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Spatial Regression Models on Factors Influencing Regional Minimum Wages

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Article Info	Abstract
Article History Received: 23-12-2019 Revised: 11-06-2020 Accepted: 07-11-2020 Keywords:	Regional minimum wages might well represent the economic development of a region. The most likely spotlight province regarding the wage determination issue is East Java. This work is intended to obtain the best regression model on factors influencing East Java's regencies/cities' minimum wages in terms of spatial approach. The methods are Spatial Autoregressive (SAR) and Spatial Error Model
Regional Minimum Wages; SAR; SEM; Spatial Regression	(SEM). This study aims to obtain the best spatial model based on the factors influencing the regional minimum wage in districts/cities in East Java and the mapping. The data source is secondary data from Statistics Indonesia (BPS) of East Java. It consists of several variables, namely the Regional Minimum Wage, Total Working Population, Gross Regional Domestic Product, Total Population, and percentage of Population with a minimum education of senior high school. It shows that two significant factors are the number of working civilians and the percentage of high school-college graduates, affecting regional minimum wages. It proves that minimum wages among regions in East Java are spatially correlated with a closed area. Spatial regressions are the better ones than classic ones since they have higher R-sq and satisfy assumptions. Meanwhile, the selected model is SAR rather than SEM as it has a smaller AIC and explains variation better in minimum regional wages.

INTRODUCTION

National development is an embodiment of government policies to improve people's welfare. Such an indicator of national development's success is economic growth, both on national and regional scales. An economy is balanced if it develops and grows consistently and evenly in all districts/cities. Several indicators can represent the economic progress of a region. One of them is the regional minimum wage [1], [2].

The determination of the regional wage is based on the standard of living costs and inflation, which are also considered economic growth. The fact is often becoming a problem in determining the wage because inflation and economic development in each region are different. In contrast, the percentage increase in pay is often unable to cover the working family [2]. In Indonesia, one of the provinces that often gets the public spotlight in determining the wage is East Java. It is due to East Java's role as a center for industry, manufacture, etc. [3]. Therefore, this study will model the factors that affect the wage in East Java in a spatial context such that it can be input in determining the wage.

Statistics modeling is generally carried out using linear regression. However, this method's weakness is the inability to capture the relationship among space, common in economic cases [4], [5]. The technique developed to deal with the spatial issue in spatial regression. This model can

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analyze the effects of spatial dependence, namely the reliance between regions on cross-sectional data. In other words, geographically close areas are seen as having a higher relationship than regions that are located far apart [6], [7].

Modeling with spatial regression, among others, is applied in criminology cases [8], human resources quality [9], even pollution [10]. Most study found that the spatial model can correct and improve the accuracy of classical linear regression modeling. Based on these findings, this study aims to obtain the best spatial model based on the factors influencing the regional minimum wage in districts/cities in East Java and the mapping.

METHOD

In this study, the data source is secondary data from Statistics Indonesia (BPS) of East Java. It consists of several variables, namely the Regional Minimum Wage (y), Total Working Population (x_1) , Gross Regional Domestic Product (x_2) , Total Population (x_3) , and percentage of Population with a minimum education of senior high school (x_4) . The reason for selecting x variable follows the study of [3], [11], and [12], which found a significant relationship between wage and the four independent variables. It means labor, economic productivity, and demographics are thought to have a relationship with wage. Thus, this study's variables are dependent, and four independent variables (see Table 1).

Variable	Description	Unit	Expected Sign
Regional Minimum Wage (y)	The minimum wage a company must pay to its workers. The amount varies between regions.	IDR 000 (thousand Rupiahs)	Positive number
Total Working Population (x_1)	The total number of working-age Population at the time of the survey was having a job	000 people (thousand people)	+ $(x_1 \text{ is expected to})$ have a positive effect on the wage)
Gross Regional Domestic Product (x ₂)	The amount of added value (goods and services) produced by all business units in a specific area	billion Rupiahs	+ $(x_2 \text{ is expected to})$ have a positive effect on the wage)
Total Population (x ₃)	The total number of people living in the area of the local government	000 people (thousand people)	+ $(x_3 \text{ is expected to})$ have a positive effect on the wage)
Population with a minimum education of senior high school (x_4)	Same with variable's name	%	+ $(x_4$ is expected to have a positive effect on the wage)

Table 1.	Variable	Description
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The year used is 2017 data for 38 districts/cities in East Java. The methods in this study include Spatial Autoregressive (SAR) and Spatial Error Model (SEM). The modeling stages are as follows.

a. Analyzing the descriptive of variables

b. Identifying the relationships between variables

The relationships between variables were identified by Pearson correlation. This is to determine the strength of the relationship between the wage and all independent variables.

c. Carrying out classical regression

Classical regression is a linear regression whose parameter estimator is obtained through the Ordinary Least Squares (OLS) by minimizing the squares of error or by maximizing the likelihood function that is normally distributed [13]. The following is a general equation for classical regression,

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \,, \tag{1}$$

with $\boldsymbol{\varepsilon}$: $N(\mathbf{0}, \mathbf{I}\sigma^2)$.

Several assumptions are ideally not violated [8], that is:

- 1. There was no multicollinearity or dependency, which was statistically significant between the predictors. If this assumption is broken, it can be overcome by stepwise regression.
- 2. Homoscedastic, the residual variance of each observation ε_i constant/homogenous.
- 3. There is no residual autocorrelation (dependency) between observations.
- 4. Residual is usually distributed.

Estimator β of the classical regression model is obtained by,

$$\hat{\boldsymbol{\beta}} = \left(\mathbf{X}^{\mathrm{T}} \mathbf{X} \right)^{-1} \mathbf{X}^{\mathrm{T}} \mathbf{Y}.$$
(2)

d. Checking the spatial correlation on the wage variable based on Moran's I

Moran's I with weight w in normalized form can be calculated by,

$$I = \frac{\sum_{i=1}^{n} (x_i - \bar{x}) \sum_{j=1}^{n} w_{ij} (x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$
(3)

where I is Moran's I index, n is the number of observation, x_i is the observation on i-th observation, x_j the observation on j-th observation, \overline{x} is the mean of x, and w_{ij} is the array of weight matrices. The value of I ranges from -1 to 1. If $I = I_0 \approx 0$, then there is no spatial autocorrelation. While $I \neq I_0$, presumably, there is a positive autocorrelation when I is positive, and vice versa [6], [7].

e. Carrying out the spatial modeling

Spatial modeling begins with determining weighting matrices. Various weights could be used, including rook contiguity and queen contiguity. Next is testing the spatial effects with the following steps.

1. Testing the spatial dependency and spatial heterogeneity

Spatial dependencies occur due to the correlation between areas closest to each other or might be far from each other (negative correlation). The effects of spatial dependence, namely lag dependency and spatial residuals, can be tested through the LM test. Such a test is to find out which model is following the rules. In the LM test, the following applies.

a. SAR (Spatial Autoregressive) model

H₀: $\rho = 0$ (no spatial lag dependency)

H₁: $\rho \neq 0$ (exist spatial lag dependency)

Statistical test:

$$LM_{\rho} = \left(\mathbf{\epsilon}^{\mathrm{T}}\mathbf{W}\mathbf{y} / \left(\mathbf{\epsilon}^{\mathrm{T}}\mathbf{\epsilon} / N\right)\right)^{2} / D$$

with $D = \left[\left(\mathbf{W}\mathbf{X}\hat{\boldsymbol{\beta}}\right)^{\mathrm{T}} \left(\mathbf{I} - \mathbf{X}\left(\mathbf{X}^{\mathrm{T}}\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\right) \left(\mathbf{W}\mathbf{X}\hat{\boldsymbol{\beta}}\right) / \hat{\sigma}^{2}\right] + tr\left(\mathbf{W}^{\mathrm{T}}\mathbf{W} + \mathbf{W}\mathbf{W}\right)$

The decision to reject H0 is when the LM_{ρ} value greater than $\chi^{2}_{(q)}$, with q, is the total number of spatial parameters. Thus, if H0 is rejected, the spatial regression model is the SAR model [6], [7].

b. SEM (Spatial Error Model) model

 $H_0: \lambda=0$ (no spatial residual dependency)

H₁: $\lambda \neq 0$ (spatial residual dependence)

Statistical test:

$$LM_{\lambda} = \left(\mathbf{\varepsilon}^{\mathrm{T}} \mathbf{W} \mathbf{\varepsilon} / \left(\mathbf{\varepsilon}^{\mathrm{T}} \mathbf{\varepsilon} / N \right) \right)^{2} / \left(tr \left[\mathbf{W}^{\mathrm{T}} \mathbf{W} + \mathbf{W} \mathbf{W} \right] \right).$$

The decision to reject H0 is when the LM_{λ} value is more significant than $\chi^2(q)$, with q being the total spatial parameters. If H₀ is rejected, thus the spatial regression model that exists is the SEM model. The residual ϵ is obtained from classical regression [6], [7].

Breusch-Pagan test can be used as an indicator of spatial heterogeneity in the dependent variable (y), namely the regional minimum wage. The hypothesis is as follows.

H₀:
$$\sigma^2_1 = \sigma^2_2 = \ldots = \sigma^2_{k-1} = 0$$
 (identical variance)

H₁: At least there is one $\sigma_k^2 \neq 0$ (non-identical variance/indicated heterogeneity) Statistical test:

$$BP = \frac{1}{2} \left(\sum_{i=1}^{n} x_i \left(\frac{\hat{\varepsilon}_i}{\hat{\sigma}} - 1 \right) \right) \left(\sum_{i=1}^{n} x_i x_i^T \right) \left(\sum_{i=1}^{n} x_i \left(\frac{\hat{\varepsilon}_i}{\hat{\sigma}} - 1 \right) \right),$$

with $\hat{\varepsilon}_i = \left(y_i - \hat{\beta}^T x_i \right)$ and $\hat{\sigma}^2 = \sum_{i=1}^{n} \hat{\varepsilon}_i^2.$

BP's statistical test follows distribution $\chi^2_{(k-1)}$ with k is the total regression parameter. The decision to reject H₀ is when BP statistical test value greater than $\chi^2_{(k-1)}$ [6], [7].

2. Carrying out spatial regression and diagnostic checking The general equation for spatial regression is

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \mathbf{u}$$

$$\mathbf{u} = \lambda \mathbf{W} \mathbf{u} + \boldsymbol{\varepsilon}$$
(4)

with $\boldsymbol{\varepsilon}$: $N(0, \sigma^2 \mathbf{I})$.

If ρ (spatial coefficient) and λ (spatial error coefficient) are statistically significant at α , then the model of spatial regression becomes SARMA (Spatial Autoregressive Moving Average).

If only one of the spatial coefficient, ρ , is significant, then the model of spatial regression becomes SAR (Spatial Autoregressive) model with the equation as follows,

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{5}$$

with $\boldsymbol{\varepsilon}$: $N(0, \sigma^2 \mathbf{I})$.

If only the coefficient λ is statistically significant, then the model of spatial regression becomes SEM (Spatial Error Model) with the equation as follows,

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$$
(6)
$$\mathbf{u} = \lambda \mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}$$

with $\boldsymbol{\varepsilon}$: $N(0, \sigma^2 \mathbf{I})$.

The assumptions of SAR and SEM models must be fulfilled similar to those of classical regression, where the residuals meet the identical, independent, and normally distributed [6],[7].

f. Analyzing the goodness-of-fit

The measure of the goodness-of-fit model being used is \mathbb{R}^2 and AIC. The coefficient of determination (\mathbb{R}^2) is a measure in explaining regional wage in East Java modeled by independent variables. The higher \mathbb{R}^2 , the more accurate the regression model describes the relationship between the wage and independent variables AIC is a measure that represents the simplicity of the regression model. The lower the AIC, the simpler the regression model is, so it is easy to interpret [4], [13]. To strengthen the decision, the spatial model significance test with the Robust LM is also used.

g. Mapping the regional wage

The forecast for wage yielded from the best regression model is then mapped to see the wage gradations between districts/cities. Mapping is carried out using ArcGIS.

RESULTS

The spatial regression model is based on secondary data involving one dependent variable (regional minimum wage) and four independent variables in Table 1. The data analyzed were for 2017, with a total of 38 observation units. The first step taken is descriptive analysis. Figure 1 presents the comparison of the UMR of East Java Province with several other provinces in Java Island in 2017.



Figure 1. Wage Comparison of Java's Provinces in 2017

Refer to Figure 1, the average wage of East Java is among the lowest ones in Java. It indicates that the welfare of workers and employees in East Java is relatively low, especially in less rapidly developing economies. Thus, study on the factors that are thought to influence the minimum wage is essential to see a more precise formula in formulating the minimum wage.



Figure 2. Minimum Wage of East Java Districts /Cities in 2017

Figure 2 indicates that inter-dependencies cause the wage in several geographically adjacent districts to have the same magnitude. Central regions in East Java (from north to south), such as Gresik Regency, Surabaya to Malang Regency, tend to have similar wages. Meanwhile, the wage between horseshoe regions (provinces in Madura Island, Jember, Banyuwangi, and surrounding areas) tends to be related, although not as strong as the central region of East Java. This suggests that the wage cannot be explained by classical regression alone, inline with [4] and [11]. Figure 3 shows the relationship between the wage as the response variable and the four independent variables that will be regressed.



Figure 3. Scatter Plot of Wages and Independent Variables

Figure 3 still cannot clearly show how strong the relationship between the UMR and the independent variables, the same with the direction of the connection (whether positive or negative). This is since the linear pattern is not visible, except in the scatter plot of wage and x_1 (Total Working Population) resembles a positive practice. Therefore, a correlation coefficient, as shown in Table 2, is needed to see this formally.

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			-		
		X1	X2	X3	X4
X ₂	Correl. coef.	0.647			
	p-value	0.000*			
X3	Correl. coef.	0.995	0.670		
	p-value	0.000*	0.000*		
X4	Correl. coef.	-0.273	0.294	-0.232	
	p-value	0.097	0.073	0.161	
Wage	Correl. coef.	0.484	0.673	0.521	0.377
-	p-value	0.002*	0.000*	0.001*	0.020*
*) signif	icant at α=5%				

Table 2. Variable Description

Based on Table 2, it can be concluded that all independent variables have a positive relationship with UMR and are statistically significant at $\alpha = 5\%$. That is, the classical regression model used is relatively good in explaining the effect of the independent variables on the wage. However, there are indications that such a regression model will violate the assumption of multicollinearity since x_1 (Total Working Population) and x_3 (Total Population) had significant correlation at $\alpha = 5\%$, so did with x_1 and x_2 (Gross Domestic, Regional Product) and variable x_2 with x_3 .

To get the factors influencing the wage, a regression model is summarized in Table 3.

Parameter	Coefficient	t-value	p-value	VIF
Intercept	905	2.53	0.016*	
X1	-2.53	-1.11	0.275	112.49
X2	0.0019	1.34	0.189	2.96
X3	1.63	1.46	0.153	111.28
X4	17.44	2.14	0.04*	1.96
R-sq	57.19%			
*) significant	at α=5%			

Table 3. Parameter Estimation and VIF

Refer to Table 3, there is indicated a multicollinearity where x_1 (Total Working Population) and x_3 (Total Population) are related, shown by a very high VIF, which exceeds the maximum VIF tolerance limit of 10. Thus, OLS regression is not appropriate to model the wage in East Java. To solve this problem, one solution is to apply stepwise regression. Such stepwise

Parameter	Coefficient	t-value	p-value	VIF
Intercept	396	1.52	0.137	
X1	1.198	5.18	0.000*	1.08
X4	28.08	4.49	0.000*	1.08
R-sq	51,47%			
*) significant	= 50/			

Table 4. Stepwise Regression Parameter Estimation and VIF

*) significant at $\alpha = 5\%$

model estimation are shown in Table 4.

Table 4 shows that almost all parameters have a significant effect on the wage at $\alpha = 5\%$. Thus, total working Population (x_1) and percentage of Population with minimum education of senior high school (x_4) are significant to the wage in East Java. In addition, multicollinearity is no longer found since the VIF value is less than 10. However, the R-sq is low which is 51.47%. The model is as follows.

$\hat{y} = 396 + 1.198x_1 + 28.08x_4$

Total Working Population (x_1) has a positive influence on the UMR. If total working population increases by 1,000 people, it will increase the wage around IDR 1,198. Besides x_1 , percentage of population with minimum education of senior high school (x_4) also has a positive effect on the UMR. If it increases 1%, it will also increase the wage around IDR 28,080. Apart from R-sq, the goodness-of-fit can also be seen based on the Akaike Information Criterion (AIC). The AIC value for this model is 572.

In each regression modeling, there are several assumptions about the model residuals that should not be violated, namely homoscedasticity, no autocorrelation, and normally distributed [14]. A summary of classical assumptions test is presented in Table 5.

	0
Assumption	Explanation
Homoscedasticity	Not Violated
Free of Autocorrelation	Violated
Normally-distributed	Not Violated

Table 5. The Summary of Residual Checking

It is concluded that the residuals of the classical model have fulfilled the IIDN. However, the autocorrelation indicates that the wage should be analyzed using other modeling approaches, that is spatial regression. The spatial dependence on the wage can be identified through Moran's I. Morans' I is an index to identify the spatial correlation of the wage between 38 districts/cities in East Java. The plot of the distribution of the wage along with Morans'I coefficient is shown in Figure 4.



Moran's I = 0.747

Figure 4. Scatter Plot of Wage (UMR) and Lagged Wage (UMR)

In Figure 4, Moran's I of 0.747 indicates that the wage has positive spatial correlation. After testing based on normal distribution approach, the statistic was 6.61. with $\alpha = 5\%$, so the statistical test = $6.61 > z_{0.95} = 1.645$, therefore H₀ is rejected. At 95% confidence level, the spatial correlation of the wage is statistically significant, meaning that districts/cities that are geographically close to each other tend to have the similar wage affecting each other. This is confirmed by the distribution of the observation points in Figure 4 which resembles a positive linear trend. As an illustration, the wage in the satellite districts of Surabaya, such as Gresik and Sidoarjo, tends to have a relatively similar value to that of Surabaya, where the effect of increasing the wage in Surabaya will also encourage that of Gresik and Sidoarjo.

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The next step is to build a spatial regression model. In this case, the weight is used to construct the spatial regression using queen contiguity. This decision was motivated by the results of the spatial correlation which proved to be statistically significant [6], [7]. This indicates that sharing boundaries are linked. After forming a spatial weightmatrix, a row-standardized matrix is normalized. To strengthen the assumption that classical regression can be better constructed using spatial information, it is necessary to measure the Morans'I Error obtained from the residuals of classical model results. Then the value of Morans'I Error is 2.4. With $\alpha = 5\%$, then the value = $2.4 > z_{0.95} = 1.645$ so the decision is reject H₀. At confidence level 95%, the residual spatial correlation of the wage regression model is statistically significant. In addition, the BP test for heterogeneity indicated no spatial heterogeneity for the wage in East Java. Thus, there are evidence supporting the spatial regression.

After ensuring there is no spatial heterogeneity, the next step is testing the spatial dependency. The LM test is carried out to test whether there is a spatial dependence on the wage of districts/cities in East Java. Table 6 presents the LM test results for two alternative spatial regression models.

Table 0. EAR Test of Opatial Woder Digitileance				
Coefficient	LM test statistics	$\chi^2(1)$	p-value	
SAR	17.80	3.841	$< 10^{-5} *$	
SEM	8.53	3.841	< 0.01 *	
*) significant at $\alpha = 5\%$				

Table 6. LM Test of Spatial Model Significance

Refer to Table 6, the LM of each model coefficient, SAR and SEM, is greater than $\chi^2_{(1)}$ at $\alpha = 5\%$. According to [8] and [15], this indicates the significance of spatial dependence of minimum wage in East Java. Therefore, the next step is to build SAR and SEM regression model.

The SAR model is characterized by $\rho \neq 0$ and $\lambda = 0$ [6], [7]. This model is based on the dependency of spatial lag. If the resulting model has spatial dependencies, then the SAR model can be used. Table 7 is the result of SAR parameters estimation for two predictor variables of stepwise regression results.

Taber 7. Tarameter	raber /. Faranceer Estimation of britte			
Variable	Coefficient	z-value	p-value	
Intercept	113.97	0.46	0.645	
Total working population	0.88	4.72	< 10-4*	
Percentage of senior-high school educated population	12.57	2.37	0.018*	
ρ (rho)	0.47	3.54	< 0.001 *	
*) significant at $\alpha = 5\%$				

Tabel 7. Parameter Estimation of SAR

Table 7 shows Total Working Population (x_1) and percentage of population with minimum education of senior high school (x_4) are significant affecting the wage in East Java at $\alpha = 5\%$. It is based on p-value of both parameters that are less than $\alpha = 5\%$. Significant ρ indicates that H₀ of SAR model is rejected such that spatial lag dependency is statistically evident on wage, particularly in West Java. The following is SAR model of regional minimum wage of East Java.

$\hat{y} = 0,47$ **Wy** + 113,97 + 0,88 x_1 + 12,57 x_4

This SAR model shows that Total Working Population (x_1) has a positive relationship with the wage in districts/cities in East Java. Such increase x_1 of 1,000 people will increase the wage

about IDR 880. In addition, percentage of minimum education of senior high school (x_4) also has a positive relationship with the wage in East Java where the 1% increase of x_1 will increase the wage about IDR. 12,570. Coefficient ρ of 0.47 indicates that the closest area to a spatial unit (regency/city) each gives almost half the effect of the wage fluctuation in that spatial unit.

High influence yielded by closest regions indicates that the welfare of workers is necessary on the spatial dependency. It is not surprising that the rally of workers in Surabaya will also be followed by similar rally in Gresik and Sidoarjo demanding increasing wage. Since this study compares spatial regression models. then next is applying SEM regression on the wage model in East Java. Such SEM is characterized by $\rho = 0$ and $\lambda \neq 0$ [6], [7]. This model is based on residual dependencies in a spatial context. If the residuals has spatial dependencies, then the SEM model can be considered. Table 8 shows the estimation results and testing of SEM parameters for two predictors selected by stepwise approach.

Table 8. Parameter Estimation of SEM				
Variable	Coefficient	z	p-value	
Intercept	970.16	4.79	< 0.001*	
Total working population	0.85	3.85	<10-4*	
Percentage of senior-high school	13.43	2.21	0.038*	
educated population	15.15	2.21	0.050	
λ (lambda)	0.49	3.33	< 0.001*	
*) significant at $\alpha = 50/2$				

*) significant at $\alpha = 5\%$

Tabel 8 shows that Total Working Population (x_1) and percentage of high school graduates (x_4) are statistically significant to the regional wage in East Java at $\alpha = 5\%$. Significant λ indicates that H0 of SEM is rejected, so that the spatial dependency residual is significant to the wage in East Java. It means there are factors that are thought to affect the wage but are not included in the model, such as inflation. Below is estimated SEM model for minimum wage in East Java.

$\hat{y} = 970,16+0,85x_1+13,43x_4+0,49$ **Wu**

Such equation indicates that the increase of Total Working Population (x_1) by 1000 people will increase the wage around IDR 850. In addition. The percentage of senior high-school graduates (x_4) also has a positive relationship with the minimum wage in East Java. Such increase in x_4 by 1% will increase the wage about IDR 13,430.

The best model can be identified based on R² value, AIC, and parameter significance. It also includes the sign of the parameter coefficient in accordance with the expected sign/prevailing theory and the fulfillment of IIDN assumptions for model residuals [14]. Table 9 shows the comparison of the classical and spatial models.

	Classic regression	SAR	SEM
R ²	51.47%	69.04%	64.06%
AIC	572	560.3	564.3
Significant parameter	All two parameters significant, except for intercept	All two parameters significant, except for intercept	All two parameters significant, including intercept
Expected sign of coefficient	All satisfied	All satisfied	All satisfied
IIDN assumption	Satisfied, except for autocorrelation	Satisfied, except for non-normal residual	Satisfied, except for non-normal residual

Table 9. Regional Minimum Wage Model Comparison

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From the comparison in Table 9, the best model is shown by SAR model since it has higher R^2 than that of SEM model. In addition, the efficiency of SAR model is also better than that of SEM model because of lower AIC of SAR model. However, the residuals of SEM model and SAR model are not normally distributed. However, this does not necessarily affect the model since it is not intended for prediction purposes. Besides, total observations that more than 30 have met the minimum sample allocation to fulfill the residual assumptions of regression model [16].

The goodness of SAR and SEM shows the improvement over the model specification error in classical regression (multiple linear regression) where R^2 of SAR and SEM models, respectively, increased to 69.04% and 64.06% from the previous 51.47% of classical regression. Almost 65% of regional minimum wage of East Java can be explained by spatial models, while the remainder is explained by other factors not included in the model.

It is decided to choose the SAR model in modeling the minimum wage of East Java based on two influential variables, namely total working Population (x_1) and percentage of Population with minimum education of senior high school (x_4) . Further testing using Robust LM statistic suggests that SAR model is better at identifying more representative spatial model. Figure 5 shows the results of the minimum wage mapping in 38 districts/cities in East Java Province using SAR model.



Figure 5. SAR Model Estimation Mapping of East Java's Minimum Wage

Figure 5 shows five categories of wage estimation generated by SAR model where Surabaya and Sidoarjo are the districts/cities with the highest wage (green gradation), if the wage is only influenced by the large total working Population and the percentage of the Population with a minimum education of SMA. This is relevant and appropriate to the real condition because those regions are the centers of medium-large scale industry which are modern and thus need a lot of labor and capital.

It was shown that region in the horseshoe zone, such as Madura Island and other districts such as Banyuwangi, Bondowoso, and Jember are classified into various categories of wage with Jember falling into the higher wage category (intervals of IDR 1,836,150-IDR 2,390,600). Most of the central zone falls into category 3, medium wage. This is due to the relatively low number of working people. Based on Figure 5, it can be concluded that the welfare of workers and employees is still not guaranteed because some of the wage estimation are in the low classification (red zone), among others, Sampang and Pamekasan Districts on Madura Island and Pacitan and Trenggalek.

Through this study study, it is shown that the wage is influenced by two aspects, namely labor (represented by the total working Population) and education (represented by the percentage of the Population with a minimum education of high school). The wage between districts/cities is also proven to be connected, especially for districts/cities that are located close to each other. This confirmed the initial notion that spatial dependence was prevalent in the economic case.

CONCLUSION

There are two factors affecting the minimum wage in East Java, namely Total Working Population and percentage of Population with minimum high school education. It is found that the minimum wage between districts/cities in East Java is spatially related. Based on the selection of the best model, spatial regression is better than classical regression because it has higher R² and does not violate whole residual assumption. The SAR model is chosen to model the minimum wage rather than SEM because it has smaller AIC and is able to better explain the minimum wage variance and it fulfills the Robust LM test.

It is recommended that local governments do not only consider the cost of living aspect, inflation, and economic growth in determining the minimum wage. Through this study, it is shown that there are other aspects which have significant role on wage, such as manpower and education. It is expected that there is no huge gap in the minimum wage of the regions and is relevant to the economic conditions of each region and does not hurt many parties, such as the factories/employers, the workers and their families. For further research, the improvement of the model from initially spatial to spatio-temporal is also interesting to study following that the wage dynamics in the labor sector are always moving.

REFERENCES

- N. N. Charysa, "Pengaruh Pertumbuhan Ekonomi dan Inflasi terhadap Upah Minimum Regional di Kabupaten/Kota Provinsi Jawa Tengah Tahun 2008-2011," *Economic Development Analysis Journal*, vol. 2, no.4, pp. 277-285, 2013.
- [2] F. Nurtiyas, "Analisis Faktor-faktor yang Mempengaruhi Upah Minimum Propinsi di Pulau Jawa Tahun 2010-2014," *Jurnal Pendidikan dan Ekonomi*, vol. 5, no. 2, pp. 166-175, 2016.
- [3] T. B. Hartanto and S.U. Masjkuri, "Analisis Pengaruh Jumlah Penduduk. Pendidikan. Upah Minimum dan Produk Domestik Regional Bruto (PDRB) terhadap Jumlah Pengangguran di Kabupaten dan Kota Provinsi Jawa Timur Tahun 2010-2014," *Jurnal Ekonomi Terapan*, vol. 2, no. 1, pp. 21-30, 2017.

- [4] R. Merdekawaty, D. Ispriyanti, and Sugito, "Analisis Faktor-faktor yang Mempengaruhi Upah Minimum Kabupaten/Kota di Provinsi Jawa Tengah Menggunakan Model Spatial Autoregressive (SAR)," *Jurnal Gaussian*, vol. 5, no. 3, pp. 525-534, 2016.
- [5] W. C. Liao and X. Wang, "Hedonic House Prices and Spatial Quantile Regression," *Journal of Housing Economics*, vol. 21, no. 1, pp. 16-27, 2012.
- [6] J. LeSage and R.K. Pace, *Introduction to Spatial Econometrics*, Chapman and Hall, 2009.
- [7] L. Anselin, *Spatial Econometrics: Methods and Models*, Springer, 1988.
- [8] A. S. Ahmar, Adiatma, and M. K. Aidid, "Crime Modeling using Spatial Regression Approach," *Journal of Physics: Conference Series 954*, 012013, 2018.
- [9] J. Susanto and D. W. Udjianto, "Human Capital Spillovers and Human Development Index in Yogyakarta Special Region and Central Java," *International Journal of Innovation and Economic Development*, vol. 5, no. 2, pp.57-64, 2019.
- [10] P. S. Kanaroglou, M. D. Adams, P. F. De Luca, D. Corr, and N. Sohel, "Estimation of sulfur dioxide air pollution concentrations with a spatial autoregressive model," *Atmospheric Environment*, vol. 79, pp. 421-427, 2013.
- [11] P. H. Idárraga, E. L. Bazo, and E. Motellón, "Regional Wage Gaps, Education and Informality in an Emerging Country: The Case of Colombia," *Spatial Economic Analysis*, vol.11, no.4, pp. 432-456, 2016.
- [12] U. S. Suharto and R. Dharmala, "Investasi Swasta. Upah Minimum Regional dan Pertumbuhan Industri Besar dan Sedang terhadap Penyerapan Tenaga Kerja di Provinsi Banten," *Jurnal Ekonomi-Qu*, vol. 6, no. 1, pp. 82-101, 2016.
- [13] M. L. S. Putera, "Peramalan Transaksi Pembayaran Non-Tunai Menggunakan ARIMAX-ANN dengan Konfigurasi Kalender," *Barekeng: Jurnal Ilmu Matematika dan Terapan*, vol.14, no. 1, pp. 135-146, 2020.
- [14] M. L. S. Putera, "Non-cash Payment Transaction Projection Using ARIMAX: Effect of Calendar," Jurnal Matematika, Statistika dan Komputasi, vol. 16, no. 3, pp. 296-310, 2020.
- [15] C. Fang, H. Liu, G. Li, D. Sun, and Z. Miao, "Estimating the Impact of Urbanization on Air Quality in China using Spatial Regression Models," *Sustainability*, vol.7, pp.15570-15592, 2015.
- [16] A. F. Schmidt and C. Finan, "Linear Regression and the Normality Assumption," *Journal of Clinical Epidemiology*, vol. 98, pp. 146-151, 2018.