variable was added to the model for a number of reasons. First, adding this variable should force some competition between the geographic and economic factors which may provide a more convincing test for the importance of geographic factors. If in fact labor and capital endowments work endogenously through geographical factors, this variable should prove statistically insignificant. Second, note that the theoretical model derived by SWCB included initial capital and labor endowments, but these were replaced with GDP per capita during 1978. The level of investment in 1985 represents a proxy for the capital endowment during the initial year of the second reform phase. (Investment should be roughly proportional to capital.) The first reform phase covered the period 1978-1984, and was aimed mostly at agricultural reform, whereas the 1985 to present period has involved non-agricultural production. SWCB draw conclusions regarding the relative lack of importance of initial endowments and even make the point that low levels of initial capital relative to labor endowments might raise capital productivity leading to capital inflows. Direct inclusion of this variable can provide a test of this conjecture, which is at the core of the SWCB theoretical model.

Other variables in the model are identical to those from one of the models estimated by SWCB. They include a constant term, the GDP per capita during 1978, and geographic variables for the coastline length and population within 100 kilometers of the coast or ocean-navigable waterways. It should be noted that other variants of the SWCB model were also estimated, producing essentially the same results as those presented here.

Least-squares estimation results are shown in Table1,

[1]MATLAB functions that implement the method can be found in the *Econometrics Toolbox* at http://www.econ.utoledo.edu.This set of MATLAB functions also contains a host of other spatial econometric methods along with a manual describing their use.

where we see results similar to those reported in SWCB.[2] The coefficient on the level of investment in 1985 was not statistically significant, so in the average overall sense, SWCB's conjecture that initial endowments are not important are confirmed by these results.

Table1. Least-squares estimation results for the SWCB model

	Least-squares estimates		
Variable	Estimate	t-statistic	t-probability
constant	7.6755	19.4404	0.0000
GDP per capita, 1978	-6.8776	-1.4270	0.1659
coastline length	7.7164	3.1658	0.0040
pop100cr	1.7606	2.9272	0.0071
investment 1985	2.6703	0.5964	0.5562
R^2	0.6767		
$\hat{\sigma}^2$	1.1408		

GWR and BGWR estimates were produced based on the exponential distance decay function presented in (4). Prior information used in the BGWR model involved setting the hyperparameter *r=3* indicating a prior belief in heteroscedastic disturbances or outliers. The first-order contiguity priors moothing relationship presented in (9) was employed. (See LeSage,1999 for details concerning other types of smoothing priors). A value of δ=1 was used in the Zellner g-prior, specifying that the least-squares variance-covariance matrix should be used to indicate our prior uncertainty regarding the parameter smoothing relationship. As indicated in the previous section, there exists a trade-off between smoothing which increases the efficiency of the estimates allowing more precise inferences and bias. This setting appears to work well in this application of the BGWR method where we wish to minimize bias.

An indication of how reasonable these prior settings are can be gained by examining the GWR and BGWR estimates for all 30 provinces in a single graph. Presenting both estimates in a single graph allows the reader to see the impact of the Bayesian prior information that imposes spatial smoothing by restricting the coefficients from each province to be similar to those from neighboring provinces. It should also provide an indication regarding the amount of bias introduced by the Bayesian prior. If the trajectory of the BGWR estimates deviate greatly from the GWR estimates as we move across the 30 provinces, we would conclude that the Bayesian prior information has introduced a large amount of bias into the estimates. On the other hand, if the Bayesian estimates are merely smoother versions of the GWR estimates, we would conclude that the prior information has served to robustify the estimates against outliers and non-constant variance as we move over space.

The GWR and BGWR estimates are presented graphically, where a single graph of these estimates is provided for each of the five parameters in the model. To facilitate interpretation, the provincial observations were sorted by the cumulative GDP growth rates, the dependent variable in the model. This means that observation 1 in the figures corresponds to the lowest growth provinces and observation 30 to the highest.

Figure 1 presents the constant term estimates for all thirty provinces from both the GWR and BGWR models. From the figure we see that the GWR and BGWR estimates of the constant term vary around 7.6, the value of the least-squares estimate. The BGWR estimates clearly represent smoothed versions of the GWR estimates, indicating no substantial bias introduced by our prior information. A point worth noting is that the variability of the constant term for the 10 provinces with the highest growth rates (the last 10 observations in the figure) appears to be much less than that for the other provinces. This is true of both the GWR and BGWR estimates. Individual estimates for each province produced by the GWR and BGWR methods are presented in Tables 2 and 3 respectively, along with indications of statistical significance. From these we see that as in the case of the least-squares estimates the constant term was significant at the 95% level in all regressions for all provinces. This is consistent with one of the conclusions drawn by SWCB.

Figure 2 shows the GWR and BGWR estimates for the GDP per capita in 1978 variable. Here we see

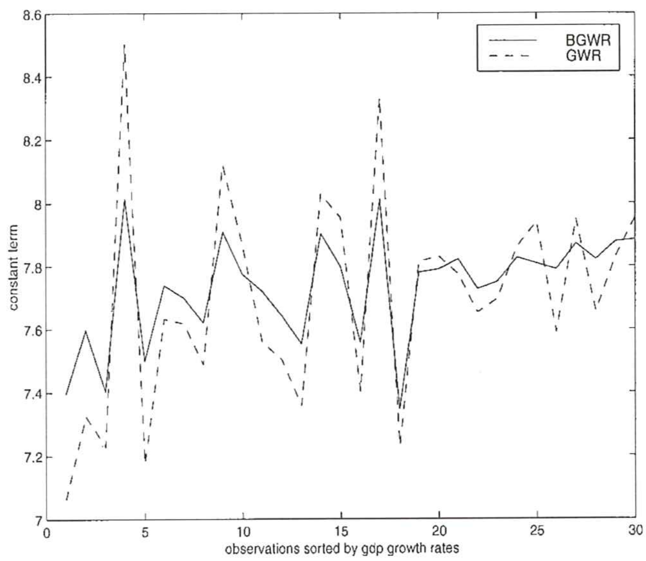

Figure 1. Constant term, GWR and BGWR estimates

[2]The data were scaled so the magnitudes of the parameter estimates were all roughly equal, whereas the data used in SWCB were unscaled producing widely varying parameter magnitudes. For the purposes of implementing the Zellner g-prior, carefully scaled data that produces parameters of roughly the same magnitude is important.

Table 2. GWR estimation results for the SWCB model

	Ordered by cumulative GDP growth (low tohigh)				
Province	Constant	GDP/POP	Coasts	POP100cr	Invest85
1. Qinghai	7.062**	-8.488	5.368**	1.488**	11.935
2. Ningxia	7.324**	-6.126	6.060**	1.452**	7.876
3. Tibet	7.229**	-16.032	5.217**	1.613**	13.493
4. Heilongjiang	8.501**	-6.253	6.339**	1.399**	-4.827
5. Gansu	7.175**	-6.475	5.473**	1.435**	9.832
6. Hunan	7.632**	-6.074	8.514**	1.705**	2.931
7. Shanxi	7.618**	-5.797	6.652**	1.437**	4.676
8. Guizhou	7.488**	-6.771	8.078*	1.743**	4.751
9. Liaoning	8.120**	-5.910*	6.774**	1.404**	-0.288
10. Tianjin	7.868**	-5.777	6.710**	1.406**	2.272
11. Guangxi	7.558**	-6.580*	8.500**	1.833**	3.339
12. Shaanxi	7.502**	-5.968	6.886**	1.489**	5.631
13. Sichuan	7.356**	-7.075*	7.365**	1.653**	6.852
14. Shanghai	8.028**	-5.677	8.690**	1.574**	-0.492
15. Inner Mongolia	7.953**	-5.938	5.330**	1.334**	1.832
16. Yunnan	7.402**	-8.344	7.642**	1.832**	6.260
17. Jilin	8.332**	-6.100	6.712**	1.417**	-2.634
18. Xinjiang	7.228**	-16.350	0.766**	1.011**	19.468
19. Beijing	7.813**	-5.775	6.378**	1.389**	2.957
20. Hebei	7.830**	-5.769	6.658**	1.406**	2.663
21. Jiangxi	7.774**	-5.795	8.872**	1.694**	1.307
22. Hubei	7.652**	-5.933	8.065**	1.593**	3.341*
23. Henan	7.695**	-5.824	7.660**	1.520**	3.306
24. Anhui	7.861**	-5.725	8.315	1.558**	1.297*
25. Shandong	7.939**	-5.745*	7.548**	1.461**	1.159**
26. Hainan	7.589**	-6.458	8.861**	2.001**	1.851
27. Jiangsu	7.949**	-5.703	8.274**	1.533**	0.568**
28. Guangdong	7.656**	-6.039	9.018*	1.856**	1.635*
29. Fujian	7.828**	-5.737	9.146**	1.734**	0.431**
30. Zhejiang	7.955**	-5.676	8.915	1.628	-0.136**

* indicates significance at the 90% level ; **indicates significance at the 95% level

evidence of outliers in two provinces where the GWR estimated parameter takes on large negative values. The BGWR estimates of course smooth over these outliers, providing a smoother set of estimates. The two outlying provinces are: Tibet and Xinjiang as can be seen in the tables reporting the GWR estimates for individual provinces. Negative values for this variable are interpreted by SWCB as indicating small initial period endowments and these two provinces that lie at the western-most part of China seem to be good candidates as outliers. SWCB also interpret the negative sign for this variable to indicate a tendency toward convergence in GDP growth over time, since a negative correlation between initial endowments and cumulative growth in GDP (the dependent variable) imply this type of result. For both the GWR and BGWR estimates we see that this parameter estimate is negative for all provinces. Note also that the GWR and BGWR estimates are centered around the least-squares estimated value of -6.87. One interesting fea-

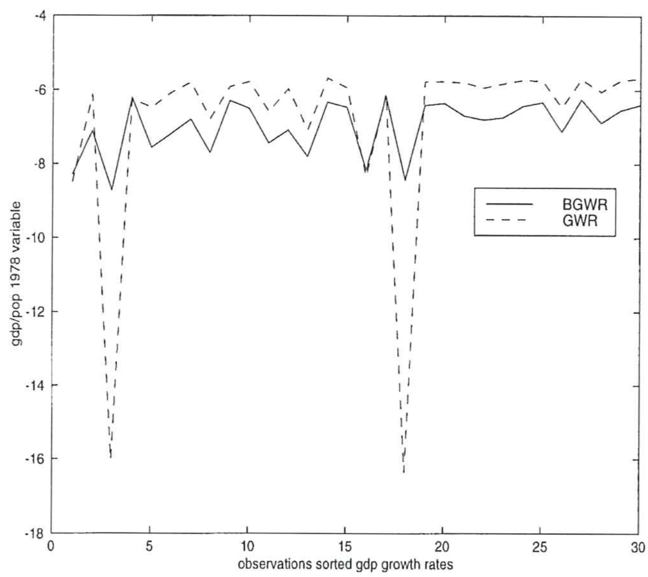

Figure 2. GDP per capita in 1978, GWR and BGWR estimates

Table 3. BGWR estimation results for the SWCB model

	Ordered by cumulative GDP growth(low to high)				
Province	Constant	GDP/POP	Coasts	POP100cr	Invest 1985
1. Qinghai	7.3949**	-8.2897**	5.8274**	1.5649**	8.691
2. Ningxia	7.5975**	-7.1068**	6.6675**	1.4880**	5.9925
3. Tibet	7.4025**	-8.7223**	5.9644**	1.6235**	8.5401
4. Heilongjiang	-6.2102**	7.0701**	1.3188**	1.9284	8.0162**
5. Gansu	7.4987**	-7.5612**	6.1883**	1.5067**	7.2786
6. Hunan	7.7390**	-7.1853**	8.2039**	1.7480**	3.2525
7. Shanxi	7.6994**	-6.7897**	7.1829**	1.5078**	4.556
8. Guizhou	7.6206**	-7.6972**	7.6979**	1.7902**	4.7982
9. Liaoning	7.9093**	-6.2912**	7.2789**	1.3802**	2.8026
10. Tianjin	7.7743**	-6.4979**	7.2972**	1.4525**	3.8448
11. Guangxi	-7.4325**	8.1849**	1.8326**	3.3509	7.7204**
12. Shaanxi	7.6424**	-7.0816**	7.1408**	1.5439**	5.1454
13. Sichuan	7.5528**	-7.8010**	7.0441**	1.6828**	6.0853
14. Shanghai	-6.3262**	8.7116**	1.6079**	1.786	7.9030**
15. Inner	-6.4649**	7.0053**	1.3659**	3.9521	7.7976**
16. Yunnan	7.5570**	-8.1634**	7.2166**	1.7901**	5.8163
17. Jilin	8.0120**	-6.1635**	7.3594**	1.3479**	1.7722
18. Xinjiang	7.3456**	-8.4296**	4.9406**	1.4522**	9.7996
19. Beijing	7.7801**	-6.4136**	7.3222**	1.4299**	3.7269
20. Hebei	7.7892**	-6.3544**	7.4567**	1.4297**	3.6722
21. Jiangxi	7.8214**	-6.6917**	8.5956**	1.7198**	2.1928
22. Hubei	7.7273**	-6.7979**	8.0224**	1.6376**	3.7483**
23. Henan	7.7499**	-6.7362**	7.7374**	1.5636**	3.7563 *
24. Anhui	7.8267**	-6.4273**	8.5554**	1.6034**	2.5182**
25. Shandong	7.8079**	-6.3275*	7.9809**	1.5007**	3.2032**
26. Hainan	7.7894**	-7.1135**	8.4870**	1.8842**	2.2456 *
27. Jiangsu	7.8715**	-6.2464**	8.4703**	1.5603**	2.3085**
28. Guangdong	7.8212**	-6.8759*	8.6479**	1.8052**	1.9680**
29. Fujian	7.8780**	-6.5392**	8.8552**	1.7255**	1.5059 *
30. Zhejiang	7.8841**	-6.3919	8.8548**	1.6627**	1.6183**

*indicates significance at the 90% level; ** indicates significance at the 95% level.

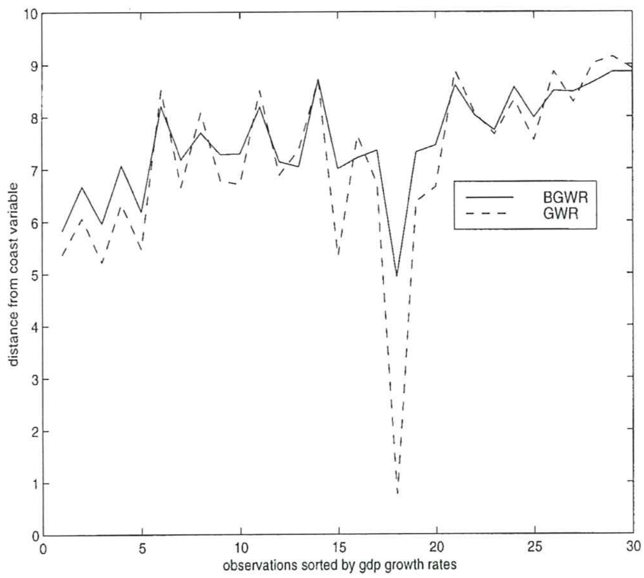

Figure 3. Coastline length, GWR and BGWR estimates

ture of the GWR versus BGWR estimates is that the GWR estimates for this variable are not statistically significant at the 95% level for any of the 30 provinces. This result is similar to the least-squares results. In contrast, the robust BGWR estimates for this parameter are significant at the 95% level for all but 3 provinces, and in two of these three cases the estimates are significant at the 90% level. This suggests that the two outliers adversely impacted the precision of the least-squares and GWR estimates. Also interesting is that the 3 provinces where significance drops off are among the 6 highest growth provinces. Using the SWCB model interpretation, this seems to suggest that for at least 3 of the highest growth provinces initial endowments were less important than in other low growth rate provinces, one of the conclusions reached by SWCB. The evidence is somewhat mixed however because there are 3 other provinces among the 6 with the highest growth rates where the initial endowment would be interpreted as significant.

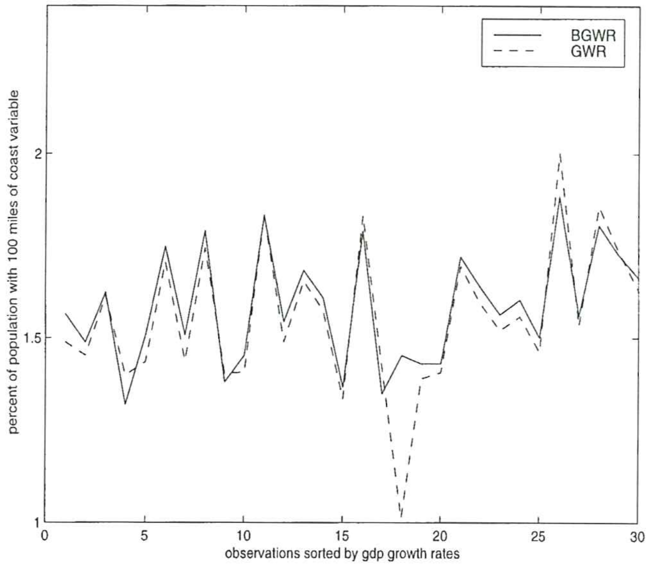

Figure 4. Population near the coasts, GWR and BGWR estimates

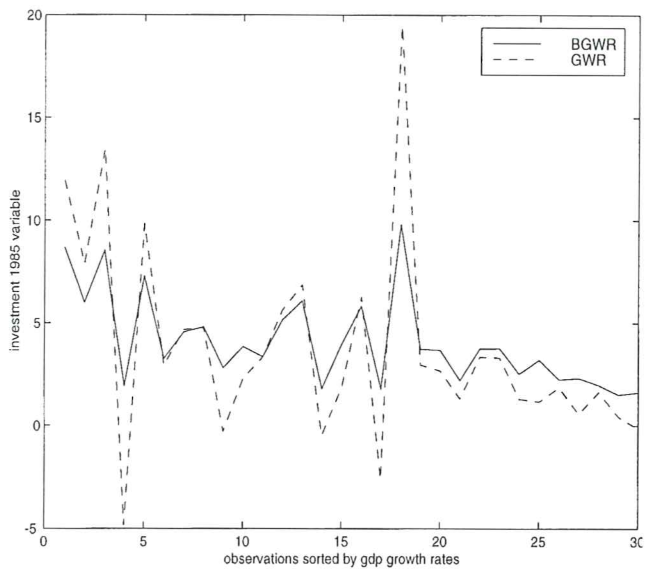

Figure 5. Investment in 1985, GWR and BGWR estimates

Estimates of the coastline variable for all provinces are shown in Figure 3. Here we see evidence of another outlier reflected by the small GWR estimate for Xinjiang province, a result that is quite believable. Xinjiang province is the western-most province and does not fair well in terms of coastline length, but still exhibits a relatively high GDP growth rate, making it an aberration to which the GWR estimates are pointing. A general upward trend for both the GWR and BGWR estimates can be seen in the figure, indicating that coastline length exerted a more important influence in provinces that exhibited higher GDP growth. An important consideration is that outliers do not contaminate estimates for neighboring provinces. Because of the locally linear character of the estimates, this is quite possible (see LeSage, 1999), but the similarity between the robust BGWR and GWR estimates for the other provinces suggests this has not happened here. Again, these estimates are near the least-squares value of 7.7, but a clear pattern emerges where the 5 lowest growth provinces have estimates of 7.0 or less and the 10 highest growth provinces have estimates above 7.7, which we could consider the overall average produced by least-squares. In fact, 8 of the 10 highest growth provinces have estimates greater than 8, suggesting that coastline length played a more important role for high growth than low growth provinces. Despite these differences in magnitude of impact (which we might intuitively expect), the estimates for this variable were significant for all provinces except two (Anhui and Zhejiang) in the case of the GWR model and in all cases for the BGWR model. Overall, we might conclude that SWCB have a good case for the importance of this variable in explaining economic growth among the Chinese provinces.

Figure 4 presents estimates for the population within 100 kilometers of the coast variable. Here again Xinjiang province represents an outlier, having a reasonably high growth rate yet low population near the coast (again because of its inland location). With the exception of the highest growth rate province (Zhejiang) the GWR estimates for this parameter are statistically significant in all cases and for the case of the BGWR in every case. This confirms the finding in SWCB. Note that the magnitude of impact on GDP growth rates is relatively constant across all provinces with the highest four growth provinces perhaps exhibiting a slightly greater magnitude.

Finally, Figure 5 shows the GWR and BGWR estimates for investment in 1985, the variable added to the SWCB model. Recall, the least-squares estimate for this parameter was not significant. In contrast the GWR estimates for this variable are significant at the 90% level in 7 of the 9 highest growth provinces. In all other cases the estimates were not significant. For the case of the BGWR estimates we find that this coefficient was significant at the 90% level in the 9 highest growth provinces and insignificant in all other provinces. These results suggest that capital endowments in 1985 (as proxied by investment levels) were an important determinant of economic growth for those provinces with the highest growth rates. An important point here is that the GWR and BGWR estimates are in substantial agreement on this, despite the apparent differences between the two sets of estimates shown in Figure 5. due to outliers. Robust estimates did not produce dramatically different inferences in this case.

From the table and the graph, we see negative GWR estimates in the case of Heilongjiang, Liaoning, Shanghai and Zhejiang provinces. This indicates that these provinces were hurt by their initial capital endowments. These results should be interpreted with caution however, because the negative coefficient estimates were significant in only one case, Zhejiang province which had the highest cumulative growth rate in GDP. The smoothed BGWR estimates do not result in negative coefficients for any of the 30 provinces, however a clear downward trend emerges in Figure 5 as we move from low to high growth provinces. This might be interpreted as an indication that capital endowments exerted a more important influence for low growth provinces than for high growth provinces. Again, we need to use caution and interpret these estimates in light of the fact that only 9 estimates shown in the figure are significantly different from zero, those associated with the highest growth provinces at the far right of the figure. This interpretation should also be viewed in light of positive BGWR estimates for these 9 provinces where the estimates were significant. Consider also that the GWR estimates for these nine provinces were positive in all cases but one.

Given this information, we would have to conclude that initial capital endowments may have exerted a significant impact on the very highest growth provinces. For lower growth provinces these endowments did not have an impact that was significantly different from zero. This interpretation of these results is in stark contrast to the conjecture by SWCB that initial endowments were unimportant in determining cumulative GDP growth over the 1978-1997 period. Their theoretical model attempts to show how geographic factors interacting with reform policies could lead to an economic takeoff. This view is in contrast to another fairly prevalent view that Chinese development policies targeted capital investments to the coastal provinces in an effort to stimulate economic growth in these areas (see Zhao, 1981 and Liu, 1992). The GWR and BGWR estimation results lend support to this view.

In this context it should be noted that the six provinces with the highest GDP growth rates are all coastal provinces. Two of the next four highest growth rate provinces (Anhui and Jiangxi) are first-order contiguous to coastal provinces, (and each other), that is they are neighbors to a coastal province. (For all practical purposes one might consider Anhui to be a coastal province as it has good access to the coast.) The two other provinces in the top ten in terms of GDP growth are first-order contiguous to Anhui which makes them second-order contiguous to the coast. This may be strong evidence of spatial spillover from the coastal provinces, indicative of a successful development policy that targeted coastal provinces. This policy has been criticized by some who feel that the spillover effects are unlikely to materialize, but casual empiricism points toward the possible existence of positive spatial spillover from development.

Finally, note that the investment level in 1985, the beginning of the second phase of the Chinese economic reform was unlikely to represent foreign direct investment, but rather the result of Chinese development policies that targeted these regions. Even if the endowment of capital was foreign direct investment, this is inconsistent with the takeoff conjecture advanced by SWCB where initial geographical and reform factors stimulate growth that in turn stimulates additional inflows of capital, serving as an engine of growth.

I should conclude this discussion by indicating that there may be other equally valid interpretations of the estimation results presented here. There are certainty scholars more knowledgeable than I about Chinese economic reforms and official development policies who would be in a better position to interpret these results. Nonetheless, these results provide an example of the value of spatial econometric analysis of phenomena based on spatial sample information at the provincial level in China.

A final issue is the estimates for the non-constant variance parameters v_i produced by the BGWR model shown in Table 4. These are sorted by GDP growth rates from low to high as were the parameter estimates. Note that the 10 lowest and 10 highest growth provinces contain 3 provinces with v_i estimates greater than 1.75, indicative of larger noise variances associated with these provinces by the model. In contrast, the middle 10 provinces have only a single v_i estimate greater than 1.25 and none greater than 1.75 in magnitude. This may suggest that the model is not adequately explaining variation in low and high growth provinces. That is, it might indicate that special circumstances not captured by the model account for growth rates that are lower and higher than average. We might interpret this to mean that caution should be used with regard to these explanatory variables. There may be other important variables that explain cases where low and high provincial GDP growth occurred during the 1978-1997 period.

IV. CONCLUSION

A large empirical literature exists that explores a variety of issues regarding China's economy. Most of this literature involves econometric analysis of spatial data samples based on the provincial statistics

Table 4. BGWR variance estimates for 30 provinces

Province	Posterior v_i estimates
1. Qinghai	1.9043
2. Ningxia	1.1506
3. Tibet	0.8365
4. Heilongjiang	0.9251
5. Gansu	0.8816
6. Hunan	2.0730
7. Shanxi	0.8542
8. Guizhou	0.7896
9. Liaoning	2.0813
10. Tianjin	1.1383
11. Guangxi	1.2279
12. Shaanxi	0.8846
13. Sichuan	0.8517
14. Shanghai	0.8734
15. Inner Mongolia	0.9437
16. Yunnan	1.0040
17. Jilin	0.9399
18. Xinjiang	0.8717
19. Beijing	1.6115
20. Hebei	0.7817
21. Jiangxi	0.8258
22. Hubei	0.7947
23. Henan	1.3913
24. Anhui	0.8052
25. Shandong	1.8352
26. Hainan	0.9831
27. Jiangsu	0.8224
28. Guangdong	0.8097
29. Fujian	1.0398
30. Zhejiang	1.7564

contained in the *Chinese Statistical Yearbook*. To this author's knowledge, no published studies have employed spatial econometric methods that are ideally suited to modeling this type of spatial data sample. This paper provided an introduction to some of the issues encountered when analyzing spatial data samples that may involve variation in regression relationships over space.

Most studies of China point to the vast spatial heterogeneity that exists in this large country, yet researchers have ignored the econometric implications of this. Standard assumptions of homogeneity for the noise process are usually invoked by those working with the provincial sample data. This paper argued that these assumptions of convenience need not be used and provided viable Bayesian alternatives. These methods allow for non-constant variance and outliers in spatial data samples and produce estimates of the variance for all spatial observations.

An applied illustration as well as a spatial examination of a study by Sacks, Woo, Chang and Bao (1999) demonstrated that the inferences drawn from spatial econometric estimation methods that allow for spatial variation in the nature of the relationship can produce inferences that differ from least-squares regression regarding substantive issues.

Regarding the examination of Sacks, Woo, Chang and Bao (1999), we found evidence that initial capital endowments during 1985, (the beginning of the second reform phase) were significant in explaining cumulative GDP growth in China's fastest growing provinces. This result is in direct contrast with the conjecture of Sacks, Woo, Chang and Bao that initial endowments were not responsible for the differences in GDP growth across provinces. This issue takes on importance because there are those that have argued against a development policy that directs capital investments to a small group of provinces in an effort to stimulate growth. Proponents of this type of policy argue that it will achieve long-run success if the targeted provinces takeoff and serve as an engine of growth that provide positive spatial spillover to neighboring provinces.

ACKNOLWDEGMENTS

I would like to thank Shuming Bao of the China Data Center, University of Michigan and Gene Chang, University of Toledo for providing data for this study.

REFERENCES

[1] Brundson, C.A.S. Fotheringham, and M. Charlton. 1996. Geographically weighted regression: a method for exploring spatial nonstationarity , *Geographical Analysis*, 28:281-298.

[2] Chen, Jian and Belton M. Fleisher. 1996. Regional income inequality and economic growth in China, *Journal of Comparative Economics*, 22(2):141-64.

[3] Howes, Stephen and Athar Hussain. 1994. Regional growth and inequality in rural China, *Sticerd Working Paper No. EF11*,London School of Economics.

[4] Khan, Azizur R. Keith Griffin and Carl Riskin. 1999. Income distribution in urban China during the period of economic reform and globalization, *American Economic Review, Papers and Proceedings*, 89(2):296-300.

[5] Knight, J. and Lina Song. 1993. The spatial contribution to income inequality in rural China, *Cambridge Journal of Economics*, 17(3):195-213.

[6] LeSage, James P., 1999. A family of geographically weighted regression models, *Recent Developments in Spatial Econometrics* , Springer-Verlag, edited by Luc Anselin and J.G.M. Florax. (forthcoming).

[7] Liu, Guoguang et al., 1992. Several problems concerning the development strategy of China's special economic zones, *Chinese Economic Studies*, 25(3):8-21.

[8] Raiser, Martin., 1998. Subsidizing inequality: economic reforms, fiscal transfers and convergence across Chinese provinces, *Journal of Development Studies*,34(3):1-26.

[9] Rozelle, Scott., 1994. Rural industrialization and in-

creasing inequality: emerging patterns in China's reforming economy, *Journal of Comparative Economics*, 19(3):362-91.

[10] Rozelle, Scott, J. Edward Taylor and Alan DeBauw.1999. Migration, remittances, and agricultural productivity in China, *American Economic Review, Papers and Proceedings*,89:287-291.

[11] Jeffrey Sachs, Wing Woo, Gene Chang, and Shuming Bao, 1999.Geographic factors, transportation costs and China's regional development under market reforms, 1978-98, *In the Proceedings of Geoinformatics'99*, June 19-21,1999, Ann Arbor, Michigan.

[12] Tsui, Kai Yuen., 1991. China's regional inequality, 1952-1985,*Journal of Comparative Economics*,15(1):1-21.

[13] Zellner, Arnold., 1971. *An Introduction to Bayesian Inference in Econometrics*. New York: John Wiley & Sons.

[14] Zhao, Ziyang., 1981. *China's Economy and Development Principles: A Report by Premier Zhao Ziyang*. Beijing: Foreign Languages Press.