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MULTINOMIAL LOGISTIC REGRESSION MODEL USING MAXIMUM LIKELIHOOD APPROACH AND BAYES METHOD ON INDONESIA'S ECONOMIC GROWTH PRE TO POST COVID-19 PANDEMIC

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ABSTRACT

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Indonesia's economic growth is a major concern in the global context, especially before and after the Covid-19 pandemic. Key sectors such as tourism, manufacturing, trade, and transportation have been severely impacted by travel and economic activity restrictions imposed to control the spread of the virus. Therefore, modeling is needed to describe the existing conditions. In this study, two approaches were used, namely the Maximum Likelihood approach and the Bayes approach. The use of methods in general as research material for researchers to further study the two methods. So far, the algorithm used for the Bayes concept method is Markov Chain Monte Carlo with Hasting's Metropolis method. The parameter estimation results obtained from the two methods are considered quite identical. However, it is necessary to pay attention to the iteration procedure that will be carried out. The selection of factors used in the iteration process is very important in obtaining the estimated parameter values. Furthermore, the results obtained so far do not contain fundamental differences regarding Indonesia's economic growth. In general, Indonesia can be said to be stable in terms of economic growth..

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1. INTRODUCTION

Indonesia's economic growth has become a major concern in the global context, especially before and after the Covid-19 pandemic. Before the pandemic, Indonesia recorded stable economic growth, with average Gross Domestic Product (GDP) growth of around 5-6% per year. In 2010, Indonesia's economic growth reached 6.2%, and this growth trend continued into the following years. In 2019, Indonesia's economic growth reached 5.02%, although there was a slowdown compared to previous years. This stable economic growth is driven by strong domestic consumption, increasing investment, and exports of key commodities such as coal, palm oil, and rubber [1].

However, the Covid-19 pandemic has changed Indonesia's economic landscape significantly. In 2020, Indonesia experienced a significant economic contraction as a direct impact of the pandemic. Indonesia's GDP in 2020 contracted by 2.07%, which was the first contraction since the Asian financial crisis in 1998. Key sectors such as tourism, manufacturing, trade and transportation were seriously affected due to restrictions on travel and economic activity imposed to control the spread of virus. This economic decline also has an impact on increasing unemployment rates and economic inequality in Indonesia [2][3].

Indonesia's economic growth before the Covid-19 pandemic reflected strong and stable economic dynamics, with significant contributions from the consumption, investment and export sectors. However, the Covid-19 pandemic has presented serious challenges to Indonesia's economic growth, triggering an unprecedented economic contraction. Therefore, an in-depth analysis of the factors influencing Indonesia's economic growth before and after the pandemic is very important to formulate appropriate economic policies to accelerate post-pandemic economic recovery [4][5].

In the context of a deeper understanding of the factors that influence Indonesia's economic growth before and after the Covid-19 pandemic, statistical analysis methods such as the Multinomial Logistic Regression Model are one tool that can be used. This method is used to model the relationship between various economic factors and economic growth, as well as provide alternative interventions regarding the impact of certain economic policies on Indonesia's economic growth in the future [6][7].

There are several types of regression, one of which is logistic regression. In its development, logistic regression was developed to obtain multinomial logistic regression. Logistic regression is a form of GLM and is used to model the relationship between a categorical response variable, Y and one or more independent variables, $X = (x_1, x_2, \dots, x_p)$. The response variable Y can have two or more categories and these categories can be nominal or ordinal. If Y only has two categories then it is called binary logistic regression. However, if Y has more than two nominal categories, then multinomial logistic regression (MLR) is more relevant to apply, whereas if Y has more than two categories and the categories can be sorted then ordinal logistic regression is more appropriate. to apply. The independent variables in a logistic regression model can be quantitative, qualitative or both (mixed). In logistic regression, the maximum likelihood method is usually applied to estimate parameters[8].

In this research, Indonesia's economic growth category is divided into three categories, namely far from target, close to target and on target. Economic growth is used as a response variable in this research. This is the basic consideration for applying the Multinomial Logistic regression model in this research. The predictor variables in this research are year, foreign investment rate, government spending rate, labor growth rate, human development index, domestic investment, star hotel occupancy rate, economic growth rate, and hotel occupancy rate. The year of Indonesia's economic growth is divided into four categories in the time interval 2019 to 2022. The first category is the pre-Covid year which was in 2019, the Covid year is 2020, the third category is the Covid transition year, and the fourth category is the post-Covid year namely 2022.

In fitting a multinomial logistic regression model, one of the most important parts is estimating the parameters. In Multinomial Logistic Regression (MLR), Maximum Likelihood Estimation (MLE) method and Bayes method with Markov Chain Monte Carlo (MCMC) approach are used to estimate parameters. MLE and the Bayesian method with the MCMC approach are suitable methods to be applied to problems related to categorical response variables because they have several advantages such as adequacy, consistency, efficiency and parameterization invariance [9]. Several previous studies related to MLR with MLE and the Bayes method with the MCMC approach were carried out by [10][11].

Using the MLE method and Bayes method with the MCMC approach, this research aims to model the dynamics of Indonesia's economic growth before and after the Covid-19 pandemic. Detailed economic growth data will be analyzed using this method to identify the main factors influencing economic growth, as well as to predict possible future economic growth trends. Thus, it is hoped that this research can make a significant contribution to a deeper understanding of the dynamics of Indonesia's economic growth before and after the Covid-19 pandemic, as well as in formulating effective economic policies to support post-pandemic economic recovery.

2. RESEARCH METHODS

2.1 Data

The data used in this research is presented in **Table 1**.

Table 1. Research Variable

Variable	Descriptions	Type	Category
$\boldsymbol{Y}$	Economic Growth	Nominal	1 = above the target 2 = at the target 3 = below the target
$\boldsymbol{X_1}$	Year	Ratio	
$\boldsymbol{X_2}$	Foreign Investment (trillions of rupiah)	Ratio	
$\boldsymbol{X_3}$	Government spending (trillions of rupiah)	Ratio	
$\boldsymbol{X_4}$	Percentage of labor absorption	Ratio	
$\boldsymbol{X_5}$	Human Development Index	Ratio	
$\boldsymbol{X_6}$	Domestic Investment (trillions of rupiah)	Ratio	
$\boldsymbol{X_7}$	Percentage of star hotel occupancy rate	Ratio	
$\boldsymbol{X_8}$	Percentage of non-star hotel occupancy rate	Ratio	

Note: Government Work Plan Target for 2022: Economic Growth 5.2% to 5.5%

2.2. Multinomial Logistic Regression

Multinomial Logistic Regression is a Logistic Regression model where the response variable is multicategory. Formulation of the multinomial logit model [12] is

$$\log\frac{\pi_{ij}}{\pi_{ic}} = \sum_{k=1}^{p} \beta_{jk}x_{ik}\ , \quad j = 1, \dots, c-1 \tag{1}$$

where π_{ij} is the probability of the j-th category in the i-th observation, while π_{ic} is the probability of the c-th category in the i-th observation which is used as the baseline category; β_{jk} is the parameter value for the k-th independent variable in the j-th category; x_{ik} is the value of the k-th independent variable at the i-th observation; p represents the number of independent variables. The formula can be expressed in the following form:

$$\pi_{ij} = \frac{\exp\left(\sum_{k=1}^{p}\beta_{jk}x_{ik}\right)}{1+\sum_{h=1}^{c-1}\exp\left(\sum_{k=1}^{p}\beta_{hk}x_{ik}\right)} \tag{2}$$

2.3. Maximum Likelihood Estimation (MLE)

The parameter estimation method in the Multinomial Logistic Regression model uses the Maximum Likelihood Estimation (MLE) method. The log-likelihood function is as follows:

$$\begin{aligned} L(\boldsymbol{\beta};\boldsymbol{y}) &= \ln\left[\prod_{i=1}^{N}\left(\prod_{j=1}^{c}\pi_{ij}^{y_{ij}}\right)\right] \\ &= \sum_{i=1}^{N}\left[\sum_{j=1}^{c-1}\left(y_{ij}\sum_{k=1}^{p}\beta_{jk}x_{ik}\right) - \ln\left[1+\sum_{j=1}^{c-1}\exp\left(\sum_{k=1}^{p}\beta_{jk}x_{ik}\right)\right]\right] \\ &= \sum_{j=1}^{c-1}\left[\sum_{k=1}^{p}\beta_{jk}\left(\sum_{i=1}^{N}x_{ik}y_{ij}\right)\right] - \sum_{i=1}^{N}\ln\left[1+\sum_{j=1}^{c-1}\exp\left(\sum_{k=1}^{p}\beta_{jk}x_{ik}\right)\right] \end{aligned} \tag{3}$$

The model parameter value, β_{jk}, that maximizes the log-likelihood function is obtained when $\frac{\partial L(\boldsymbol{\beta},\boldsymbol{y})}{\partial \beta_{jk}} = 0$, then

$$\frac{\partial L(\boldsymbol{\beta},\boldsymbol{y})}{\partial \beta_{jk}} = \sum_{i=1}^{N}x_{ik}y_{ij} - \sum_{i=1}^{N}\left[\frac{x_{ik}\exp\sum_{k=1}^{p}\beta_{jk}x_{ik}}{1+\sum_{h=1}^{c-1}\exp\left(\sum_{k=1}^{p}\beta_{hk}x_{ik}\right)}\right] = \sum_{i=1}^{N}x_{ik}\left(y_{ij}-\pi_{ij}\right) = 0 \tag{4}$$

So, the following equation is obtained:

$$\sum_{i=1}^{N}x_{ik}y_{ij} = \sum_{i=1}^{N}x_{ik}\pi_{ij} \tag{5}$$

Next, the search for the parameter value β_{jk} is carried out iteratively [12][13].

2.4 MLE Model Fit Test

2.4.1 Likelihood Ratio Test (Simultaneous Test)

This test was carried out to determine the significance of the β parameter on the response variable together using the Likelihood ratio test statistic. Test hypothesis :

H_0 : $\beta_1 = \beta_2 = \cdots = \beta_p = 0$
H_1 : at least there is one $\beta_j \neq 0, j = 1, 2, \dots, p$
test statistics:

$$\Lambda = -2\ln\left(\frac{L(\beta_0;y)}{L(\beta_1;y)}\right) \tag{6}$$

where $L(\beta_0;y) = \max[\sum_{i=1}^{n}\log f(y_i|\beta_0)]$ is a parameter less finite model and $L(\beta_1;y) = \max\left[\sum_{i=1}^{n}\log f\left(y_i|\beta_j\right)\right]$ is the full model with all parameters [14]. Test criteria: Reject H_0 if $\Lambda > \chi^2_{(\alpha,v)}$ with significance level α and degrees of freedom v.

2.4.2 Wald Test (Partial Test)

The Wald test is a statistical test used to assess whether the parameters in a statistical model are significantly different from specified values. The Wald test can be used to test a hypothesis about a single coefficient or parameter [15]. Test hypothesis:

H_0: $\beta_i = 0$
H_1: $\beta_i \neq 0$

test statistics:

$$W_i = \left(\frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}\right)^2 \tag{7}$$

Under null hypothesis, W_i follows a chi-squared distribution with one degree of freedom. If W_i is greater than the critical value, reject the null hypothesis [16].

2.5. Bayes Method

The Bayes method is a statistical approach based on Bayes' theorem, which provides a framework for updating knowledge about an event based on new evidence or acquired data. There are several main components in the Bayes method [9], are :

a) Prior Distribution

Prior distribution is a probability distribution that describes initial beliefs or knowledge about parameters before seeing the data, for example $h(\theta)$, where θ is the parameter you want to estimate. These priors become the foundation for updating knowledge based on new data. In this research, the prior distribution used is a normal distribution. Using a normal distribution as a prior distribution because the normal distribution is a commonly used choice for prior distributions due to its mathematical convenience and the central limit theorem, which states that the sum of a large number of independent and identically distributed random variables, regardless of their original distribution, will be approximately normally distributed. The formula is

$$h(\theta) = \exp\left(-\frac{(\theta-\mu)^2}{2\sigma^2}\right) \tag{8}$$

b) Likelihood Function

The likelihood function is a probability distribution of the data given by a parameter, for example $f(y\,|\,\theta)$. This function is used to calculate how well certain parameters explain the observed data. The likelihood function for multinomial distribution k category is

$$f(y|\theta) = \frac{n!}{y_1!.\,y_2!\dots y_k!}\prod_{i=1}^{k} p_i^{y_i} \tag{9}$$

where p_i is the probability of i-th category.

c) Posterior Distribution

The Posterior Distribution is the probability distribution of the parameters after the data is entered. This distribution is obtained by combining the Prior distribution and the likelihood function using Bayes' theorem. The Posterior Distribution reflects updated beliefs after viewing the data. The formula for forming the Posterior distribution is as follows:

$$h(\theta|y) = \frac{f(y|\theta).\,h(\theta)}{f(y)} \tag{10}$$

2.5.1 Markov Chain Monte Carlo

Markov Chain Monte Carlo (MCMC) is a statistical method used to generate samples from complex probability distributions, especially posterior distributions in the context of Bayesian analysis. One of the most popular MCMC algorithms is Metropolis-Hastings. The following is the Metropolis-Hastings formula [17][18][19]:

1. Initialization: Select an initial value for the Markov chain, X_0.
2. Iteration: for each iteration $t = 1,2,\dots,T$, do
   a) Select X' from the distribution of propositions, $q(X'|X_{t-1})$.
   b) Calculate the acceptability ratio, $\alpha = \frac{P(X')}{P(X_{t-1})} \times \frac{q(X_{t-1}|X')}{q(X'|X_{t-1})}$
   c) Accept $X_t = X'$ with probability $\min(1, \alpha)$
   d) If rejected, $X_t = X_{t-1}$
3. Output: Use $X_1, X_2, \dots, X_T$ as samples from the target distribution.

2.5.2 Bayesian Confidence Interval

A Bayesian Confidence Interval is the most likely range of parameter values based on information from the available data. This confidence interval is obtained from the posterior distribution of the parameters and is measured using the HPD (Highest Posterior Density) interval which includes the parameter values that have the highest probability in it [9]. Several general steps in determining Bayesian confidence intervals using the HPD method [20] are as follows:

1. Determine the posterior distribution of the parameters you want to estimate, for example using the MCMC method.
2. Sort the samples from the posterior distribution and determine certain quantiles, for example for the HPD interval with a 95% confidence level, the quantiles are 2.5% and 97.5% in the posterior distribution.
3. Identify the interval in the posterior distribution that has the highest probability in it.
4. Define the HPD interval as the range between two values corresponding to the previously calculated quantiles. For example, for a 95% confidence level, the HPD interval is defined as the interval between the 2.5% and 97.5% quantiles.

3. RESULTS AND DISCUSSION

3.1. Categorization and Descriptive Statistics of Data

The data used in this research was obtained from data from the Indonesian Central Bureau of Statistics, from 2019 to 2022. The data consists of nine variables as explained in 2.1. The response variable used in this research is economic growth data. The data is further processed by changing it into categories based on the Government Work Plan (RKD) target for 2022, namely 5.2%-5.5%, where category 3 is used for economic growth of more than 5.5%, 2 is for economic growth of greater than 5.2% and less than 5.5%, while category 1 is for less than 5.2%. In general, the plot of all predictors against the response variable is shown in Figure 1.

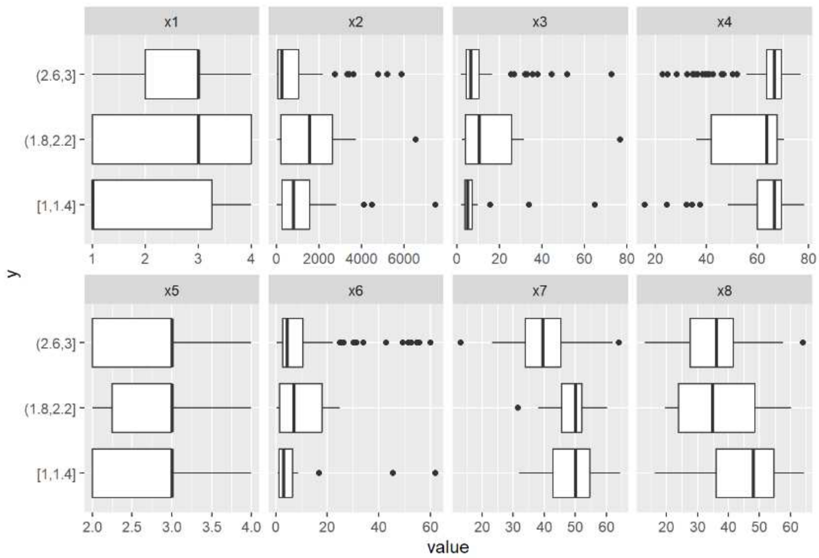

Figure 1. Boxplot of Predictor Variables Against Variable y

Foreign Investment (X_2) has a lower median at an economic growth rate that is more than the target ($y = 1$) compared to an economic growth rate that is at the target ($y = 2$) and an economic growth rate that is less than the target ($y = 3$). This means that the tendency for foreign investment at a level of economic growth that is more than the target ($y = 1$) is lower than the tendency for foreign investment at a level of economic growth that is at the target ($y = 2$) and a level of economic growth that is less than the target ($y = 3$).

Government spending (X_3) has a lower median at an economic growth rate that is more than the target ($y = 1$) compared to an economic growth rate that is at the target ($y = 2$), but is still higher than at an economic growth rate that is less than target ($y = 3$). This means that the tendency for government spending at a level of economic growth that is more than the target ($y = 1$) is lower than the tendency for foreign investment at a level of economic growth that is at the target ($y = 2$) but higher at a level of economic growth that is less than the target ($y = 3$).

The Percentage of Labor (X_4) has a higher median at an economic growth rate that is more than the target ($y = 1$) than at an economic growth rate that is at the target ($y = 2$), but the same at an economic growth rate that is less than the target ($y = 3$). This means that the tendency for the Percentage of Labor at an economic growth rate that is more than the target ($y = 1$) is higher than the tendency for the Percentage of the Labor Force at an economic growth rate that is at the target ($y = 2$) but the same at an economic growth rate that is less than the target ($y = 3$).

The Human Growth Index (X_5) has the same median at an economic growth rate that is more than the target ($y = 1$), at an economic growth rate that is at the target ($y = 2$), and at an economic growth rate that is less than the target ($y = 3$). This means that the tendency of the Human Growth Index at a level of economic growth that is more than the target ($y = 1$) is the same as the tendency of the Percentage of Labor at a level of economic growth that is at the target ($y = 2$) and at a level of economic growth that is less than the target ($y = 3$).

Domestic Investment (X_6) has a lower median at an economic growth rate that is more than the target ($y = 1$) compared to an economic growth rate that is at the target ($y = 2$), but is still higher than at an economic growth rate that is less from the target ($y = 3$). This means that the tendency for domestic investment at a level of economic growth that is more than the target ($y = 1$) is lower than the tendency for foreign investment at a level of economic growth that is at the target ($y = 2$) but higher at a level of economic growth that is less than the target ($y = 3$).

The percentage of star hotel occupancy rates (X_7) has a lower median at an economic growth rate that is more than the target ($y = 1$) compared to an economic growth rate that is at the target ($y = 2$) and an economic growth rate that is less than the target ($y = 3$). This means that the tendency for star hotel occupancy rates at an economic growth rate that is more than the target ($y = 1$) is lower than the tendency for foreign investment at an economic growth rate that is at the target ($y = 2$) and an economic growth rate that is less than the target ($y = 3$).

The percentage of non-star hotel occupancy rates (X_8) has a higher median at an economic growth rate that is more than the target ($y = 1$) than at an economic growth rate that is at the target ($y = 2$), but lower than the economic growth rate that is above the target. less than the target ($y = 3$). This means that the tendency for non-star hotel occupancy rates at economic growth rates that are more than the target ($y = 1$) is higher than the tendency for foreign investment at economic growth rates that are at the target ($y = 2$) and much lower than economic growth rates that are less from the target ($y = 3$).

3.2. Testing Steps in the Likelihood Approach

3.2.1. Simultaneous Test

Simultaneous tests in this research were carried out to determine the parameters of jointly estimated results for the response variable. Based on the test results, the results presented in **Table 1.**

Table 1. Simultaneous Test Results

Model	Model Fitting Criteria	Likelihood Ratio Test		
	-2 log-likelihood	Chi-square	df	Sig
Intercept Only	105.574			
Final	74.515	62.188	16	0.000

Based on the results of simultaneous testing, it was found that the log likelihood value without explanatory variables was greater than with explanatory variables. This shows that the model can be said to fit the data or in other words there is at least 1 significant explanatory variable. In line with this, the Chi-square value obtained was 62.188 with a chi-square of 26.296 and a p-value of less than 0.05, strengthening the assumption that the decision to reject H_0 could be made.

3.2.2. Partial Test

Partial testing in this research was carried out to test how each independent variable independently influences the independent variable. This test is carried out to see how each independent variable influences the response variable. However, in order to continue the aim of the study, namely comparison between the approaches used and the importance of evaluating the variables used, all variables will continue to be used even though they are shown. The results obtained are presented in Table 2.

Table 2. Partial Test Results

Predictor Variable	Df	Deviance	Df Residual	Df Residual Deviance	Pr(>Chi)
X_1	2	5.05	256	154.08	0.08
X_2	2	11.02	256	160.05	0.00
X_3	2	6.99	256	156.02	0.03
X_4	2	6.39	256	155.41	0.04
X_5	2	0.24	256	149.27	0.88
X_6	2	11.11	256	160.14	0.00
X_7	2	3.68	256	152.71	0.16
X_8	2	5.17	256	154.20	0.08

Based on Table 2, in general the variables X_2, X_3, X_4, and X_6 are significant at an error level of 5%. In line with this, variables X_1 and X_8 are significant at an error level of 10%. However, variables X_5 and X_7 are considered insignificant at the specified 10% limit. For the two variables, namely the HDI variable and the occupancy rate of non-star hotels, they remain a concern and are included in the analysis.

3.3. Testing Steps in the Bayes Approach

3.3.1. Simulation Setup Using Markov Chain Monte Carlo (MCMC)

1. Establishing a baseline

   In this research, the baseline used is category 1, namely economic growth that is far from the target. The reason for choosing a baseline is with the assumption that there is an interpretation value that will be more valuable if economic growth in Indonesia falls into the category of meeting or exceeding the stated target. Thus, better interpretation of the results is expected.

2. MCMC method

   The Bayesian approach used in this research is the MCMC method. The algorithm used is the Metropolis Hasting (MH) algorithm. This algorithm is used to help generate random samples from the desired posterior distribution. The statistic used to measure the degree of dependence between sequential decisions in a Markov chain is autocorrelation. The algorithm used is in the MCMCpack library with the MCMCpack function.

3. Determination of assumptions about priors

   Determining expectations about priors is a very important step. However, due to the lack of information obtained regarding the analysis to be carried out, the prior is set uniformly with a default value of 0. This is normal for analysis if the supporting information is not known.

4. Verbose assignment

   Verbose is defined as a switch value that can determine whether the sampler progress will be printed on the screen or not. The verbose in this study was set at 500.

5. Total number of iterations

   Determining the number of iterations allows the researcher to regulate and subjectively determine whether the iteration has been deemed convergent enough to be stopped or continued. In the implementation carried out, the researcher compared the total number of iterations used, namely starting from 500, 1000, 12000, 100000, 200000, 1000000, and 2000000. Based on the results obtained, the researcher considered that taking 2000000 iterations was better than the other iterations.

6. Determining the thin and tune values

Thin is defined as an effort to reduce the number of iterations to provide space for other iteration values. Meanwhile, tune is a Metropolis parameter that is used in the form of a scalar or vector. In this research the thin used was 10 while the tune used was 0.5.

3.3.2. Description of Iteration Results

1. Posterior scatter plot

After the preparation of the iteration procedure was carried out, several outputs were obtained, one of which was a posterior distribution plot as described in **Figure 2**. In general, the resulting plot looked less smooth and close to a normal curve. The researcher stopped the iteration, namely 2000000 iterations, assuming that the plot was representative enough to describe the posterior distribution. The existence of other supporting statistics also strengthens the suspicion so that the iteration is stopped.

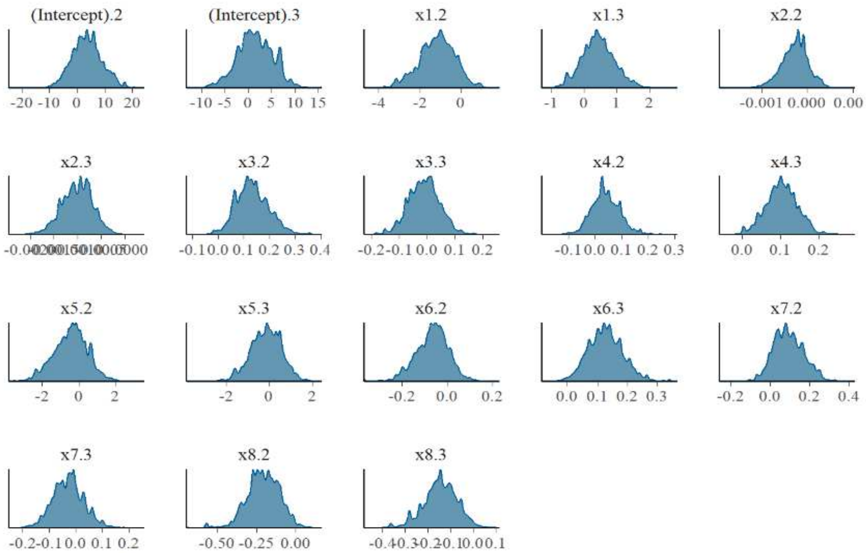

Figure 2. Posterior Distribution

2. Trace Plot

Based on the trace plot obtained, it can be said that the value of the iteration process has converged towards a certain point **[21]**, **[22]**. Other statistics also support the assumption that the trace plot is sufficient to state that the iteration can be stopped because the iteration process has converged to a certain value. The trace plots up to the 2000000th iteration in this research is presented in **Figure 3**.

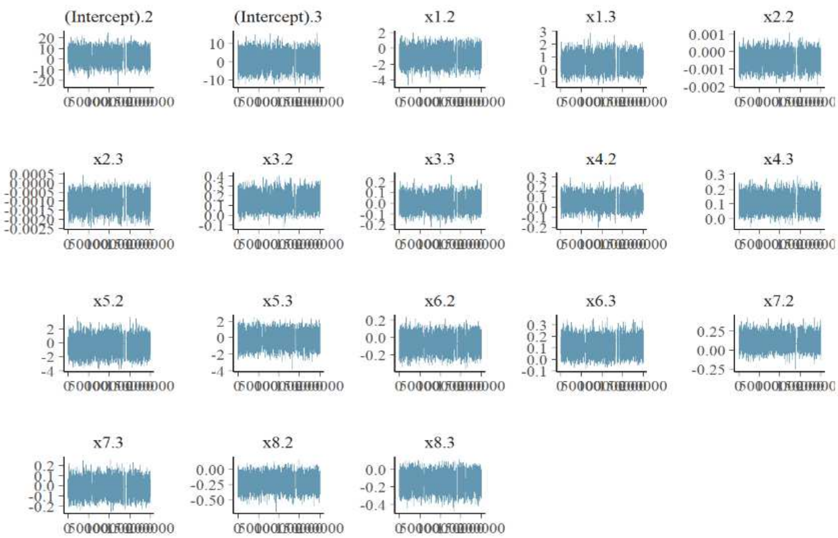

Figure 3. Trace plot

3. Autocorrelation Plot

In general, ergodic mean is a term that shows the mean value up to the iteration carried out. The plot between iterations and the mean value is called the ergodic mean plot. If after several iterations the ergodic mean is stable, then this is an indication or tendency for convergence of the algorithm to have been achieved. These trends are presented in Figure 4, as follows:

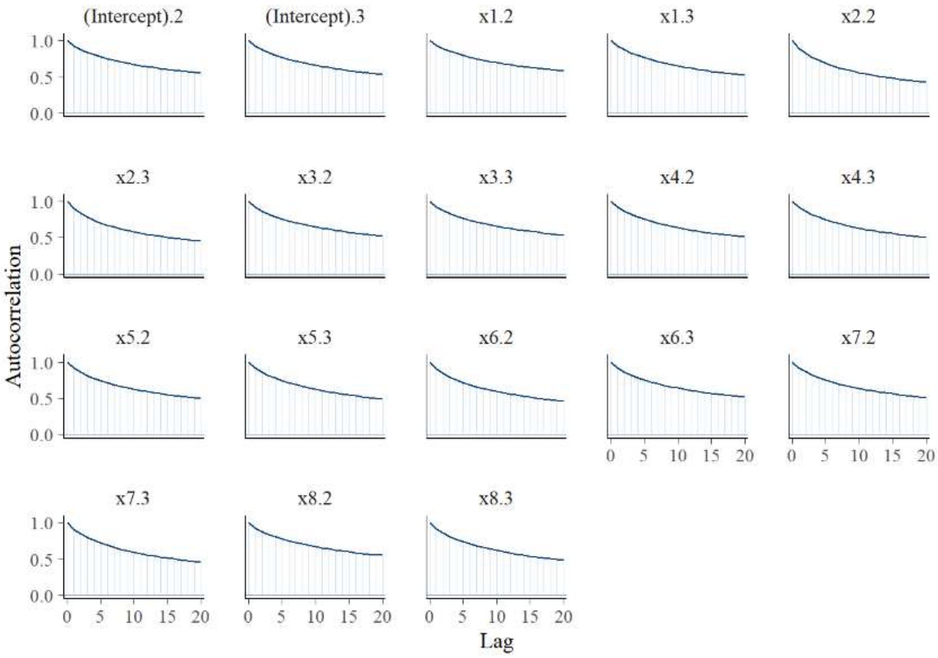

Figure 4. Autocorrelation Plot

3.3.3 Comparison of Parameter Estimation Results

Based on the estimation procedure carried out, parameter estimates were obtained using both the Maximum Likelihood and also Bayes using the MCMC method by applying the Metropolis Hasting procedure. Based on the overall estimation results, it appears that there are differences in the estimated parameter values. However, the differences in estimates are not considered to be significantly different. Apart from that, the difference in results is still considered normal without choosing which procedure is much better. The estimation results carried out using the Maximum Likelihood and Bayes approaches are presented in **Table 3.**

Table 3. Comparison of Maximum Likelihood and Bayes Approaches

Parameter Estimation	Maximum Likelihood			Bayes Method			
	Estimate	SE	Pr(>|z|)	Mean	SD	Median	95% CI
(Intercept).2	3.73	5.00	0.45	3.66	5.39	3.53	[-6.51,14.43]
(Intercept).3	1.38	3.43	0.69	1.54	3.80	1.44	[-6.07,8.83]
$X_{1.2}$	-1.00	0.78	0.20	-1.16	0.86	-1.12	[-3.02,0.42]
$X_{1.3}$	0.40	0.45	0.37	0.44	0.50	0.43	[-0.51,1.50]
$X_{2.2}$	-0.002	0.00	0.45	-0.002	0.00	0.00	[0.00,0.00]
$X_{2.3}$	-0.009	0.00	0.00	-0.001	0.00	0.00	[0.00,0.00]
$X_{3.2}$	0.09	0.05	0.07	0.13	0.06	0.13	[0.02,0.27]
$X_{3.3}$	-0.01	0.05	0.75	-0.01	0.06	-0.01	[-0.12,0.10]
$X_{4.2}$	0.03	0.05	0.51	0.04	0.05	0.04	[-0.05,0.15]
$X_{4.3}$	0.09	0.04	0.02	0.10	0.04	0.1	[0.02,0.18]
$X_{5.2}$	-0.40	0.86	0.64	-0.43	0.92	-0.37	[-2.31,1.31]
$X_{5.3}$	-0.06	0.64	0.91	-0.13	0.71	-0.11	[-1.62,1.20]

Parameter Estimation	Maximum Likelihood			Bayes Method			
	Estimate	SE	Pr(>|z|)	Mean	SD	Median	95% CI
$X_{6.2}$	-0.04	0.06	0.53	-0.07	0.07	-0.06	[-0.21,0.06]
$X_{6.3}$	0.12	0.05	0.04	0.13	0.06	0.13	[0.02,0.24]
$X_{7.2}$	0.07	0.07	0.28	0.09	0.08	0.09	[-0.04,0.25]
$X_{7.3}$	-0.03	0.06	0.56	-0.03	0.06	-0.03	[-0.04,0.09]
$X_{8.2}$	-0.17	0.09	0.06	-0.20	0.10	-0.20	[-0.41,-0.02]
$X_{8.3}$	-0.12	0.07	0.07	-0.14	0.07	-0.14	[-0.29,-0.01]

3.4 Multinomial Logistic Regression Equation

Based on **Table 3**, an interpretation of the results can be written in the form of a logistic regression equation using both the Maximum Likelihood (ML) and Bayes approaches. The form of the resulting logistic regression equation can be written as follows:

$$\log\frac{\pi_2}{\pi_1} = 3.37 - X_1 - 0.002X_2 + 0.09X_3 + 0.03X_4 - 0.40X_5 - 0{,}04X_6 + 0.07X_7 - 0.17X_8$$

and

$$\log\frac{\pi_3}{\pi_1} = 1.38 - 0.04X_1 - 0.009X_2 - 0.01X_3 + 0.09X_4 - 0.06X_5 + 0{,}12X_6 - 0.03X_7 - 0.12X_8$$

Meanwhile, the logistic regression equation using the Bayes approach can be written as follows:

$$\log\frac{\pi_2}{\pi_1} = 3.36 - 1.16X_1 - 0.002X_2 + 0.13X_3 + 0.04X_4 - 0.43X_5 - 0{,}07X_6 + 0.09X_7 - 0.20X_8$$

and

$$\log\frac{\pi_3}{\pi_1} = 1.54 - 0.44X_1 - 0.001X_2 - 0.01X_3 + 0.10X_4 - 0.13X_5 + 0.13X_6 - 0.03X_7 - 0.14X_8$$

The exponential values of the two parameter approaches are presented in **Table 4**.

Table 4. Exponential value

Predictor	$\mathrm{Exp}(\beta_x)$	
	Maximum Likelihood	Bayes
(Intercept).2	41.68	38.86
(Intercept).3	3.97	4.66
$X_{1.2}$	0.37	0.31
$X_{1.3}$	1.49	1.55
$X_{2.2}$	1.00	1.00
$X_{2.3}$	1.00	1.00
$X_{3.2}$	1.09	1.14
$X_{3.3}$	0.99	0.99
$X_{4.2}$	1.03	1.04
$X_{4.3}$	1.09	1.11
$X_{5.2}$	0.67	0.65
$X_{5.3}$	0.94	0.88
$X_{6.2}$	0.96	0.93
$X_{6.3}$	1.13	1.14
$X_{7.2}$	1.07	1.09
$X_{7.3}$	0.97	0.97
$X_{8.2}$	0.84	0.82
$X_{8.3}$	0.89	0.87

Based on Table 4, it can be seen that the difference in the exponential values of the parameters is not too big. The results obtained from both methods are identical. By noting that the baseline value used is 1 or does not meet the target, it shows that in general economic growth conditions are relatively stable.

4. CONCLUSIONS

Based on what has been conveyed, conclusions can be drawn regarding the methodology that has been carried out. based on the approach that has been taken using either the Maximum Likelihood or Bayes method, both of which are good approaches. The results obtained from both methods are identical. However, it should be noted that the preparations made before using the Bayes method need to be carefully considered. The selection of criteria in iteration determines the results obtained. In general, regarding the multinomial model, the variable coefficients obtained are considered relatively low so that the influence on economic growth is relatively the same for each year.

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