Application of VEC Model in Modeling Hypertension and Comorbidities Related Data

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ABSTRACT

The study investigated multivariate analysis of hypertension and its comorbidities related data in River's state of Nigeria. The objectives of the study include to; estimate the interaction existing among systolic, diastolic and BMI and determine the direction of causality, significance of the causality and hence summaries the causal chambers among systolic, diastolic and BMI. The data for the study was sourced from the patients' files who visited and were admitted at the University of Port Harcourt Teaching Hospital spanning from 6th January, 2017 to 28th January, 2021, while the software used for data analysis is Eview version twelve. The study adopted an ex-post-facto design. The study used the Vector Error Correction Model (VECM) for the data analysis. The results of the estimation show that age of the patients and Body Mass Index are negatively correlated, diastolic and the age of the patients are positively but weakly correlated, systolic and the age of the patients are positively associated with a weak correlation. Also, diastolic and Body Mass Index has weak negative correlation. Body Mass Index and systolic negatively weak correlated and it was found that there exists strong positive correlation between systolic and diastolic. It was found that there is a co-integrating (long-run) relationship between hypertension and comorbidities related data. The results of the VECM model shows that the order of co-efficient of determinations (R^2) were 0.648, 0.795, 0.761 when the age of the patients, Body Mass index, Diastolic and systolic were considered as dependent variable. This implied that 64.8%, 79.5% and 76.1% variation in the dependent variables is explained by variations in their respective independent variables. The remaining 31.3%, 20.5 and 23.9 are variations expounded by other variables not included in the model. Also, the correction of the previous period's deviation from the long-run equilibrium in the subsequent period at an adjustment speed were 53.0%, 49.4%, and 32.8%. respectively. It was found that body mass index granger cause aging of the patients. However, the causality between them was uni-directional while Bi- directional causality was found to exists systolic and diastolic. It can be concluded that there is an interaction between hypertension and comorbidities related data and it can be determine based on the fractions in each hypertension variable. Therefore, there is need for formulation of health policies to regulate hypertension as conditions. This because response to shock or the dynamic behaviour between hypertension and its comorbidities should be control, having noted that the significantly interactions between its comorbidities cause aging of the patients. In modeling the fractions in each hypertension variable explained by the

innovations on its comorbidities related data   impulse response analysis for comorbidities should be considered instead of dumping coefficient and natural frequency.

Key words: *Application, Model, Hypertension, Comorbidities, Data*

Introduction

1.1   Background to the study

High blood pressure (hypertension) can silently damage the body for years before symptoms appear. Uncontrolled high blood pressure can lead to disability, poor quality of life, or even a fatal heart attack or stroke. Treatment and lifestyle changes can help control high blood pressure to reduce the risk of life-threatening complications. According to my According to Ezzati *et al.,* (2002) High blood pressure is a condition in which the force of the blood against the walls of the arteries is too high. High blood pressure is generally defined as blood pressure higher than 140/90 and is considered severe if the pressure is higher than 180/120 and when it continues for some time it can cause health problems such as heart disease, accident cerebrovascular disease, diabetes, kidney failure, etc. The incidence of arterial hypertension is increasing and its effect is worse than that of malaria. High blood pressure is a silent killer. In some populations, it is misdiagnosed, mismanaged, and when not properly treated and managed, can cause serious complications, including death. The danger of high blood pressure is that there are no clear signs associated with it until it leads to cardiovascular disease (CVD), especially stroke or heart disease. According to the study by Ezzat *et al.* (2002), about two-thirds of stroke cases, for example, and about half of all heart disease worldwide, can be attributed to high blood pressure. Several studies have pointed to the fact that awareness of high blood pressure in African countries is very low. Therefore, by expanding awareness of associated diseases, it can also be non-existent. Another issue of concern is that most people with high blood pressure are people in their prime. Obviously, this will have negative effects on most of the economies of African countries (Nigeria). It will also create a lot of social problems because many of the breadwinners may have an unhealthy job. Despite these gloomy scenarios, the required priority has not been given to arterial hypertension and related diseases, such as knowledge of the disease, its complications and the speed at which they increase, which would motivate initiatives aimed at improving access to early detection and treatment before it leads to irreversible complications. Statistical projections are required to help the government budget wisely and accurately for these cardiovascular diseases in these tough economic days. Specific forecasts are needed for different regions (or regions). King *et al.* (1998) also conducted research on the worldwide prevalence of diabetes among adults. They reported that the estimated prevalence was 4.0% in 1995 and may increase to 5.4% by 2025. The study also showed that the prevalence is higher in developed countries than in developing countries and that the number of adults with diabetes worldwide will increase from 135 million to 300 million by 2025. Additionally, Bin-Lu *et al.* (2010) conducted an investigation to determine the prevalence of diabetic peripheral neuropathy (DPN) and risk factors associated with DPN in patients with type 2 diabetes in central Shanghai. About 435 diabetic patients were selected for the study. These subjects were evaluated on the basis of a comprehensive foot examination, body mass measurement, resting blood pressure, fasting blood measurement, and urine albumin-to-creatinine ratio (ACR). The study showed that the

prevalence of DPN was 61.8% among Chinese patients diagnosed with type 2 diabetes at the Shanghai center. Similarly, Aekplakom *et al.* (2011) found that the prevalence of diabetes was higher in women, the elderly, and urban areas; However, undiagnosed diabetes as a proportion of all types of diabetes was higher in men and in those with less than a high school education. They compared their findings with the 2004 study, where the prevalence of diabetes in 2004 increased slightly from the 2009 study and people with diabetes were more likely to be obese and have higher cholesterol. The proportion of people with diabetes diagnosed, treated, and controlled for blood glucose, blood pressure, and blood cholesterol improved in 2009. However, the proportion remained significantly lower.

Catherine *et al.* (2006) also conducted an investigation to determine the prevalence of diabetes and fasting glucose in adults in the US population. The study revealed that the crude prevalence of diabetes overall between 1999 and 2002 was 9.3% (19.3 million, 2002 US population), consisting of 6.5% diagnosed and 2.8% undiagnosed. . Approximately 26.0% had impaired fasting glucose, representing 35.3% (73.3 million) with diabetes mellitus or impaired fasting glucose. The overall prevalence of diabetes in people 65 years and older was 21.6%. The study also showed that the prevalence of diagnosed diabetes was similar by sex, but that the prevalence of undiagnosed diabetes and glucose misinclusion was significantly higher in men. There was an increase in crude prevalence from 5.1% in 1988 to 1994, 6.5% in 1999 to 2002 but the crude remained constant for undiagnosed diabetes. El Alamein, *et al* (2015) evaluated the effect of fasting in healthy Muslims of three different nationalities in Dubai. Parameters studied included body mass index, fasting fat percentage, blood glucose, and hypertension in 49 healthy Muslim volunteers. These individuals belong to three different races; Pakistanis, Sudanese and Emirati. The study showed a significant difference in body weight and body mass index in all people of three nationalities. Total cholesterol increased significantly in the Pakistani group compared to the other population at the end of Ramadan. There was a statistically significant increase in hypertension among women. In this context, this study uses the VEC model to model hypertension and its comorbidities. specifically, **to;** Know the trend of data related to hypertension and comorbidities, estimate the interaction that exists between systolic, diastolic, and BMI, determine the direction of causality and the importance of causation, and then summarize the causal chambers between systolic, diastolic, and BMI , and identify fractions in each variable explained through innovations in other variables

METHODOLOGY

3.1 Source of Data

The study used secondary time series data. Specifically, the datasets were collected from patients' files who visited and were admitted at the University of Port Harcourt Teaching Hospital. The data for the study was sourced from the patients' files who visited and admitted at the University of Port Harcourt Teaching Hospital spanning from 6th January, 2017 to 28th January, 2021, while the software used for data analysis is Eview version twelve.

3.2 Model Specification

The Vector Error Correction Model (VECM) specified for the data analysis is given as;

$$\Delta LINY_t = \alpha_0 + \alpha_1 \Delta LINY_{t-1} + \alpha_2 \Delta LINX_{t-1} + \alpha_3 \Delta LINZ_{t-1} + \alpha_4 \Delta LINM_{t-1} + \theta_1 ECT_{t-1} + \varepsilon_{1t}$$

$$\Delta LINX_t = b_0 + b_1 \Delta LINY_{t-1} + b_2 \Delta LINX_{t-1} + b_3 \Delta LINZ_{t-1} + b_4 \Delta LINM_{t-1} + \theta_2 ECT_{t-1} + \varepsilon_{2t}$$

$$\Delta LINZ_t = \varphi_0 + \varphi_1 \Delta LINY_{t-1} + \varphi_2 \Delta LINX_{t-1} + \varphi_3 \Delta LINZ_{t-1} + \varphi_4 \Delta LINM_{t-1} + \theta_3 ECT_{t-1} + \varepsilon_{3t}$$

(3.1)

$$\Delta LINM_t = d_0 + d_1 \Delta LINY_{t-1} + d_2 \Delta LINX_{t-1} + d_3 \Delta LINZ_{t-1} + d_4 \Delta LINM_{t-1} + \theta_4 ECT_{t-1} + \varepsilon_{4,t}$$

Where $\Delta LINY_t, \Delta LINX_t, \Delta LINZ_t, and \ \Delta LINM_t$, represents differenced logarithm of Age, Differenced logarithm of BMI, Differenced logarithm of Diastolic and Differenced logarithm of Systolic respectively. While the a priori expectation: $\alpha_0, b_0, \varphi_0, d_0 > 0$, these represents the intercept $\alpha_i, \beta_i, \lambda_i, and \ \theta_i =$ Short-run dynamic coefficients of the model's adjustment long-run equilibrium, $\varepsilon_{i,t} =$ Errors, impulses, shocks or innovations.

3.3 Model Estimation procedure

The first procedures used to estimate the parameters of the VEC model is to do the graphical representation of the undervaluation of variables over time and is done to visualize the movement, direction and change in variables over time. Time series plot is done to visualize whether there is a trend and changes that could cause a biased estimate if not handled properly. Also, descriptive statistics is performed to check whether the data is normally distributed. This statistic is performed using the statistics of the Jarque-Bera test. According to Chinyere *et al.* (2015), the Jarque–Bera test statistic defines the combined test for skewness and kurtosis, and examines whether the data scores exhibit a characteristic of a normal distribution. The hypothesis of a normal distribution has a degree of freedom two (2) and the null hypothesis is states that the time series variable is normally distributed versus the alternative hypothesis of the time series variable is not normally distributed. The variable is normally distributed if the chi-square statistics is greater than (standard probability value). Similarly, the discussion will be considered for hypothesis testing, if the variable investigated comes from a normal distribution. The Jarrque-Bera (JB) is said to be asymptotic, if the chi-square distribution has a degree of freedom of two (2). It means accepting the null hypothesis and rejecting the alternative; If it is the other way around, then the alternative hypothesis is accepted. However, after testing the variables and not being normally distributed, we move on to checking the statistic behavior of the variables and this is done through unit root test (Deebom and Essi, 2017). **Also , a** unit root test for stability is performed using the augmented Dickey-Fuller (ADF) unit root test, which is commonly used in random variable analysis to determine the order of integration of a series. Unit root test is very vital in time series analysis and this is mostly done using the Augmented Dickey Fuller Test (ADF) and Philip Perron (PPT).

In another development, the order of lag length of a VAR model is determined using some model selection criteria using Schwarz Information Criterion (SIC) or Schwartz Bayesian Information Criterion (SBIC), Ultimate Predator Error (FPE), and Akaike Information Criterion (AIC), and the Hanan Quinn Information Standard (HQ)(Tuaneh,2018). However, the study adopted the Akaike information criterion because it chooses a length value that reduces the model selection criterion (Lutkepohl, 2005). Also, since adding more parameters to your model will always increase your value of the maximum likelihood, the AIC balances this by penalizing for the number of parameters, hence searching for models with few parameters but fitting the data well. Looking at the models with the lowest AIC is a good way to select to best one. The lower this value is, the better the model is performing. Also, the Johansen co-integration test result to determine the presence of long-run relationship among the study variables and Normalized co-integrating coefficients (standard error in parentheses).

Away from the pre-estimation, there are post estimation carried out in the study and they include; the VAR systems stability test, granger causality test, impulse response functions and variance decomposition. The necessary and sufficient condition for stability is that all characteristic roots lie inside the unit circle. Then, the stability function (Π) is of full rank and all variables are stationary. In this section, we assume this is the case. Later we allow for less than full rank matrices. Following the calculation of the eigenvalues and eigenvectors. Similarly, Granger's causality tests the null hypothesis that the coefficients of past values in the regression equation are zero. In simpler terms, the past values of time series (X) do not cause the other series (Y). So, if the p-value obtained from the test is less than the significance level of 0.05, then, you can safely reject the null hypothesis. Also, Impulse response functions show how one variable might react to sudden changes in the other variable and the Variance Decomposition is another way to evaluate how market affect each other using the VEC model. The variance decomposition innovation of a VEC model indicates the amount of information each variable contributes to the other variables in the autoregression. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. In Variance Decomposition innovation, forecast errors are considered for each equation in the fitted VEC model, then the fitted VEC model is used to determine how much error realization is coming from unexpected changes (forecast errors) in the other variable. This estimates how much of forecast error can be attributed to unpredictability in each variable in the VEC
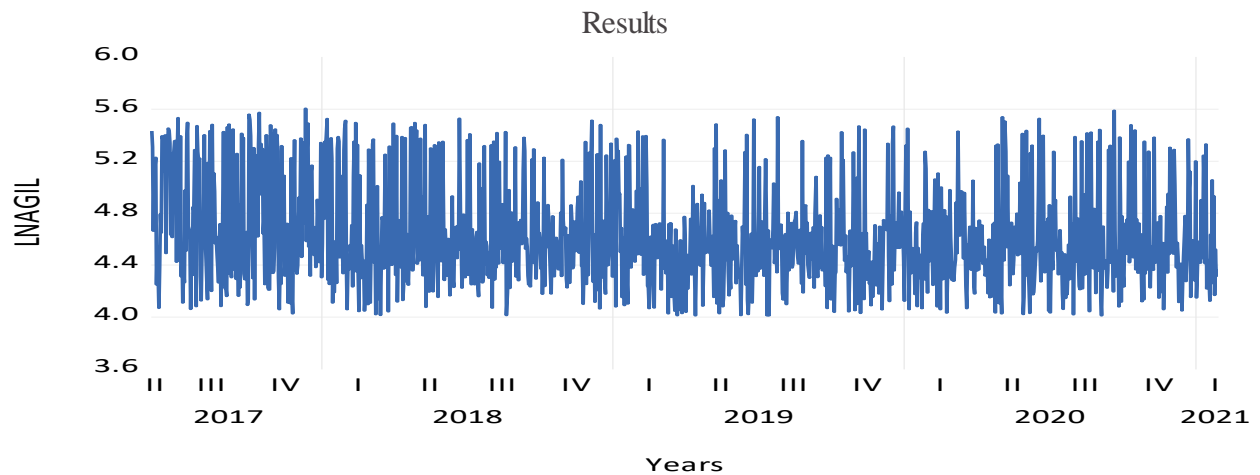

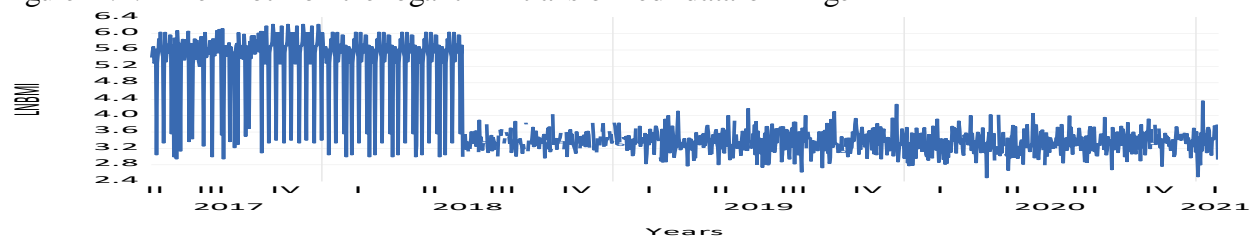Figure 4.1: Time Plot on the logarithm transformed data on Age

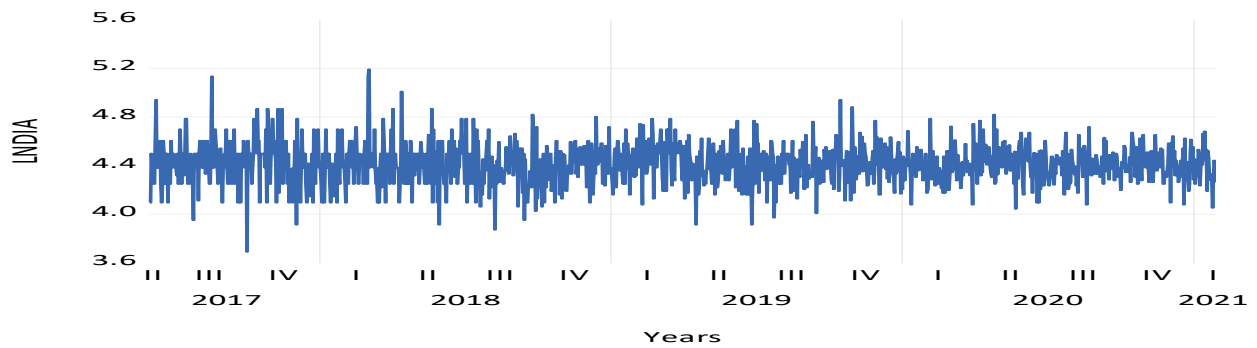Figure 4.2: Time Plot on the logarithm transformed data on BMI

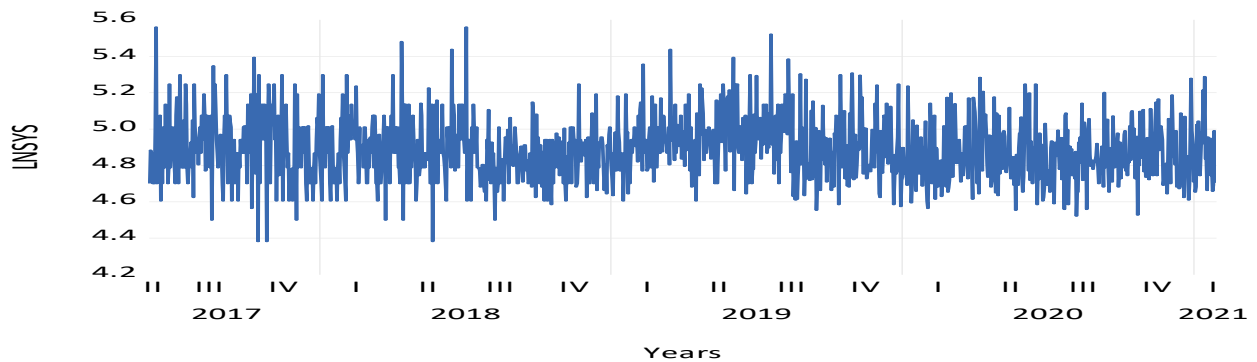Figure 4.3: Time Plot on the logarithm transformed data on DIATOLIC

Figure 4.4: Time Plot on the logarithm transformed data on **SYSTOLIC**

4.1.2 Descriptive Test for Normality

The descriptive test for normality is done provides basic information about the variables and highlights potential relationship between logarithm transformed data on Age, BMI, DIA And SYS and the results are shown in table 4.1 below

Table 4.1: Descriptive Test for Normality for logarithm transformed data on Age, BMI, DIA and SYS

	INAGE	DLNBMI	LNDIA	LNSYS
Mean	0.002	-0.004	0.004	0.001
Median	0.008	0.012	0.000	0.000
Maximum	1.513	3.129	0.916	0.916
Minimum	-1.402	-3.176	-0.811	-0.860
Std. Dev.	0.522	0.758	0.229	0.225
Skewness	0.016	-0.188	0.101	0.099
Kurtosis	3.103	8.300	3.805	3.638
Jarque-Bera	0.593	1443.551	35.246	22.825
Probability	0.743	0.000	0.000	0.000
Sum	2.929	-4.426	0.472	1.555
Sum Sq. Dev.	334.013	703.729	64.046	62.016
Observations	1227	1227	1227	1227

Source: *Researcher's Computation with Eviews 12.0*

4.1.3   Unit Test

The unit test is done to determine the stationary level of the variables (logarithm transformed data on (**Age, BMI, DIA and SYS**) under investigations and the results is shown Table 4.2

Table 4.2: Unit Root Test for the logarithm transformed data on Age, BMI, DIA and SYS using Augmented Dickey fuller (ADFT) and Phillip Perron (PPT)

Var(s)	Stat Level	Augmented Dickey Fuller Test (ADFT)				Phillip Perron Test (PPT)				
		1%	5%	10%	ADFTS	1%	5%	10%	PPTS	Remarks
Age	1(0)	-3.435	-2.863	-2.568	-34.495	-2.568	-2.863	-3.435	-35.995	Stationary
BMI	1(0)	-2.569	-2.865	-3.438	-0.705	-2.568	-2.864	-3.435	-19.349	Stationary
	1(1)	-2.569	-2.865	-3.438	-12.408	-	-	-	-	
DIA	1(0)	-2.569	-2.863	-3.435	-35.735	-2.567	-2.863	-3.435	-35.767	Stationary
SYS	1(0)	-2.569	-2.864	-3.435	-22.935	-2.568	-2.863	-3.435	-35.946	Stationary

Source: *Researcher's Computation with Eviews 12.0.*

4.1.4   Correlation Test for the Logarithm Transformed Data on Age, BMI, DIA and SYS

This is done to determine how Age, BMI, DIA and SYS are the associated with each other. The results are shown in the table 4.3 below.

Table 4.3: Correlation Test for the logarithm transformed data on Age, BMI, DIA and SYS

Variables	INAGE	DLNBMI	LNDIA	LNSYS
INAGE	1			
DLNBMI	-0.085	1		
LNDIA	0.205	-0.018	1	
LNSYS	0.277	-0.015	0.732	1

Source: *Researcher's Computation with Eviews 12.0.*

4.1.5 Johansen Co-Integration Test

Table 4.5 contains the results of the Johansen co-integration test result to determine the presence of long-run relationship among the study variables and normalized co-integrating coefficients (standard error in parentheses)

Table 4.4:   Johansen co-integration Test Result to Determine the Presence of Long-run Relationship among the Study Variables.

		Unrestricted Co-integration Rank Test (Trace & Maximum Eigenvalue)						
Hypothesized No. of CE(s)	Eigen value	Trace Statistics	Critical Value (0.005)	Prob.**	Max-Eigen stat	Critical Value	Prob.**
None *	0.400	1935.445	47.856	0.0000	532.067	27.584	0.000

At most 1 *	0.377	1403.378	29.798	0.0000	493.384	21.132	0.000
At most 2 *	0.356	909.994	15.495	0.0000	457.842	14.265	0.000
At most 3 *	0.352	452.153	3.841	0.0000	452.153	3.841	0.000

Trace test indicates no cointegration at the 0.05 level
Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Source: *Researcher's Computation with Eviews 12.0.*

1 Cointegrating Equation(s):		Log likelihood	-1164.874
Normalized cointegrating coefficients (standard error in parentheses)			
INAGIL	DLNBMI	LNDIA	LNSYS
1.000	0.113	-2.651	0.092
	(0.039)	(0.180)	(0.178)

Source: *Researcher's Computation with Eviews output*

4.1.6 VAR Lag Length Order Selection

Table 4.4 contains the result for the lag order selection to ascertain the VAR lag length before estimation. This is done to determine the lagged of VAR model parameters of the variables under investigations.

Table 4.5: Result for the Lag Order Selection to Ascertain the VAR Lag Length before Estimation.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1511.195	NA	0.000265	3.114481	3.134544	3.122116
1	-954.0875	1108.489	8.70e-05	2.002235	2.102552	2.040413
2	-696.7245	509.9650	5.30e-05	1.506114	1.686683	1.574834
3	-587.2329	216.0574	4.37e-05	0.824402*	1.486489*	1.413204
4	-481.6935	207.3908	3.64e-05	1.129894	1.470969	1.259699
5	-425.3772	110.2018	3.35e-05	1.047024	1.468352	1.207371
6	-365.6859	116.3151	3.06e-05	0.957217	1.458798	1.148106
7	-321.6265	85.49260	2.89e-05	0.899540	1.481375	1.120972
8	-269.0714	101.5452*	2.68e-05*	1.313942	1.574764	1.076375*

LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion

4.2 Model Estimation

Vector Error Correction Model (VECM) using each variable as dependent variable to be consistently estimating the effect of one another as shown in

Long run:

$$LNAGE_t = 1.000LNAGE_{t-1} + 0.000DLNBMI_{t-1} + 0.000LNDIA_{t-1} - 4.991LNSYS_{t-1} + 0.002$$

Short-run:

$$LNAGE_t = -0.530*ECT_{t-1} - 0.661LNAGE_{t-1} - 0.374LNAGE_{t-2} + 0.141DLNBMI_{t-1}$$
$$+ 0.059DLNBMI_{t-2} - 0.685LNDIA_{t-1} - 0.366LNDIA_{t-2} - 0.980LNSYS_{t-1}$$
$$- 0.321LNSYS_{t-2} - 0.001$$

4.1

Long Run

$$LNBMI_t = 0.000LNAGE_{t-1} + 1.000DLNBMI_{t-1} + 0.000LNDIA_{t-1} + 1.304LNSYS_{t-1} + 0.003$$

Short-run:

$$LNBMI_t = -0.494*ECT_{t-1} - 0.335LNAGE_{t-1} + 0.335LNAGE_{t-2} + 0.741DLNBMI_{t-1}$$
$$+ 0.202DLNBMI_{t-2} + 0.287LNDIA_{t-1} + 0.099LNDIA_{t-2} + 0.282LNSYS_{t-1}$$
$$+ 0.154LNSYS_{t-2} - 0.001$$

4.2

	EQUATION 4.1	EQUATION 4.2	EQUATION 4.3
R^2	0.648	0.795	0.761
$AdjR^2$	0.644	0.793	0.754

Long Run

$$LNBMI_t = 0.000LNAGE_{t-1} + 0.000DLNBMI_{t-1} + 1.000LNDIA_{t-1} - 0.855LNSYS_{t-1} + 9.68E-06$$

Short-run:

$$LNBMI_t = 0.328*ECT_{t-1} - 0.229LNAGE_{t-1} + 0.095LNAGE_{t-2} + 0.061DLNBMI_{t-1}$$
$$+ 0.020DLNBMI_{t-2} + 0.725LNDIA_{t-1} + 0.247LNDIA_{t-2} - 0.239LNSYS_{t-1}$$
$$- 0.086LNSYS_{t-2} - 0.001$$

4.3

Note:
ECT =   Error Correction Term
AGE =   Age of the patients
BMI =   Body Mass Index
DIA = Diastolic
SYS = Systolic

4.3   Post Estimation Test on the Vector Autoregressive Model

Post estimation test particularly **VEC Model Stability Tests (AR Root Circle),** serial correlation, normality of the residuals and heteroscedasticity were conducted on the Vector Autoregressive Correction (VEC) Model and the results summarized in Table 4.6 as shown below.

4.3.1   VEC Model Stability Tests (AR Root Circle)

Inverse Roots of AR Characteristic Polynomial
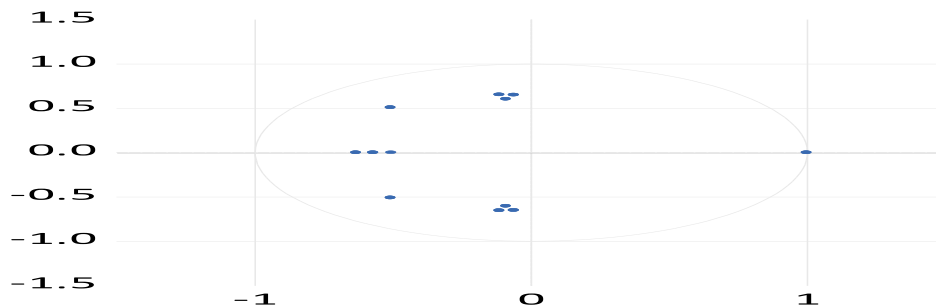
4.3.2   Post Estimation Summary for the Serial Correlation, Normality of the Residuals and Heteroscedasticity

The **Post Estimation Summary for serial** correlation, normality of the residuals and heteroscedasticity were conducted on the Vector Error Correction (VECM) Model and the results summarized in Table 4.8 as shown below.

Table 4.6:   Summary of Post Estimation Test Result on the Vector Error Correction Model

S/n	Type of Test Conducted	Null Hypothesis.	Test Statistics	Prob. Value	Decision	Conclusion
1	Residual serial correlation LM test	No serial correlation at lag 1	Rao F-stat (15.04494)	0.5600	Accepted	No serial correlation at lag 1
2	Residual serial correlation LM test	No serial correlation at lag 2	Rao F-stat (25.52078)	0.3120	Accepted	No serial correlation at lag 2
3	Jarque-Bera residual	Residual is	Jarque-Bera	0.0000	Rejected	Multivariate normal

	Normality test on LAGE component	multivariate normal	(729.9620)			
4	Jarque-Bera residual Normality test on BIM component	Residual is multivariate normal	Jarque-Bera (2413.237)	0.0000	Rejected	Multivariate normal
5	Jarque-Bera residual Normality test on SYM component	Residual is multivariate normal	Jarque-Bera (157.2755)	0.0000	Rejected	Residual is Multivariate normal
6	Jarque-Bera residual Normality test on SYM component	Residual is multivariate normal	Jarque-Bera (3143.199)	0.0000	Rejected	Residual is Multivariate normal
7	Residual Heteroskedasticity test	Residual is Heteroskedastic	Chi-Sq (418.199)	0.0563	Rejected	Residual is Homoscedastic

Source: *Researcher's extract from Eviews output*

4.3.3   Granger Causality Test Results

This is done check the causation and direction of causality among variables under investigations respond to shocks. The result is shown in Table 4.7

Table 4.7:   **Granger Causality Test Results**

| Dependent variable: INAGE			
Excluded	Chi-sq	df	Prob.
DLNBMI	8.265	2	0.016
LNDIA	10.043	2	0.007
LNSYS	22.177	2	0.000
All	108.126	6	0.000
Dependent variable: DLNBMI			
Excluded	Chi-sq	df	Prob.
INAGE	55.258	2	0.000
LNDIA	1.5479	2	0.461
LNSYS	1.284	2	0.526
All	173.793	6	0.000
Dependent variable: LNDIA			
Excluded	Chi-sq	df	Prob.
INAGE	270.165	2	0.000
DLNBMI	15.572	2	0.000
LNSYS	9.743	2	0.008
All	499.979	6	0.000
Dependent variable: LNSYS			
Excluded	Chi-sq	df	Prob.
INAGE	325.771	2	0.000
DLNBMI	6.525	2	0.038
DLNDIA	0.274	2	0.872

All	401.775	6	0.000

Source: *Researcher's extract from Eviews output*

Table 4.8: Impulse Response Functions

Response of LNAGIL: Period	LNAGIL	DLNBMI	LNDIA	LNSYS
1	0.432	0.039	0.033	-0.004
2	-0.273	0.045	0.040	0.028
3	0.049	0.005	-0.002	-0.042
4	0.045	0.042	0.037	0.002
5	0.024	0.021	0.013	-0.016
6	0.095	0.032	0.003	-0.008
7	0.021	0.039	0.010	-0.007
8	0.038	-0.035	0.032	0.027
9	0.032	0.070	0.017	-0.035
10	0.029	0.026	0.023	0.001
Response of DLNBMI: Period	LNAGIL	DLNBMI	LNDIA	LNSYS
1	0.064	0.722	-0.012	0.044
2	0.035	-0.348	-0.037	-0.032
3	0.066	0.103	-0.011	0.020
4	0.004	0.197	-0.012	0.004
5	0.080	0.100	-0.002	0.023
6	0.057	0.106	-0.004	0.038
7	0.009	0.114	-0.0292	-0.011
8	-0.010	0.072	-0.005	-0.029
9	0.095	0.140	-0.011	0.044
10	0.044	0.101	-0.010	0.0174
Response of LNDIA: Period	LNAGIL	DLNBMI	LNDIA	LNSYS
1	0.016	-0.0034	0.209	0.149
2	0.0012	-0.005	-0.088	-0.060
3	0.005	-0.017	0.035	0.032
4	-0.0004	0.014	0.031	0.020
5	0.009	-0.006	0.047	0.033
6	0.013	-0.014	0.052	0.044
7	0.006	0.001	0.030	0.023
8	-0.016	0.000	-0.002	-0.004
9	0.018	-0.007	0.056	0.044
10	0.007	-0.0008	0.036	0.028
Response of LNSYS: Period	LNAGIL	DLNBMI	LNDIA	LNSYS
1	-0.002	0.013	0.150	0.211
2	-0.010	0.003	-0.063	-0.095
3	-0.018	-0.002	0.029	0.040
4	-0.001	0.012	0.022	0.033
5	-0.006	0.007	0.036	0.042
6	-0.005	9.98E-05	0.032	0.050
7	0.002	0.003	0.026	0.029

8	-0.013	0.004	-0.004	0.003
9	-0.007	0.007	0.046	0.056
10	-0.004	0.008	0.024	0.031

Response to Generalized One S.D. Innovations
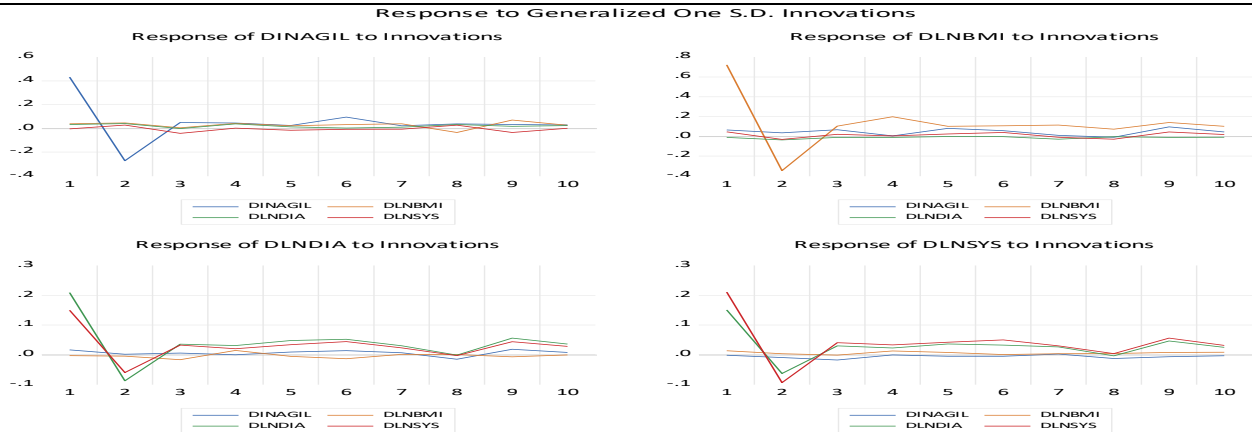
5.1. Discussion of Results

The results of descriptive test for normality for logarithm transformed data on the age of the patients, diastolic and the systolic is shown in Table 4.1. The descriptive statistics was done to determine whether the distribution of the logarithm transformed series on the age of the patients, the body mass index, diastolic and the systolic follow the normal distribution assumption. The result shows that all the series (the age of the patients, dystolic and the systolic)have positive mean except the body mass index that have negative mean as shown in table 4.1 which implies that all the series are all positive mean revert except body mass index that is negative mean reverting. Also, all the series (the age of the patients, dystolic and the systolic) are positively skewed except the body mass index that is negative skewed as shown in table 4.1 which implies that all the series are skewed to the right except that is skewed the left. The jarque-bera test statistic are all statistically significant and the probability value of all the variables are also statistically significant (0.000) except the data on the age of the patients whose jarque-bera test statistic (0.743). Therefore, the null hypothesis of not normally distributed is upheld. Which means that the respective series are not normally distributed except the data on the age of the patients that is normally distributed with the probability value of (0.743).

Table 4.2 is the result for the unit root test. Most time series are inherently non-stationary and may cause spurious or biased estimation. However, to ascertain the stationarity, the Augmented Dickey-Fuller and the Phillip-Perron unit root tests was adopted. From the results obtained in Table 4.2 of unit root test, Augmented Dickey-Fuller and Phillips-Perron tests showed that at level, all the variables had unit root (Non-stationary) as the probability value (p-value) is greater than 5% level of significance. All the variables are stationary at level except BMI that is stationary at first difference. All the variables had no unit root (stationary) as the probability value (p-value) is less than 5% level of significance. The time plot for the differenced variables which clearly shows that all the series were de-trended as shown in figure 4.5, 4.6, 4.7 and 4.8 respectively . The variables vary within the zero (O) mean, showing that it is stationary with the evidence of clustering volatility at constant variance.

The results of the correlation test for the logarithm transformed data on the age of the patients, dystolic and the systolic is shown in table 4.3. From the results obtained the age of the patients, and Body Mass Index are negatively associated with correlation coefficient of (-0.085), dystolic and the age of the patients, has positive correlation with a weak correlation coefficient determination of (0.205). Similarly, the systolic and the age of the patients are positively associated but with a weak correlation coefficient determination of (0.277). Also, dystolic and Body Mass Index has negative correlation with a weak correlation coefficient determination of (-0.018). Body Mass Index and systolic negatively associated with a weak correlation coefficient determination of (-0.015) and it was found that there exists strong positive correlation between systolic and dystolic correlation coefficient determination of (0.732).

The results of Johansen co-integration test using trace and maximum-eigen value is shown in Table 4.4. According to Johansen, co-integration exists if two or more variables have a long-run relationship among them. The result presented in Table 4.4 from the trace statistic indicates that the null hypothesis of no co-integrating relationship was accepted and the alternative hypothesis of co-integration rejected. More so, from the Maximum Eigen statistic, the null hypothesis of no co-integrating relationship is rejected against the alternative hypothesis of co-integrating relationship. Therefore, there is co-integrating (long-run) relationship between hypertension and comorbidities related data such as the age of the patients , Body Mass index (BMI), dystolic and the systolic . The Johansen Normalized co-integrating equation.

In the above normalized co-integrating equation, coco-bean Prices is positioned as the dependent variable. In the interpretation, the co-efficient of the variables are reversed. This simply means that in the long-run, the age of the patients have negative impact on Body Mass index (BMI) and the systolic while the age of the patients had positive impact on dystolic ceteris paribus. The co-efficient of Body Mass index is statistically significant at the 5% level. However, since there exists a co-integration between the variables, the estimation of the vector autoregressive correction model was necessary in modelling co-integrating (long-run) relationship between hypertension and comorbidities related data such as the age of the patients, Body Mass index, dystolic and the systolic.

Table 4.5 contains the VAR Lag Order Selection Criteria for the model. The lag order is selected using statistical information criteria. The result obtained in Table 4.3 of VAR lag order selection are as shows that Akaike Information Criteria (0.824402*) and Schwartz Information Criteria -10.88983* respectively has the smallest AIC and SIC among others. Hence, the VAR model in first difference indicating loss a lag. Consequently, the VAR analysis is done at lag 2.

The result in equation (4.1)shows a coefficient of determination (R^2) of 0.648. This implied that 64.8% variation in the age of the patients is explained by variations in body mass index, diastolic and systolic. The remaining 31.3% are variations expounded by other variables not included in the model. In the long-run, systolic did not have any significant impact on the age of the patients having hypertension and comorbidities related issues. On the other hand, the positive sign of body mass index and diastolic indicates increase in the age of the patients lead to increase in body mass index and diastolic *ceteris paribus*.

The error correction term shows the speed with which the model returns to equilibrium following an external shock. In equation 4.1, the results obtained shows a negative coefficient ($-0.530*ECT_{t-1}$) of error correction term. The negative sign however indicates a backward

movement towards equilibrium. $-0.530*ECT_{t-1}$ shows the correction of the previous period's deviation from the long-run equilibrium in the subsequent period at an adjustment speed of 53.0%. This is statistically significant at 5% level of significance (at an absolute value of t-stat = |-11.498| > t-crit. = 1.96) The error correction term was significant at 5% level of significance (as the absolute value of t-$_{cal}$ = |-11.498| > t-$_{crit}$ =1.96). The short-run result in Table 4.5 also shows that, age of the patients at lag 1 and lag 2; (t = |16.506| > 1.96, and t = |-13.576| > 1.96 respectively), and the patient's body mass index (BMI) at lag 1 and lag 2; (t = |2.829| > 1.96, and t =| 2.230| > 1.96 respectively), had significant effect on age of the patients at 0.05 level of significance while diastolic and systolic did not have any significant effect on the age of the patients at 0.05 level of significance.

The result in equation 4.2 shows a coefficient of determination (R^2) of 0.795. This implied that 79.5% variation in the body mass index of a patient is explained by variations in body mass index, diastolic and systolic. The remaining 20.5% are variations expounded by other variables not included in the model. In the long-run, systolic of the patients did not have any significant impact on the body mass index of the patients having hypertension and comorbidities related issues.

On the other hand, the positive sign of the age of the patients and diastolic indicates increase in the age of the patients lead to increase in body mass index and diastolic *ceteris paribus*. The error correction term shows the speed with which the model returns to equilibrium following an external shock. In equation 4.2, the results obtained shows a negative coefficient ($-0.494*ECT_{t-1}$) of error correction term. The negative sign however indicates a backward movement towards equilibrium. ($-0.494*ECT_{t-1}$) shows the correction of the previous period's deviation from the long-run equilibrium in the subsequent period at an adjustment speed of 49.4%. This is statistically significant at 5% level of significance (Calculated p-value < Standard P-value =0.05). The error correction term was significant at 5% level of significance (as the Calculated p-value < Standard P-value =0.05). The short-run result in Table 4.5 also shows that, age of the patients at lag 1 and lag 2; (Calculated p-value < Standard P-value =0.05, and Calculated p-value < Standard P-value =0.05 respectively), and the patient's body mass index (BMI) at lag 1 and lag 2; (Calculated p-value < Standard P-value =0.05, and Calculated p-value < Standard P-value =0.05 respectively), had significant effect on the patient's Body mass index at 0.05 level of significance while diastolic and systolic did not have any significant effect on the age of the patients at 0.05 level of significance.

The result in equation 4.3 shows a coefficient of determination (R^2) of 0.761. This implied that 76.1% variation in the diastolic of a patient is explained by variations in body mass index, diastolic and systolic. The remaining 23.9% are variations expounded by other variables not included in the model. In the long-run, systolic have significant impact on the diastolic of patients having hypertension and comorbidities related issues. The error correction term shows the speed with which the model returns to equilibrium following an external shock. In equation 4.3, the results obtained shows a negative coefficient ($0.328*ECT_{t-1}$) of error correction term.

The positive sign however indicates a forward movement towards equilibrium. ($0.328*ECT_{t-1}$) shows the correction of the previous period's deviation from the long-run equilibrium in the subsequent period at an adjustment speed of 32.8%. This is statistically significant at 5% level of significance (Calculated p-value < Standard P-value =0.05). The error correction term was

significant at 5% level of significance (as the Calculated p-value < Standard P-value =0.05). The short-run result in equation 4.3 also shows that, age of the patients at lag 1 and lag 2; (Calculated p-value < Standard P-value =0.05, and Calculated p-value < Standard P-value =0.05 respectively), and the patient's body mass index (BMI) at lag 1 and lag 2(Calculated p-value < Standard P-value =0.05, and Calculated p-value < Standard P-value =0.05 respectively), had significant effect on the patient's diastolic at 0.05 level of significance while diastolic and systolic did not have any significant effect on the age of the patients at 0.05 level of significance.

The results of this study is synonymous to Ahmed, Okpe & Adenomon (2019) on Vector Autoregressive and Vector Error Correction modelling of impacts of health and education sectors on Nigerian economy. In Ahmed. Okpe & Adenomon (2019), it was found that cointegration (long term) relationship exist between the variables. It was also established that the response of GDP towards the shocks in the contribution of the education and health sector of the economy fluctuate and temporary over time. the proportion of shock towards the changed in GDP provides a negative response while proportion of shock in the change in GDP did not have a high contribution (effect) upon the education and health sector. The results of this study is also synonymous to Oladele & Adeniji (2015), exploring the effect of health on economic growth in Nigeria: a vector error correction model approach. In Oladele & Adeniji (2015), it was the unit root test revealed that all the variables were stationary at first difference i.e. I(1) while Schwarz Information Criterion (SC) confirmed the appropriateness of two lag length and the trace statistic and the max-Eigen statistic Johansen co-integration test both revealed the existence of five co-integrating equation. The VECM result showed that all the explanatory variables were in line with the a priori expectation.

Post estimation test conducted on the vector error correction model as summarized in table 4.6 includes the test for serial correlation, normality of the residuals and heteroscedasticity. From the result obtained, the model had no serial correlation at lag 1 and lag 2. This is because at lag 1, Rao F-stat equal to 15.045 and the probability value of 0.560 is greater than the 5% level of significance. Also at lag 2, Rao F-stat equal to 25.521 and the probability value of 0.312 which is greater than 5% level of significance. The result also shows that the residuals of the multivariate variables on the hypertension and comorbidities follow normal distribution process. The post estimation test carried out on heteroscedasticity revealed that the value of chi-square (418.199) with the probability value of 0.0563 greater than 5%. This point to the fact that there is absence of heteroscedasticity in the residuals, hence, residual is homoscedastic. The stability test was also conducted and the result was presented in Figure 4.9. The graph shows that all roots lie inside the unit root circle and the detailed result shows that all modulus were less than one. The Inverse roots of a characteristic polynomial satisfy the stability condition (of the diagnostic test) since no root lied outside the unit root circle. Therefore, the estimated VECM is stable.

To test this hypothesis, the results are the results is shown in table 4.7 and this is done check the causation and direction of causality among variables under investigations respond to shocks. In the first section of table 4.9 test the hypothesis which says that LNBMI does not Granger Cause the age of the patients (AGIL) is rejected as the calculated p-values of all the estimator is less than Standard P-value of 0.05, while the alternative hypothesis which says that LNBMI does Granger Cause the age of the patients (AGIL) is accepted. Therefore, LNBMI Granger Cause the age of the patients (AGIL). This shows that uni-directional causality exists between them.

Similarly, in the second section of table 4.9 test the hypothesis which says that LNSYS does not Granger Cause age (AGIL) is rejected as the calculated p-values of the estimator is less than Standard P-value of 0.05, while the alternative hypothesis which says that LNSYS does Granger Cause age (AGIL) is accepted. Also, the hypothesis which says that age (AGIL) does not Granger Cause systolic (LNSYS) is accepted as the calculated p-values of the estimator is greater than Standard P-value of 0.05, while the alternative hypothesis which says that AGIL does Granger Cause systolic (LNSYS) is rejected. Therefore, systolic (LNSYS) does Granger Cause age(AGIL). This shows that uni-directional causality exists between systolic and age.

In another development, no causality exists in the third, fourth and five section in the table as the results show that the estimated p-value for the granger causality test between hypertension and comorbidities related data are all greater than the standard probability value of 0.005 except between systolic (LNSYS) and diastolic (LNDIA), therefore the null hypothesis which says that LNDIA does not Granger Cause LNSYS is rejected, while the alternative which says LNDIA does Granger Cause LNSYS (systolic) is accepted. Similarly, the null hypothesis which says that systolic does not Granger Cause diastolic is rejected while the alternative which says that LNSYS (systolic) does Granger Cause diastolic is accepted. This confirmed bi-directional causality exists between systolic and diastolic. The results of this study are synonymous to Oladele & Adeniji (2015), exploring the effect of health on economic growth in Nigeria: a vector error correction model approach. In Oladele & Adeniji (2015), the model satisfied the stability condition while the granger causality result depicts a uni-directional relationship between health indicators and economic growth in Nigeria. Therefore, it was suggested that government should increase the allocation of fund to the health sector and develop strategies for the monitoring of the disbursement of such fund as well as increase the awareness of the availability of various health services to the society.

The percentage of the forecast error variance as shown in Table 4.8 shows that in the long run 100% forecast variance in the age of the patients are self-explained. BMI, diastolic and systolic however, shows very weak influence in predicting age of the patients (INAGE), therefore they are strongly exogenous. As we move into the future age of the patients (INAGE) decreases while BMI, diastolic (LNDIA) and systolic (LNSYS) but they were not strongly exogenous as the percentage forecast variance of the age of the patients 98.50% in the long run while the percentage forecast variance of BMI, diastolic (LNDIA) and systolic (LNSYS) were 0.252%, 0.297% and 0.951% respectively.

Similarly, the variance decomposition of LNBMI show that in the long run 99.95141 % forecast variance in BMI are self-explained. The age of the patients (INAGE), diastolic and systolic however, shows very weak influence in predicting BMI, therefore they are strongly exogenous. As we move into the future BMI decreases while age of the patients (INAGE), diastolic (LNDIA) and systolic (LNSYS) but they were not strongly exogenous as the percentage forecast variance of the age of the patients 98.50% in the long run while the percentage forecast variance of age of the patients (INAGE), diastolic (LNDIA) and systolic (LNSYS)were 0.370085%, 0.076036% and 0.084629% respectively.

Also, the variance decomposition of diastolic (LNDIA) show that in the long run 99.91241% forecast variance in diastolic (LNDIA) are self-explained. Systolic, age of the patients (INAGE), BMI, however, shows very weak influence in predicting diastolic, therefore they are strongly exogenous. As we move into the future diastolic decreases while age of the patients (INAGE), BMI and systolic (LNSYS) but they were not strongly exogenous as the percentage forecast variance of diastolic (LNDIA) 97.93697% in the long run while the percentage forecast variance of age of the patients (INAGE), BMI and systolic (LNSYS) were 0.037893%, 1.262129% and 0.763008% respectively.

In another development, the variance decomposition of systolic (LNSYS) show that in the long run 50.62239% forecast variance in systolic (LNSYS) are self-explained. Diastolic (LNDIA), age of the patients (INAGE), BMI, however, shows very weak influence in predicting systolic (LNSYS), therefore they are strongly exogenous. As we move into the future diastolic decreases while Diastolic (LNDIA), age of the patients (INAGE) and BMI but they were not strongly exogenous as the percentage forecast variance of systolic (LNSYS) 50.08639% in the long run while the percentage forecast variance of Diastolic (LNDIA), age of the patients (INAGE), and BMI were 48.77557%, 0.851916% and 0.286117% respectively.

Table 4.8 contains the results of the impulse response functions. The fractions in each variable are measure in term of the impulse response innovations among the variables. This is because any shock to some endogenous variables does not only affect the variable in question but the effect is also transmitted to the other endogenous variables through the lag innovational structure of the VEC. Generally, the reaction of any dynamic system in response to some external change otherwise refers to as the impulse response function traces the effect of one-time shock to one of the innovations(lags) on current and future values of the endogenous variables.

5.1 Conclusion

It is concluded that the series were not normally distributed except the data on the patient's age that is normally distributed with the probability value of (0.743). The unit test shows that all the variables are stationary at level except BMI that is stationary at first difference. The age of the patients and Body Mass Index are negatively correlation, diastolic and the age of the patients are positively but weak correlation, systolic and the age of the patients are positively associated with a weak correlation. Also, diastolic and Body Mass Index has weak negative correlation. Body Mass Index and systolic negatively weak correlated and it was found that there exists strong positive correlation between systolic and diastolic. There is co-integrating (long-run) relationship between hypertension and comorbidities related data such as the age of the patients, Body Mass index, diastolic and the systolic. The Johansen Normalized co-integrating equation show that in the long-run, the age of the patients have negative impact on Body Mass index and the systolic but had positive impact on diastolic all things been equal. In term of the interaction between variables variation in one variable as explained by variations in another variable with respect to their infraction. From their direction of causality, significance of the causality among hypertension and comorbidities related data such as Age, Body Mass index, Diastolic and systolic. It was found that body mass index granger cause aging of the patients. However, the causality between them was uni-directional. Bi- directional causality was found to exists systolic and diastolic

5.2 Recommendations

The following recommendations were made based on the results obtained in the study and they include:

1. Hypertension as condition in which it is persistently on the increase as it is shown in the time plot evaluating the trend, there is need to model with the inclusion of the lags of the response variable among the determinants, particularly when dealing with its comorbidities related data. The use of lags will be useful in determine interaction existing among its comorbidities related data

2. There is also the need for health policies, which will regulate hypertension as condition so that their response to shock or the dynamic behaviour of hypertension and its comorbidities in the system significantly cause aging of the patients.

3. In modeling the fractions in each hypertension variable explained by the innovations on its comorbidities related data impulse response analysis for comorbidities, instead of dumping coefficient and natural frequency.

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