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Open Unemployment Rate Modeling In Indonesia Using Spatial Bayes Regression Analysis

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Abstract: Unemployment is defined as people over the age of 15 who are looking for or do not have a job. The imbalance between the number of jobs and the number of labor force leads to the potential for spatial labor mobility between villages and cities. Therefore, data on the open unemployment rate (TPT) in Indonesia may have spatial effects. The spatial regression analysis method is a commonly used method to estimate the parameters of spatial econometrics models. However, this method is not good enough to estimate the model parameters when there are many spatial units. To overcome this problem, an alternative Bayesian method can be used. This study uses the Bayesian method approach to the Spatial Autoregressive (SAR) model applied to modeling the open unemployment rate in Indonesia in 2022. The data used is secondary data obtained from the Indonesian Central Bureau of Statistics (BPS) in 2022. The results that have been obtained show that the variable labor force participation rate is significant to the open unemployment rate in Indonesia with an acceptance rate of 0.55.

Keyword: Open Unemployment Rate, Bayesian, Spatial Autoregressive

INTRODUCTION

Post-pandemic, several provinces in Indonesia have experienced a decrease in the unemployment rate (TPT). Among them, South Sulawesi saw a decrease in TPT by 1.24%, East Kalimantan by 1.06%, and West Nusa Tenggara by 1.03%. However, there are also several provinces that have experienced an increase in TPT, including West Nusa Tenggara by 0.69%, East Java by 0.68%, and Bangka Belitung Islands by 0.59%. Upon further investigation, many provinces in Indonesia still have an unemployment rate higher than the national TPT of 5.86%. Among these are the Riau Islands with 8.23% and West Java Province with 8.31% (BPS, 2022). The high unemployment rates in each province in Indonesia are influenced by the surrounding provinces. This can also be affected by the characteristics of each province which are almost similar.

One of the issues that can be influenced by regions is unemployment. Unemployment is defined as individuals over the age of 15 who are actively seeking work or do not have a job

(BPS,2022). The imbalance between the number of available jobs and the size of the labor force creates the potential for spatial labor mobility between rural and urban areas (Todaro, 2003). Therefore, the unemployment rate (TPT) data in Indonesia may likely be affected by spatial effects.

Based on the description above, the researcher suspects that the factors influencing the open unemployment rate in Indonesia vary across regions due to differences in the characteristics of each region. In this study, the Bayesian method is used to estimate the parameters. The estimation stages include forming the prior distribution, the likelihood function, the posterior distribution, and generating the posterior distribution values using the MCMC method. As a result, significant factors affecting the open unemployment rate in Indonesia and its spatial regression model will be identified. Over time, data has emerged providing information about correlations between regions in observational results. This type of data, which includes information related to regions, is called spatial data (Anselin, 1988). If spatial data is analyzed using linear regression analysis, the resulting model is inaccurate because linear regression analysis assumes no dependency among errors in each region and constant error variance. Spatial data can be addressed using spatial regression analysis.

Parameters are values that can explain the characteristics of a population. Parameter estimation can be either interval estimation or point estimation. Point estimation can be performed using classical methods or Bayesian methods. The classical method only uses sample data information to estimate parameters, whereas the Bayesian method considers the sample data distribution information and incorporates the prior distribution. Another advantage of the Bayesian method is that it can yield better results even with small sample sizes compared to classical methods (Soodejani et al. 2021).

METHOD

Data Type and Source

In this study, the type of data used is secondary data obtained from the Central Statistics Agency (BPS) with the observation unit used in this study is 34 Provinces in Indonesia

Research Variables

Open unemployment rate, literacy rate, percentage of poor people, growth rate of gross regional domestic product (GRDP) at constant prices, labor force participation rate, and proportion of young adults 15-59 years old with ICT skills in 2022.

Bayes Method

The first step is to determine the prior distribution of the parameters to be estimated. This distribution can originate from previous research data or based on a researcher's intuition. The posterior distribution forms the basis for all inferences because it contains all relevant information regarding the estimation problem. This relevant information includes sample data information derived from the likelihood as well as the prior distribution assigned to the parameters. The Bayesian approach to estimation arises from several basic probability axioms. (LeSage & Kelley Pace, 2009).

For two random variables A and B, the joint probability P (A, B) can be expressed in terms of conditional probabilities $P(A|B)$ or $P(B|A)$ and marginal probabilities P(B) or P(A) as shown in equations (1) and (2).

$$P(A,B) = P(A|B)P(B) \quad (1)$$

$$P(A,B) = P(B|A)P(A) \quad (2)$$

If these two equations are equalized, it will result in Bayes' rule:

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \tag{3}$$

Bayesian Spatial Autoregressive (BSAR)

The Bayesian Spatial Autoregressive (SAR) model with a multivariate normal inverse gamma prior is a SAR model that uses the normal inverse gamma distribution as the prior distribution for the model parameters. The likelihood function in the SAR model is given as follows:

$$p(D|\beta,\sigma,\rho) = (2\pi\sigma^2)^{-\frac{n}{2}}|A| \exp\left(-\frac{1}{2\sigma^2}(Ay - X\beta)'(Ay - X\beta)\right) \tag{4}$$

with $A = (I_n - \rho W)$ and $|A|$ denotes the determinant of matrix A

Parameters β and σ^2 in the SAR model follow the *inverse gamma* normal distribution (LeSage & Kelley Pace, 2009).

1. Distribution of *prior* $\pi(\beta|\sigma^2)$ follows a normal distribution

$$\pi(\beta|\sigma^2) \sim \mathrm{N}(\mathrm{c},\sigma^2\mathrm{T})$$
$$= \frac{1}{(2\pi)^{\frac{p}{2}}(\sigma^2)^{\frac{p}{2}}\,|\mathrm{T}|^{\frac{1}{2}}} \exp\left(-\frac{1}{2\sigma^2}(\beta - \mathrm{c})'\,\mathrm{T}^{-1}(\beta - \mathrm{c})\right) \tag{5}$$

2. Distribution *prior* $\pi\,(\sigma^2)$ follows the *inverse gamma* distribution

$$\pi(\sigma^2) \sim \mathrm{IG}(a,b)$$
$$= \frac{b^a}{\Gamma(a)}\,(\sigma^2)^{-(a+1)} \exp(-b/\sigma^2) \tag{6}$$

3. Distribution *prior* $\pi(\beta,\sigma^2)$ follow the *normal inverse gamma distribution*

Distribution *prior* $\pi(\beta,\sigma^2)$ obtained from Equations (5) and (6)

$$\pi(\beta,\sigma^2) \sim \mathrm{NIG}\,(\mathrm{c},\mathrm{T},a,b)$$
$$= \pi(\beta|\sigma^2)\,\pi(\sigma^2)$$
$$= \mathrm{N}\,(\mathrm{c},\sigma^2\mathrm{T}) \times \mathrm{IG}(a,b)$$
$$= \frac{1}{(2\pi)^{\frac{p}{2}}(\sigma^2)^{\frac{p}{2}}|\mathrm{T}|^{\frac{1}{2}}} \exp\left(-\frac{1}{2\sigma^2}(\beta - \mathrm{c})'\,\mathrm{T}^{-1}(\beta - \mathrm{c})\right) \tag{7}$$
$$\times \frac{b^a}{\Gamma(a)}(\sigma^2)^{-(a+1)} \exp\left(-\frac{b}{\sigma^2}\right)$$
$$= \frac{b^a}{(2\pi)^{\frac{p}{2}}\,|\mathrm{T}|^{\frac{1}{2}}\Gamma(a)}(\sigma^2)^{-\left(a+\left(\frac{p}{2}\right)+1\right)}$$
$$\times \exp\left(-\frac{1}{2\sigma^2}[(\beta - \mathrm{c})'\mathrm{T}^{-1}(\beta - \mathrm{c}) + 2b]\right)$$

4. Distribution *prior* $\pi(\rho)$

$$(\rho) \sim \mathrm{U}\,(\lambda_{\min}^{-1}, \lambda_{\max}^{-1}) \tag{8}$$
$$= \frac{1}{\lambda_{\max}^{-1}, \lambda_{\min}^{-1}}$$

with $(\lambda_{\min}^{-1}, \lambda_{\max}^{-1})$ stating the minimum and maximum eigenvalues of the spatial weighting matrix

Based on the likelihood function and prior distribution above, the posterior distribution obtained is as follows:

$$p(\beta, \rho, \sigma^2|D) = (2\pi\sigma^2)^{-\frac{n}{2}} |A| \exp\left(-\frac{1}{2\sigma^2}(\mathrm{Ay} - \mathrm{X}\beta)'(\mathrm{Ay} - \mathrm{X}\beta)\right)$$
$$\times \frac{b^a}{(2\pi)^{\frac{p}{2}}|\mathrm{T}|^{\frac{1}{2}}\,\Gamma(a)}(\sigma^2)^{-\left(a+\left(\frac{p}{2}\right)+1\right)}$$
$$\times \exp\left(-\frac{1}{2\sigma^2}[(\beta - \mathrm{c})'\mathrm{T}^{-1}(\beta - \mathrm{c}) + 2b]\right)$$
$$\times \left(\frac{1}{\lambda_{\max}^{-1}, \lambda_{\min}^{-1}}\right)$$
$$\propto (\sigma^2)^{-\left(a+\frac{n+p}{2}+1\right)}|A|$$
$$\times \exp\left(-\frac{1}{2\sigma^2}[(\mathrm{Ay} - \mathrm{X}\beta)'\,(\mathrm{Ay} - \mathrm{X}\beta) + (\beta - \mathrm{c})'\mathrm{T}^{-1}(\beta - \mathrm{c}) + 2b]\right) \tag{9}$$

Equation (2.49) can be written as follows:

$$P(\beta,\rho,\sigma^2|D) = \propto (\sigma^2)^{-(a^*+1)}|\mathrm{A}| \times \exp\left(-\frac{1}{2\sigma^2}[n2b^* + (\beta - c^*)'(T^*)^{-1}(\beta - c^*)]\right) \tag{10}$$

with:

$$\mathrm{T}^* = (\mathrm{X}^\mathrm{T}\mathrm{X} + \mathrm{T}^{-1})^{-1} \tag{11}$$
$$\mathrm{c}^* = (\mathrm{X}'\mathrm{X} + \mathrm{T}^{-1})^{-1}\,(\mathrm{X}'\mathrm{Ay} + \mathrm{T}^{-1}\mathrm{c}) \tag{12}$$
$$b^* = b + ((\mathrm{c}'\mathrm{T}^{-1}\mathrm{c} + \mathrm{y}^\mathrm{T}\mathrm{A}^\mathrm{T}\mathrm{Ay}) - (\mathrm{c}^*)'(\mathrm{T}^*)^{-1}\mathrm{c}^*) \tag{13}$$
$$a^* = a + \frac{n+p}{2} \tag{14}$$

The parameter (β,σ,ρ) can be estimated by combining Gibbs and Metropolis-Hastings through sequential sampling from the conditional distribution of the estimated parameters.

1. The conditional distribution for parameter $\beta|\rho,\sigma^2$

$$P(\beta|\rho,\sigma_{(0)}^2) \sim N(c^*, \sigma_{(0)}^2 T^*) \tag{15}$$

with $\beta|\rho,\sigma^2$ follows a multivariate normal distribution

$$\mathrm{c}^* = (\mathrm{X}'\mathrm{X} + \mathrm{T}^{-1})^{-1}\,(\mathrm{X}'\mathrm{Ay} + \mathrm{T}^{-1}\mathrm{c})$$
$$\mathrm{T}^* = (\mathrm{X}'\mathrm{X} + \mathrm{T}^{-1})^{-1}$$
$$A = I_n - \rho W$$

2. The conditional distribution for $\sigma^2|\rho,\beta$

$$P(\sigma^2|\beta_{(1)},\rho) \sim IG(a^*, b^*) \tag{16}$$
$$a^* = a + \frac{n+p}{2}$$
$$b^* = b + ((\mathrm{c}'\mathrm{c} + \mathrm{y}'\mathrm{A}'\mathrm{Ay}) - (\mathrm{c}^*)'(\mathrm{T}^*)^{-1}\mathrm{c}^*)$$
$$A = I_n - \rho W$$

3. The conditional distribution for $\rho|\beta_{(1)},\sigma_{(1)}^2$

$$P(\rho|\beta,\sigma^2) = \frac{P(\rho,\beta,\sigma^2|D)}{P(\beta,\sigma^2|D)}$$
$$\propto P(\rho,\beta,\sigma^2|D)$$
$$\propto |I_n - \rho W_\rho| \exp\left(-\frac{1}{2\sigma^2}(\mathrm{Ay} - \mathrm{X}\beta)'(\mathrm{Ay} - \mathrm{X}\beta)\right) \tag{17}$$

Sampling for the parameter ρ must be done using an alternative approach, such as Metropolis-Hastings. A combination of Metropolis-Hastings (M-H) sampling for the ρ parameter in the model and Gibbs sampling from the inverse gamma normal distribution for the β and σ parameters is performed to generate MCMC estimates for the SAR model (Lesage, 1998). This type of procedure is often labeled Metropolis within Gibbs sampling.

Markov Chain Monte Carlo (MCMC)

It is one method for simulating sample data. Simulation with the MCMC method generates sample data from a specific distribution using the properties of a Markov chain, which is used to obtain the posterior distribution in Bayesian methods with high accuracy. MCMC uses an algorithm called Gibbs sampling and Metropolis-Hastings. The Gibbs sampling algorithm uses the full conditional distribution, which is then combined in the posterior distribution with the notation $p(\theta \mid d\ a\ t\ a)$ p(θ|data). The Gibbs sampling algorithm can be applied if the joint probability distribution is not explicitly known. The steps in performing MCMC simulation using the Gibbs sampling algorithm are as follows (Ntzoufras, 2008):

a) Deciding on initial values $(\beta, \sigma^2)^0$
b) Where $t = 1, \dots, T,$ Then, the sample generation stage is carried out with the following iterative steps:
$\beta_1^{(t)}$ dari $f(\beta_1 | \beta_2^{(t-1)}, \beta_3^{(t-1)}, \dots, \beta_p^{(t-1)}, (\sigma^2)^{(t-1)}, Z_y),$

$\beta_2^{(t)}$ dari $f(\beta_2 | \beta_1^{(t)}, \beta_3^{(t-1)}, \dots, \beta_p^{(t-1)}, (\sigma^2)^{(t-1)}, Z_y),$

$\beta_3^{(t)}$ dari $f(\beta_3 | \beta_1^{(t)}, \beta_2^{(t)}, \dots, \beta_p^{(t-1)}, (\sigma^2)^{(t-1)}, Z_y),$

$\beta_p^{(t)}$ dari $f(\beta_p | \beta_1^{(t)}, \beta_2^{(t)}, \dots, \beta_p^{(t)}, (\sigma^2)^{(t-1)}, Z_y),$

$(\sigma^2)^{(t)}$ dari $f(\sigma_p^2 | \beta_1^{(t)}, \beta_2^{(t)}, \dots, \beta_p^{(t)}, (\sigma^2)^{(t-1)}, Z_y)$

c) Constructing $(\beta, \sigma^2)^{(t)}$and then storing it as a set of values generated in iteration t t in the Gibbs Sampling algorithm.

The Metropolis-Hastings algorithm can be used to help generate random samples from the desired posterior distribution. The Metropolis-Hastings algorithm is as follows:

1. Generate $Y_t \sim q(y | x^{(t)})$.
2. Take
$$X^{(t+1)} = \begin{cases} Y_t, & \text{dengan peluang } \alpha(x^{(t)}, Y_t), \\ x_t, & \text{dengan peluang } 1 - \alpha(x^{(t)}, Y_t) \end{cases}$$
3. with
$$\alpha(x, y) = \min\left\{\frac{f(y)q(x|y)}{f(x)q(x|y)}, 1\right\}$$

Validity of Bayesian Estimates

Validity in Bayesian methods is used to ensure that the model obtained from Bayesian estimation is appropriate. The conditions that must be met are convergence and no autocorrelation. Model validation is done for each model parameter (Jaya et al., 2017). Convergence can be detected using a trace plot. If no pattern is observed in the trace plot, it can be concluded that the obtained parameters are good (Jaya et al., 2017).

Data Analysis Steps

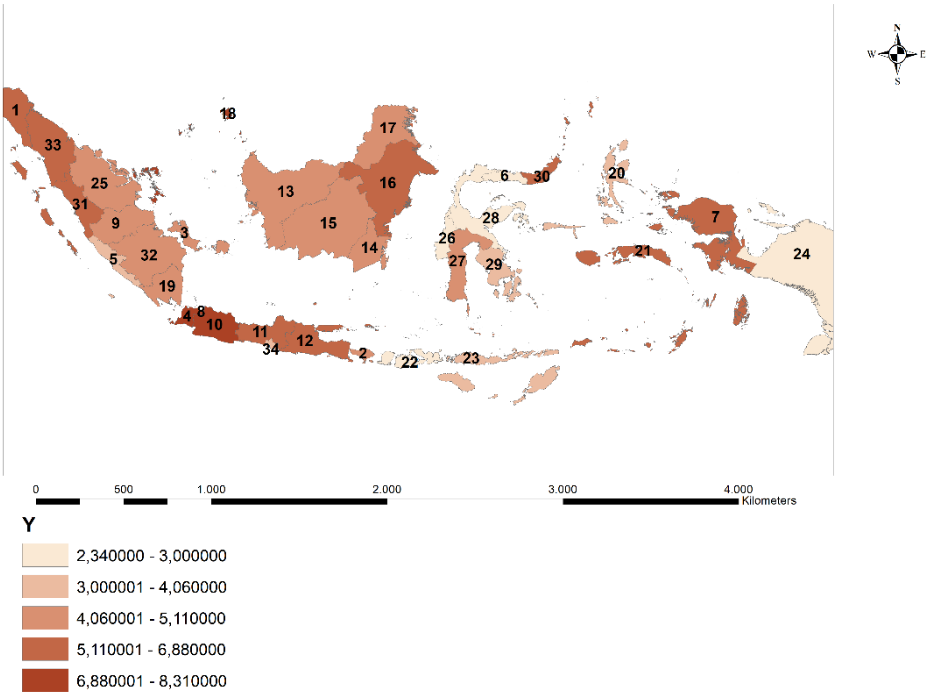
The technique used to analyze data in this study is Bayesian spatial regression analysis. The steps for data analysis after data collection are as follows:

1. Visualization of data in thematic map form to observe the distribution of data between provinces.
2. Estimation of Bayesian linear regression parameters.

3. Determination of the spatial weighting matrix using the inverse distance weight (IDW) method.
4. Estimation of SAR model parameters for spatial regression using the Bayesian method with the following steps:
   a. Finding the prior distribution using the prior distribution according to equation (7).
   b. Creating the likelihood function from n n random samples according to equation (4).
   c. Forming the posterior distribution based on the prior distribution and likelihood function.
   d. Performing Monte Carlo simulation.
5. Bayesian estimation validity by creating a trace plot.
6. Performing interpretation.

RESULTS AND DISCUSSION

Data Visualization



Source: research data 2024

Figure 1: Map of the Distribution of Open Unemployment Rate in Indonesia in 2022

Figure 1 illustrates the percentage of open unemployment rate in Indonesia in 2022 categorized as low, with a range of 2.34% to 3%, found in West Sulawesi, Gorontalo, Papua, West Nusa Tenggara, and Central Sulawesi provinces. The lowest open unemployment rate in Indonesia, at 2.34%, is recorded in West Sulawesi Province. Conversely, the percentage of open unemployment rate categorized as high, ranging from 6.88% to 8.31%, is observed in Maluku, Jakarta, Banten, and West Java provinces. The highest open unemployment rate, at 8.31%, is found in West Java Province

Bayesian Regression Analysis

The first step is to estimate Bayesian linear regression using MCMC simulation, as shown in Table 1 and Table 2.

Table 1. Credible Interval of Bayesian Linear Regression

Variable	Mean	Standard Deviation	Markov Chain Standard Error	Quantile		Decision
				5%	95%	
Intercept	49,4	27,1	0,5	5,37	94,29	Significant
X_1	$-0{,}4$	0,3	0,0	$-0{,}78$	0,07	Non Significant
X_2	0,0	0,1	0,0	$-0{,}12$	0,13	Non Significant
X_3	$-0{,}1$	0,1	0,0	$-0{,}18$	0,07	Non Significant
X_4	$-0{,}2$	0,1	0,0	$-0{,}32$	$-0{,}08$	Significant
X_5	0,1	0,0	0,0	0,01	0,14	Significant

Source: research data 2024

Table 2: Significance of Bayesian Linear Regression Parameters

Parameter	Parameter Estimated	Mean
β_0	50,220142600	49,4
β_1	$-0{,}364296565$	$-0{,}4$
β_2	0,003418939	0,0
β_3	$-0{,}053466181$	$-0{,}1$
β_4	$-0{,}198115741$	$-0{,}2$
β_5	0,073324795	0,1

Source: research data 2024

The estimated linear regression model obtained based on Table 1 and Table 2 is:

$$\hat{Y}_i = 50{,}2201426 - 0{,}1981157X_{4,i} + 0{,}0733247X_{5,i} \tag{18}$$

The estimated linear regression model based on Table 2 interprets that if the labor force participation rate TIK (X_4) and the proportion of young adults with TIK (X_5) are both 0, then the open unemployment rate in Indonesia is 50.2201426. If the labor force participation rate TIK (X_4) increases by one unit, it can reduce the unemployment rate in Indonesia in 2022 by 0.1981157, assuming other factors remain constant. If the proportion of young adults with TIK (X_5)increases by one unit, it can increase the unemployment rate in Indonesia by 0.0733247, assuming other factors remain constant.

Bayesian Spatial Regression Analysis

According to equation (9), the following posterior is used:

$$p(\beta,\rho,\sigma^2|D) = (2\pi\sigma^2)^{-\frac{n}{2}}|A|\exp\left(-\frac{1}{2\sigma^2}(\mathrm{Ay}-\mathrm{X}\beta)^{\mathrm{T}}(\mathrm{Ay}-\mathrm{X}\beta)\right)$$

$$\times\frac{b^a}{(2\pi)^{\frac{p}{2}}|\mathrm{T}|^{\frac{1}{2}}\,\Gamma(a)}(\sigma^2)^{-\left(a+\left(\frac{p}{2}\right)+1\right)}$$

$$\times\exp\left(-\frac{1}{2\sigma^2}[(\beta-\mathrm{c})^{\mathrm{T}}\mathrm{T}^{-1}(\beta-\mathrm{c})+2b]\right)$$

$$\times \left(\frac{1}{\lambda_{\max}^{-1}, \lambda_{\min}^{-1}}\right)$$

$$\propto (\sigma^2)^{-\left(a+\frac{n+p}{2}+1\right)}|A|$$

$$\times \exp\left(-\frac{1}{2\sigma^2}[(\mathrm{Ay}-\mathrm{X}\beta)^{\mathrm{T}}(\mathrm{Ay}-\mathrm{X}\beta)+(\beta-\mathrm{c})^{\mathrm{T}}\mathrm{T}^{-1}(\beta-\mathrm{c})+2b]\right)$$

The solution process for this equation uses MCMC simulation because the posterior equation is difficult to solve analytically.

Parameter Estimated

The parameter estimation used is the average of the sample values obtained after simulating using a posterior sample size of 1000, and the results can be seen in Table 3.

Table 3. Credible Interval of Bayesian Spatial Regression

Variable	Mean	Deviation Standard	Markov Chain Standard Error	Quantile		Decision
				5%	90%	
Intercept	48,2	25,8	0,4	4,93	92,32	Significant
X_1	$-0,4$	0,2	0,0	$-0,78$	0,14	Non Significant
X_2	0,0	0,1	0,0	$-0,13$	0.14	Non Significant
X_3	$-0,1$	0,1	0,0	$-0,19$	0.07	Non Significant
X_4	$-0,2$	0,1	0,0	$-0,33$	-0.07	Significant
X_5	0,1	0,0	0,0	0,0	0,15	Non Significant

Source: research data 2024

Hypothesis testing against the value of the credible interval to estimate parameters with a 90% credible interval. The process of calculating the credible interval value is observed at the 5% and 95% quantiles. If there is no value of 0 between the 5% and 95% quantiles, then the response variable significantly influences the open unemployment rate in Indonesia.

Hypothesis testing:

$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$

H_1: at least one $\beta_p \neq 0, p = 1,2,3,4,5$

In Table 4.3, the results of the parameter estimation test using a 95% credible interval are shown. The quantile values between 5% and 95% indicate that the labor force participation rate variable (X_4) is significant in relation to the open unemployment rate in Indonesia in 2022.

Table 4. Estimated Parameters of SAR Bayes Regression Model

Parameters	Parameters Estimation
ρ	0,6190106
β_0	55,9999578
β_4	0,1969373
β_5	$-0,0890727$

Source: research data 2024

The estimated linear regression model obtained based on Table 3 and Table 4 is:

$$\hat{Y}_i = 55{,}9999578 + 0{,}6190106 \sum_{1}^{34} w_{ij} y_j + 0{,}1969373\, X_{4,i} \tag{19}$$

Model Interpretation

Interpretation of the SAR Bayes Model in Table 3 is as follows:

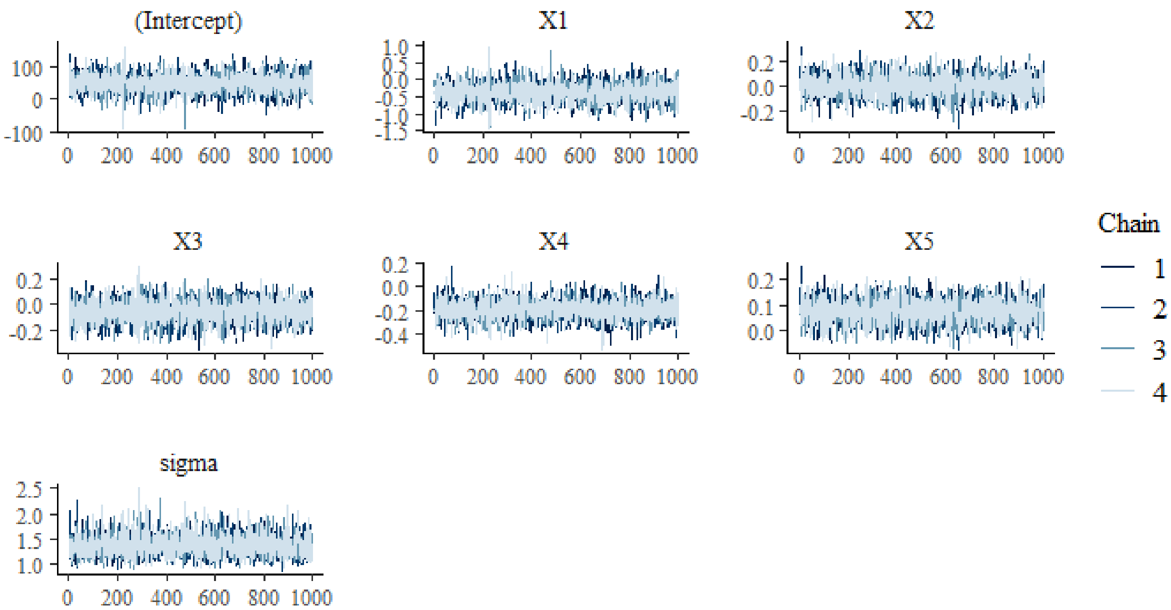
a. The coefficient ρ =0,6190106 means that if a province is surrounded by other provinces, the influence of the surrounding provinces can be measured as 0,6190106 times the total open unemployment rate in the neighboring provinces, assuming all other factors remain constant.
b. The coefficient β_4 = 0,1969373 means that if the labor force participation rate in a province increases by one percent, it will increase the open unemployment rate in that province by 0,1969373, assuming all other factors remain constant.

From the SAR Bayes model in Equation (19), a different model is obtained for each province. Therefore, there are a total of 34 equation models. For example, the province of Aceh, which has three neighbors: Riau Province, West Sumatra Province, and North Sumatra Province, has the following equation model:

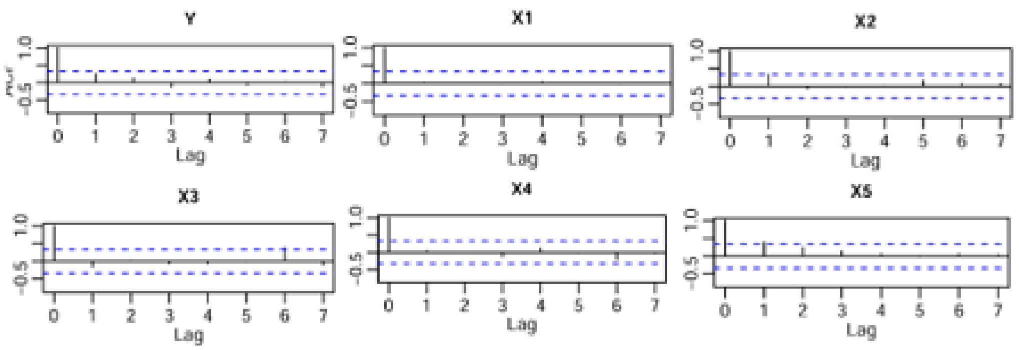
$$\hat{Y}_{\text{Aceh}} = 0{,}6190106 + 0{,}001253_{\text{Riau}} + 0{,}001244_{\text{Sumatera Barat}} + 0{,}002597_{\text{Sumatera Utara}} + 0{,}1969373X_{4,\text{Aceh}}$$

The Validity of Bayesian Estimation

To check the convergence of the estimates, trace plots and ergodic plots are used. The trace plot of the SAR Bayes model in R software is as follows:



Source: research data 2024
Figure 2. Trace Plot of SAR Bayes Model



Source: research data 2024

Figure 3. ACF Plot of SAR Bayes Model

Based on Figures 2 and 3, it can be observed that the trace plot does not form a specific pattern or trend. This indicates that the burn-in period has ended, meaning that the generated samples are within the target distribution area. After the burn-in period, the generated samples are considered more stable. Therefore, it can be said that the algorithm has achieved convergence. Additionally, based on the ACF plot, there is no significant lag observed, thus meeting the assumption of non-autocorrelation.

CONCLUSION

Based on the results and discussion obtained, several conclusions can be drawn:

1. The significant variable in the open unemployment rate (TPT) in Indonesia using Bayesian spatial regression method is labor force participation. The SAR Bayes model used to model the open unemployment rate in Indonesia is:

$$\hat{Y}_i = 55{,}9999578 + 0{,}6190106 \sum_{1}^{34} w_{ij} y_j + 0{,}1969373\, X_{4,i}$$

2. The SAR Bayes model was obtained with an acceptance rate of 0.55. This indicates that the labor force participation variable (X4) is capable of explaining the case of open unemployment rate in Indonesia, while the rest is influenced by other variables outside the model.
3. The factors influencing the open unemployment rate (TPT) in Indonesia are the labor force participation rates in each province of Indonesia.
   Based on the research conducted, there is only one significant variable, namely the labor force participation rate (TPAK). The government plays a crucial role in managing the labor force participation rate and the unemployment rate in Indonesia. It is hoped that the government and the labor force can work towards improving skills and education, and engage in training that can enhance the qualifications of the workforce, making it easier to secure employment.

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