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Regional Economic Growth: A Spatial Durbin Model Approach

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Spatial Durbin Model, Spatial Autoregressive Model, Model Spatial, Spatial Autocorrelation, Pertumbuhan Ekonomi.

Abstrak. Tujuan penelitian ini adalah untuk mengetahui pengaruh ketergantungan spasial (*spatial dependence*) terhadap Produk Domestik Regional Bruto (PDRB) di Provinsi Jawa Tengah. Spatial Durbin Model (SDM) merupakan model regresi yang terdiri dari struktur data spasial yang merupakan pengembangan dari Spatial Autoregressive Model (SAR). Terdapat tambahan efek spasial pada komponen variabel independen yang tidak terdapat dalam model SAR atau biasa disebut efek tidak langsung pada variabel independen. Hal ini mengindikasikan SDM memiliki kelebihan dibandingkan dengan SAR karena terdapat efek spasial pada variabel dependen dan independent, matriks pembobot spasial yang digunakan dalam penelitian adalah row-normalized binary contiguity. Data yang digunakan dalam penelitian ini bersumber dari Badan Pusat Statistik (BPS) Jawa Tengah tahun 2019 untuk 35 kabupaten dan kota, dimana terdiri dari PDRB sebagai variabel dependen dan tenaga kerja, sumber daya manusia, dan infrastruktur jalan sebagai variabel independen. Berdasarkan hasil analisis, nilai AIC menunjukkan bahwa SDM secara signifikan lebih baik daripada model *ordinary least square* (OLS) dan SAR. Hasil SDM menunjukkan bahwa sumber daya manusia memiliki tanda postifi dan pengaruh langsung (direct effect) sebesar 88.5 persen serta memiliki pengaruh tidak langsung (indirect effect) sebesar 13.1 persen. Selain itu, variabel tenaga kerja memiliki pengaruh tidak langsung (indirect effect) terhadap PDRB sebesar 22.2 persen.

Keywords:
Spatial Durbin Model, Spatial Autoregressive Model, Spatial Modeling, Spatial Autocorrelation, Economy Growth.

Abstract. The purpose of this study is to determine the effect of spatial dependence on Gross Regional Domestic Product (GRDP) in Central Java Province. Spatial Durbin Model (SDM) is a regression model consisting of a spatial data structure which is the development of the Spatial Autoregressive Model (SAR). There is an additional spatial effect on the component of the independent variable that is not included in the SAR model or commonly referred to as an indirect effect on the independent variable. This indicates that SDM has advantages compared to SAR because there are spatial effects on the dependent and independent variables, the spatial weighted matrix used in this study is row-normalized binary contiguity. The data used in this study is sourced from the Central Java Statistics Agency (BPS) in 2019 for 35 districts and cities, which GRDP as the dependent variable, labor, human resources, and road infrastructure as independent variables. Based on the results of the analysis, the AIC value shows that SDM is significantly better than the ordinary least square (OLS) and SAR models. SDM results show that human resources have a positive sign and a direct effect of 88.5 percent and an indirect effect of 13.1 percent. In addition, the labor variable has an indirect effect on GRDP of 22.2 percent.

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1. Introduction

Gross Regional Domestic Product (GRDP) is one of important indicators to determine the economic conditions of a region within a particular period. GRDP is defined as the amount of added value produced by all business units in an area or the total value of final goods and services produced by all economic units. It is not only an important indicator in determining the success of regional economic growth achieved, but GRDP can also be used as a basis for determining the direction of development in the future, [1] .

GRDP is a record of total value in Rupiah from the final goods and services produced by an economy in a region for one year, [2]. In other words, an area experiences economic growth when there is an increase in real GRDP with the production added value created by the increase of all economic activity sectors (business field) in a region. It can be used as a success indication of economic development.

Central Java is a province with a quite potential contribution in national economic growth. As the province with the third largest population after West Java and East Java, the economy of Central Java is relatively stable. Based on the data from the Indonesian Central Statistics Agency of 2012 and 2013, Indonesia's economic growth was at the level of 5.34 percent and 5.14 percent respectively, while there was an upward trend in 2014 of 5.42 percent and 5.44 percent in 2015. Different from the Indonesia's declining economic growth in the last three years, Central Java's economic growth has experienced an upward trend higher than the level of national economic growth.

The other form of spatial data-based regression analysis in regression model is spatial regression, and one of the most popular models is spatial autoregressive model (SAR). This model defines the effect of lag spatial on response variable [3]. The development of this model is Spatial Durbin Model (SDM). SDM is a special case of spatial autoregressive, which is the addition of lag spatial effect on dependent and independent variables [4]. SDM involves lag spatial from dependent and independent variables, resulting in different estimates for the β parameters of general regression. This model is able to define the indirect impacts arising from the changes in dependent and independent variables.

According to [5], many studies in spatial model for economic growth had been conducted, for example, the regional spillovers from transportation infrastructure by applying spatial durbin model for the period of 1978-2009 and three sub-periods of 1978-1990, 1991-2000, and 2001-2009. The results show that the spillovers are positively at national level in each period due to the characteristics of transportation infrastructure connectivity. At regional level, the spillover effect of transportation infrastructure varied greatly throughout the year in four major regions of China.

SDM was utilized by [6] to define transportation infrastructure to GRDP in 47 cities in Spain. The result is that the variable of road infrastructure has a positive significant effect on GRDP. Similar conclusions are also derived from the analysis of [7] that transport infrastructure plays a major role in the New Silk Road Economic Belt (NSREB) regional economic growth, and economic growth strengthens development in the surrounding region. In addition, the mode of road transportation influences regional economic growth is higher than the mode of railway transportation.

The aim of this study was to determine the direct and indirect effects of transportation infrastructure through spatial dependency test to the dependent and independent variables of the data of the Gross Regional Domestic Product (PDRB) in Central Java Province using spatial durbin model.

2. Theoretical Framework

2.1. Spatial Dependence

Regression models for spatial data require diagnostic testing for spatial dependence in errors using Moran's I test. Spatial dependence test is needed to measure the autocorrelation between regions or observations.[8] The following is Moran's I test when using an unstandardized weighted matrix **W***,

$$I_M = \frac{\mathrm{n}}{S_0}\frac{\mathbf{e'W^*e}}{\mathbf{e'e}} \tag{1}$$

with $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}*$

and when the standardized weighted matrix **W** is used, equation 1 is simplified to

$$I_M = \frac{\mathbf{e'We}}{\mathbf{e'e}} \tag{2}$$

because of $S_0 = n$, I_M interpretable as the coefficient of an OLS regression of **W*e** on **e** or **We** on **e**, respectively. **e** represent n x 1 vector of OLS residuals, **W** is a weighted matrix, with elements $w_{ij} = 1$ when two cities share a common border, and 0 otherwise.

2.2. Spatial Durbin Model

Spatial Auto Regressive (SAR) model includes a lagged-response regressor and is specified in equation 3,[9]

$$y_i = \alpha_i + \rho\sum_{j=1}^{n} W_{ij} y_j + X_i\beta_i + \varepsilon_i. \tag{3}$$

when written in the form of matrix:

$$\mathbf{y} = \rho\mathbf{Wy} + \mathbf{X\beta} + \boldsymbol{\varepsilon} \tag{4}$$

where **y** is an n by 1 vector of the dependent variable, ρ is spatial lag coefficient, **W** is a row-normalized binary contiguity weighted matrix, with the element of wij = 1 when two cities share a common border, and 0 otherwise. **X** is an n by k matrix of the independent variables, $\boldsymbol{\beta}$ is a k by 1 vector of parameters and $\boldsymbol{\varepsilon}$ is an n by 1 vector errors.

The development of the spatial autoregressive (SAR) model is a spatial mixed regressive-autoregressive model, which is also called the Spatial Durbin Model (SDM). There is an addition of spatial lag to the independent variables. This model was developed because the spatial dependencies do not only occur in the dependent variables. [10] This model has the following equations,

$$\begin{aligned} y_\mathrm{i} = {} & \rho\sum_{\mathrm{j}=1}^{\mathrm{n}} w_{\mathrm{ij}} y_\mathrm{j} + \beta_0 + \left(\beta_{11}x_{1\mathrm{i}} + \beta_{12}x_{2\mathrm{i}} + \ldots. + \beta_{1\mathrm{k}}x_{\mathrm{ki}} + \ldots. + \beta_{1l}x_{l\mathrm{i}}\right) + \\ & \left(\beta_{21}\sum_{\mathrm{j}=1}^{\mathrm{n}} w_{\mathrm{ij}}x_{1\mathrm{j}} + \beta_{22}\sum_{\mathrm{j}=1}^{\mathrm{n}} w_{\mathrm{ij}}x_{2\mathrm{j}} + \ldots. + \beta_{2\mathrm{k}}\sum_{\mathrm{j}=1}^{\mathrm{n}} w_{\mathrm{ij}}x_{\mathrm{kj}} + \ldots. + \beta_{2l}\sum_{\mathrm{j}=1}^{\mathrm{n}} w_{\mathrm{ij}}x_{l\mathrm{j}}\right) + \varepsilon_\mathrm{i}. \end{aligned} \tag{5}$$

$$y_\mathrm{i} = \rho\sum_{\mathrm{j}=1}^{\mathrm{n}} w_{\mathrm{ij}} y_\mathrm{j} + \beta_0 + \sum_{\mathrm{k}=1}^{l}\beta_{1\mathrm{k}}x_{\mathrm{ki}} + \sum_{\mathrm{k}=1}^{l}\beta_{2\mathrm{k}}\sum_{\mathrm{j}=1}^{\mathrm{n}} w_{\mathrm{ij}}x_{\mathrm{kj}} + \varepsilon_\mathrm{i}. \tag{6}$$

when written in the form of matrix:

$$\mathbf{y} = \rho\mathbf{Wy} + \mathbf{Z\beta} + \boldsymbol{\varepsilon}, \tag{7}$$

with

$$\mathbf{Z} = \left[\mathbf{I} \quad \mathbf{X} \quad \mathbf{WX} \right], \qquad \boldsymbol{\beta} = \left[\boldsymbol{\beta}_0 \quad \boldsymbol{\beta}_1 \quad \boldsymbol{\beta}_2 \right]^T,$$

The method of Maximum Likelihood Estimation (MLE) was used to estimate the parameters. From equation 7 above, the likelihood function is formed, and the formation of the likelihood function is done through error ε.

$$\mathbf{y} - \rho \mathbf{W}\mathbf{y} = +\mathbf{Z}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$
$$\left(\mathbf{I} - \rho \mathbf{W} \right) \mathbf{y} = \mathbf{Z}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$
$$\mathbf{y} = \left(\mathbf{I} - \rho \mathbf{W} \right)^{-1} \mathbf{Z}\boldsymbol{\beta} + \left(\mathbf{I} - \rho \mathbf{W} \right)^{-1} \boldsymbol{\varepsilon},$$
$$\boldsymbol{\varepsilon} = \left(\mathbf{I} - \rho \mathbf{W} \right) \mathbf{y} - \mathbf{Z}\boldsymbol{\beta}.$$

Jacobian value is obtained from the result of the equation:

$$J = \left| \frac{\partial \boldsymbol{\varepsilon}}{\partial \mathbf{y}} \right| = \left| \mathbf{I} - \lambda \mathbf{W} \right|$$

So that it results in;

$$L\left(\rho, \boldsymbol{\beta}, \sigma^2; \mathbf{y} \right) = \left(2\pi \right)^{-\frac{n}{2}} \left(\sigma^2 \right)^{-\frac{n}{2}} \left| J \right| e^{\left\{ -\frac{1}{2\sigma^2} \boldsymbol{\varepsilon}^T \boldsymbol{\varepsilon} \right\}},$$
$$L\left(\rho, \boldsymbol{\beta}, \sigma^2; \mathbf{y} \right) = \left(2\pi \right)^{-\frac{n}{2}} \left(\sigma^2 \right)^{-\frac{n}{2}} \left| I - \lambda \mathbf{W} \right| e^{\left\{ -\frac{1}{2\sigma^2} \left[\left(I - \rho \mathbf{W} \right) \left(\mathbf{y} - \mathbf{Z}\boldsymbol{\beta} \right) \right]^T \left[\left(\mathbf{I} - \rho \mathbf{W} \right) \left(\mathbf{y} - \mathbf{Z}\boldsymbol{\beta} \right) \right] \right\}}.$$

The natural logarithm operation (ln likelihood) in the equation above:

$$\ln L\left(\rho, \boldsymbol{\beta}, \sigma^2; \mathbf{y} \right) = c - \frac{n}{2} \ln\left(\sigma^2 \right) + \ln\left| I - \rho \mathbf{W} \right| - \frac{1}{2\sigma^2} \left[\left(\mathbf{I} - \rho \mathbf{W} \right) \left(\mathbf{y} - \mathbf{Z}\boldsymbol{\beta} \right) \right]^{\mathbf{T}} \left[\left(\mathbf{I} - \rho \mathbf{W} \right) \left(\mathbf{y} - \mathbf{Z}\boldsymbol{\beta} \right) \right].$$

From the equation above, the parameter estimations of $\hat{\boldsymbol{\beta}}$, ρ and $\hat{\sigma}^2$ are obtained.

2.3. Goodness of Fit

In this paper, we use akaike information criteria (AIC) for goodness of fit. According to [11], AIC is a tool to measure of information that contains the best measurements in the feasibility test of model estimates. AIC is usually used to choose which model is best among the models obtained. Selection of the model is based on the least expected error results that form new observation data (error) that are equally distributed from the data used, AIC defined:

$$AIC = -2\log\left(L \right) + 2p \tag{8}$$

where L represent the likelihood under the fitted model p is the number of parameters in the model. The best model is the model that has the minimum AIC value.

3. Methods

3.1. Description of data and variables

The data used in this study were the data obtained from the Central Java Provincial Statistics Agency (BPS) in 2019 for 35 districts and cities. The variables used in this study referred to the research of [12][13]. The followings are the research variables used:

Table 1. Definition of Operational Variables

No	Variables	Indicator	Analysis Unit
Dependent Variable			
1)	Economic Growth (GRDP)	Gross Regional Domestic Product (GRDP)	Million Rupiah
Independent Variables			
2)	Labor (L)	Labor value for each city in Central Java	person
3)	Human capital (HC)	Human capital is the number of residents with the lowest education of Junior High School for each city in Central Java	person
4)	Transportation Infrastructure (INF)	Length of roads with the conditions of good and medium (km) for each city in Central Java	Km

3.2. Model Specification

The estimated model specification in this study was based on log linear Cobb-Douglas production product [6]. The following is the estimated spatial durbin model:

$$\begin{aligned} GRDP_i = \rho \mathbf{W} GRDP_i + \beta_0 + INF_i\beta_1 + L_i\beta_2 + HC_i\beta_3 + \mathbf{W} INF_i\gamma_1 + \mathbf{W} L_i\gamma_2 \\ + \mathbf{W} HC_i\gamma_3 + \varepsilon_i \end{aligned} \quad (9)$$

where the variables from the equation in logarithms with ε as the error term and the subscripts states the cities in Central Java. The dependent variable of economic growth was measured based on the added value of each business field originated from the Statistics of Central Java. Then, the independent variable of labor was measured by each city in Central Java. Human Capital was measured by total labor with the lowest education for each city in Central Java, and Transportation Infrastructure was measured by length of roads with the conditions of good and medium for each city in Central Java. In addition, the equation above includes the spatial lags (**W**) in the dependent and independent variables recognized as spillover effect. **W** is defined as a row-normalized binary contiguity weighted matrix, with the element of $w_{ij} = 1$ when two cities share a common border, and 0 otherwise.

4. Result and Discussion

We used Moran's I test of the OLS model residuals as an assumption in spatial modeling. The assumption for SDM is that there is a spatial dependence. To test spatial dependencies, Moran's I test was used. The Moran's I test results show the Moran's I value of 3.982 and p-value 0.000. It can be concluded that there are spatial dependencies in the OLS model so that spatial modeling can be performed involving spatial lag on the dependent variable. The Moran's I value is along with its significance presented in the table:

Table 2. Moran's I value of OLS residuals

Moran's I	Expectation	P-value
3.982	-0.029	0.000

At the beginning of the discussion section, it needs to be carefully re-understood in terms of the interpretation of the model that had been produced. According to [13], SDM allows for spatial lag effects on the dependent variable and does not allow for spatial lag effects on error terms. Spatial durbin model simplifies the interpretation of the direct impacts represented by the parameter of model β and the indirect impact on γ. In other words, the global and local multipliers that exist in the spatial durbin model facilitated the interpretation of the model estimates.

Table 3 shows the estimation results of the ordinary least square (OLS) and SDM models in which the parameters of the two models appeared to have the effects on the GRDP of Central Java Province. Based on these results, the AIC value indicates that the spatial durbin model is better than the ordinary least square model because the AIC value of the spatial durbin model is smaller than that of the ordinary least square model.

Table 3. The parameter estimation results of the OLS and SDM models

Parameter	OLS Coefficient (P-value)	SAR Coefficient (P-value)	SDM Coefficient (P-value)
β_0	-0.000	0,0150	4.429
	(1.000)	(0,8807)	(0.000)*
β_1	-0.009	-0,0845	-0.095
	(0.559)	(0,5438)	(0.471)
β_2	-0.198	-0,1911	0.002
	(0.405)	(0,3738)	(0.991)
β_3	0.978	0,9536	0.885
	(0.000)*	(0,000)*	(0.000)*
γ_1	-	-	-0.102
	-	-	(0.051)**
γ_2	-	-	-0.222
	-	-	(0.016)*
γ_3	-	-	0.131
	-	-	(0.031)*
ρ	-	0,0127	0.0083
	-	(0,53348)	(0.7232)
AIC	74.221	75,8330	72.929

Notes: *Significant at α = 5 percent; ** Significant at α = 10 percent

The direct effect of Human Capital on the GRDP of Central Java province was positive and significant. This result is in line with [14]. Moreover, the results are very stable at approximately 0.88. In other hand, the results of the direct effect estimation from Transportation Infrastructure and Labor were not suitable with the model specifications. They are negative which are similar to the estimation results conducted by [15] and [6]. However, these two variables had no significant effect on the GRDP of Central Java province. This result can be interpreted that the GRDP of Central Java province was influenced by Human Capital globally.

In the spatial durbin model, although the indirect effects of all variables had a significant effect on the GRDP of Central Java province, Transportation Infrastructure and Labor were not suitable with the negative model specifications. The indirect effects of the Spatial Durbin Model results can be interpreted that Transportation Infrastructure and Labor for each city have a close relationship with the surrounding cities. The negative mark proves that the uneven development of Transportation Infrastructure and the uneven distribution of Labor are still evident in Central Java. Some cities have good Transportation Infrastructures and a lot of Labor, but the surrounding areas have the opposite condition. In addition, Human Capital has a tendency for positive dependence between cities. Furthermore, the value of rho in the spatial durbin model is not significant indicating that there is no spatial lag on economic growth. In other words, there is no association between the economic growth of a city and other cities. The economic progress in a city does not have an impact on the increase of the economy in the surrounding cities.

Thus, the results of this analysis provide the evidence that the presence of unequal Transportation Infrastructure has an impact on the inequality in economic growth in Central Java.

5. Conclusion

Today, Indonesia is involved in the construction of large-scale transportation infrastructures, while the municipal economy faces quite high disparities. Furthermore, we used the spatial durbin model to analyze the impact of road transportation infrastructure and other economic factors on the economic growth in 35 cities in Central Java Province. The conclusions of this paper are as follows: First, road transportation infrastructure and labor do not have direct impact on economic growth, whereas human capital has a positive and significant direct effect on economic growth. Second, transportation infrastructure and labor have a negative spatial spillover effect on economic growth, while the spatial spillover effect of human capital is positive.

Therefore, we recommend that the government should improve the connectivity of transportation infrastructures and optimize transportation layouts. The local governments may improve the coordination and break the barriers with the central government.

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