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Modeling the Impact of Economic Growth on Carbondioxide Emission and Poverty in Indonesia with Simultaneous Equations

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Abstract— Economic growth is an important instrument to decrease poverty but causes carbon dioxide emissions, as it increases energy consumption. Simultaneous modeling the impact of economic growth, poverty, and carbon dioxide emissions would show the important causal relationships to be used in the policy formulation. This research focuses on simultaneously modeling energy consumption, economic growth, human resources, carbon dioxide emissions, poverty, and inflation with 3SLS system equation method. Simultaneous modeling using time series data often face the problem of incomplete data which have to be handled prior to modeling. This research used multiple imputation with MCMC algorithm to deal with incomplete data problem. Simultaneous equation modeling results has showed the impact of 1 % decrease in economic growth rate annually could reduce carbon dioxide emissions of 10 % in 2030 but would raise poverty level of 2.27 % in 2025 and 0.5 % decrease in deforestation annually could reduce carbondioxide emissions of 13.64 % in 2030.

Index Terms— economic growth, carbon dioxide emission, poverty, multiple imputations, simultaneous equation model, 3SLS, global warming.

1 Introduction

GLOBAL warming is one of the most important issues today due to some impacts such as climate change and extreme weather. The biggest factor contributing to the global warm-ing was the emission of greenhouse gases (GHG), such as carbon dioxide. It was caused primarily by human activities such as fossil fuels burning for transportation, deforestation, agricultural activities, and industrial processes [15].

The highest concentration GHG in the atmosphere af-ter water vapour was carbon dioxide. Indonesia was among the top ten largest carbon dioxide emitting countries in the world. Indonesia's carbon dioxide emissions produced from the burning of fossil fuels which tended to increase every year inline with increased economic growth and population [5]. Today Indonesia's carbon dioxide emissions shared in the world reached 4 percent [7].

Economic growth is an important instrument to re-duce poverty [8,11]. Based on data from the Indonesia Statistics (BPS), Indonesia's economic growth rate in 2016 was 5.02 %, increased from 2015 of 4.88 %. While the number of poor people in Indonesia in September 2016 reached 27.76 million people (10.70 %), de-creased by 0.75 million people compared with September 2015 of 28.51 million people (11.13 %). This data indicates that the increasing economic growth rate could reduce pov-erty in Indonesia. Modeling the impact of economic growth on poverty and carbon dioxide emissions simultaneously could show causal relationships that important to be used to evaluate policies in Indonesia.

The simultaneous modelling of economic growth, poverty, and carbon dioxide emissions could not be modeled through ordinary regression because it could lead to a simultaneous bias due to the correlation between explanato-ry variables and errors [19]. Therefore, Three-Stages Least Squares (3SLS) system method used to estimate parameter of simultaneous equation model. 3SLS was used because 3SLS is more efficient than 2SLS asymptotically [20]. The goals of this research is modeling the consump-tion of energy, economic growth, human resources, carbon dioxide emissions, poverty, and inflation simultaneously with 3SLS system equation method.

The modeling used annual time series data which contains incomplete data so that it must be handled prior to modeling. Incomplete data handling techniques were evolv-ing along with the improvement of computation performance. The usage of modern incomplete data handling techniques such as multiple imputations is growing, but practitioner still used traditional techniques such as listwise deletion [23]. This research used mul-tiple imputation with MCMC algorithm to deal with incomplete data problem

Research on modeling the impact of economic growth on GHG emissions has been widely conducted such as The modeling framework for the OECD Environmental Outlook to 2050 [5] which showed the relationship between economic growth and GHG emission. The others research of U.S. Energy Information Administration [4] showed that the main factors affecting energy demand are GDP and population.

Research about the factors affecting Indonesia's pov-erty rate conducted by Dartanto [17] showed that poverty rate in Indonesia was influenced by Government fiscal poli-cy through direct assistance, subsidies to commodities, infrastructure development, and inflation. Cassandra [16] in her research stated that provincial minimum wage, unemployment rate, gross regional domestic product (GRDP) and human development index (HDI) affects poverty rate in Indonesia. While research on factors influencing HDI in Indonesia was conducted by Trunajaya [27] which showed that the GRDP, income inequality, health, and education infrastructure, the percentage of illiteracy and poverty rate have a significant effect on HDI in Indonesia.

Based on previous research, the modelling frame-work proposed in this research could be seen in Figure 1.

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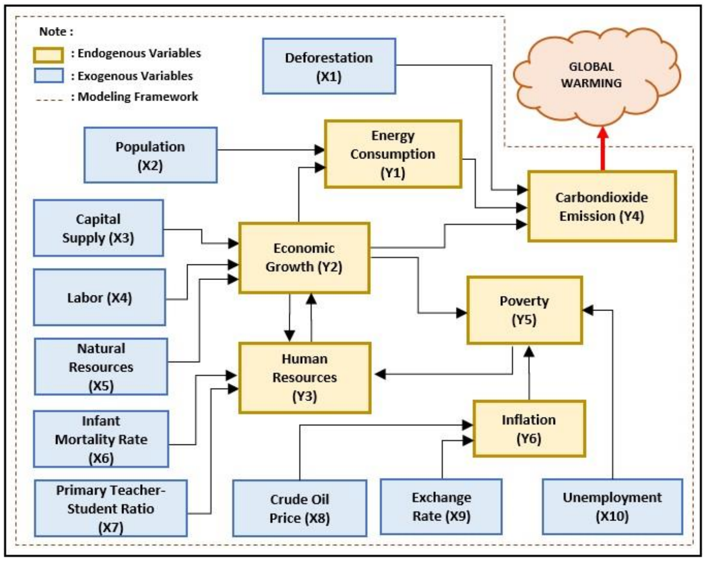

Figure 1 Model Framework

2 Methods

2.1 Data

This research used numerical secondary data from BPS Indonesia Statistics, United Nations (UN), World Bank, International Monetary Fund (IMF), and British Petroleum (BP) Statistical Review of World Energy. All data used was annual time series data of Indonesia from 1980 to 2015 as showed in Table 1.

2.2 Methods of Analysis

Stages of analysis in this research performed are as follows:

a. Incomplete data imputation used multiple imputation with MCMC algorithm.
b. Exploration of complete data.
c. Specification of simultaneous equation model
d. Examination the problem of identifying equations.
e. Estimation of the model parameter used 3SLS.
f. Examination regression assumptions.
g. Interpretation of model parameters
h. Policy evaluations scenario

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Table 1 Variables and Data

	Variables / Data	Units
Endogenous Variables		
1.	Energi Consumption(Y_1)[a]	Million tons
2.	Economic Growth/ GDP at Constant Price (Y_2)[b]	Trillion rupiahs
3.	Human Resources/ HDI (Y_3)[c]	Index (0-100)
4.	Carbon dioxide emission (Y_4)[a]	Million ton
5.	Poverty Rate (Y_5)[d]	%
6.	Inflation Rate/ General Inflation (Y_6)[e]	%
Exogenous Variables		
1.	Deforestation/ Percentation of Deforested Area (X_1)[c]	%
2.	Population (X_2)[c]	Million People
3.	Capital supply/ Domestic Savings (X_3)[b]	Billion rupiah
4.	Labour/ Number of Productive Age Population (X_4)[b]	Million People
5.	Natural Resources/ Indonesia's Crude Oil Production (X_5)[a]	Million tons
6.	Infant Mortality Rate (X_6)[c]	Per 1000 births
7.	Teacher-Student Ratio of Primary School (X_7)[c]	-
8.	World Oil Price Growth (X_8)[a]	%
9.	Rupiahs Exchange Rate Growth (X_9)[b]	%
10.	Unemployment Rate (X_{10})[d]	%
Auxiliary Variables		
1.	Population Growth Rate (Z_1)[c]	%
2.	GNP Per Capita (Z_2)[b]	Million rupiah
3.	Life Expectancy (Z_3)[c]	Year

Source : BP Statistical Review of World Energy[a], World Bank[b], UN[c], BPS[d], IMF[e]

3 Results and Discussion

3.1 Incomplete Data Imputation

Incomplete data imputation used multiple imputation with MCMC algorithm performed using 25 imputations based on the relative efficiency in Table 2. Relative efficiency of all incomplete data conditions using 25 imputations rela-tively high (0.99).

Table 2 Relative Efficiency

Incomplete	Number of Imputations							
Data Percentage	1	5	10	15	20	25	30	35
6 %	0.947	0.989	0.994	0.996	0.997	0.998	0.998	0.998
19 %	0.837	0.963	0.981	0.987	0.990	0.992	0.994	0.994
28 %	0.783	0.947	0.973	0.982	0.986	0.989	0.991	0.992

Multiple imputation performed on grouped variables with the assumption that variables within the group were highly correlated. Auxiliary variables outside the model were added into group to improve the prediction of incomplete data values. These variables were choosed due to complete data and strongly correlated with incomplete data. Five group has been created, in the group 1 included human resources and infant mortality. Group 2 included poverty rate, economic growth, inflation rate, monetary crisis dummy, GNP per capita, and life expectancy. Group 3 in-cluded deforestation, population growth rate, and carbon dioxide emissions. Group 4 included teacher-student ratio of primary school and population. Group 5 included unem-ployment rate and economic growth. Figure 2 showed 25 imputation on 5 variables with incomplete data.

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Grouped multiple imputation produced incomplete data imputation that follows the trend of the data.

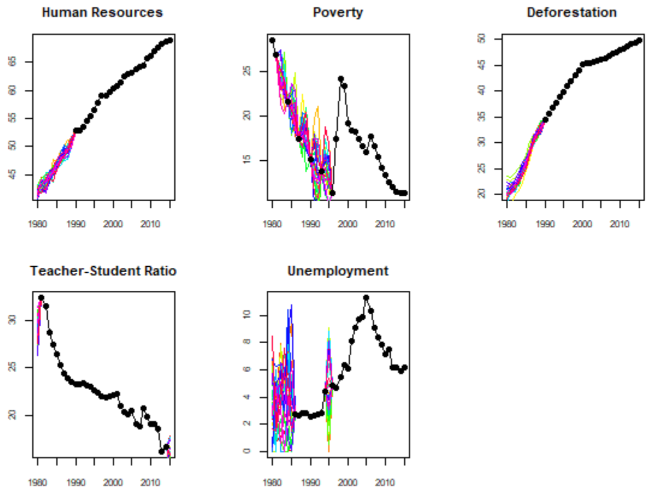

Figure 2 Incomplete Data Imputation

3.2 Data Explorations

Data exploration used complete data from imputation on previous stage.

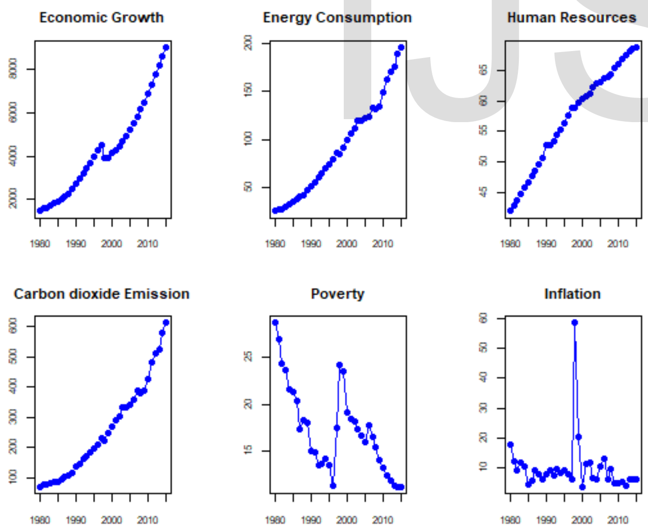

Figure 3 Endogenous Variables Time Series Plot

Figure 3 showed that monetary crisis in Indonesia af-fects many variables such as economic growth and poverty rate. Dummy variables inserted within model to accomodate this phenomena.

3.3 Model Specifications

Model specifications are based on the relationships derived from theory, previous research results, and data exploration delivered a complete equation system with 6 equations, 6 endogenous variables, 15 predetermined variables, and 11 exogenous variables including those of the following monetary crisis dummy variables X_{11t} as follow.

i. Energy Consumption Equation:

$$Y_{1t} = \beta_{10} + \beta_{11} Y_{1t-1} + \gamma_{11} Y_{2t} + \beta_{12} X_{2t} + \beta_{13} X_{11t} + \varepsilon_{1t}$$

ii. Economic Growth Equation:

$$Y_{2t} = \beta_{20} + \beta_{21} Y_{2t-1} + \gamma_{21} Y_{3t} + \beta_{22} X_{3t} + \beta_{23} X_{4t} + \beta_{24} X_{5t} + \beta_{25} X_{11t} + \varepsilon_{2t}$$

iii. Human Resources Equation:

$$Y_{3t} = \beta_{30} + \gamma_{31} Y_{2t} + \gamma_{32} Y_{5t} + \beta_{31} X_{6t} + \beta_{32} X_{7t} + \beta_{33} X_{11t} + \varepsilon_{2t}$$

iv. Carbon dioxide Emission Equation:

$$\ln Y_{4t} = \beta_{40} + \beta_{41} \ln Y_{4t-1} + \gamma_{41} Y_{1t} + \gamma_{42} Y_{2t} + \beta_{42} X_{1t} + \beta_{43} X_{11t} + \varepsilon_{4t}$$

v. Poverty Equation:

$$Y_{5t} = \beta_{50} + \gamma_{51} Y_{2t} + \gamma_{52} Y_{6t} + \beta_{51} X_{10t} + \beta_{52} X_{11t} + \varepsilon_{5t}$$

vii. Inflation Equation:

$$Y_{6t} = \beta_{60} + \beta_{61} Y_{6t-1} + \beta_{62} X_{8t} + \beta_{63} X_{9t} + \beta_{64} X_{11t} + \varepsilon_{6t}$$

3.4 Examination of the Identification Problems

Examination of the identification problems of the simultaneous equation model was performed by examining the two conditions that must be met, so that all parameter coefficients of structural form had unique solution. Both conditions were order condition and rank condition.

Table 3 showed that all equations are overidentified so the whole system of equations could be identified because it had a unique structural form parameter coefficients.

Table 3 Examination of the Identification Problems

Equation	Order Condition				Rank Condition	Conclusion
	k_1	$k-k_1$		g_1-1		
i. Enegy Consumption (Y_1)	3	12	>	1	5	*Overidentified*
ii. Economic Growth (Y_2)	5	10	>	1	5	*Overidentified*
iii. Human Resources (Y_3)	3	12	>	2	5	*Overidentified*
iv. Carbon dioxide emission (Y_4)	3	12	>	2	5	*Overidentified*
v. Poverty (Y_5)	2	13	>	2	5	*Overidentified*
vi. Inflation (Y_6)	4	11	>	0	5	*Overidentified*

Note : k = Number of predetermined variables
k_1 = Number of predetermined variables in specified equation
g_1 = Number of endogenous variable in specified equation

3.5 Parameter Estimation by 3SLS

Table 4 showed the parameter coefficients of all equa-tion by using 3SLS. Table 5 showed model's goodness of fit such as

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MSE, R-Squared and Adjusted R-Squared. R-Squared and Adjusted R- Squared of each equation were larger than 0.7 that showed the predetermined variables in each equation were able to explain most of the variance of endogenous variables.

Table 4 Parameter Coefficient Estimation by 3SLS

Equation	Coefficient	SE	Equation	Coefficient	SE
Energy Consumption			**Ln Carbondioxide Emission**		
(Intercept)	-11.218	14.254	(Intercept)	1.386*	0.264
Lag1 Energy Consumption	0.703*	0.123	Lag1 Ln Carbondioxide Emission	0.582*	0.078
Economic Growth	0.006*	0.002	Energy Consumption	0.002*	0.001
Population	0.075	0.097	Economic Growth	0.000	0.000
Dummy	4.186	3.406	Deforestation	0.016*	0.003
Economic Growth			Dummy	-0.023	0.028
(Intercept)	-293.447	1273.546	**Poverty**		
Lag1 Economic Growth	0.588*	0.065	(Intercept)	23.348*	2.123
Human Resources	-142.198***	92.451	Economic Growth	-0.002*	0.000
Capital Supply	0.129	0.102	Inflation	0.125*	0.053
Labor	82.581*	31.807	Unemployment	-0.101	0.360
Natural Resources	-0.070	3.585	Dummy	5.548*	2.505
Dummy	-728.940*	105.975	**Inflation**		
Human Resources			(Intercept)	3.239*	0.905
(Intercept)	77.245*	2.638	Lag1 Inflation	0.350*	0.055
Economic Growth	0.000**	0.000	Crude Oil Price	0.000	0.021
Poverty	0.058	0.051	Exchange Rate	0.208*	0.013
Infant Mortality Rate	-0.392*	0.034	Dummy	0.611	1.046
Primary Teacher-Student Ratio	-0.120	0.090			
Dummy	-0.748	0.650			

Note : Lag1 = t-1
Ln = Natural Logarithm
* Significant at alpha of 5%
** Significant at alpha of 10%
*** Significant at alpha of 15%

Table 5 MSE, R-Squared, and Adjusted R-Squared

Equations	MSE	R-Squared	Adj R-Squared
i. Energy Consumption (Y_1)	9.698	0.997	0.996
ii. Economic Growth (Y_2)	7904.252	0.999	0.998
iii. Human Resouce (Y_3)	0.256	0.997	0.996
iv. Carbon dioxide emission (Y_4)	0.00085	0.998	0.998
v. Poverty (Y_5)	5.090	0.743	0.708
vi. Inflation (Y_6)	10.366	0.889	0.873

3.6 Residual Diagnostics

Residual diagnostics performed to check whether classic regression assumption were fulfilled by the model. Examination of classic regression assumption of normality performed by using quantile-quantile (QQ) plots and Shapiro-Wilk statistical test. Figure 4 and Table 5 showed that both QQ plots and Shapiro-Wilk statistical test conclud-ed that the residuals was normally distributed.

Table 5 Shapiro-Wilk Test on Normality Assumption

Equation	Value of Statistic Test	P-Value
i. Energy Consumption (Y_1)	0.948	0.101
ii. . Economic Growth (Y_2)	0.988	0.956
iii. Human Resouce (Y_3)	0.949	0.105
iv. Carbon dioxide emission (Y_4)	0.991	0.993
v. Poverty (Y_5)	0.963	0.285
vi. Inflation (Y_6)	0.966	0.345

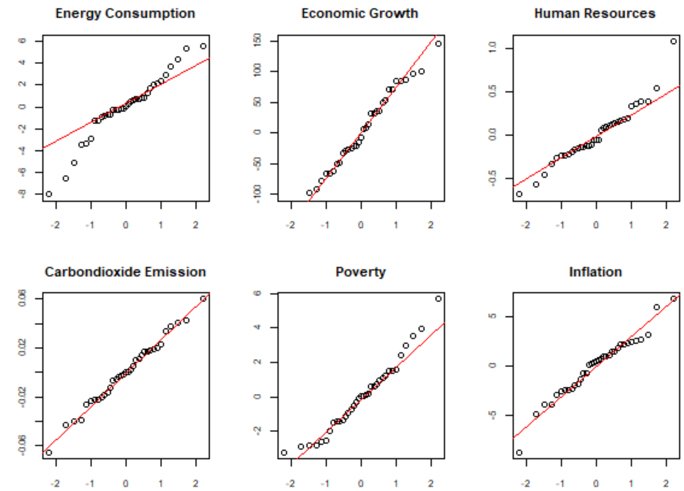

Figure 4 QQ Plot of Residuals

Classic regression assumption of variance homogeneity examined by using endogenous fitted values and residual plot, as shown in Figure 5, showed that variance of residual relatively homogen due to no serious pattern in the plot.

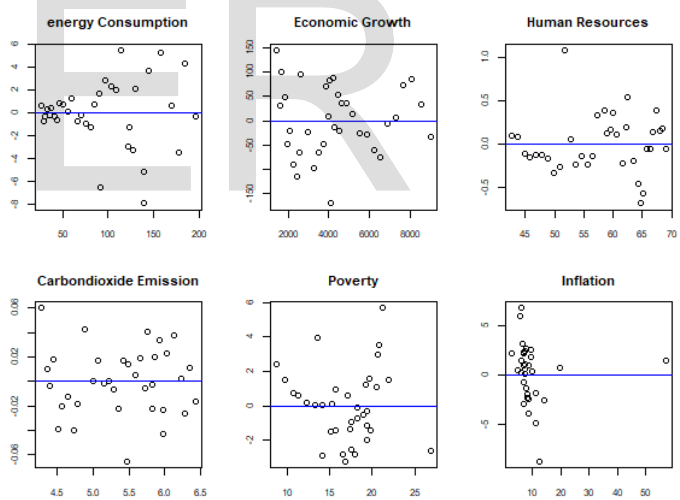

Figure 5 Plot of Residuals and Endogenous Fitted Values

Classic regression assumption of independency exam-ined by using Durbin-Watson statistical test, as shown in Table 7, showed that there were no strong evidence of auto-correlation or independency assumption violation of resid-uals.

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Table 1 Durbin-Watson Statistical Test

Equation	k*	dL	dU	DW Statistics	Conclusion
i. Energy Consumption (Y_1)	4	1.222	1.726	1.939	No autocorrelation
ii. Economic Growth (Y_2)	6	1.097	1.884	1.319	Indecision
iii. Human Resouce (Y_3)	5	1.160	1.803	1.659	Indecision
iv. Carbon dioxide emission (Y_4)	5	1.160	1.803	1.859	No autocorrelation
v. Poverty (Y_5)	4	1.222	1.726	1.296	Indecision
vi. Inflation (Y_6)	4	1.222	1.726	2.043	No autocorrelation

Note : k* = Number of explanatory variables in the equation
dL = Lower Bound of Durbin-Watson
dU = Upper Bound of Durbin-Watson

Based on residual diagnostics results, there is no evidence of serious violation of the classical regression assumption, so it could be concluded that the proposed model was good enough.

3.7 Interpretation of Model Parameter

Interpretation of model parameter performed for each equation as follows

a. Economic growth was significantly affects energy consumption. Increasing of economic growth by 1 tril-lion rupiahs would increase the energy consumption 0.006 million tons.

b. Labour was significantly affects economic growth. In-creasing of the number of labour by 1 million people would increase economic growth 82.581 trillion rupi-ahs.

c. Economic growth and infant mortality rate were sig-nificantly affects human resources. Increasing of eco-nomic growth by 1 trillion rupiahs would increase the human re-sources 0.0003. Increasing infant mortality rate by 1 per 1000 births would decrease the human resources 0.392.

d. Deforestation and energy consumption were signifi-cantly affects carbon dioxide emissions. Increasing of defor-estation by 1 % would increase 1.017 million tons of the carbon dioxide emissions. Increasing of energy consumption of 1 mil-lion tons would increase carbon dioxide emissions 1.002 mil-lion tons.

e. Economic growth and inflation were significantly af-fects poverty. Increasing of economic growth by 1 tril-lion ru-piahs would reduce the poverty rate of 0.002 %. Increasing of inflation by 1 % would increase poverty 0.125 %.

f. Rupiahs exchange rate significantly affests inflation. Depreciating of rupiahs exchange rate by 1 % would increase inflation 0.208 %.

3.8 Policy Evaluation Scenario

Scenarios were created to project the carbon dioxide emis-sion in 2030 and poverty rate in 2025. The scenario used were decreasing economic growth by 1 % while other variables such as rupiahs exchange rate and infant mortali-ty rate were as-sumed constant. Figure 6 and 7 had showed that decreasing of economic growth by 1 % each year, could have a positive im-pact on carbon dioxide emissions reduc-tion in 2030 by 10.01 % but negatively affects poverty reduc-tion slower in 2025 by 2.27 %. Another scenario were per-formed with decreasing deforestation by 0.5 % each year, as shown in Figure 8. De-creasing deforestation of 0.5 % per year would reduce carbon dioxide emissions in 2030 by 13.64 percent.

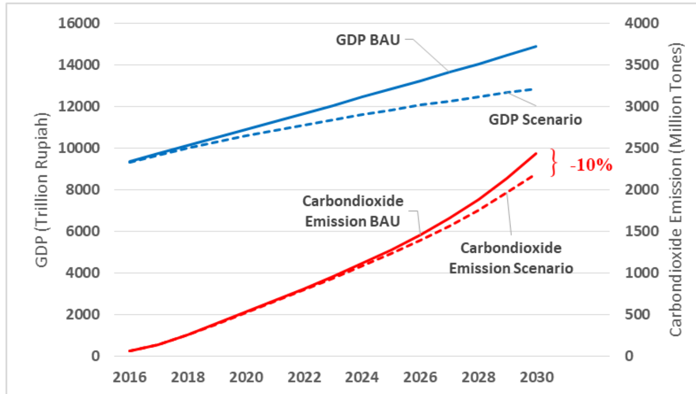

Figure 6 Scenario of Decreasing Economic Growth Impacts on Carbon Dioxide Emissions

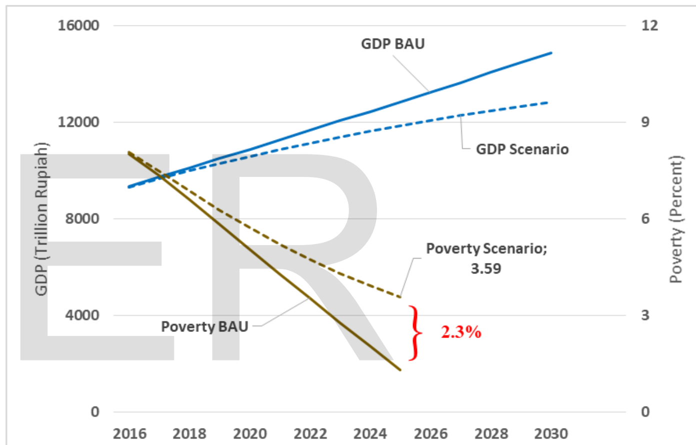

Figure 7 Scenario for Decreasing Economic Growth Impacts on Poverty Reduction

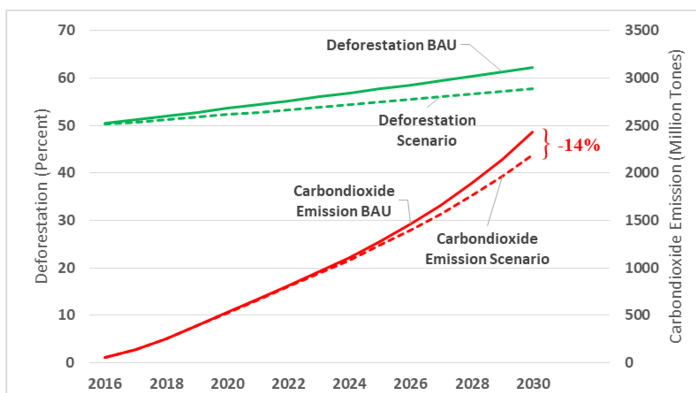

Figure 8 Scenario of Reducing Deforestation Impacts on Carbon Dioxide Emissions

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4 Conclusions

Proposed simultaneous equation model by using 3SLS method and multiple imputation with MCMC algo-rithm were good enough due to no violation of classical re-gression assumption. Based on the model concluded that economic growth was significantly affects the carbon diox-ide emission via energy consumption and also affects poverty simultaneously. The scenarios has showed that decreasing of economic growth by 1 % each year positively impacts carbon dioxide emissions reduction in 2030 by 10.01 % but also negatively impacts slower poverty reduction in 2025 by 2.27 %. Another scenarios showed that decreasing deforesta-tion by 0.5 % each year positively impact carbon dioxide emissions reduction by 13.64 % in 2030. Based on these sce-narios could be concluded that Indonesia's Government should decreased deforestation because it has large impact on carbon dioxide emission reduction. Another policy recommendation is to convert fossil fuel energy consumption to low carbon fuel energy so could keep high economic growth and low carbon dioxide emission.

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