The efficiency of Spatial Durbin Model (SDM) parameters estimation on advertisement tax revenue in Malang City

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Abstract. The Spatial Durbin Model (SDM) is a development of the Spatial Autoregressive Model (SAR), in which the effect of spatial lag takes into account on the independent and dependent variables. In determining the parameter estimations in the SDM model, it is necessary to determine appropriate method. The estimation methods that can be used are Maximum Likelihood Estimation (MLE), Bayesian, Generalized Method of Moment, and Method of Moment (MM). In this paper, we will determine the best estimation method for obtaining the advertisement tax revenue model. We further conduct mapping the area to optimize advertisement tax revenue in Malang. From the comparative analysis process of the MLE and MM methods, the results show that the MLE method is a suitable method for estimating SDM parameters in advertisement tax revenue data in Malang City. From the variables that have been used to the model of SDM, all variables significantly affect the advertisement tax revenue. The mapping results show that the Gadang and Bandulan villages are the places with the most potential to increase advertisement tax revenue. This is because those villages are border areas in which many vehicles pass the border, and there are also many companies/industries.

1. Introduction
Spatial regression is the development of simple linear regression, in which there exists a spatial effect on the data to be analyzed. The spatial effects that arise on the spatial regression are spatial heterogeneity and spatial dependence. The spatial heterogeneity shows the differences in characteristics from one region to another, while the spatial dependence shows the dependence between adjacent areas [1]. In general, there are several types of spatial models, namely Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), and Spatial Autoregressive Moving Average (SARMA).

Spatial Durbin Model (SDM) is a spatial regression model developed from the Spatial Autoregressive Model (SAR) [2]. The SAR model only considers the effect of the spatial lag on the independent variables. Meanwhile, the SDM model considers the effect of the spatial lag on the independent variables and the dependent variable. The SDM model therefore has been widely applied, such as [3] which discusses nature and impacts of spatial effects on real estate values, [4] which discusses environmental regulation, green innovation, and green industrial development, [5] which discusses the effects of air pollution control on urban development quality in Chinese cities based on the Spatial Durbin Model.
Several references have mentioned the Durbin model's spatial parameter estimation method. Research on Maximum Likelihood Estimation for SDM, which has been conducted by [6], develops parameter estimates for the SDM using the Maximum Likelihood Estimation (MLE) and [7] methods which are implemented to analyse factors affecting unemployment in Central Java province. [8] wrote a discussion of the Bayesian estimator on SDM regarding analysing regional income disparities in Japan in the period after the bubble burst using the Bayesian spatial Durbin model, which considers both spatial dependence and heterogeneity. [9] regarding the estimated parameters of the Bayesian Spatial Durbin Model using state wide real per capita GDP data computed from the Central Statistical Organization (CSO) during the period 1980 - 2010, [10] regarding GRDP Modelling using the Bayesian Spatial Durbin Model (SDM) approach. The Generalized Method of Moments (GMM) method has been discussed by [11] and [12] discussing about parameter estimation in spatial regression with GMM. Another parameter estimation method is the moment method (MM), which [13] has discussed and is applied to optimize the advertisement tax in Malang.

Since 2000, the government has started to implement regional autonomy, written in [14], which was later updated by [15] concerning Regional Government. With the regional autonomy policy, local governments have a significant role and are required to be creative in exploring the potential of their regions to maximize Regional Original Income (ROI) and Regional Taxes [16]. According to [17], the definition of tax is the contribution that must be paid by individuals or entities to the State, which is compelling based on law. Tax is one component that has the potential to contribute to increasing Regional Original Income (ROI).

Malang city is one of the big cities in East Java, which is experiencing development with more and more immigrants studying and working. It causes an increasing number of businesses and industries in Malang. By the increasing number of businesses and industries, the increasing need for advertisement services can increase billboard tax revenue. The advertisement tax is one of the potential sources of regional income and plays an essential role in increasing the Regional Original Income (ROI) of Malang City. In the Regulation of the Mayor of Malang Number 4 of 2008, it is explained that billboards are objects, tools, actions, or media which, according to their form, structure, and variety for commercial purposes, are used to introduce, recommend, or praise a product, service, or person or to attract public attention to a product, service, or person that is placed or which can be seen, read, or heard from a place by the public, except those carried out by the Government or Regional Government. To optimize advertisement tax revenue, Malang’s city government needs to know the factors that have a significant influence and map the areas that can increase the advertisement tax price. Several studies have discussed the factors that influence advertisement tax revenue, including [18] and [19] total population, GRDP, number of industries, length of roads [20], many billboards, installation time of advertisements, and types of advertisements [21].

The amount of tax revenue in one area will affect other regions. Likewise, with advertisement tax revenue, so it can be said that advertisement tax revenue has a spatial effect. Research on the influence of territoriality in billboard tax revenue has also been written by [22], who discusses exploration the effects of immigration on labour tax avoidance using SDM and [23], which discusses exploration the spatial effects of green tax policies on energy efficiency using SDM.

In this paper, we will discuss the efficiency of the SDM model parameter estimation by using the MLE and MM methods in which the population data take account, many billboards, advertisement installation period, types of advertisements, number of industries, and GRDP as independent variables that affect billboard tax revenue.
2. Literature review

2.1 Spatial Durbin Model (SDM)

Spatial Durbin Model (SDM) is an extension of the Spatial Autoregressive (SAR) model because of the spatial interaction of the dependent variable and independent variables. SDM models, in general, can be written in the form of a matrix-like the following [24]:

\[ Y = \delta WY + X\beta + WX\theta + \epsilon \]

2.2 Estimation of SDM parameters using Maximum Likelihood Estimation (MLE)

The SDM model can be written as a SAR (Spatial Autoregressive Models) model by defining matrice \( Z = [I \quad X \quad WX] \) and vector \( \beta = [\beta \quad \theta]^T \). So that the equation can be written as

\[ Y = \delta WY + Z\beta + \epsilon \]

The likelihood function of \( \epsilon \) is as follows [1]:

\[ L(\sigma^2; \epsilon) = f(\epsilon) = \left(1/2\pi\sigma^2\right)^n \exp\left(-1/2\sigma^2(x^T\epsilon)\right) \]

So that the log-likelihood function is obtained as follows:

\[ \ln(L(\delta, \beta, \sigma^2|Y)) = -n/2 \ln(2\pi) - n/2 \ln(\sigma^2) + \ln[I - \delta W] \]

\[ -1/2\sigma^2 \left( (I - \delta W)Y - Z\beta \right)^T \left( (I - \delta W)Y - Z\beta \right) \]

Parameter \( \beta \) are estimated by maximizing the log-likelihood function by deriving the equation for \( \sigma^2 \) obtaining stationarity conditions. So that the estimator parameter \( \beta \) are:

\[ \hat{\beta} = (Z^TWZ)^{-1}Z^TY - \delta(Z^TWY) \]

Parameter \( \sigma^2 \) are estimated by maximizing the log-likelihood function by deriving the equation for \( \sigma^2 \) is:

\[ \hat{\sigma}^2 = \left( (I - \delta W)Y - Z\beta \right)^T \left( (I - \delta W)Y - Z\beta \right) \]

Let \( \hat{\rho}_0 = (Z^TW)^{-1}Z^TY \) and, then \( \hat{\rho}_1 = (Z^TW)^{-1}Z^TY \)

\[ \hat{\rho}_0 - \delta \hat{\rho}_1 \]

\[ \sigma^2 = \left( Y - \delta W - Z\hat{\rho}_0 + \delta Z\hat{\rho}_1 \right)^T \left( Y - \delta W - Z\hat{\rho}_0 + \delta Z\hat{\rho}_1 \right) \]

Let \( e_0 = Y - Z\hat{\rho}_0 \) dan \( e_1 = WY - Z\hat{\rho}_1 \), we get

\[ \sigma^2 = \left( e_0 - \delta e_1 \right)^T \left( e_0 - \delta e_1 \right) \]

So that we get the natural logarithmic function to predict \( \delta \).

\[ f(\delta) = c = n/2 \ln(|(e_0 - \delta e_1)^T(e_0 - \delta e_1)|) + \ln[I - \delta W] \]

with \( c = -n/2 \ln(2\pi) + n/2 \ln(n) - n/2 \)

2.3 Estimation of SDM parameters using the moment method

Moment condition of the equation

\[ Y = \delta WY + Z\beta + \epsilon \]

defined by \( E(z_ie_i) = 0 \). Furthermore, the sample moment analog is defined with [11]

\[ g(\beta) = n^{-1}Z'((I - \delta W)Y - Z\beta) \]

and

\[ g(\delta) = n^{-1}Z'((I - \delta W)Y - Z\beta) \]
Parameter $\hat{\beta}$ can be obtained by completing the function $g(\delta)=0$. So that the estimator parameter $\beta$ are:

$$\hat{\beta}=(Z'Z)^{-1}Z'Y - \delta(Z'Z)^{-1}Z'WY$$

Based on this equation, it can show that the parameter estimate for $\beta$ using the moment method produces the same estimate as to the maximum likelihood (MLE) method or $\hat{\beta}_{MM} = \hat{\beta}_{MLE}$.

Parameter $\hat{\delta}$ can be obtained by completing the function $g(\delta)=0$. So that the estimator parameter $\delta$ are:

$$\hat{\delta}=(Z'WY)^{-1}Z'(Y-Z\hat{\beta})$$

3. Research method

3.1 Types, data sources, and research variables

The Spatial Durbin Model (SDM) data used in this study are secondary data obtained from the Malang City Regional Tax Service Agency in 2018. The data used are advertisement tax data as a $Y$ variable, population ($X_1$), many billboards ($X_2$), installation period of billboard ($X_3$), type of billboard ($X_4$), number of industries ($X_5$), and GRDP ($X_6$). Statistical software used in this study is R 4.0.2 software.

3.2 Data analysis steps

The steps taken are as follows:

a. Multicollinearity testing using Variance Inflation Factor (VIF)
b. SDM parameter estimation using MLE and MM.
c. Testing the model residuals of MLE and MM.
   1. Testing for normality uses the Jarque Bera test.
   2. The test for spatial heterogeneity used the Breusch Pagan test.
   3. Testing of spatial autocorrelation using Moran’s I test.
d. Determine the best estimate for SDM using MSE.
e. Data mapping and data interpretation.

4. Results and discussion

4.1. Multicollinearity detection

Multicollinearity detection can be seen from the Variance Inflation Factor (VIF) value. Based on the results of linear regression analysis, the VIF value was obtained, which is presented in Table 1.

Table 1. VIF Value for each independent variable

| Variable            | VIF value |
|---------------------|-----------|
| $X_1$ (Total population) | 2.06      |
| $X_2$ (The number of advertisements) | 1.47      |
| $X_3$ (Advertisement Installation Period) | 1.03      |
| $X_4$ (Types of advertisements) | 1.30      |
| $X_5$ (Number of Industries) | 3.95      |
| $X_6$ (GRDP) | 3.17      |

Based on the results in Table 1, it is known that the VIF value of all independent variables is less than 10, so it can be concluded that there is no multicollinearity.

4.2. Test spatial autocorrelation

The autocorrelation test was carried out using the Moran’s I test statistic. The results of Moran’s I testing are presented in Table 2.
Table 2. Results of Moran's I model OLS test

| Variable | I     | E (I) | p-value |
|----------|-------|-------|---------|
| error    | 0.1707| -0.0179| 0.0165  |
| Y        | 0.1978| -0.0179| 0.0057  |
| X1       | 0.1491| -0.0179| 0.0382  |
| X2       | 0.0982| -0.0179| 0.1341  |
| X3       | -0.0313| -0.0179| 0.8677  |
| X4       | 0.0240| -0.0179| 0.6015  |
| X5       | 0.2888| -0.0179| 0.0001  |
| X6       | 0.3336| -0.0179| 8.5873×10^{-6} |

Based on Table 2, it can be seen that the p-value of Moran's I on the remaining is less than the real level of 5%, so $H_0$ is rejected.

4.3 Estimation of parameter Data SDM by using the MLE

Based on the results of parameter estimation using MLE, which is applied to the advertisement tax data, the results are presented in Table 3 below:

Table 3. Parameter estimation using MLE

| Variable | Coefficient | p-value |
|----------|-------------|---------|
| $\beta_0$ | -4.28×10^7 | 0.0475  |
| $\beta_1$ | 1.02×10^5  | 0.0223  |
| $\beta_2$ | -9.69×10^6 | 0.0393  |
| $\beta_3$ | -1.79×10^8 | 0.0302  |
| $\beta_4$ | 1.04×10^9  | 0.0138  |
| $\beta_5$ | -3.11×10^7 | 0.0196  |
| $\beta_6$ | 7.78×10^7  | 0.0221  |
| $\theta_1$ | 2.75×10^5  | 0.0118  |
| $\theta_2$ | 1.70×10^7  | 0.0408  |
| $\theta_3$ | -7.30×10^7 | 0.0422  |
| $\theta_4$ | 3.68×10^9  | 0.0087  |
| $\theta_5$ | 4.83×10^9  | 0.0326  |
| $\theta_6$ | -1.18×10^9 | 0.0004  |
| $\delta$  | 0.013968   | 0.0457  |

The estimation equation for the SDM model that is formed is as follows:

$$\hat{y}_i = 0.013968×10^5 - 4.28×10^7 \sum_{j=1}^{57} w_{ij} y_j + 1.02×10^5 x_{1i} - 9.69×10^6 x_{2i} - 1.79×10^8 x_{3i} +$$

$$1.04×10^9 x_{4i} - 3.11×10^7 x_{5i} + 7.78×10^7 x_{6i} + 2.75×10^5 \sum_{j=1}^{57} w_{ij} x_{1j} + 1.7×10^5 \sum_{j=1}^{57} w_{ij} x_{2j} -$$

$$7.3×10^7 \sum_{j=1}^{57} w_{ij} x_{3j} + 3.68×10^9 \sum_{j=1}^{57} w_{ij} x_{4j} + 4.83×10^7 \sum_{j=1}^{57} w_{ij} x_{5j} - 1.18×10^9 \sum_{j=1}^{57} w_{ij} x_{6j} + \epsilon_i$$

4.4 Testing the rest of the Spatial Durbin Model (SDM) using MLE

4.4.1 Spatial autocorrelation testing

The spatial autocorrelation test is carried out to determine whether there is a spatial interaction in the SDM model left. Based on the Moran's I test results on the rest of the SDM model can be seen that the
p-value of Moran's I is 0.7815 that is more than the real level of 5%. These results indicate that there is no autocorrelation in the error.

4.4.2 Testing of spatial heterogeneity
The spatial heterogeneity test is used to determine the spatial variance instability. The p-value in the Breusch-Pagan test is 0.5727 that is known to be higher than the real level of 5%. These results indicate that there is no spatial heterogeneity in the error.

4.4.3 Normality testing
The normality test was carried out by using the Jarque Bera test statistic. The p-value in the Jarque Bera test is 0.0766 that is known to be higher than the real level of 5%. These results indicate that the error of the SDM model is normally distributed.

4.5 Estimation of parameter data SDM using the moment method
Based on the results of parameter estimation using the moment method applied to the advertisement tax data, the results are presented in Table 4 below:

| Variable | Coefficient | p-value |
|----------|-------------|---------|
| $\beta_0$ | $-4.28 \times 10^7$ | 0.0475 |
| $\beta_1$ | $1.02 \times 10^5$ | 0.0223 |
| $\beta_2$ | $-9.69 \times 10^6$ | 0.0393 |
| $\beta_3$ | $-1.79 \times 10^8$ | 0.0302 |
| $\beta_4$ | $1.04 \times 10^9$ | 0.0138 |
| $\beta_5$ | $-3.11 \times 10^7$ | 0.0196 |
| $\beta_6$ | $7.78 \times 10^5$ | 0.0221 |
| $\theta_1$ | $2.75 \times 10^5$ | 0.0118 |
| $\theta_2$ | $1.70 \times 10^7$ | 0.0408 |
| $\theta_3$ | $-7.30 \times 10^7$ | 0.0422 |
| $\theta_4$ | $3.68 \times 10^9$ | 0.0087 |
| $\theta_5$ | $4.83 \times 10^7$ | 0.0326 |
| $\theta_6$ | $-1.18 \times 10^9$ | 0.0004 |
| $\delta$ | $0.02996687$ | 0.0274 |

The estimation equation for the SDM model that is formed is as follows:

$$y_j = 0.02996687 \times 10^5 - 4.28 \times 10^7 \sum_{j=1}^{57} w_{ij} y_j + 1.02 \times 10^5 x_{1i} - 9.69 \times 10^6 x_{2i} - 1.79 \times 10^8 x_{3i} +$$

$$1.04 \times 10^9 x_{4i} - 3.11 \times 10^7 \times 10^5 x_{5i} + 7.78 \times 10^7 x_{6i} + 2.75 \times 10^5 \sum_{j=1}^{57} w_{ij} x_{ij} + 1.7 \times 10^7 \sum_{j=1}^{57} w_{ij} x_{2j} -$$

$$7.3 \times 10^7 \sum_{j=1}^{57} w_{ij} x_{3j} + 3.68 \times 10^9 \sum_{j=1}^{57} w_{ij} x_{4j} + 4.83 \times 10^7 \sum_{j=1}^{57} w_{ij} x_{4j} - 1.18 \times 10^9 \sum_{j=1}^{57} w_{ij} x_{4j} + \epsilon_i$$

4.6. Testing the rest of the Spatial Durbin Model (SDM) using method of moment
4.6.1 Spatial autocorrelation testing
The spatial autocorrelation test was carried out to determine whether the error in the SDM model had spatial interactions in the error model. Based on Moran’s I test results on the rest of the SDM model can be seen that the p-value of Moran’s I is 0.8139 that is more than the real level of 5%. These results indicate that there is no autocorrelation in the error.
4.6.2 Spatial heterogeneity testing
The spatial heterogeneity test is used to determine the spatial variance instability. This test is performed using the Breuch-Pagan test. The p-value in the Breusch-Pagan test is 0.9643 that is known to be higher than the real level of 5%. These results indicate that there is no spatial heterogeneity in the error.

4.6.3 Normality testing
The normality test was carried out by using the Jarque Bera test statistic. The p-value in the Jarque Bera test is 0.4189 that is known to be higher than the real level of 5%. These results indicate that the error of the SDM model is normally distributed.

4.7 Testing the goodness of the parameter estimation method
The goodness of the model is determined based on the MSE value obtained in each parameter estimation method. The MSE values in the MLE method and the moment method are presented in Table 5 below.

| Parameter Estimation Method | MSE Value |
|----------------------------|-----------|
| MLE                        | 818565    |
| Moment Method              | 834076    |

Based on Table 5, it can be seen that the MLE method has a smaller MSE value than the moment method MSE. It shows that the MLE method is more suitable for modeling advertisement tax data in Malang.

4.8 Mapping
Based on the results of the analysis with the SDM approach, it is obtained that the advertisement tax revenue value is divided into five classes, where the classification can be seen in Table 6.

| Classification | Category  | Colour |
|----------------|-----------|--------|
| Grade 1        | Very high | Red    |
| Grade 2        | High      | Orange |
| Grade 3        | Moderate  | Yellow |
| Grade 4        | Low       | Green  |
| Grade 5        | Very low  | Blue   |

The results of the prediction mapping of advertisement tax revenue in Malang are presented in Figure 1 below.
Based on Figure 1, it can be seen that two urban villages fall into the "very high" category, namely Gadang and Bandulan Village, respectively. The Gadang Village is in the "very high category" because there are terminals and lots of shops. Meanwhile, the Bandulan Village is a village located on the border between the regency and the city. Besides, there are several factories. Therefore, the installation of billboards in the two villages has an excellent opportunity to be read.

Nine sub-districts fall into the "high" category, namely Samaan, Sumbersari, Ketawanggede, Tulusrejo, Bakalan Kragen, Kebonsari, Bandungrejosari, Pisang Candi, and Mulyorejo village, respectively. Because the nine sub-districts are located in the vicinity of the "very high" category, there are many shops and campuses.

There are 18 sub-districts that are classified into the "medium" category, namely Arjowinangun, Bumiayu, Buring, Mergosono, Bareng, Kasin, Gadingkasri, Klojen, Rampal Celaket, Penanggungan, Kesatrian, Pandanwangi, Merjosari, Dinoyo, Batumulyo, Tanjungrejo, and Karang Besuki village, respectively. These villages are located near public facilities such as markets, shopping centres and shops.

There are 19 sub-districts that fall into the "low" category, namely Kotalama, Kedungkandang, Madyopuro, Cemorokandang, Sukoharjo, Kidul Dalem, Kauman, Oro Oro Dowo, Jodipan, Bunulrejo, Blimbing, Purwodadi, Balearjosari, Lowokwaru, Mojolangu, Tlogomas, Tunggulwulung, Tunjungsakar, and Sukun village, respectively. These villages are located in the vicinity of settlements and schools.

Nine sub-districts fall into the "very low" category, namely Tlogowaru, Wonokoyo, Lesanpuro, Sawojajar, Polehan, Purwantoro, Arjosari, Polowijen, and Tasikmadu villages. Most of the areas of these sub-district are residential or residential, so vehicles are rarely traversed.

5. Conclusion

Based on the MSE value, Spatial Durbin Model parameter estimation using MLE is better than the moment method for analyzing advertisement tax revenue in Malang City in 2018. The SDM model obtained is

\[
\hat{y}_i = 0.013968 \times 10^5 - 4.28 \times 10^7 \sum_{j=1}^{57} w_{ij} y_j + 1.02 \times 10^5 x_{1i} - 9.69 \times 10^6 x_{2i} - 1.79 \times 10^8 x_{3i} + 1.04 \times 10^7 x_{4i} - 3.11 \times 10^7 x_{5i} + 7.78 \times 10^2 x_{6i} + 2.75 \times 10^5 \sum_{j=1}^{57} w_{ij} x_{ij} + 1.7 \times 10^7 \sum_{j=1}^{57} w_{iy} x_{2j} - 7.3 \times 10^2 \sum_{j=1}^{57} w_{ij} x_{yj} + 3.68 \times 10^1 \sum_{j=1}^{57} w_{ij} x_{4y} - 4.83 \times 10^7 \sum_{j=1}^{57} w_{ij} x_{4j} + 1.18 \times 10^9 \sum_{j=1}^{57} w_{ij} x_{4j} + e_i
\]

In the resulting SDM model, it appears that the total population, the number of advertisements, advertisement installation period, types of advertisements, number of industries, and GRDP have a significant effect on advertisement tax.

Based on the advertisement tax revenue obtained from the SDM model with the MLE approach, obtained as many as two urban villages are in the "very high" category, nine villages are classified as "high" category, 18 villages are in the "medium" category, 19 villages fall into the "low" category, and 9 villages in the "very low" category.

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