Dynamic Spatial Durbin Modeling  
(Case: Percentage of Poor Population in Indonesia 2010-2019)

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Abstract. The dynamic panel model assumes that each observation unit is independent of each other. But sometimes this assumption is violated, so there are spatial effects in the model. This study aimed to make percentage modeling of poverty in Indonesia using the Dynamic Spatial Durbin Model (DSDM). The data used in this study were secondary data obtained from the Statistics Indonesia in the period 2010-2019. The parameter estimation method used in this model was the Maximum Likelihood (ML). According to Moral-Benito, Allison and Williams the ML method has the best performance when used on panel data that has small cross-section data dimensions. The results of this study indicated that spatial dependence, time lag, variables of Poverty Gap Index, Poverty Severity Index and Logarithm of Expenditures per Capita affect poverty in Indonesia significantly. Other results showed that DSDM was able to explain the diversity in models at 95.6%. This seemed higher when it's compared to the Spatial Durbin Model (SDM). Thus, the result of the study proved that DSDM is the best model for modelling dynamic poverty data panel in Indonesia during 2010-2019.

1. Introduction
Regression is the analysis of studies concerning on the dependence of the dependent variables with one or more independent variables. In the regression analysis, data used can be in the form of cross-section data (data collected at a time), time series data, or panel data. Panel data is a combination of cross-section and time series data, where the same cross-section units are measured at different times. Regression that uses panel data is called panel regression. Panel data regression can be dynamic. This is because basically the relation of certain variables is a dynamic, that is, the dependent variable is not only influenced by the independent variable, but it is also influenced by the dependent variable in the previous time.

The dynamic panel regression model assumes that each unit of observation is mutually independent. But sometimes this assumption is violated. This is caused by the correlation between one unit with another observation unit. Therefore, dynamic spatial panel regression models can be formed. One of the spatial models that can be used in dynamic panel regression is the Spatial Durbin Model. This model explains the spatial dependence of the independent variable and the dependent variable unit one with other observation units. The combination of dynamic panel data regression models with the Durbin Spatial Model is called the Dynamic Spatial Durbin Model (DSDM). Estimating DSDM parameters can be through several methods. One of them is the Maximum Likelihood (ML) method. According to [1]...
the ML method has the best performance when used on panel data that has small cross-section data dimensions.

The DSDM model can be applied to several data. One of them is poverty data. This is because basically the relation that occurs in poverty variables is not only influenced by the variables at the same time, but is also influenced by the variables in the previous time. In addition, the factors of poverty are interrelated. So that the spatial model can also be applied to poverty data. Therefore, researchers are interested in modeling the percentage of poor people in Indonesia through DSDM. Estimating parameters using the Maximum Likelihood (ML) method. The data to be used comes from Statistics Indonesia in the period 2010-2019. Observations covered 33 provinces in Indonesia.

2. Research Methods

2.1 Spatial Statistics
Spatial statistics are statistical methods used to analyze spatial data. Spatial data is data that contains "location" information, so not only "what" is measured but shows the location where the data is [2]. Spatial data can be information about geographic locations such as the latitude and longitude of each region and borders among regions. Tobler argues that all things are related to one another, but something close will be more related than far apart. This law is the pillar of regional science studies. It can be concluded that spatial effects are a natural occurrence between one region and another.

The very important matrix in spatial analysis is the spatial weight matrix. This matrix is used to determine the weighting between locations that are observed based on neighborhood relations among locations. Several forms of spatial weighting matrices can be used. Kukenova et.al. used a row standardized distance matrix $W_r = \{d_{ij}\}; i = j = 1, \ldots, N$ [3]. Yan and Dong used the row standardized inverse distance matrix $W_{dis} = \{1/d_{ij}\}; i = j = 1, \ldots, N$ [4]. Shrui, et.al. used the standardized nearest neighbor matrix, the $w_{ij}$ value of 1 if $i$ and $j$ are neighbors, otherwise zero [5]. Furthermore, Sarries used a negative exponential matrix of the distance at which $W_d = \exp\{-d_{ij}\}; i = j = 1, \ldots, N$ [6].

2.2 Spatial Autocorrelation
Spatial autocorrelation is the correlation between the observed values related to the spatial location on the same variable. The measurement of spatial autocorrelation estimators for spatial data can be calculated by using the methods Cross-sectional Dependency (CD) and the Moran's Index. To test the spatial dependence on the response variable, according to Pesaran, the CD Pesaran method is more efficient used when $N > T$ [7]. Furthermore, the Moran Index (Moran's I) is the method most widely used to calculate spatial autocorrelation globally. This method can be used to detect the beginning of spatial randomness. This spatial randomness may indicate patterns that clumped or establish a trend toward space.

2.2.1 CD Pesaran Test
To test the spatial dependence on the response variable, the CD Pesaran test was performed with the following hypothesis [7]:

$H_0$: $\rho_{ij} = \rho_{ji} = 0$ for $i \neq j$

$H_1$: $\exists \rho_{ij} \neq \rho_{ji}, \quad i \neq j$

The test statistic used is:

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

Where $\rho_{ij}$ is the estimator of the remaining correlation which has the formula:

$$\rho_{ij} = \rho_{ji} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{\frac{1}{2}} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{\frac{1}{2}}}$$
2.2.2 Moran Index Test
To test spatial autocorrelation on independent variables, the Moran Index can be used [8]. Moran index is an indicator of spatial autocorrelation that compares the value of a variable at one location with the same variable value at another location. The hypothesis used [9]:

- \[ H_0: I = 0 \] (there is not a positive spatial autocorrelation)
- \[ H_1: I = 0 \] (there is a positive spatial autocorrelation)
- \[ I < 0 \] (there is a negative spatial autocorrelation)

The test statistic used is:

\[
Z(I) = \frac{I - E(I)}{\sqrt{\text{var}(I)}} \sim N(0, 1)
\]  
(2)

Where

\[
I = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(y_i - \bar{y})(y_j - \bar{y})
\]

\[
E(I) = -\frac{1}{n-1}; \quad \text{and} \quad \text{var}(I) = \frac{N^2 S_1 - N S_2 + 35 \sum_{i=1}^{N} \left( y_i - \bar{y} \right)^2}{(n-1) S_0^2} - [E(I)]^2
\]

\[
S_0 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}; \quad S_1 = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \left( w_{ij} + w_{ji} \right)^2; \quad S_2 = \sum_{i=1}^{N} \left( \sum_{j=1}^{N} w_{ij} + \sum_{j=1}^{N} w_{ji} \right)^2
\]

Rejected \( H_0 \) at the significance level \( \alpha \) if \( Z(I) > Z_1 - \alpha \). \( Z_1 - \alpha \) is a quantile from the Standard Normal Distribution.

Testing with the Moran Index is performed on each variable. The range of values from the Moran Index in the case of standardized spatial weight matrices is \(-1 \leq I \leq 1\). Values \(-1 \leq I \leq 0\) indicate negative spatial autocorrelation, while values \(0 < I \leq 1\) indicate positive spatial autocorrelation, a Moran Index value of zero indicates no spatial influence. The Moran Index value does not guarantee the accuracy of the measurement if the weighted matrix used is a standardized weighted matrix. To identify whether or not spatial autocorrelation was performed, the Moran Index significance test was performed.

2.3 Autoregressive Dynamic Model
The autoregressive dynamic model is a model in which the lag dependent variable appears as an independent variable on the model. The equation of the autoregressive dynamic model is written as follows:

\[
Y_t = \phi Y_{t-1} + Z' \beta' + A^{-1} \epsilon_t
\]

Where \( t = 1, 2, ..., T \). In the dynamic panel regression model, the coefficient \( \beta' \) is also a short-term effect of change \( z'_{it} \). While \( \frac{\beta'}{1 - \phi} \) is a long-term effect of change \( z'_{it} \). The lag coefficient of the explanatory endogenous variable must be more than zero but not more than one \((0 < \phi \leq 1)\) or \(| \phi | < 1 [10] \).

Significance test of autoregressive parameters (AR):

- \( H_0: \phi = 0 \) vs \( H_0: \phi \neq 0 \)

Test statistic:

\[
Z = \frac{\hat{\phi}}{SE(\hat{\phi})}
\]  
(3)

Reject \( H_0 \) the level of significance \( \alpha \) if \( Z > Z_{1-\alpha} \) with \( Z_{1-\alpha} \) is the quantile of the Standard Normal Distribution.

2.4 Spatial Dynamic Panel Regression
Dynamic panel regression is a regression method that adds a dependent variable lag to be used as an independent variable. Dynamic has the meaning that the value of a variable is influenced by the value of other variables and the value of the related variable in the past. Linear regression model on dynamic panel data that there is an interaction among the unitsspatial will have variable spatial lag in the response variable or variables spatial processes on the usual error. [11] and [12] introduced an autoregressive
spatial panel model that has the influence of unit and time. The most common models when written in vector for cross-section observations at time t are as follows [13]:

\[
y_t = \lambda y_{t-1} + \rho W y_t + \eta W y_{t-1} + X_t \beta_1 + WX_t \beta_2 + X_{t-1} \beta_3 + WX_{t-1} \beta_4 + \pi Z_1 + \upsilon_t
\]

(4)

\[
\mu = \kappa W \mu + \zeta
\]

Research on dynamic spatial panels has been conducted by researchers. Some of them are Taspinar, Dogan, and Bera [14]; Zhao, Burnett, and Donald (2015); Atems [16]; Chen et al. [17]; Evans and Kim (2014); Lu and Wang (2015); Montmartin and Herrera (2014); Andrića, et al. (2019); Song, Chen, and Qingxian [18]; and Yan and Dong [4].

Based on the general pattern of the spatial dynamic panel model (4), the Dynamic Spatial Durbin Model (DSDM) was built when the \( \beta_3 = \beta_4 = 0 \), \( \eta = \pi = \delta = \lambda = \kappa = \zeta = 0 \). DSDM Formula was written in vector form for cross-section observations at time t is as follows:

\[
y_t = \lambda y_{t-1} + \rho W y_t + X_t \beta_1 + WX_t \beta_2 + \mu + \xi_t I_N + \epsilon_t
\]

(5)

\( y_t \) is an N-dimensional vector of the dependent variable while \( W y_t \) is its spatial lag allowing to capture the presence of spillovers for each spatial unit (i = 1, ..., N) in the sample at time t \( (t = 1, ..., T) \). Also, \( \rho \) is the spatial autoregressive parameter representing the intensity of spatial autocorrelation. Moreover, \( \lambda \) is the autoregressive time dependence parameter. The Matrix \( X_t \) the K independent variables. The NxN matrix \( W \) is a non-negative spatial weighting matrix. The parameters \( \lambda \) and \( \rho \) are the response parameters of successively the dependent variable lagged in time, \( y_{t-1} \) and the dependent variable lagged in space, \( W y_t \). The Kx1 vector \( \beta_1 \) and \( \beta_2 \) represent response parameters of the independent variables. \( \xi_t \) \((t = 1, ..., T)\) denote time-period specific effects, where \( I_N \) is an Nx1 vector of ones, meant to control for all time-specific, unit-invariant variables whose omission could bias the estimates in a typical time-series study. These spatial and time-period specific effects may be treated as fixed or as random effects. Finally, \( \epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Nt})' \) are vectors of i.i.d. disturbance terms, whose elements have zero mean and finite variance, respectively. Lee and Yu [19] has identified panel model Spatial Durbin [19]. Moreover, Li and Wu [20]; and Shurui et al. [5] conducted a study on Dynamic Spatial Durbin Model. In addition, Qian Hu and Chen [21] estimated Nonparametric Dynamic Spatial Durbin Model with Fixed Effects [21].

2.5 Estimation of Dynamic Durbin Spatial Model Parameters (DSDM)

In [13], [3], and [22] state that four methods have been developed in literature to estimate DSDM parameters. These methods are the Maximum Likelihood (ML) [23], Quasy-Maximum Likelihood (QML) [12], Generalized Moment Method (GMM) [24], and Bayesian Markov Chain Monte Carlo (MCMC) [25]. In this study, the ML method was used.

Let \( X' = (X_t, WX_t, 1_t, 1_N, ) \), \( A = I - \rho W \), \( \beta' = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta \end{pmatrix} \), \( A^{-1} y_{t-1} = y'_{t-1} \), and \( Z' = A^{-1} X' \),

DSDM Formula in Equation (2) was parameterized be:

\[
y_t - \rho W y_t = \lambda y_{t-1} + (X_t, WX_t, 1_t, 1_N, ) \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta \end{pmatrix} + \epsilon_t
\]

\[
y_t = \lambda A^{-1} y_{t-1} + A^{-1} X' \beta' + A^{-1} \epsilon_t
\]

Where

\[
\epsilon_t = A y_t - \lambda y_{t-1} + X' \beta'
\]

The DSDM log-likelihood function is written as follows [22]:
\[ \ln L_T(v) = -\frac{NT}{2} \ln(2\pi) - \frac{1}{2} \ln|\Omega| + T \sum_{i=1}^{N} \ln[1 - \rho_{\omega_i}] - \frac{1}{2} e'\Omega^{-1}e \]  

(6)

Where  \( \Omega = (T \sigma_{\mu}^2 + \sigma_{\epsilon}^2)(\overline{I}_T \otimes I_N) + \sigma_{\epsilon}^2[(I_I - \overline{I}_T) \otimes I_N]; \; \overline{I}_T = \frac{I_I}{N}; \; v = (\beta_1, \beta_2, \lambda, \rho, \sigma^2_{\epsilon}); \; \omega_i = \text{eigen value to} - i W; \; \text{dan} \; e = \tilde{e}, \) Estimator of  \( v = (\beta_1, \beta_2, \lambda, \rho, \sigma^2_{\epsilon}) \) can be obtained by maximizing the log-likelihood function in Equation (6).

2.6 Test the Significance of Parameters

The parameter significance test is used to determine whether there is a relation in the model. Wald test was used as a test of the significance of the model simultaneously [26], the Wald hypotheses and statistics test in Equation (7).

- \( H_0: \beta_1^* = \beta_2^* = \cdots = \beta_p^* = 0 \) (There is no significant coefficient on the model)
- \( H_1: \exists \beta_j^* \neq 0, j = 1, 2, \ldots, p \) (There is at least one significant coefficient on the model)

\[ w = \tilde{\beta}^* V^{-1} \tilde{\beta}^* \sim \chi^2_k \]  

(7)

Where \( K = p - 1 \) is the number of independent variables. The decision is \( H_0 \) when is rejected if the value of the test statistic is greater than the table Chi-square (\( \chi^2 \)) or a p-value <a.

The Z test was used as a partial test of the model's significance because of the large number of observations [27]. Hypothesis and statistics of the Z test in Equation (8).

- \( H_0: \beta_j^* = 0 \) vs 1: \( \beta_j^* \neq 0, j = 1, 2, \ldots, p \).

\[ Z_{\text{hitung}} = \frac{\hat{\beta}_j^*}{SE(\hat{\beta}_j^*)} \]  

(8)

Reject \( H_0 \) the level of significance \( \alpha \) if \( Z > Z_{1-\alpha} \). \( Z_{1-\alpha} \) is the quantile of the Standard Normal Distribution.

2.7 Goodness of Fit Measures

Measurement criteria for the good of the model is done by measuring the coefficient of determination (\( R^2 \)) [28]. The formula for the (pseudo) \( R^2 \) spatial panel model is as follows:

\[ R^2 = 1 - \frac{e'e}{(y - \overline{y})(y - \overline{y})} \]  

(9)

It shows how well the model matches the data. \( R^2 \) tend to be more unstable when the number of independent variables increase. Therefore, it is used \( R^2 - \text{Adjusted} \) (\( R^2 - \text{Adj} \)) to measure the goodness of the model. It is a modified form of the number of independent variables that have been corrected. The value of \( R^2 - \text{Adj} \) will always be less than or equal to \( R^2 \). The \( R^2 - \text{Adj} \) formula can be seen in Equestion (10).

\[ R^2 - \text{Adj} = 1 - \frac{\frac{e'e}{(y - \overline{y})(y - \overline{y})}}{\frac{NT - p - 1}{NT - 1}} \]  

(10)

By substituting Equation (9) for Equation (10) a relation is obtained

\[ R^2 - \text{Adj} = R^2 - \frac{(1 - R^2)K}{n - K - 1} \]

Where \( e \) is the sum of the squares remaining in the model. Values of \( R^2 \) ignore the diversity explained by the influence of time and spatial.

2.8 Data

The data used are secondary data obtained from the Statistics Indonesia during 2010-2019 for each province, except North Kalimantan Province. This is because the province is a new province that is less
than ten years old. So the data during 2010-2019 is incomplete. Therefore, 33 provinces became the observation unit. The dependent variable used in this study was the Percentage of Poor Population. Whereas the independent variables were Poverty Gap Index (P1), Poverty Severity Index (P2), Expected Years of Schooling (RLS), Life Expectancy of Population (HH), and Average Monthly Expenditure per Capita (PPK).

Table 1. Operational Definitions

| No. | Variable name                        | Definition                                                                                         | Units of measurement |
|-----|--------------------------------------|---------------------------------------------------------------------------------------------------|----------------------|
| 1   | Percentage of poor population (PM)   | The percentage of the population who are below the poverty line. The cause of poverty itself is usually due to the scarcity of means of meeting basic needs, or the difficulty of access to fulfillment of employment and education needs. | Percent              |
| 2   | Poverty Gap Index (P1)               | the average size of the expenditure gap of each poor population against the poverty line. The higher the index value, the further the average population expenditure is from the poverty line. | -                    |
| 3   | Poverty Severity Index (P2),         | Spread of expenditure among the poor. The higher the index value, the higher the disparity in expenditure among the poor. | -                    |
| 4   | Expected Years of Schooling (RLS)    | The Expected Years of Schooling shows the number of years of study of residents aged 15 years and over who have completed in formal education (not counting repeat years). | Year                 |
| 5   | Life Expectancy of Population (HH)   | The average life year that will still be lived by someone who has reached the age of x, in a certain year, in a situation of mortality that prevails in his community. | Year                 |
| 6   | Average Monthly Expenditure per Capita (PPK) | Costs incurred for the consumption of all household members for a month are divided by the number of household members. | Rupiah               |

2.9 Method
The analysis steps undertaken in applying the poverty panel data modeling in Indonesia using the Dynamic Spatial Durbin Model are as follows:
1. Description of dependent and dependent variable data
2. Spatial dependency test
   a. Test Cross-sectional Dependency (CD) Pesaran using Equation (1)
   b. Test Moran's Index (Moran index) for each independent variable using Equation (2)
   c. Select the weighting matrix used for further analysis
3. AR (1) autoregressive test using Equation (3)
4. Modeling the poverty panel data Indonesia with Dynamic Spatial Durbin Model using spatial weighting matrix exponential negative distance
   a. Modeling using Equations (4)
   b. Estimating Parameters using Equation (6)
   c. Testing the significance of parameters using Equation (8)
5. Selection of the best model using Equations (9) and (10)
3. Results And Discussion

3.1 Data Exploration

Poverty is a multidimensional problem that is related to the lack of inability access to economic, social, cultural, political, and participation in society. According to several variables, map the distribution of poverty for every province in Indonesia can be seen in Figure 1. Map visualized by using color gradation of white which is an Indicator low value to high-value red indicator. When viewed according to the variables of the Average Percentage of Poor Population, The Average Poverty Gap Index, And The Average Poverty Severity Index, the spread of poverty in Indonesia has a trend that tends to be the same. The provinces of Papua and West Papua have the highest value compared to other provinces.

Based on the variable average life expectancy population, West Sulawesi Province has the smallest average life expectancy of 63.4 years. While the highest is owned by Yogyakarta Province by 74.6 years. Then followed by Central Java Province (73.64 years) and East Kalimantan Province (73.57 years). In addition, according to the average expected years of Schooling and average monthly Expediture per capita in the Province Papua has a value of smallest 6 years and Rp. 6, 630.00, respectively. While the Jakarta Province has an Expected Years of Schooling and the highest average per capita expenditure is 10.69 years and Rp. 17, 029.8.

![Map of the Percentage of Poor Population, Average of Indonesia](image1)

![Map of the Poverty Gap Index (Pi) Average of Indonesia](image2)

![Map of the Poverty Severity Index (Pi) Average of Indonesia](image3)

![Map of the Percentage of Poor Population, Average of Indonesia](image4)

![Map of the Average Monthly Expenditure per Capita of Indonesia](image5)

**Figure 1.** The spread of Indonesian Poverty is based on several variables

3.2 Spatial Dependency Test

Before conducting further analysis, a statistical test is needed to determine the existence of spatial dependence on dynamic panel data. To test the spatial dependence on the response variable, when $T > N$ the test commonly used is the Lagrange Multiplier (LM) test developed by Breusch and Pagan in 1980. The LM test is appropriate for fixed $N$ and $T \to \infty$. However, if $N > T$ the size of $N$ is large or $N > T$ that is with Cross-sectional Dependency (CD) statistics. Based on test statistics obtained by using Software R values of $CD = 10.79$ and values of $p < 2.2e - 16 < \alpha = 0.05$ are obtained so that it can be concluded that the null hypothesis is rejected, in other words poverty panel data in Indonesia has a spatial dependence on the response variable. This indicates that poverty in a province other than influenced by variable smoking also affected by poverty in the province of the other.
In addition, to know the spatial dependence on independent variables, the Moran Index is used for each independent variable by using a weighted matrix. Then we compared the independent variables Moran index on each weighted matrix. Furthermore, selected weighted matrix was exponential negative distance weighted matrix of weighting best. Table 2 showed the value of Moran Index of each independent variable used. Based on Table 2 it is known that on average, the variables P1, P2, HH, and PPK showed Moran index values that are not equal to 0 (significant <10%) meaning that the variables showed the existence of a spatial association pattern. Whereas the RLS variable is not indicated to have a spatial association pattern.

### Table 2. Moran Index of Poverty Variables in Indonesia

| Variable                        | Statistics I | p-value |
|---------------------------------|--------------|---------|
| Poverty Gap Index (P1)          | 0.60         | <00     |
| Poverty Severity Index (P2)     | 0.60         | <00     |
| Expected Years of Schooling (RLS)| -0.05        | 0.89    |
| Life Expectancy of Population (HH)| 0.39         | 0.00    |
| Average Monthly Expenditure per Capita (PPK)| 0.22         | 0.06    |

#### 3.3 Autoregressive AR (1) Test

To see the significance of the effect of dynamic effects, a lag-1 autocorrelation test was used by the Z test and with ACF and PACF visualization. Based on the Z Test, obtained, \( z = 38.94 \) with \( p-value < 2.2e - 16 \). This indicated that there was correlation between present time and past time AR (1) of 0.90. Reinforced by Figure 2, the ACF and PACF plots showed that the first lag is the most significant. While the next lags are in the interval area. This means that the dependent variable lag \( y_t \) is affected by \( y_{t-1} \).

![ACF and PACF Diagrams Percentage of Indonesia's Poor Population](image)

#### 3.4 Modeling on Indonesia’s poverty panel data with the Dynamic Spatial Durbin Model (DSDM)

Modeling Indonesian poverty panel data have done through DSDM using the matrix of distance negative exponential weighting for both the dependent variable lag and the independent variable lag. The DSDM that was built was compared with the Spatial Durbin Model (SDM) in the panel data. The general form of DSDM in poverty panel data in Indonesia is:

\[
y_t = \lambda y_{t-1} + \beta W y_t + X_t \beta_1 + WX_t \beta_2 + \mu + \xi_t I_N
\]

Where \( X_t = (P1_t, P2_t, RLS_t, HH_t, \log(PPK)_t) \), \( \beta_1 = (\beta_{11}, \beta_{12}, \beta_{13}, \beta_{14}, \beta_{15}) \), \( \beta_2 = (\beta_{21}, \beta_{22}, \beta_{23}, \beta_{24}, \beta_{25}) \), \( \mu = (\mu_1, \ldots, \mu_{33}) \) is individu effect (province), and \( \xi_t = (\xi_1, \ldots, \xi_{10}) \) is time effect (year) with \( i = 1, \ldots, 33 \) and \( t = 1, \ldots, 10 \).

Table 3 showed estimators of the DSDM and SDM parameters and their significance. In Table 3, it can be seen the magnitude and significance of the estimated DSDM parameters through the ML
method. In DSDM, the influence of spatial dependence and time dependence significantly influence poverty at a significance level of 10%. As for the influence of independent variables, variables P1, P2, and log (PPK) significantly ($\alpha < 1\%$) affect poverty in Indonesia. Meanwhile, all lag-independent variables do not have a significant effect on poverty in Indonesia. Similar to DSDM, the DSM variables P1, P2, and log (PPK) significantly ($\alpha < 1\%$) influence poverty in Indonesia. In addition, the lag $\log(PPK)$ also has a significant effect on poverty in Indonesia ($\alpha < 1\%$).

### Table 3. Parameter Estimators of DSDM and MSD

| Parameter | DSDM | | | | MSD | | | |
|-----------|------|------|------|------|------|------|------|------|
|           | Estimator (sig) | Std Error | Estimator (sig) | Std Error | | | | |
| $\rho$    | 0.34 (. ) | 0.19 | 0.00 | 0.19 | | | | |
| $\lambda$ | -0.26 (. ) | 0.14 | - | - | | | | |
| $\beta_1$ | | | | | | | | |
| P1        | 0.48 (*** ) | 0.07 | 1.67 (*** ) | 0.16 | | | | |
| P2        | 1.84 (*** ) | 0.25 | 4.04 (*** ) | 0.38 | | | | |
| RLS       | 0.09 | 0.60 | -0.16 | 0.16 | | | | |
| HH        | -0.51 | 0.33 | 0.03 | 0.06 | | | | |
| LOG (PPK) | -12.41 (*** ) | 3.35 | -6.28 (*** ) | 1.03 | | | | |
| $\beta_2$ | | | | | | | | |
| Lag-P1    | -0.01 | 0.02 | 0.13 | 0.12 | | | | |
| Lag-P2    | 0.04 | 0.06 | -0.32 | 0.23 | | | | |
| Lag-RLS   | 0.01 | 0.04 | -0.12 | 0.08 | | | | |
| Lag-HH    | -0.02 | 0.01 | -0.08 | 0.06 | | | | |
| Lag-LOG (PPK) | 0.14 | 0.12 | 1.41 (*** ) | 0.46 | | | | |

Sig Code: '***' 0.001, '*' 0.01, '. ' 0.1

In addition to estimating the independent variable parameters, through DSDM, estimation of individual parameters and time is done. Table 4 showed estimators of individual (provincial) influence on Indonesian poverty. The estimated influence of time (years) on Indonesian poverty can be seen in Table 5. It can be known that all provinces have significant ($\alpha < 1\%$) individual (province) influences on poverty in Indonesia. Table 4 shows the significance of the influence of time (year) on poverty in Indonesia. Through DSDM, the data for 2011 to 2017 has an influence (significance <10%) on poverty when compared to the 2010 data.

### Table 4. Estimating Effect of time (years) on Poverty in Indonesia

| Parameter | DSDM | | | | |
|-----------|------|------|------|------|------|
|           | Estimator (sig) | Standard Error | | | |
| 2011      | -0.80 (*** ) | 0.23 | | | |
| 2012      | -1.28 (*** ) | 0.29 | | | |
| 2013      | -0.87 (*) | 0.35 | | | |
| 2014      | -1.27 (**) | 0.41 | | | |
| 2015      | -0.98 (*) | 0.49 | | | |
| 2016      | -1.20 (*) | 0.57 | | | |
| 2017      | -1.13 (. ) | 0.68 | | | |
| 2018      | -0.83 | 0.82 | | | |
| 2019      | -0.63 | 0.98 | | | |

Sig Code: '***' 0.001, '*' 0.01, '. ' 0.1

### Table 5. Estimator of individual (provincial) influence on poverty in Indonesia
The poverty model in Indonesia uses DSDM through the ML method produced $R^2 - adj = 0.956$. It means covariates of poverty used was able to explain the diversity in the models of 95.6%. At Table 6 can be found that DSDM has $R^2$ the greatest value if compared to SDM, the panel data model with a fixed effect (FEM), and the panel data model with a random effect (REM). This means that DSDM is the best model in modeling dynamic Indonesian poverty panel data during 2010-2019.

| Parameter                      | DSDM     | Estimator | Standard Error |
|--------------------------------|----------|-----------|----------------|
| Aceh                           | 162.67 (***)| 37.65    |
| Kepulauan Bangka Belitung      | 158.17 (***)| 38.46    |
| Bali                           | 159.05 (***)| 39.06    |
| Banten                         | 158.33 (***)| 38.33    |
| Bengkulu                       | 164.18 (***)| 37.62    |
| DIYogyakarta                   | 170.12 (***)| 39.70    |
| Gorontalo                      | 163.35 (***)| 37.24    |
| Jawa barat                     | 160.60 (***)| 38.49    |
| Jakarta                        | 163.48 (***)| 40.15    |
| Jambi                          | 158.94 (***)| 38.03    |
| Jawa Tengah                    | 166.44 (***)| 38.75    |
| Jawa Timur                     | 162.98 (***)| 38.23    |
| Kalimantan Barat               | 155.52 (***)| 37.48    |
| Kalimantan Selatan             | 155.10 (***)| 37.93    |
| Kalimantan Tengah              | 155.76 (***)| 38.00    |
| Kalimantan Timur               | 159.43 (***)| 39.17    |
| Kepulauan Riau                  | 159.02 (***)| 38.83    |
| Lampung                        | 162.82 (***)| 37.70    |
| Maluku                         | 161.75 (***)| 36.70    |
| Maluku Utara                   | 151.90 (***)| 36.83    |
| Nusa Tenggara Barat            | 161.88 (***)| 36.96    |
| Nusa Tenggara Timur            | 161.73 (***)| 36.35    |
| Papua Barat                    | 162.53 (***)| 36.26    |
| Papua                          | 164.58 (***)| 35.99    |
| Riau                           | 159.44 (***)| 38.39    |
| Sulawesi Barat                 | 157.11 (***)| 36.43    |
| Sulawesi Selatan               | 160.40 (***)| 38.04    |
| Sulawesi Tengah                | 160.84 (***)| 37.23    |
| Sulawesi Tenggara              | 160.68 (***)| 37.80    |
| Sulawesi Utara                 | 159.03 (***)| 38.31    |
| Sumatera Barat                 | 157.46 (***)| 37.84    |
| Sumatera Selatan               | 162.97 (***)| 37.78    |
| Sumatera Utara                 | 158.02 (***)| 37.73    |

**Sig Code:** '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1

Table 6. The Goodness of Fit Measures DSDM on poverty in Indonesia
4. Conclusion

On Model Spatial Dynamic Durbin (DSDM), the estimate of the effect of spatial dependence $\rho$ and time dependence $\lambda$ significantly affects poverty at 10% significance level. Whereas for the influence of the independent variable, the Poverty Gap Index (P1), the Poverty Severity Index (P2), and the log (Expenditure per Capita) significantly ($\alpha < 1\%$) influence poverty in Indonesia. In addition, all predictors of individual (provincial) influence have a significant ($\alpha < 1\%$) effect on Indonesian poverty. Moreover, the significance of the influence of time (years) on poverty in Indonesia is evident in the data from 2011 to 2017 when compared to the data in 2010. The poverty model in Indonesia used DSDM through the ML method of producing $R^2 - \text{adj} = 0.956$. DSDM has the $R^2 - \text{adj}$ greatest value when compared to SDM, the panel data model with a fixed effect (FEM), and the panel data model with a random effect (REM). This means that DSDM is the best model in modeling dynamic Indonesian poverty panel data during 2010-2019.

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