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Reconsidering the Environmental Kuznets Curve: Geographically Weighted Regression Approach

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1 Introduction

China has sustained remarkably rapid economic growth over the last 20 years. Per capita GDP increased from 1,757 yuan in 1978, when China declared its economic reform, to 14,002 yuan in 2005. This is primarily due to gradually conducted openmarket policies and subsequent expansion of industrial sector. Meanwhile, however, such rapid industrialization has induced serious pollution problems. Future trend of both economic and environmental performance is of great concern in China.

To address relationship between economic growth and environment, a number of studies investigate an existence of Environmental Kuznets Curve (EKC) in China (for example, De Groot, Withagen, and Minliang (2004); He (2006); Shen (2006)). Many of these studies analyze the EKC relationships in various pollutants such as SO2 emission and waste water discharges from industrial sources. For example, Shen (2006) validates the EKC in SO2 and three water pollutants (Arsenic, Cadmium, and COD). De Groot, Withagen, and Minliang (2004) find that the EKC exists in industrial waste gas and solid waste at intermediate levels of economic development.

One major limitation of existing EKC studies is that most of them depend on global regression models. In other words, these EKC studies evaluate the average relationship between environmental quality and economic development. An average relationship from the global regression model, however, may not be representative of the situation in
any particular part of study region. Furthermore, the estimated average relationship may overlook significant and important local relationships between environment and economic growth. In addition, it might well be that there are contrasting relationships in different parts of China which tend to cancel each other out in the calculation of the global parameter estimate (Fotheringham, Brunsdon, and Charlton, 2002).

Thus, it may be far more informative to produce a set of local statistics by applying the locally-weighted regression approach and to map estimated values than simply to rely on the assumption that a single global estimate will be an accurate representation of all parts of the study area. In the field of environmental economics, the Geographically Weighted Regression (GWR), one of locally-weighted regression models, has been gaining greater attention in several areas including the Hedonic Pricing Model (for example, see Cho, Bowker, and Park (2006)). However, to our knowledge, no study applies the GWR or any other locally-weighted models to the EKC relationships.

The primary objective of this study is to investigate the EKC relationship in China using locally-weighted regression approach. Environmental performances are measured by three different pollutants from industrial sources: those include SO₂ emission, waste water discharge, and solid waste production. This study also investigates the impacts of other socio-economic factors (e.g. population density and environmental pressure from civil society) on pollutants above. These objectives are achieved by applying the GWR model to 29 provinces in China (figure 1) during 1994-2005.

This paper is organized as follows. The next section briefly introduces the GWR model and data used for empirical estimations. Section three reports and interprets the estimated results from the three GWR models. The last section summarizes and concludes this study.

2 The Model
2.1 Geographically Weighted Regression
This section briefly describes the basics of GWR model and its estimation. Further details can be found in Fotheringham, Brunsdon, and Charlton (2002) and LeSage (2004). Consider first a global regression model:

$$y_{it} = \beta_0 + \sum_k \beta_k x_{itk} + \varepsilon_{it}$$

where $y_{it}$ denotes an observation of the $i$th point in space at period $t$. $x_{itk}$ and $\varepsilon_{it}$
represent \( k \)th regressor and disturbance term with conventional assumptions, respectively. The GWR approach extends this traditional regression framework by allowing local rather than global coefficients to be estimated. Thus, the GWR model can be defined as follows:

\[
y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \epsilon_i
\]

(2)

where \((u_i, v_i)\) denotes the coordinates of the \(i\)th point in space and \(\beta(u_i, v_i)\) is a realization of the continuous function \(\beta_i(u, v)\) at point \(i\). That is, we allow a continuous surface of parameter values, and measurements of this surface are taken at certain points to denote the spatial variability of the surface (Fotheringham, Brunsdon, and Charlton, 2002).

Calibration of the locally weighted regression model follows a local weighted least squares approach. Unlike OLS, the locally weighted regression assigns weights based on their spatial proximity to location \(i\) in order to account for the fact that an observation near location \(i\) has more of an influence in the estimation of the \(\beta_k(u, v)\) than do observations located farther from \(i\). That is,

\[
\hat{\beta}(u_i, v_i) = \left(X'W(u_i, v_i)X\right)^{-1}X'W(u_i, v_i)Y
\]

(3)

where, \(\hat{\beta}\) represents an estimate of \(\beta\), \(X\) is a vector of the variables of structural, neighborhood, and location characteristics \(x_{ik}\), \(Y\) is a vector of \(y_i\), \(W(u_i, v_i)\) is an \(nxn\) diagonal matrix with diagonal elements \(w_i\) denoting the geographical weighting of observed data point for location \(i\). To better understand how locally weighted regression operates, consider the locally weighted regression equivalent of the classical regression equation,

\[
Y = (\beta \otimes X)1 + \epsilon
\]

(4)

where \(\otimes\) is a logical multiplication operator in which each element of \(\beta\) is multiplied by the corresponding element of \(X\), and 1 is a conformable vector of 1’s. If there are \(n\) data points and \(k\) explanatory variables including the constant term, both \(\beta\) and \(X\) will have dimensions \(nxk\). The matrix \(\beta\) now consists of \(n\) sets of local parameters and has the following structure:

\[
\beta = \begin{bmatrix}
\beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \cdots & \beta_k(u_1, v_1) \\
\beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \cdots & \beta_k(u_2, v_2) \\
\vdots & \ddots & \vdots & \vdots \\
\beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \cdots & \beta_k(u_n, v_n)
\end{bmatrix}
\]

(5)
$W(i)$ is an nxn spatial weighting matrix of the form:

$$W(i) = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{bmatrix}$$  \hspace{1cm} (6)$$

where $w_{ij}$ is the weight given to data point $j$ in the calibration of the model for location $i$. The diagonal elements of the weight matrix, $w_{ii}$, are equal to:

$$w_{ii} = \begin{cases} 1 - \left(\frac{d_{ij}}{b}\right)^2 & \text{if } d_{ij} < b \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (7)$$

where $d_{ij}$ is the Euclidean distance between point $i$ and $j$ and $b$ is a chosen bandwidth. At the regression point $i$, the weight of the data point is unity and falls to zero when the distance between $i$ and $j$ equals the bandwidth or higher.

As $b$ tends to be infinity, $w_{ij}$ approaches 1 regardless of $d_{ij}$ in which case the parameter estimates become uniform and locally weighted regression is equivalent to OLS. Conversely, as $b$ becomes smaller, the parameter estimates will increasingly depend on observations in close proximity to location $i$ and hence have increased variance. A cross-validation (CV) approach is suggested for local regression for a selection of optimal bandwidth (Cleveland (1979)). CV takes the following form:

$$CV = \sum_{i=1}^{n} \left[ y_i - \hat{y}_{ai}(b) \right]^2$$  \hspace{1cm} (8)$$

where $\hat{y}_{ai}$ is the fitted value of $y_i$ with the observations for point $i$ omitted from the fitting process. The bandwidth is chosen to minimize CV. Thus, in the local weighted regression model, only houses up to the optimal level of $b$ are assigned nonzero weights for the nearest neighbors of census-block group $i$. The weight of these points will decrease with their distance from the regression point. Sensitivity analysis was conducted for bandwidths of plus and minus 50% of the $b$ selected by the CV approach.

Because the local model allows regression coefficients to vary across space, the spatially varying relationships between environmental performance and their determinants can be estimated locally. This allows us to quantify the impacts of economic development and other factors on environmental performance at provincial level in China. Furthermore, spatially varying parameters and elasticities can be displayed in spatial maps using Geographic Information System (GIS). These
advantages of the GWR model are demonstrated later in this paper.

2.2 Model Specification and Data
This study estimates equation (2) in previous subsection using the following specification:

\[
Y_{it} = \beta_0 + \beta_1 \text{GRPP}_{it} + \beta_2 \text{GRPPSQ}_{it} + \beta_3 \text{POPDENSE}_{it} + \beta_4 \text{CLAIM}_{it} + \beta_5 D_{\text{COAST}}_{it} + \beta_6 D_{\text{2003}}_{it} + \beta_7 D_{\text{2004}}_{it} + \beta_8 D_{\text{2005}}_{it} + \epsilon_{it}
\]

where \(Y_{it}\) is per capita environmental performance (SO\(_2\) emission, waste water discharge, and solid waste production from industrial sector) in province \(i\) at year \(t\). GRPP and GRPPSQ denote provincial gross regional product per capita and its squared term. POPDENSE is population density (in person/m\(^2\)). CLAIM is the number of citizen’s complaints for pollution problems (air pollution, water pollution, solid waste) to local government. D\(_{\text{COAST}}\), D\(_{\text{2003}}\), D\(_{\text{2004}}\), and D\(_{\text{2005}}\) are dummy variables for coastal provinces\(^2\) and three different time periods (years of 2003, 2004, and 2005), respectively. Finally, \(\beta\)'s are parameters to be estimated. Provincial GRP is adjusted by CPI (1993=100).

This study uses the data of three pollutants from industrial sources (SO\(_2\) emission, waste water discharge, and solid waste production) in 29 provinces and metropolitan cities in China\(^3\). Variables used for estimation of equation 9 are obtained from China Statistical Yearbook and China Environmental Yearbook (State Environmental Protection Agency (1995-2006); State Statistical Bureau (1995-2006)). Descriptive statistics of variables used in this study are presented in table 1.

3 Results
The estimated coefficients for SO\(_2\), waste water, and solid waste models are presented in tables 2, 3, and 4, respectively. Figures indicate that local GWR models outperforms global OLS models in all three pollutants in terms of Adjusted \(R^2\) and AIC. Thus, model fits are significantly improved by estimating locally rather than globally.

The parameter estimates for the seven independent variables vary widely over space. The p-value from a Monte Carlo significance test in table 4 indicates that the spatial variations in GRPP and GRPPSQ are significant at the 1% level or higher. This provides strong evidence that the EKC relationships are not constant, but vary among provinces and cities in China. Most other variables are also significant but CLAIM S is
not significant in solid waste model. This indicates that CLAIM is constant across space. In other words, local OLS estimates can produce reasonable "average relationship" only on dummy variables in three models and the number of complaints solid waste model.

One of the advantages of the GWR model is that estimated results are spatially displayed, based upon resolution of data used in the study. Since this study conducts province-level locally regression, all results can be displayed using provincial data of China and GIS software such as ESRI’s ArcGIS.

Figure 2 illustrates spatial variations in EKC relationships in SO2, waste water, and solid waste from industrial sources in China. Upper-left figure indicates that 20 out of 29 provinces are shown to have EKC relationship in SO2 emission (i.e., $\beta_1 > 0$ and $\beta_2 < 0$ in equation 9). This is remarkably different from OLS estimates in table 3 that EKC is “on average” satisfied in entire China. Our results indicate that economic growth is not likely to mitigate SO2 pollution problems in 9 central and western provinces. In other words, some specific policies (e.g. environmental standard, environmental management enhancement, etc.) will be needed to induce air quality improvement in these provinces. Similarly, upper-right figure indicates that EKC relationship in waste water discharge is found in all provinces except one province in the western part of China (Xinjiang province). In solid waste production (lower-left figure), EKC relationship holds in most provinces except three landlocked provinces (Gansu, Qinghai, and Shaanxi) and two southern provinces (Yunnan and Hainan).

Figure 3 depicts spatial variations in the impacts of citizen’s complaints to local government on SO2 emission and waste water discharge in China. Figure does not include the case of solid waste production because spatial variability of CLAIM S is not significant at any statistical level (table 5). Figure 3 predicts that the number of citizen’s complaints is negative inducement on SO2 emission in 19 out of 29 provinces in China. This suggests that citizen’s pressure will effectively improve air quality in these 19 provinces. In other words, citizen’s pressure is not likely to reduce SO2 emission in 10 southern and costal provinces. Such difference may be due to the fact that per capita SO2 emission is relatively low in these provinces with positive coefficients. However, negative sign of CLAIM A may imply that institutions moderating environmental disputes (e.g., local governments and local environmental NGOs) have not sufficient capacity for the problem. Further analysis is needed to reveal factors causing such difference.
Finally, the number of citizen’s complaints is estimated to be negative inducements in industrial waste water discharge in only three Northern provinces (Inner Mongolia, Jilin, and Heliongjiang). Environmental disputes in these three provinces are relatively serious than many other provinces in China. In Heliongjiang province, for example, industrial waste water discharged to the Heliongjiang River (also called the Amur River in Russia) has resulted in serious river quality problems in both local and transboundary scales. Thus, growing concern of waste water pollution problems may result in significant and positive coefficient of CLAIM W in these three provinces.

4 Summary and Conclusions
This study evaluated environmental performance and their determinants in China during 1994-2005. SO₂ emission, water discharge, and solid waste production from industrial sources are analyzed Geographically Weighted Regression (GWR) model. We applied the three GWR models to estimate an existence of Environmental Kuznets Curve (EKC) as well as identify factors affecting environmental performance in 29 provinces in China.

Our results provide strong evidence that the GWR model is valid in explaining relationships between environmental performance and economic growth as well as other socio-economic factors. Locally-regressed GWR models outperform globally regressed ordinary least squares (OLS) model in all three pollutants. The GWR model estimates indicate existence of EKC relationships in SO₂, waste water, and solid waste in many of 29 provinces in China. Spatial variations in EKC relationships vary among pollutants. Similarly, the effects of other socio-economic factors such as the number of citizen’s complaints for environmental pollution also vary spatially among provinces.

This study is limited because factors affecting environmental performance are not fully evaluated. For example, industrial structure, capital intensity, environmental management capacities are not considered in this study. This is mostly due to existence of multicollinearity. However, more trials may be needed to find better specifications, in both theoretically and statistically. In addition, spatial variations of estimated results are displayed in terms of only sign of parameters (figures 2 and 3). More detailed analysis is much needed to make further investigation of factors affecting environmental performance and to derive effective policy implications toward balanced economic growth in China.
Endnotes

1 These values are in 2005 constant prices. The rate of exchange in 2005 was approximately 1 US dollars = 8.19 Yuan.

2 Coastal provinces denote: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan provinces.

3 Tibet is not included in our analysis due to lack of some information from statistical data sources. Chongqing is also not included because it was split from Sichuan during the estimation period (in 1997). To keep consistency of data, we combined Chongqing and Sichuan together and treated them as a single province in this study.
References


Table 1. Descriptive Statistics of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SO2P</td>
<td>Industrial SO$_2$ emission per capita</td>
<td>kg</td>
<td>13.89</td>
<td>8.42</td>
<td>2.27</td>
<td>54.32</td>
</tr>
<tr>
<td>WWP</td>
<td>Industrial waste water discharge per capita</td>
<td>ton</td>
<td>17.09</td>
<td>10.79</td>
<td>3.99</td>
<td>87.11</td>
</tr>
<tr>
<td>SWP</td>
<td>Industrial solid waste production per capita</td>
<td>ton</td>
<td>0.75</td>
<td>0.51</td>
<td>0.09</td>
<td>3.34</td>
</tr>
<tr>
<td>GRPP</td>
<td>Provincial gross regional product per capita</td>
<td>1,000 yuan</td>
<td>14.83</td>
<td>13.25</td>
<td>1.85</td>
<td>91.85</td>
</tr>
<tr>
<td>GRPPSQ</td>
<td>(GRPP)$^2$</td>
<td>1,000 yuan</td>
<td>395.05</td>
<td>948.26</td>
<td>3.43</td>
<td>8436.55</td>
</tr>
<tr>
<td>POPDENS</td>
<td>Population density</td>
<td>person/m$^2$</td>
<td>3644.61</td>
<td>4432.37</td>
<td>64.82</td>
<td>27353.85</td>
</tr>
<tr>
<td>CLAIM_A</td>
<td>The number of citizen's complaints for air pollution</td>
<td>count</td>
<td>3451.18</td>
<td>5336.68</td>
<td>12.00</td>
<td>39347.00</td>
</tr>
<tr>
<td>CLAIM_W</td>
<td>The number of citizen's complaints for waste water</td>
<td>count</td>
<td>1122.20</td>
<td>1756.49</td>
<td>6.00</td>
<td>10310.00</td>
</tr>
<tr>
<td>CLAIM_S</td>
<td>The number of citizen's complaints for solid waste</td>
<td>count</td>
<td>187.18</td>
<td>256.03</td>
<td>0.00</td>
<td>1495.00</td>
</tr>
<tr>
<td>D_Coast</td>
<td>Dummy variable for coastal provinces</td>
<td></td>
<td>0.41</td>
<td>0.49</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>D_2003</td>
<td>Dummy variable for year 2003</td>
<td></td>
<td>0.08</td>
<td>0.27</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>D_2004</td>
<td>Dummy variable for year 2004</td>
<td></td>
<td>0.08</td>
<td>0.27</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>D_2005</td>
<td>Dummy variable for year 2005</td>
<td></td>
<td>0.08</td>
<td>0.27</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: GRP and expenditure are adjusted by CPI (1993=100).

Table 2. The Model Estimates: Industrial SO$_2$ Emission

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coeff.</th>
<th>Std. Error</th>
<th>Minimum</th>
<th>Lwr</th>
<th>Median</th>
<th>Upr quartile</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>100.711</td>
<td>10.149</td>
<td>8.796</td>
<td>55.495</td>
<td>130.152</td>
<td>202.350</td>
<td>254.302</td>
</tr>
<tr>
<td>GRPP</td>
<td>29.022</td>
<td>12.344</td>
<td>-148.635</td>
<td>-39.776</td>
<td>0.163</td>
<td>18.870</td>
<td>108.741</td>
</tr>
<tr>
<td>POPDENSE</td>
<td>436.137</td>
<td>148.131</td>
<td>-4022.485</td>
<td>-864.459</td>
<td>795.444</td>
<td>1109.829</td>
<td>12580.677</td>
</tr>
<tr>
<td>CLAIM</td>
<td>-0.002</td>
<td>0.001</td>
<td>-0.022</td>
<td>-0.008</td>
<td>-0.003</td>
<td>0.002</td>
<td>0.013</td>
</tr>
<tr>
<td>D_Coast</td>
<td>-16.911</td>
<td>11.364</td>
<td>-124.439</td>
<td>-12.994</td>
<td>0.000</td>
<td>65.079</td>
<td>181.731</td>
</tr>
<tr>
<td>D_2004</td>
<td>31.103</td>
<td>18.161</td>
<td>-86.802</td>
<td>19.161</td>
<td>38.693</td>
<td>63.577</td>
<td>136.138</td>
</tr>
<tr>
<td>D_2005</td>
<td>58.616</td>
<td>18.981</td>
<td>-128.280</td>
<td>40.914</td>
<td>65.239</td>
<td>101.706</td>
<td>203.704</td>
</tr>
</tbody>
</table>

$n$: 348  
Adjusted $R^2$: 0.080  
AIC: 4053.991

Note: Dependent variable: Industrial SO$_2$ per capita
### Table 3. The Model Estimates: Industrial Waste Water Discharge

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS Coeff.</th>
<th>Std. Error</th>
<th>Minimum</th>
<th>Lwr</th>
<th>Median</th>
<th>Upr quartile</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>6.561 ***</td>
<td>10.149</td>
<td>1.404</td>
<td>4.972</td>
<td>7.150</td>
<td>8.456</td>
<td>16.036</td>
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<tr>
<td>GRPP</td>
<td>3.550 ***</td>
<td>12.344</td>
<td>-5.491</td>
<td>0.630</td>
<td>2.555</td>
<td>3.521</td>
<td>4.668</td>
</tr>
<tr>
<td>GRPPSQ</td>
<td>-0.780 ***</td>
<td>1.414</td>
<td>-1.134</td>
<td>-0.801</td>
<td>-0.575</td>
<td>-0.467</td>
<td>0.715</td>
</tr>
<tr>
<td>POPDENSE</td>
<td>180.934 ***</td>
<td>148.131</td>
<td>-56.936</td>
<td>129.531</td>
<td>173.452</td>
<td>214.455</td>
<td>281.421</td>
</tr>
<tr>
<td>CLAIM</td>
<td>0.001 ***</td>
<td>0.001</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>D_2004</td>
<td>-1.658</td>
<td>18.161</td>
<td>-3.465</td>
<td>-1.878</td>
<td>-1.076</td>
<td>-0.402</td>
<td>3.253</td>
</tr>
<tr>
<td>D_2005</td>
<td>1.284 ***</td>
<td>18.981</td>
<td>-1.133</td>
<td>1.290</td>
<td>2.454</td>
<td>3.219</td>
<td>7.037</td>
</tr>
</tbody>
</table>

\[ n = 348 \quad \text{Adjusted } R^2 = 0.60 \quad \text{AIC} = 2338.426 \]

Note: Dependent variable: Industrial Waste Water Discharge per capita

### Table 4. The Model Estimates: Industrial Solid Waste Production

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS Coeff.</th>
<th>Std. Error</th>
<th>Minimum</th>
<th>Lwr</th>
<th>Median</th>
<th>Upr quartile</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.584 ***</td>
<td>0.061</td>
<td>0.262</td>
<td>0.513</td>
<td>0.737</td>
<td>1.137</td>
<td>2.039</td>
</tr>
<tr>
<td>GRPP</td>
<td>0.201 ***</td>
<td>0.071</td>
<td>-0.764</td>
<td>0.038</td>
<td>0.302</td>
<td>0.497</td>
<td>1.237</td>
</tr>
<tr>
<td>GRPPSQ</td>
<td>-0.020 **</td>
<td>0.008</td>
<td>-0.854</td>
<td>-0.040</td>
<td>-0.028</td>
<td>-0.006</td>
<td>1.128</td>
</tr>
<tr>
<td>POPDENSE</td>
<td>-0.340</td>
<td>0.885</td>
<td>-48.146</td>
<td>-21.635</td>
<td>-8.997</td>
<td>2.559</td>
<td>21.280</td>
</tr>
<tr>
<td>CLAIM</td>
<td>0.000 **</td>
<td>0.000</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>D_Coast</td>
<td>-0.143 **</td>
<td>0.068</td>
<td>-0.823</td>
<td>-0.257</td>
<td>-0.104</td>
<td>0.000</td>
<td>1.556</td>
</tr>
<tr>
<td>D_2003</td>
<td>0.155 **</td>
<td>0.103</td>
<td>-0.292</td>
<td>0.031</td>
<td>0.097</td>
<td>0.136</td>
<td>0.293</td>
</tr>
<tr>
<td>D_2004</td>
<td>0.247 ***</td>
<td>0.109</td>
<td>-0.887</td>
<td>0.100</td>
<td>0.178</td>
<td>0.423</td>
<td>0.547</td>
</tr>
<tr>
<td>D_2005</td>
<td>0.374 ***</td>
<td>0.115</td>
<td>-1.656</td>
<td>0.108</td>
<td>0.280</td>
<td>0.552</td>
<td>1.057</td>
</tr>
</tbody>
</table>

\[ n = 348 \quad \text{Adjusted } R^2 = 0.100 \quad \text{AIC} = 492.193 \]

Note: Dependent variable: Industrial Solid Waste Production per capita

### Table 5. Test for Spatial Variability of the GWR Coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>SO₂ Emission</th>
<th>Waste water</th>
<th>Solid waste</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>GRPP</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>GRPPSQ</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>POPDENSE</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>CLAIM_A</td>
<td>***</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>CLAIM_W</td>
<td>n/a</td>
<td>***</td>
<td>n/a</td>
</tr>
<tr>
<td>CLAIM_S</td>
<td>n/a</td>
<td>n/a</td>
<td></td>
</tr>
<tr>
<td>D_Coast</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>D_2003</td>
<td>**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>D_2004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D_2005</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 1. Provinces and Major Cities in China
Figure 2. Spatial Variations in EKC Relationships in China

Figure 3. Spatial Variations in the Effect of CLAIM on Air and Water Qualities
Hiroshima University, The 21st Century COE Program
“Social Capacity Development for Environmental Management and International Cooperation”
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