M – 3

MODELING ECONOMIC GROWTH OF DISTRICTS IN THE PROVINCE OF BALI USING SPATIAL ECONOMETRIC PANEL DATA MODEL

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Abstract

Economic growth is an important indicator to point out the success of regional development. On the framework of planning and evaluating regional development, an econometric model used to model the economic growth will be required. Since regional economic growth is often related to other regions, it is necessary to propose an econometric model that can accommodate spatial dependencies between regions. The application of spatial econometric model in modeling economic growth of districts in the Province of Bali will be constrained due to limitation on the cross sectional unit which are only nine districts. It can be overcome by using panel data, hence spatial econometric panel data models will be used to model the economic growth of districts in the Province of Bali. The kind of spatial weight used in this research is customized in order to suit the characteristics of the regions in the Province of Bali. Customized weight is formed based on the share of common side or vertex as the queen contiguity and also consider the existence Denpasar and Badung as the center of economic activities. Therefore, it can be assumed that they have a relationship with each district in the Province of Bali. The result of this research shows that the best model is Spatial Error Model (SEM) random effect and the significant variables on influencing the economic growth of districts in the Province of Bali such as: local revenue, capital expenditures, electrification ratio, mean years school and gross enrollment rate.

Key words: econometrics, economic growth, panel data, spatial

INTRODUCTION

Modeling for economic growth is needed as a reference in planning and evaluation of development. Some experts have introduced econometric model for economic growth, one of them is Robert Solow (Sardadvar, 2011) who was introduced the neoclassical model. Along with the development of closed economy to the concept of an open economy, the neoclassical Solow model of economic growth developed with the addition of technological progress factor. Mankiw, Romer, and Weil (Sardadvar, 2011) proposed to include the human resources factor (human capital) in addition to physical capital (physical capital).

Neoclassical economic growth model previously developed from the hypothesis that the economic of a region is fundamentally closed. But nowdays this hypothesis is less appropriate to be applied due to the inter-regional trade and migration. It led to a condition where economic growth of a region often related with neighboring regions. Therefore, spatial econometric approach that can take into account the existence of spatial interaction will be required. In this study, the subject of interest is dependencies between regions. The ways to model the spatial dependencies are by using Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM). Spatial Autoregressive Model (SAR) assumes the dependent variable of a region is influenced by dependent variable of other regions. In the other hand, Spatial Error Model (SEM) assumes the error of the model of one region and the other regions is spatially correlated (Anselin, 1988).

The aim of this study is modeling the economic growth of districs in the Province of Bali. In the analysis of economic growth of the region, the indicators that show the real economic growth per capita population of a region is the GDP per capita at constant prices (Badan Pusat Statistik [BPS], 2014). Based on BPS data in 2007-2012, GDP per capita of districts in the Province of Bali recorded an increase from year to year. Hence, the factors that affect the economic growth of districts in the Province of Bali seems particularly important. This study also going to consider the existence of spatial interaction to model the economic growth of districts in the Province of Bali, hence the spatial econometric model will be used. However, the application of spatial econometric model in modeling economic growth of districts in the Province of Bali will be constrained due to limitations on the cross sectional unit which are only nine districts. Therefore, it is necessary to use panel data to accommodate the limitation of the cross section units. Panel data is a combination of cross section data and time series data where the same cross section units are measured at different times (Baltagi, 2005).

This study focuses on examine the characteristics of economic growth in Bali by considering the spatial dependencies between districts using panel data. Two spatial panel econometric models will be proposed, they are Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM) with fixed effect and random effect and will be estimated using Maximum Likelihood Estimation (MLE).

RESEARCH METHOD

The secondary data of economic growth variables obtained from the Badan Pusat Statistik (BPS) of Bali from 2007 until 2012 will be used in this study. The cross section units are 9 districts in the Province of Bali.

Table 1. Research Variables

Variable		Variable Name	Data Scale	Denomination
Dependen Variable	Y	GDRP per Capita	Ratio	Rupiah
Independen Variable	X_1	Local Revenue	Ratio	Thousand rupiah
	X_2	Capital Expenditures	Ratio	Thousand rupiah
	X_3	Labour	Ratio	People
	X_4	Electrification Ratio	Ratio	Household
	X_5	Mean Years School	Ratio	Year
	X_6	Gross Enrollment Rate	Ratio	Persen

This variables were been selected based on Mankiw, Romer, and Weil model (Sardadvar, 2011), hence it will be using log-normal (ln) form. There are two spatial panel models will be built in this study, they are Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM). Both spatial models will be including fixed effect and random effect panel model. The model specifications were described in Table 2.

Table 2. Model Specification

Spatial Autoregressive Model (SAR) panel	Spatial Error Model (SEM) panel
a. Spatial Autoregressive Model (SAR) pooling $y_{it} = \rho\sum_{j=1}^{9} w_{ij}y_{jt} + \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + \varepsilon_{it}$	a. Spatial Error Model (SEM) pooling $y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + u_{it}$ $u_{it} = \lambda\sum_{j=1}^{9} w_{ij}u_{jt} + \varepsilon_{it}$
b. Spatial Autoregressive Model (SAR) fixed effect $y_{it} = \rho\sum_{j=1}^{9} w_{ij}y_{jt} + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + \mu_i + \varepsilon_{it}$ where spatial specific effects (μ_i) assumed to be fixed	b. Spatial Error Model (SEM) fixed effect $y_{it} = \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + \mu_i + u_{it}$ $u_{it} = \lambda\sum_{j=1}^{9} w_{ij}u_{jt} + \varepsilon_{it}$

c. Spatial Autoregressive Model (SAR) random effect

$$y_{it} = \rho \sum_{j=1}^{9} w_{ij} y_{jt} + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + \mu_i + \varepsilon_{it}$$

where spatial specific effects (μ_i) assumed to be random

where $i = 1, 2, ..., 9$ dan $t = 1, 2, ..., 6$

where spatial specific effects (μ_i) assumed to be fixed

c. Spatial Error Model (SEM) random effect

$$y_{it} = \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \beta_5 x_{5it} + \beta_6 x_{6it} + \mu_i + u_{it}$$

$$u_{it} = \lambda \sum_{j=1}^{9} w_{ij} u_{jt} + \varepsilon_{it}$$

where spatial specific effects (μ_i) assumed to be random

where $i = 1, 2, ..., 9$ dan $t = 1, 2, ..., 6$

This study uses two spatial weights as the comparison, they are queen contiguity and customized. Queen contiguity (side-vertex contiguity) defines $w_{ij} = 1$ for regions that share a common side or vertex with the region of interest, and $w_{ij} = 0$ for all other elements (LeSage, 1999). Customized weight is formed based on characteristics of problem of interest (Baltagi *et al.*, 2012). In forming the customized weight, it is necessary to consider the presence of Denpasar and Badung as the center of all economic activities in the Province of Bali. Therefore, customized weight wil be formed based on the share of common side or vertex as the queen contiguity and also assumed that Denpasar and Badung have dependencies to every districts in the Province of Bali, then the weight between each districts in the Province of Bali and those two districs (Denpasar and Badung) will be given 1 ($w_{ij} = 1$).

Based on the above explanation, the two spatial weight to be used in this study are as follow:

$$\mathbf{W}_{queen} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \qquad \mathbf{W}_{customize} = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

The procedure to model the economic growth in Bali using spatial econometric panel data models (SAR panel, SEM panel) described in this following steps: creating a panel regression model and calculate the parameter estimates and residual value; first testing the spatial dependencies by using lagrange multiplier test (LM) and robust lagrange multiplier for lag and error, with provisions: if the LM lag test or robust LM lag test significant, then the appropriate model is SAR panel, otherwise if the LM error test or robust LM error significant, then the appropriate model is SEM panel; modeling the panel fixed effect and random effect for both of spatial panel models; comparing the fixed effect model and random effect between each spatial panel models using Haussman specifications test; selecting the best model of each spatial panel models by R^2, $corr^2$, σ^2 criterions; comparing models obtained by using both of spatial weights (queen contiguity and customized) and selecting the best model by R^2, $corr^2$, σ^2 criterions; and the last is interpretating the best model.

RESULT AND DISCUSSION

The first step before modeling the economic growth using spatial econometric panel data models is performing a test for spatial dependencies on economic growth data of districts in the Province of Bali. The statistical test for testing the spatial dependencies are lagrange multiplier test (LM) and robust lagrange multiplier test.

Table 3. Lagrange Multiplier (LM) Test

LM test	Queen Contiguity				Customized			
	Pooled Regression		Spatial Fixed Effect		Pooled Regression		Spatial Fixed Effect	
	LM	P-value	LM	P-value	LM	P-value	LM	P-value
LM lag	2.7123	0.100*	14.3186	0.000**	11.6493	0.001**	20.3130	0.000**
LM error	8.4197	0.004**	31.5835	0.000**	19.3372	0.000**	32.2439	0.000**
Robust LM lag	3.3946	0.065*	0.1400	0.708	2.6407	0.104*	0.0254	0.873
Robust LM error	9.1020	0.003**	17.4049	0.000**	10.3285	0.001**	11.9564	0.001**

Note:
* : significant at $\alpha = 10\%$
** : significant at $\alpha = 5\%$

The results of lagrange multiplier test using either queen contuguity and customized indicate that spatial dependencies are occurred among districts in the Province of Bali in terms of economic growth, therefore modeling economic growth using spatial econometric panel data models will be required.

A. Queen Contiguity

1. SAR panel

Table 4. Estimation Results of Spatial Autoregressive Model (SAR) Pooling

Variable	Coefficient	Asymptot t-stat	P-value
intercept	13.51132	10.64626	0.000000**
X1	0.174235	6.188763	0.000000**
X2	0.103175	2.768826	0.005626**
X3	-0.13634	-1.51498	0.129776
X4	-0.22412	-2.6797	0.007369**
X5	1.740042	11.9148	0.000000**
X6	0.063186	0.826285	0.408642
WY	-0.15998	-1.87251	0.061136*
R^2	0.9456		
$Corr^2$	0.9488		
σ^2	0.0082		

Table 5. Estimation Results of Spatial Autoregressive Model (SAR) Fixed Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	0.071175	3.952351	0.000077**
X2	0.012217	1.263065	0.206566
X3	-0.00175	-0.03839	0.969374
X4	-0.04172	-1.93257	0.053289*
X5	-0.23459	-1.16178	0.245327
X6	0.035505	1.989736	0.046620**
WY	0.604979	7.143315	0.000000**
R^2	0.9979		
$Corr^2$	0.9307		
σ^2	0.0004		

Table 6. Estimation Results of Spatial Autoregressive Model (SAR) Random Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	-0.0013	-0.10233	0.918493
X2	0.02694	2.610766	0.009034**
X3	0.130168	3.998366	0.000064**
X4	-0.05255	-2.19793	0.027954**
X5	0.100581	0.531961	0.594753
X6	0.031705	1.631076	0.102874
WY	0.878993	29.69974	0.000000**
ϕ	0.025267	3.000631	0.002694**
R^2	0.9969		
$Corr^2$	0.0077		
σ^2	0.0005		

2. SEM Panel

Table 7. Estimation Results of Spatial Error Model (SEM) Pooling

Variable	Coefficient	Asymptot t-stat	P-value
intercept	11.56679	13.54937	0.000000**
X1	0.17751	6.474996	0.000000**
X2	0.114396	3.222185	0.001272**
X3	-0.25014	-3.41568	0.000636**
X4	-0.14416	-1.90019	0.057408*
X5	1.54404	12.93803	0.000000**
X6	0.078104	1.063218	0.287683
WU	0.325989	2.223445	0.026186**
R^2	0.9405		
$Corr^2$	0.9410		
σ^2	0.0080		

Table 8. Estimation Results of Spatial Error Model (SEM) Fixed Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	0.13762	7.104316	0.000000**
X2	0.007562	0.659032	0.509875
X3	0.042458	0.77751	0.436858
X4	-0.0261	-0.9521	0.341045
X5	0.11466	0.458416	0.646653
X6	0.067971	3.187319	0.001436**
WU	-0.16698	-0.90601	0.364933

R^2	0.9962
$Corr^2$	0.8883
σ^2	0.0006

Table 9. Estimation Results of Spatial Error Model (SEM) Random Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	-0.07577	-2.09282	0.036366**
X2	0.103235	3.580497	0.000343**
X3	0.855631	12.52872	0.000000**
X4	-0.04403	-0.63631	0.524576
X5	2.221174	4.714015	0.000002**
X6	0.135698	2.412771	0.015832**
WU	0.074064	0.393468	0.693974
ϕ	43.81408	2.059207	0.039474**
R^2	0.9726		
$Corr^2$	0.4773		
σ^2	0.0041		

Based on Haussman specification test for SAR, where Haussman test-statistic is 19.9740 with p-value 0.0056, it could be concluded that SAR fixed effect is better to model the economic growth. Otherwise, for SEM, where Haussman test-statistic is 200.8543 with p-value 0.0000, it could be concluded that SEM fixed effect is is better to model the economic growth. By comparing SAR and SEM, SAR fixed effect has bigger R^2 and $corr^2$ and smaller σ^2 than SEM fixed effect, therefore the best model is Spatial Autoregressive Model (SAR) fixed effect.

B. Customized

1. SAR panel

Table 10. Estimation Results of Spatial Autoregressive Model (SAR) Pooling

Variable	Coefficient	Asymptot t-stat	P-value
intercept	19.34825	12.67734	0.000000**
X1	0.175446	7.480929	0.000000**
X2	0.089688	2.881733	0.003955**
X3	-0.22806	-3.39621	0.000683**
X4	-0.17882	-2.65665	0.007892**
X5	1.464808	14.0415	0.000000**
X6	0.133551	2.076163	0.037879
WY	-0.45798	-5.55354	0.000000**
R^2	0.9622		
$Corr^2$	0.9599		
σ^2	0.0057		

2. SEM panel

Table 13. Estimation Results of Spatial Error Model (SEM) Pooling

Variable	Coefficient	Asymptot t-stat	P-value
intercept	11.36762	13.34591	0.000000**
X1	0.17921	6.343422	0.000000**
X2	0.115439	3.122217	0.001795**
X3	-0.22063	-2.90382	0.003686**
X4	-0.16464	-2.08526	0.037046**
X5	1.596035	13.7653	0.000000**
X6	0.056511	0.784047	0.433013
WU	0.399969	2.55548	0.010604**
R^2	0.9402		
$Corr^2$	0.9412		
σ^2	0.0080		

Table 11. Estimation Results of Spatial Autoregressive Model (SAR) Fixed Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	0.056612	4.070055	0.000047**
X2	0.006375	0.835318	0.403538
X3	-0.00705	-0.19634	0.844343
X4	-0.04376	-2.57581	0.010001**
X5	-0.33516	-2.11702	0.034258**
X6	0.030912	2.200082	0.027801**
WY	0.764969	13.08116	0.000000**
R^2	0.9985		
$Corr^2$	0.9233		
σ^2	0.0002		

Table 12. Estimation Results of Spatial Autoregressive Model (SAR) Random Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	0.007227	0.666758	0.504927
X2	0.016561	1.948555	0.051349*
X3	0.103901	4.006247	0.000062**
X4	-0.04941	-2.45589	0.014054**
X5	-0.02971	-0.18499	0.853240
X6	0.031661	1.936642	0.052789*
WY	0.907997	36.97348	0.000000**
ϕ	0.016155	3.000258	0.002698**
R^2	0.9978		
$Corr^2$	0.0001		
σ^2	0.0003		

Table 14. Estimation Results of Spatial Error Model (SEM) Fixed Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	0.021347	1.376748	0.168590
X2	0.006843	0.932529	0.351063
X3	-0.03656	-1.24697	0.212410
X4	-0.04743	-3.2657	0.001092**
X5	-0.45653	-3.36116	0.000776**
X6	0.013286	1.05157	0.292997

WU	0.931972	45.92462	0.000000**
R^2	0.9607		
$Corr^2$	0.2153		
σ^2	0.0002		

Table 15. Estimation Results of Spatial Error Model (SEM) Random Effect

Variable	Coefficient	Asymptot t-stat	P-value
X1	-0.09694	-3.02687	0.002471**
X2	0.094679	3.573705	0.000352**
X3	0.889735	13.55812	0.000000**
X4	-0.05353	-0.74518	0.456164
X5	2.344282	4.685696	0.000003**
X6	0.136429	2.423911	0.015354**
WU	-0.30106	-1.07526	0.282259
ϕ	44.52811	1.970854	0.048741**
R^2	0.9736		
$Corr^2$	0.4686		
σ^2	0.0040		

Based on Haussman specification test for SAR, where Haussman test-statistic is 16.8131 with p-value 0.0186, it could be concluded that SAR fixed effect is is better to model the economic growth. Otherwise for SEM, where Haussman test-statistic is 307.5550 with p-value 0.0000, it could be concluded that SEM fixed effect is is better to model the economic growth. By comparing SAR and SEM, SAR fixed effect has bigger R^2 and $corr^2$ and smaller σ^2 than SEM fixed effect, therefore the best model is Spatial Autoregressive Model (SAR) fixed effect.

From the best model using queen contiguity and custumized spatial weight, one of the best model will be selected using R^2, $corr^2$, and σ^2 criterions. Spatial Autoregressive Model (SAR) fixed effect using customized spatial weight has bigger R^2 and smaller σ^2 than Spatial Autoregressive Model (SAR) fixed effect using queen contiguity but smaller $corr^2$, it also have more significant variables, therefore it can be concluded that the best model is Spatial Autoregressive Model (SAR) fixed effect using customized spatial weight.

Spatial Autoregressive Model (SAR) fixed effect using customized spatial weight could be written as:

$$y_{it} = 0.764969\sum_{j=1}^{9} w_{ij} y_{jt} + 0.056612x_{1it} + 0.006375x_{2it} - 0.00705\, x_{3it} - 0.04376x_{4it} - 0.33516x_{5it} + 0.030912x_{6it} + \varepsilon_{it}$$

From this model, it could be shown that higher electrification ratios restrain GDRP per capita with elasticity amounts to 0.04376 and higher mean years school also restrain GDRP per capita with elasticity amounts to 0.33516. The interpretation of this model is inappropriate to economic growth model, which are all the predictors should give a positive effects to output of economic growth, in this case GDRP per capita. It could be happen due to multicollinearity among predictors. To detect multicollinearity, one may calculate the Variance Inflation Factor (VIF) and correlation among predictors.

Table 16. Variance Inflation Factors (VIF)

Variable	VIF
X1	7.522
X2	2.667
X3	7.905
X4	12.914
X5	3.142
X6	1.798

Table 17. Pearson's Correlation among Predictors

Variable	Y	X1	X2	X3	X4	X5
X1	0.786 0.000**					
X2	0.509 0.000**	0.660 0.000**				
X3	0.280 0.040**	0.676 0.000**	0.299 0.028**			
X4	0.572 0.000**	0.839 0.000**	0.458 0.000**	0.884 0.000**		
X5	0.872 0.000**	0.690 0.000**	0.249 0.069*	0.448 0.001**	0.687 0.000**	
X6	0.557 0.000**	0.498 0.000**	0.172 0.214	0.128 0.355	0.356 0.008**	0.489 0.000**

Table 16 shows Variance Inflation Factor (VIF) of X4 is more than 10, it indicate that multicollinearity was occurred. From the correlation among predictors on Table 17, it could be shown there are positive correlation between predictors. This multicollinearity problem causes inconsistency in parameter estimation, as a result the coefficient of parameters have a wrong sign. To overcome this problem, the predictors that may cause multicollinearity will not be included to model. One way to select those predictors is considering the predictor that have a bigger correlation to other predictors than to response, in this case are X1, X2, X3 and X4. Therefore, those predictors will be deleted from model one by one and also considering its combination. Tables below show the best model using each spatial weights.

Table 18. Estimation Results of Spatial Error Model (SEM) Random Effect (without Labour and Electrification Ratio) using Queen Contiguity Spatial Weight

Variable	Coefficient	Asymptot t-stat	z-probability
X1	0.366654	5.498841	0.000000**
X2	0.190752	5.250846	0.000000**
X5	2.211259	3.901859	0.000095**
X6	0.210023	2.664311	0.007715**
WU	0.805171	13.85293	0.000000**
ϕ	23.66447	2.126499	0.033462**
R^2	0.9365		
$Corr^2$	0.8068		
σ^2	0.0096		

Table 19. Estimation Results of Spatial Error Model (SEM) Random Effect (without Labour) using Customized Spatial Weight

Variable	Coefficient	Asymptot t-stat	z-probability
X1	0.346365	5.301239	0.000000**
X2	0.158785	4.002521	0.000063**
X4	0.156773	1.929859	0.053624*
X5	1.966090	3.340348	0.000837**
X6	0.157756	2.194700	0.028185**
WY	0.830123	15.780649	0.000000**
ϕ	28.233915	2.057099	0.039677**
R^2	0.9478		
$Corr^2$	0.7761		
σ^2	0.0079		

The best model will be selected using R^2, $corr^2$, and σ^2 criterions. Spatial Error Model (SEM) random effect using customized spatial weight has bigger R^2 and smaller σ^2 than Spatial Error Model (SEM) random effect using queen contiguity but smaller $corr^2$, it also have more significant variables, therefore it can be concluded that the best model is Spatial Error Model (SEM) random effect using customized spatial weight.

Spatial Error Model (SEM) random effect using customized spatial weight could be written as:

$$y_{it} = 0.346365x_{1it} + 0.158785x_{2it} + 0.156773x_{4it} + 1.966090x_{5it} + 0.157756x_{6it} + u_{it}$$

$$u_{it} = 0.830123\sum_{j=1}^{9} w_{ij}u_{jt} + \varepsilon_{it}$$

From this model, it could be shown that higher local revenues have a positive significant effects to GDRP per capita with elasticity amounts to 0.346365. Higher capital expenditures have a positive significant effects to GDRP per capita with elasticity amounts to 0.158785. Higher electrification ratios have a positive significant effects to GDRP per capita with elasticity amounts to 0.156773. Higher mean years school have a positive significant effects to GDRP per capita with elasticity amounts to 0.966090. And the last, higher gross enrollment rates have a positive significant effects to GDRP per capita with elasticity amounts to 0.157756. The spatial error model shows that error of the model of one region and the neighboring regions is spatially correlated.

CONCLUSION AND SUGGESTION

This study gives a systematic overview of application spatial econometric panel data models using two different kinds of spatial weights. This method applied to model the econometric growth of districts in the Province of Bali. In modeling the economic growth, multicollinearity problem was occurred. It causes inconsistency in parameter estimation, as a result the coefficient of parameters have a wrong sign. To overcome this problem, the predictors that may cause multicollinearity were deleted from the model. The best model is selected using R^2, $corr^2$, and σ^2 criterions. Spatial Error Model (SEM) random effect using customized spatial weight is the best model and the significant variables on influencing the economic growth of districts in the Province of Bali are local revenue, capital expenditures, electrification ratio, mean years school and gross enrollment rate.

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