



Analysis and Modeling Gross Domestic Product, Carbon Dioxide Emission, Population Growth, and Life Expectancy at Birth: Case Study in Qatar

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ABSTRACT

Studies on Life Expectancy at Birth (LEB) and Population Growth (PG) with several economic variables for cases in Qatar have not been carried out much. The study of the relationship between Life expectancy at Birth (LEB), Carbon Dioxide (CO₂) emission, Population growth (PG), and Gross Domestic Product (GDP) for the case of Qatar is interesting because it is a developed country based on oil and gas. The aims of this study is to build a dynamic model for vector time series that describes the relationship between the variables discussed. From the analysis results based on Criterion Information, Akaike's Information Criterion Correction (AICC), and Cointegration Rank, the best model obtained is the Vector Error Correction Model with order 4 (VECM [4]) and with Cointegration Rank $r=4$. Based on this dynamic model, Granger-Causality analysis, Impulse Response Function (IRF), and Forecasting will be discussed.

Keywords: Life Expectancy at Birth, Population Growth, CO₂, Gross Domestic Product, VECM(p), Cointegration

JEL Classifications: O11, Q00, E22

1. INTRODUCTION

Long life expectancy represents a nation's better welfare or standard of living because life expectancy directly correlates with social welfare, human health, and economic development (Lomborg, 2002). In recent years, life expectancy has shown an increasing trend globally, although the figures differ in every country. This increase in life expectancy is due to a better working and living environment, preventive care, increased education, and increased per capita income. Life expectancy measures a nation's health, influenced by many socioeconomic and environmental factors. Ali and Ahmad (2014) emphasized that the factors influencing life expectancy are the food production index, gross enrollment rate, population growth, inflation, per capita income, and carbon dioxide (CO₂) emissions. Life Expectancy

is a statistical measure of how long an individual can live based on their birth year, current age, and other demographic factors, including gender. At a given age, life expectancy is the average number of years a group of individuals exposed to the same mortality condition might live until they die. The most commonly used measure of life expectancy is life expectancy at age zero, namely Life Expectancy at Birth (LEB).

The state will make efforts to improve the health of its population even by using different measures. Efforts and programs are generally made to reduce mortality and improve health (Girosi and King, 2007). Life expectancy at birth is a summary indicator widely used to describe population health and longevity in a country (Rabbi, 2013; Sharma, 2018; Bilas et al., 2014). Bloom et al. (2018); Jones (2016); Jones and Klenow (2016);

Kuhn and Prettnner (2016); and Weil (2014) found a positive correlation between health and economic growth in various countries. Furthermore, Deaton (2013) and Weil (2015) stated that technological advances, increased institutional quality, and income per capita can promote health.

Research on the relationship between Gross Domestic Product (GDP) and LEB has been carried out by researchers in various countries. Those who discuss life expectancy with per capita income include Ademoh (2017), Luo and Xie (2020), Huang et al. (2020), Wang et al. (2020), Miladinov (2020), and He and Li (2018). The Preston curve illustrates the relationship between life expectancy and per capita income. However, according to Schultz (2008), life expectancy in many countries tends to increase regardless of changes in income levels in each country. Lutz and Kebede (2018) show that education explains the Preston curve well.

The population will continue to be one of the most important factors in society and the economy of any country. In the US, future population growth is predicted to increase through international immigration, while population fertility, mortality, and aging will reduce population growth (Vespa et al., 2020). At the macro level, maintaining, expanding, and improving the health of the human population is considered one of the main policies for sustainable development (Bayati et al., 2013). Accordingly, mortality estimates are very important in providing information relevant to government policies governing pension and health care policies (Shkolnikov et al., 2011). Meanwhile, Sarma and Choudhury (2014) confirmed that life expectancy at birth is considered an important indicator of the death rate of a population. However, the results of research by Nkalu and Edeme (2019) found that population growth was able to extend life expectancy (LEB) by 5 years and 5 months. This is because the increase in population can increase agricultural productivity in Africa.

In the last decade, the impact of energy consumption and CO₂ emissions on economic growth has become a topic of great interest both at the national and international levels (Saputra et al., 2021). Many countries, especially developing countries, face major challenges, namely, the multi-directional relationship between economic, social, and environmental development. Increasing CO₂ emissions is a major threat to climate change, a major concern worldwide. Less developed countries have the smallest contribution to climate change while maintaining population growth (Ahmadalipour et al., 2019; Bathiany et al., 2018). While research that discusses the relationship between emissions and GDP includes (Kim et al., 2010; ACaravci and Ozturk, 2010; Cowan et al., 2014; Saidi and Hammami, 2015; Heidari et al., 2015; Sulaiman and Rahim, 2017). On the other hand, local and regional-level research on climate and population growth was conducted by (Dawadi and Ahmad, 2013; Pricope et al., 2013; Wang and Wang, 2017). As supported by Asefi-Najafabady et al., 2018; Jones et al., 2015; Liu et al., 2017), population growth has become the main driver of future climate risks. And specifically, Lefler et al. (2019) saw that CO₂ emissions positively impacted mortality over time. And carbon dioxide (CO₂) emissions from solid fuel consumption reduce life expectancy (LEB) by 1 month and 3 weeks (Nkalu and Edeme, 2019).

The illustrations and research results above illustrate a partial relationship between Life Expectancy at birth, (LEB) Gross Domestic Product (GDP), Population Growth (PG), and Carbon Dioxide (CO₂) emissions with different conclusions. Therefore, it is necessary to develop a model that can describe the relationship pattern of the four variables in the best model. The research will use multivariate time series analysis, which is still challenging to find in previous research papers, especially in the case of Qatar. This study attempts to find the empirical relationship of four variables, namely LEB, CO₂ emissions, economic growth, and population growth, especially in Qatar. The direction of causality between LEB, GDP, PG, and CO₂ emissions is important to frame policies because Qatar is a group of countries with the world's highest economic growth, a small population, and the world's highest energy producer.

For this reason, it is important to examine how all these factors relate to LEB. The research results are expected to provide policymakers input and contribute to determining economic development with low pollution, optimal population growth, and higher life expectancy. This research will produce a novelty, namely the best multivariate modelling of Life Expectancy at birth (LEB), Gross Domestic Product (GDP), Population Growth (PG), and Carbon Dioxide (CO₂) emission cases in Qatar, which can be used as a basis for making policies related to health and the environment.

2. STATISTICAL MODEL

In this study, the random vector is defined as follows:

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

LEB is Life Expectancy at Birth, CO₂ is Carbon Dioxide, PG is population Growth, and GDPG is GDP growth. The data used in the analysis is data from 1950 to 2020.

2.1. Model Dynamic

In multivariate time series data modelling, the main objective of modelling and analysis is to explain the dynamic relationship among variables of interest and improve prediction accuracy (Pena et al., 2001; Wei, 2006; Montgomery et al., 2008; Tsay, 2010; 2014). 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 modelling. Therefore, one needs to understand the nature of the relationship between variables to be analyzed to obtain a good and appropriate model and produce accurate predictions (Brockwell and Davis, 2002; Lutkepohl, 2005; Tsay, 2014).

The analysis of time series data assumes that the data are stationary, so the probability distribution of a random collection of X_t is time-invariant (Tsay, 2014). In a k -dimensional vector time series, X_t is stationary if (a) $E(X_t) = \mu$, k -dimensional vector constant, and (b) $Cov(X_t) = \Sigma$, $k \times k$ matrix constant and positive definite (Brockwell

and Davis, 2002; Hamilton, 1994; Tsay, 2014). The stationarity of multivariate time series data can be checked by examining the graph and analyzing the data's behavior to check whether it is stationary. Analytically, one can check for stationary data using the Augmented Dicky Fuller test (ADF test) or the unit root test (Warsono et al., 2019a; 2019b; 2020; Brockwell and Davis, 2002). In addition, we can examine the graph of the autocorrelation function (ACF). In the ADF test or Unit Root Test with p-lag, the model defines as follows:

$$\Delta X_t = \beta_0 + \lambda X_{t-1} + \sum_{i=1}^{p-1} \lambda_i^* \Delta X_{t-i} + \varepsilon_t \quad (1)$$

Where $\Delta X_t = X_t - X_{t-1}$ and ε_t It is white noise. The null hypothesis is $H_0: \lambda = 0$, or the data are non-stationary. The statistic test is the τ (tau) test or ADF test, where the distribution approximately has a t-ratio (Brockwell and Davis, 2002; Tsay, 2014). For the level of significance ($\alpha = 0.05$), reject the null hypothesis (H_0) if $\tau < -2.57$ or if the $P < 0.05$ (Brockwell and Davis, 2002; Tsay, 2005; Virginia et al., 2018). The statistic test is as follows:

$$ADF\tau = \frac{\lambda}{Se(\lambda)} \quad (2)$$

2.2. Calculation of a Cross-Correlation Matrix

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

$$\hat{\Gamma}_k = \frac{1}{T} \sum_{t=k+1}^T (X_t - \bar{X})(X_{t-k} - \bar{X})', \quad k > 0.$$

Where $\bar{X} = \frac{1}{T} \sum_{t=1}^T X_t$ 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 $m \times m$ the matrix diagonal from the sample standard deviation from the series component.

2.3. 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:

$$H_0: \rho_1 = \rho_2 = \dots = \rho_k = 0,$$

With the alternative

$$H_a: \rho_i \neq 0 \quad \text{for some } i \in \{1, 2, \dots, k\}.$$

The test statistic is as follows:

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

Where T is the sample size, m is the dimension of X_t , and $\text{tr}(A)$ is a trace of a matrix A . Under the null hypothesis, $Q_m(k)$ asymptotically has a Chi-square distribution with degrees of freedom $m^2 k$. 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 X_t . If H_0 is rejected, the class of vector autoregressive model should be involved in building a multivariate model for the time series data studied.

2.4. Cointegration

Engle and Granger (1987) introduced the concept of cointegration and developed the concept of estimation and inferential, provided by Johansen (1988). The time series X_t is said to be integrated with order one process, $I(1)$, if $(1-B)X_t$ 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 $(1-B)^d X_t$ is stationary (Hamilton, 1994; Tsay, 2005, 2014). The fact that some time series data with unit roots or non-stationary, 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 forecasting (Tsay, 2014). In cointegration,

$$Z_t = \beta' X_t \text{ is stationary,}$$

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

$$\hat{Z}_t(m) \xrightarrow{p} E(Z_t) = \mu_z, m \rightarrow \infty$$

This mean that $\beta' \hat{Z}_T(m) \rightarrow \mu_z$ as m increase. Therefore, the point forecast of Z_t satisfy a long-term stable forecast. If in the Vector Autoregressive (VAR) model, there exists cointegration between variables, then the model needs to be modified into VECM (Hamilton, 1994; Lutkepohl and Kratzig, 2004; Tsay, 2005; 2014; Wei, 2006; 2020). If a cointegration relationship is present in a system of variables, the VAR model is not the most convenient model (Tsay, 2014; Wei, 2020). If there is cointegration between vector time series, then one needs to test the cointegration rank. Some methods of testing the rank of cointegration are as follows: Trace test and maximum eigenvalue test. The trace test is as follows:

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

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

$$\lambda_{\max}(r, r+1) = -T \ln(1 - \lambda_i) \quad (6)$$

2.5. Vector Autoregressive (VAR) Model

To quantitatively analyze time series data involving more than one variable (vector time series), one 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:

$$X_t = \sum_{i=1}^p \Phi_i X_{t-i} + \varepsilon_t \quad (7)$$

Where X_t is the $n \times 1$ vector observation at the time t , Φ_i is the $n \times n$ matrix coefficient of vector X_{t-p} , for $i = 1, 2, \dots, p$, p is the lag length, and ε_t is the $n \times 1$ vector of shock.

2.6. Vector Error Correction Model

VECM is a restricted VAR model designed to be used on non-stationary 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):

$$\Delta X_t = \beta_0 + \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \varepsilon_t \quad (8)$$

Where Δ is the operator of differencing, $\Delta X_t = X_t - X_{t-1}$, X_{t-1} is the vector of an endogenous variable at lag-1, ε_t is the $k \times 1$ vector white noise, β_0 is vector constant, 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.

2.7. Normality Test of Residuals

The normality test of residuals is used to evaluate the distribution of the residuals. The normality test was performed using the Jarque-Bera (JB) test of normality, which uses skewness and kurtosis. JB test is as follows:

$$JB = \left[\frac{N}{6} b_1^2 + \frac{N}{24} (b_2 - 3)^2 \right] \quad (9)$$

Where N is the sample size, b_1 is the expected skewness, and b_2 is the expected excess kurtosis. The JB test of normality has χ^2 distribution with 2° of freedom (Jarque and Berra, 1980).

2.8. 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:

$$y_t = c + \Phi_1 y_{t-1} + \dots + \Phi_p y_{t-p} + \varepsilon_t \quad (10)$$

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

$$\det(I_{kp} - \Phi_Z) = \det(I_K - \Phi_1 Z - \dots - \Phi_p Z^p) \quad (11)$$

Have a modulus smaller than one, all of them within the unit circle.

2.9. Granger Causality

The existence of cointegration indicates a long-term relationship between variables. Even when the variables are not cointegrated in a long-term relationship, these variables are still likely to have a short-term relationship. To understand the interdependence between variables, the Granger Causality Test is used. Consider the following models:

$$X_t = \begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} B_{11,1} & B_{12,1} \\ B_{21,1} & B_{22,1} \end{bmatrix} \begin{bmatrix} X_{1t-1} \\ X_{2t-1} \end{bmatrix} + \dots + \begin{bmatrix} B_{11,p} & B_{12,p} \\ B_{21,p} & B_{22,p} \end{bmatrix} \begin{bmatrix} X_{1t-p} \\ X_{2t-p} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad (12)$$

X_t consists of vectors X_{1t} and X_{2t} . X_{2t} is said not to be a Granger causality for X_{1t} if the coefficient matrix of the parameter $B_{21,i} = 0$ for $i = 1, 2, \dots, p$ (Lutkepohl, 2005). Granger Causality Test is used to evaluate and examine whether one variable or group of variables affects other variables. A variable X_t is said to be Granger because of variable Y_t if the past and present values of X_t can predict the current value of Y_t . If a variable of X_t is the Granger causality of variable Y_t and not vice versa, then it is called direct Granger causality. If Granger causality exists in both, from X_t to Y_t and from Y_t to X_t , then it is named bidirectional Granger causality (Brooks, 2014).

2.10. 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 could be written in vector MA (∞) as follows:

$$X_t = \mu + \mu_t + \Psi_1 \mu_{t-1} + \Psi_2 \mu_{t-2} \quad (13)$$

Thus, the matrix is interpreted as follows:

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

The element of the i^{th} row and j^{th} column indicated the consequence of the increase of one unit in the innovation of variable j at time t (μ_{jt}) for the i variable at time $t + s$ ($X_{i,t+s}$) 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 δ_2, \dots , and the n th element will change by δ_n , then the common effect from all of these changes on the vector X_{t+s} will become

$$\Delta X_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}} \delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}} \delta_2 + \dots + \frac{\partial X_{t+s}}{\partial u_{nt}} \delta_n = \Psi_s \delta \quad (14)$$

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

Forecasting m -Steps ahead Forecasting will be performed after obtaining the best model for data vector-valued multivariate time

series $\{X_t\}$. Using the best model that fits the data, forecasting is performed directly for the next 12 periods (months).

2.11. 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; Tsay, 2014).

3. RESULTS AND DISCUSSION

Figures 1-4 shows a plot of Qatar’s LEB, CO₂, PG, and GDPG data from 1950 to 2020. (Figure 1a) shows that the LEB data has a relatively strong upward trend from 1950 to 1990 and from 1950 to 1990. From 1990 to 2020, the upward trend is small. In 1950 Qatar’s LEB was about 53.68 years. In 1990 was around 75.82 years. There was an increase of 22.14 years from 1950 to 1990, while in 2020, Qatar’s LEB was around 80.36 years. So there is an increase of 4.54 years from 1990 to 2020. The Qatar LEB

Figure 1: (a) Data time series for LEB from 1950 to 2020, (b) Autocorrelation function for LEB

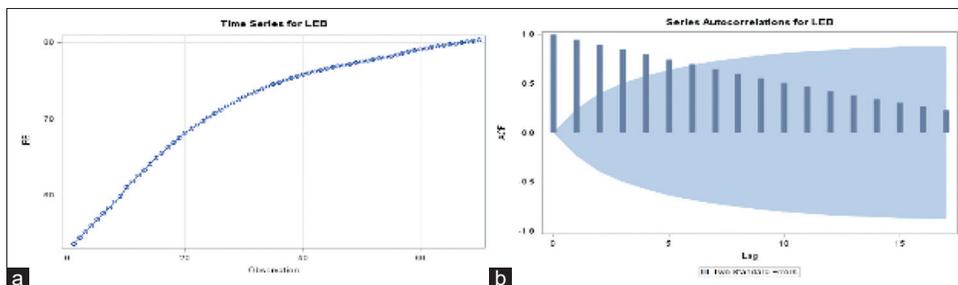


Figure 2: (a) Data time series for CO₂ from 1950 to 2020, (b) Autocorrelation function for CO₂

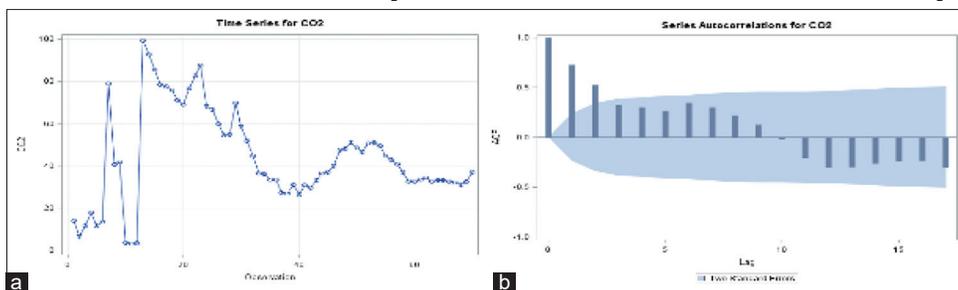


Figure 3: (a) Data time series for PG from 1950 to 2020, (b) Autocorrelation function for PG

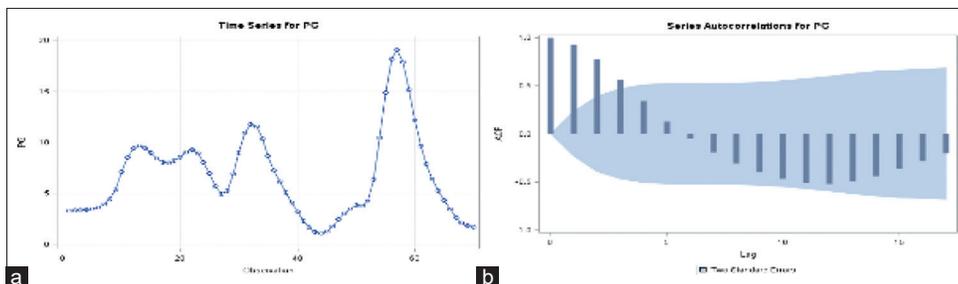
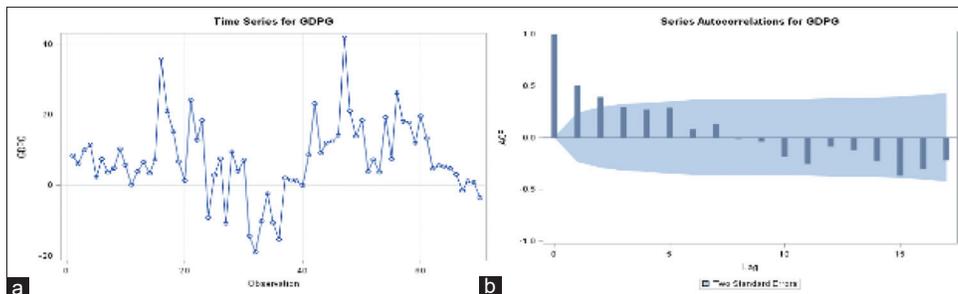


Figure 4: (a) Data time series for GDPG from 1950 to 2020, (b) Autocorrelation function for GDPG



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 can be seen that the Autocorrelation Function shows that ACF decays very slowly. This indicates that the data is not stationary.

(Figure 2a) shows the change in the behavior of Qatar’s CO₂ data from 1950 to 2020. From 1950 to 1955, the CO₂ data trended horizontally, fluctuating in the range of values from 65,008 to 17,8621. In 1956 it rose drastically to 78.94. From 1959 to 1961, Qatar’s CO₂ data was around 3,715, 3,137, and 3,389, respectively. In 1962 it rose drastically to 99,457, and from 1962 to 1990, it fluctuated downward. From 1990 to 2000, the trend was up, and from 2000 to 2010, the trend was down. From 2010 to 2020, the trend was flat at around 33. Figure 2 shows that Qatar’s CO₂ data is not stationary. (Figure 2b) shows that the ACF value decays very slowly; this indicates that the data is non-stationary.

(Figure 3a) shows the fluctuating population growth from 1950 to 2020. The growth range is between 1.11% and 19.14%. The lowest growth occurred in 1994, 1.11%, and the highest in 2007. Low growth occurred from 1992 to 1996 and in 2019 and 2020; high growth occurred from 2006 to 2010, above 12%. From the Autocorrelation Function (ACF) analysis results, (Figure 3b) ACF shows that it decays very slowly; this indicates that Qatar PG data from 1950 to 2020 is non-stationary.

(Figure 4a) Qatar’s GDP growth from 1950 to 2020 shows a fluctuating trend of down and up. From 1950 to 1976, GDPG was positive; in 1977, GDPG was negative by -10.81; from 1978 to 1980, growth was positive; from 1981 to 1986, growth was negative; from 1987 to 2016, growth was positive; in 2017, growth was negative, the last year 2018-2019 growth is positive, and in 2020 growth is negative. From 1950 to 1964, the trend of growth was flat and fluctuating; in 1965, GDP growth rose drastically by 35.72, and from 1965 to 1982, the trend was downward and fluctuating; from 1986 to 1997, the trend was up and fluctuating, from 1998 to 2003 the trend was downwards, from 2004 to 2010 the trend was up, and from 2010 to 2020 the trend was decreasing. Figure 4 shows that the GDPG data is non-stationary. (Figure 4b) ACF decays very slowly, indicating that the data is non-stationary. Table 1 shows the results of the unit root test showing that the results are significant, so the data is stationary after being differentiated once, in other words the data is integrated with order 1, I(1).

3.1. Test for Cointegration

To test the presence or absence of cointegration, the Johansen test at lag optimum from the VAR model is used. If the value of trace statistics is greater than a critical value, we conclude that there are at least two cointegration relations among the variables. The null hypothesis: H₀: Rank=r (there is no cointegration) against H₁: Rank > r (there is cointegration), for the values of r=0, 1, 2, 3, 4. Table 2 obtained the rank cointegration test using trace r=4. Table 3 obtained the rank cointegration test using trace under restriction obtained r=4. The VECM (4) model will be used in data modeling with rank cointegration r=4.

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

Variables	Type	Rho	P-values	You know	P-values
LEB	Zero means	-1.65	0.3718	-2.40	0.0169
	Single means	-1.51	0.8314	-1.22	0.6633
	Trends	-4.89	0.8199	-1.27	0.8854
CO ₂	Zero means	-78.94	<.0001	-6.19	<0.0001
	Single means	-79.07	0.0006	-6.14	0.0001
	Trends	-80.60	0.0002	-6.15	<0.0001
PG	Zero means	-112.99	0.0001	-7.39	<0.0001
	Single means	-112.99	0.0001	-7.33	0.0001
	Trends	-118.52	0.0001	-7.46	<0.0001
GDPG	Zero means	-138.00	0.0001	-8.17	<0.0001
	Single means	-138.11	0.0001	-8.11	0.0001
	Trends	-138.40	0.0001	-8.06	<0.0001

LEB: Life expectancy at birth, PG: Population growth

Table 3 is an autocorrelation test using the Box-Pierce Test, with the null hypothesis that there is an autocorrelation of up to lag 12 for each LEB, CO₂, PG, and GDPG data. From the results of the cross-correlations test for multivariate data on LEB, CO₂, PG, and GDPG with the null hypothesis that there is no cross-correlation. The results of the Portmanteau test for cross-correlation show that (Table 4) there are cross-correlations up to lag-13. Therefore, modeling must involve the concept of autocorrelation. For the multivariate time series analysis, we can model the data, which involved Vector Autoregressive (VAR) model, Vector Autoregressive Moving Average (VARMA), or Vector Error Correction Model (VECM).

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

Based on results of Table 5, the VECM(4) model with cointegration rank r=4 is chosen. The VECM(4) models with cointegration rank r=4 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

$$X_t = \begin{bmatrix} LAB_t \\ CO2_t \\ PG_t \\ GDPG_t \end{bmatrix},$$

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

C is constant vector, Π is vector 4×4 parameter cointegration, and Π=αβ', β is vector cointegration, and Φ₁, Φ₂, and Φ₃ coefficient parameters,

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

Table 2: Cointegration rank test using trace

H ₀ : Rank=r	H1: rank>r	Eigenvalue	Trace	P-values	Drift in ECM	Drift in process
0	0	0.4617	79.2670	<0.0001	Constant	linear
1	1	0.2202	38.3916	0.0041		
2	2	0.1824	21.9724	0.0046		
3	3	0.1233	8.6831	0.0033		

Table 3: Autocorrelation check for white noise

Variable	Autocorrelation check for white noise									
	To lag	Chi-square	DF	P-value	Autocorrelations					
LEB	6	309.99	6	<0.0001	0.949	0.898	0.848	0.798	0.748	0.699
	12	454.66	12	<0.0001	0.650	0.602	0.555	0.510	0.466	0.424
CO ₂	6	88.74	6	<0.0001	0.725	0.526	0.323	0.299	0.266	0.349
	12	112.96	12	<0.0001	0.298	0.218	0.128	-0.025	-0.208	-0.306
PG	6	142.44	6	<.0001	0.933	0.776	0.565	0.339	0.130	-0.046
	12	229.40	12	<0.0001	-0.189	-0.303	-0.396	-0.465	-0.509	-0.519
GDP	6	49.09	6	<0.0001	0.503	0.392	0.296	0.271	0.290	0.080
	12	59.66	12	<0.0001	0.132	-0.010	-0.038	-0.186	-0.253	-0.089

LEB: Life expectancy at birth, GDP: Gross domestic product, PG: Population growth

Table 4: Portmanteau test for cross correlations of residuals

Up To Lag	DF	Chi-square	Pr>Chi-square
5	16	67.85	<0.0001
6	32	91.60	<0.0001
7	48	93.88	<0.0001
8	64	109.55	0.0003
9	80	132.25	0.0002
10	96	142.98	0.0013
11	112	159.25	0.0022
12	128	165.37	0.0146
13	144	175.57	0.0377
14	160	187.47	0.0678
15	176	197.41	0.1286

$$\begin{bmatrix} 0.1153 & -0.0004 & -0.0267 & 0.0004 \\ -26.0924 & 0.1682 & -4.5301 & -0.2393 \\ 1.4792 & -0.0013 & -1.8231 & 0.0004 \\ -7.2749 & 0.0911 & -7.3496 & -0.0956 \end{bmatrix} \Delta \begin{bmatrix} LAB_{t-2} \\ CO2_{t-2} \\ PG_{t-2} \\ GDPG_{t-2} \end{bmatrix} + \begin{bmatrix} 0.2687 & 0.0016 & 0.0131 & -0.0001 \\ 182.3392 & -0.0651 & 4.1291 & -0.1622 \\ 0.0017 & -0.0011 & 0.6814 & 0.0001 \\ 19.0852 & 0.2435 & 4.5725 & -0.1141 \end{bmatrix} \Delta \begin{bmatrix} LAB_{t-3} \\ CO2_{t-3} \\ PG_{t-3} \\ GDPG_{t-3} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}$$

Table 5: Minimum information criterion based on AICC

Lag	AR0	AR1	AR2	AR3	AR4	AR5
AICC	17.8776	5.3849	3.6769	3.2113	1.9145	2.6872

And the covariance innovation is:

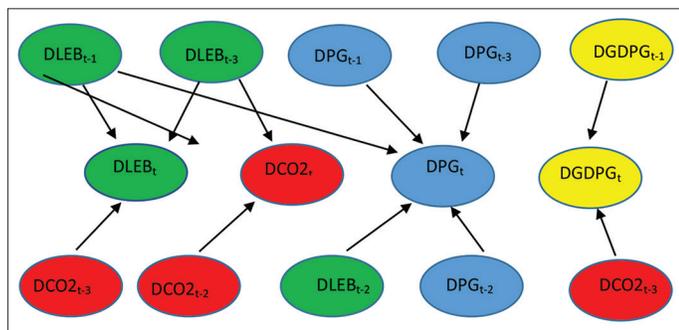
$$Var \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} = \begin{bmatrix} 0.0015 & -0.1541 & 0.0028 & -0.0933 \\ -0.1541 & 95.9606 & 0.1876 & 17.3368 \\ 0.0028 & 0.1876 & 0.0607 & 0.0434 \\ -0.0933 & 17.3368 & 0.0434 & 71.8539 \end{bmatrix}$$

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

$$\Delta \begin{bmatrix} LAB_t \\ CO2_t \\ PG_t \\ GDPG_t \end{bmatrix} = \begin{bmatrix} 1.1822 \\ -240.1395 \\ 2.0982 \\ -77.7092 \end{bmatrix} + \begin{bmatrix} -0.0145 & 0.0001 & 0.0021 & -0.0002 \\ 3.1406 & -0.5147 & -0.8419 & 0.3838 \\ -0.0239 & 0.0035 & -0.0393 & -0.0018 \\ 1.0426 & -0.1052 & -0.1549 & -0.3168 \end{bmatrix} \begin{bmatrix} LAB_{t-1} \\ CO2_{t-1} \\ PG_{t-1} \\ GDPG_{t-1} \end{bmatrix} + \begin{bmatrix} 0.1916 & 0.0001 & 0.0169 & 0.0005 \\ -61.7747 & 0.0667 & 3.5938 & -0.2215 \\ -2.1474 & -0.0032 & 2.1039 & -0.0039 \\ -1.2075 & 0.0585 & 4.8092 & -0.28708 \end{bmatrix} \Delta \begin{bmatrix} LAB_{t-1} \\ CO2_{t-1} \\ PG_{t-1} \\ GDPG_{t-1} \end{bmatrix} +$$

Figure 5 shows that LEB_t is significantly influenced by LEB_{t-1}, LEB_{t-3}, and CO_{2,t-3} this indicates that information on LEB one and 3 years prior and information on ΔCO₂ 3 years prior significantly affects current LEB; shows that CO_{2,t} is significantly influenced by LEB_{t-1}, LEB_{t-3}, and CO_{2,t-2} this indicates that information on LEB 1 and 3 years before and information on ΔCO₂ 3 years before significantly affects current ΔCO₂; that PG_t is significantly affected by LEB_{t-1}, LEB_{t-2}, PG_{t-1}, PG_{t-2}, PG_{t-3} this indicates that information on LEB 1 and 2 years prior and information on PG 1, 2 and 3 years previously significantly affected PG at the moment; that GDPG_t is significantly influenced by GDPG_{t-1} and CO_{2,t-3} this indicates that information on GDPG 1 year before and information on CO₂ in the previous 3 years significantly affects current GDPG.

Figure 5: Arrows ($X \rightarrow Y$) indicates exists significant influence from variable X to variable Y.



3.3. Diagnostic Models

Univariate models from the VECM (4) model with cointegration rank $r=4$, get written as following:

$$\begin{aligned} \Delta LAB_t = & 1.1822 - 0.0145 LEB_{t-1} + 0.0001 CO2_{t-1} + 0.0021 PG_{t-1} \\ & - 0.0002 GDPG_{t-1} + 0.1916 \Delta LEB_{t-1} + 0.0001 \Delta CO2_{t-1} \\ & + 0.0169 \Delta PG_{t-1} + 0.0005 \Delta GDPG_{t-1} + 0.1153 \Delta LEB_{t-2} \\ & - 0.0004 \Delta CO2_{t-2} - 0.0267 \Delta PG_{t-2} + 0.0004 \Delta GDPG_{t-2} \\ & + 0.2687 \Delta LEB_{t-3} + 0.0016 \Delta CO2_{t-3} + 0.0131 \Delta PG_{t-3} - \\ & 0.1622 \Delta GDPG_{t-3} \end{aligned} \tag{16}$$

$$\begin{aligned} \Delta CO2_t = & -240.1395 + 3.1406 LEB_{t-1} - 0.5147 CO2_{t-1} \\ & - 0.8419 PG_{t-1} + 0.3838 GDPG_{t-1} - 61.7747 \Delta LEB_{t-1} \\ & 0.0667 \Delta CO2_{t-1} + 3.5938 \Delta PG_{t-1} - 0.2215 \Delta GDPG_{t-1} \\ & - 26.0924 \Delta LEB_{t-2} + 0.1682 \Delta CO2_{t-2} - 4.5301 \Delta PG_{t-2} \\ & - 0.2393 \Delta GDPG_{t-2} + 182.3392 \Delta LEB_{t-3} \\ & - 0.0651 \Delta CO2_{t-3} + 4.1291 \Delta PG_{t-3} - 0.0001 \Delta GDPG_{t-3} \end{aligned} \tag{17}$$

$$\begin{aligned} \Delta PG_t = & 2.0982 - 0.239 LEB_{t-1} + 0.0035 CO2_{t-1} - 0.0393 PG_{t-1} \\ & - 0.0018 GDPG_{t-1} - 2.1474 \Delta LEB_{t-1} + 0.0032 \Delta CO2_{t-1} \\ & + 2.1039 \Delta PG_{t-1} - 0.0039 \Delta GDPG_{t-1} + 1.4792 \Delta LEB_{t-2} \\ & - 0.0013 \Delta CO2_{t-2} - 4.5301 \Delta PG_{t-2} - 0.2393 \Delta GDPG_{t-2} \\ & + 182.3392 \Delta LEB_{t-3} - 0.0651 \Delta CO2_{t-3} + 4.1291 \Delta PG_{t-3} - \\ & 0.0001 \Delta GDPG_{t-3} \end{aligned} \tag{18}$$

$$\begin{aligned} \Delta GDPG_t = & -77.7092 + 1.0426 LEB_{t-1} - 0.1052 CO2_{t-1} \\ & - 0.1549 PG_{t-1} - 0.3168 GDPG_{t-1} - 1.2075 \Delta LEB_{t-1} + \\ & 0.0585 \Delta CO2_{t-1} + 4.8092 \Delta PG_{t-1} - 0.2870 \Delta GDPG_{t-1} \\ & - 7.2749 \Delta LEB_{t-2} + 0.0911 \Delta CO2_{t-2} \\ & - 7.3496 \Delta PG_{t-2} - 0.0956 \Delta GDPG_{t-2} \\ & + 19.0852 \Delta LEB_{t-3} + 0.2435 \Delta CO2_{t-3} \\ & + 4.5725 \Delta PG_{t-3} - 0.1141 \Delta GDPG_{t-3} \end{aligned} \tag{19}$$

Table 6 shows the univariate model test, model (1)-(4). Model (1) LEB as the dependent test variable $F=125.92$ with $P < 0.0001$ with $R\text{-square}=0.9763$ which means that 97.63% LEB diversity is explained by the model; model (2) CO_2 as the dependent test variable $F=5.67$ with $P < 0.0001$ with $R\text{-square}=0.6492$ which means 64.92% of CO_2 diversity is explained by the model; model (3) PG as the dependent variable test results $F=91.57$ with $P < 0.0001$ and $R\text{-square}=0.9676$, which means 96.76% of the variance of PG is explained by the model; and model (4) GDPG as the dependent variable test results $F=2.00$ with $P = 0.0321$ and $R\text{-square} = 0.3955$ which means that 39.55% of GDPG diversity is explained by the model. Table 7 shows the results of the normality test using the Jarque-Bera test (JB test) with the null hypothesis that the residual has normally distributed, the normality test results for residual LEB, CO_2 , PG and GDPG, the $P < 0.0001$, <0.0001 , <0.0001 , and 0.0065 respectively (Figure 6). So null hypotheses are rejected, therefore the residuals are normally distributed are rejected. However, if seen from Figure 7 the distribution of residual (prediction error) LEB, there are only two data whose error is greater than the two standard errors. Figure 8 also shows that the residual distribution does not deviate too much from the normal distribution; Figure 9 distribution of residual (prediction error) CO_2 , there are only two data whose error is greater than the two standard errors. Figure 10 also shows that the residual distribution does not deviate too much from the normal distribution; Figure 11 distribution of residual (prediction error) PG, there are only three data whose error is greater than the two standard errors. Figure 12 also shows that the residual distribution does not deviate too much from the normal distribution; Figure 13 distribution of residuals (prediction error) GDPG, there are only three data whose error is greater than the two standard errors. Figure 14 also shows that the residual distribution does not deviate too far from the normal distribution.

Table 8 shows the results of F-test for testing AR(1), AR(1,2), AR(1,2,3) and AR(1,2,3,4) model of residual to test the null hypotheses that the residual are uncorrelated. The results show that most of the test that the $P > 0.05$, therefore we do not reject the null hypothesis. We conclude that the residuals are uncorrelated. Table 9 shows the results of the model stability test. The stability test of the model is used to determined the stability of the VECM(4) with rank cointegration $r=4$. Table 9 shows that all modulus is all within the unit circle. Therefore, we conclude that the VECM(4) with rank cointegration $r=4$ is a stable model and can be used for further analysis.

3.4. Granger Causality Test

Table 10 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 of variables. 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 10, the test 1, where the variable in group 1 is LEB and the variable in group 2 is CO_2 , the $P < 0.0001$, which is significant. Therefore, the null hypothesis that the LEB variable is influenced by itself and not influenced by CO_2 is rejected. So that it can be concluded that the variable LEB is not

only influenced by past information itself but is also influenced by current and past information of CO₂. Based on Table 10, the test 4, where the variable in group 1 is CO₂ and the variable in group 2 is LEB, the P < 0.0001, which is significant. Therefore, the null hypothesis that the variable CO₂ is influenced by itself and not influenced by LEB is rejected. So that it can be concluded that the variable CO₂ is not only influenced by past information itself but is also influenced by current and past information of LEB. Based on Table 10, the test 8, where the variable in group 1 is PG and

the variable in group 2 is LEB, the P = 0.0156 < 0.05, 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 itself but is also influenced by current and past information of LEB. Based on Table 10, the test 12, where the variable in group 1 is GDPG and the variable in group 2 is CO₂, the P = 0.0757 < 0.10, which is significant. Therefore, the null hypothesis that the variable GDPG is influenced by itself and not influenced by CO₂ is rejected. So that it can be concluded that the variable GDPG is not only influenced by past information itself but is also influenced by current and past information of CO₂. Figure 10 provides an illustration of the relationship pattern of granger causality where LEB is granger causality to CO₂, CO₂ is granger causality to LEB; LEB is granger-causality to PG; and CO₂ is granger causality to GDPG.

Table 6: Univariate model ANOVA diagnostic

Variables	R-square	Standard deviations	F-values	P-values
LEB	0.9763	0.03917	125.92	<0.0001
CO ₂	0.6492	9.79595	5.67	<0.0001
PG	0.9676	0.24653	91.57	<0.0001
GDPG	0.3955	8.47667	2.00	0.0321

ANOVA: Analysis of variance, LEB: Life expectancy at birth, GDP: Gross domestic product, PG: Population growth

Table 7: Univariate model white noise diagnostics

Variables	Durbin Watson	Normality		ARCH	
		Chi-square	P-values	F-values	P-values
LEB	2.0475	1092.84	<0.0001	0.00	0.9860
CO ₂	2.2890	800.17	<0.0001	0.47	0.4972
PG	2.0262	30.87	<0.0001	24.68	<0.0001
GDPG	2.1052	10.09	0.0065	0.06	0.8027

LEB: Life expectancy at birth, GDP: Gross domestic product, PG: Population growth

Table 8: Univariate models of AR diagnostics

Variables	AR1		AR2		AR3		AR4	
	F-values	P-values	F-values	P-values	F-values	P-values	F-values	P-values
LEB	0.08	0.7757	0.07	0.9313	0.16	0.9236	0.14	0.9672
CO ₂	1.56	0.2164	0.86	0.4302	3.87	0.0135	5.70	0.0006
PG	0.02	0.8861	0.10	0.9075	0.32	0.8123	0.69	0.5997
GDPG	0.24	0.6260	0.12	0.8892	0.17	0.9181	0.12	0.9751

Figure 6: (a) Prediction errors for LEB, (b) Prediction error normality for LEB

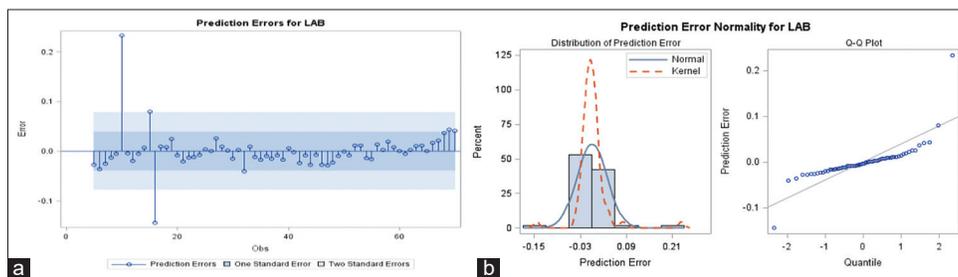


Figure 7: (a) Prediction errors for CO₂, (b) Prediction error normality for CO₂

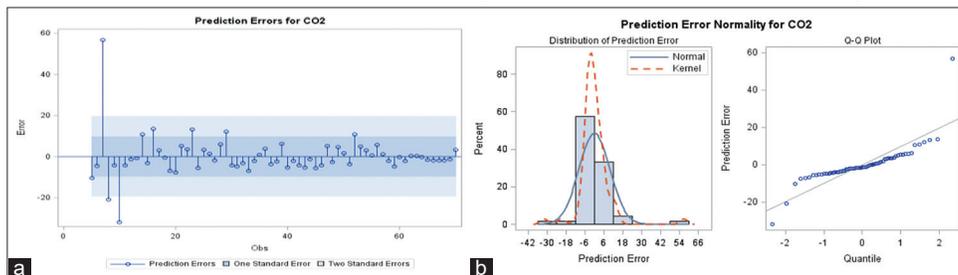


Figure 8: (a) Prediction errors for PG, (b) Prediction error normality for PG

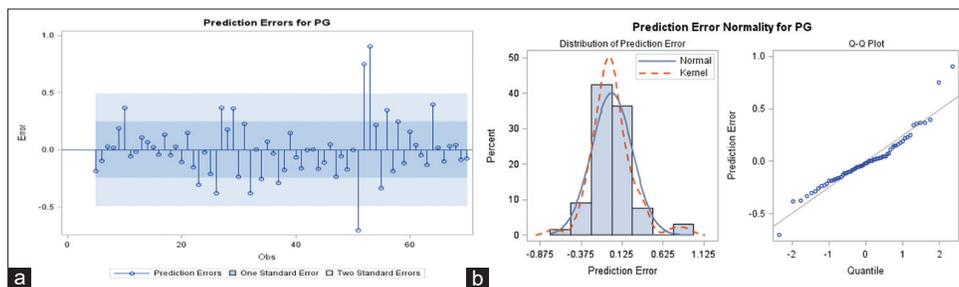


Figure 9: (a) Prediction errors for GDPG, (b) Prediction error normality for GDPG

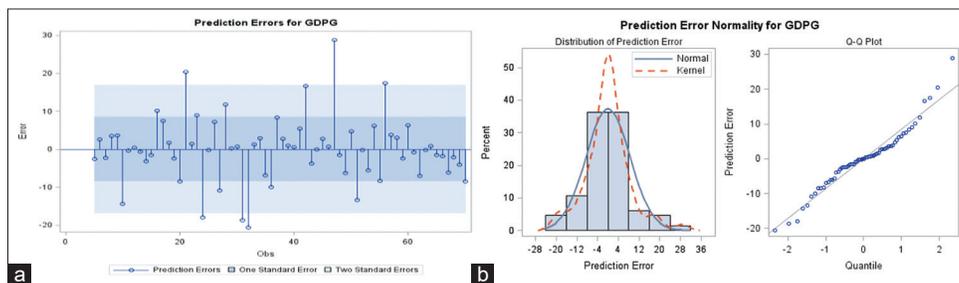


Figure 10: Granger-causality between variables LEB, CO₂, PG and GDPG

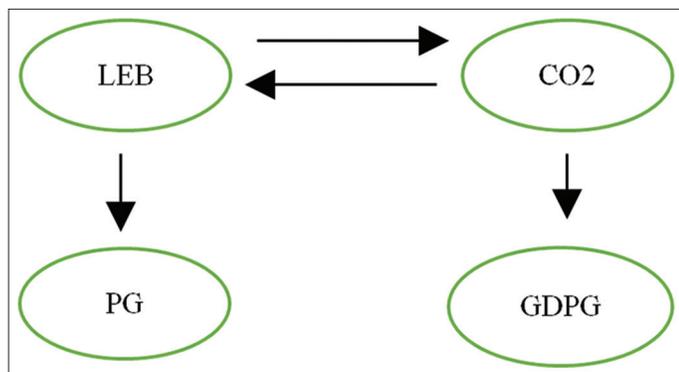
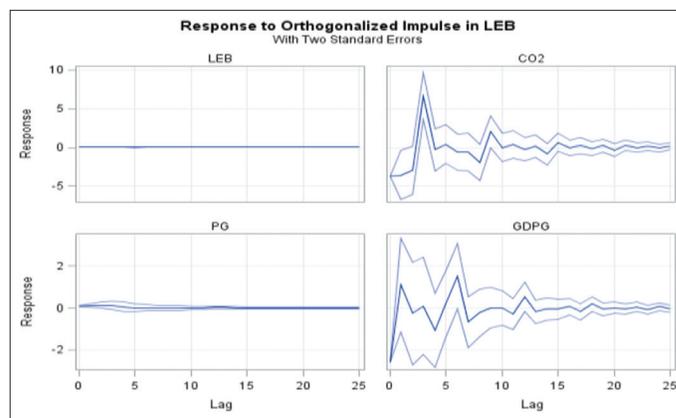


Figure 11: IRF for shock in variable LEB



causes the LEB to respond weakly. This is shown in the figure where the response is flat around zero, the equilibrium point. Likewise, with a one standard deviation shock at LEB, PG has a small response, shown in Figure 11. A shock of one standard deviation in LEB causes the CO₂ response in the following years, and the response fluctuates in the next 10 years. The response was negative in the first 3 years, namely -3.7187, -3.5840, and -2.9445. In the 4th year, the response was positive, namely 6.6619; in the 5th year, the response was negative by -0.2957; in subsequent years, the response weakened. The one standard deviation shock in LEB caused GDPG to respond in the following years. In the 1st year, the response was negative, namely -2.5733, in the 2nd year, the response was positive, namely 1.0913, the 3rd year, the response was positive, namely -0.2649, in the 4th year, the response was positive, namely 0.1010, the 5th year the response was negative, namely -1.0742, the 6th and 7th years the response was positive, namely 0.1874 and 1.5176, respectively. From the 8th year onwards, the effect weakens and moves toward equilibrium.

Figure 12 is a graph of IRF if there is a shock of one standard deviation in CO₂ and its effect on the variables LEB, CO₂ itself, PG, and GDPG. Suppose the graph from IRF moves to the original equilibrium (zero) line. In that case, this means that the response of a variable to shock other variables disappears, so the shock does not permanently affect that variable. Figure 12 also presents the confidence interval of the effect caused by shock on one variable. The shock of one standard deviation in CO₂ has a weak impact on LEB and PG. This is shown in Figure 12, where the response is flat at zero or the equilibrium point. Meanwhile, the impact on CO₂ and GDPG fluctuated and weakened several periods later. A one standard deviation shock in CO₂ causes CO₂ to respond in subsequent years. In the 1st year, the response was 13.3876. In the second to 4th year, the response was negative, namely -2.8164, -1.1636, and -3.7488. In the 5th year, the response was positive by 0.5569. In the 6th year, the response was negative by -1.9659. In the 7th year, the response was 4.4448, and in the following years, the impact weakened. A one standard deviation shock in CO₂ causes GDPG to respond in the next years. The figure shows that

the impact in the first 5 years fluctuated and, after that, weakened towards equilibrium. The impact in the first 5 years is 1.5729, -0.8885, 0.4108, 2.0819, and -1.5851. In the 6th year onwards, the impact is weakened and towards balance.

Figure 13 is a graph of IRF if there is a shock of one standard deviation in PG and its effect on the variables LEB, CO₂, PG itself, and GDPG. Suppose the graph from IRF moves to the original equilibrium (zero) line. In that case, this means that the response of a variable to shock other variables disappears, so the shock does not permanently affect that variable. Figure 13 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, and this is shown in Figure 13, where the impact flattens out around zero. A one standard deviation shock in PG causes CO₂ to respond in the following years. The response in the next 10 years will fluctuate around zero, namely 0.0000, 0.3894, -0.0949, -0.3859, 0.5368, 0.2417, -0.1951, -0.2846, -0.3362, and 0.3807. Seventh to the 10th year, the negative response is

-0.1051, -0.2279, -0.2054, and -0.0865. In the following years, the impact weakened. A one standard deviation shock in PG causes GDPG to respond in the first 4 years, and after that, the response weakens towards equilibrium. In the first 4 years, the impact was 0.5087, 0.7095, 0.0118, and -0.1531.

Figure 14 is a graph of IRF if there is a shock of one standard deviation in GDPG and its effect on the variables LEB, CO₂, PG itself, and GDPG. Suppose the graph from IRF moves to the original equilibrium (zero) line. In that case, this means that the response of a variable to shock other variables disappears, so the shock does not permanently affect that variable. Figure 14 also presents the confidence interval of the effect caused by shock on one variable. A shock of one standard deviation on GDPG has a weak impact on LEB and PG; this is shown in Figure 14, where the response is very small. Figure 14 also shows that the impact on PG is weak, but the standard deviation in the first 5 years is relatively high. This can be seen in the confidence interval in the first 5 years. A one standard deviation shock in GDPG causes CO₂ to respond in subsequent years. The response will fluctuate for the next 8 years, namely 0.5233, -1.3685, -0.0810, 0.7265, 0.5968, -0.8969, 0.4734, and -0.2831. In the 9th year and so on, the impact is weakened. A one standard deviation shock in GDPG causes GDPG to respond in the following years. The response fluctuated in the first 6 years, namely 9.6082, -4.8624, -0.2595, -0.6326, 1.5138, and -0.7514. From the 7th year onwards, the impact weakens towards balance.

Table 9: Roots of AR characteristic polynomials

Index	Real	Imaginary	Modulus	Radians	Degrees
1	0.95840	0.00000	0.9584	0.0000	0.0000
2	0.90342	0.26034	0.9402	0.2806	16.0753
3	0.90342	-0.26034	0.9402	-0.2806	-16.0753
4	0.84089	0.18883	0.8618	0.2209	12.6561
5	0.84089	-0.18883	0.8618	-0.2209	-12.6561
6	0.83254	0.00000	0.8325	0.0000	0.0000
7	0.62479	0.60951	0.8728	0.7730	44.2906
8	0.62479	-0.60951	0.8728	-0.7730	-44.2906
9	0.47095	0.72807	0.8671	0.9966	57.1030
10	0.47095	-0.72807	0.8671	-0.9966	-57.1030
11	-0.01476	0.46721	0.4674	1.6024	91.8096
12	-0.01476	-0.46721	0.4674	-1.6024	-91.8096

3.6. Forecasting and Proportion Prediction Error Covariance Decomposition

The VECM(4) model with cointegration rank r=4 is the best model and is suitable for LEB, CO₂, PG and GDPG data. (Figure 15a) shows that the LEB model shows that the predicted value and the

Table 10: Granger-causality wald test

Test	Group variables	DF	Chi-squares	P-values	Conclusion
1	Group 1: LEB variables Group 2: Variable CO ₂	4	35.19	<0.0001	Significant***
2	Group 1: LEB variables Group 2: PG variables	4	3.42	0.4898	Non-significant
3	Group 1: LEB variables Group 2: GDPG variables	4	0.74	0.9466	Non-significant
4	Group 1: Variable CO ₂ Group 2: LEB variables	4	57.32	<0.0001	Significant***
5	Group 1: Variable CO ₂ Group 2: PG variables	4	0.81	0.9372	Non-significant
6	Group 1: Variable CO ₂ Group 2: GDPG variables	4	1.99	0.7374	Non-significant
7	Group 1: PG variables Group 2: Variable CO ₂	4	2.78	0.5951	Non-significant
8	Group 1: PG variables Group 2: LEB variables	4	12.25	0.0156	Significant**
9	Group 1: PG variables Group 2: GDPG variables	4	2.60	0.6266	Non-significant
10	Group 1: GDPG variables Group 2: LEB variables	4	0.26	0.9923	Non-significant
11	Group 1: GDPG variables Group 2: PG variables	4	1.48	0.8298	Non-significant
12	Group 1: GDPG variables Group 2: Variable CO ₂	4	8.47	0.0757	Significant*

Figure 12: IRF for shock in variable CO₂

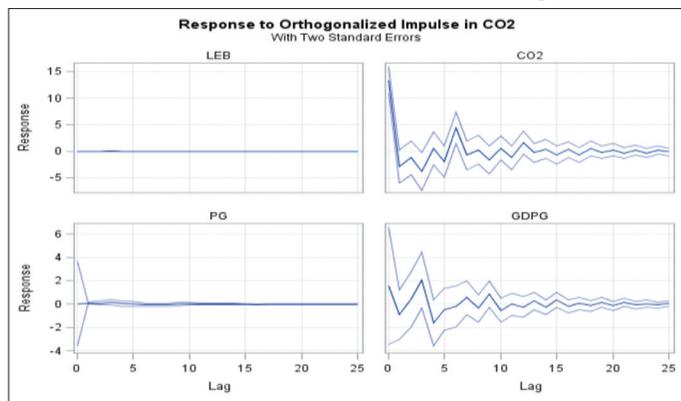


Figure 13: IRF for shock in variable PG

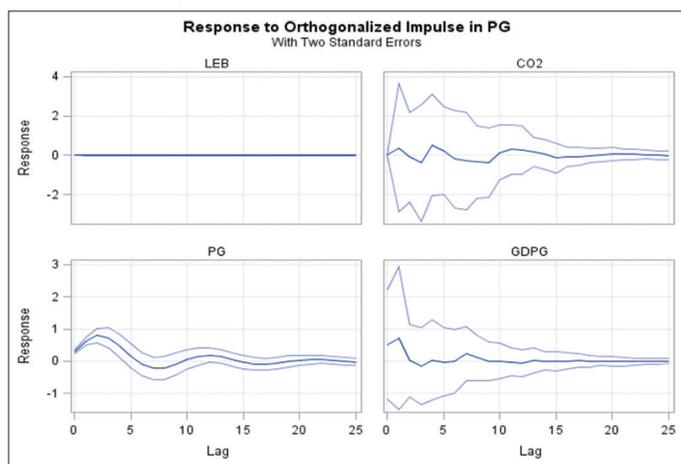
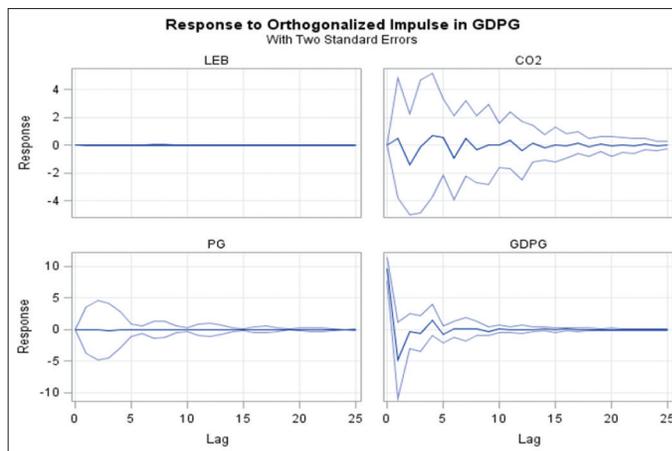


Figure 14: IRF for shock in variable GDPG



From the Proportion prediction Error Covariance decomposition of LEB, (Figure 15b), it appears that for the next 3 years forecasting, explained by itself (LEB), are 100%, 99.00%, and 97.89%. But for long-term forecasting for LEB above 10 years, LEB is able to explain 85.50% of diversity, CO₂ explains 5.07% of diversity, and PG explains 9.31% of diversity. While the influence of GDPG can be ignored. Viewed from Proportion prediction Error Covariance decomposition LEB, Figure 15, Appears for forecasting 3 year future the LEB is explained by itself (LEB) are 100%, 99.00%, and 97.89% and the influence of the other variable for the first 3 years can be ignored. But for long-term forecasting for LEB over 10 years, LEB is explained by LEB, CO₂, PG are 85.50% variance, 5.07% variance, and 9.31% variance, respectively Whereas GDPG influence can ignored.

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 16a) shows that the CO₂ 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 CO₂. (Figure 17a) 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 18a) 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 11 and (Figure 15a) shows the forecast value is relatively increasing. The further away the forecast is, the larger the standard residual value (Table 11), and the farther the forecast, the larger the confidence interval (Figure 15a). Forecasting values for the next 10 years are 80.4453, 80.5305, 80.6244, 80.6955, 80.7729, 80.8532, 80.126, 80.9720, 81.0379, and 81.0930. So in 10 years Qatar's LEB will increase by 0.6477 years.

The forecast value of CO₂ for the next 10 years from Table 11 and (Figure 16a) shows the forecast value is relatively rising in the first 3 years, and then the trend is flat and fluctuates. The further away the forecast is, the larger the standard residual value (Table 11), and the farther the forecast, the larger the confidence interval (Figure 16a). Forecasting values for the next 10 years are 37.7328, 45.4280, 50.8942, 46.6975, 45.6289, 47.0742, 44.7597, 45.3747, 46.2985, and 42.6191. So in the next 10 years Qatar's CO₂ will increase by 4.8863. Judging from the Proportion prediction Error Covariance decomposition of CO₂, Figure 16, it appears that for forecasting the next 5 years, the 1st year described by LEB and CO₂, is 16.13% and 83.87%, respectively. In the 2nd year described by LEB, CO₂, and PG and GDPG were 25.22%, 73.24%, and 1.54%, respectively. In the 3rd year CO₂ is explained by the error covariances of LEB, CO₂, and PG and GDPG of 31.49%, 66.78%, and 1.70%, respectively. In the 4th year CO₂ was explained by the error covariances of LEB, CO₂, PG and GDPG which were 337.81%, 59.52%, 0.37%, and 2.29%, respectively. In the 5th year CO₂ explained by the error covariances of LEB, CO₂, and PG and GDPG were 38.97%, 54.19%, 0.35%, and 6.47%, respectively. And for long-term CO₂ forecasting, the error covariance of LEB, CO₂, and PG and GDPG is explained by 42.85%, 44.71%, 1.68%, and 10.757%, respectively.

The PG forecast value for the next 10 years from Table 11 and (Figure 17a) shows that the forecast value is relatively increasing

Figure 15: (a) Model and Forecast for LEB, (b) Proportion prediction error covariances for LEB

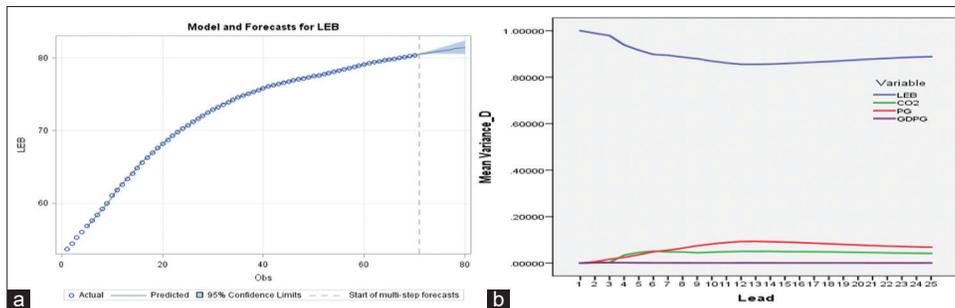


Figure 16: (a) Model and Forecast for LEB, (b) Proportion prediction error covariances for CO₂

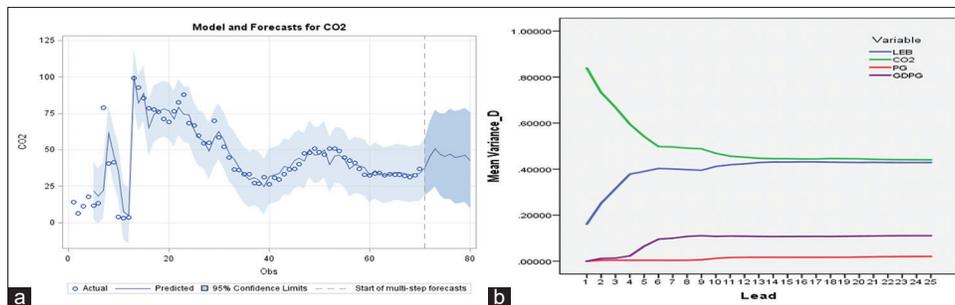


Figure 17: (a) Model and Forecast for PG, (b) Proportion prediction error covariances for PG

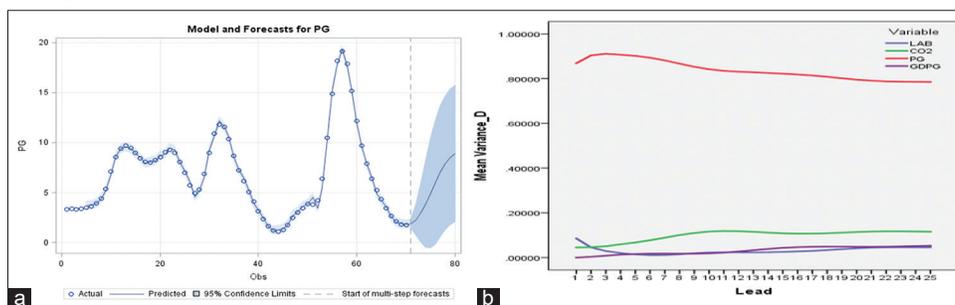
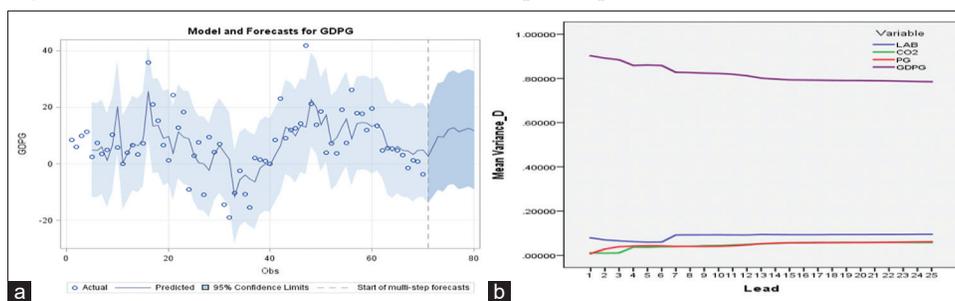


Figure 18: (a) Model and Forecast for GDPG, (b) Proportion prediction error covariances for GDPG



in the next 10 years. The further away the forecast is, the larger the standard residual value (Table 11), and the farther the forecast, the larger the confidence interval (Figure 17a). Forecasting values for the next 10 years are 1.8473, 2.2468, 2.9479, 3.8713, 4.9538, 6.0630, 7.0585, 7.8905, 8.5240, and 8.9215. Judging from the Proportion prediction Error Covariance decomposition of PG, Figure 17, it appears that for forecasting PG for the next 5 years, the 1st year described by LEB, CO₂, and PG is 8.56%, 4.54%, and 8689%, respectively. In the 2nd year it is explained by the error covariances of LEB, CO₂, PG and GDPG which are 4.54%, 4.66%,

90.43% and 0.36%, respectively. In the 3rd year CO₂ explained by the error covariances of LEB, CO₂, PG and GDPG were 2.94%, 5.08%, 91.11% and 0.85%, respectively. In the 4th year CO₂ is explained by the error covariances of LEB, CO₂, PG and GDPG which are 2.03%, 5.94%, 90.71% and 1.31%, respectively. In the 5th year CO₂ is explained by the error covariances of LEB, CO₂, PG and GDPG which are 4.54%, 4.66%, 90.43% and 0.36%, respectively. And for long-term forecasting of PG, the error covariance of LEB, CO₂, and PG and GDPG is 2.39%, 11.87%, 83.49% and 2.24%, respectively.

Table 11: Forecast for the next 10 years

Var	Obs	Forecast	Standard error	95% confidence limits		Var	Obs	Forecast	Standard error	95% confidence limits	
LEB	71	80.4453	0.0391	80.3685	80.5220	PG	71	1.8473	0.2465	1.3641	2.3305
	72	80.5305	0.0605	80.4118	80.6492		72	2.2468	0.7747	0.7283	3.7653
	73	80.6244	0.0801	80.4673	80.7815		73	2.9479	1.5005	0.0070	5.8889
	74	80.6955	0.1013	80.4969	80.8942		74	3.8713	2.2453	-0.5294	8.2721
	75	80.7729	0.1208	80.5361	81.0097		75	4.9538	2.8385	-0.6095	10.5173
	76	80.8532	0.1372	80.5842	81.1222		76	6.0630	3.2075	-0.2236	12.3496
	77	80.9126	0.1595	80.5999	81.2254		77	7.0585	3.3833	0.4272	13.6898
	78	80.9720	0.1804	80.6184	81.3256		78	7.8905	3.4508	1.1270	14.6541
	79	81.0379	0.1996	80.6466	81.429		79	8.5240	3.4814	1.7005	15.3474
	80	81.0930	0.2181	80.6653	81.5206		80	8.9215	3.5075	2.0470	15.7961
CO ₂	71	37.7328	9.7959	18.5331	56.9325	GDPG	71	2.7567	8.4766	-13.857	19.3706
	72	45.4280	12.1398	21.6343	69.2217		72	6.4293	9.1705	-11.544	24.4032
	73	50.8942	13.4609	24.511	77.2772		73	9.6747	9.5925	-9.1263	28.4758
	74	46.6975	14.2792	18.7108	74.6842		74	9.4435	9.8606	-9.8829	28.7700
	75	45.6289	14.9663	16.2954	74.9624		75	12.1717	10.1172	-7.6576	32.0010
	76	47.0742	15.7443	16.2157	77.9326		76	12.8554	10.2193	-7.1742	32.8850
	77	44.7597	16.1774	13.0525	76.4670		77	11.4425	10.4755	-9.0890	31.9741
	78	45.3747	16.3468	13.3354	77.4140		78	12.0113	10.5413	-8.6493	32.6720
	79	46.2985	16.4167	14.1223	78.4747		79	12.6494	10.5737	-8.0747	33.3735
	80	42.6191	16.8060	9.6799	75.5582		80	11.6777	10.5834	-9.0655	32.4209

The GDPG forecast value for the next 10 years from Table 11 and (Figure 18a) 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 11), and the farther the forecast, the larger the confidence interval (Figure 18a). Forecasting values for the next 10 years are 2.7567, 6.4293, 9.6747, 9.4435, 12.1717, 12.8554, 11.4425, 12.0113, 12.6494, and 11.6777. Judging from the Proportion prediction Error Covariance decomposition of GDPG, Figure 18, it appears that for forecasting GDPG for the next 5 years, the 1st year described by LEB, CO₂, PG and GDPG are 7.91%, 1.09%, 0.75% and 90.24%, respectively. In the 2nd year it is explained by the error covariance of LEB, CO₂, PG and GDPG which are 6.98%, 0.97%, 2.84% and 89.20%, respectively. In the 3rd year CO₂ is explained by the error covariances of LEB, CO₂, PG and GDPG which are 6.55%, 1.05%, 3.93% and 88.46%, respectively. In the 4th year CO₂ is explained by the error covariances of LEB, CO₂, PG and GDPG which are 6.21%, 3.74%, 4.18% and 85.86%, respectively. In the 5th year CO₂ is explained by the error covariances of LEB, CO₂, PG and GDPG which are 5.97%, 3.67%, 4.28% and 86.07%, respectively. And for long-term forecasting of PG, the error covariance of LEB, CO₂, and PG and GDPG is 9.35%, 5.38%, 5.56% and 79.71%, respectively.

4. DISCUSSION

The results also show a correlational (reciprocal) relationship between Life Expectancy of birth and CO₂ emissions. The effect of CO₂ emissions on LEB is supported by the results of research by Huang et al. (2012), that abnormal temperature can complicate the health condition of people with cardiovascular problems because of its effect on blood pressure. And supported by Salau (2016) and Zivin and Shrader (2016) who found that an increase in average temperature is harmful to people's lives because it will lead to an increase in heat-related health problems such as stroke, asthma and harm the developing fetus. In addition, Bardi and Perini (2013) also found that healthy life expectancy decreased with increasing

temperature. Likewise, with the results of research Fakhri et al. (2015) that life expectancy is negatively affected by CO₂ emissions in both the short and long term in all MENA countries (Middle East and North Africa). Specifically, the results of the Chigozie and Edemi (2019) study in Nigeria, found estimates that CO₂ has reduced LEB by 1 month and 3 weeks. On the other hand, LEB affects CO₂, this finding can be interpreted that the increase in LEB has increased the population's activity in using energy, resulting in an increase in CO₂ emissions. Several studies have shown that LEB has a negative impact on CO₂, meaning that the increase in LEB has resulted in a good and healthy quality of life, the use of environmentally friendly and energy-efficient products. In addition, a good level of environmental literacy, access to safe drinking water and an adequate level of education (Gulis, 2000) can reduce CO₂ emissions. Statistical analysis also found the relationship between LEB and Qatar's population growth (Seo, 1999). According to Chen and Ching (2000) LEB is positively correlated with population growth. However, Ademoh (2017) found a negative relationship between LEB and population growth. Because with low population growth, it will reduce the pressure of life and stress in meeting family needs which will have an impact on a longer life expectancy.

Qatar as a high-income country produces high CO₂ emissions as well. The result of statistical findings is that there is a correlation between CO₂ emissions and economic growth (GDP). Increased CO₂ emissions can increase economic growth in Qatar. These results are in line with Saidi and Hamammi (2015); Heidari et al. (2015), that energy consumption plays an important role in increasing economic growth. Qatar's economic growth is not only caused by the contribution of the industry that produces high CO₂ emissions, it is also supported by economic growth from the previous year. The positive impact of CO₂ on economic growth is due to an increase in energy consumption in an effort to move the industry to process basic materials into higher quality products. In the long term the relationship between CO₂ emissions and

economic growth is expected to follow the Kuznet curve, with increasing economic growth (GDP), CO₂ emissions can be reduced as a result of public awareness of the need for a healthy and clean environment. Meanwhile, LEB affects Qatar's economic growth (GDP) through increasing CO₂ emissions. Residents' activities with Long LEB are able to contribute to Qatar's economic growth by increasing the amount of CO₂ emissions. This result is supported by Chen and Ching (2000) who found that LEB is positively correlated to economic growth (GDP). The relationship between population growth and economic growth in Qatar was not found. This can happen because the population in Qatar is relatively small compared to the resulting very high economic growth (GDP) from time to time.

5. CONCLUSION

In this study, data multivariate time series Qatar: LEB, CO₂, PG, and GDPG from year 1950 to 2020 are analyzed. From the assumption analysis, it is found that the variables are integrated with order one, I(1), and there is cointegration with rank cointegration $r=4$, and the optimum lag using the AICC Information criterion is found at lag-4. Therefore, the model built is the VECM(4) with cointegration rank $r=4$. From the results of the analysis with granger-causality variables LEB and CO₂ are bidirectional Granger-causality, namely LEB is granger-causality to CO₂ and CO₂ is granger-causality to LEB; CO₂ is the granger causality of GDPG, and LEB is the granger causality of PG.

Qatar is one of the oil and gas producing countries and is an oil and gas exporter. Energy consumption in Qatar also plays an important role in increasing economic growth (GDP). High energy use has implications for increasing CO₂ emission levels. In addition, there was no direct effect of economic growth (GDP) on LEB. This result can be interpreted that the level of LEB in Qatar is not related to economic growth. However, through CO₂ emissions, the age of Qatar's population significantly impacts economic growth. The long life span leads to an increase in energy use activities and an increase in CO₂ emissions. On the other hand, LEB also affects population growth (PG) in Qatar, and CO₂ emissions indirectly affect population growth. Furthermore, the increasing age of the Qatari population can increase or decrease population growth. From the forecasting results for the next 10 years the LEB, PG, and GDPG variables have an increasing trend, but CO₂ in the next 3 years will increase and will then tend to be stable (flat) and fluctuate. From the analysis of the proportion predicted error covariances for long-term forecasting of one variable, the other three variables also influence the results of forecasting.

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