International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2024, 14(4), 484-500.

Modeling the Relationship between Life Expectancy, Population Growth, Carbon Dioxide Emission, and GDP Growth in Indonesia

Sri Hasnawati[1]*, Mustofa Usman[2], Faiz AM Elfaki[3], Ahmad Faisol[1], Edwin Russel[1]

[1]Department of Management, Faculty of Economic and Business, University of Lampung, Indonesia, [2]Department of Mathematics, Faculty of Mathematics and Natural Sciences, Unviersity Lampung, Indonesia, [3]Department of Mathematics, Statistics and Physics, College of Arts and Sciences, Qatar University, Qatar. *Email: hasnaunila@gmail.com

Received: 26 Feburary 2024 **Accepted:** 05 June 2024 **DOI:** https://doi.org/10.32479/ijeep.16303

ABSTRACT

Research on life expectancy at birth (LEB) and its relationship with several economic variables is interesting to be studied. LEB also describes the welfare condition of a country, where generally developed countries have a high level of LEB. This research will discuss the relationship between the variables of LEB, Corbon Dioxide (CO_2) Emissions, population growth (PG), and growth gross domestic product (GDPG) in the case of Indonesia from 1950 to 2020. The aims of this study is to build a model of the relationship between variables LEB, CO_2, PG and GDPG, and based on the best model obtained then will discuss the causal relationship between variables using Granger-Causality, impulse response function (IRF), and forecasting and the proportion of error covariance decompositions. From the analysis results, the best model that describes the relationship between variables: LEB, CO_2, PG, and GDPG is the vector error correction model (VECM). The results showed that there is a bidirectional relationship between the LEB variable and population growth. Partially, economic growth is proxied by GDPG affecting LEB and CO_2 affecting PG. However, there was no effect of CO_2 on LEB and GDPG in Indonesia. Based on the analysis results obtained, the chosen country is encouraged to consider the variables PG and GDPG in an effort to increase LEB in the future.

Keywords: Corbon Dioxide Emissions, Population Growth, Growth, Gross Domestic Product

JEL Classifications: C22, I12, J11, O44, O53, Q54

1. INTODUCTION

Many countries are trying to increase the LEB of their citizens, as part of efforts to improve the welfare and health of their citizens. In the current study modeling the relationship simultaneously among variables: Life Expectancy at Birth (LEB), gross domestic product (GDP), population growth (PG), and carbon dioxide (CO_2) emissions in case of Indonesia and this research has never been done for the case in Indonesia. LEB is defined as the average number of years that a newborn can expect to live if current mortality rates remain constant. However, the precise age-specific date rate for any given birth cohort cannot be predicted in `advance. LEB reflects a population's overall mortality rate across all age groups: Adolescents, adults, and the elderly. The concepts of LEB is very important for government, which can be used for projection of total number of population, planning of retirement, and so on. GDP per capita is calculated by dividing gross domestic product by the mid-year population. GDP growth is frequently used to measure a country's economic growth. The population figures are based on the de facto definition of population, which includes all people regardless of legal status or citizenship, and carbon dioxide CO_2 emissions are generated by the combustion of fossil fuels, steel mills, and cement manufacture. Carbon dioxide (CO_2) is also produced from the consumption of solid, liquid and gaseous fuels and the combustion of gases. It is known that the impact of the increment of CO_2 can cause the increment of global warming. Partial analysis and modeling of the four variables above has been carried out by many researchers.

Those who studied about LEB can be seen (Laaksonen, 2008; Jacobs et al., 2010; Canudas-Romo and Becker, 2011; Barnes et al., 2013; Sarma and Choudhury, 2014; Mishra, 2019; Gu et al., (2020) discussed population growth; Marcellino (2008) and Sugimoto (2011) discussed GDP; Munir et al. (2020), Di Lorenzo et al. (2013) and Balsalobre-Lorente et al. (2018) discussed the relationship of CO_2 and Economic Growth (GDP); Amuka et al. (2018) discussed the impact of CO_2 on LEB; Linden and Ray (2017) discussed the relationship of GDP and LEB; Begum et al. (2015); Dong et al. (2018) discussed the relationship of CO_2, GDP, and Population growth. Mishra (2019) in his studied found that the increasing aged population (65+) and LEB in India and he found that the aged females (65+) are more than aged males. Amuka et al. (2018) studied the impact of carbon dioxide (CO_2) emission on LEB in Nigeria. They used linear regression method to analyze the data. Carbon dioxide emission coefficient became positive, indicating the possibility of a positive link between carbon dioxide CO_2 emissions and life expectancy. However, it is not significant, implying that CO_2 emissions have had no effect on the average number of years lived in Nigeria. Thus, even as carbon dioxide emissions increased, life expectancy continued to rise.

Dong et al. (2018) studies the relationship among economic and population growth, CO_2 and renewable energy across regions, and he found that the population size and economic growth positively and significantly influence CO_2 emission levels. Begum et al. (2015) study the dynamic impacts of GDP growth, population growth and energy consumption on CO_2 emissions using timeseries analysis. The data indicate that between 1970 and 1980, CO_2 per capita emissions fell as per capita GDP (economic growth) increased; but, from 1980 to 2009, CO_2 per capita emissions climbed rapidly as per capita GDP increased further.

The studies above show that the simultaneous modeling study for the variables: LEB, gross domestic product (GDP), population growth (PG), and carbon dioxide (CO_2) emission have not been done in Indonesia case. Data source in this study are from the World Bank and United Nation data (World Bank, 2022a; 2022b; 2022c; United Nation, 2022). The problem in this study is how to model the relationship between the variables LEB, gross domestic product (GDP), population growth (PG), and carbon dioxide (CO_2) emission for cases of Indonesia. The purpose of this study is to find the best model that describes the pattern of the relationship between the four variables. The modeling method that will be used is multivariate time series analysis modeling. The research that deal with this type of problem by using multivariate time series analysis are still difficult to be found in research papers, especially in the cases of Indonesia. This research will produce innovation research, especially in multivariate modeling for the relationship of the LEB, gross domestic product (GDP), population growth (PG), and carbon dioxide (CO_2) emission for cases in Indonesia, as well as the nature of the relationship among these variables.

2. LITERATURE REVIEW

LEB is the number of years a newborn will live assuming the current pattern of death at birth remains constant throughout his life. GDP, generally expressed in US dollars, is the sum of the gross values produced by all producers in the economy plus product taxes and minus non-taxable subsidies; The population is calculated according to the definition of de facto (real) population, namely the total population regardless of their legal status or citizenship. Carbon Dioxide (CO_2) comes from factories and burning fossil fuels. CO_2 is also produced from the consumption of solid, liquid and gaseous fuels and the combustion of gases. Currently, studies on the phenomenon of global warming caused by the use of fossil fuels, energy use, use of electricity consumption have been carried out by many scientists (Di Lorenzo et al., 2013; Aye and Edoja, 2017; Munir et al., 2020).

Linden and Ray (2017) discuss the relationship between income and health: LEB and GDP per capita in 148 countries and the results for income inequality as measured by the GINI coefficient (a tool that measures the degree of inequality in population distribution) show that the effect of inequality is on health is insignificant in rich countries, but very significant in poor countries. LEB is an important indicator of the mortality rate of a population (Sarma and Choudhury, 2014). Currently, many studies have been conducted in an effort to find the relationship between health and housing conditions where the research focus is mostly on housing conditions and their impact on chronic suffering (Jacobs et al., 2010). Laaksonen et al. (2008), Barnes et al. (2013), Baker et al. (2013), and Gu et al. (2020), discusses the conditions of the home environment and life expectancy. Sarma and Choudhury (2014) discuss modeling estimates for LEB in India. Chang et al. (2011), Lawrence et al. (2013), and Das-Munshi et al. (2020), discussing the relationship of serious mental illness (SMI) and LEB concluding that people with SMI experience a marked decrease in LEB compared to the general population. Between 1980 and 2010, Queiroz et al. (2020) investigated the mortality estimates of adults with LEB in Brazil.

Amuka et al. (2018) studied the impact of CO_2 emissions on LEB in Nigeria using a linear regression method to analyze the data. The carbon dioxide emission coefficient becomes positive, indicating a possible positive relationship between carbon dioxide CO_2 emissions and life expectancy. However, it was not significant, implying that CO_2 emissions had no effect on the average number of years lived in Nigeria. So even as carbon dioxide emissions increase, life expectancy continues to increase. Dong et al. (2018) studied the relationship between economic growth and population, CO_2 and renewable energy across regions, and he found that population size and economic growth positively and significantly affect CO_2 emission levels. Begum et al. (2015) studied the dynamic impact of GDP growth, population growth and energy consumption on CO_2 emissions using a time series analysis. The data show that between 1970 and 1980, per capita CO_2 emissions fell as per capita GDP (economic growth) increased; however, from 1980 to 2009, per capita CO_2 emissions rose rapidly as per capita GDP increased.

Studies on the impact on life expectancy of the level of economic development and environmental factors are relatively numerous (Chen et al., 2021). According to Bilas et al. (2014) One of the main goals of the government in every country, both developed and developing countries is to increase the life expectancy of its citizens by reducing the mortality rate to the lowest achievable level. This can be realized by encouraging increased economic development in order to lead to better social conditions and an increase in life expectancy for its citizens. In other words, life expectancy is used to overestimate the standard of living and human welfare of a nation, because it is associated with socio-economic development (Lomborg, 2002). From the last few decades, life expectancy has tended to increase in the world and this increase was especially witnessed in developed countries. On the one hand, an increase in life expectancy is accompanied by prevention and maternal care, a better working and living environment, an increase in education and per capita income. On the other hand, life expectancy provides detailed information on environmental quality and measures of a nation's health (Audi and Ali, 2016). Luo and Xie (2020) conducted a study in China found that higher economic growth can increase life expectancy, but higher income inequality can reduce life expectancy. This is in line with research conducted by Claessens and Feijen (2007); Wang et al. (2020); and Murthy et al. (2021) which shows that there is an influence between economic growth on life expectancy. Shahbaz et al. (2016) focused on life expectancy drivers in Pakistan concluding that rural and urban inequality in terms of income and economic hardship has a substantial inverse impact on life expectancy, but urbanization supports life expectancy, while illiteracy lowers it.

Research that discusses population growth and life expectancy has not been done much. Some theories state that increasing population growth can have a negative impact on the health status of citizens and their life expectancy because with a larger population there will be more pressure on health facilities, especially in developing countries. While others explain that increased population growth can lead to greater productivity either by encouraging innovation, generating innovation or through the creation of greater economies of scale even in medical care services (Žokalj, 2016; Popoola, 2018; Khamjalas, 2024). Popoola (2018), found that increasing population growth has a positive and insignificant impact on life expectancy.

Ali and Ahmad (2014) investigated the impact of food production, school enrollment, inflation, population growth, per capita income and CO_2 emissions on the life expectancy of the Sultanate of Oman. The results showed that population growth was negatively and significantly related to the life expectancy of the Sultanate of Oman. In the long term CO_2 emissions are positively and not significantly related to life expectancy but in the short term are negatively and significantly associated with life expectancy. The findings show that the government of the Sultanate of Oman should seriously examine socio-economic factors to increase life expectancy. Increasing population growth can have a negative impact on the health status of citizens and their life expectancy because with a larger population there will be more pressure on health facilities, especially in developing countries (Popoola, 2018).

Kunze (2014) investigated the relationship between life expectancy and economic growth and found that life expectancy will decrease economic growth due to an increase in the number of people aged over 60 years. The rate of economic growth is declining although the level is still higher than in countries with low life expectancy. Lorentzen et al. (2008) found in growth regression that increased longevity was associated with higher growth rates, whereas Acemoglu and Johnson (2007) found no evidence of a positive growth effect.

Population growth rate is the increase in the number of people living in a country, state, or city over time (Popoola, 2018). The debate about the relationship between life expectancy and population growth rates has been ongoing and varied in various countries (Ademoh, 2017). However, there is no consensus as to whether population growth is beneficial or detrimental to life expectancy because the relationship between the two varies between countries. The results of this research from Ademoh (2017) state that although the population growth rate increases, life expectancy tends to decrease and vice versa through the use of regression and correlation approaches.

Research on the relationship between economic growth and CO_2 emissions has attracted the interest of many researchers with varying results in different countries and regions (Akram, 2012; Shahbaz et al., 2013; Rusiawan et al., 2015; Esso and Keho, 2016; Wang et al., 2017; and Widyawati et al., 2021). A large number of empirical studies from the last two decades confirm the existence of a strong historical correlation between these two variables, with most of the empirical results showing that economic growth can indeed lead to an increase in energy consumption (Akinlo, 2008; Apergis and Payne, 2009). Wang et al. (2012) found economic growth to be one of the main factors in increasing CO_2 emissions in the City of Beijing, and Al-Mulali et al. (2013) in Latin America and the Caribbean. This research mostly uses time series analysis or dynamic panel data approach to determine the existence and degree of cointegration relationship. Hossain (2011) found that there is no evidence of a long-term causal relationship of economic growth with CO_2 emissions and of economic growth. Begum et al. (2015) conducted a study in Malaysia found that during the period 1970-1980, CO_2 emissions decreased with economic growth; however, from 1980 to 2009, CO_2 emissions increased sharply with a further increase in GDP. The results of research conducted by Esso and Keho (2016) based on the Granger Causality test show that in the short term economic growth (GDP) causes CO_2 emissions in several African countries such as Benin, Ghana, Democratic Republic of Congo, Senegal, and Nigeria, which means that expansion Economics cannot be achieved without affecting the environment. The results of this study are in line with the research conducted by Shahbaz et al. (2013), where the results of his research found that there was a positive influence between economic growth on CO_2 emissions. Economic growth can increase environmental pollution caused by excessive burning of fossil fuels, resulting in CO_2 emissions. In addition, Burke et al. (2015) explored the short-term effect of GDP growth on CO_2 emissions for 189 countries finding evidence of a delayed effect between energy-economic causality dialogue: In particular, emissions tend to grow faster after a boom and more slowly after a recession. However, the results of research from Esso and Keho (2016) and Shahbaz et al. (2013) contradicts the research conducted by Akram (2012) and Widyawati et al. (2021) which states that economic growth has a negative effect on CO_2 emissions where the higher the economic growth of a country, the less CO_2 emissions will be because a country that has high economic growth, is able to reduce CO_2 emissions by paying attention to the environment and supported by various sustainable development policies that will affect the quality of the environment and can reduce CO_2 emissions.

Zhang and Tan (2016), suggest that population growth can increase the amount of CO_2 emissions. The increase in population is due to the increase in population every year. This population growth has the potential to encourage the activities of rural and urban communities. Guo et al. (2017) examined the correlation between emissions from air pollution (CO_2), logistics services, GDP, and population growth in Beijing, China. One of the findings is that population growth has only a small impact on air pollution, namely the increase in population only exacerbates air pollution immediately after the initial impact, over time it becomes a positive effect where it supports government policies to shift industry so as to reduce urban air pollution, especially in Beijing, China.

3. STATISTICAL MODEL

The study modeling the relationship simultaneously among variables: LEB gross domestic product (GDP), population growth (PG), and carbon dioxide (CO2) emissions in case of Indonesia are the interested variables to be studied. The multivariate time series or vector time series for the said variable can be written as follows:

$$Z_t = \begin{pmatrix} LEB_t \\ CO_{2t} \\ PG_t \\ GDPG_t \end{pmatrix}$$

Where LEB_t is LEB at time t, CO_{2t} is Carbon Dioxide at time t, PG_t is population Growth at time t, and $GDPG_t$ is GDP growth at time t. The data used in this study is the data for case in Indonesia from year 1950 to 2020.

3.1. Model Dynamic

In vector time series data modeling, the main objective is to explain the dynamic relationship among variables of interest and improve prediction accuracy (Pena et al., 2001; Wei, 2006; Tsay, 2010; Tsay, 2014; Wei, 2019). In multivariate time series or vector time series data, one of the assumptions is that the data are correlated, with this assumption, the model built must involve autocorrelation modeling. Therefore, one needs to understand the nature of the relationship between variables to be analyzed in order to obtain a good and appropriate model and produce accurate predictions (Brockwell and Davis, 1991; Lutkepohl, 2005; Tsay, 2014; Wei, 2019).

The first step before we analyze data time series, the condition that must be checked in the data is the assumption of stationarity, this assumption is very fundamental in time series analysis (Virginia, 2018; Warsono et al., 2019a; 2019b; Warsono, 2020). In this study, to check or to test the stationarity of the data time series can be done by checking the plot of the data and by testing using Augmented Dickey-Fuller test (ADF test). To check the stationarity of the data time series by using the Augmented Dickey-Fuller (ADF) test of parameter can be conducted by the following model:

$$\Delta Z_t = \mu + \beta_t + \delta Z_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Z_{t-1} + e_t \quad (1)$$

The null and the alternative hypotheses are as follows:

$$H_0: \delta = 0 \text{ and } H_1: \delta < 0$$

The statistical test, to test the null hypothesis, we use test-τ or Dickey-Fuller test as follows:

$$\tau = \frac{\delta}{S_\delta} \quad (2)$$

null hypothesis is rejected if the $P \leq \alpha$, for $\alpha = 0.05$ (Brockwell and Davis, 1991; Warsono et al., 2019a; 2019b; Warsono, 2020).

3.2. Calculation of a Cross-Correlation Matrix

Given the data $\{X_t \mid t = 1, 2, \ldots, T\}$, the cross-covariance matrix Γ_k can be estimated by

$$\hat{\Gamma}_k = \frac{1}{T} \sum_{t=k+1}^{T} (Z_t - \bar{Z})(Z_{t-k} - \bar{Z})', \qquad k > 0.$$

where $\bar{Z} = \frac{1}{T}\sum_{t=1}^{T} Z_t$ is the vector sample mean. The cross-correlation ρ_k is estimated by

$$\hat{\rho}_k = [\hat{\rho}_{ij}(k)] = \hat{D}^{-1}\hat{\Gamma}_k \hat{D}^{-1} \quad (3)$$

where $k \geq 0$ and $\hat{D}$ is $m \times m$ matrix diagonal from the sample standard deviation from the component of the series.

3.3. Multivariate Portmanteau Test

Hosking (1980; 1981) have adapted the univariate Ljung-Box statistic Q(m) for multivariate situations. The null hypothesis for multivariate time series is as follows:

Ho: $\rho_1=\rho_2=\ldots=\rho_k=0$,

With the alternative

Ha=$\rho i \neq 0$ for some i ∈ {1,2., k}.

The test statistic is as follows:

$$Q_m(k) = T^2 \sum_{s=1}^{k} \frac{1}{T-s} tr\left[\hat{\Gamma}_s' \hat{\Gamma}_0^{-1} \hat{\Gamma}_s \hat{\Gamma}_0^{-1} \right] \quad (4)$$

Where T is the sample size, m is the dimension of Z_t, and tr (B) is a trace of a matrix B. Under the null hypothesis, $Q_m(k)$ asymptotically has a Chi-square distribution with degrees of freedom m^2k. Reject the null hypothesis if $P < 0.05$, which means that the test confirms the interdependence of the time series at a significance level of 5%. The $Q_m(k)$ statistic is a joint test to check the first k cross-correlation matrix Z_t. If Ho is rejected, the class of vector autoregressive model should be involved in building a multivariate model for the time series data studied.

3.4. Cointegration

Engle and Granger (1987) introduced the concept of cointegration, and the development of the concept of estimation and inferential is provided by Johansen (1988). The time series Z_t is said to be integrated with order one process, I(1), if $(1-B)\,Z_t$ is stationary. If the time series data is stationary, then the process is called to be I(0). In general, the univariate time series X_t is an I(d) process, if $(1-B)^d\,Z_t$ is stationary (Hamilton, 1994; Tsay, 2010; 2014). The fact that some time series data with unit roots or nonstationary, but their linear combination can become stationary. Rachev et al. (2007) stated that cointegration is a feedback mechanism that forces processes to stay close together or large data sets are driven by the dynamics of a small number of variables, this is one of the important concepts of the theory of econometrics. The cointegration implies a long-term stable relationship between variables in forcasting (Tsay, 2014). In cointegration,

$X_t = \beta' Z_t$ is stationary,

It is mean-reverting so that m-steps ahead forecast of Z_{t+m} at the forecast origin T satisfies

$$\hat{X}_t(m) \xrightarrow[p]{} E(X_t) = \mu_x, m \to \infty$$

This means that $\beta' \hat{X}_T(m) \to \mu_X$ as m increase. Therefore, the point forecast of X_t satisfy a long-term stable forecast.

If in the Vector Autoregressive (VAR) model, there exists cointegration between variable, then the model needs to be modified into VECM (Hamilton, 1994; Lütkepohl and Krätzig, 2004; Tsay, 2010; Tsay, 2014; Wei 2006; Wei, 2019). If a cointegration relationship is present in a system of variables, the VAR model is not the most convenient model (Tsay, 2014; Wei, 2019). If there is cointegration between vector time series, then one needs to test the cointegration rank. Some methods of testing of the rank of cointegration are as follows: trace test and maximum eigenvalue test. The trace test is as follows:

$$Tr(r) = -T\sum_{i=r+1}^{k} \ln(1-\widehat{\lambda}_i) \quad (5)$$

With the null hypothesis, there is an r positive eigenvalue. In the maximum eigenvalue test, the statistic test is as follows:

$$\lambda_{\max}(r, r+1) = -\mathrm{T}\ln\left(1-\widehat{\lambda}_i\right) \quad (6)$$

3.5. Vector Autoregressive (VAR) Model

To quantitatively analyze time series data involving more than one variable (vektor time series), one of the method that can be used is Vector Autoregressive (VAR) method. The VAR method treats all variables symmetrically. One vector contains more than two variables, and on the right side, there is a lag value (lagged value) of the dependent variable as a representation of the autoregressive property in the model. The VAR(p) model can be written as follows:

$$Z_t = C + \sum_{i=1}^{p} {}_i Z_{t-i} + \varepsilon_t \quad (7)$$

Where C is constant vector, Z_t is the $n \times 1$ vector observation at the time t, Φ_j is the $n \times n$ matrix coefficient of vector Z_{t-i}, for $i = 1,2,\ldots p$, p is the lag length, and ε_t is the $n \times 1$ vector of shock.

3.6. Vector Error Correction Model

VECM is a restricted VAR model designed to be used on a nonstationary time series data (Hamilton, 1994), but has a cointegration. VECM can be used to estimate the short-term and long-term effects between the variables. The VECM(p) model with endogenous variable and has cointegration rank $r \leq k$ is as follows (Lutkepohl, 2005):

$$\Delta Z_t = C + \Pi Z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Z_{t-i} + \varepsilon_t \quad (8)$$

Where Δ is the operator of differencing, $\Delta Z_t = Z_t - Z_{t-1}$, ε_t is the $k \times 1$ vector white noise, C is $k \times 1$ vector constant, Π is the matrix coefficient of cointegration, and $\Pi = \alpha\beta'$, α = matrix adjustment, $(k \times r)$ and β = matrix cointegration $(k \times r)$, Γ_i = matrix coefficient $(k \times k)$ for the i variable endogenous, and Φ_i = matrix coefficient $(r \times k)$ for the i variable exogenous.

3.7. Normality Test of Residuals

Some methods are available to check the normality of the errors (residuals). Some methods are commonly used to check whether the errors (residuals) are normally distributed: (1) check the histogram of the residuals; (2) check the Q-Q plot of the data or error (residuals); and (3) use the statistical test, the Jarque–Bera (JB) test, with the null hypothesis that the data are normally distributed (Tsay, 2010). The JB test is calculated as follows:

$$JB = \frac{T}{6}\left[S^2 + \frac{(K-3)^2}{4}\right], \quad (9)$$

where T is the sample size, S is the expected skewness, and K is the expected excess kurtosis.

3.8. Stability Test

The stability of the VAR system is evident from the inverse roots of the AR polynomial characteristics. A VAR system is said to be stable (stationary, in both the mean and variance) if all its roots have a modulus smaller than one and all of them lie within the unit circle. The following is a description according to Lutkepohl (2005) that the VAR(p) model can be written as:

$$Z_t = c + \Phi_1 Z_{t-1} + \ldots + \Phi_p Z + \varepsilon_t \quad (10)$$

The given definition of the characteristic polynomial on the matrix is called the characteristic polynomial of the VAR(p) process, so that it is said to be stable if

$$\mathrm{Det}\,(I_{Kp} - \Phi z) = \det\,(I_K - \Phi_1 Z - \ldots - \Phi_p Z^p) \quad (11)$$

have a modulus smaller than one and all of them lie within the unit circle.

3.9. Granger Causality

In this section, the question to be investigated is whether the value of a variable can help forecast another value of a variable Z_{jt}. If it cannot, then we say that Z_{it} is not Granger causality Z_{jt}. To test that Z_{it} is Granger causality Z_{jt}, we construct the following steps:

$$Z_{jt} = \alpha_0 + \alpha_1 Z_{jt-1} + \alpha_2 Z_{jt-2} + \ldots + \alpha_p Z_{jt-p}$$
$$+\theta_1 Z_{it-1} + \theta_2 Z_{it-2} + \ldots + \theta_p Z_{it-p} + u_t \qquad (12)$$

By Ordinary Least Squares we conduct an F-test of the null hypothesis,

Ho: $\theta_1 = \theta_2 = \ldots \theta_p = 0$.

We calculate the Sum of Square Residuals (RSS) of (12),

$$RSS_1 = \sum_{t=1}^{T} \hat{u}_t^2 .$$

Under the null hypothesis, model (12) can be written as:

$$Z_{jt} = \gamma_0 + \gamma_1 Z_{jt-1} + \gamma_2 Z_{jt-2} + \ldots + \gamma_p Z_{jt-p} + a_t . \qquad (13)$$

We calculate the Sum of Square Residuals (RSS) of (13),

$$RSS_1 = \sum_{t=1}^{T} \hat{a}_t^2 .$$

The test statistic is given by:

$$S = \frac{T(RSS_0 - RSS_1)}{RSS_1} . \qquad (14)$$

S asymptotically has chi-square distribution with p degrees of freedom. We reject the null hypothesis if $P < 0.05$ (Hamilton, 1994).

3.10. Impulse Response Function (IRF)

Wei (2006) and Hamilton (1994) stated that the IRF is an analytical technique used to analyze a response of a variable due to shock in another variable. Wei (2006) stated that the VAR model can be written in vector MA (∞) as follows:

$$Z_t = \mu + \mu_t + \Psi_1 \mu_{t-1} + \Psi_2 \mu_{t-2} \qquad (15)$$

Thus, the matrix is interpreted as follows:

$$\frac{\partial Z_{t+s}}{\partial \mu_t} = \Psi_s$$

The element of the *i*th row and *j*th column indicates the consequence of the increase of one unit in innovation of variable j at time t (μ_{jt}) for the i variable at time t + s ($Z_{i,t+s}$) and fixed all other innovation. If the element of μ_t changed by δ_1, at the same time, the second element will change by $\delta_2, \ldots$, and the nth element will change by δ_n, then the common effect from all of these changes on the vector Z_{t+s} will become

$$\Delta Z_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}} \delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}} \delta_2 + \ldots + \frac{\partial X_{t+s}}{\partial u_{nt}} \delta_n = \Psi_s \delta \qquad (16)$$

The plot of the *i*th row and *j*th column of Ψ_s as a function of *s* is called IRF.

3.11. Forecasting *m*-Steps ahead

Forecasting will be performed after obtaining the best model for data vector-valued multivariate time series $\{Z_t\}$. By using the best model that fits the data, forecasting is performed directly for the next 12 periods (months).

3.12. Proportion of Prediction Error Covariance

The proportion of predicted error covariance will be used to explain the contribution of other variables to a variable in forecasting for the next several periods ahead, and the contribution of other variables to the long-term forecasting results of a variable will also be evaluated (Hamilton, 1994; Lutkepohl, 2005; Florens et al., 2007; Tsay, 2014).

4. RESULTS AND DISCUSSION

Figures 1-4 shows a plot of Indonesia's LEB, CO_2, PG, and GDPG data starting from 1950 to 2020. Figure 1 shows that the LEB data has a fairly sharp upward trend from 1950 to 2020, the upward trend is quite high, where in 1950 Indonesia's LEB was 40.43 and in 2020 Indonesia's LEB was 71.91, so there was an increase of 31.48 years. Indonesian LEB data shows that it does not have a constant mean from 1950 to 2020 and the data has an upward trend. If seen from Figure 1b it appears that the Autocorrelatin Function shows that ACF decays very slowly, this indicates that the data is not stationary.

Figure 2 shows changes in the behavior of Indonesia's CO_2 data from 1950 to 2020. From 1950 to 2020 CO_2 data has an upward and fluctuating trend. Where in 1950 Indonesia's CO_2 data was 0.133 and in 2020 it reached 2.16/capita. Figure 2 shows that Indonesia's CO_2 data is not stationary. From Figure 2b shows that the value of ACF CO_2 decays very slowly this shows that the data is not stationary. Figure 3 shows the fluctuating population growth from 1950 to 2020. The growth range is between 1.07% and 2.76%. The lowest growth occurred in 2020, namely 1.07% and the highest growth occurred in 1967, which was 2.76%. Indonesia's population growth from 1950 to 1986 was above 2.00%, and since 1987 until now population growth is below 2.00%. Population growth from 1950 to 1970 is trending up, and from 1970 to 2020 it is trending down.

From the results of the Autocorrelation Function (ACF) analysis, Figure 3b ACF shows that it decays very slowly, this shows that Indonesian PG data from 1950 to 2020 is not stationary. Figure 4 shows the Indonesia's GDP growth from 1950 to 2020 shows a fluctuating trend down and up. From 1950 to 1966 GDPG had a downward and fluctuating trend and was negative in 1957 and 1962, i.e., it grew −3.64 and −2.24 respectively in 1957 and 1962. GDP growth from 1967 to 2020 trended downward

Figure 1: (a) LEB Indonesia data series from 1950 to 2020 (b) ACF for LEB data

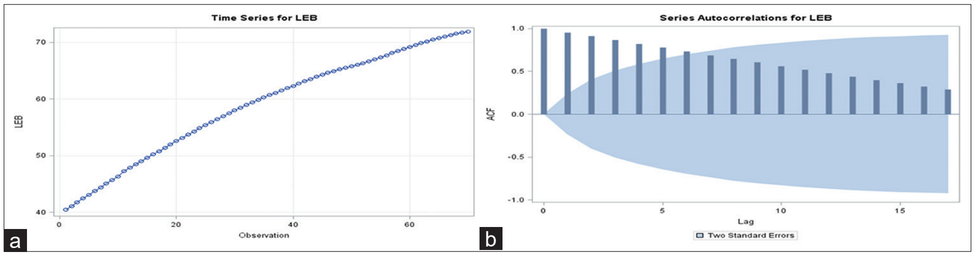


Figure 2: Indonesian CO_2 data from 1950 to 2020 (b) ACF for CO_2 data

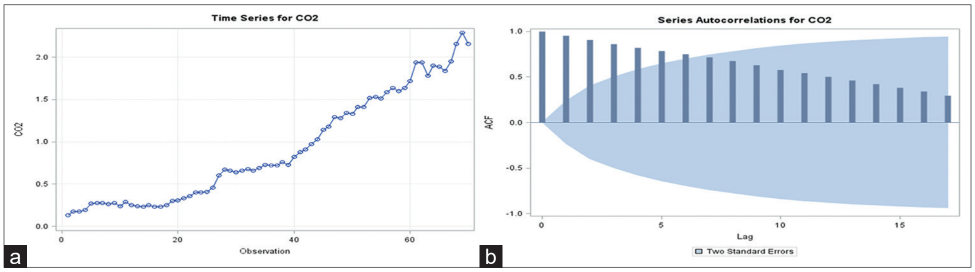


Figure 3: (a) Indonesian PG data from 1950 to 2020 (b) ACF for PG data

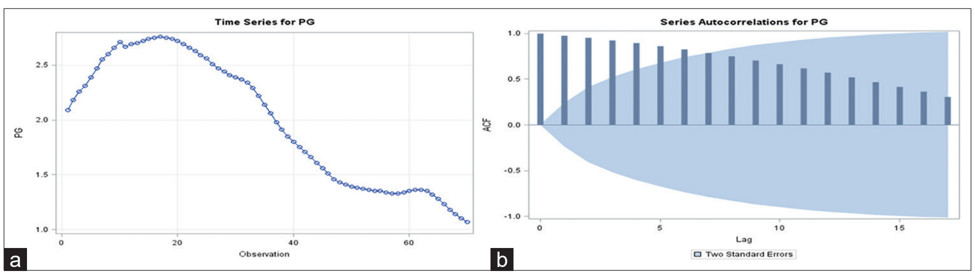
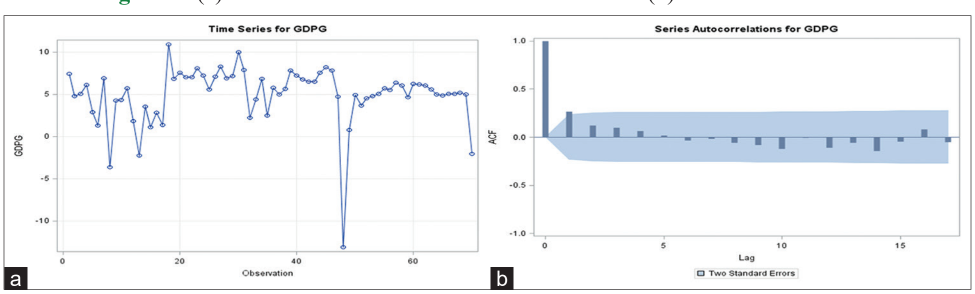


Figure 4: (a) Indonesia's GDPG data from 1950 to 2020 (b) ACF for GDPG data



and fluctuated and most of the growth in the 1967-2020 range is above 5.00%. GDPG was negative in 1997 and 2020. In 1997 there was a monetary and political crisis in Indonesia and in 2020 there was a COVID-19 pandemic. From Figure 4 ACF shows the GDPG data is relatively stationary. A nonstationary time series data for which the first differences X_t-X_{t-1} is stationary is said to have a unit root (Milhoj, 2016). Table 1 shows the results of the unit root test for the data before differences and after differences one (d = 1). Table 1 shows the results of unit root test before and after differences. Before before differencing for variable LEB where the first row is the zero mean model, which is the simplest regression, with no constant term and no trend included the null hypothesis that there is a unit root is not rejected; In the third row, if we include a linear trend, also the null hypothesis that the data has unit root is nor rejected and this results is in line with the Figure 1a, where the graph shows upward trend. After diffrencing once (d = 1), only the model with linear trend the null hypothesis is rejected. Before before differencing for variable CO_2 where the first row is the zero mean model, second row is model with single mean, and third row model with linear trend, in all situation the null hypothesis is nor rejected, this mean that the data CO_2 has a unit root. After differencing once (d = 1) CO_2 become stationary.

Before before differencing for variable PG where the first row is the zero mean model, second row is model with single mean, and third row model with linear trend, in all situation the null hypothesis is not rejected (Table 1), this mean that the data PG has a unit root. After differencing once (d = 1) PG is significant for zero mean model, and this results is in line with the Figure 3a and the data become stationary after first differencing. Before

Table 1: Dickey-fuller unit root test After first differencing (d=1)

Variables	Type	Before differencing				After differencing once (d=1)			
		Rho	P-value	τ-test	P-value	Rho	P-value	τ-test	P-value
LEB	Zero means	0.30	0.7503	0.62	0.8472	−1.10	0.4529	−1.63	0.0971
	Single means	−1.05	0.8782	−5.30	0.0001	−1.96	0.7791	−0.84	0.8008
	Trends	−0.80	0.9893	−1.50	0.8204	−27.99	0.0062	−3.63	0.0350
CO_2	Zero means	1.82	0.9811	3.27	0.9997	−62.23	<0.0001	−5.39	<0.0001
	Single means	1.00	0.9874	1.16	0.9976	−118.19	0.0001	−7.20	0.0001
	Trends	−6.59	0.6802	−1.94	0.6246	−147.41	0.0001	−7.79	<0.0001
PG	Zero means	−0.99	0.4724	−1.88	0.0582	−5.18	0.1137	−1.95	0.0494
	Single means	−1.27	0.8562	−0.64	0.8539	−7.11	0.2533	−2.57	0.1036
	Trends	−7.83	0.5749	−2.71	0.2350	−6.93	0.6513	−2.16	0.5040
GDPG	Zero means	−8.57	0.0392	−2.11	0.0345	−167.49	0.0001	−8.77	<0.0001
	Single means	−43.85	0.0007	−4.42	0.0007	−167.59	0.0001	−8.70	0.0001
	Trends	−43.90	0.0002	−4.37	0.0045	−167.32	0.0001	−8.64	<0.0001

before differencing for variable GDPG where the first row is the zero mean model, second row is model with single mean, and third row model with linear trend, in all situation the null hypothesis is rejected (Table 1), this mean that the data GDPG has no unit root, and Figure 4a shows that the data GDPG are stationary.

4.1. Test for Cross Correlation and Cointegration

Table 2 shows the results of the cross correlation test by using portmanteau test with the null hypothesis that there is no cross correlation. The results shows that there is a cross correlation up to lag-8 with $P < 0.05$. This means that there is a significant cross correlation between variables: LEB, CO_2, PG and GDPG. Therefore, in the modeling vector time series has to involve the modeling vector autoregressive. To test the presence or absence of cointegration of Indonesia's LEB, COC, PG, and GDPG data from 1950 to 2020, the Johansen test at lag optimum from the VAR model is used. If the value of trace statistics is greater than critical value, then we conclude that there are at least two cointegration relations among the variables. The null hypothesis: Ho: Rank = r (there is no cointegration) against H1: Rank > r (there is cointegration), for the values of r = 0, 1, 2, 3, 4. From Table 3, shows the results for cointegration test where for Ho: Rank = 1 (r = 1) against Ha: Rank > 1 is rejected with the P = 0.0167, and for testing Ho: Rank = 2 against Ha: Rank > 2 is not rejected with the P = 0.1219. Therefore, the rank cointegration test using trace is r = 2. So that, in modeling Indonesia's LEB, CO_2, PG and GDPG data, the VECM model will be used with the cointegration rank r = 2.

Table 4 shows that the minimum information criterion based on IACC, the the minimum value occurs in lag-2, namely IACC = −17.8196, but this value is not too far from the AICC value in lag-3 and lag-4. In this case, we will compare the VECM (2) model with cointegration rank r = 2, and the VECM (4) model with cointegration rank r = 2. Table 5 shows that based on the number of significant parameters in the two models, VECM (4) model with cointegration rank r = 2 and the VECM (2) model with rank cointegration r = 2, VECM(4) with rank cointegration r = 2 is better than VECM (2) with rank cointegration r = 2 in terms of either number of parameters which are significant, or the R-square and its P-value for the univariate model with respective LEB, CO_2, PG and GDPG as independent variable. Therefore, the model VECM(4) with rank cointegration r = 2 will be used for further analysis.

4.2. The Estimation of Parameters VECM (4) Model with Cointegration rank r = 2

Based on results from the above analysis, the VECM (4) model with cointegration rank r = 4 is chosen. The VECM (4) models with cointegration rank r = 2 is as following:

$$\Delta X_t = C + \Pi X_{t-1} + \Phi_1 \Delta X_{t-1} + \Phi_2\, X_{t-2} + \Phi_3 \Delta X_{t-3} + \varepsilon_t$$

Where:

$$X_t = \begin{bmatrix} LAB_t \\ CO_{2t} \\ PG_t \\ GDPG_t \end{bmatrix},$$

$$\Delta X_t = X_t - X_{t-1},$$

C is constant vector, Π is vector 4×4 parameter cointegration, and $\Pi = \alpha\beta'$, β is vector 4×2 cointegration, and Φ_1, Φ_2 and Φ_3 are 4×4 coefficient parameters,

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}$$

Then the estimate model VECM (4) with rank cointegration r = 2 for Indonesian data is as follows:

$$\Delta \begin{bmatrix} LAB_t \\ CO_{2t} \\ PG_t \\ GDPG_t \end{bmatrix} = \begin{bmatrix} 0.2632 \\ 0.7059 \\ 0.1096 \\ -48.7742 \end{bmatrix}$$

$$+ \begin{bmatrix} -0.0024 & -0.0101 & 0.0649 & 0.0109 \\ -0.0080 & 0.0205 & -0.0368 & 0.0083 \\ -0.0018 & 0.0119 & -0.0422 & -0.0018 \\ 0.6854 & -1.9075 & 3.8599 & -0.6317 \end{bmatrix} \begin{bmatrix} LAB_{t-1} \\ CO_{2t-1} \\ PG_{t-1} \\ GDPG_{t-1} \end{bmatrix} +$$

Table 2: Portmanteau test for cross correlations of residuals

Up To Lag	DF	Chi-square	P-value	Up to Lag	DF	Chi-square	P-value
5	16	48.27	<0.0001	9	80	96.66	0.0991
6	32	65.03	0.0005	10	96	108.78	0.1757
7	48	79.77	0.0027	11	112	118.93	0.3092
8	64	87.81	0.0258	12	128	127.13	0.5052

Table 3: Cointegration rank test using trace

H0: Rank=r	H1: Rank >r	Eigenvalue	trace	P-values	Drift in ECM	Drift in Process
0	0	0.3767	64.9537	0.0006	Constant	linear
1	1	0.2720	33.7513	0.0167		
2	2	0.1513	12.8006	0.1219		
3	3	0.0295	1.9739	0.1597		

Table 4: Minimum information criterion based on AICC

Lag	AR0	AR1	AR2	AR3	AR4	AR5
AICC	0.8794	−16.9822	−17.8196	−17.4369	−16.9832	−16.5972

Table 5: Schematic Representation of parameter estimates for comparison of VECM (2) with r=2 and VECM (4) with r=2

VECM (2), r=2	C	AR1	AR2			Univariate Model	
						R-square	P-value
LEB	+	****	+ • + •			0.9208	<0.0001
CO_2	•	****	• • • •			0.0623	0.8585
PG	•	****	+ • + •			0.8782	<0.0001
GDPG	−	****	• • + •			0.4315	<0.0001
VECM (4), r=2	**C**	**AR1**	**AR2**	**AR3**	**AR4**	**Univariate Model**	
						R-square	**P-value**
LEB	•	****	+ • +−	• • • •	• • •−	0.9228	<0.0001
CO_2	+	****	• • • •	•−• •	• • •−	0.2728	0.3434
PG	•	****	+ • + •	• • • •	• • • +	0.8884	<0.0001
GDPG	−	****	+ • + •	• • • •	•−• •	0.4682	0.0040

+ is>2*std error,−is < -2*std error, • is between, *is N/A

$$\begin{bmatrix} 0.3472 & -0.1604 & 1.2133 & -0.0061 \\ -0.1481 & -0.1400 & 0.1247 & -0.0063 \\ 0.1226 & 0.0311 & 0.6700 & 0.0012 \\ 21.0299 & -7.2640 & 57.9961 & -0.1451 \end{bmatrix} \Delta \begin{bmatrix} LAB_{t-1} \\ CO_{2t-1} \\ PG_{t-1} \\ GDPG_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} 0.0577 & -0.0867 & 0.4120 & -0.0020 \\ -0.0155 & -0.4749 & 0.2308 & -0.0030 \\ 0.0408 & 0.0134 & 0.1029 & 0.0007 \\ -6.1383 & -3.8108 & 10.7694 & -0.1226 \end{bmatrix} \Delta \begin{bmatrix} LAB_{t-2} \\ CO_{2t-2} \\ PG_{t-2} \\ GDPG_{t-2} \end{bmatrix} +$$

$$\begin{bmatrix} -0.0040 & -0.1685 & -0.7008 & -0.0042 \\ -0.1943 & -0.1806 & -0.6684 & -0.0037 \\ -0.0041 & 0.0128 & -0.1843 & 0.0010 \\ -0.8107 & -12.8336 & -48.5820 & -0.0798 \end{bmatrix}$$

$$\Delta \begin{bmatrix} LAB_{t-3} \\ CO_{2t-3} \\ PG_{t-3} \\ GDPG_{t-3} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}$$

And the covariance innovation is:

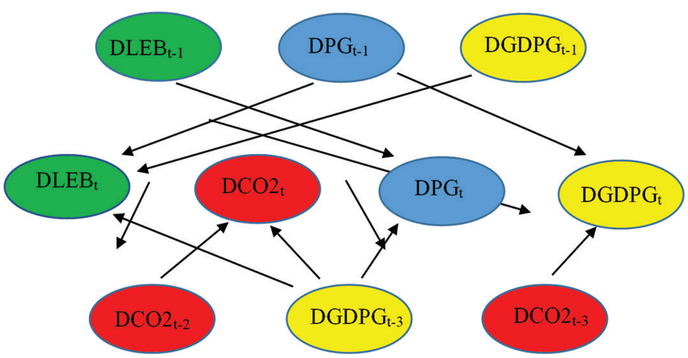
$$Var \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} = \begin{bmatrix} 0.0016 & -0.0001 & -0.0003 & 0.0314 \\ -0.0001 & 0.0028 & 0.0001 & 0.0308 \\ -0.0003 & 0.0001 & 0.0001 & -0.0041 \\ 0.0314 & 0.0308 & -0.0041 & 8.8940 \end{bmatrix}$$

Figure 5 shows that LEBt is significantly influenced by LEBt-1, PGt-1, GDPGt-1 and GDPGt-3 this shows that information on LEB 1 year before, PG information 1 year before, and GDPG one and 3 years before significantly affect current LEB_t; Figure 5 shows that CO_{2t} is significantly affected by CO_{2t-2}, and $GDPG_{t-3}$, this shows that information on CO_2 2 years earlier, and GDPG 3 years earlier significantly affects current ΔCO_2; PG_t was significantly affected by LEB_{t-1}, PG_{t-1}, and $GDPG_{t-3}$, this indicates that information on LEB and PG 1 year earlier and information on GDPG 3 years earlier significantly affected current PG; $GDPG_t$ was significantly affected by LEB_{t-1}, PG_{t-1}, and CO_{2t-3}, this indicates that information on LEB and PG 1 year earlier and information on ΔCO_2 3 years earlier significantly affected current GDPG.

4.3. Granger Causality Test

Table 6 shows the results of the Granger-causality test. Granger causality test is used to test whether there is a causal relationship between one group variable and another group variable. The null hypothesis in the granger-causality wald test is that group 1 is influenced by itself and not by variables in group 2. Granger causality test based on wald test and has Chi-square distribution or F-distribution. Based on Table 6, the test 2, where the variable in group 1 is LEB and the variable in group 2 is PG, the P = 0.0053, which is significant. Therefore, the null hypothesis that the LEB variable is influenced by itself and not influenced by PG is rejected. So that it can be concluded that the variable LEB is not only influenced by past information of itself but is also influenced by current and past information of PG. Based on Table 6, the test 3, where the variable in group 1 is LEB and the variable in group 2 is GDPG, the P = 0.0135, which is significant. Therefore, the null hypothesis that the LEB variable is influenced by itself and not influenced by GDPG is rejected. So that it can be concluded that the variable LEB is not only influenced by past information of itself but is also influenced by current and past information of GDPG. Based on Table 6, the test 7, where the variable in group 1 is PG and the variable in group 2 is CO_2, the P = 0.0390, which is significant. Therefore, the null hypothesis that the variable PG is influenced by itself and not influenced by CO_2 is rejected. So that it can be concluded that the variable PG is not only influenced by past information of itself but is also influenced by current and past information of CO_2. Based on Table 6, the test 8, where the variable in group 1 is PG and the variable in group 2 is LEB, the P < 0.0001, which is significant. Therefore, the null hypothesis that the variable PG is influenced by itself and not influenced by LEB is rejected. So that it can be concluded that the variable PG is not only influenced by past information of itself but is also influenced by current and past information of LEB.

Figure 5: Arrows ($X \rightarrow Y$) indicates there exists a significant influence from variable X to variable Y.
Note: (LEB^{**}_{t-1}, PG^{**}_{t-1}, $GDPG^{**}_{t-1}$, $GDPG^{**}_{t-3}$) $\rightarrow LEB_t$; ($CO2^{***}_{t-2}$, $GDPG^{*}_{t-3}$) $\rightarrow CO2_t$;) LEB^{***}_{t-1}, PG^{***}_{t-1}, $GDPG^{**}_{t-3}$) $\rightarrow PG_t$; and (LEB^{**}_{t-1}, PG^{*}_{t-1}, $CO2^{*}_{t-3}$) $\rightarrow LEB_t$; where
* significant at $\alpha = 0.10$, ** significant at $\alpha = 0.05$, and *** significant at $\alpha = 0.01$



4.4. Impulse Response Function (IRF)

Figure 6 is a graph of the IRF if there is a shock of one standard deviation in the LEB and its effect on the LEB variables themselves, CO_2, PG and GDPG. If the graph from the IRF moves to the original equilibrium (zero) line, this means that the response of a variable to shock other variables disappears, so that the shock has no permanent effect on that variable. Figure 6 also presents the confidence interval of the effect caused by shock on one variable. The shock of one standard deviation in LEB causes LEB to respond weakly but significantly, this is shown in Figure 6 where the confidence interval up to 15 years does not include zero, the equilibrium point. The response during the first 7 years fluctuated around 0.02, namely 0.0485, 0.0198, 0.0162, 0.0202, 0.0233, 0.0221, and 0.0139, and in the 8th year onwards

Table 6: Granger causality wald test

Test	Group Variables	Null hypothesis	DF	Chi-squares	P-values	Conclusion
1	Group 1: LEB variables Group 2: Variable CO_2	Variable LEB is influenced by itself and not influenced by CO_2	4	1.33	0.8563	Non-significant
2	Group 1: LEB variables Group 2: PG Variables	Variable LEB is influenced by itself and not influenced by PG	4	14.71	0.0053	Significant**
3	Group 1: LEB variables Group 2: GDPG Variables	Variable LEB is influenced by itself and not influenced by GDPG	4	12.58	0.0135	Significant**
4	Group 1: Variable CO_2 Group 2: LEB variables	Variable CO_2 is influenced by itself and not influenced by LEB	4	4.36	0.3598	Non-significant
5	Group 1: Variable CO_2 Group 2: PG Variables	Variable CO_2 is influenced by itself and not influenced by PG	4	7.38	0.1171	Non-significant
6	Group 1: Variable CO_2 Group 2: GDPG Variables	Variable CO_2 is influenced by itself and not influenced by GDPG	4	7.02	0.1350	Non-significant
7	Group 1: PG Variables Group 2: Variable CO_2	Variable PG is influenced by itself and not influenced by CO_2	4	10.09	0.0390	Significant**
8	Group 1: PG Variables Group 2: LEB variables	Variable PG is influenced by itself and not influenced by LEB	4	26.26	<0.0001	Significant**
9	Group 1: PG Variables Group 2: GDPG Variables	Variable PG is influenced by itself and not influenced by GDPG	4	6.14	0.1892	Non-significant
10	Group 1: GDPG Variables Group 2: LEB variables	Variable GDPG is influenced by itself and not influenced by LEB	4	2.95	0.5663	Non-significant
11	Group 1: GDPG Variables Group 2: PG Variables	Variable GDPG is influenced by itself and not influenced by PG	4	5.59	0.2320	Non-significant
12	Group 1: GDPG Variables Group 2: Variable CO_2	Variable GDPG is influenced by itself and not influenced by CO_2	4	2.19	0.7003	Non-significant

Figure 6: IRF for shock in variable LEB

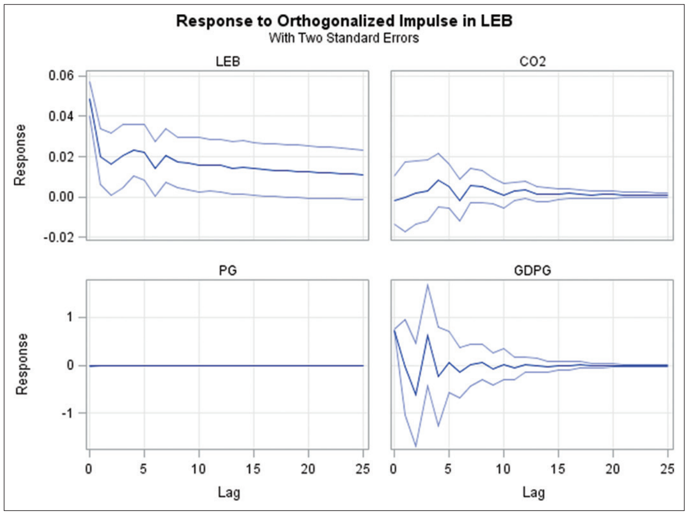
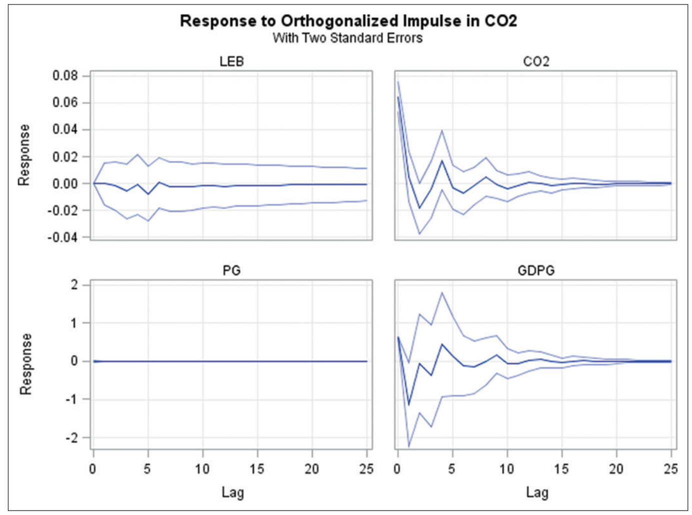


Figure 7: IRF for shock in variable CO_2



the impact weakened. The shock of one standard deviation on the LEB causes CO_2 to respond in the following years and in the next 10 years the response is weak and fluctuates around zero, namely −0.0017, 0.0000, 0.0020, 0.0029, 0.0080, 0.0052, −0.0017, 0.0055, 0.0048 and 0.0029. The shock of one standard deviation in LEB causes PG to respond in the following years and in the next 10 years the response is weak negative and fluctuates around zero, namely −0.0112, −0.0061, −0.0059, −0.0052, −0.0062, −0.0054, −0.0033, −0.0043, −0.0031, and −0.0027. The shock of one standard deviation in the LEB caused GDPG to respond in the following years. At 7 years the average response fluctuates around zero, namely 0.7364, −0.0370, −0.6118, 0.6140, −0.2311, 0.0681, and −0.1456, and in the 8th year onwards it weakens towards equilibrium.

Figure 7 is a graph of the IRF if there is a shock of one standard deviation in CO_2 and its effect on the variables LEB, CO_2 itself, PG and GDPG. If the graph from the IRF moves to the original equilibrium (zero) line, this means that the response of a variable to shock other variables disappears, so that the shock has no permanent effect on that variable. Figure 7 also presents the confidence interval of the effect caused by Shoch on one variable. The shock of one standard deviation of CO_2 impact on LEB and weak PG is shown in Figure 7. The shock of one standard deviation of CO_2 causes CO_2 to respond less in the following years. In the first 6 years the CO_2 response was 0.0047, 0.0005, −0.0186, −0.0043, 0.0171, and −0.0028. The shock of one standard deviation in CO_2 caused GDPG to respond in the following years. The figure shows that the impact in the first 10 years fluctuates and thereafter weakens towards equilibrium. The impact in the first 10 years is 0.6339, −1.1264, −0.0537, −0.3771, 0.4429, 0.1479, −0.1169, −0.1472, −0.0021, and 0.1778. The 11th year onwards the impact weakens and goes to balance.

Figure 8 is a graph of the IRF if there is a shock of one standard deviation in PG and its effect on the variables LEB, CO_2, PG itself and GDPG. If the graph from the IRF moves to the original equilibrium (zero) line, this means that the response of a variable to shock other variables disappears, so that the shock has no permanent effect on that variable. Figure 8 also presents the confidence interval of the effect caused by shock on one variable. The shock of one standard deviation in PG has a weak impact on LEB, this is shown in Figure 8 where the impact is positive, but <0.02. In the next 7 years the impacts are 0.0000, 0.0118, 0.0209, 0.0108, 0.0140, 0.0134, and 0.0178. The shock of one standard deviation in PG causes CO_2 to respond in the following years. The response in the next 6 years fluctuates around zero and is weak, namely 0.0000, 0.0036, 0.0031, −0.0043, −0.0061, and −0.0030. And in the following years the impact weakened. A shock of one standard deviation in PG has a weak impact on PG itself, this is shown by the IRF graph which is flat around zero. A shock of one standard deviation in PG causes GDPG to respond in the first 7 years and after that the response weakens towards equilibrium. In the first 7 years the impacts were −0.1501, 0.6150, 0.4146, −0.6975, 0.0212, 0.0708, and 0.0663.

Figure 8: IRF for shock in variable PG

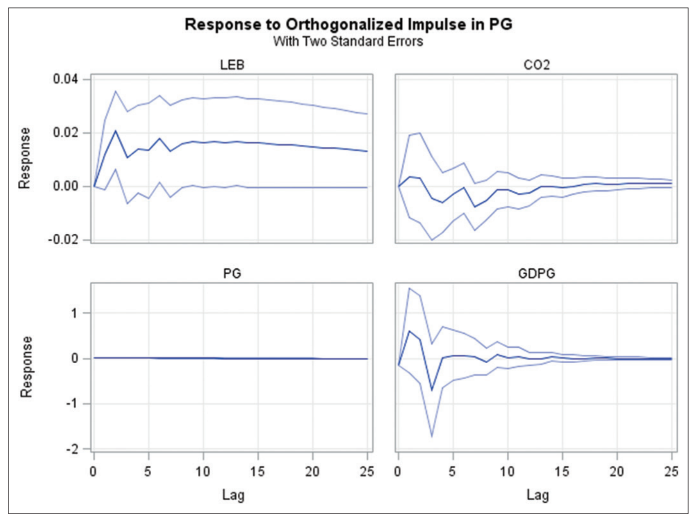
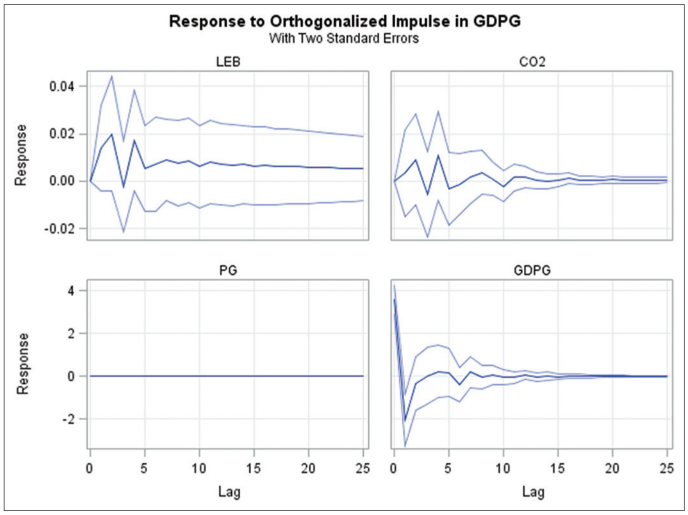


Figure 9 is a graph of the IRF if there is a shock of one standard deviation in GDPG and its effect on the variables LEB, CO_2, PG itself and GDPG. If the graph from the IRF moves to the original equilibrium (zero) line, this means that the response of a variable to shock other variables disappears, so that the shock has

Figure 9: IRF for shock in variable GDPG



no permanent effect on that variable. Figure 9 also presents the confidence interval of the effect caused by Shoch on one variable. The shock of one standard deviation in GDPG impact on LEB is weak, this is shown in Figure 9 where the response is very small. For the next 5 years the responses are 0.0000, 0.0139, 0.0200, −0.0020, and 0.0169. The 6th year onwards the impact weakens. The shock of one standard deviation in GDPG caused CO_2 to respond in the following years. For the next 4 years the response will fluctuate, namely 0.0000, 0.0033, 0.0091, and −0.0053. The 5th year onwards the impact weakens. The shock of one standard deviation on GDPG has a weak impact on PG, this is indicated where PG does not respond and the graph is flat around zero. The shock of one standard deviation on GDPG, the impact on GDPG itself is quite large in the first 9 years the impact is 3.5921, −2.0464, −0.3393, 0.0334, 0.2305, 0.1761, −0.3842, 0.1978 and −0.0484. And the 10th year and so on the impact weakened.

4.5. Forecasting and Proportion Prediction Error Covariance Decomposition

The VECM(4) model with cointegration rank r = 2 is the best model and is suitable for Indonesia's LEB, CO_2, PG and GDPG data. Figure 10a shows that the LEB model shows that the predicted value and the actual data value are very close to each other. This shows that the model obtained is reliable and can be used for further analysis, especially for forecasting and further analysis of the behavior of the LEB variable. Figure 11a shows that the CO_2 model shows that the predicted value and the actual data value are very close to each other. This shows that the obtained model is reliable and can be used for further analysis, especially for forecasting, analysis and further study of CO_2. Figure 12a shows that the PG model shows that the predicted value and the actual data value are very close to each other. This shows that the obtained PG model is reliable and can be used for further analysis, especially for forecasting, analysis and further study of PG. Figure 13a shows that the GDPG model predicted values and actual data values are very close to each other. This shows that the GDPG model obtained is reliable and can be used for further analysis, especially for forecasting, analysis and further studies on GDPG.

The LEB forecast value for the next 10 years from Table 7 and Figure 10a shows the forecast value is relatively increasing. The further away the forecast is, the larger the standard residual value (Table 7), and the farther the forecast, the larger the confidence interval (Figure 10b). Forecasting values for the next 10 years are 72.0953, 72.2736, 72.4861, 72.6511, 72.8220, 72.9993, 73.1870, 73.3698, 73.5433, and 73.7209. So in the next 10 years, Indonesia's LEB will increase by 1.6276 years.

From the proportion prediction error covariance decomposition of LEB, Figure 10b, it appears that for the next 10 years forecasting, it is explained by itself (LEB), CO_2, PG and GDPG, respectively, as follows. For the 1st year 100% of the variation of LEB are explained by LEB itself; In the 2nd year explained by LEB, PG and GDPG are 91.38%, 3.81% and 4.03% respectively; In the forecasting for the next 3 years the variation of LEB are explained by LEB, CO_2, PG, and GDPG are 74.86%, 1.08%, 13.04% and 11.00% respectively; In the forecasting for the next 4 years the variation of LEB are explained by LEB, CO_2, PG, and GDPG are 65.37%, 2.09%, 21.35% and 11.17% respectively; For the long-term forecasting above 10 years of LEB, the variation of LEB are explained by LEB, CO_2, PG, and GDPG are 44.38%, 2.03%, 37.20% and 16.37% respectively:

The forecast value of CO_2 for the next 10 years from Table 7 and Figure 11a shows the forecast value is increasing. The further away the forecast is, the larger the standard residual value (Table 7), and the farther the forecast, the larger the confidence interval (Figure 11b). Forecasting values for the next 10 years are 2.1766, 2.3010, 2.4038, 2.4104, 2.4400, 2.5110, 2.5867, 2.6344, 2.6710, and 2.7235. So in the next 10 years, Indonesia's CO_2 will increase by 0.4225. Judging from the proportion prediction error covariance decomposition of CO_2, Figure 11b, it appears that for the next 4 years forecasting, the 1st year CO_2 is explained by CO_2 itself as big as 99.58% and other variables have not contributed; In the 2nd year the variation of CO_2 are explained by LEB, CO_2 are 1.57%, and 97.80% respectively, and other variables have not contributed. In the 3rd year CO_2 is explained by the error covariances of LEB, CO_2, and GDPG as big as 1.98%, 94.58%, and 3.23%, respectively. In the 4th year CO_2 is explained by the error covariances of LEB, CO_2, and GDPG of 2.39%, 93.61%, and 3.75%, respectively. For the long-term forecasting above 10 years of CO_2, the variation of CO_2 are explained by LEB, CO_2, PG, and GDPG are 3.83%, 84.11%, 6.02% and 6.04% respectively:

The PG forecast value for the next 10 years from Table 7 and Figure 12a shows that the forecast value is relatively decreasing in the next 10 years. The further away the forecast is, the larger the standard residual value (Table 7), and the farther the forecast, the larger the confidence interval (Figure 12b). Forecasting values for the next 10 years are 1.0371, 1.0055, 0.9717, 0.9528, 0.9352, 0.9195, 0.9033, 0.8910, 0.8826, and 0.8753. From the proportion prediction error covariance decomposition of PG, Figure 12b, it appears that for forecasting PG for the next 4 years, the 1st year is explained by LEB, PG is 42.77%, and 57.17%, respectively. In the 2nd year it was explained by the error covariance of LEB, CO_2, and PG which were 30.71%, 1.29%, and 67.46%, respectively. In the 3rd year CO_2 is explained by the error covariances of LEB, CO_2, PG and GDPG

Figure 10: (a) Model and Forecast for LEB, (b) Proportion prediction error covariance decomposition LEB

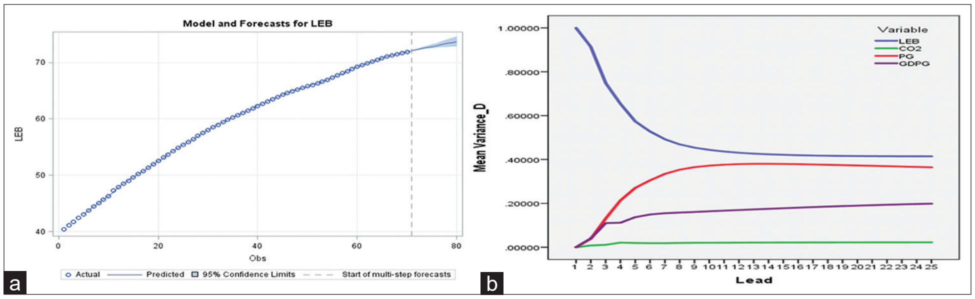


Figure 11: (a) Model and Forecast for CO_2, (b) Proportion prediction error covariance decomposition CO_2

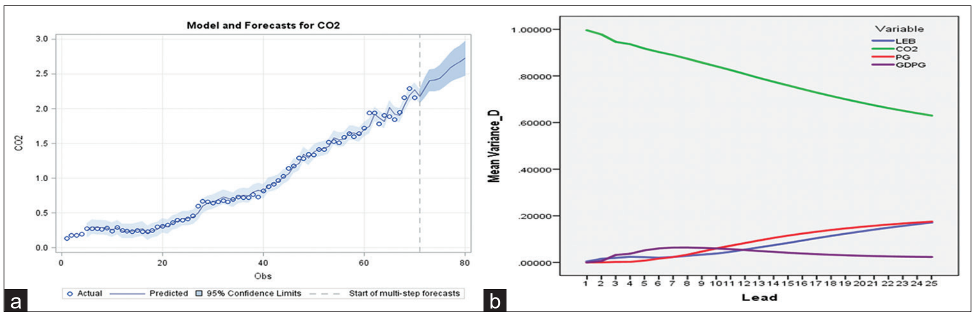


Figure 12: (a) Model and forecast for PG, (b) Proportion prediction error covariance decomposition PG

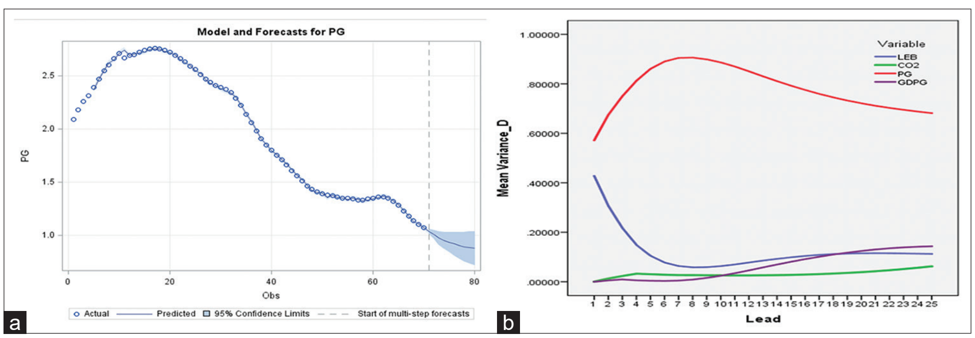
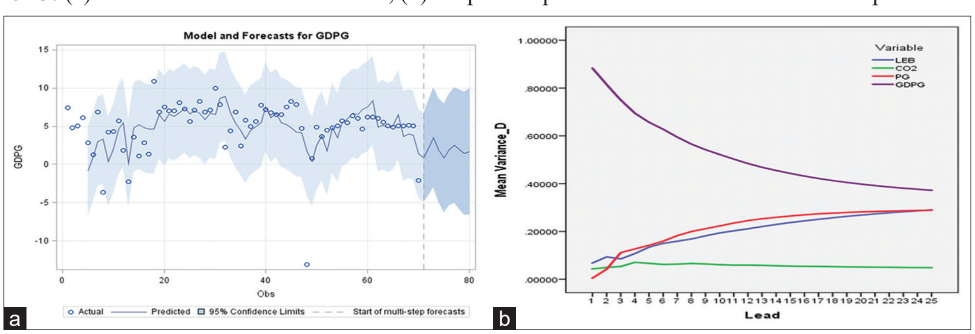


Figure 13: (a) Model and forecast for GDPG, (b) Proportion prediction error covariance decomposition GDPG



which are 21.76%, 2.34%, 74.96% and 1.00%, respectively. In the 4th year CO_2 is explained by the error covariances of LEB, CO_2, PG and GDPG which are 14.91%, 3.27%, 81.25% and 0.55%, respectively. For the long-term forecasting above 10 years of PG, the variation of PG are explained by LEB, CO_2, PG, and GDPG are 6.33%, 2.58%, 88.65% and 2.43%, respectively.

The GDPG forecast value for the next 10 years from Table 7 and Figure 13a shows the forecast value is relatively increasing in the next 10 years. The further away the forecast is, the larger the standard residual value (Table 7), and the farther the forecast, the larger the confidence interval (Figure 13a). Forecasting values for the next 10 years are 0.8494, 2.2485, 3.5195, 1.8656, 0.8203, 1.9225, 2.4819, 1.9898, 1.4562, and 1.6966.

From the proportion prediction error covariance decomposition of GDPG, Figure 13b, it appears that for forecasting GDPG for the next 4 years, the first the variation of GDPG are explained

Table 7: Forecasting of LEB, CO_2, PG, GDPG for the next 10 years

Var	Obs	Forecasts	Standard error	95% confidence limits		Var	Obs	Forecasts	Standard error	95% confidence limits	
LEB	71	72.0953	0.0403	72.0162	72.1745	PG	71	1.0371	0.0123	1.0130	1.0612
	72	72.2736	0.0658	72.1445	72.4027		72	1.0055	0.0215	0.9634	1.0477
	73	72.4861	0.0970	72.2958	72.6764		73	0.9717	0.0311	0.9107	1.0327
	74	72.6511	0.1315	72.3933	72.9089		74	0.9528	0.0401	0.8741	1.0314
	75	72.8220	0.1743	72.4803	73.1637		75	0.9352	0.0486	0.8399	1.0305
	76	72.9993	0.2234	72.5613	73.4373		76	0.9195	0.0565	0.8087	1.0303
	77	73.1870	0.2768	72.6444	73.7295		77	0.9033	0.0636	0.7786	1.0281
	78	73.3698	0.3344	72.7143	74.0253		78	0.8910	0.0702	0.7533	1.0288
	79	73.5433	0.3958	72.7676	74.3191		79	0.8826	0.0764	0.7328	1.0325
	80	73.7209	0.4606	72.8181	74.6236		80	0.8753	0.0821	0.7143	1.0364
CO_2	71	2.1766	0.0537	2.0714	2.2819	GDPG	71	0.8494	2.9823	−4.9957	6.6946
	72	2.3010	0.0730	2.1577	2.4442		72	2.2485	3.1819	−3.9879	8.4849
	73	2.4038	0.0794	2.2481	2.5594		73	3.5195	3.3391	−3.0250	10.0640
	74	2.4104	0.0831	2.2475	2.5733		74	1.8656	3.4891	−4.9728	8.7042
	75	2.4400	0.0921	2.2594	2.6205		75	0.8203	3.6188	−6.2724	7.9131
	76	2.5110	0.1010	2.3129	2.7091		76	1.9225	3.7435	−5.4147	9.2598
	77	2.5867	0.1074	2.3761	2.7973		77	2.4819	3.8639	−5.0913	10.0551
	78	2.6344	0.1128	2.4133	2.8555		78	1.9898	3.9894	−5.8293	9.8089
	79	2.6710	0.1191	2.4375	2.9046		79	1.4562	4.1144	−6.6079	9.5203
	80	2.7235	0.1263	2.4758	2.9712		80	1.6966	4.2407	−6.6149	10.0082

by LEB, CO_2, PG and GDPG are 6.82%, 4.38%, 0.50% and 88.30%, respectively. In the 2nd year the variation of GDPG are explained by LEB, CO_2, PG and GDPG are 9.37%, 4.96%, 4.22% and 81.43%, respectively. In the 3rd year the variation of GDPG is explained by LEB, CO_2, PG and GDPG of 8.51%, 5.36%, 11.12% and 74.99%, respectively. In the 4th year the variation of GDPG is explained LEB, CO_2, PG and GDPG are 10.74%, 7.10%, 12.70% and 69.44%, respectively. For the long-term forecasting above 10 years of GDPG, the variation of GDPG are explained by LEB, CO_2, PG, and GDPG are 19.38%, 6.09%, 22.30% and 52.21%, respectively.

5. DISCUSSION

This study aims to analyze the relationship between LEB, population growth, economic growth (GDP) and CO_2 emissions in Indonesia. The results of statistical analysis show that the life expectancy (LEB) of people in Indonesia has a simultaneous relationship with population growth in Indonesia, and population growth has a significant effect on life expectancy. These results are in line with the research of Ali and Ahmad (2014) in Aman. However, it is different from Popoola (2018) which states that population growth has no effect on life expectancy. On the other hand, increasing life expectancy has an effect on increasing population growth. Population growth in Indonesia in 2021 is 1.17%, with a life expectancy of 73.5 years. On the other hand, the life expectancy of the Indonesian population is also influenced by economic growth. Economic growth can increase life expectancy as a result of increasing the welfare of the population with a healthier lifestyle. This result is supported by the fact that the life expectancy of the Indonesian population has increased significantly from year to year. In 2017 the life expectancy of the Indonesian population is 72.9 to 73.5 in 2021, an increase of 0.6 points. In this study, there was no simultaneous or partial relationship between CO_2 and life expectancy. This means that the increase in life expectancy in Indonesia can occur as a result of public welfare (GDP), education levels and increased health spending. These results can be associated with research results (Bilas et al., 2014; Jaba et al., 2014). Conditions in Indonesia are supported by research by Amuka et al. (2018) in Nigeria, that there is no correlation between CO_2 and life expectancy.

In Indonesia, the level of CO_2 emissions in 2019 was generated from energy producers, transportation, manufacturing and construction industries. CO_2 emissions per capita in Indonesia are 2.29 metric tons higher than India and Malaysia (World Bank, 2022). The results of the study found that CO_2 emissions in the short term will increase. This increase is the result of Granger CO_2 causality and economic growth over time. In theory, population growth can increase greenhouse CO_2 emissions through increased human activities. This opinion refers to the results of research by Liddle (2015), Wang et al. (2017) that an increase in population density can encourage an increase in energy use. In India, population density has a positive impact on energy consumption so that CO_2 emissions increase both in the short and long term (Ohlan, 2015). However, in Indonesia, the condition is reversed. CO_2 significantly affects population growth. The negative effect of CO_2 on the decline in population growth occurs because of an unhealthy environment, air pollution, and polluted water. It is possible that the decline in population growth is not only due to CO_2 emissions, but also because of the government program that proclaimed happy and prosperous small families. On the other hand, population growth in Indonesia has no correlation with economic growth.

The relationship between economic growth and CO_2 emissions has been explored by many researchers, including Begum et al. (2015) Manu and Sulaiman (2017); Dong et al. (2018); Dong et al. (2018); Zaidi and Ferhi (2019), they found that the increasing use of energy goes hand in hand with the economic growth of a country. However, the results of research in Indonesia there is no relationship between CO_2 emissions and economic growth

(GDP). This can happen because Indonesia's economic growth is supported by high export commodities from the plantation and agricultural sectors which have an important role in economic growth such as palm oil, rubber, coconut oil, plywood whose production processes produce fewer CO_2 emissions compared to coal, natural gas and industry. The results of this study are in line with Aiyetan and Olomola (2017) in Nigeria that in the short term economic growth there is no relationship between CO_2 emissions. However, in the long term, the relationship between economic growth and CO_2 emissions will increase (Mohiuddin et al., 2016).

6. CONCLUSION AND RECOMENDATIONS

Analysis and modeling results found that the best model that fits the data is the dynamic vector error correction model (VECM) order 4 with cointegration rank r = 2. Based on this best modet, VECM(4) with cointegration rank r = 2, it were found that LEB and PG are mutually Granger-Causality (bidirectional Granger-Causality), this means that changes in LEB are not only influenced by itself, but also influenced by past information of PG; Likewise, changes in PG are not only influenced by itself, but also influenced by past information of LEB. CO_2 is Granger-Causality to PG, this means that changes in PG are not only influenced by itself, but also is influenced by past information of CO_2. GDPG is Granger-Causality to LEB, this means that changes in LEB are not only influenced by itself, but also is influenced by past information of GDPG. From the results of the impulse response function (IRF) analysis, if a shock of one standard deviation occurs in the LEB, CO_2, PG, or GDPG variables, the LEB, CO_2, and GDPG variables give a fluctuating response in the future, while the PG variable does not affect, PG remains stable up. From the LEB forecasting results, the trend is rising; the forecasting CO_2 the trend is increase; the forcasting PG the value are positive, but the trend is decreasing; the forecasting of GDPG the trend is decreasing the next 10 years. From the analysis of the proportion prediction error covariance model VECM(4) with cointegration rank r = 2, it can be concluded that for long-term forecasting of one variable, other variables also have an effect.

Based on the best model resulting from the research, the Indonesian government should be able to make policies in an effort to increase LEB by taking into account related variables such as population growth and economic growth. The prediction from the resulting model is that CO_2 will increase in the future, the government makes policies to carry out economic activities that can reduce CO_2, such as developing green finance, using Biodiesel, and using green products. Meanwhile, to increase economic growth (GDPG), the government can carry out downstream in an effort to improve product quality, increase exports, strengthen technology and entrepreneurship, and improve the quality of human resources.

This research has limitations in terms of using time series data with the Granger model. Future researchers can consider adding other variables, such as health facilities, education level, and gender. Additionally, they can also explore research related to LEB using modeling approaches beyond time series analysis.

7. ACKNOWLEDGEMENTS

The authors would like to thank to HETI Project Universitas Lampung for the financial support for this study through Innovation and Collaboration Research Program (International Scheme) with Contract Number: 6058/UN26/HK.01.03/2022 on 03 August 2022.

REFERENCES

Acemoglu, D., Johnson, S. (2007), Disease and development: The effect of life expectancy on economic growth. Journal of Political Economy, 115, 925-985.

Ademoh, S.E (2017), Population growth and life expectancy: Predicting the relationship. Scientific Modeling and Research, 2(1), 19-36.

Aiyetan, I.R., Olomola, P.A. (2017), Environmental degradation, energy consumption, population growth and economic growth: Does environmental kuznets curve matter for Nigeria? Economic and Policy Review, 16(2).

Akinlo, A.E. (2008), Energy consumption and economic growth: Evidence from 11 Sub-Saharan African countries. Energy Economics, 30(5), 2391-2400.

Akram, N. (2012), Is climate change hindering economic growth of ASIAN economies? Asia-Pacific Development Journal, 19(2), 1-18.

Ali, A., Ahmad, K. (2014), The impact of socio-economic factors on life expectancy for sultanate of Oman: An empirical analysis. Middle East Journal of Scientific Research 22(2), 218-224.

Al-Mulali, U., Lee, J.Y.M., Mohammed, A.H., Sheau-Ting, L. (2013), Examining the link between energy consumption, carbon dioxide emission, and economic growth in Latin America and the Caribbean. Renewable and Sustainable Energy Reviews, 26, 42-48.

Amuka, J.I., Asogwa, F.O., Ugwuanyi, R.O., Omeje, A.N., Onyechi, T. (2018), Climate change and life expectancy in a developing country: Evidence from greenhouse gas (CO_2) emission in Nigeria. International Journal of Economics and Financial Issues, 8(4), 113.

Apergis, N., Payne, J.E. (2009), Energy consumption and economic growth in Central America: Evidence from a panel cointegration and error correction model. Energy Economics, 31(2), 211-216.

Audi, M., Ali, A. (2016), Socio-economic status and life expectancy in Lebanon: An empirical analysis. Archives of Business Research, 5(11), 159-170.

Aye, G.C, Edoja, P.E. (2017), Effects of economic growth on emission in developing countries: Evidence from a dynamic panel threshold model. Cogent Economics and Finance, 5, 1-22.

Baker, E., Mason, K., Bentley, R., Mallett, S. (2013), Exploring the bi-directional relationship between health and housing in Australia. Urban Policy and Research, 32(1), 71-84.

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., Farhani, S. (2018), How economic growth, renewable electricity and natural resources contribute to CO_2 emissions? Energy Policy, 113, 356-367.

Barnes, M., Cullinane, C., Scott, S., Silvester, S. (2013), People Living in Bad Housing: Numbers and Health Impacts. London: In Shelter.

Begum, R.A., Sohag, K., Abdullah, S.M.S., Jaafar, M. (2015), CO_2 emissions, energy consumption, economic and population growth in Malaysia. Renewable and Sustainable Energy Reviews, 41, 594-601.

Bilas, V., Franc, S., Bošnjak, M. (2014), Determinant factors of life expectancy at birth in the European Union countries. Collegium Antropologicum, 38(1), 1-9.

Brockwell, P.J., Davis, R.A. (1991), Time Series: Theory and Methods. 2nd ed. NewYork: Springer Verlag.

Burke, P.J., Shahiduzzaman, M., Stern, D.I. (2015), Carbon dioxide emissions in the short run: The rate and sources of economic growth matter. Global Environmental Change, 33, 109-121.

Canudas-Romo, V., Becker, S. (2011), The crossover between life expectancies at birth and at age one: The imbalance in the life table. Demographic Research, 24, 113-144.

Chang, C.K., Hayes, R.D., Perera, G., Broadbent, M.T.M., Fernandes, A.C., Lee, W.E., Stewart, R. (2011), Life expectancy at birth for people with serious mental illness and other major disorders from a secondary mental health care case register in London. PLoS One, 6, e19590.

Chen, Z., Ma, Y., Hua, J., Wang, Y., Guo, H. (2021), Impacts from economic development and environmental factors on life expectancy: A comparative study based on data from both developed and developing countries from 2004 to 2016. International Journal of Environmental Research and Public Health, 18(16), 8559.

Claessens, S., Feijen, E. (2007), Financial Sector Development and the Millennium Development Goals No. 89. Washington, DC: World Bank Publications.

Das-Munshi, J., Chang, C.K., Dregan, A., Hatch, S.L., Morgan, C., Thornicroft, G., Stewart, R., Hotopf, M. (2020), How do ethnicity and deprivation impacts on life expectancy at birth in people with serious mental illness? Observational study in the UK. Psychological Medicine, 51, 2581-2589.

Di Lorenzo, G., Barbera, P., Ruggieri, G., Witton, J., Pilidis, P., Probert, D. (2013), Pre-combustion carbon-capture technologies for power generation: An engineering-economic assessment. International Journal of Energy Research, 37(5), 389-402.

Dong, K., Hochman, G., Zhang, Y., Sun, R., Li, H., Liao, H. (2018), CO_2 emissions, economic and population growth, and renewable energy: Empirical evidence across regions. Energy Economics, 75, 180-192.

Engle, R.F., Granger, C.W.J. (1987), Cointegration and error corrections representation, estimation and testing. Econometrica, 55, 251-276.

Esso, L.J., Keho, Y. (2016), Energy consumption, economic growth and carbon emissions: Cointegration and causality evidence from selected African countries. Energy, 114, 492-497.

Florens, J.P., Marimoutou, V., Péguin-Feissolle, A. (2007), Econometric Modeling and Inference. New York: Cambridge University Press.

Gu, L., Rosenberg, M., Yang, L., Yu, J., Wei, B. (2020), A spatial multilevel analysis of the impacts of housing conditions on county-level life expectancy at birth in China. Applied Geography, 124, 102311.

Guo, X., Shi, J., Ren, D., Ren, J., Liu, Q. (2017), Correlations between air pollutant emission, logistics services, GDP, and urban population growth from vector autoregressive modeling: A case study of Beijing. Natural Hazards, 87(2), 885-897.

Hamilton, J.D. (1994), Time Series Analysis. New Jersey: Princeton University Press.

Hosking, J.R. (1980), The multivariate portmanteau statistic. Journal of the American Statistical Association, 75(371), 602-608.

Hosking, J.R.M. (1981), Lagrange-multiplier tests of multivariate time-series models. Journal of the Royal Statistical Society: Series B (Methodological), 43(2), 219-230.

Hossain, M.S. (2011), Panel estimation for CO_2 emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries. Energy Policy, 39, 6991-6999.

Jaba, E., Balan, C.B., Robu, I.B. (2014), The relationship between life expectancy at birth and health expenditures estimated by a cross-country and time-series analysis. Procedia Economics and Finance, 15, 108-114.

Jacobs, D.E., Brown, M.J., Baeder, A., Sucosky, M.S., Margolis, S., Hershovitz, J., Kolb, L., Morley, R.L. (2010), A systematic review of housing interventions and health: Introduction, methods, and summary findings. Journal of Public Health Management and Practice, 16(5), S5-S10.

Johansen, S. (1988), Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12(2-3), 231-254.

Khamjalas, K. (2024), Nexuses between food, energy, and water consumption on urban-rural income gap in South-Eastern Asian countries using difference in difference in modelling technique. International Journal of Economics and Financial Issues, 14(2), 186-195.

Kunze, L. (2014), Life expectancy and economic growth. Journals of Macroeconomics, 39(PA), 54-65.

Laaksonen, M., Martikainen, P., Nihtilä, E., Rahkonen, O., Lahelma, E. (2008), Home ownership and mortality: A register-based follow-up study of 300 000 finns. Journal of Epidemiology and Community Health, 62(4), 293-297.

Lawrence, D., Hancock, K.J., Kisely, S. (2013), The gap in life expectancy from preventable physical illness in psychiatric patients in Western Australia: Retrospective analysis of population based registers. BMJ: British Medical Journal, 346, f2539.

Liddle, B. (2015), What are the carbon emissions elasticities for income and population? Bridging STIRPAT and EKC via robust heterogeneous panel estimates. Global Environmental Change, 31, 62-73.

Linden, M., Ray, D. (2017), Aggregation bias-correcting approach to the health-income relationship: Life expectancy and GDP Per Capita in 148 Countries, 1970-2010. Economic Modelling, 61, 126-136.

Lomborg, B. (2002), How healthy is the world? BMJ: British Medical Journal, 325(7378), 1461-1466.

Lorentzen, P., McMillan, J., Wacziarg, R. (2008), Death and development. Journal of Economic Growth, 13, 81-124.

Luo, W., Xie, Y. (2020), Economic growth, income inequality and life expectancy in China. Social Science and Medicine, 256, 113046.

Lutkepohl, H. (2005), New Introduction to Multiple Time Series Analysis. Berlin: Springer Verlaag.

Lütkepohl, H., Krätzig, M., editors. (2004), Applied Time Series Econometrics. Cambridge: Cambridge University Press.

Manu, S.B., Sulaiman, C. (2017), Environmental kuznets curve and the relationship between energy consumption, economic growth and CO_2 emissions in Malaysia. Journal of Economics and Sustainable Development, 8(16), 142-148.

Marcellino, M. (2008), A linear benchmark for forecasting GDP growth and inflation? Journal of Forecasting, 27(4), 305-340.

Milhoj, A. (2016), Multiple Time Series Modeling Using THE Sas Varmax Procedure. Cary, NC: SAS Institute Inc.

Mishra, V. (2019), India's projected aged population (65+), projected life expectancy at birth and insecurities faced by aged population. Ageing International, 45, 72-84.

Mohiuddin, O., Asumadu-Sarkodie, S., Obaidullah, M. (2016), The relationship between carbon dioxide emissions, energy consumption, and GDP: A recent evidence from Pakistan. Cogent Engineering, 3(1), 1210491.

Munir, Q., Lean, H.H., Smyth, R. (2020), CO_2 emissions, energy consumption and economic growth in the ASEAN-5 countries: A cross-sectional dependence approach. Energy Economics, 85, 104571.

Murthy, U., Shaari, M.S., Mariadas, P.A., Abidin, N.Z. (2021), The relationships between CO_2 emissions, economic growth and life expectancy. The Journal of Asian Finance, Economics and Business, 8(2), 801-808.

Ohlan, R. (2015), The impact of population density, energy consumption, economic growth and trade openness on CO_2 emissions in India. Natural Hazards, 79, 1409-1428.

Pena, D., Tiao, G.C., Tsay, R.S. (2011), A Course in Time Series Analysis. New York: John Wiley and Sons.

Popoola, O.T. (2018), Population growth and life expectancy in Nigeria: Issues and further considerations. Humanities and Social Science Research, 1(1), 1-30.

Queiroz, B.L., Gonzaga, M.R., Vasconcelos, A.M.N., Lopes, B.T., Abreu, D.M.X. (2020), Comparative analysis of completeness of death registration, adult mortality and life expectancy at born in Brazil at the subnational level. Population Health Metrics, 18(Suppl 1), 11.

Rachev, S.T., Mittnik, S., Fabozzi, F.J., Focardi, S.M., Jasic, T. (2007), Financial Econometrics: From Basics to Advanced Modeling Techniques. United States: John Wiley and Sons, Inc. p553.

Russianwan, W., Tjiptoherijanto, P., Suganda, E., Darmajanti, L. (2015), System dynamics modeling for urban economic growth and CO_2 emission: A case study of Jakarta, Indonesia. Procedia Environmental Sciences, 28, 330-340.

Sarma, R., Choudhury, L. (2014), A new model for estimating district life expectancy at birth in india, with special reference to assam state. Canadian Studies in Population, 41(1-2), 180-191.

Shahbaz, M., Hye, Q.M.A., Tiwari, A.K., Leitão, N.C. (2013), Economic growth, energy consumption, financial development, international trade and CO_2 emissions in Indonesia. Renewable and Sustainable Energy Reviews, 25, 109-121.

Shahbaz, M., Nanthakumar, L., Nooreen, M., Amjad, A., Ahmed, N. (2016), Determinants of life expectancy and its prospects under the role of economic misery: A case of Pakistan. Social Indic Research, 126, 1299-1316.

Sugimoto, I. (2011), Economic Growth of Singapore in the Twentieth Century: Historical GDP Estimates and Empirical Investigations. Vol. 2. Singapore: World Scientific.

Tsay, R.S. (2010), Analysis of Financial Time Series. 2nd ed. New Jersey: John Wiley and Sons, Inc.

Tsay, R.S. (2014), Multivariate Time Series Analysis: With R and Financial Applications. New Jersey: John Wiley and Sons, Inc.

United Nation. (2022), Per Capita CO_2 Emissions. Available from: https://ourworldindata.org/co2/country/indonesia [Last accessed on 2022 Sep 05].

Virginia, E. (2018), Application of GARCH model to forecast data and volatility of share price of energy (study on Adaro energy Tbk, LQ45). International Journal of Energy Economics and Policy, 8(3), 131-140.

Wang, Y., Kang, Y., Wang, J., Xu, L. (2017), Panel estimation for the impacts of population-related factors on CO_2 emissions: A regional analysis in China. Ecological Indicators, 78, 322-330.

Wang, Z., Asghar, M.M., Zaidi, S.A.H., Nawaz, K., Wang, B., Zhao, W., Xu, F. (2020), The dynamic relationship between economic growth and life expectancy: Contradictory role of energy consumption and financial development in Pakistan. Structural Change and Economic Dynamics, 53, 257-266.

Wang, Z.H., Yin, F.C., Zhang, Y.X., Zhang, X. (2012), An empirical research on the influencing factors of regional CO_2 emissions: Evidence from Beijing city, China. Applied Energy, 100, 277-284.

Warsono, W. (2020), Dynamic modeling using vector error-correction model: Studying the relationship among data share price of energy PGAS Malaysia, AKRA, Indonesia, and PTT PCL-Thailand. International Journal of Energy Economics and Policy, 10, 360-373.

Warsono, Widiarti, Russel, E., Wamiliana, W., Usman, M. (2019a), Vector autoregressive with exogenous variable model and its application in modeling and forecasting energy data: Case study of PTBA and HRUM energy. International Journal of Energy Economics and Policy, 9(2), 390-398.

Warsono, Widiarti, Russel, E., Wamiliana, W., Usman, M. (2019b), Modeling and forecasting by the vector autoregressive moving average model for export of coal and oil data (case study from indonesia over the years 2002-2017). International Journal of Energy Economics and Policy, 9(4), 240-247.

Warsono, Russel, E, Putri, A.R., Wamiliana, Widiarti, Mustofa Usman (2020), Dynamic modeling using vector error-correction model: Studying the relationship among data share price of energy PGAS Malaysia, AKRA, Indonesia, and PTT PCL-Thailand. International Journal of Energy Economics and Policy, 10(2),360-373.

Wei, W.W.S. (2006), Time Series Analysis Univariate and Multivariate Methods. 2nd ed. Boston: Pearson Education, Inc.

Wei, W.W.S. (2019), Multivariate Time Series Analysis and Applications. New Jersey: John Wiley and Sons, Inc.

Widyawati, R.F., Hariani, E., Ginting, A.L., Nainggolan, E. (2021), Influence economic growth, population townspeople, openness trading international to carbon dioxide (CO_2) emissions in ASEAN countries. Jambura Agribusiness Journal, 3(1), 37-47.

World Bank. (2022a), Life Expectancy at Birth. Available from: https://ourworldindata.org/life-expectancy [Last accessed on 2022 Sep 05].

World Bank. (2022b), GDP-Per Capita Growth. Available from: https://ourworldindata.org/grapher/gdp-per-capita-growth [Last accessed on 2022 Sep 05].

World Bank. (2022c), Population Growth. Available from: https://ourworldindata.org/population-growth [Last accessed on 2022 Sep 05].

Zaidi, S., Ferhi, S. (2019), Causal relationships between energy consumption, economic growth and CO_2 emission in Sub-Saharan: Evidence from dynamic simultaneous-equations models. Modern Economy, 10(9), 2157-2173.

Zhang, C., Tan, Z. (2016), The relationship between population factors and China's carbon emissions: Does population aging matter? Renewable and Sustainable Energy Reviews, 65, 1018-1025.

Žokalj, M. (2016), The impact of population aging on public finance in the European Union. Financial Theory and Practice, 40(4), 383-412.