A Dynamic Spatial Durbin Panel Model for Analyzing Poverty Rates in West Java Province

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ABSTRAK

Kemiskinan merupakan permasalahan sosial ekonomi yang kompleks dan dipengaruhi oleh berbagai faktor baik internal maupun eksternal. Kemiskinan masih menjadi isu utama di Indonesia. Berdasarkan data Badan Pusat Statistik, tingkat kemiskinan di Indonesia pada tahun 2025 sebesar 8.57%, mengalami penurunan sebesar 0.1% dari tahun sebelumnya. Di Provinsi Jawa Barat, meskipun tingkat kemiskinan mengalami tren penurunan tiap tahunnya, provinsi ini memiliki jumlah penduduk miskin terbanyak kedua, yaitu sekitar 3.67 juta jiwa. Penelitian ini bertujuan untuk menganalisis faktor-faktor yang mempengaruhi tingkat kemiskinan di Provinsi Jawa Barat dengan mempertibangkan pengaruh spasial dan temporal antarwilayah. Data yang digunakan meliputi persentase kemiskinan kabupaten/kota di Provinsi Jawa Barat beserta variabel yang mempengaruhinya pada periode 2019–2024. Metode yang digunakan adalah model regresi panel spasial dinamis dengan pendekatan spasial durbin. Hasil penelitian menunjukkan bahwa terdapat pengaruh signifikan baik secara spasial maupun dinamis terhadap tingkat kemiskinan. Variabel PDRB per kapita berpengaruh signifikan terhadap kemiskinan di wilayahnya sendiri. Sementara itu, variabel tingkat pengangguran terbuka, PDRB per kapita, dan laju pertumbuhan penduduk pada wilayah tetangga juga berpengaruh signifikan terhadap kemiskinan. Model tersebut mampu menjelaskan 99.59% variasi kemiskinan antarwilayah. Dengan demikian, penting adanya koordinasi antarwilayah dan kebijakan berkelanjutan dalam pengentasan kemiskinan, terutama melalui peningkatan lapangan kerja, pemerataan ekonomi, dan pengendalian pertumbuhan penduduk.
Kata kunci: kemiskinan, analisis panel spasial, model panel spasial durbin dinamis

ABSTRACT

Poverty is a complex socioeconomic issue influenced by various internal and external factors and remains a major concern in Indonesia. Based on data from the Statistics Indonesia (BPS), the national poverty rate in 2025 reached 8.57%, decreasing by 0.1% from the previous year. In West Java Province, although poverty shows a declining trend, it remains the second-highest in terms of the number of poor residents, totaling about 3.67 million people. This study analyzes the factors affecting poverty levels in West Java by considering spatial and temporal interregional effects. The data consist of the poverty percentages of districts and cities in West Java and their related variables from 2019 to 2024. The method used is a dynamic spatial panel regression model with a spatial durbin approach. The results reveal significant spatial and dynamic effects on poverty. GRDP per capita significantly influences poverty within a region, while the unemployment rate, GRDP per capita, and population growth rate in neighboring regions also have significant effects. The model explains 99.59% of the interregional variation in poverty. These findings highlight the importance of regional coordination and sustainable policies for poverty reduction, particularly through job creation, economic equity, and population growth control.
Keywords: *poverty, spatial panel analysis, dynamic spatial durbin panel model*

INTRODUCTION

Poverty is a highly complex socioeconomic problem. It is not only related to the inability of individuals to meet basic needs but also to limited access to education, healthcare, employment, and social participation. According to data from Central Statistics Agency [1], the national poverty rate in 2025 is 8.47%, slightly lower than the previous year's rate of 8.57%. In West Java Province, the poverty rate has shown a declining trend each year, reaching 7.08% in September 2024, a decrease of 0.54% from the previous year. However, West Java Province has the second-largest number of poor people after East Java Province, totaling 3,668,350 individuals. Therefore, poverty alleviation efforts must continue to be strengthened, particularly in West Java Province.

Poverty is a development issue influenced by various internal and external factors of a region. The poverty conditions of a particular area may be related to those of other regions, as well as factors within the region itself or its surrounding areas. This aligns with the theory of spatial externalities, which explains that the economic and demographic dynamics in one region can generate external effects on other regions through labor mobility, trade flows, market interactions, and infrastructure integration [2]. Moreover, poverty is also dynamic, indicating that current poverty conditions may be influenced by the conditions in previous periods [3]. This phenomenon occurs due to various structural factors, such as low human capital, limited access to quality employment, and long-term economic imbalances that make it difficult for households to escape the poverty trap. Therefore, the model used must be able to capture these temporal effects. Several studies indicate that education level, employment opportunities, economic growth, and infrastructure significantly affect poverty levels [4], [5]. Low education limits an individual's skills, knowledge, and understanding necessary for daily life. In addition, limited employment opportunities can increase unemployment and suppress income. Restricted infrastructure limits mobility and economic activity. These factors operate both directly within a region and indirectly through interactions among regions.

Panel regression is a widely used approach in economic research, as it combines variations across time and regions. The model is considered dynamic when the dependent variable is influenced by its value in the previous period. Moreover, conventional panel approaches are often insufficient due to spatial dependence among observational units. To address this, a dynamic spatial panel regression model is employed. One commonly used approach is the Spatial Durbin Model (SDM), as it accounts for the influence of both dependent and independent variables across units. In contrast, the Spatial Autoregressive Model (SAR) considers only spatial dependence in the dependent variable, while the Spatial Error Model (SEM) focuses solely on spatial dependence in the error term. Therefore, this study uses the SDM, as it can capture the interregional linkages in poverty levels and the influence of socioeconomic factors in surrounding areas.

Several studies on poverty have employed spatial panel approaches, either in static or dynamic forms. For instance, [6] and [7] analyzed poverty in West Java using SEM and SAR models with fixed effect, while [8] examined poverty in East Java using the SDM models. Furthermore, [9] conducted an analysis of poverty factors in West Kalimantan using the SEM model with random effects. Meanwhile, dynamic analyses of poverty have been carried out by [3] using the Spatial Durbin Model and by [10] using the GMM approach on national data. In Aceh, [11] also applied the GMM method to analyze poverty. Previous studies have certain limitations, as the data used were restricted to the national level or employed a static spatial model. In fact, poverty is dynamic and spatially interconnected. Poverty in one region may be influenced by the socioeconomic conditions of neighboring areas through economic interactions, labor mobility, and the diffusion of public policies. Ignoring these spatial and temporal aspects may lead to less accurate analyses and inappropriate policy recommendations, particularly at the regional level. Considering these limitations, this study applies a dynamic spatial panel regression model using the spatial durbin approach to analyze the factors influencing poverty in West Java Province. The data consist of the percentage of poverty and its determinants for districts and cities in West Java from 2019 to 2024, obtained from Statistics Indonesia (BPS) – West Java Province. This study is expected to provide insights into the spatial and temporal interregional effects of poverty and offer valuable input for local governments in formulating more effective poverty reduction policies.

METHOD

The methodological design of this study follows the conceptual argument that poverty in West Java exhibits both spatial and temporal dependence. Therefore, the analytical stages proceed to identify these dependencies and to estimate a model that can capture interregional interactions. This section explains the dataset, spatial structure, dependence tests, and estimation procedures.

Data Sources

The data used in this study are secondary data on the percentage of poor population in 27 districts and cities of West Java Province from 2019 to 2024, along with several influencing factors [12]. The data were obtained from the official website of Statistics Indonesia (BPS) – West Java Province. The variables used in this study are as follows: percentage of poor population (Y), unemployment rate (X_1), human development index (HDI) (X_2), percentage of households with access to proper sanitation (X_3), gross regional domestic product (GRDP) per capita at constant prices (X_4), and population growth rate (X_5).

Spatial Panel Data Statistics

Spatial panel data statistics is a panel data regression method that incorporates spatial interaction effects (spatial dependence among regions) into a panel data model. Spatial dependence implies that the value of a variable in location i may be influenced by the values of the same variable in location j ($j \neq i$) [13]. This approach is suitable for poverty data, where economic conditions in one district often influence or resemble those of nearby districts. Panel data are used because they can handle heterogeneity among observational units, thereby reducing bias compared to cross-sectional or time-series studies. Additionally, panel data allowing for the study of dynamic processes such as labor mobility, unemployment, and economic policy responses [14].

Spatial Weight Matrix

To model interregional interactions, a spatial weight matrix is constructed using the queen contiguity criterion. Queen contiguity defines spatial relationships between regions based on shared borders and vertices with the region of interest [15]. This matrix determines the intensity of spillover effects across districts. Therefore, the matrix is standardized by rows as follows:

$$W_{ij} = \begin{cases} 0, & \text{if } i \text{ and } j \text{ are not adjacent or } i = j \\ \frac{1}{n_i}, & \text{if } i \text{ and } j \text{ are adjacent} \end{cases} \quad (1)$$

Spatial Dependence Test

Before estimating the spatial panel model, spatial dependence must be confirmed. Spatial dependence refers to the relationship between nearby regions, indicating that adjacent locations tend to have similar values. Two methods commonly used for detecting spatial autocorrelation are the Cross-sectional Dependency (CD) test and Moran's Index. The CD test is used to detect dependence among cross-sectional units in general. This method is more efficient when the number of cross-sectional units (N) is greater than the number of time periods (T) [15]. Meanwhile, Moran's Index is used to measure global spatial autocorrelation and can be applied to detect spatial patterns. Detecting significant dependence justifies the use of spatial panel modeling.

The Pesaran CD test examines autocorrelation in the dependent variable to determine whether cross-sectional units are interdependent. This step is crucial, as ignoring spatial correlation among units may introduce bias. The hypotheses and the statistical tests are presented as follows [16]:

H_0 : $\rho_{ij} = \rho_{ji} = 0$ for $i \neq j$ (no spatial correlation among individuals)

H_1 : $\rho_{ij} = \rho_{ji} \neq 0$ for some $i \neq j$ (spatial correlation exists among individuals)

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \right) \quad (2)$$

$$\rho_{ij} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2 \right)^{\frac{1}{2}} \left(\sum_{t=1}^{T} e_{jt}^2 \right)^{\frac{1}{2}}} \quad (3)$$

where ρ_{ij} denotes the correlation between residuals of individuals i and j, T is the number of time periods, and N is the number of cross-sectional units.

Moran's Index measures the degree to which the value of a variable in one location correlates with the same variable in other locations. The Moran's Index test is used to examine spatial autocorrelation in the independent variables.The hypotheses are [15]:

$H_0 : I = 0$ (no spatial dependence)

$H_1 : I \neq 0$ (spatial dependence exists)

The standardized test statistic is expressed as:

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \approx N(0,1) \quad (4)$$

with $E(I) = -\frac{I}{n-1}$; $Var(I) = \frac{n^2 S_1 - n S_2 + 3 S_0^2}{(n^2-1) S_0^2} - [E(I)]^2$; $I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_j - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{n} (x_i - \bar{x})^2}$

$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$; $S_1 = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (w_{ij} + w_{ji})^2$; $S_2 = \sum_{i=j}^{n} \left(\sum_{i=1}^{n} w_{ij} + \sum_{i=1}^{n} w_{ji} \right)^2$.

H_0 is rejected if $\left| Z_{hitung} \right| > Z_{\frac{\alpha}{2}}$ or p-value $\leq \alpha$.

Dynamic Spatial Durbin Panel Model

The Dynamic Spatial Durbin Panel Model integrates three key components: temporal lag, spatial lag, and spatially lagged covariates [17]. The temporal lag component indicates that poverty in the current year depends on poverty in the previous year. The spatial lag component means that poverty in a given region is influenced by poverty levels in neighboring regions. The spatially lagged covariate component shows that the socioeconomic characteristics of neighboring regions affect local poverty outcomes. By integrating these three components, the model captures both spatial spillover effects and temporal persistence, making it a robust and comprehensive approach for analyzing the spatiotemporal dynamics of poverty [18]. The model can be expressed as:

$$\boldsymbol{y}_t = \lambda \boldsymbol{y}_{t-1} + \rho \boldsymbol{W} \boldsymbol{y}_t + \boldsymbol{X}_t \boldsymbol{\beta}_1 + \boldsymbol{W} \boldsymbol{X}_t \boldsymbol{\beta}_2 + \boldsymbol{\mu} + \xi_t \boldsymbol{I}_N + \boldsymbol{\varepsilon}_t \qquad (5)$$

where $\boldsymbol{y}_t$ is an $N \times 1$ vector of the dependent variable, λ is the temporal lag coefficient, ρ is spatial autocorrelation coefficient, $\boldsymbol{W}$ is the $N \times N$ spatial weight matrix, $\boldsymbol{X}_t$ is the $N \times K$ matrix of independent variables, $\boldsymbol{\beta}_1$ is a $K \times 1$ vector of coefficients for the independent variables, $\boldsymbol{\beta}_2$ is a $K \times 1$ vector of coefficients for the spatially lagged independent variables, $\boldsymbol{\mu}$ is individual fixed effects, ξ_t is time effect in *t* period, $\boldsymbol{I}_N$ is an $N \times 1$ vector of ones, and $\boldsymbol{\varepsilon}_t$ is the error component vector in *t* period, where $\varepsilon_t \sim IID(0, \sigma^2 I_N)$.

Parameter Estimation

According to [3], there are four main estimation methods for Dynamic Spatial Durbin Panel Model parameters: Maximum Likelihood (ML), Quasi-Maximum Likelihood (QML), Generalized Method of Moments (GMM), and Bayesian Markov Chain Monte Carlo (MCMC). This study uses the Maximum Likelihood (ML) method, as it provides consistent and efficient estimates under normality and captures spatial and temporal dependencies simultaneously. ML is particularly suitable for panel data with a relatively small cross-sectional dimension [19], which aligns with the characteristics of the data used in this study. In contrast, GMM is more appropriate for panels with large N and small T [20], while Bayesian MCMC requires complex prior specifications and intensive computations [21], [22], making it less efficient for the data structure used.

For example $\boldsymbol{X}^* = (\boldsymbol{X}_t, \boldsymbol{W}\boldsymbol{X}_t, \boldsymbol{1}_t, \boldsymbol{1}_N), \boldsymbol{A} = \boldsymbol{I} - \rho \boldsymbol{W}, \boldsymbol{\beta}^* = \begin{pmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \boldsymbol{\mu} \\ \xi_t \end{pmatrix}, \boldsymbol{A}^{-1}\boldsymbol{y}_{t-1}$, and $\boldsymbol{Z}^* = \boldsymbol{A}^{-1}\boldsymbol{X}^*$**,** so the dynamic spatial durbin panel model in equation (5) is parameterized as:

$$\boldsymbol{y}_t - \rho \boldsymbol{W} \boldsymbol{y}_t = \lambda \boldsymbol{y}_{t-1} + (\boldsymbol{X}_t, \boldsymbol{W}\boldsymbol{X}_t, \boldsymbol{1}_t, \boldsymbol{1}_N) \begin{pmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \boldsymbol{\mu} \\ \xi_t \end{pmatrix} + \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{y}_t = \lambda \boldsymbol{A}^{-1} \boldsymbol{y}_{t-1} + \boldsymbol{A}^{-1} \boldsymbol{X}^* \boldsymbol{\beta}^* + \boldsymbol{A}^{-1} \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{y}_t = \lambda \boldsymbol{y}^*_{t-1} + \boldsymbol{Z}^* \boldsymbol{\beta}^* + \boldsymbol{A}^{-1} \boldsymbol{\varepsilon}_t$$

where $\boldsymbol{\varepsilon}_t = \boldsymbol{A}\boldsymbol{y}_t - \lambda \boldsymbol{y}_{t-1} + \boldsymbol{X}^*\boldsymbol{\beta}^*$. The log-likelihood function is maximized to estimate the parameters, as detailed in [23].

$$ln\boldsymbol{L}_{\boldsymbol{T}}(\boldsymbol{v}) = -\frac{NT}{2}\ln(2\pi) - \frac{1}{2}\ln|\boldsymbol{\Omega}| + T\sum_{i=1}^{N}\ln|1 - \rho\omega_i| - \frac{1}{2}\boldsymbol{e}'\boldsymbol{\Omega}^{-1}\boldsymbol{e} \qquad (6)$$

where $\boldsymbol{\Omega} = (T\sigma_\mu^2 + \sigma_\varepsilon^2)(\bar{\boldsymbol{J}}_t \otimes \boldsymbol{I}_N) + \sigma_\varepsilon^2[(\boldsymbol{I}_T - \bar{\boldsymbol{J}}_t) \otimes \boldsymbol{I}_N]$; $\bar{\boldsymbol{J}}_t = \frac{J_t}{N}$; $v = (\boldsymbol{\beta}, \gamma, \lambda, \rho, \sigma_\varepsilon^2)$; ω_i is *i*-th eigen value; and $\boldsymbol{\varepsilon} = \hat{\boldsymbol{\varepsilon}}_t$. Estimator of $v = (\boldsymbol{\beta}, \gamma, \lambda, \rho, \sigma_\varepsilon^2)$ can be obtained by maximizing the log likelihood function in equation (6).

To ensure the reliability of the estimation results, several robustness checks were performed, including tests for multicollinearity, normality, and residual homoscedasticity. Multicollinearity among the independent variables was assessed using the Variance Inflation Factor (VIF) [24], normality of the residuals was evaluated with the Shapiro–Wilk test [25], and homoscedasticity was examined using the Breusch–Pagan test [26]. These tests were conducted to ensure that the model satisfies the classical assumptions, so that the estimated results and statistical inferences obtained can be considered reliable.

Analysis Steps

The first step is to determine the dependent and independent variables and perform data exploration. Next, a spatial weight matrix is constructed using the Queen Contiguity method, and the matrix is standardized using equation (1). Then, spatial autocorrelation is tested using the Pesaran CD test based on equation (2) and Moran's Index using equation (4). The selection of the panel data model approach can be carried out using the Hausman test. If the spatial autocorrelation test indicates the presence of spatial dependence, the parameters of the dynamic spatial Durbin panel model are estimated using equation (6), and it is ensured that the model satisfies the classical assumptions. Based on the results obtained, parameter significance testing is performed. Last, the adjusted R^2 value of the dynamic spatial durbin panel model is calculated to assess the goodness of fit of the model.

RESULT AND DISCUSSION

Data Exploration

On average, poverty levels across regencies and cities in West Java increased during 2020 and 2021 compared to previous years. This was caused by the COVID-19 pandemic that occurred during that year. Subsequently, with the improvement of economic conditions from 2022 to 2024, poverty levels across districts and cities tended to decrease. A similar decrease was observed in poverty-related variables such as the unemployment rate and population growth rate. In contrast, other development indicators—including the Human Development Index, the percentage of households with access to proper sanitation, and the Gross Regional Domestic Product (GRDP) per capita at constant prices—showed steady annual increases. These trends are illustrated in Figure 1, which presents the average annual values of each variable across 27 regencies and cities in West Java. Furthermore, the multicollinearity test results using R software indicated that all independent variables had Variance Inflation Factor (VIF) values smaller than 10, ranging from 1.05 to 1.43. This suggests that there was no multicollinearity among the independent variables.

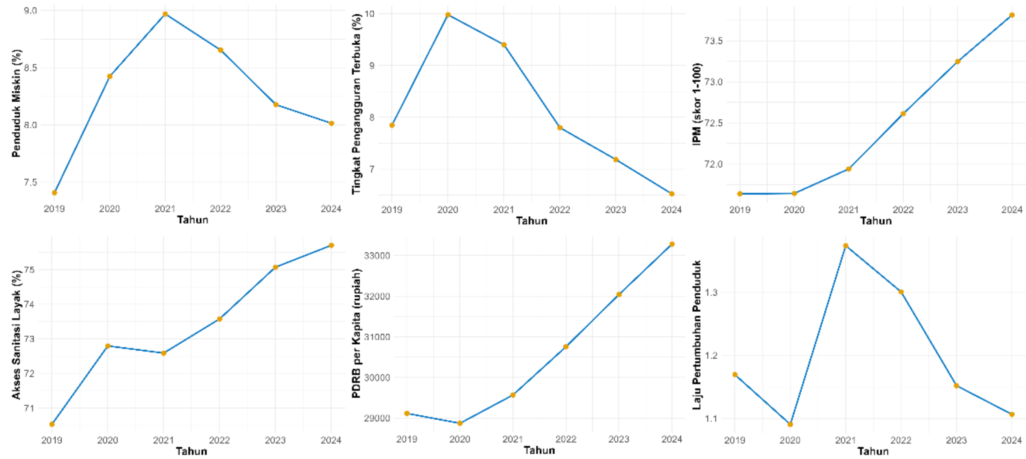

Figure 1. Average Value of Each Variable per Year

Figure 2 shows a spatial map of poverty across regencies and cities in West Java Province from 2019 to 2024. The map reveals that the percentage of the poor population in adjacent areas tends to have similar values, indicating spatial dependence. Although the spatial pattern appears relatively stable over time, it remains uneven across regions. The highest poverty rates are observed in the eastern-northern areas, such as Cirebon, Indramayu, Majalengka, and Kuningan Regencies. In contrast, the western-central regions—such as Bekasi, Depok, Bogor, and the Bandung Raya area—show lower poverty rates. This pattern remains relatively consistent each year, as indicated by the color distribution across time. These findings suggest the presence of temporal effects in the poverty data of West Java, where regions with high poverty rates in one period tend to maintain similarly high levels in subsequent periods. Thus, the poverty data exhibit dynamic spatiotemporal characteristics.

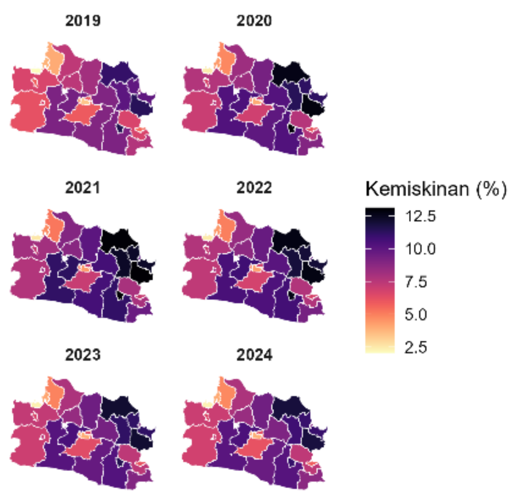

Figure 2. Spatial Map of Poverty Rate by Year

Spatial Dependence Testing

Spatial dependence testing was conducted prior to spatial data analysis to determine whether there were interregional linkages. Since the number of regencies/cities (N) exceeds the number of time periods (T), the Pesaran Cross-Sectional Dependence (CD) test was employed to detect overall spatial dependence. The analysis, performed using R software, produced the following results:

Table 1. Pesaran CD Test Results

CD	p-value
32.933	$< 2.2 \times 10^{-16*}$

Note: (*) significant at 5% level.

Based on Table 1, the Pesaran CD test result shows that the p-value is much smaller than the 5% significance level; thus, H_0 is rejected. This indicates the presence of spatial correlation among units, meaning that poverty rate in one regency/city are influenced by those in neighboring regions.

Subsequently, Moran's I test was applied to measure spatial autocorrelation for each observed variable using a queen contiguity spatial weight matrix. The results are as follows:

Table 2. Moran's I

Variable	Year	Moran's I	p-value	Variable	Year	Moran's I	p-value
Y	2019	0.3106	0.0057*	X_3	2019	0.0330	0.3045
Y	2020	0.3103	0.0058*	X_3	2020	0.0767	0.2032
Y	2021	0.3198	0.0047*	X_3	2021	0.0524	0.2556
Y	2022	0.3137	0.0054*	X_3	2022	0.0142	0.3525
Y	2023	0.3257	0.0042*	X_3	2023	-0.0004	0.3925
Y	2024	0.3300	0.0039*	X_3	2024	-0.0098	0.4187
X_1	2019	-0.1211	0.7257	X_4	2019	-0.0593	0.5622
X_1	2020	-0.0501	0.5336	X_4	2020	-0.0403	0.5056
X_1	2021	0.0130	0.3527	X_4	2021	-0.0391	0.5020
X_1	2022	0.0628	0.2266	X_4	2022	-0.0382	0.4993
X_1	2023	0.0208	0.3284	X_4	2023	-0.0409	0.5074
X_1	2024	-0.0469	0.5254	X_4	2024	-0.0380	0.4986
X_2	2019	0.3320	0.0034*	X_5	2019	0.2042	0.0315*
X_2	2020	0.3253	0.0039*	X_5	2020	-0.0044	0.4020
X_2	2021	0.3226	0.0042*	X_5	2021	-0.0062	0.4071
X_2	2022	0.3083	0.0056*	X_5	2022	-0.0043	0.4016
X_2	2023	0.3054	0.0060*	X_5	2023	-0.2599	0.9447
X_2	2024	0.3116	0.0053*	X_5	2024	-0.2657	0.9490

Note: (*) significant at 5% level.

Based on Table 2, the poverty rate variable (Y) exhibits positive and significant spatial autocorrelation across all years, indicating a spatial clustering pattern — regencies/cities with high poverty rates tend to be adjacent to other high-poverty areas, and vice versa. Similarly, the human HDI (X_2) also shows positive and significant autocorrelation across all years. This indicates that districts and cities with high HDI tend to be located near other districts and cities with similarly high HDI, and vice versa. In contrast, the unemployment rate (X_1), access to proper sanitation (X_3), GRDP per capita (X_4), and population growth rate (X_5) mostly show insignificant spatial autocorrelation. This indicates the absence of a spatial pattern, meaning that districts and cities with high or low values are not clustered but randomly distributed. Consequently, a spatial panel model is appropriate for this study to capture spatial interdependencies among regions.

Dynamic Spatial Durbin Panel Model

The spatial model applied in this study is the spatial durbin model with fixed effect. The spatial durbin model is selected because it accounts for the influence of both dependent and independent variables across units. The fixed effects model was selected based on the results of the Hausman test, which yielded a chi-square value of 74.725 with 5 degrees of freedom and a p-value of 1.062×10^{-14}. These results indicate that the p-value is much smaller than the 5% significance level, leading to the rejection of H_0. In the fixed effect model, there is a correlation between the individual effects and the independent variables. A dynamic model is employed to capture temporal effects, as evidenced by the annual spatial maps showing the impact of different time periods. The estimation results are summarized as follows:

Table 3. Parameter Estimation for the Dynamic Spatial Durbin Panel Model

Parameter	Estimate	Standard Error	p-value
ρ	0.3996	0.084505	$2.265 \times 10^{-06***}$
λ	0.2258	0.052307	$1.579 \times 10^{-05***}$
β_1			
X_1	-1.4696×10^{-02}	2.7059×10^{-02}	0.587052
X_2	-7.3883×10^{-02}	1.3131×10^{-01}	0.573671
X_3	-2.4673×10^{-03}	3.8615×10^{-03}	0.522852
X_4	2.3292×10^{-05}	1.3182×10^{-05}	0.077241*
X_5	-8.9520×10^{-02}	8.9505×10^{-02}	0.317229
β_2			
WX_1	8.5482×10^{-02}	4.6668×10^{-02}	0.066996*
WX_2	-1.8972×10^{-01}	1.6019×10^{-01}	0.236281
WX_3	3.4739×10^{-03}	6.5823×10^{-03}	0.597664
WX_4	4.5545×10^{-05}	2.1902×10^{-05}	0.037570**
WX_5	5.0308×10^{-01}	1.6273×10^{-01}	0.001991***
R^2_{adj}	0.9959		

Note: (*) significant at 10% level, (**) significant at 5% level, (***) significant at 1% level.

The parameter estimation of the dynamic spatial durbin panel model presented in Table 3 satisfies the assumptions of homoscedastic and normally distributed residuals. The assumption testing was conducted using the Breusch–Pagan test for homoskedasticity and the Shapiro–Wilk test for normality. The Breusch–Pagan and Shapiro–Wilk tests from R software show p-values of 0.3024 and 0.4159 (>0.05). Thus, it can be concluded that the model residuals are homogeneous and normally distributed. This indicates that the statistical tests are valid, and the parameter estimates are efficient and unbiased. Furthermore, the adjusted R^2 is 0.9959, implying that the model can explain approximately 99.59% of the variation in poverty levels. The high adjusted R^2 value demonstrates that the combination of independent variables, spatial effects, and dynamic temporal effects in the model can explain data variations very well. Hence, the model is considered appropriate and reliable for representing the dynamics of poverty in West Java, as it satisfies the assumptions of normality and homoscedasticity and exhibits a high adjusted R^2.

Based on Table 5, it can be seen that the spatial autocorrelation coefficient (ρ) and the temporal lag coefficient (λ) have p-values smaller than the 5% significance level. Thus, it can be concluded that both spatial dependence and dynamic effects influence poverty levels in West Java Province. In other words, poverty is affected not only by the internal conditions of a region but also by the conditions of neighboring regions (spatial spillover) and the poverty level in the previous period (persistence effect). This is consistent with the findings of [8], which indicate a linkage between the poverty rate in a given region and that of adjacent regions.

Among the independent variables, only the per capita GRDP at constant prices (X_4) significantly affects the poverty level in West Java at the 10% significance level, with a positive coefficient. This implies that an increase in GRDP leads to an increase in poverty. This result contradicts the findings of [4], where higher GRDP was associated with a reduction in poverty. The positive relationship observed here reflects income disparities across regencies and cities in West Java. Economic growth, as indicated by rising GRDP, has not been evenly distributed, as its benefits are largely enjoyed by upper-middle-class groups and regions with high economic activity, such as Bandung, Karawang, and Bekasi. In contrast, other areas in West Java are still dominated by the agricultural sector with lower productivity. This aligns with the Kuznets curve hypothesis, which states that at early stages of economic growth, poverty reduction is not yet significant. Therefore, an increase in GRDP has not translated into lower poverty, particularly in regions with uneven income distribution. Consequently, local governments need to promote equitable economic growth by developing productive sectors in high-poverty areas, improving public access to economic activities, and providing skills training for low-income communities.

Meanwhile, the unemployment rate (X_1) did not have a significant effect on the poverty level in West Java. Conceptually, this insignificance may occur when most of the labor force is employed but earns low income (working poor) [27]. This weakens the statistical relationship between unemployment and poverty. Consequently, in addition to creating jobs, local governments need to improve job quality through skills training and protection for workers in the informal sector. This would enable workers to earn adequate income and escape the poverty line.

The variables HDI (X_2), the percentage of households with access to proper sanitation (X_3), and population growth rate (X_5) also did not have a significant effect on poverty levels in West Java. The HDI and basic infrastructure generally exert long-term influences, and therefore their impacts may not be immediately observable within a shorter analytical horizon. Improvements in sanitation initiated through government programs do not necessarily translate into increased household income, implying that their effects on poverty are indirect. Meanwhile, a relatively stable population growth rate may reduce interregional variation, resulting in a non-significant relationship with poverty. Although these three variables do not show statistically significant effects, they should remain a priority for local governments. Policy interventions need to be directed toward aspects that produce direct economic impacts. Enhancements in HDI and sanitation must be accompanied by community economic empowerment to ensure that the benefits are felt by low-income groups. In addition, the relatively controlled population growth rate should be supported by equitable employment opportunities to minimize potential poverty arising from interregional economic disparities.

For the spatially lagged independent variables, the unemployment rate in neighboring regions (WX_1) significantly affects the poverty level in West Java at the 10% significance level, with a positive coefficient. This indicates the presence of spatial effects from labor market conditions, whereby higher unemployment in adjacent districts/cities increases economic vulnerability in a given area. This can occur due to economic linkages and labor mobility between geographically proximate regions. Meanwhile, the variables GRDP per capita at constant prices (WX_4) and population growth rate (WX_5) is significant at the 5% level with a positive coefficient. This implies that increases in GRDP and population growth in neighboring districts/cities contribute to higher poverty levels in the observed region. This finding suggests that the GRDP generated by industrial areas such as Bekasi, Karawang, and Bandung City has not been fully transmitted as benefits to the surrounding regions. Such conditions may arise when there is inequality in employment opportunities, where residents of neighboring areas are unable to access jobs in industrial regions due to skill constraints. Furthermore, high population growth in surrounding areas may intensify competition for employment, causing poverty to remain high despite proximity to more advanced economic centers.These results are consistent with the theory of spatial externalities, which states that economic and demographic dynamics in one region generate external effects on other regions through labor interactions, population movements, and regional economic linkages. Therefore, regional governments should strengthen inter-district cooperation in job creation and urbanization control to prevent negative spillover effects from economic growth.

The variables HDI (WX_2) and the percentage of households with access to proper sanitation (WX_3) in neighboring districts/cities did not have a significant effect on the poverty level of a given district/city. This indicates that improvements in HDI and sanitation tend to generate benefits primarily for the local population. The spillover effects of Human Development Index and basic infrastructure are more limited compared to economic variables such as GRDP or unemployment rates. Therefore, efforts to enhance human capital and develop basic infrastructure—such as sanitation—need to be implemented evenly across regions, rather than being concentrated only in urban areas.

Overall, the findings indicate that regions with high poverty levels tend to be located near other regions with similar characteristics. Therefore, poverty alleviation efforts cannot be undertaken by each region independently; instead, coordinated interregional strategies are required, particularly in the areas of job creation, equitable economic growth, and population growth management. In addition, poverty reduction efforts must be carried out in a sustainable manner, as poverty is inherently dynamic and cannot be resolved in a short period of time. Consequently, poverty alleviation will be more effective when implemented based on spatial interdependence and temporal dynamics.

CONCLUSION

Based on the analysis, the spatial autocorrelation coefficient (ρ) and the temporal lag coefficient (λ) significantly affect poverty rate in West Java Province. Among the independent variables, GRDP per capita at constant prices (X_4) significantly affects the poverty rate in West Java at the 10% significance level. For neighboring-region variables, unemployment rate (WX_1) significantly affects the poverty rate in West Java at the 10% significance level, while GRDP per capita at constant prices (WX_4) and population growth rate (WX_5) significantly affect the poverty rate in West Java at the 5% significance level. The model has an adjusted R^2 of 99.59%, indicating that the dynamic spatial durbin panel model with a fixed effect approach can explain approximately 99.59% of the variation in poverty levels across regions in West Java during the 2019–2024 period. These results highlight the need for collaborative interregional poverty reduction strategies, focusing on job creation, equitable economic growth, and population control. Furthermore, poverty alleviation must be sustainable and continuous, considering the dynamic nature of poverty that cannot be resolved in the short term.

The limitation of this study lies in the possibility of omitted variables that may influence the poverty rate but were not included in the model. Therefore, future research is recommended to incorporate additional variables that may affect poverty, to conduct the analysis at a smaller spatial level, and to compare the results with alternative spatial models in order to assess the robustness of the findings and gain further insights into the dynamics of poverty in West Java Province.

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