

REGIONAL OUTPUT AND OPEN UNEMPLOYMENT ACROSS INDONESIAN PROVINCES: A SPATIAL SIMULTANEOUS EQUATION APPROACH

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ABSTRACT

Indonesia's regional output in 2024 reveals disparities among provinces, and open unemployment rates also differ between regions. In the context of the regional economy, regional output and unemployment can exhibit a reciprocal relationship and spatial interdependence among provinces, whereas most previous studies examine them using single-equation models. Therefore, this study aims to analyze the relationship between regional output, measured by Gross Regional Domestic Product (GRDP) at constant prices, and the open unemployment rate (OUR) by considering potential simultaneity and spatial dependence between provinces. This study uses cross-sectional secondary data for 38 provinces in 2024 from the Central Statistics Agency of Indonesia. The two-equation system is estimated using Generalized Spatial Two-Stage Least Squares (GS2SLS) with spatially autocorrelated errors and a k-nearest neighbor spatial weight matrix ($k = 6$) based on distances between provincial capitals. GRDP is positively and significantly associated with OUR (0.080; $p = 0.015$), as is average years of schooling (0.674), while the labor force participation rate is negatively associated with OUR (-3.848). In the GRDP equation, population is significant (0.725), whereas the coefficients of OUR (0.482) and domestic investment (0.206) are not significant under heteroskedasticity-robust standard errors. Exogeneity is not rejected, and spatial error dependence appears only in the OUR equation at the 10% level. The positive association disappears when Java is excluded or GRDP per capita is used, indicating a scale and composition effect. Higher regional output therefore does not coincide with lower open unemployment, so labor absorption needs separate policy attention, although the single cross-section limits causal interpretation.

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1. INTRODUCTION

Regional output and unemployment rates are two important indicators that reflect the economic conditions of a region. Regional output is defined as the production of goods and services in a region, measured using the Gross Regional Domestic Product at Constant Prices, while economic growth refers to the increase in this real output over time (BPS Indonesia, 2025; Sukirno, 2011). Meanwhile, unemployment is defined as the population that is unemployed, looking for work, preparing for a business, feeling it is impossible to find work, or has been accepted for work but has not yet started work (BPS Indonesia, 2024). The unemployment rate is generally measured using the Open Unemployment Rate (OUR) indicator. Based on data from the Central Statistics Agency of Indonesia in 2024, the GRDP at Constant Prices value of provinces on the island of Java is higher than other provinces. This indicates that Indonesia's economic activity is not evenly distributed and is more concentrated on the island of Java. Meanwhile, the open unemployment rate in August 2024 was recorded at 4.91%, or around 7.47 million people, a decrease of 0.41 percentage points compared to August 2023 (BPS Indonesia, 2024). Across provinces, the rate ranged from 1.32% in Papua Pegunungan to 6.75% in Jawa Barat. This condition indicates that the issues of regional output and unemployment require attention in efforts to realize sustainable economic development in Indonesia.

According to Okun's Law, introduced by economist Okun (1962), it is one of the basic rules of macroeconomics. Okun's Law measures the trade-off between unemployment and output. One interpretation of Okun's Law explains how much growth is needed to reduce unemployment by one percentage point (Elhorst & Emili, 2022). In line with Okun's Law, economic growth is expected to have a negative effect on unemployment, as higher output growth is generally associated with a decline in the unemployment rate (Ball et al., 2017). In other words, the relationship between the two variables is ideally negative. Increased economic growth is expected to create jobs, thereby reducing unemployment, while a decrease in the unemployment rate can increase productivity, thereby increasing a region's economic output. Porras-Arena and Martín-Román (2023) found that economic growth and unemployment are systematically related, although the magnitude of this relationship varies across countries. At the regional level, the relationship also differs between regions and is affected by spatial interactions between regional labor markets (Elhorst & Emili, 2022; Kosfeld & Dreger, 2006). However, Okun's Law is formulated in terms of changes over time, whereas a comparison of output levels across regions at one point in time also reflects differences in the size and economic structure of regions. Therefore, this study uses Okun's Law as a reference for interpreting the cross-provincial relationship between GRDP and the open unemployment rate, rather than as a direct test of the law. This evidence motivates the use of regional output and unemployment as the two main variables in the present study. However, unlike conventional analyses that examine the relationship from a single-equation perspective, this study considers their potential simultaneity while also accounting for spatial dependence across Indonesian regions.

In addition to influencing each other, regional output and unemployment are also influenced by various other socioeconomic factors. Several previous studies have shown that economic growth is significantly influenced by poverty, population size, and domestic investment (Bao & Liao, 2024; Marrero & Servén, 2022; Shabbir et al., 2021; Syaifullah et al., 2024). Meanwhile, poverty, average years of schooling, and the labor force participation rate significantly influence the unemployment rate (Meliala et al., 2025; Saputri & Samsuddin, 2025). In addition to reciprocal relationships, regional output and unemployment in a province can also be influenced by conditions in neighboring regions or spatial dependence. When an explanatory variable is endogenous, as in a simultaneous relationship, estimates using the Ordinary Least Squares (OLS) method are biased and inconsistent. Spatial dependence in the error term alone leaves OLS coefficient estimates consistent but inefficient, with invalid standard errors, whereas a spatially lagged dependent variable also makes OLS estimates inconsistent (Anselin, 1988; LeSage & Pace, 2009). Therefore, an estimation method that can accommodate both potential endogeneity and spatial dependence is needed, namely the Generalized Spatial Two-Stage Least Squares (GS2SLS) (Kelejian & Prucha, 2004).

This method has been extended to heteroskedastic disturbances (Arraiz et al., 2010; Kelejian & Prucha, 2010) and to models that combine endogenous regressors with spatial lag and spatial error terms (Drukker et al., 2013). One study that applies the GS2SLS method is Liu et al. (2023) who analyzed the relationship between green innovation and carbon emissions in China. In addition, Wang et al. (2026) also used GS2SLS to analyze how foreign direct investment affects urban air pollution and when green technology innovation can mitigate this impact.

Based on the previous description, the expected signs in this study are as follows. In the GRDP equation, the open unemployment rate is expected to have a negative effect in line with Okun's Law, domestic investment and population are expected to have positive effects, and poverty is expected to have a negative effect. In the open unemployment rate equation, GRDP is expected to have a negative effect, poverty is expected to have a positive effect, and average years of schooling is expected to have a positive effect, reflecting the phenomenon of educated unemployment (Yulietta et al., 2025). The labor force participation rate is expected to have a positive effect, because higher participation increases the number of people actively looking for work and thus raises the measured unemployment rate. Spatial dependence in the error term is expected to be positive, meaning that unobserved factors in one province are related to those in neighboring provinces. Accordingly, this study aims to analyze the relationship between regional output and the open unemployment rate in Indonesia and the factors associated with each of them by considering the potential reciprocal relationship between variables and spatial dependence between provinces in Indonesia.

2. RESEARCH METHODS

This study aims to analyze the relationship between regional output and the open unemployment rate in Indonesia and the factors associated with each of them. This study not only examines the relationship between the explanatory variables and the dependent variables but also considers the potential simultaneous relationship between variables and the spatial dependence that often occurs in regional economic models. This approach is expected to provide a more comprehensive picture of regional economic dynamics.

In this study, the data are secondary data sourced from the Central Statistics Agency of Indonesia for 2024. The data are a single cross-section of 38 provinces in Indonesia, with all variables measured on a ratio scale. The variables used in this study are presented in Table 1. All variables are transformed into natural logarithms, so that the coefficients can be interpreted as elasticities. As a robustness check, the time-related underemployment rate (TSP) in 2024 is also used to construct an alternative measure of labor underutilization. Data were analyzed using R software version 4.4.2 in RStudio with the *spdep* (Bivand, 2022), *sphet* (Piras, 2010), and *ivreg* (Fox et al., 2021) packages.

Table 1. Research Variables

Variable	Definition	Unit	Role
GRDP	Gross regional domestic product at constant prices	Billion rupiah	Endogenous
OUR	Open unemployment rate	Percent	Endogenous
DI	Realized domestic investment	Billion rupiah	Exogenous
POP	Total population	Thousand people	Exogenous
POV	Percentage of poor population	Percent	Exogenous
LFPR	Labor force participation rate	Percent	Exogenous
AYS	Average years of schooling	Years	Exogenous

Source: Central Statistics Agency of Indonesia (2024)

The socioeconomic data exhibit spatial characteristics and potential interrelationships among socioeconomic variables across provinces. Therefore, the spatial simultaneous equation model was employed as the main analytical method. The spatial simultaneous equation model is an extension of the spatial single equation model introduced by Cliff and Ord (1973, 1981).

This model consists of a simultaneous equation in cross-sectional data with spatial dependence, which may occur in both the error components and the dependent variable. According to Kelejian and Prucha (2004), the spatial simultaneous equation model for cross-sectional data can be expressed as follows.

$$Y_n = Y_n B + X_n C + \bar{Y}_n \Lambda + U_n ; U_n = \bar{U}_n R + E_n \dots\dots\dots (1)$$

where $Y_n = (y_{1,n}, \dots, y_{M,n})$ is the $n \times M$ matrix of endogenous variables, $X_n = (x_{1,n}, \dots, x_{K,n})$ is the $n \times K$ matrix of exogenous variables, $U_n = (u_{1,n}, \dots, u_{M,n})$ is the matrix of disturbances, and $E_n = (\varepsilon_{1,n}, \dots, \varepsilon_{M,n})$ is the matrix of innovations. The spatial lags are defined as $\bar{Y}_n = W_n Y_n$ and $\bar{U}_n = W_n U_n$, where W_n is the $n \times n$ row-standardized spatial weight matrix. B is the $M \times M$ matrix of coefficients of the endogenous variables with zero diagonal elements, C is the $K \times M$ matrix of coefficients of the exogenous variables, $\Lambda = \text{diag}(\rho_j)$ contains the spatial lag parameters, and $R = \text{diag}(\lambda_j)$ contains the spatial error parameters, $j = 1, 2, \dots, M$. In this study, $n = 38$ and $M = 2$.

In this study, the spatial simultaneous equation model consists of two structural equations as follows.

$$\ln(\text{GRDP})_i = \beta_{10} + \beta_{11} \ln(\text{OUR})_i + \beta_{12} \ln(\text{DI})_i + \beta_{13} \ln(\text{POP})_i + \beta_{14} \ln(\text{POV})_i + u_{1i} \dots\dots\dots (2)$$

$$\ln(\text{OUR})_i = \beta_{20} + \beta_{21} \ln(\text{GRDP})_i + \beta_{22} \ln(\text{POV})_i + \beta_{23} \ln(\text{AYS})_i + \beta_{24} \ln(\text{LFPR})_i + u_{2i} \dots\dots\dots (3)$$

where $u_{ji} = \lambda_j \sum_{r=1}^n w_{ir} u_{jr} + \varepsilon_{ji}$ for $j = 1, 2$. Based on these two equations, the model has two endogenous variables ($M = 2$), namely $\ln(\text{GRDP})$ and $\ln(\text{OUR})$, and five exogenous variables ($K = 5$), namely $\ln(\text{DI})$, $\ln(\text{POP})$, $\ln(\text{POV})$, $\ln(\text{AYS})$, and $\ln(\text{LFPR})$. Identification of each equation relies on exclusion restrictions. AYS and LFPR are excluded from the GRDP equation, assuming that labor quality and participation are associated with total output mainly through the labor market outcome captured by OUR . POP and DI are excluded from the OUR equation, because OUR is a ratio that does not depend on the absolute size of the population, and investment is assumed to affect unemployment through output. Because these restrictions are assumptions, their validity is examined using an overidentification test.

The order condition requires $K - k \geq m - 1$, where k is the number of exogenous variables included in the equation and m is the number of endogenous variables included in the equation. Because the order condition is only necessary, the rank condition and instrument strength are examined using the first-stage F statistic of the excluded instruments, where a value above 10 indicates that the instruments are not weak. The validity of the overidentifying restrictions is tested using the Sargan test, and the endogeneity of the explanatory endogenous variable is tested using the Durbin-Wu-Hausman test.

The spatial weight matrix is constructed using the k-Nearest Neighbor (KNN) approach based on great-circle distances between provincial capitals. Because Indonesia is an archipelago, a contiguity-based matrix would leave island provinces without neighbors, whereas KNN ensures that each province has the same number of neighbors (Rey et al., 2023). There is no theoretical basis for a single value of k in an archipelagic setting, so $k = 6$ is used in the main specification and the results are compared with $k = 3$ to 8 and with inverse-distance matrices. Spatial dependence is first described using Moran's I and Lagrange Multiplier tests on OLS residuals. Because these tests are not valid when the regressors are endogenous, the Anselin-Kelejian test on 2SLS residuals is used to test for spatial error autocorrelation (Anselin & Kelejian, 1997). The choice between the spatial error, spatial lag, and combined (SARAR) specifications is based on these tests and on the significance of the spatial parameters.

The parameters of the spatial simultaneous equation model are estimated using the Generalized Spatial Two-Stage Least Squares (GS2SLS) method. The GS2SLS estimation method is a method used to estimate the parameters in the j -th equation in a system of simultaneous spatial

equations. This procedure is a generalization of the estimator introduced by Kelejian and Prucha (1998) for single-equation autoregressive spatial models. Let $Z_{j,n}$ denote the matrix of explanatory variables in the j -th equation, which contains the included endogenous and exogenous variables, and let H_n denote the matrix of instruments, which contains the constant and all exogenous variables in the system. In general, the GS2SLS estimation procedure is carried out in three stages (Kelejian & Prucha, 2004).

The first stage is an initial estimation of the parameters δ_j using the Two Stage Least Squares (2SLS) method, as follows.

$$\hat{\delta}_{j,n} = (\hat{Z}'_{j,n} \hat{Z}_{j,n})^{-1} \hat{Z}'_{j,n} y_{j,n} \dots\dots\dots (4)$$

where $\hat{Z}_{j,n} = P_H Z_{j,n}$ and $P_H = H_n(H'_n H_n)^{-1} H'_n$. The residuals from the 2SLS estimation are then given by:

$$\hat{u}_{j,n} = y_{j,n} - Z_{j,n} \hat{\delta}_{j,n} \dots\dots\dots (5)$$

In the second stage, these residuals are used to estimate the spatial autoregressive parameter of the error component in each equation using the generalized moments method, as follows.

$$\hat{\alpha}_j = (\hat{\lambda}_j, \hat{\lambda}_j^2, \hat{\sigma}_j^2)' = [G'_{j,n} G_{j,n}]^{-1} G'_{j,n} g_{j,n} \dots\dots\dots (6)$$

where $G_{j,n}$ and $g_{j,n}$ are the matrix and vector of sample moments constructed from $\hat{u}_{j,n}$, $W_n \hat{u}_{j,n}$, and $W_n W_n \hat{u}_{j,n}$ (Kelejian & Prucha, 1998).

In the third stage, the estimated parameter $\hat{\lambda}_j$ from the second stage is used to apply a Cochrane-Orcutt type transformation to the model, so that the spatial correlation in the error term is removed, as follows.

$$y^*_{j,n}(\hat{\lambda}_j) = Z^*_{j,n}(\hat{\lambda}_j) \delta_j + \varepsilon_{j,n} \dots\dots\dots (7)$$

where $y^*_{j,n}(\hat{\lambda}_j) = y_{j,n} - \hat{\lambda}_j W_n y_{j,n}$ and $Z^*_{j,n}(\hat{\lambda}_j) = Z_{j,n} - \hat{\lambda}_j W_n Z_{j,n}$. Equation (7) is then estimated by 2SLS using $\hat{Z}^*_{j,n}(\hat{\lambda}_j) = P_H Z^*_{j,n}(\hat{\lambda}_j)$, which yields the GS2SLS estimator of δ_j .

Inference in the main specification is based on heteroskedasticity-robust standard errors (Arraiz et al., 2010; Kelejian & Prucha, 2010), and results with conventional standard errors are also reported. Each equation is estimated separately, so the correlation of disturbances across equations is not used, which may reduce efficiency compared with a system estimator. Because the R^2 is not a valid goodness-of-fit measure for two-stage estimators, it is not used to evaluate the model. In a spatial error specification, a change in an explanatory variable in one province does not affect the dependent variable in other provinces, so the coefficients represent direct effects and there are no indirect (spillover) effects. To examine robustness, the model is re-estimated using alternative spatial weight matrices, excluding DKI Jakarta, Java, and the six Papua provinces, using GRDP and domestic investment per capita, and replacing OUR with labor underutilization in the unemployment equation.

3. RESULTS AND DISCUSSION

3.1. RESULTS

The first step in this analysis is to examine the general overview and characteristics of the variables across Indonesia's 38 provinces in 2024. The descriptive statistics of the variables in their original units are presented in Table 2.

Table 2. Descriptive Statistics of Research Variables

Variable	Mean	Std. Dev.	Minimum	Maximum	Province (Min)	Province (Max)
GRDP (billion rupiah)	343,843.94	529,576.41	13,798.74	2,151,041.33	Papua	DKI Jakarta
OUR (%)	4.38	1.41	1.32	6.75	Papua Pegunungan	Jawa Barat
DI (billion rupiah)	21,421.52	30,224.94	82.00	128,402.10	Papua Pegunungan	DKI Jakarta
POP (thousand people)	7,410.63	11,330.00	542.10	50,345.20	Papua Pegunungan	Jawa Barat
POV (%)	10.66	6.37	3.80	29.66	Bali	Papua Pegunungan
LFPR (%)	70.32	4.39	64.63	87.87	Aceh	Papua Pegunungan
AYS (years)	9.29	1.15	5.10	11.49	Papua Pegunungan	DKI Jakarta

Source: BPS 2024, processed by researchers (2026)

Table 2 shows that the variables differ widely across provinces, especially GRDP, domestic investment, and population, whose standard deviations exceed their means. The spatial distribution of GRDP and the open unemployment rate is presented in Figure 1 and Figure 2.

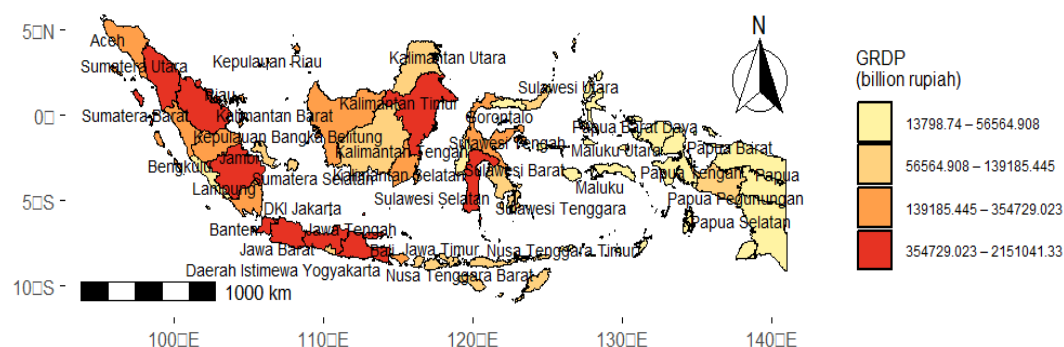


Figure 1. GRDP

Source: BPS 2024, processed by researchers (2026)

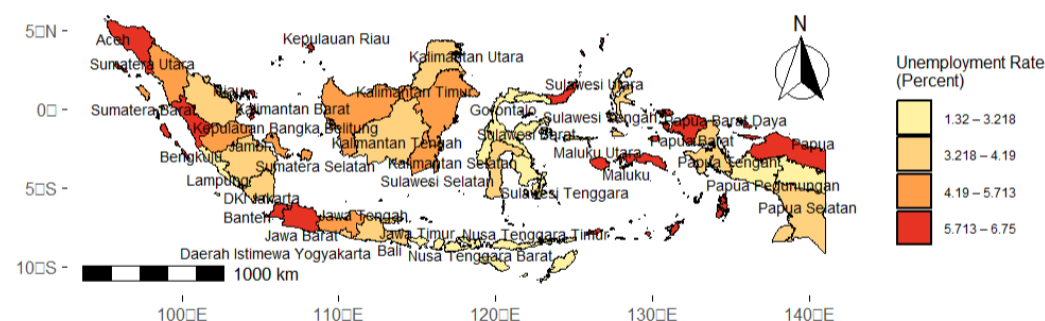


Figure 2. Open Unemployment Rate

Source: BPS 2024, processed by researchers (2026)

Based on Figure 1, Indonesia's GRDP in 2024 tends to be higher in provinces on Java Island compared to provinces in eastern Indonesia, which tend to be lower. The highest GRDP is in DKI Jakarta at 2,151,041 billion rupiah and the lowest is in Papua Pegunungan at 13,799 billion rupiah. This condition illustrates the existence of GRDP inequality between provinces in Indonesia. Meanwhile, Figure 2 shows that the open unemployment rate between provinces in Indonesia in 2024 ranges from 1.32% in Papua Pegunungan to 6.75% in Jawa Barat, with an average of 4.38%. Provinces with high open unemployment rates include large provinces on Java, such as Jawa Barat, Banten, and DKI Jakarta, as well as several provinces in eastern Indonesia, such as Papua and Papua Barat Daya.

After examining the characteristics and general overview of the data, the relationships between variables were identified to determine the direction and strength of the relationships within each structural equation. This analysis is based on the correlation coefficient values presented in the correlation graph in Figure 3. The results of this identification are used as an initial basis for understanding the relationship patterns between variables in each structural equation.

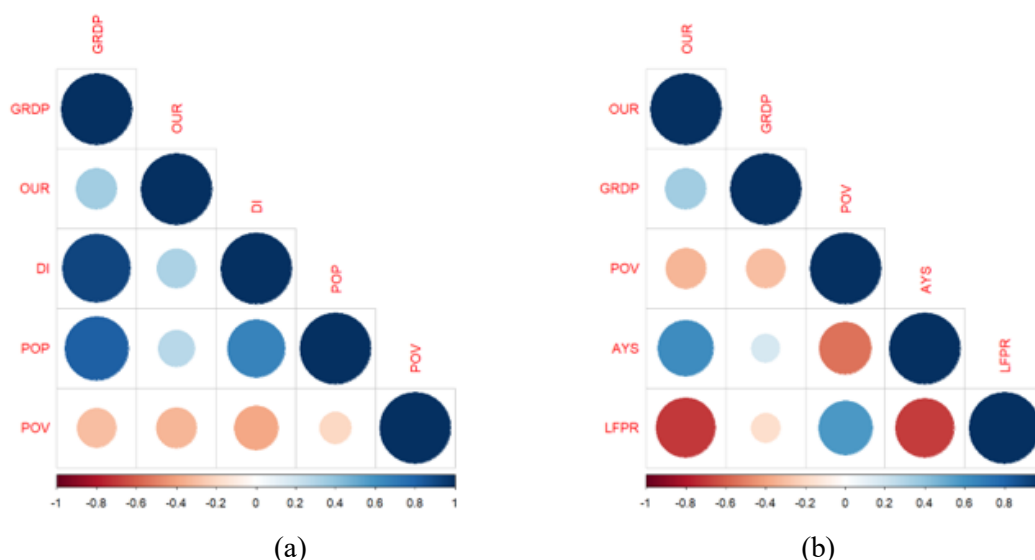


Figure 3. Correlation between variables in the structural equation (a) GRDP;
(b) Unemployment

Source: Data processed by researchers (2026)

The correlation patterns presented in Figure 3 indicate that GRDP is closely associated with domestic investment and population, both of which show strong positive relationships with GRDP. A moderate positive association is observed between GRDP and the open unemployment rate. The open unemployment rate demonstrates a strong positive correlation with average years of schooling and a strong negative correlation with the labor force participation rate. Average years of schooling and the labor force participation rate are also strongly negatively correlated with each other, which indicates that both variables reflect differences in the structure of provincial labor markets.

The identification of each structural equation using the order condition, together with the instrument and endogeneity diagnostics, is presented in Table 3.

Table 3. Model Identification and Instrument Diagnostics

Equation	K – k	m – l	Status	First-stage F (p-value)	Wu-Hausman (p-value)	Sargan (p-value)
ln(GRDP)	2	1	Overidentified	30.10 (0.000)	0.455 (0.505)	0.000 (0.985)
ln(OUR)	2	1	Overidentified	69.72 (0.000)	0.348 (0.559)	2.565 (0.109)

Source: Data processed by researchers (2026)

Based on Table 3, both structural equations satisfy the order condition with $K - k = 2 > m - 1 = 1$, so both equations are overidentified. The first-stage F statistics of the excluded instruments are 30.10 for the GRDP equation and 69.72 for the open unemployment rate equation, both well above 10, so the rank condition is satisfied and the instruments are not weak. The Sargan test does not reject the validity of the overidentifying restrictions in the GRDP equation ($p = 0.985$), while in the open unemployment rate equation the p-value of 0.109 is close to the 10% level, so the exclusion restrictions in this equation should be interpreted with caution. The Wu-Hausman test does not reject the null hypothesis that the explanatory endogenous variable is exogenous in either equation ($p = 0.505$ and $p = 0.559$). Therefore, the data do not provide statistical evidence of simultaneity between GRDP and the open unemployment rate, and the GS2SLS estimator is used because it remains consistent whether or not the explanatory variables are endogenous.

The spatial dependence test was conducted using Moran's I and Lagrange Multiplier tests on OLS residuals and the Anselin-Kelejian test on 2SLS residuals, with KNN spatial weight matrices for $k = 3$ to 8 and inverse-distance matrices. The null hypothesis of each test is that there is no spatial dependence. The results of the spatial dependence test are shown in Table 4.

Table 4. Spatial Dependence Test Results

Spatial Weights	Equation	Moran's I	p-value	LM Lag	p-value	LM Error	p-value	Anselin-Kelejian	p-value
KNN (k = 3)	ln(GRDP)	0.046	0.352	2.488	0.115	0.144	0.704	0.133	0.715
KNN (k = 3)	ln(OUR)	0.115	0.111	0.343	0.558	0.911	0.340	0.728	0.394
KNN (k = 4)	ln(GRDP)	0.012	0.479	1.856	0.173	0.012	0.914	0.006	0.938
KNN (k = 4)	ln(OUR)	0.137	0.038*	1.231	0.267	1.639	0.200	1.293	0.255
KNN (k = 5)	ln(GRDP)	-0.016	0.646	1.744	0.187	0.027	0.871	0.030	0.862
KNN (k = 5)	ln(OUR)	0.152	0.011*	2.378	0.123	2.488	0.115	2.003	0.157
KNN (k = 6)	ln(GRDP)	-0.010	0.547	2.533	0.111	0.014	0.907	0.017	0.895
KNN (k = 6)	ln(OUR)	0.167	0.002*	2.236	0.135	3.546	0.060*	3.052	0.081*
KNN (k = 7)	ln(GRDP)	-0.075	0.699	3.693	0.055*	0.828	0.363	0.739	0.390
KNN (k = 7)	ln(OUR)	0.137	0.004*	1.346	0.246	2.802	0.094*	2.225	0.136
KNN (k = 8)	ln(GRDP)	-0.074	0.657	3.318	0.069*	0.923	0.337	0.805	0.370
KNN (k = 8)	ln(OUR)	0.142	0.001*	1.423	0.233	3.425	0.064*	2.533	0.111
Inverse distance	ln(GRDP)	-0.045	0.814	2.154	0.142	0.759	0.384	0.765	0.382
Inverse distance	ln(OUR)	0.012	0.100	0.083	0.773	0.055	0.815	0.023	0.879
Inverse distance squared	ln(GRDP)	-0.043	0.967	1.753	0.185	0.195	0.659	0.255	0.613
Inverse distance squared	ln(OUR)	0.043	0.274	0.128	0.720	0.188	0.665	0.110	0.741

Note: *Significant at $\alpha = 10\%$

Source: Data processed by researchers (2026)

The results in Table 4 show that Moran's I on OLS residuals is significant for the open unemployment rate equation for KNN matrices with $k = 4$ to 8, but not for the GRDP equation. However, the Moran's I and Lagrange Multiplier tests are computed on OLS residuals and are not valid when the regressors are endogenous. Based on the Anselin-Kelejian test, which is valid under endogeneity, spatial error autocorrelation is detected only in the open unemployment rate equation with $k = 6$ at the 10% level ($p = 0.081$), and it is not detected for any other weight matrix or in the GRDP equation. The LM lag test is significant at the 10% level only for the GRDP equation with $k = 7$ and $k = 8$. These results indicate that the evidence of spatial dependence is weak and sensitive to the choice of weight matrix.

To determine the spatial specification, the spatial lag and SARAR models were also estimated with GS2SLS using the KNN matrix with $k = 6$. The spatial lag parameter is not significant in either the GRDP equation ($\rho = -0.217$; $p = 0.114$) or the open unemployment rate equation ($\rho = 0.615$; $p = 0.185$), and neither spatial parameter is significant in the SARAR model. Therefore, the spatial error specification with the KNN matrix with $k = 6$ is used as the main model, because it is the only specification in which the spatial test indicates dependence, and the other specifications are reported as robustness checks. The results of parameter estimation for each structural equation are presented in Tables 5 and 6.

Table 5. Parameter Estimates for the GRDP Equation using GS2SLS with Spatially Autocorrelated Errors

Variable	Coefficient	Robust z-stat	Robust p-value	Conventional p-value
Intercept	3.687	3.598	0.000***	0.314
ln(OUR)	0.482	1.529	0.126	0.153
ln(DI)	0.206	1.603	0.109	0.075*
ln(POP)	0.725	6.840	0.000***	0.000***
ln(POV)	-0.116	-0.464	0.643	0.661
λ_1	0.826	1.140	0.254	0.214

Note: ***, **, * significant at $\alpha = 1\%$, 5% , and 10% , respectively

Source: Data processed by researchers (2026)

Table 6. Parameter Estimates for the Open Unemployment Rate Equation using GS2SLS with Spatially Autocorrelated Errors

Variable	Coefficient	Robust z-stat	Robust p-value	Conventional p-value
Intercept	15.016	3.059	0.002***	0.000***
ln(GRDP)	0.080	2.443	0.015**	0.047**
ln(POV)	0.141	1.385	0.166	0.097*
ln(AYS)	0.674	2.230	0.026**	0.032**
ln(LFPR)	-3.848	-3.660	0.000***	0.000***
λ_2	0.536	1.717	0.086*	0.081*

Note: ***, **, * significant at $\alpha = 1\%$, 5% , and 10% , respectively

Source: Data processed by researchers (2026)

Based on Tables 5 and 6, the spatial simultaneous equation model is obtained as follows:

$$\ln(GDRP)_i = 3.687 + 0.482 \ln(OUR)_i + 0.206 \ln(DI)_i + 0.725 \ln(POP)_i - 0.116 \ln(POV)_i + u_{1i}$$

$$u_{1i} = 0.826 \sum_{r=1}^n w_{ir} u_{1r} + \varepsilon_{1i} \dots\dots\dots (8)$$

$$\ln(OUR)_i = 15.016 + 0.080 \ln(GRDP)_i + 0.141 \ln(POV)_i + 0.674 \ln(AYS)_i - 3.848 \ln(LFPR)_i$$

$$+ u_{2i}$$

$$u_{2i} = 0.536 \sum_{r=1}^n w_{ir} u_{2r} + \varepsilon_{2i} \dots\dots\dots (9)$$

In the GRDP equation, population is the only variable with a significant coefficient. The coefficient of $\ln(\text{POP})$ is 0.725, which means that a province with a 1% larger population has, on average, 0.725% higher GRDP, holding other variables constant. The coefficient of $\ln(\text{OUR})$ is 0.482 and the coefficient of $\ln(\text{DI})$ is 0.206, but neither is significant under heteroskedasticity-robust standard errors, and only domestic investment is significant at the 10% level under conventional standard errors. Poverty has a negative but insignificant coefficient, and the spatial error parameter λ_1 is not significant.

In the open unemployment rate equation, the coefficient of $\ln(\text{GRDP})$ is 0.080, which means that a province with 1% higher GRDP has, on average, a 0.080% higher open unemployment rate. The coefficient of $\ln(\text{AYS})$ is 0.674, which means that a province with 1% higher average years of schooling has, on average, a 0.674% higher open unemployment rate. The coefficient of $\ln(\text{LFPR})$ is -3.848 , which means that a province with a 1% higher labor force participation rate has, on average, a 3.848% lower open unemployment rate. Poverty is significant only at the 10% level under conventional standard errors. The spatial error parameter λ_2 is 0.536 and significant at the 10% level, which indicates that unobserved factors affecting the open unemployment rate are positively correlated between neighboring provinces. Because the model contains a spatial error term only, these coefficients represent direct effects, and there are no indirect (spillover) effects.

The robustness of the main results was examined by re-estimating the model with alternative spatial weight matrices, alternative samples, and variables measured per capita. The results are presented in Table 7.

Table 7. Robustness Checks

Specification	GRDP eq.: $\ln(\text{OUR})$	GRDP eq.: $\ln(\text{DI})$	GRDP eq.: $\ln(\text{POP})$	GRDP eq.: $\ln(\text{POV})$	OUR eq.: $\ln(\text{GRDP})$	OUR eq.: $\ln(\text{POV})$	OUR eq.: $\ln(\text{AYS})$	OUR eq.: $\ln(\text{LFPR})$
Main model (KNN $k = 6$, robust)	0.482	0.206	0.725***	-0.116	0.080**	0.141	0.674**	-3.848***
Conventional standard errors	0.483	0.206*	0.725***	-0.117	0.081**	0.140*	0.675**	-3.843***
KNN ($k = 4$)	0.486*	0.208*	0.724***	-0.120	0.072**	0.143	0.650**	-3.925***
KNN ($k = 5$)	0.489	0.197*	0.728***	-0.122	0.073**	0.139	0.642**	-3.938***
KNN ($k = 8$)	0.465*	0.222*	0.708***	-0.096	0.076**	0.137	0.665**	-3.879***
Inverse distance	0.487*	0.208*	0.725***	-0.082	0.076**	0.159*	0.640**	-3.952***
Excluding DKI Jakarta	0.406	0.178	0.725***	-0.119	0.082***	0.130	0.715**	-3.840***
Excluding Java	0.484*	0.158	0.715***	-0.166	0.020	0.084	0.814**	-3.697***
Excluding Papua	0.763**	0.298***	0.705***	-0.318	0.106***	0.053	0.179	-4.195***
Per capita	0.477	0.242**	-	-0.012	-0.454	-0.039	1.029*	-5.344***

Note: ***, **, * significant at $\alpha = 1\%$, 5% , and 10% , respectively. In the per capita specification, GRDP and DI are divided by population, so POP is not included.

Source: Data processed by researchers (2026)

Table 7 shows that the coefficients of population and the labor force participation rate are stable in sign, size, and significance across all specifications. The coefficient of GRDP in the open unemployment rate equation remains positive and significant across alternative weight matrices and when DKI Jakarta or the Papua provinces are excluded, but it becomes small and insignificant when the six provinces of Java are excluded (0.020) and turns negative and insignificant when GRDP is measured per capita (-0.454). The coefficient of average years of schooling becomes insignificant when the Papua provinces are excluded. The coefficients of the open unemployment rate and domestic investment in the GRDP equation are significant in some specifications but not in others.

Finally, the open unemployment rate was replaced by the time-related underemployment rate (TSP) and by the combined underutilization rate (OUR + TSP) in the unemployment equation. The results are presented in Table 8.

Table 8. Robustness Check with Labor Underutilization

Variable	ln(OUR)	ln(TSP)	ln(OUR + TSP)
ln(GRDP)	0.080**	0.068	0.069**
ln(POV)	0.141	0.539***	0.389***
ln(AYS)	0.674**	0.149	0.355
ln(LFPR)	-3.848***	-1.983	-2.547*
λ	0.536*	0.170	-0.108

Note: ***, **, * significant at $\alpha = 1\%$, 5% , and 10% , respectively. All models are estimated with GS2SLS with spatially autocorrelated errors, KNN ($k = 6$), and robust standard errors.

Source: Data processed by researchers (2026)

The correlation between the open unemployment rate and the time-related underemployment rate across provinces is 0.008, which shows that the two indicators capture different aspects of labor market conditions. Based on Table 8, GRDP remains positively and significantly associated with the combined underutilization rate, while poverty becomes the strongest correlate of both underemployment and combined underutilization. The coefficient of average years of schooling is not significant for either alternative measure, and the spatial error parameter is no longer significant.

3.2. DISCUSSION

This study uses an econometric approach based on a simultaneous equation model and a spatial approach to capture spatial dependence between regions. To represent the spatial dependency structure, this study uses the k-Nearest Neighbor (KNN) spatial weight matrix, which ensures that each regional unit has a certain number of neighbors and prevents isolated regions, as can occur with contiguity weighting in an archipelago (Rey et al., 2023). However, the evidence of spatial dependence in this study is weak. The Anselin-Kelejian test, which remains valid when the regressors are endogenous, detects spatial error autocorrelation only in the unemployment equation at the 10% level and only for $k = 6$. The spatial lag parameter is not significant in either equation, so the spatial lag and SARAR specifications are not supported. Because the model contains a spatial error term only, a change in an explanatory variable in one province does not affect outcomes in neighboring provinces, and the spatial approach mainly corrects the error structure rather than identifying spillover effects (LeSage & Pace, 2009). Spatial dependence in the error term leaves the coefficient estimates consistent, so this weak evidence does not change the main coefficients, which are similar across the 2SLS, spatial error, spatial lag, and SARAR specifications (Anselin, 1988).

The results also show that the instruments are strong, but the Durbin-Wu-Hausman test does not reject exogeneity in either equation. This means that the data do not provide statistical evidence of a reciprocal relationship between GRDP and the open unemployment rate. A significant endogeneity test would not prove reciprocal causation in any case, because it can also arise from omitted variables or measurement error. The GS2SLS estimator remains consistent whether or not the explanatory variables are endogenous (Kelejian & Prucha, 2004), so its estimates are used here as estimates that remain valid under potential simultaneity rather than as proof of simultaneity.

The GS2SLS estimation results indicate a positive association between GRDP and the open unemployment rate, which differs from the negative relationship predicted by Okun's Law (Ball et al., 2017; Okun, 1962). Okun's Law describes how changes in unemployment respond to output growth over time, and its magnitude varies across countries and regions (Elhorst & Emili, 2022; Kosfeld & Dreger, 2006; Porras-Arena & Martín-Román, 2023). This study instead compares output levels across provinces at one point in time, so the positive coefficient does not test or contradict Okun's Law. The robustness checks show that the association disappears when the six provinces of Java are excluded and turns negative but insignificant when GRDP per capita is used.

This pattern indicates that the positive association is driven by the scale and composition of provinces, since provinces with large populations and high output, such as Jawa Barat, Banten, and DKI Jakarta, also have the highest open unemployment rates. Khalid et al. (2021) found a reciprocal relationship between unemployment and economic growth in South Africa using time series data, which is a different setting from the cross-provincial comparison in this study. The phenomenon of “jobless growth”, in which output increases without sufficient labor absorption (Bhargava et al., 2025), may be relevant, but it describes a process over time and cannot be identified from a single cross-section.

In the GRDP equation, population has a positive and significant effect, and this result is stable across all specifications. A larger population increases the consumption of goods and services and the size of the labor force, which drives aggregate demand and output (Manik et al., 2026). Domestic investment has a positive coefficient, but it is not significant under heteroskedasticity-robust standard errors, although it becomes significant when the Papua provinces are excluded and when GRDP and investment are measured per capita. This partly supports previous studies showing that domestic investment increases economic growth (Shabbir et al., 2021; Syaifullah et al., 2024; Yuliani et al., 2023). Poverty has a negative but insignificant coefficient, so this study does not confirm the relationship between poverty and growth found by Bao & Liao (2024) and Marrero & Servén (2022).

In the open unemployment rate equation, average years of schooling has a positive and significant coefficient. In an economic context, this result is consistent with the phenomenon of educated unemployment, which occurs when improvements in labor quality are not matched by the availability of suitable jobs (Yulietta et al., 2025). This finding is consistent with Kholis et al. (2026) who showed that average years of schooling had a positive effect on unemployment in Bojonegoro. However, the coefficient becomes insignificant when the Papua provinces are excluded, because provinces such as Papua Pegunungan and Papua Tengah have both the lowest average years of schooling and low open unemployment rates. The labor force participation rate has a negative and significant coefficient, which is consistent in sign with Ayu (2024) for Banten Province and with Meliala et al. (2025), but it differs from the positive sign expected from the definition of the unemployment rate. The provinces with the highest participation rates, such as Papua Pegunungan, Bali, Nusa Tenggara Timur, and Nusa Tenggara Barat, also have among the lowest open unemployment rates, so this coefficient reflects a compositional correlation between provincial labor markets rather than a causal effect of participation on unemployment. For the unemployment equation, the positive spatial error coefficient indicates that unobserved factors influencing the unemployment rate in a province are related to those in neighboring provinces, which aligns with Mahmud and Pasarib (2021) for Bangka Belitung Province, although this evidence is significant only at the 10% level.

The robustness check with labor underutilization provides further insight into the composition of provincial labor markets. The time-related underemployment rate is not correlated with the open unemployment rate across provinces, which shows that the two indicators capture different dimensions of labor market problems. When the open unemployment rate is replaced by the combined underutilization measure, GRDP remains positively associated with labor underutilization, but average years of schooling is no longer significant and poverty becomes the strongest correlate. This result is consistent with Saputri and Samsuddin (2025), who found that poverty influences unemployment in Maluku Province, and indicates that in poorer provinces labor market problems appear more as underemployment than as open unemployment. Overall, the results show that the relationship between regional output and unemployment across Indonesian provinces is largely shaped by differences in provincial size and labor market structure. A direct test of the dynamic relationship described by Okun’s Law would require panel data with growth rates within a spatial panel framework (Elhorst, 2014).

4. CONCLUSION

This study analyzed the relationship between regional output and the open unemployment rate across 38 Indonesian provinces in 2024 using a spatial simultaneous equation model estimated by GS2SLS with spatially autocorrelated errors. In the open unemployment rate equation, GRDP and average years of schooling are positively and significantly associated with the open unemployment rate, while the labor force participation rate is negatively associated with it. In the GRDP equation, population is the only variable with a significant effect, whereas the coefficients of the open unemployment rate and domestic investment are not significant under heteroskedasticity-robust standard errors. The diagnostic tests show that the instruments are strong, but exogeneity of the endogenous explanatory variables is not rejected, and spatial error dependence appears only in the unemployment equation at the 10% level and only for the KNN weight matrix with $k = 6$. Therefore, the GS2SLS estimates are best interpreted as estimates that remain valid under potential simultaneity and spatial dependence, rather than as evidence that both are present.

The positive association between GRDP and the open unemployment rate differs from the negative relationship predicted by Okun's Law. This difference does not contradict Okun's Law, because the law describes changes in unemployment and output over time, whereas this study compares output levels across provinces at one point in time. The association disappears when the provinces of Java are excluded or when GRDP per capita is used, which indicates that it reflects differences in the size and economic structure of provinces. In addition, the time-related underemployment rate is not correlated with the open unemployment rate across provinces and is more strongly associated with poverty, so the open unemployment rate alone does not fully describe labor market conditions in poorer provinces. These findings imply that higher regional output in large provinces does not coincide with lower open unemployment, so regional labor policies need to address labor absorption directly in those provinces, while in poorer provinces policy attention needs to extend beyond open unemployment to underemployment.

This study has several limitations. First, the data are a single cross-section of 38 provinces, so the results describe associations between provinces and cannot be interpreted as causal effects or as a test of Okun's Law. Second, the variables are measured in levels rather than growth rates, so the results are influenced by the size of provinces. Third, identification relies on exclusion restrictions that are assumed rather than derived from theory, and the overidentification test in the unemployment equation is close to rejection. Fourth, the evidence of spatial dependence is weak and sensitive to the choice of weight matrix. Fifth, each equation is estimated separately, so the correlation of disturbances across equations is not used. Finally, the open unemployment rate does not capture underemployment, which is substantial in several provinces.

Future research should use provincial or district panel data with growth rates of output and changes in unemployment, so that Okun's Law can be tested directly within a spatial panel framework. Future studies should also use instruments with stronger theoretical justification, estimate the system jointly to account for the correlation between equations, and include broader measures of labor underutilization alongside the open unemployment rate.

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