Bayesian analysis of population agglomeration and ecological efficiency in Beijing-Tianjin-Hebei region

Jianming Chen\(^1\), Na Wei\(^1,3\), Yanli Zhou\(^2\) and Xiangyu Ge\(^1\)

\(^1\)School of Statistics and Mathematics, Zhongnan University of Economics and Law, Wuhan, China
\(^2\)School of Finance, Zhongnan University of Economics and Law, Wuhan, China
\(^3\)Email: nawei2006@126.com

Abstract. By using 35 cities data directly under the jurisdiction of Beijing-Tianjin-Hebei region, this paper improved Bayesian spatial quantile regression method to explore the relationship between population aggregation and eco-efficiency and its mutual influence under the background of Beijing, Tianjin and Hebei urban agglomeration construction theme. The study found that population aggregation has a significant negative impact on the urban eco-efficiency. In addition, the number of primary schools, the scale of urban economic development and investment in real estate development also have a significant negative impact on urban eco-efficiency. While the number of secondary schools and the number of beds in medical and health institutions has a significant positive impact on urban eco-efficiency.

1. Introduction

The empirical studies on the ecological efficiency of urban agglomeration are generally based on the historical data of urban agglomeration. Hosseini and Kaneko studied the spatial spill over effect of ecological efficiency through the establishment of spatial autocorrelation model, and also explored the influence of different regions on the ecological environment of neighboring regions [1]. Wei and Shuting used spatial econometric model to test the spatial spill over effect and its influencing factors of energy ecological efficiency in different provinces [2]. In order to evaluate urban ecological efficiency more precisely, we establishes a producer efficiency model based on DEA, which contains a random element and aims to separate the influence of luck from management efficiency and environmental impact.

In Bayesian economics, Koenker and Bassett proposed the quantile regression method [3]. Yu and Moyeed combined quantile regression method and Bayesian theory for the first time [4]. Kakamu and Wago put forward the Bayesian spatial quantile regression method [5]. Firpo et al. proposed the unconditional quantile regression method [6]. Antonio and Galvao proposed the quantile regression method for dynamic panel data [7]. Yang and He proposed a Bayesian empirical likelihood quantile regression model [8]. Kozumi and Kobayashi put forward Gibbs algorithm of the Bayesian quantile regression model by using Laplace distribution [9]. Yu studied the hierarchical linear quantile regression model under the Bayesian framework [10]. In terms of empirical research, income and pollution emissions are studied by using a quantile regression panel data model. [11] [12] [13].

A typical problem in the research of urban agglomeration is the small city number and related data volume. The classic independence condition and others required by the regression method are hardly to meet, which cannot guarantee the regression accuracy. However, the Bayesian regression analysis can
make up this deficiency. Therefore, we use the Bayesian spatial quantile regression model to analyze the empirical data. The stationarity test of the model shows that the Bayesian spatial quantile model is very suitable for the empirical study of small sample such as the Beijing-Tianjin-Hebei region urban agglomeration.

In this paper, the ecological efficiency calculated by the Super-Efficiency Three-Stage DEA (Data Envelopment Analysis) is taken as the explained variable, agglomeration index of Beijing-Tianjin-Hebei urban agglomeration as the core explanatory variable, and scale level and public service level of the city itself are control variables to construct the Bayesian spatial quantile model and carry out the numerical analysis.

2. Eco-efficiency measurement and data processing
Andersen and Petersen proposed a super-efficient DEA model based on the comparison between the DEA model and the efficiency of effective decision-making units [14]. The super-efficient DEA model considers the urban ecosystem as an input/output system by taking into account the essential characteristics of urban eco-efficiency to accurately evaluate the relative effectiveness of ecological units. This paper uses the super-efficient DEA method to calculate the ecological efficiency of urban agglomerations in Beijing-Tianjin-Hebei region. Although the DEA method can be used to evaluate the technical efficiency of a decision unit, it is not possible to directly compare the sizes especially when the multiple decision making units (Decision Making Units, DMU) are in a fully active state. Super-efficiency is required to further determine the efficiency value between valid DMUs. The effective DUM of the evaluation is removed from the Production Probability Set (PPS), measuring the distance between the DMU and the PPS, and the effective DMU is then arranged according to the distance. Assuming that the number of decision units meets the comparability requirements, each DMU has one input variable and one output variable to construct an ultra-efficient linear programming equation model.

2.1. Construct three-stage DEA model
First stage of the three-stage DEA suppose that there are \( k \) DMU to be evaluated, which is denoted as \( \lambda=[\lambda_1, \lambda_2, \ldots, \lambda_k] \). Thus, each decision making unit corresponds to \( n \) inputs \( X=[X_1, X_2, \ldots, X_n] \) and \( m \) outputs \( Y=[Y_1, Y_2, \ldots, Y_m] \), which can be denoted as:

\[
X_j=(x_{1j}, x_{2j}, \ldots, x_{nj})^T, \quad Y_j=(y_{1j}, y_{2j}, \ldots, y_{mj})^T, \quad j=0,1,2,\ldots, k
\]

The input guidance model is given as follows:

\[
\begin{align*}
\zeta^* &= \max (\mu^Ty + \mu_0) \\
\text{s.t.} & \quad v^TX - \mu^Ty - \mu_0 \geq 0, j=1,2,\ldots, k \\
& \quad v^TX_0 = 1 \\
& \quad v \geq 0, \mu \geq 0
\end{align*}
\]

where \( \mu=[\mu_1, \mu_2, \ldots, \mu_n]^T \), \( v=[v_1, v_2, \ldots, v_n]^T \). The linear programming equation is obtained by introducing a non-Archimedes infinitely small \( \varepsilon(f=10^{-6}) \):

\[
\begin{align*}
\max & (\theta - \varepsilon(\varepsilon^TS + \varepsilon^T\varepsilon^T)) = \hat{\theta} \\
\text{s.t.} & \quad \sum_{j=1}^k X_j\lambda_j + S = \theta X_0 \\
& \quad \sum_{j=1}^k Y_j\lambda_j - S^* = Y_0 \\
& \quad S^* \geq 0, S^* \geq 0, \lambda \geq 0, j=1,2,\ldots, k
\end{align*}
\]

where \( \varepsilon=(1,1,\ldots,1) \in E_n, \varepsilon=(1,1,\ldots,1) \in E_m \), the relaxation values are \( S^*=(s_1^*, s_2^*, \ldots, s_n^*)^T \), \( S^*=(s_1^*, s_2^*, \ldots, s_n^*)^T \).
In the second stage, suppose there are $p$ environment index variables $z_j = (z_{1j}, z_{2j}, \ldots, z_{pj})$, $\hat{\beta}$ corresponding to the coefficient estimates value of $p$ environmental factor index. The regression equation is constructed and adjusted based on the most effective DMU as follows:

$$
\hat{x}_j = x_j + \left[ \max_j \left( z_j \hat{\beta} \right) - z_j \bar{\beta} \right] + \left[ \max_j \left( \hat{v}_j \right) - \bar{\hat{v}}_j \right],
$$

(3)

where $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, k$, $x_j$ corresponding to the actual value of the $i$th input indicator of the $j$th DUM. By adjusting the actual value we get $\hat{x}_j$, $\hat{v}_j$ is an estimate value of the random interference, $\max_j \left( z_j \beta^t \right)$ is the impact process with environmental factors removed, $\max_j \left( \hat{v}_j \right) - \bar{\hat{v}}_j$ is an environmental factor adjustment for the random error of all DUMs.

In the third stage of three-stage DEA, instead of the original mass $x_j$, we use the input data of $x_j$ obtained from DEA second phase processing, which eliminate the environmental effects. By only changing the inputs and keeping the output value unchanged, we again repeated the operation of the first stage DEA model. Then, we use the method of efficiency evaluation of the first stage, and obtain the efficiency of decision making unit value, which eliminates the environmental and random disturbance influences.

2.2 Calculate the management inefficiency separation formula.
Following the study of Jondrow et al. in [15], this paper deduces the formula of management inefficiency, and the separation formula:

$$
E(\mu | \phi) = \frac{\sigma_{\mu} \sigma_{\varepsilon}}{\sigma} \left[ \phi(\varepsilon_{\mu}/\sigma) - \frac{\varepsilon_{\mu}}{\sigma} \right],
$$

where $\phi$ and $\Phi$ represent the standard normal density and the standard normal distribution function. The random error term $\varepsilon$ can be calculated by the following formula:

$$
E[\varepsilon_j | v_j + \mu_j] = x_j - z_j \bar{\beta} - E[\mu_j | v_j + \mu_j]
$$

(4)

2.3 The super-efficiency DEA model
The classical production function shows that the basic input factors of production include capital and labor. And land use is the space carrier of urban economy. Therefore, the input factors of eco-efficiency in this paper include labor input, land use and capital investment. Among them, labor is invested in land, which is measured by the number of employees at the end of the county and city. The land is represented by the area of the built-up area. Capital investment is expressed as the total actual capital of fixed assets investment in the current year. This paper calculates the actual capital investment based on the 2004 price basis and selects GDP and urban green space coverage as the expected output indicators of ecological efficiency. The eco-efficiency input and output indicators are shown in Table 1.
Table 1. Input-output indexes of eco-efficiency.

| Primary indexes | Secondary indexes | Third class indexes |
|-----------------|-------------------|---------------------|
|                 | Capital investment| Investment in Fixed Assets (Total Real Capital in Place for the Year) |
| ECO-EFFICIENCY -INPUT | Resource input | Consumption of Oil and Natural Gas |
| INDEXE-P         | Urban construction land area | Urban water supply |
|                  | Number of Employees in Urban Units at the End of the Year |
| ECO-EFFICIENCY-OUTPUT | Expected output | GDP |
| INDEXE-O         | Urban Greening Coverage Rate |

3. Bayesian spatio-temporal model of population agglomeration and eco-efficiency

Economic correspondence and financial data often show non-normal and asymmetrical features, which lead to the assumptions of traditional mean regression models very difficult to be satisfied. Unlike the mean regression, the quantile regression model relaxes the assumptions of the model and has an even better fitting effect on the non-normal and heteroscedastic data. At the same time, the quantile regression model can describe the influence of independent variables on dependent variables under different conditions very well. Based on the existing research, this paper takes ecological efficiency as the general explained variable, takes the Beijing-Tianjin-Hebei urban agglomeration population aggregation index as the core explanatory variable, and constructs the Bayesian spatial segmentation model with the urban scale and urban public service level as the control variables.

\[ Q_{ECO_i}(\tau|x_i, x_{ij}) = \alpha_i + \rho \sum W_{ij} ECO_j + \sum \beta_{it} SCALE_{it} + \sum \beta_{it} SERVICE_{it} \]  

(6)

Where \( \tau \) is the level of the \( \tau \)-quantile level, \( ECO_i \) is the ecological efficiency value of each city obtained from the three-stage DEA method above, \( W_{ij} \) is the element with the column \( j \) and the row \( i \) of the spatial weight matrix \( W \), \( AGGLO_i \) is the population concentration of the \( i \)-th city in the \( t \) period, and \( SCALE_{it} \) is the size of the city. GDP panel data is to maximize the process of urban development, and \( SERVICE_{it} \) express the level of urban public services. Assume that the number of beds in primary schools and secondary schools, the number of health care institutions, and the number of real estate development investments are the control variables that measure the level of urban public services. The data selected in this paper are only within the municipal jurisdiction, and exclude from subordinate administrative units.

Because of the different influences of population aggregation in two cities, this paper introduces position entropy to improve the aggregation formula proposed by [16]. The new population aggregation formula is given: \( C_{\sigma} = \frac{1}{N} \sum_{j} s_{ij}^k / \sigma_{ij} + s_{ij}^k / \sigma_{ij} \times 100 \). Where \( s_{ij}^k \) represent the location entropy of the population of the region, \( \sigma_{ij} \) represents the straight distance between regional capitals of \( i \)-th city and \( j \)-th city, and \( \sigma_{ij} \) represents the intra zone distance of city \( i \). By applying the above theories and models, the numerical results are reported as follows:

It can be seen from Table 2 that in the case of increasing scale returns, the efficiency output (urban green space coverage and GDP) of Beijing-Tianjin-Hebei region is the same as that in the case of the same urban resource input. The top ten cities are Nangong, Tianjin, Anguo, Huang Wei, Tangshan, Gaobeidian, Renqiu, Zhangzhou, Bazhou, Shijiazhuang. Based on the results, this paper calculates the ecological efficiency of urban agglomerations and also makes the relevant improvement.
Table 2. Numerical results of DEA super-efficiency model.

| CITY  | ECO-TECH | Tech  | ECO-Pure Teco | ECO-Scale | Total ranking |
|-------|----------|-------|--------------|-----------|---------------|
| BJ    | 0.954    | 1.126 | 1.000        | 0.954     | 1.073         | 14            |
| TJ    | 1.000    | 1.141 | 1.000        | 1.000     | 1.141         | 2             |
| SJZ   | 0.98     | 1.115 | 0.989        | 0.991     | 1.093         | 10            |
| TS    | 1.000    | 1.108 | 1.000        | 1.108     |               | 5             |
| QHD   | 1.037    | 0.995 | 1.004        | 1.033     | 1.032         | 27            |
| HD    | 1.007    | 1.053 | 1.000        | 1.007     | 1.061         | 22            |
| XT    | 1.000    | 1.036 | 1.001        | 0.999     | 1.037         | 26            |
| BD    | 1.000    | 1.064 | 1.000        | 1.000     | 1.064         | 18            |
| ZJK   | 1.042    | 1.002 | 0.998        | 1.044     | 1.044         | 25            |
| CD    | 1.023    | 0.977 | 1.000        | 1.023     | 1.000         | 32            |
| CZ    | 1.000    | 1.097 | 1.000        | 1.097     |               | 8             |
| LF    | 1.000    | 1.009 | 1.000        | 1.009     |               |               |
| HS    | 0.993    | 1.002 | 1.000        | 0.993     | 0.995         | 33            |
| AG    | 1.179    | 0.953 | 0.999        | 1.18      | 1.124         | 3             |
| BZ    | 1.131    | 0.969 | 1.000        | 1.13      | 1.095         | 9             |
| BT    | 1.122    | 0.945 | 0.999        | 1.123     | 1.061         | 20            |
| DZ    | 1.113    | 0.975 | 0.999        | 1.113     | 1.085         | 12            |
| GBD   | 1.145    | 0.967 | 1.000        | 1.145     | 1.107         | 6             |

Based on the above analysis, we draw conclusions from improved by [17]. Other methods are used to calculate the ecological efficiency of urban agglomerations. We obtain the urban ecological efficiency values of 35 cities in Beijing-Tianjin-Hebei region from 2003 to 2016, which are as shown in Table 3.

Table 3. Partial data of estimated ecological efficiency for 35 cities in Beijing-Tianjin-Hebei region from 2003 to 2016.

| CITY  | 2003 | 2005 | 2007 | 2009 | 2011 | 2013 | 2015 | 2016 |
|-------|------|------|------|------|------|------|------|------|
| BJ    | 0.9  | 0.84 | 1.67 | 0.85 | 1.01 | 0.95 | 2.07 | 0.6  |
| TJ    | 1.3  | 1.24 | 1.07 | 1.18 | 1.14 | 1.84 | 0.63 |      |
| SJZ   | 1.18 | 1.18 | 1    | 1.15 | 1.07 | 0.91 | 1.02 |      |
| TS    | 1.17 | 1.03 | 0.96 | 1.25 | 1.65 | 1.25 | 0.8  |      |
| QHD   | 0.61 | 1.02 | 1.04 | 1.16 | 1.11 | 1.13 | 0.86 |      |
| HD    | 0.91 | 1.08 | 1.19 | 1.17 | 1.11 | 0.98 | 1.09 | 0.99 |
| XT    | 0.86 | 1.04 | 1.02 | 1.14 | 1.14 | 1.01 | 0.04 | 0.8  |
| BD    | 1.06 | 1.13 | 1.06 | 1.04 | 1.07 | 1.27 | 0.82 |      |
| ZJK   | 0.54 | 1.15 | 0.91 | 1.12 | 1.07 | 1.01 | 0.98 | 0.91 |
| CD    | 0.7  | 1    | 1.11 | 0.97 | 0.11 | 0.18 | 0.84 |      |
| CZ    | 1.29 | 1.3   | 1.07 | 1.03 | 1.07 | 1.44 | 0.73 |      |
| LF    | 1    | 0.99 | 1.15 | 1.03 | 1.04 | 0.96 | 1.27 | 0.8  |
| HS    | 1.11 | 1.13 | 1.33 | 1.08 | 1.05 | 1.21 | 0.76 |      |
| AG    | 0.1  | 1    | 1.14 | 1.3   | 0.89 | 0.95 | 0.97 |      |
| BZ    | 0.2  | 1.02 | 1.03 | 1.01 | 1.08 | 0.99 | 0.66 | 0.99 |
| BT    | 0.2  | 1.08 | 1.11 | 1.61 | 0.96 | 1     | 0.97 | 1.01 |
| DZ    | 0.2  | 1.11 | 1.21 | 2.46 | 1.08 | 0.99 | 0.95 | 0.99 |
| GBD   | 0.14 | 1.01 | 1.09 | 1.44 | 1.07 | 1     | 0.98 | 0.96 |

By using the distribution map of variables in this research model, our paper chooses Bayesian spatial quantification model to carry out the statistical analysis of the research variables, and then uses Bayesian
analysis theory and Markov Chain Monte Carlo (MCMC) simulation algorithm to solve the model parameters.

In this paper, we use covariance prior method in prior distribution model and maximum likelihood method for estimation [18]. Gibbs sampling is used to update the model parameters. In order to reduce the influence of initial values on the results and ensure that the Markov chain is in a stable state. MCMC algorithm is used to update 50,000 times of simulation, leaving out the initial 20,000 times. At the same time, in order to eliminate the autocorrelation of the chain, one of the two adjacent random samples is selected to form a Markov chain with a sample size of 5000 when estimating parameter. Ten loci are estimated at the same time (0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, and 0.90). The MCMC sampling algorithm is used to simulate the parameter estimates and also the posterior distribution kernel density curve in Bayesian spatial quantile regression model. The estimated results of Bayesian spatial quantification model are shown in Table 4.

| Table 4. Population agglomeration and urban eco-efficiency. |
|---------------------------------------------------------------|
| **0.1** | mean | s.d. | MCSE | median | 95% confidence |
| GDP($\beta_1$) | -0.1910657 | 0.6138825 | 0.006139 | -0.1949269 | -1.341345 |
| Aggro ($\beta_2$) | -0.013469 | 0.0429853 | 0.00200434 | -0.0138843 | -0.0964439 |
| Investment in real estate ($\beta_3$) | -0.0825432 | 0.3302008 | 0.003302 | -0.0775564 | -0.7364612 |
| Number of ordinary primary schools ($\beta_4$) | -0.135776 | 0.285468 | 0.002808 | -0.1339523 | -0.6821988 |
| Number of General Secondary Schools ($\beta_5$) | 0.2786144 | 0.765062 | 0.007651 | 0.2817276 | -1.246536 |
| Number of beds in medical and health institutions ($\beta_6$) | 0.2403585 | 0.4682928 | 0.004683 | 0.2389168 | -0.6652962 |
| $\rho$ | 1.036684 | 0.021428 | 0.000214 | 1.036731 | 0.994695 |
| Log marginal likelihood=-169.31406 |

| **0.5** | mean | s.d. | MCSE | median | 95% confidence |
| GDP($\beta_1$) | -0.343421 | 0.4624829 | 0.036391 | -0.1819401 | -1.433833 |
| Aggro ($\beta_2$) | 0.1643506 | 0.3436624 | 0.010424 | 0.0147365 | -0.1035474 |
| Investment in real estate ($\beta_3$) | -0.1125961 | 1.334872 | 0.053335 | -0.0834839 | -0.7263015 |
| Number of ordinary primary schools ($\beta_4$) | -0.1635645 | 1.2876902 | 0.032877 | -0.132877 | -0.684926 |
| Number of General Secondary Schools ($\beta_5$) | 0.5655097 | 0.9674805 | 0.017837 | 0.2741965 | -1.229152 |
| Number of beds in medical and health institutions ($\beta_6$) | 2.2334556 | 0.7681311 | 0.006681 | 0.2278245 | -1.6521303 |
| $\rho$ | 2.036653 | 1.0217972 | 0.010218 | 1.036607 | 0.4324496 |
| Log marginal likelihood=-174.37525 |

| **0.9** | mean | s.d. | MCSE | median | 95% confidence |
| GDP($\beta_1$) | -0.1913457 | 0.6142 | 0.0061456 | -0.1952135 | -1.342227 |
| Aggro ($\beta_2$) | -0.013464 | 0.0429 | 0.0004435 | -0.013883 | -0.0964428 |
| Investment in real estate ($\beta_3$) | -0.082534 | 0.3302 | 0.0033331 | -0.0775206 | -0.7365052 |
| Number of ordinary primary schools ($\beta_4$) | -0.135868 | 0.2855 | 0.0028353 | -0.1340394 | -0.6826167 |
| Number of General Secondary Schools ($\beta_5$) | 0.27894 | 0.7655 | 0.0076908 | 0.2821715 | -1.24702 |
| Number of beds in medical and health institutions ($\beta_6$) | 0.24039 | 0.4684 | 0.0046146 | 0.2388934 | -0.6652676 |
| $\rho$ | 1.03668 | 0.0214 | 0.000245 | 1.036728 | 0.99469 |
| Log marginal likelihood=-178.27861 |
From Figure 1 and Figure 2, we can see that the model is convergent and MCMC sampling algorithm is effective. However, from the estimated results of the model at 0.50 bits, it is found that there are many ‘hilltops’ at the top of the Kernel density map of the posterior distribution of each parameter, which indicates that the variables in the model have strong spatial autocorrelation. From the symbols of each parameter coefficient, population agglomeration has a significant negative effect on the ecological efficiency of the city, namely the higher the degree of population agglomeration, the lower the ecological efficiency of the city. For the rural area, the number of primary schools, the scale of urban economic development and the investment in real estate development also have significant negative effects on urban ecological efficiency, but the number of secondary schools and the number of beds in medical and health institutions have significant positive effects on urban ecological efficiency.

![Figure 1. \( \tau =0.1 \) posterior distribution Kernel density curve of each parameter.](image1)

![Figure 2. \( \tau =0.5 \) posterior distribution Kernel density curve of each parameter.](image2)
4. Conclusions

Based on the statistics of 35 cities in the Beijing-Tianjin-Hebei region, this paper combines the ultra-efficient EDA method with the Bayesian space fractional regression method to empirically analyze the relationship between population aggregation and eco-efficiency. The results show that:

Firstly, in the perspective of influencing factors, population concentration, the number of primary schools, the scale of urban economic development and investment in real estate development have a significant negative impact on urban ecological efficiency. The number of secondary schools and the number of beds in health care institutions have a significant positive impact on urban eco-efficiency. Secondly, with the evolution of population size over time, we find that the parameter of population aggregation to urban eco-efficiency is estimated to be 0.50, and the impact of population aggregation on urban eco-efficiency is consistent with the inverted U-shaped curve economy theory.

Thirdly, from the perspective of space, only two municipalities directly under the Central Government of Beijing and Tianjin, where the contribution rate of non-local population is more than 20%, have the high urbanization rate in Beijing-Tianjin-Hebei region at present. It is unavoidable that the population of prefecture-level cities has drastically decreased. The lack of urban population concentration will also lead to a decline in urban economic output. If the utilization efficiency of urban resources could not be improved, the ecological efficiency will be low.

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