E-ISSN 2586-9027
Homepage : https://tci-thaijo.org/index.php/SciTechAsia
Science & Technology Asia
Vol.30 No.3 July - September 2025
Page: [189-198]
Original research article

Modeling the Spatial Durbin Error Model on Open Unemployment Rate Data in Indonesia 2023

Arbain, Memi Nor Hayati*, Siti Mahmuda

Statistics Study program, Department of Mathematics, Faculty of Mathematics Natural Sciences, Mulawarman University, East Kalimantan 75123, Indonesia

Received 21 February 2025; Received in revised form 22 May 2025
Accepted 19 June 2025; Available online 30 September 2025

ABSTRACT

This study applies the Spatial Durbin Error Model (SDEM) to analyze the factors influencing the Open Unemployment Rate (OUR) across 34 provinces in Indonesia in 2023. The model incorporates both direct effects and spatial spillover effects of the independent variables. The Maximum Likelihood Estimation (MLE) method was used for parameter estimation. The spatial weight matrix was constructed using a customized contiguity approach. The results show that the Labor Force Participation Rate (LFPR) and Gender Development Index (GDI) have significant direct effects on OUR, while Population Growth Rate (PGR) and GDI also exhibit significant spatial lag effects. The spatial autoregressive coefficient λ is 0.371, indicating significant spatial dependence in the error term. The model's AIC value 104.750 is lower than the MLR model, confirming better model fit.

Keywords: Customized contiguity; Maximum likelihood estimator; Spatial durbin error model; Open unemployment rate; The lagrange multiplier test

1. Introduction

Spatial regression modeling aims to establish the relationship between independent and dependent variables by incorporating spatial dependencies among locations. Two commonly used approaches in this modeling are the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM). The SEM, which excludes spatial lags of the dependent variable, allows the β parameter estimates to be interpreted similarly to those in standard regression. An extension of the SEM is the Spatial Durbin Error Model (SDEM), which does not include spatial lags of the dependent variable but accounts for spatial errors and

***Corresponding author:** meminorhayati@fmipa.unmul.ac.id **doi:** 10.14456/scitechasia.2025.61

spatial lags in the independent variables. This structure enables the SDEM to provide clear interpretations of both the direct effects through the β parameters and the indirect (spatial spillover) effects through the γ parameters [1].

The number of workers who are actively looking for work is shown by a figure called unemployment [2]. Open unemployment is those who do not have a job, are looking for work or setting up a business, do not have a job and are not looking for work because they feel it is impossible to get a job, and have not started working but have a job. One factor that influences and has a negative impact on the unemployment rate is the Labor Force Participation Rate (LFPR). When LFPR increases, more individuals actively look for work, which can reduce the Open Unemployment Rate (OUR) if jobs are available [3]. The factor of increasing the Pure Upper Middle Participation Rate (PUMPR) tends to have a positive impact on reducing OUR in the long term through increasing skills and adapting education to labor market needs. Another factor that is thought to influence OUR is the Population Growth Rate (PGR) which can increase pressure on the labor market, especially if there is no increase in economic investment that creates new jobs. The Gender Development Index (GDI) can influence OUR because gender equality in the education and economic sectors has an impact on labor force participation [4].

Previous research [5], using the SDEM method on Human Development Index (HDI) data in Central Java, showed that the SDEM model met all the criteria for selecting the best model compared to the Ordinary Least Square (OLS) and SEM models. In research [6], using The SDEM method on data on the Percentage of Poor Population (PPP) in South Sulawesi Province states that the best model based on the coefficient of determination is SDEM which is greater than the OLS model. Other research [7], using the SDEM method in modeling OUR in East Nusa Tenggara Province stated that the results of the comparison of values Akaike's Information Criterion (AIC) from OLS, SEM and SDEM modeling, shows that SDEM modeling has the smallest AIC value, namely 73.2, so it is good for modeling OUR in East Nusa Tenggara Province. The spatial structure of regional economies suggests that unemployment in a given province may be influenced by socio-economic factors in neighboring regions. Labor mobility, interregional investment flows, and policy externalities often create spatial dependencies. Prior research has established the relevance of spatial econometric models for analyzing such phenomena. Therefore, this study applies SDEM to account for both direct and spatial spillover effects. While the SDEM model has been widely used in regional socio-economic analysis, the application of this model to Indonesia's 2023 unemployment data across all 34 provinces provides updated empirical insights that reflect recent economic conditions and broader geographic scope compared to previous studies.

This research aims to obtain modeling results on OUR data in 34 Indonesian provinces in 2023 using the SDEM method, as well as to determine the factors that significantly influence OUR in 34 Indonesian provinces in 2023, both through direct influence from independent variables and indirect influences. Directly through spatial lag.

2. Materials and Methods

2.1 Linear regression analysis

Multiple linear regression is a statistical method used to examine how one dependent variable is simultaneously affected by two or more independent variables. This approach helps in understanding and quantifying the combined influence of several predictors on a single outcome. Generally, the formulation of the multiple linear regression (MLR) model can be represented as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + +\beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i, \tag{2.1}$$

where y_i is the observed value of the i, dependent variable β_0 is the regression model constant, x_{ik} is the k independent variable for the i observation, ε with the assumption $N(0, \sigma^2 I)$ and p is the number of independent variables [8].

2.2 Spatial analysis

Spatial analysis encompasses all analytical techniques that measure the distribution of an event based on spatial characteristics. Spatial analysis is also related to spatial modeling, meaning that spatial data types have two different approaches, point-based and area-based, each with its own method of resolution [11].

2.3 Spatial patterns

As explained in [12], spatial patterns refer to how objects or phenomena are distributed or arranged across the Earth's surface. These patterns can reveal whether the distribution is clustered, dispersed, or random, providing valuable insights into spatial processes. One of the key concepts used to identify and measure such patterns is spatial autocorrelation.

According to [13], spatial autocorrelation evaluates the degree of similarity or correlation between observations of a specific variable based on their geographic locations. In other words, it measures whether nearby or neighboring locations tend to have similar values. This concept is essential in spatial analysis, as it helps distinguish whether the observed distribution is influenced by spatial relationships or merely random variation.

One of the tests in spatial autocorrelation is Moran's I. The following is the formula for the Moran's I test:

$$I = \frac{\sum_{i=j}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, \tag{2.2}$$

where I is the Moran's index, xi and xj are the values of the variable at locations i and j, $\bar{x}$ is the mean of the data, and w_{ij} is the element of the spatial weight matrix obtained from row standardization.

2.4 Spatial Error Model (SEM)

The Spatial Error Model (SEM) is a spatial model that arises due to the presence of spatial effects in the error term. If $\rho = 0$ and $\lambda \neq 0$, the general form of the SEM equation is as follows:

$$y = X\beta + u, \tag{2.3}$$

where

$$u = \lambda W u + \varepsilon, \tag{2.4}$$

where y is the observation data vector for the dependent variable with a size of $n \times 1$, u is the error vector from the spatial regression model with a size of $n \times 1$, λ is the spatial lag coefficient parameter for the error, and W is the spatial weight matrix with a size of $n \times n$ [14].

2.5 Spatial Durbin Error Model (SDEM)

The Spatial Durbin Error Model (SDEM) [15] represents a spatial regression technique that integrates spatial lags of the independent variables into the analysis. Unlike the SEM, which excludes spatial lag effects on the dependent variable, the SDEM permits spatial lag influences on the independent variables while still accounting for spatial error components.

$$y = X\beta + WX\theta + u, \quad (2.5)$$

Where y is the observation data vector for the dependent variable with a size of $n \times 1$ (OUR), X is independent variables (LFPR, PUMPR, PGR, GDI), u is the error vector from the spatial regression model with a size of $n \times 1$, λ is the spatial lag coefficient parameter for the error, and W is the spatial weight matrix with a size of $n \times n$ is customized contiguity, θ. The vector of spatial lag parameters for the independent variables has a size of $p \times 1$.

The selection of the SDEM model over alternatives such as SAR and SEM was based on the results of Lagrange Multiplier (LM) tests and the Akaike Information Criterion (AIC). The customized contiguity matrix was developed by modifying the standard Queen contiguity approach to better reflect inter-provincial economic relationships that are not strictly geographic.

2.6 Estimation of SDEM parameters

The estimation of SDEM parameters can be performed using the Maximum Likelihood Estimator (MLE) method, resulting in the error term as shown in the following equation:

$$\begin{aligned} y &= Z\beta + (I - \lambda W)^{-1}\varepsilon \\ (I - \lambda W)y &= (I - \lambda W)Z\beta + \varepsilon \\ \varepsilon &= (I - \lambda W)y - (I - \lambda W)Z\beta \\ \varepsilon &= (I - \lambda W)(y - Z\beta). \quad (2.6) \end{aligned}$$

To estimate the parameters, the likelihood function below is maximized:

$$L(\lambda, \beta, \sigma^2; y) = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} \exp[-\frac{\varepsilon^T\varepsilon}{2\sigma^2}]. \quad (2.7)$$

The log-likelihood equation that can be used to estimate each parameter is as follows:

$$\begin{aligned} \ln L = &\frac{n}{2}\ln\left(\frac{1}{2\pi\sigma^2}\right) + \ln(|I - \lambda W|) \\ &- \frac{1}{\sigma^2}(((I - \lambda W)y - Z\beta)^T(I - \lambda W)y - Z\beta). \end{aligned} \quad (2.8)$$

From this equation, we can calculate the estimates for each parameter in SDEM.

3. Results and Discussion

3.1 Descriptive statistical analysis

The calculation of descriptive statistical analysis, performed using R software, is presented in Table 1.

Table 1. Descriptive statistical analysis.

Variable	mean	Min	Max	Standard Deviation
y	4,614	2,270	7,520	1,419
x_1	69,090	63,510	77,090	3,657
x_2	63,890	48,320	76,370	5,920
x_3	1,282	0,380	1,690	0,305
x_4	91,090	81,640	95,240	3,049

The average Open Unemployment Rate (OUR) (y) in Indonesia in 2023 was 4.614%, with a minimum value of 2.270%, a maximum of 7.520%, and a standard deviation of 1.420%. The average Labor Force Participation Rate (LFPR) (x_1) was 69.090%, with a minimum value of 63.510%, a maximum of 77.090%, and a standard deviation of 3.657%. The Pure Upper Middle Participation Rate (PUMPR) (x_2) was 63.890%, with a minimum value of 48.320%, a maximum of 76.370%, and a standard deviation of 5.920%. The average Population Growth Rate (PGR) (x_3) was 1.282%, with a minimum value of 0.380%, a maximum of 1.690%, and a standard deviation of 0.305%. The average Gender Development Index (GDI) (x_4) was 91.090, with a minimum value of 81.640, a maximum of 95.240, and a standard deviation of 3.049.

The description of the dependent and independent variables is also presented through thematic maps of 34 provinces in 2023, created using QGIS software. The classification on each map was done by grouping the data into two categories based on the average value, as shown in the following figure.

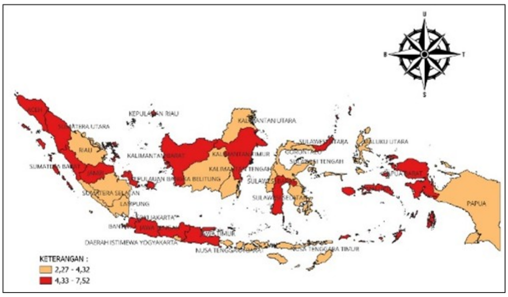

Fig. 1. Thematic Map of OUR.

Fig. 1 shows the classification of the OUR in each province of Indonesia, represented by different colors; yellow colors indicate provinces with OUR below the average, while red colors represent provinces with OUR above the average. There are 20 provinces with OUR below the average, South Sulawesi, North Kalimantan, North Sumatra, South Kalimantan, Gorontalo, Bengkulu, East Kalimantan, West Sulawesi, Riau, Jambi, Banten, DI Yogyakarta, West Papua, East Nusa Tenggara, Central Sulawesi, Central Java, Central Kalimantan, Southeast Sulawesi, Lampung, and Bali. Meanwhile, 14 provinces have OUR above the average, DKI Jakarta, West Java, Riau Islands, East Java, North Sulawesi, Papua, North Maluku, Aceh, Maluku, West Kalimantan, South Sumatra, West Nusa Tenggara, Bangka Belitung Islands, and West Sumatra.

3.2 Analysis MLR

In MLR, a good independent variable is one that has no correlation with other independent variables. Therefore, multicollinearity detection is necessary to determine whether there is a linear relationship between independent variables in the regression model. The results of multicollinearity detection are presented in Table 2.

Table 2. Multicollinearity Detection.

Variable	VIF	Indication of Multicollinearity
x_1	1,005	No Multicollinearity Detected
x_2	1,331	No Multicollinearity Detected
x_3	1,374	No Multicollinearity Detected
x_4	1,760	No Multicollinearity Detected

Based on the VIF values in Table 2, it can be concluded that there is no multicollinearity among the independent variables. This is indicated by the VIF values of each variable being less than 10, allowing the regression modeling in this study to include all four independent variables, x_1 to x_4.

MLR model formed for modeling the OUR in 34 provinces of Indonesia in 2023 is as follows:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \hat{\beta}_3 x_{i3} + \hat{\beta}_4 x_{i4} + \varepsilon_i. \quad (3.1)$$

The estimation results that form the MLR model are as follows:

$$\hat{y}_i = 16,668 + 0.254x_{i1} + 0.004x_{i2} + 0.164x_{i3} + 0.065x_{i4}. \quad (3.2)$$

The simultaneous parameter test aims to determine the significance of the parameters on the dependent variable as a whole. Based on the results of the simultaneous parameter test, at a significance level of 0.05, the decision is to reject H_0. This is indicated by $F_{calculated} = 7.043 > F_{0,05:4:29}$=2.701 or $p_{value} = 4.329 \times 10^{-4} < \alpha = 0,05$. Thus, based on the hypothesis test results, it is concluded that, simultaneously, the variables x_1 to x_4 significantly influence the dependent variable y.

The partial test is conducted on each independent variable individually to determine whether a specific independent variable has a significant effect on the dependent variable. The results of the partial parameter test can be seen in Table 3.

Table 3. Hypothesis testing results.

Variable	$\lvert Z_{calculate}\rvert$	$Z_{0.025}$	Decision
β_0	$\lvert 2.033\rvert$	2.045	H_0 fails to be rejected
β_1	$\lvert -4.941\rvert$	2.045	H_0 fails to be rejected
β_2	$\lvert 0.129\rvert$	2.045	H_0 fails to be rejected
β_3	$\lvert -0.852\rvert$	2.045	H_0 fails to be rejected
β_4	$\lvert 0.806\rvert$	1.960	H_0 fails to be rejected

Based on Table 4, it is concluded that x_1 has a significant partial effect on y in 34 provinces of Indonesia. This is because, at a significance level of 0.05, the variable has a $|t| = 4.941 > 2.405$, which is greater than 2.405. Meanwhile, $x_2, x_3 x_4$ do not have a significant partial effect on y in 34 provinces of Indonesia, as their □t□|t| values are less than $|t| < t_{0,025:29} = 2,405$.

AIC is a method used to obtain the best regression model. The AIC value for the MLR model is calculated using R software. The AIC value obtained for the MLR model is 107.280.

The next step is the autocorrelation test, which aims to determine whether there is a correlation between errors in the multiple linear regression model. The autocorrelation test is conducted using the Durbin-Watson method. At a significance level of 0.05, the test results lead to rejecting H_0 since the obtained $p_{value} = 0.044 < \alpha = 0.05$. This indicates that the error values in the multiple linear regression model exhibit autocorrelation at the observation locations. Thus, multiple linear regression is suspected to be unsuitable for modeling the OUR data in 34 provinces of Indonesia. Therefore, an alternative modeling approach is required. Consequently, the researcher applies spatial regression to continue the modeling process.

3.3 Analysis spatial

The contiguity matrix used in the spatial analysis is the queen contiguity matrix, which has been modified into a customized contiguity matrix. A brief overview of the modified queen contiguity matrix, now referred to as the customized contiguity matrix, is presented in Table 4.

Table 4. Queen contiguity matrix and customized contiguity matrix.

		j							
	C	1	2	3	⋯	15	16	⋯	34
	1	0	1	0		0	0		0
	2	1	0	1		0	0		0
	3	0	1	0		0	0		0
i	⋮								
	15	0	0	0		0	0		0
	16	0	0	0		0	0		0
	⋮								
	34	0	0	0		0	0		0

The weighting matrix used is the spatial weighting matrix W, which is derived from the standardized contiguity matrix. A brief overview of the spatial weighting matrix W is presented in Fig. 2.

	C	j							
		1	2	3	⋯	15	16	⋯	34
	1	0,000	0,333	0,000		0,000	0,000		0,000
	2	1,000	0,000	0,250		0,000	0,000		0,000
	3								
i	⋮	0,000	0,333	0,000		0,000	0,000		0,000
	15								
	16								
	⋮	0,000	0,000	0,000		0,000	0,000		0,000
	34	0,000	0,000	0,000		0,000	0,000		0,000

Fig. 2. Matrix customized contiguity.

The next step in the spatial analysis is to examine spatial autocorrelation using the Moran's Index. The complete results of the Moran's Index calculation are presented in Table 5.

Table 5. Moran's index value.

Variable	Moran's Index
x_1	0.267
x_2	-0.003
x_3	0.340
x_4	0.467
ε RLB	0.345

Table 5 presents the Moran's Index values for the independent variables and error terms. Based on Table 6, variables x_1, x_3, x_4, and the error term exhibit positive spatial autocorrelation, as all their Moran's Index values are greater than ($I > 0$). Meanwhile, variable x_2 shows negative spatial autocorrelation, as its Moran's Index value is less than $I < 0$.

The next test performed is the spatial dependency test. The spatial dependency test results for the independent variables x_1 to x_4 and the error term are presented in Table 6.

Table 6. Dependency test value.

Variable	$\lvert Z_{calculate} \rvert$	$Z_{0.025}$	Decision
x_1	$\lvert 1.772 \rvert$	1.960	H_0 fails to be rejected
x_2	$\lvert 0.162 \rvert$	1.960	H_0 fails to be rejected
x_3	$\lvert 2.263 \rvert$	1.960	H_0 is rejected
x_4	$\lvert 3.053 \rvert$	1.960	H_0 is rejected
ε RLB	$\lvert 2.241 \rvert$	1.960	H_0 is rejected

It is concluded that the variables that exhibit significant spatial dependency are the error term, x_3 and x_4. Since there is spatial dependency in both the error term and the independent variables, the next step is to perform the Lagrange Multiplier (LM) test. Based on the LM test at a significance level of $\alpha = 0.05$, the test result $showsM_{error} = 3.994 > \chi^2_{(0.05;1)} = 3.841$. Thus, the decision is to reject H_0 indicating the presence of spatial error dependence.

Considering the results of the LM test and Moran's Index test, it is concluded that the data can be modeled using the Spatial Durbin Error Model (SDEM). The SDEM model formulated for the Open Unemployment Rate data in 34 provinces of Indonesia for the year 2023 is as follows:

$$\begin{aligned}\hat{y}_i &= \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \hat{\beta}_3 x_{i3} + \hat{\beta}_4 x_{i4} \\ &+ \hat{\theta}_1 \sum_{j=1}^{34} w_{ij} x_{j1} + \hat{\theta}_2 \sum_{j=1}^{34} w_{ij} x_{j2} \\ &+ \hat{\theta}_3 \sum_{j=1}^{34} w_{ij} x_{j3} + \hat{\theta}_4 \sum_{j=1}^{34} w_{ij} x_{j4} \\ &+ \hat{\lambda} \sum_{j=1}^{34} w_{ij} u_j. \end{aligned} \tag{3.3}$$

The estimated parameters of the SDEM model can be seen in Table 7. Based

Table 7. Estimation of SDEM parameters.

Parameters	Estimation
β_0	27.676
β_1	−0.219
β_2	−0.006
β_3	0.387
β_4	0.173
θ_1	-0.060
θ_2	0.002
θ_3	-2.129
θ_4	-0.187
λ	0.371

on Table 7, the estimated results form the following SDEM model:

$$\begin{aligned}\hat{y}_i &= 27.676 - 0.219_{xi1} - 0.006_{xi2} + 0.387_{xi3} \\ &+ 0.173_{xi4} - 0.060 \sum_{j=1}^{34} w_{ij} x_{j1} \\ &+ 0.002 \sum_{j=1}^{34} w_{ij} x_{j2} - 2.129 \sum_{j=1}^{34} w_{ij} x_{j3} \\ &- 0.187 \sum_{j=1}^{34} w_{ij} x_{j4} + 0.371 \sum_{j=1}^{34} w_{ij} x_{ji} \end{aligned} \tag{3.4}$$

The significance test for the parameters of the SDEM model was conducted using the Wald test. The partial significance test result for the parameter λ at a significance level of $\alpha = 0.05$ shows that $Wald = 6.882 > \chi^2_{(0.05;1)} = 3.841$. Thus, the decision is to reject H_0, concluding that there is a significant spatial error effect in the SDEM model. The partial significance test results for the parameter β_k or independent variables can be seen in Table 8.

Table 8. Wald test value for parameters β_k.

Parameter	value Wald	$\chi^2_{0.05;1}$	Decision
β_0	6.261	3.841	H_0 is rejected
β_1	23.486	3.841	H_0 is rejected
β_2	0.047	3.841	H_0 fails to be rejected
β_3	0.441	3.841	H_0 fails to be rejected
β_4	6.526	3.841	H_0 is rejected

Based on Table 8, with a significance level of $\alpha = 0.05$ and the decision rule to reject H_0 if $Wald\ \beta_k > \chi^2_{(0.05;1)}$, the Wald values for β_0, β_1 and β_4 are 6.261, 23.980 and 6.526 Berdasarkan nilai Wald, respectively. Based on these Wald values, the decision is to reject H_0 concluding that the independent variable k has a significant effect on the dependent variable in the SDEM model. The significance test results for the parameter θ_k which represents the spatially lagged effect, can be seen in Table 9.

Table 9. Wald test value for parameters θ_k.

Parameter	value Wald	$\chi^2_{0.05;1}$	Decision
θ_1	1.219	3.841	H_0 fails to be rejected
θ_2	0.002	3.841	H_0 fails to be rejected
θ_3	4.349	3.841	H_0 is rejected
θ_4	4.442	3.841	H_0 is rejected

Based on Table 9, with a significance level of $\alpha = 0.05$ and the decision rule to reject H_0 if $Wald\ \theta_k > \chi^2_{(0.05;1)}$, the Wald values for θ_3 and θ_4 are 4.349 and 4.442. respectively. Based on these Wald values H_0 is rejected, leading to the conclusion that the spatial lag parameters θ_k (lag spatial) is θ_3 and θ_4 have an effect on the dependent variable.

The AIC value is obtained from Equation (13). The AIC calculation for the SDEM model was performed using R software. The AIC value obtained for the SDEM model is 104.750, which is lower than the AIC value of the MLR model, indicating that the SDEM model is more suitable for this study.

After conducting the SDEM parameter tests, it can be concluded that the variables influencing OUR from the independent variables and spatial lags are x_1, x_4, θ_3 and θ_4. The spatial error coefficient λ of 0.371 indicates the presence of spatial error dependence, or the influence of the location of each neighboring province on the observed OUR variable.

The coefficient for LFPR ($\beta_1 = -0.219$) indicates that a 1% increase in LFPR is associated with a 0.219% decrease in OUR, suggesting that more labor market participation reduces unemployment. GDI ($\beta_4 = 0.173$) shows a positive direct impact, implying gender equity improvements may initially increase measured unemployment due to higher female participation.

The significant negative spatial lag of PGR ($\theta_3 = -2.129$) implies that a 1% increase in PGR in neighboring provinces significantly reduces local OUR, possibly due to labor outmigration or job creation in adjacent regions. GDI's spatial lag ($\theta_4 = -0.187$) similarly suggests positive gender development in neighboring regions has a suppressing effect on local unemployment.

4. Conclusion

The results of the Spatial Durbin Error Model (SDEM) that can be applied to the Open Unemployment Rate data in Indonesia for the year 2023 are as follows:

$$\begin{aligned}\hat{y}_i = {} & 27.676 - 0.219x_{i1}0.006x_{i2} + 0.387x_{i3} \\ & + 0.173x_{i4} - 0.060\sum_{j=1}^{34} w_{ij}x_{j1} \\ & + 0.002\sum_{j=1}^{34} w_{ij}x_{j2} - 2.129\sum_{j=1}^{34} w_{ij}x_{j3} \\ & - 0.187\sum_{j=1}^{34} w_{ij}x_{j4} + 0.371\sum_{j=1}^{34} w_{ij}u_{ji}.\end{aligned} \tag{4.1}$$

The estimation results using the SDEM model indicate that the factors significantly influencing the Open Unemployment Rate in 34 provinces of Indonesia in 2023 are the Labor Force Participation Rate (x_1) and the Gender Development Index (x_4) for direct effects. Meanwhile, through indirect effects or spatial lags, the Population Growth Rate (θ_3) and the Gender Development Index (θ_4) have a significant impact on OUR.

This study confirms the significance of spatial effects in modeling unemployment. Policymakers should consider interregional collaboration to tackle unemployment. Improvements in education and gender development in one province can benefit neighboring provinces, highlighting the importance of coordinated regional development programs.

Acknowledgements

The researcher would like to express gratitude to all parties who have contributed to this research, especially to the extended family, including the late father and late mother, as well as siblings, who have always provided motivation, prayers, and unparalleled material support. Deepest thanks also go for all the love and patience given to the author from childhood until the completion of this research.

References

[1] LeSage JP. The theory and practice of spatial econometrics. New York: Department of Economics, University of Toledo; 1999.

[2] Badan Pusat Statistik. Statistik Indonesia: Statistical yearbook of Indonesia 2023. Jakarta: Badan Pusat Statistik; 2023.

[3] Sukirno S. Makro ekonomi. Jakarta: Raja Grafindo Persada; 2008.

[4] Andriyani D, Rivanka D. Pengaruh indeks pembangunan manusia, rasio perbandingan gender dan inflasi terhadap tingkat pengangguran terbuka di Kota Medan. Jurnal Ekonomi Publik Malikussaleh. 2023;6(1):50.

[5] Nisa II, Karim A, Wasono R. Pemodelan Spatial Durbin Error Model (SDEM) pada data indeks pembangunan manusia (IPM) di Jawa Tengah. Jurnal Statistika. 2017;5(1):33-40.

[6] Akbar A, Kartiko. Spatial Durbin Error Model pada pemodelan persentase penduduk miskin (PPM) di Provinsi Sulawesi Selatan. Jurnal Statistika Industri dan Komputasi. 2018;3(2):74-83.

[7] Teku HP, Noeryanti, Bekti RD. Spatial Durbin Error Model pada pemodelan tingkat pengangguran terbuka di Provinsi Nusa Tenggara Timur. Jurnal Statistika Industri dan Komputasi. 2023;8(2):1-15.

[8] Irianto A. Statistik: Konsep dasar dan aplikasinya. Jakarta: Kencana; 2009.

[9] Widarjono A. Ekonometrika: Teori dan aplikasi untuk ekonomi dan bisnis. Yogyakarta: Ekonisia; 2007.

[10] Manurung J, Adler H, Ferdinand D. Ekonometrika. Jakarta: Elex Media Computindo; 2005.

[11] Cressie N. Statistics for spatial data. Rev ed. New York: John Wiley Sons, Inc.; 1993.

[12] Lee J, Wong DWS. Statistical analysis with ArcView GIS. New York: John Wiley Sons, Inc.; 2001.

[13] Hayati MN, Purnamasari I, Wahyuningsih S. Analysis of spatial autocorrelation of diarrhea events in East Kalimantan in 2015-2017 using a local indicator of spatial autocorrelation. J Phys Conf Ser. 2019;1277(1):012045.

[14] Afifah DL, Rahardjo S, Kholifia N. Optimization of tax revenue in East Java: an empirical analysis of Spatial Durbin Error Model. J Phys Conf Ser. 2021;1872(1):012025.

[15] Kholifia N, Rahardjo S, Muksar M, Atikah N, Afifah DL. Spatial analysis of factors influencing Gross Regional Domestic Product (GRDP) in East Java: a Spatial Durbin Error Model analysis. J Phys Conf Ser. 2021;4(04):20-44.