

SECTORAL EMPLOYMENT IN INDONESIA WITH SPATIAL AND SEEMINGLY UNRELATED REGRESSION (SUR) MODEL APPROACH

Vivin Novita Dewi, Setiawan, Santi Puteri Rahayu

Institut Teknologi Sepuluh Nopember, Faculty of Mathematics and Natural Sciences,
Surabaya, Indonesia

Vivin14@mhs.statistika.its.ac.id (Vivin Novita Dewi)

Abstract

Employment becomes one of the most important focuses of development in Indonesia. Analysis of employment and its factors could be the consideration in making employment policies. Several studies of employment related to a particular economic sector have been carried out. For a comparison, this paper discussed the model of labor absorption with three economic sectors. The source of data was derived from all the provinces in Indonesia for five years. Spatial model was estimated with Maximum Likelihood Estimation (MLE) for each year of observation. Moran's I and LM test were used to identify the spatial dependency. SUR model was estimated with Ordinary Least Square (OLS) and General Least Square (GLS). The variables used to estimate labor absorption were the output and real wage. The result indicated that the spatial dependency was significant particularly in the agricultural sector with a spatial error model. Meanwhile, labor absorption was significantly affected by the output and real wage for both OLS estimation and GLS estimation for SUR model. Service sector had the highest R^2 value. UR model with GLS estimation was evidenced to be more efficient than OLS estimation, in addition, standard error of parameters using GLS estimation evenly was lower than OLS estimation.

Keywords: sectoral employment, spatial, SUR, GLS, MLE.

Presenting Author's biography



Vivin Novita Dewi was born in Klaten, Central Java, Indonesia, September 29th 1985. She received bachelor degree in statistics from Sekolah Tinggi Ilmu Statistik (STIS), Jakarta, in 2008. In 2009, she starting worked at BPS (Badan Pusat Statistik-Central Bureau of Statistics) Karimun, Riau Islands. In 2014, she is continuing master degree major in statistics in Institut Teknologi Sepuluh Nopember (ITS), Surabaya.

1. Introduction

Employment becomes one of the most important priorities of development in Indonesia. Despite of its large number of population Indonesia ranks number 4 in the list of countries by population after China, The United States, and India the issue of employment is increasingly complicated. It is mainly due to the amount of millions of labor which is worsened by the economic, social, welfare, and socio-political dimension of the country.

Statistics Indonesia (*Badan Pusat Statistik/BPS*) has projected the amount of Indonesia population in 2015 will reached 255.5 million and 271.1 million by 2020. The rate of population growth in Indonesia has been under control from 1.49 percent in 2000-2010 to 1.4 percent in 2010-2014, yet the structure of the population began to change from year to year. The dependency ratio in 2010 which amounted to 50.5 percent as projected in 2015 decreased as much as 48.6 percent and 47.7 percent in 2020. The decline of the dependency ratio indicated the number of productive population (the age between 15-64 years) increased. It will be accompanied by the increased labor force, as the productive population is the working-age population. In consequence, there will be an increase of supply of labor. The National Labor Force Survey (*Survei Tenaga Kerja Nasional/Sakernas*) reported the number of workforce in Indonesia has increased approximately 1 million each year. In 2014, the workforce in Indonesia had reached 121.9 million compared to 117.8 million in 2010.

The imbalance between the number of labor force and employment opportunities will increase the number of unemployed. Although the number of people working in Indonesia is increasing from year to year and Open Unemployment Rate (*Tingkat Pengangguran Terbuka/TPT*) in Indonesia has declined, but the unemployment rate is still quite large. In 2014, the unemployment rate in Indonesia amounted to 5.94 percent. The sizable of unemployment number if not resolved soon it will cause social unrest. And vice versa if the number of unemployed decreased, it could improve social welfare and reduce poverty.

Labor absorption is very important in the effort to reduce unemployment. One of the policies that the government could do related to labor is to look at where the most effective sector to absorb labor and the factors that influence labor absorption. Several studies have associated with employment in Indonesia, among others, [2] with a study entitled employment in Jakarta using Cobb Douglas production equation to see the magnitude of labor absorption in Jakarta. Results from these studies are GDP, wage and investment significantly affect employment. However, for the variable investment is contrary to the theory of affect negatively on labor absorption. A path analysis is used to determine the factors that affect labor absorption of creative industries in Denpasar [8]. Variables used are capital, wages, technology and investment.

In a regression equation system, if there is a correlation between the model system error equation then seemingly unrelated regression (SUR) would be more efficient than the classical multiple linear regression model. SUR models were first introduced by Zellner in 1962 [1]. One of study in Indonesia using SUR methods is [4], He discusses the UKM development strategy based on economic sectors in order to increase employment in Indonesia. [1] introduce the estimation of SUR model with Ordinary Least Square (OLS) method, Generalized Least Square (GLS) and Feasible Generalized Least Square (FGLS) and [14] for the empirical model. With the ease of transportation and open access to current information, the labor easily moved from one area to another and into the economic sector from other economic sectors. Changes in labor policy in a region will also influence the structure of employment in other areas. Thus, it can be said that there are linkages between regions (spatial correlation) that affect labor absorption. Ignoring heterogeneity or spatial correlation of estimation for forecasting make RMSE has bigger result and maybe there will be biased and inconsistent in estimating the dynamics of labor [10].

This study was aimed to analyze labor absorption with spatial effect in each year of observation for three sectors of the economy. SUR model was used to compare labor absorption model in the three sectors of the economy. In this paper, the estimation methods used in the SUR model were OLS and GLS. Comparison of two methods of analysis in SUR models was also performed on this paper. To achieve these objectives, this research used the entire province in Indonesia as the object within a

period of five years (2010-2014). Three sectors of economy, namely, agriculture sector, industrial sector, and services sector were examined. These three sectors represent the primary sector, the secondary sector, and the tertiary sector. Labor absorption was scrutinized with Cobb Douglas model with derived from the demand. Variable explanatory used in this paper were the output and real wage according to [3].

2. Theoretical Background

2.1 Spatial Model

Spatial regression models developed by [1] using cross section data. Form of spatial regression equation is a general model:

$$\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \mathbf{u} \quad (1)$$

$$\mathbf{u} = \lambda \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon} \quad (2)$$

$$\boldsymbol{\varepsilon} \sim N(0, \sigma^2)$$

Where is,

y: the dependent variable vector $n \times 1$

X: independent variables matrix $n \times (p + 1)$

β : regression coefficients parameter vector $(p + 1) \times 1$

ρ : spatial lag coefficient in the main equation

λ : spatial lag coefficient in error

u: error vector $n \times 1$, normally distributed with zero mean and variance $\sigma^2 I$

ε : error vector $n \times 1$, normally distributed with zero mean and variance $\sigma^2 I$

n: number of observations or territory

p: number of independent variables

W_1, W_2 : ($n \times n$) spatial weight matrix with diagonal elements zero value. The spatial weight matrix is a function of distance from the region.

$$W_1 + W_2 = W.$$

Spatial weight matrix is based on the proximity distance, the intersection region, or both. According to Le Sage and Pace in [12] there are several methods to define the relationship intersection between regions, namely Linear Contiguity (intersection edge), Rook Contiguity (intersection side), Bishop Contiguity (intersection corner), Double Linear Contiguity (intersection of double edge), Double Rook Contiguity (intersection of double sided), and Queen Contiguity (intersection angle side). In addition, beside contiguity spatial weight matrix, also there is customize method. And in this paper, spatial weight matrix use queen contiguity (intersection angle side).

[1] recommends use of Moran's I and Lagrange Multiplier (LM) to determine the spatial dependencies. Moran's I index is a measure of the correlation between adjacent observations. If the value of Moran's I and Lagrange Multiplier significant reject H_0 then there is spatial autocorrelation.

Some models can be formed from the general equation of spatial regression, as follows:

1. Spatial Autoregressive (SAR), If there is a spatial effect on the dependent variable ($\rho \neq 0$) and no effect on the spatial error ($\lambda = 0$), then the model is obtained the following equation:

$$\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad (3)$$

$$\boldsymbol{\varepsilon} \sim N(0, \sigma^2)$$

2. Spatial Error Model (SEM), If there is no spatial effect on the dependent variable ($\rho = 0$) but there is a spatial effect on the error ($\lambda \neq 0$), then the model is obtained the following equation:

$$\mathbf{y} = \mathbf{X} \boldsymbol{\beta} + \mathbf{u} \quad (4)$$

$$\mathbf{u} = \lambda \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon} \quad (5)$$

so the merger Eq.20 and Eq.21 become:

$$\mathbf{y} = \mathbf{X} \boldsymbol{\beta} + \lambda \mathbf{W}_2 \mathbf{u} + \boldsymbol{\varepsilon} \quad (6)$$

$$\boldsymbol{\varepsilon} \sim N(0, \sigma^2)$$

3. Spatial Autoregressive Moving Average (SARMA), If there is spatial effect on the dependent variable ($\rho \neq 0$) and there is a spatial effect on the error ($\lambda \neq 0$), the obtained models like Eq.1 and Eq.2.

2.2 Seemingly Unrelated Regression (SUR) Model

SUR model was first introduced by Zellner in 1962, SUR models is the classical linear regression model where the variable in an equation system is not contained in the other equation, which means the system of equations is not a system of simultaneous equations. Number of independent variables in the model SUR for each equation may be different for each equation.

Generally SUR models can be expressed as a set of equations (G) due to related disturbances (error) between the different equations. SUR models can be written into the linear regression equation as follows [7]:

$$y_i = X_i\beta_i + u_i ; i = 1, 2, \dots, G \quad (7)$$

The above equation can be written in matrix form as follows

$$\begin{bmatrix} Y_1 \\ (Tx1) \\ Y_2 \\ (Tx1) \\ \vdots \\ Y_G \\ (Tx1) \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \dots & 0 \\ (Txk) & X_1 & \dots & 0 \\ 0 & (Txk) & \dots & \vdots \\ \vdots & \vdots & \dots & X_1 \\ 0 & 0 & \dots & (Txk) \end{bmatrix} \begin{bmatrix} \beta_1 \\ (kx1) \\ \beta_1 \\ (kx1) \\ \vdots \\ \beta_1 \\ (kx1) \end{bmatrix} + \begin{bmatrix} u_1 \\ (Tx1) \\ u_1 \\ (Tx1) \\ \vdots \\ u_1 \\ (Tx1) \end{bmatrix} \quad (8)$$

or

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \quad (9)$$

Where \mathbf{y} is the vector $GT \times 1$, \mathbf{X} is $GT \times k$, $\boldsymbol{\beta}$ is the vector $k \times 1$, \mathbf{u} is the vector of disturbances $GT \times 1$ and $k = \sum_{i=1}^G k_i$. This model assumed that the disturbances between equations are contemporaneously correlated and Σ is variance covariance matrix. $\Omega = \Sigma \otimes \mathbf{I}$, where \otimes is a Kronecker product operator, \mathbf{I} is the identity matrix $T \times T$ and $\Sigma = ((\sigma_{ij}))$, so that

$$\begin{aligned} E(u_i u_j) &= \sigma_{ii} I, & i &= j \\ &= \sigma_{ij} I, & i &\neq j; \quad i, j = 1, 2, \dots, G \end{aligned} \quad (10)$$

There are several estimators that can be used to estimate the model SUR, that is:

1. Ordinary Least Squares (OLS) estimator

The first estimator of $\boldsymbol{\beta}$ is the ordinary least squares (OLS) estimator,

$$\hat{\boldsymbol{\beta}}_{OLS} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} \quad (11)$$

And the variance covariance matrix is

$$V(\boldsymbol{\beta}) = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Omega}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \quad (12)$$

This is just the vector that stacks the equation by equation OLS estimators.

2. Generalized Least Squares (GLS) estimator

GLS estimator in estimating parameters SUR model consider the variance - covariance matrix of residuals. When the system covariance matrix Σ is known:

$$\hat{\boldsymbol{\beta}}_{GLS} = (\mathbf{X}'\boldsymbol{\Omega}\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{Y} \quad (13)$$

And the variance covariance matrix is

$$V(\hat{\boldsymbol{\beta}}) = (\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{X})^{-1} \quad (14)$$

The important result is in the SUR model, when the error term are uncorrelated between the equation, truly unrelated and all equation have the same set of regressors, the efficient estimator is single-equation ordinary least squares, OLS is the same as GLS [7].

3. Methodology

3.1 Spatial Model of Labor Absorption

The step to form spatial model of labor absorption are:

1. Form the $(n \times n)$ weight matrix (w_{ij}) , in this paper used Queen Contiguity.
2. Diagnostics for spatial dependence with Moran's I and Lagrange Multiplier. When the probability value less than alpha (α) showed significant evidence that there are significant spatial correlation in the model.

3. Form the spatial model of labor absorption. The following general spatial model that can be formed:

$$\widehat{\ln E}_i = \theta_0 + \rho \sum_{j=1, i \neq j}^n w_{ij} \ln E_i + \theta_1 \ln Y_{i,t} + \theta_2 \ln RW_{i,t} + \lambda \sum_{j=1, i \neq j}^n w_{ij} u_i \quad (15)$$

When $\lambda = 0$, SAR (Spatial Autoregressive) or Spatial lag model in general can be formed:

$$\widehat{\ln E}_i = \rho \sum_{j=1, i \neq j}^n w_{ij} \ln E_i + \theta_1 \ln Y_{i,t} + \theta_2 \ln RW_{i,t} \quad (16)$$

When $\rho = 0$, SEM (Spatial Error Model) in general can be formed:

$$\widehat{\ln E}_i = \theta_0 + \theta_1 \ln Y_{i,t} + \theta_2 \ln RW_{i,t} + u_i \quad (17)$$

where, $u_i = \lambda \sum_{j=1, i \neq j}^n w_{ij} u_i$

3.2 Seemingly Unrelated Regression (SUR) Model of Labor Absorption

In deriving employment function, is assumed that the firm minimize cost subject to given level of output. Thus, it incorporates two important characteristics of labor demand, that is, it is derived demand (for a given level of output) and a profit maximizing (or cost minimizing) employers employ workers by weighing the wage it has to pay against the price it receive for its product (i.e. real wage) [3]. The empirical model for sectoral employment in Indonesia:

$$\ln E_i = \theta_0 + \theta_1 \ln Y_{it} + \theta_2 \ln RW_{it} + u_{it} \quad (18)$$

The dependent variable $\ln E_{it}$ is the natural log of number of sectoral employment of sector i at time t . $\ln Y_{it}$ is natural log of output (Regional Gross Domestic Product-RGDP) and $\ln RW_{it}$ is natural log of real wage, is sectoral nominal wage deflated by sectoral real GDP deflator) and u_{it} is the time-variant error term.

Here below is the equation of a three-sector economy used in this paper for SUR model:

$$\widehat{\ln EAGR} = \alpha_0 + \alpha_1 \ln YAGR + \alpha_2 \ln RWAGR \quad (19)$$

$$\widehat{\ln EIND} = \beta_0 + \beta_1 \ln YIND + \beta_2 \ln RWIND \quad (20)$$

$$\widehat{\ln ESER} = \gamma_0 + \gamma_1 \ln YSER + \gamma_2 \ln RWSER \quad (21)$$

Tab.1 Variables description

Dependent variable	Variable description
<i>EAGR</i>	Number of employment in agriculture sector
<i>EIND</i>	Number of employment in industry sector
<i>ESER</i>	Number of employment in services sector
Independent variable	
<i>YAGR</i>	Output in agriculture sector
<i>RWAGR</i>	Real wage in agriculture sector
<i>YIND</i>	Output in industry sector
<i>RWIND</i>	Real wage in industry sector
<i>YSER</i>	Output in services sector
<i>RWSER</i>	Real wage in services sector

4. Data Description

Data used for this study come from Sakernas conducted in Indonesia, over a five year period (2010-2014) for all provinces di Indonesia except North Kalimantan (33 province). Data obtained from Sakernas include the number of people working for each sectoral employment and real wage. For output data (real GDP) is taken from the publication of regional account publication by sector of BPS.

Sectoral real wage is obtained by deflating sectoral nominal wage by sectoral output deflators or implicit index of GDP by sector.

Sectors that are used in this study were divided into three sectors: agriculture sector (primary), industry sector (secondary) and services sector (tertiary). The definition of the primary sector is the sector that includes the agricultural sector, with the sub-sectors of agriculture, livestock, forestry and fisheries as well as mining and quarrying sector. Secondary sector includes manufacturing, electricity, gas and water and construction sectors. Tertiary sector includes large trade sector, retail, restaurants and hotels, the services sector and other sectors.

4. Result and Discussion

The number of people who work in Indonesia increase every year (Fig.2). In 2010, the number of employment amounted to 109.6 million people and to increase amounted to 114.6 million people in 2014. This is in line with the number of labor force increased from year to year (Fig.2). Judging from the economic sector, the most number of people who work is the services sector, followed by agriculture and industry. The trend of Industrial sector and the services sector tend to rise, while the agricultural sector tends to fall.

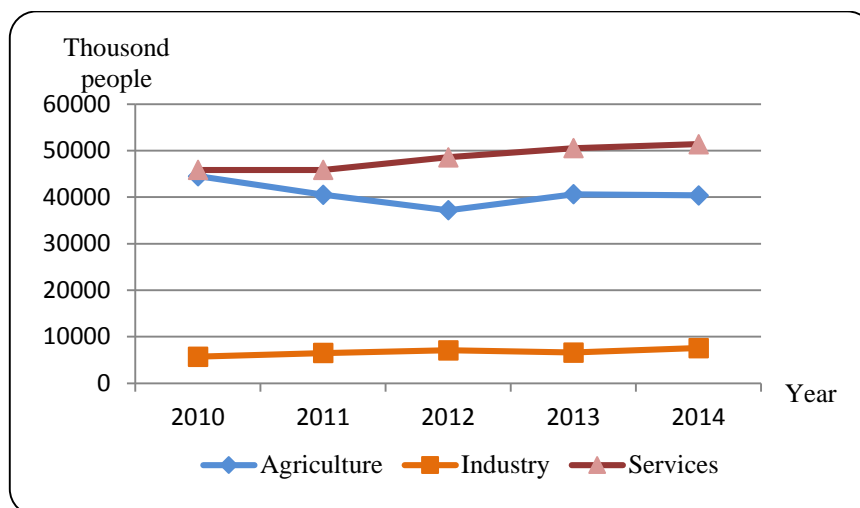


Fig.1 Number of sectoral employment (source: BPS)

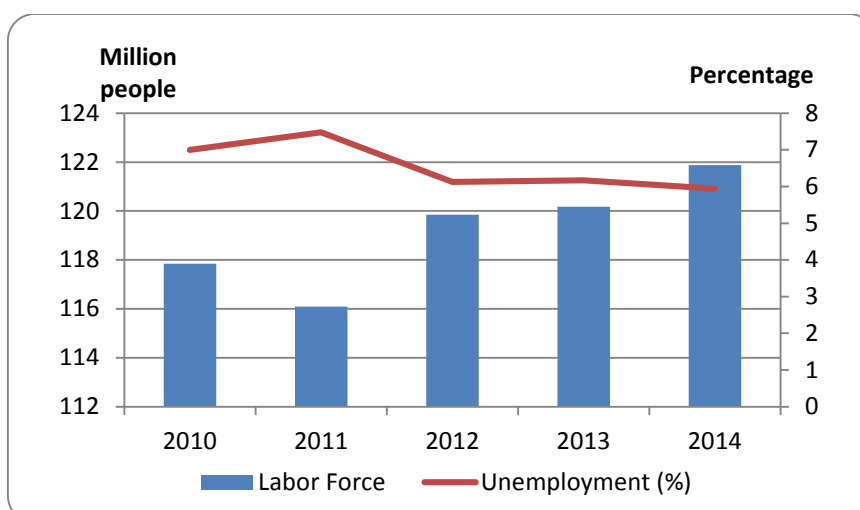


Fig.2 Labor force and unemployment in Indonesia (source: BPS)

Fig.2 shows the number of labor force in Indonesia. Every year from 2010 to 2014, the number of labor force tends to increased. The average increase in the labor force each year is one million people. While the percentages of unemployment tends to decreased every year. Since 2012, unemployment is

stagnant. The percentage of unemployment in Indonesia is about 5 to 6 percent from 2012 to 2014. The unemployment rate is still quite large so it needed an increase in employment opportunities in order to reduce unemployment.

Development of infrastructure and ease of access to information led to the ease of labor to move from one area to another area to work. The policy of the local government workforce could alter the composition of the workforce. The relationship because of the proximity of the area can be seen from the spatial effect between regions. Spatial analysis is done to know the spatial effects on employment. On the Tab.2, diagnostics for spatial dependencies is made for each year on each sector. Moran's I test (error) is only significant in the agricultural sector (2010-2014) and the industrial sector in 2012. In general, this means only the agricultural sector there are significant spatial autocorrelation. At Lagrange Multiplier tests shows that only LM (error) which significant while LM (lag) is not significant. Spatial autocorrelation in the agricultural sector only occurs in the equation error rather than the lag dependent.

Tab.2 Diagnostics for spatial dependence with Queen contiguity (OLS estimation)

Year	Test	Agriculture	Industry	Services
2010	Moran's I (error)	3.3535***	0.6376	-0.0792
	LM (lag)	1.9975	1.0755	0.7560
	LM (error)	9.5752***	0.1206	0.1255
2011	Moran's I (error)	1.4954	1.0621	-0.0105
	LM (lag)	0.8071	0.5564	0.0666
	LM (error) test	1.7200	0.6103	1.3923
2012	Moran's I (error)	1.8172*	1.9714**	-0.6626
	LM (lag)	1.6675	0.2489	0.0020
	LM (error)	2.7346*	2.8580*	0.7705
2013	Moran's I (error)	1.9811*	0.8649	-0.9531
	LM (lag) test	1.1693	0.1746	0.1500
	LM (error)	3.0432*	0.3472	1.3748
2014	Moran's I (error)	2.4221**	1.2888	-0.3229
	LM (lag) test	1.3945	0.2507	0.0668
	LM (error)	4.8327**	0.9683	0.3209

(*), (**), (***) denote significance at 10%, 5%, 1%

In this paper, we just analyze spatial model in agriculture sector according to Tab.2, it is because only the agriculture sector that significant there is spatial autocorrelation by year to year. Fig.3 shows the relationship between the observations at a location (standardized) with an average value of observations of locations adjacent to the location in question. Data patterns on Fig.3 (agriculture sector) spread in quadrants I-IV so that the global value Moran's I tend to be small. Value Moran's I on the agricultural sector in 2010-2014 was 0.2236; 0.1420; 0.1416; 0.1261.

On the Lagrange Multiplier test Tab.2 was only significant in the LM (error) so that the model established (Tab.3) only spatial model error. In the spatial error regression models, the effect of spatial correlation accommodate in the model by incorporating spatially variable weights lambda. Lambda in 2010, 2012, 2013 and 2014 are significant, which means addition of lambda variables significantly influential in the model. This is in line with the test Likelihood Ratio (LR) is significant, which means that the model of spatial error regression gives a better explanation than the classical regression model. The probability value of Breusch-Pagan test is lower than alpha or insignificant which means that the model is formed (Tab.3) has no influence spatial heterogeneity in the model.

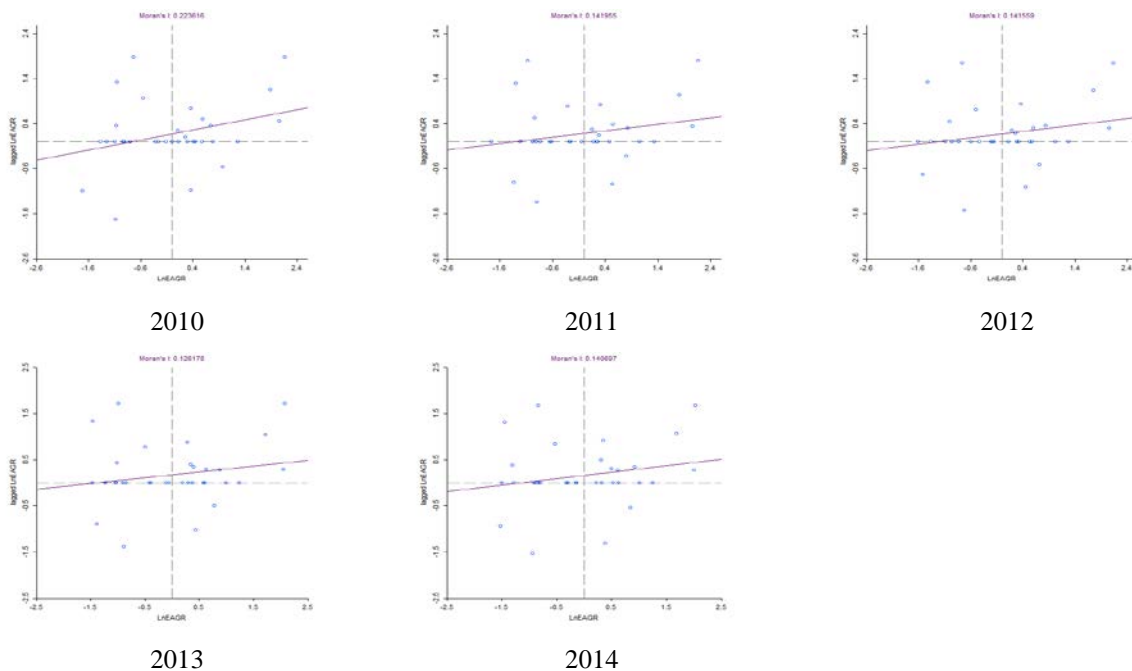


Fig.3 Scatter plot global Moran's I index of agriculture sector

Tab.3 Spatial Error Model (Maximum Likelihood Estimation) of agriculture labor absorption

	2010	2011	2012	2013	2014
Constant	9.6178***	10.2271***	11.6515***	0.3790**	10.5422***
lnYAGR	0.9776***	0.8818***	0.8740***	0.9018***	0.9485***
lnRWAGR	-0.8576***	-0.8015***	-0.9443***	-0.4181*	-0.9217***
Lambda (λ)	0.5197***	0.2494	0.3057*	0.3086*	0.3810**
R ²	0.8199	0.7825	0.8131	0.7333	0.8294
AIC	61.5574	61.4659	55.9323	72.8784	54.1956
B-P test	0.0824	1.234	0.3862	2.8180	0.2641
LR Test	10.0803***	0.1848	2.7746*	3.1175*	4.7390**

(*), (**), (***) denote significance at 10%, 5%, 1%

Spatial model in this paper cannot compare labor absorption across economic sector because only agriculture sector that there is significant spatial autocorrelation. Thus, in this paper used SUR model to compare labor absorption across economic sectors. Estimation method uses in this model are OLS and GLS. First of all, we employed the Ordinary least Squares regression to see the labor absorption pattern on each sector economy while ignoring any correlation between the error terms of all equation.

Tab.1 appears that output and real wage both in agriculture, industry and services significantly affect labor absorption in Indonesia 2010-2014. Real wage in all sectors have a negative effect on labor absorption, while output positive effect on labor absorption and this is in accordance with the theory. Models created with OLS estimation is $\ln \widehat{EAGR} = 9.3158 + 0.9273 \ln YAGR - 0.7545 \ln RWAGR$ (agriculture), $\ln \widehat{EIND} = 14.7080 + 0.8655 \ln YIND - 1.2170 \ln RWIND$ (industry sector) and $\ln \widehat{ESER} = 11.2724 + 0.8983 \ln YSER - 0.8334 \ln RWSER$ (the service sector). For the services sector means the addition of 1 percent of output will increase 0.9 percent of labor absorption, ceteris paribus. And 1 percent increase in real wage will drop 0.8 percent of labor absorption, ceteris paribus. The service sector has coefficient of determination (R²) the largest on the regression equation compared to other sectors (0.9525), which means that the independent variable is used (output and real wages) are able to explain 95% of the labor absorption, and 5 percent influenced by other variables.

Tab.4 SUR model of labor absorption with OLS and GLS estimation

	Agriculture		Industry		Services	
	OLS	GLS	OLS	GLS	OLS	GLS
Intercept (Std. Error)	9.3158*** (1.0381)	7.6835*** (0.9979)	14.7080*** (1.6894)	11.0162*** (1.5182)	11.2724*** (0.9403)	10.0998*** (0.8781)
lnY (Std. Error)	0.9273*** (0.0443)	0.9341*** (0.0428)	0.8655*** (0.0309)	0.7782*** (0.0290)	0.8983*** (0.0156)	0.8538*** (0.0151)
lnRW (Std. Error)	-0.7545*** (0.1012)	-0.5911*** (0.0968)	-1.2170*** (0.1799)	-0.7392*** (0.1611)	-0.8334*** (0.0995)	-0.6625*** (0.0926)
R-squared	0.7402	0.7360	0.8267	0.8136	0.9525	0.9498
Chi-Square	470.15***	497.25***	787.01***	719.48***	3310.31***	3204.76***
RMSE	0.6089	0.6138	0.5885	0.6102	0.2268	0.2331

(*), (**), (***) denote significance at 10%, 5%, 1%

Tab.5 Correlation matrix of residuals

	lnEAGR	lnEIND	lnESER
lnEAGR	1.0000		
lnEIND	0.3654	1.0000	
lnESER	0.1340	0.4772	1.0000

Breusch-Pagan test of independent: Chi-Square= 62,577, Pr= 0,0000

(*), (**), (***) denote significance at 10%, 5%, 1%

Models created with GLS estimation is $\ln \widehat{EAGR} = 7.6835 + 0.9341 \ln YAGR - 0.5911 \ln RWAGR$ (agriculture), $\ln \widehat{EIND} = 11.0162 + 0.7782 \ln YIND - 0.7392 \ln RWIND$ (industry sector) and $\ln \widehat{ESER} = 10.0098 + 0.8538 \ln YSER - 0.6625 \ln RWSER$ (the service sector). For the agriculture sector means the addition of 1 percent of output will increase 0.9341 percent of labor absorption, ceteris paribus. And 1 percent increase in real wage will drop 0.591 percent of labor absorption, ceteris paribus. The service sector has coefficient of determination (R^2) the largest on the regression equation compared to other sectors (0.9498), which means that the independent variable is used (output and real wages) are able to explain 95% of the labor absorption, and 5 percent influenced by other variables.

SUR model with OLS and GLS estimation all the independent variables significantly influence to the dependent variable. SUR model with GLS estimation be more efficient than OLS estimation, since standard error of parameters using GLS estimation uniformly lower than OLS estimation. The coefficient of determination (R^2) in the GLS estimation for all sectors decreased when compared to OLS estimation.

Seemingly Unrelated Regression models are appropriate for multivariate regression analysis when error terms are assumed to be correlated. Tab.4 shows the Seemingly Unrelated Regression results. Three multiple equation models were developed to simultaneously predict agriculture, industry and services labor absorption with GLS estimation. GLS estimation better than OLS estimation in SUR model in this paper because the error term of equation is correlated (Tab.5). The error correlation between agriculture and industry is 0.3654, agriculture and service is 0.1340, industrial and service is 0.4772. The probability value of chi-square is lower than alpha (α) means that overall, there are correlation of error term across economic sector.

6. Conclusion

According to Moran's I test and Lagrange Multiplier, the agriculture sector was evidenced to be significant since there was spatial autocorrelation. Spatial model of agriculture labor absorption formed as follow (spatial error model or SEM):

$$\widehat{\ln E}_{2010} = 9.6178 + 0.9776 \ln y_{agr} - 0.8576 \ln r_{wagr} + 0.5197 \sum_{j=1, i \neq j}^n w_{ij} u_i,$$

$$\widehat{\ln E}_{2011} = 10.2271 + 0.8818 \ln y_{agr} - 0.8015 \ln r_{wagr} + 0.2494 \sum_{j=1, i \neq j}^n w_{ij} u_i$$

$$\widehat{\ln E}_{2012} = 11.6515 + 0.8740 \ln y_{agr} - 0.9443 \ln r_{wagr} + 0.3057 \sum_{j=1, i \neq j}^n w_{ij} u_i$$

$$\widehat{\ln E}_{2013} = 0.3790 + 0.9018 \ln y_{agr} - 0.4181 \ln r_{wagr} + 0.3086 \sum_{j=1, i \neq j}^n w_{ij} u_i$$

$$\widehat{\ln E}_{2014} = 10.5422 + 0.9485 \ln y_{agr} - 0.9217 \ln r_{wagr} + 0.3810 \sum_{j=1, i \neq j}^n w_{ij} u_i$$

Lambda in 2010, 2012, 2013, and 2014 were significant, which means addition of lambda variables significantly affected in the model. Likewise, Likelihood Ratio (LR) test was significant, which means that the model of spatial error regression provides a better explanation compared to the classical regression model.

OLS and GLS used to estimate parameters in this SUR model of labor absorption. GLS estimation was evidenced to have better yields than OLS estimation. This finding was similar to the previous study of Zellner [7] in which when there are correlation error across equation, SUR model (with GLS) will be more efficient than classical regression or in this case was OLS estimation.

References

- [1] L. Anselin. A Test for Spatial Auto-Correlation in Seemingly Unrelated Regressions. *Economics Letters* 28, 335-341, 1988.
- [2] Dimas and Woyanti. Penyerapan Tenaga kerja di DKI Jakarta. *Jurnal Bisnis dan Ekonomi (JBE)*, 16: 32-41, 2009.
- [3] M.Z Tadjoeidin and A. Chowdhury Employment Function for Indonesia: An Econometric Analysis At The Sectoral Level. *The Journal of Developing Areas*, Vol. 46, No. 1, 2012.
- [4] M. Setiawan. *Strategi Pengembangan UKM Berdasarkan Sektor Ekonomi Dalam Rangka Peningkatan Penyerapan Tenaga Kerja di Indonesia*. Seminar Internasional Simposium kebudayaan Indonesia-Malaysia ke-X (SKIM X), 2007.
- [5] L. Anselin. *Spasial Econometric: Methods and Models*. Kluwer Academic publishers, 1988.
- [6] D. Gujarati. *Basic Econometric 4th Edition*. Mc.Grow Hill, 2004.
- [7] W.H. Greene. *Econometric Analysis: Fifth Edition*. Ney Jersey: Pearson Education LTD, 2002.
- [8] J.P Lesage and K. Pace. *Spatial and Spatiotemporal Econometrics*. Elsevier, 1999.
- [9] L.D.C Cahyadi. *Analisis Faktor-Faktor yang Mempengaruhi Penyerapan Tenaga Kerja Industri kreatif kota Denpasar*, Tesis, Udayana University, 2013.
- [10] <http://www.rii.wvu.edu/wp-content/uploads/2013/07/Fullpaper>
- [11] <http://www.bps.go.id/index.php/publikasi>

[12] <http://sourceforge.net/projects/jump-pilot/files/OpenJUMP/1.8.0/>

[13] https://www.academia.edu/10758035/Panduan_Operasional_Analisis_Data_Spasial

[14] <http://www.aacr.org/web/congresos/2010/htdocs/pdf/p131.pdf>