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**Article**

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# 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 ($CO_2$) 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, $CO_2$, 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 ($CO_2$) 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 Prettner (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 $CO_2$ 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 $CO_2$ 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 $CO_2$ emissions positively impacted mortality over time. And carbon dioxide ($CO_2$) 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 ($CO_2$) 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, $CO_2$ emissions, economic growth, and population growth, especially in Qatar. The direction of causality between LEB, GDP, PG, and $CO_2$ 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 ($CO_2$) 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:

$$X_t = \begin{pmatrix} LEB_t \\ CO2_t \\ PG_t \\ GDPG_t \end{pmatrix}$$

LEB is Life Expectancy at Birth, $CO_2$ 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 dan 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 Xt 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) $\mathrm{Cov}(X_t) = \Sigma_t k \times k$ 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:

$$\Delta X_t = \beta o + \lambda X_{t-1} + \sum_{i=1}^{p-1} \lambda_1^* \Delta X_{t-1} + \varepsilon_t \quad (1)$$

Where $\Delta X_t = X_t - X_{t-1}$ and $\varepsilon_t$ 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:

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

## 2.2. Calculation of a Cross-Correlation Matrix

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

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

Where $\overline{X} = \frac{1}{T}\sum_{t=1}^{T} X_t$ is the vector sample mean. The cross-correlation $\rho_k$ 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 seriesis as follows:

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

With the alternative

$$Ha: \rho_i \neq 0 \quad for\ some \quad i \in \{1, 2, \ldots, k\}.$$

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 $X_t$, and 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 $m^2k$. 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 $X_t$. If Ho is rejected, the class of vector autoregressive model should be involved in building a multivariate model for the time series data studied.

## 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,

$Z_t = \beta' X_t$ is stationary,

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

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

This mean that $\beta' \hat{Z}_T(m) \to \mu_Z$ 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:

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

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

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

## 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:

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

Where $X_t$ is the $n \times 1$ vector observation at the time $t$, $\Phi_i$ is the $n \times n$ matrix coefficient of vector $X_{t-i}$, for $i = 1,2,\ldots\ p$, $p$ is the lag length, and $\varepsilon_t$ 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):

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

Where $\Delta$ 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, $\varepsilon_t$ is the $k \times 1$ vector white noise, $\beta_0$ is vector constant, is the matrix coefficient of cointegration, and $\Pi = \alpha\beta^t$, $\alpha$ = matrix adjustment, $(k \times r)$ and $\beta$ = matrix cointegration $(k \times r)$, $\Gamma_i$ = matrix coefficient $(k \times k)$ for the $i$ variable endogenous, and $\Phi_i$ = 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:

$$\mathrm{JB} = \left[ \frac{\mathrm{N}}{6} \mathrm{b}_1^2 + \frac{\mathrm{N}}{24} (\mathrm{b}_2 - 3)^2 \right] \quad (9)$$

Where $N$ is the sample size, $\mathrm{b}_1$ is the expected skewness, and $\mathrm{b}_2$ is the expected excess kurtosis. The JB test of normality has $\chi^2$ 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:

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

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

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

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:

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

$X_t$ 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 $i = 1,2,\ldots,\ p$ (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 $i^{\text{th}}$ row and $j^{\text{th}}$ column indicated the consequence of the increase of one unit in the innovation of variable $j$ at time $t$ $(\mu_{jt})$ for the $i$ variable at time $t + s$ $(X_{i,\,t+s})$ and fixed all other innovation. If the element of $\mu_t$ changed by δ1, at the same time, the second element will change by $\delta_2,\ldots$, and the $n$th element will change by $\delta_n$, then the common effect from all of these changes on the vector $X_{t+s}$ will become

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

The plot of the $i^{\text{th}}$ row and $j^{\text{th}}$ column of $\Psi_s$ 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, $CO_2$, 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

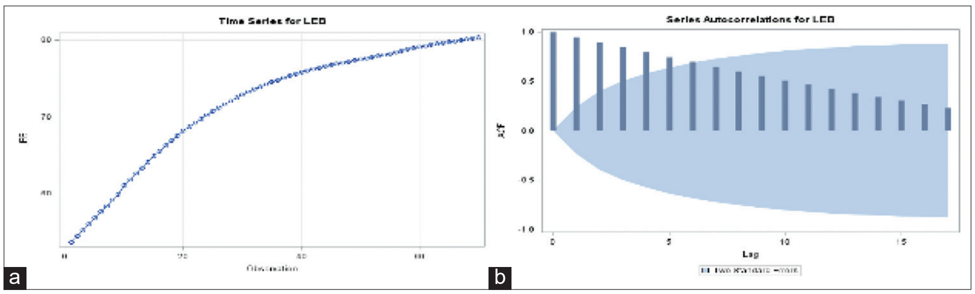



**Figure 2:** (a) Data time series for $CO_2$ from 1950 to 2020, (b) Autocorrelation function for $CO_2$

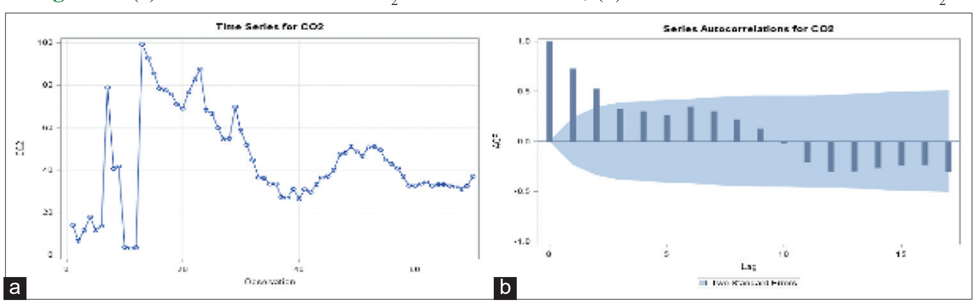



**Figure 3:** (a) Data time series for PG from 1950 to 2020, (b) Autocorrelation function for PG

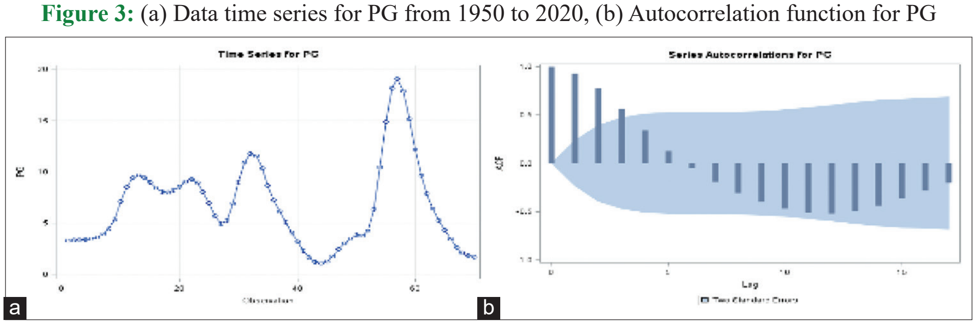
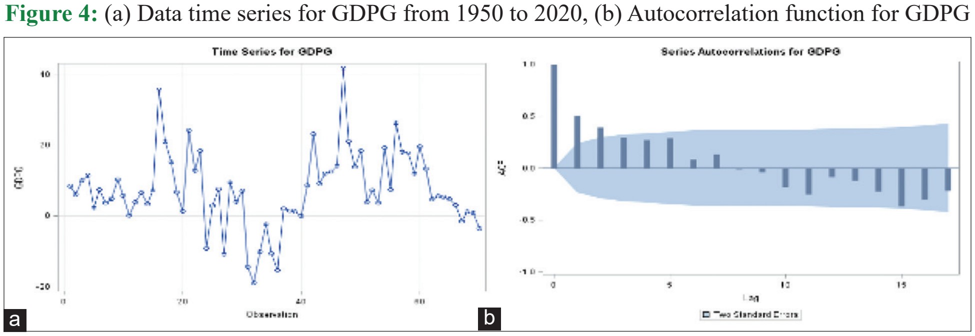



**Figure 4:** (a) Data time series for GDPG from 1950 to 2020, (b) Autocorrelation function for GDPG



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 $CO_2$ data from 1950 to 2020. From 1950 to 1955, the $CO_2$ 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 $CO_2$ 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 $CO_2$ 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: $H_0$: Rank=r (there is no cointegration) against $H_1$: 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, $CO_2$, PG, and GDPG data. From the results of the cross-correlations test for multivariate data on LEB, $CO_2$, 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, $\Pi$ is vector $4 \times 4$ parameter cointegration, and $\Pi = \alpha\beta'$, $\beta$ is vector cointegration, and $\Phi_1, \Phi_2$, *and* $\Phi_3$ 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 |

**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 |

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

$$\Delta\begin{bmatrix} LAB_t \\ CO2_t \\ PG_t \\ GDPG_t \end{bmatrix} = \begin{bmatrix} 1.1822 \\ -240.1395 \\ 2.0982 \\ -77.7092 \end{bmatrix}$$

$$+\begin{bmatrix} -0.0145 & 0.0001 & 0.0021 & -0.0002 \\ 3.1406 & -0.5147 & -0.8419 & 0.3838 \\ -0.0239 & 0.0035 & -0.0393 & -0.0018 \\ 1.0426 & -0.1052 & -0.1549 & -0.3168 \end{bmatrix}\begin{bmatrix} LAB_{t-1} \\ CO2_{t-1} \\ PG_{t-1} \\ GDPG_{t-1} \end{bmatrix}+$$

$$\begin{bmatrix} 0.1916 & 0.0001 & 0.0169 & 0.0005 \\ -61.7747 & 0.0667 & 3.5938 & -0.2215 \\ -2.1474 & -0.0032 & 2.1039 & -0.0039 \\ -1.2075 & 0.0585 & 4.8092 & -0.28708 \end{bmatrix}\Delta\begin{bmatrix} LAB_{t-1} \\ CO2_{t-1} \\ PG_{t-1} \\ GDPG_{t-1} \end{bmatrix}+$$

$$\begin{bmatrix} 0.1153 & -0.0004 & -0.0267 & 0.0004 \\ -26.0924 & 0.1682 & -4.5301 & -0.2393 \\ 1.4792 & -0.0013 & -1.8231 & 0.0004 \\ -7.2749 & 0.0911 & -7.3496 & -0.0956 \end{bmatrix}\Delta\begin{bmatrix} LAB_{t-2} \\ CO2_{t-2} \\ PG_{t-2} \\ GDPG_{t-2} \end{bmatrix}+$$

$$\begin{bmatrix} 0.2687 & 0.0016 & 0.0131 & -0.0001 \\ 182.3392 & -0.0651 & 4.1291 & -0.1622 \\ 0.0017 & -0.0011 & 0.6814 & 0.0001 \\ 19.0852 & 0.2435 & 4.5725 & -0.1141 \end{bmatrix}$$

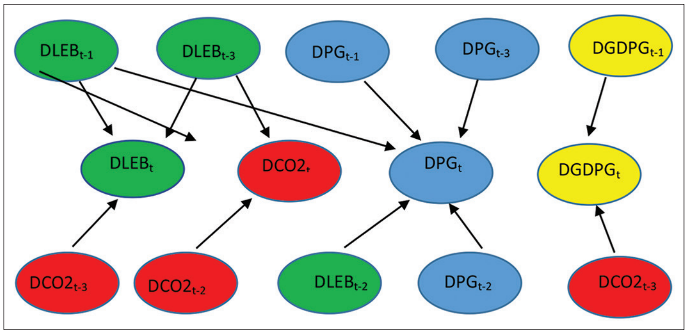
$$\Delta\begin{bmatrix} LAB_{t-3} \\ CO2_{t-3} \\ PG_{t-3} \\ GDPG_{t-3} \end{bmatrix}+\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}$$

And the covariance innovation is:

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

Figure 5 shows that LEBt is significantly influenced by $LEB_{t-1}$, $LEB_{t-3}$, and $CO_{2t-3}$ this indicates that information on LEB one and 3 years prior and information on $\Delta CO_2$ 3 years prior significantly affects current LEB; shows that $CO_{2t}$ is significantly influenced by $LEB_{t-1}$, $LEB_{t-3}$, and $CO_{2t-2}$ this indicates that information on LEB 1 and 3 years before and information on $\Delta CO_2$ 3 years before significantly affects current $\Delta CO_2$; that PGt 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 GDPGt is significantly influenced by $GDPG_{t-1}$ and $CO_{2t-3}$ this indicates that information on GDPG 1 year before and information on $CO_2$ 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:

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

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

$$\begin{aligned}\Delta PG_t =& 2.0982 - 0239\ LEB_{t-1} + 0.0035 CO2_{t-1} - 0.0393 PG_{t-1} \\ & -0.0018 GDPG_{t-1} - 2.1474 \Delta LEB_{t-1} 0.0032 \Delta CO2_{t-1} \\ & +2.1039 \Delta PG_{t-1} - 0.0039\ \Delta GDPG_{t-1} + 1.4792 \Delta LEB_{t-2} \\ & -0.0013 \Delta CO2_{t-2} - 4.5301 \Delta PG_{t-2} - 0.2393 \Delta GDPG_{t-2} \\ & +182.3392\ \Delta LEB_{t-3} - 0.0651 \Delta CO2_{t-3} + 4.1291 \Delta PG_{t-3} - \\ & 0.0001 \Delta GDPG_{t-3}\end{aligned} \quad (18)$$

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

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-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-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-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-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 $CO_2$. Based on Table 10, the test 4, where the variable in group 1 is $CO_2$ and the variable in group 2 is LEB, the P < 0.0001, which is significant. Therefore, the null hypothesis that the variable $CO_2$ is influenced by itself and not influenced by LEB is rejected. So that it can be concluded that the variable $CO_2$ 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 $CO_2$, 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 $CO_2$ 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 $CO_2$. Figure 10 provides an illustration of the relationship pattern of granger causality where LEB is granger causality to $CO_2$, $CO_2$ is granger causality to LEB; LEB is granger-causality to PG; and $CO_2$ is grander 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

## 3.5. Impulse Response Function (IRF)

Figure 11 is a graph of IRF if there is a shock of one standard deviation in LEB and its effect on the LEB variables themselves, $CO_2$, 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 11 also presents the confidence interval of the effect caused by shock on one variable. A shock of one standard deviation in the LEB

**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

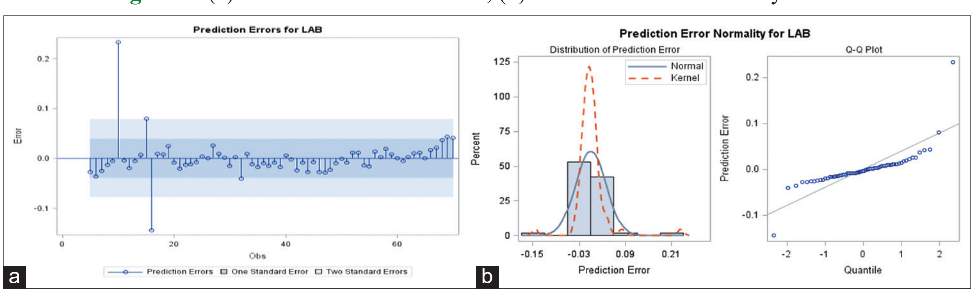



**Figure 7:** (a) Prediction errors for $CO_2$, (b) Prediction error normality for $CO_2$

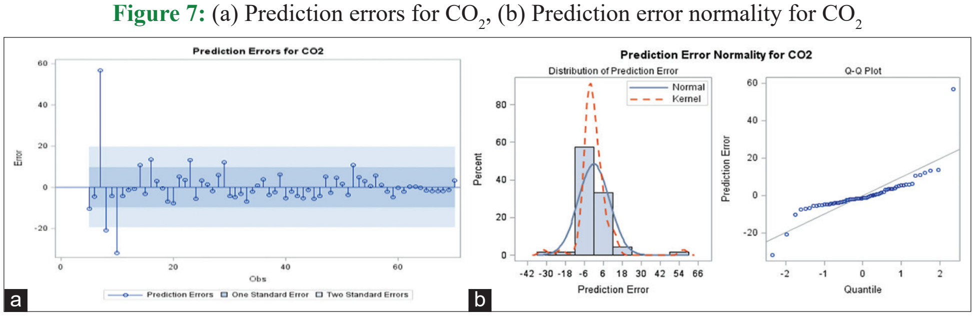


**Figure 8:** (a) Prediction errors for PG, (b) Prediction error normality for PG

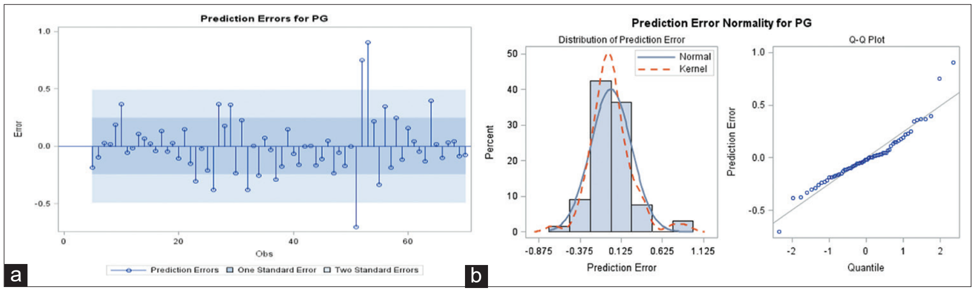



**Figure 9:** (a) Prediction errors for GDPG, (b) Prediction error normality for GDPG

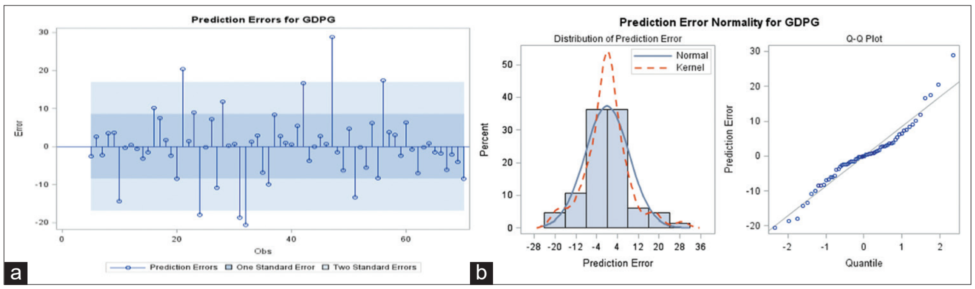



**Figure 10:** Granger-causality between variables LEB, CO 2, PG and GDPG

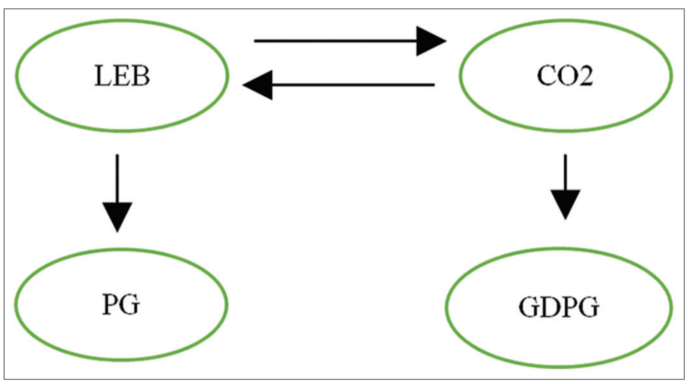
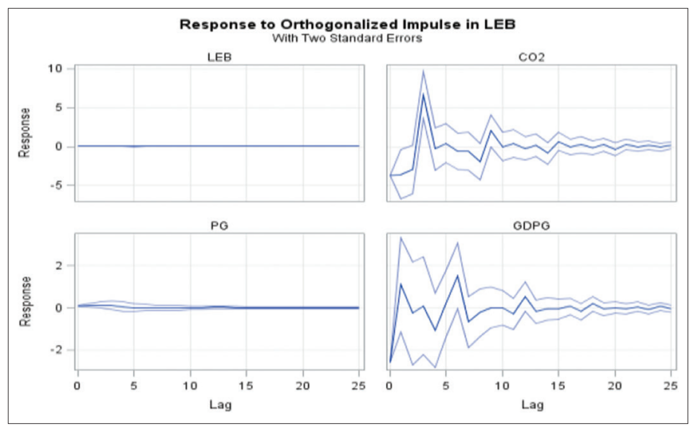



**Figure 11:** IRF for shock in variable LEB




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 $CO_2$ 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 $CO_2$ and its effect on the variables LEB, $CO_2$ 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 $CO_2$ 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 $CO_2$ and GDPG fluctuated and weakened several periods later. A one standard deviation shock in $CO_2$ causes $CO_2$ 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 $CO_2$ 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, $CO_2$, 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 $CO_2$ 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.

**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 |

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, $CO_2$, 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 $CO_2$ 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.

### 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, $CO_2$, 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<br>Group 2: Variable $CO_2$ | 4 | 35.19 | <0.0001 | Significant*** |
| 2 | Group 1: LEB variables<br>Group 2: PG variables | 4 | 3.42 | 0.4898 | Non-significant |
| 3 | Group 1: LEB variables<br>Group 2: GDPG variables | 4 | 0.74 | 0.9466 | Non-significant |
| 4 | Group 1: Variable $CO_2$<br>Group 2: LEB variables | 4 | 57.32 | <0.0001 | Significant*** |
| 5 | Group 1: Variable $CO_2$<br>Group 2: PG variables | 4 | 0.81 | 0.9372 | Non-significant |
| 6 | Group 1: Variable $CO_2$<br>Group 2: GDPG variables | 4 | 1.99 | 0.7374 | Non-significant |
| 7 | Group 1: PG variables<br>Group 2: Variable $CO_2$ | 4 | 2.78 | 0.5951 | Non-significant |
| 8 | Group 1: PG variables<br>Group 2: LEB variables | 4 | 12.25 | 0.0156 | Significant** |
| 9 | Group 1: PG variables<br>Group 2: GDPG variables | 4 | 2.60 | 0.6266 | Non-significant |
| 10 | Group 1: GDPG variables<br>Group 2: LEB variables | 4 | 0.26 | 0.9923 | Non-significant |
| 11 | Group 1: GDPG variables<br>Group 2: PG variables | 4 | 1.48 | 0.8298 | Non-significant |
| 12 | Group 1: GDPG variables<br>Group 2: Variable $CO_2$ | 4 | 8.47 | 0.0757 | Significant* |

**Figure 12:** IRF for shock in variable $CO_2$

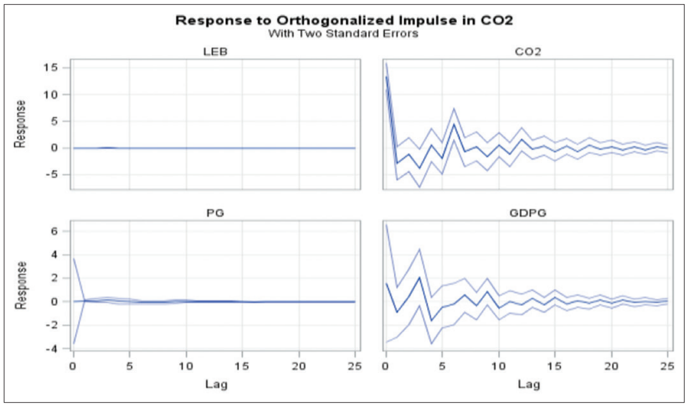
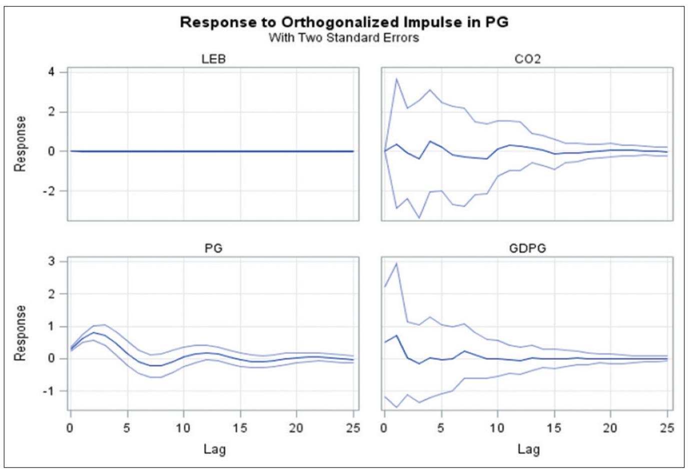


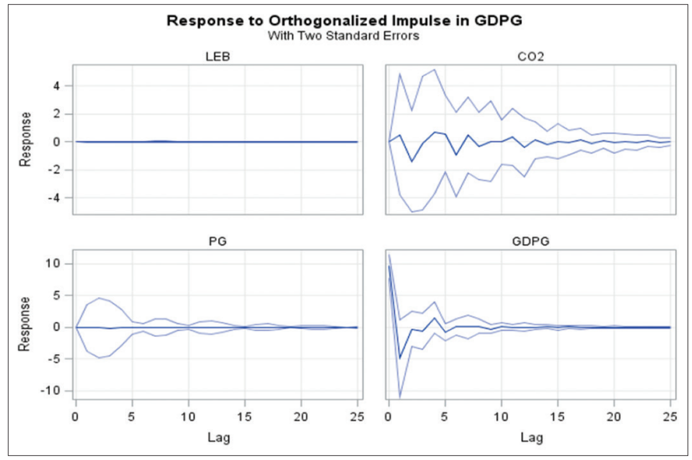

**Figure 13:** IRF for shock in variable PG




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 $CO_2$ 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 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.

**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, $CO_2$ 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, $CO_2$, PG are 85.50% variance, 5.07% variance, and 9.31% variance, respectively Whereas GDPG influence can ignored.

The forecast value of $CO_2$ 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 $CO_2$ will increase by 4.8863. Judging from the Proportion prediction Error Covariance decomposition of $CO_2$, Figure 16, it appears that for forecasting the next 5 years, the 1[st] year described by LEB and $CO_2$, is 16.13% and 83.87%, respectively. In the 2[nd] year described by LEB, $CO_2$, and PG and GDPG were 25.22%, 73.24%, and 1.54%, respectively. In the 3[rd] year $CO_2$ is explained by the error covariances of LEB, $CO_2$, and PG and GDPG of 31.49%, 66.78%, and 1.70%, respectively. In the 4[th] year $CO_2$ was explained by the error covariances of LEB, $CO_2$, PG and GDPG which were 337.81%, 59.52%, 0.37%, and 2.29%, respectively. In the 5[th] year $CO_2$ explained by the error covariances of LEB, $CO_2$, and PG and GDPG were 38.97%, 54.19%, 0.35%, and 6.47%, respectively. And for long-term $CO_2$ forecasting, the error covariance of LEB, $CO_2$, 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

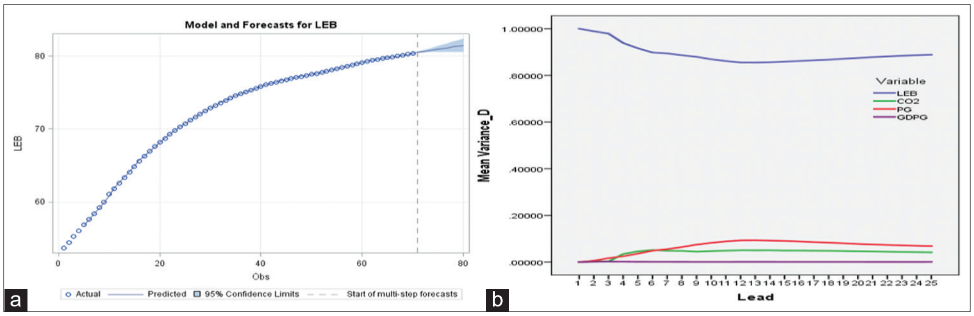



**Figure 16:** (a) Model and Forecast for LEB, (b) Proportion prediction error covariances for $CO_2$

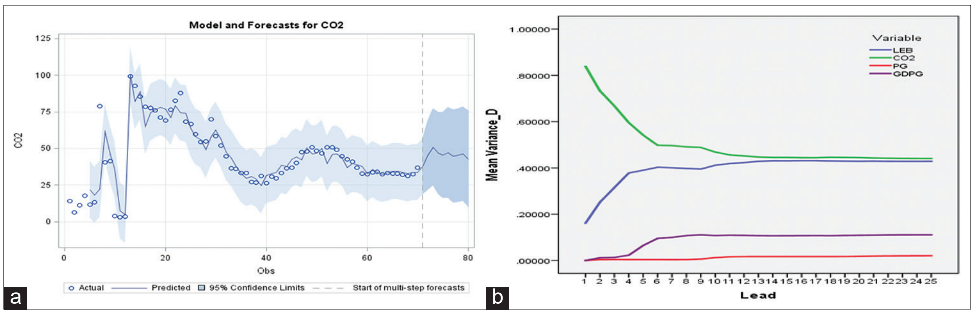



**Figure 17:** (a) Model and Forecast for PG, (b) Proportion prediction error covariances for PG

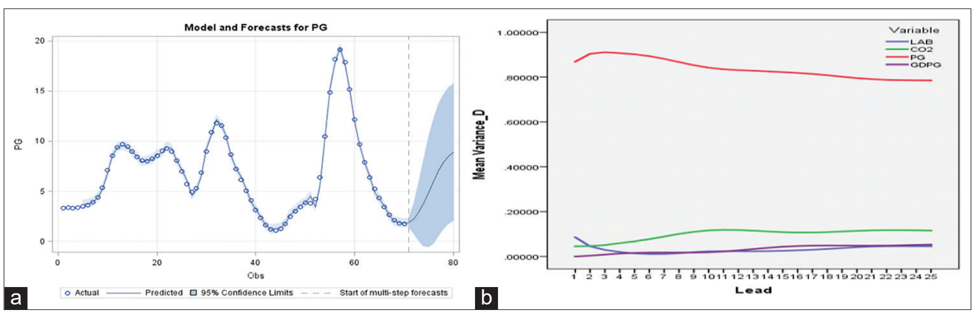
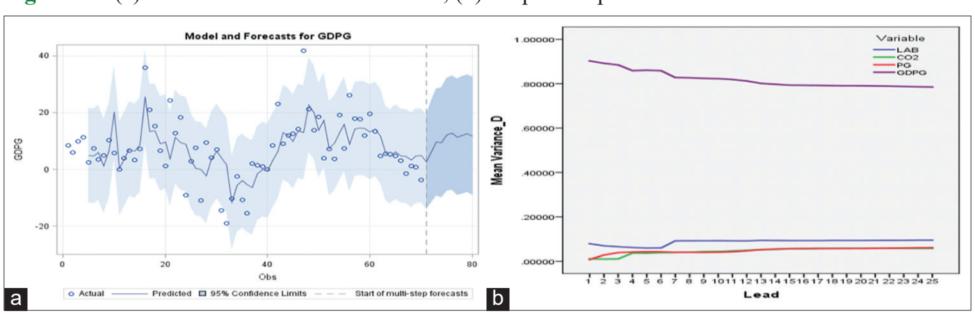



**Figure 18:** (a) Model and Forecast for GDPG, (b) Proportion prediction error covariances for GDPG




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 1$^{st}$ year described by LEB, $CO_2$, and PG is 8.56%, 4.54%, and 8689%, respectively. In the 2$^{nd}$ year it is explained by the error covariances of LEB, $CO_2$, PG and GDPG which are 4.54%, 4.66%, 90.43% and 0.36%, respectively. In the 3$^{rd}$ year $CO_2$ explained by the error covariances of LEB, $CO_2$, PG and GDPG were 2.94%, 5.08%, 91.11% and 0.85%, respectively. In the 4$^{th}$ year $CO_2$ is explained by the error covariances of LEB, $CO_2$, PG and GDPG which are 2.03%, 5.94%, 90.71% and 1.31%, respectively. In the 5$^{th}$ year $CO_2$ is explained by the error covariances of LEB, $CO_2$, 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, $CO_2$, 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, $CO_2$, 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, $CO_2$, PG and GDPG which are 6.98%, 0.97%, 2.84% and 89.20%, respectively. In the 3rd year $CO_2$ is explained by the error covariances of LEB, $CO_2$, PG and GDPG which are 6.55%, 1.05%, 3.93% and 88.46%, respectively. In the 4th year $CO_2$ is explained by the error covariances of LEB, $CO_2$, PG and GDPG which are 6.21%, 3.74%, 4.18% and 85.86%, respectively. In the 5th year $CO_2$ is explained by the error covariances of LEB, $CO_2$, 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, $CO_2$, 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 $CO_2$ emissions. The effect of $CO_2$ 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 $CO_2$ 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 $CO_2$ has reduced LEB by 1 month and 3 weeks. On the other hand, LEB affects $CO_2$, this finding can be interpreted that the increase in LEB has increased the population's activity in using energy, resulting in an increase in $CO_2$ emissions. Several studies have shown that LEB has a negative impact on $CO_2$, 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 $CO_2$ 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 $CO_2$ emissions as well. The result of statistical findings is that there is a correlation between $CO_2$ emissions and economic growth (GDP). Increased $CO_2$ 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 $CO_2$ emissions, it is also supported by economic growth from the previous year. The positive impact of $CO_2$ 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 $CO_2$ emissions and economic growth is expected to follow the Kuznet curve, with increasing economic growth (GDP), $CO_2$ 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 $CO_2$ emissions. Residents' activities with Long LEB are able to contribute to Qatar's economic growth by increasing the amount of $CO_2$ 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, $CO_2$, 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 $CO_2$ are bidirectional Granger-causality, namely LEB is granger-causality to $CO_2$ and $CO_2$ is granger-causality to LEB; $CO_2$ 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 $CO_2$ 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 $CO_2$ 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 $CO_2$ emissions. On the other hand, LEB also affects population growth (PG) in Qatar, and $CO_2$ 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 $CO_2$ 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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