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VECTOR AUTOREGRESSIVE AND COINTEGRATION ANALYSIS OF ECONOMIC GROWTH INDICATORS IN ETHIOPIA

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DEPARTMENT OF STATISTICS

VECTOR AUTOREGRESSIVE AND COINTEGRATION ANALYSIS OF ECONOMIC GROWTH INDICATORS IN ETHIOPIA

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DECLARATION

I, the undersigned, declare that this thesis is my original work and has not been presented for any other university for award of any academic degree, diploma or certificate, and that all sources of materials used for the thesis have been duly acknowledged.

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This thesis has been submitted for examination with my approval as a University advisor.

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Approval Sheet

This is to certify that, the thesis prepared by Endalew Tesfa, entitled: Vector Autoregressive and Cointegration Analysis of Economic Growth Indicators In Ethiopia , and submitted in partial fulfillment of the requirements for the Degree of Masters of Science in Statistics (Specialied Econometrics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ACRONYMS AND ABBREVIATIONS

ADF	Augmented Dickey Fuller
AIC	Akaike Information riterion
ARCH	Auto Regression Conditional Heteroscedasticity
CPI	Consumer Price Index
DFID	Department for International Development
EEA	Ethiopia Economic Association
FEVDs	Forecast Error Variance Decompositions
GARCH	Generalized Auto Regression Conditional Heteroscedasticity
GDP	Gross Domestic Product
GTP	Growth and Transformation Plan
HQIC	Hannan-Quininformation Criteria
ILO	International Labour Organization
IMF	International Monetary Fund
MDG	Millennium Development Goals
MoFED	Ministry of Finance and Economic Development
NAIRU	Non-Accelerating Inflation Rate of Unemployment
OLS	Ordinary Least Square
RGDP	Real Gross Domestic Product
SBIC	Schwarz-Bayesian Information Criterion
UN	United Nation
UNCTD	United Nations Conference onTrade and Development
UNDP	United Nation Development Programme
UR	Unemployment Rate
USD	United States Dollar
VAR	Vector Auto regression
VECM	Vector Error Correction Model
WB	World Bank

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Abstruct

Economic growth is one of the most powerful measurement for eliminating poverty and improving the quality of life satndards in developing countries. The objective of this study is used to investigate the relationship among some economic growth indicator variables such as RGDP, inflation rate and unemployment rate using multivariate time series approch for the anually data that was obtained from the national bank of Ethiopia and World Bank website statistical bulletin for the period 1983-2017. This study used the most popular method of ADF and PP unit root test for stationarity test of RGDP, inflation rate and unemployment rate in this study Differencing used for transform non-stationary time series to stationary time series. The cointegration analysis is used to determine the long run relationship and VECM used to determine the short run relationship among economic indicators in Ethiopia. Here also Johensen cointegration test methodology was used to determine the number of cointegrating equation. In the same way structural VAR such as Granger causality test was used to check for direction of causal relationship among the variables either unidirectional or bidirectional and feedback. On the other hand Inpulse response function indicate the effects of an exogenous shock on the whole process over time and FEVDs tells us the prroportion of movements in sequence due to its shocking innovations versus shocks to other variables and it shows that the portion of the variance in the forecast error for each variable due to innovations to all variables in the system. There is long run relationship based on Johansson Cointegration test and short run relationship based on VECM among economic growth indicator variables and the VECM is appropriate than VAR model infers that the current real economic growth of Ethiopia. Granger causality shows unidirectionally the change in consumer price index(inflation) and unemployment leads to changes to real GDP growth and unidirectionally from UR to CPI which shows that unemployment leads to change of inflation. Empirical results of impulse response function analysis show that shock to RGDP leads to negative response from unemployment which dies out after four years horizons, while the shock to RGDP from inflation of goods and services produces continuous positive responses.The FEVDs test results indicate that most of the variance in each variable is attributable or explained by own shocks at first and second horizon.

Key words: *Economic growth,Unemployment rate, Inflation rate,VECM,VAR, cointegration and FEVDs*

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Economic growth is one of the most powerfull measurement for eliminating poverty and improving the quality of life satndards in developing countries. Both cross-country research and country casestudies provide evidence that rapid and sustained growth is critical to making faster progress towards the MDG. It is also creat job opportunities and strong demand for labour force. Increasing employment is a crucial in delivering point of economic growth. Maroeconomic variables such as inflation, export and labour force, helps to provide how much employment is created by economic growth. While the relationship between economic growth and employment remains strongly positive,the strength of the limk has weakend slightly since the turn of the millennium. This has rised concerns about jobless growth in some countries (DFID, 2008).

Economic growth not only related with reducing poverity but also indicates a clear evidence that positively associated with human development. It is also a crucial point of expnding that having a separate and independent existence of freedom of people value. These freedom is highly related to with the improvement of living standard of people, greatest opportunity to become richest, better to eat and long to live (Sen, 1999).

All countries whether underdeveloped, developing or industrialized have to monitor of its general economic well being which arises from various economic policies and decision making instituted by the government over the years. The GDP is known as the primary indicator of economic activity as described by the United Nation System of Accounts 1993 and the European System of Accounts 1995. GDP is a critical tool used to estimate the total value of all goods and surviecs produced within an economic each year by economists and governments whom rely heavily on the output figures to implement policies and determine the extent which public expenditure should be made(Lee, 2012).

The GDP describes the values of final goods and survices which were produced within the boundaries of counties during the time period of one year. When people are actively seeking for a jobe, they are unable to fond a work is known as unemployment. Accourding to International Labour Organization definition unemployment as people looking for apast four week but they can not found a work. Increase in general price level of goods and survices over specific time period in an economic is known as inflation. Uemployment and inflation are macroeconomic variables and it have very important effect on economic growth (Awad, 2009).

Unemployment is a multi dimentional problem of economic growth. It is also an economic problem of that indicates the inbalance of economic growth of the country. So that economic growth is one of the main objective of economic policy either of monetary or of fiscal policy. The investment leads achieve high rates of sustained economic growth in the national economiy and eliminating or removing the problem of unemployment. The greater the unemployment rate is the less opportunities to achieve high economic growth as well as the emergence of the negatively affects social wealfare (Al-Habees and Rumman, 2012).

Globally economic growth is projected to grow up from 2.9% in 2016 to 3.2% in 2017. Here on the average global inflation continues to decline and persistently subdued economic growth modestly labour growth and lower goods and survices prices. In 2015, globally consumer price index is pland to falling to 2.6%, the lower level since 2009. Inflation in developing countries is expected to rise moderately in 2016, mainly driven by higher levels of inflation in transition economies. Globally, the total number of unemployed is estimated to have reached 203 million and rising by 2 million in 2016. Unemployment rate is reached 36% of all unemployed world wide population. Uemployment rates in most countries are expected to stabilize or reced only modestly in 2016 and 2017 against the backdrop of a moderate improvement in investment and economic growth during the forcast period (UN, 2016).

According to (UNDP, 2014) report Ethiopia is registerd remarkable economic growth activities with annual growth averagically 10.9% over the previous ten years. It is also increasing by double the subsahara Africa and triples the world average economic growth over this period and it is one of the fatest economic growth in the world. Similarly, according to International Monetary Fund IMF order of rank Ethiopia is among the five growing economies in the world. After a decead of continuous exapansion Ethiopia, having registered high economic growth since 2005 at average 10.8% per annum, stands out as one of the fatest griwing economies in the world. In 2014/15, real GDP grew by 10.2%, keeping the momentum of the 10.3% growth rate of 2013/14(Admit et al., 2016).

Historical , Ethiopia is one of the low inflation economies with average inflation rate of less than 5%. Since 2006 ethiopia has no longer been considered a low inflation country and in July 2008 high inflation rate of 44% was recorded(UNDP, 2014). According to central statistical agency report from 1980 to 2016 the average inflation rate is 12.4% in 1980 reducing in to 5.2% in1990 in derge regime and the inflation rate is reducing from 44.4% in 2008 to 7.3% in 2016 but it is strongly rising from 8.1% in 2010 to 33.2% in 2011. Similarly in Ethiopia unemployment rate is decreasing from 17.4% in 2014 to 16.8% in 2015 and on the average unemployment rate is also 19088% from 199 untill 2015, reaching high of 26.4% in 199 and recrded low of 16.8% in 2015(The trading economics, January,2018)

To the best of the researcher knowledge, there have been little empirical studies done on the causal relationship between inflation, money supply and economic growth in the country. A study conduted by (Wolde-Rufael, 2008) modeled to investigate the causal relationship among inflation, money and budget deficits for the period 1964 to 2003 using the bounds test approach to co-integration and a modified version of the Granger causality test. While, (Fekadu, 2012) analyzed the relationship between inflation and economic growth for the period 1980-2011 using Vector Auto regression (VAR) model. Unlike these studies, in this study the causal relationship between inflation rate and unemployment on economic growth and also between inflation and unemployment rate will be examined by using VAR model and Vector Error Correction Model for the period 1983 upto 2017

1.2 Statement of the Problem

Macroeconomics problems arise when the economy does not adequately achieve the goals of full employment, stability and economic growth. Unemployment results when full employment is not achieved and Inflation moving slowly when the economy falls the short of the goal of stability. All these problems are either caused by too little or too much demand for gross production. For instance, unemployment results from too little demand and inflation emerges with too much demand. Unemployment and inflation tend arise at different phases of the business cycle. The probability of these problems will vary according to sometimes, unemployment is less of a problem and inflation is more and in other times, unemployment is more of a problem and inflation is less. Now we would understand how these two problems are connected to the two primary phases of the business cycle (Madhuri, 2014).

Unemployment is the macroeconomic problem that affects people most directly and harshly by reduced in the living standard and psychological distress for most of the people. Unemployment is a frequent topic of political debate and that most of the politicians often claim that their proposed policies would help to reduce it by creating jobs(Mankiw, 2014).

Unemployment is fundamental and critical problem of urban and youth population in Ethiopia. The unemployment rate remined above 20% which is a serious concern in a subsistence economy like Ethiopia. The unemployment type is largely structural and demaned deficient . In the reform period employment growth lagged behind economic growth. The nature and type of unemployment provide clues as to what policies might have contributed to massive unemployment (EEA, 2007).

Inflation, that raises the price level in a country, creates financial problems in raising the prices of commodities, services, and other factors(Rashid and Abdul Razzaq, 2015). It is, therefore, found that inflation is one of the major reasons of raising the price level of different commodities. The role of inflation in the economies is found to be the cause of decline in the value of money. Therefore, inflation is creating problems in the form of raising the price level and declining the value of money. The raising value of inflation with the passage of time is to be examined in relation to unemployment to determine the phenomenon relationship statistically. The study is planned to examine the changing role of inflation with the passage of time in the economy and its relationship with unemployment.

Developing countries are more victimized than others and Ethiopia has its own long history of unemployment than any other countries. Ethiopia is a poor agrarian country with per capita income of USD 350 (WB, 2011). Unemployment is high and is one of the socio economic problems in the country. This shows that the economy cannot provide adequate jobs for the growing population in both rural and urban areas. There are few studies that show the employment challenges with economic growth in Ethiopia. Most of the studies give a narrow view of the labor market few studies tend to concentrate on the incidence of unemployment in specific categories, such as urban youth unemployment (Serneels, 2004, World Bank, 2007).

A study conducted by (Teshome, 2011) explains the relationship between inflation and economic growth in Ethiopia using descriptive analysis, even though the method he applies to the analysis is open to critique. Accordingly, he states that it is difficult to specify the exact relationship between inflation and growth. Another study by Hailay (2013) showed that the causality of financial sector development and economic growth in Ethiopia using a time series data the long run model revealed interest rate margin, physical capital stock, and labor growth remained significant variables. Moreover, the net interest rate margin is positively related to economic growth.

A study conduted by (Eden, 2012) modeled inflation volatility and analyzed its effect on economic growth in Ethiopia. Cointegrated VAR model and granger causality test were used to see the relationship between inflation, inflation uncertainty and growth. From the cointegrated VAR model, she concluded that the growth rate of GDP affects inflation positively in the long run and negatively in the short run. The granger causality result also indicates that inflation granger causes inflation uncertainty positively and inflation uncertainty granger causes output growth negatively.

The researcher understands that still it is difficult to choose the factors that affecting GDP growth a whole bunch of list of potential factors can be used as explanatory variables. However it is difficult to fix on certain variables that are strong enough to explain GDP growth. This may be due to the availability of data, different characteristics of countries, different time period and other possibilities.

Previous researchers can deal on the relationship between inflation and economic growth by using VAR, multiple time series analysis, ARDL with descriptive statistics, but in this study, we would see the relationship between unemployment with inflation and unemployment with economic growth in addition to inflation with economic growth by using VAR, Cointegration and VECM approaches.

Therefore the following research questions would be addressed to fill the gap of other studies.

- What kind of relationships exists among inflation rate, unemployment rate and economic growth in the Ethiopian?
- Which time series analysis model best describes the relationship among the study variables and can be used for forecasting purpose?
- Is economic growth affected by the inflation rate and unemployment rate? If so, what kind of effect do they have?

1.3 Objective of the Study

1.3.1 General Objective

- The general objective of the study is to investigate the relationship among economic growth indicators variables in Ethiopia using multivariate time series approach.

1.3.2 Specific Objectives

- To examine the short-run and long-run relationship between economic growth indicator variables in Ethiopia
- To investigate the direction of causality between economic growth indicator variables in Ethiopia.
- To show the various statistical techniques of analyzing multivariate time series data.
- To forecast the economic growth indicators in Ethiopia using the appropriate fitting VAR models

1.4 Significance of the Study

The out come of this study would be provide very important information for macroeconomists, financial analysist, and policy makers in understanding the responsiveness of real GDP to the change in the general price level and labour force with the relevanet policies. It is necessary for policy makers to clear doubt as many studies on the relationship between inflation and economic growth, inflation and unemployment and also unemployment and economic growth remain inconclusive-several empirical studies confirm the existence of either a positive or negative relationship between these three macroeconomic variables.

In addition, the study is useful to find out the impact of certain macroeconomic factors like inflation and unemployment on economic growth of Ethiopia, the relationship between inflation and unemployment and to find what steps or measures could be taken by the government in order to boost economic growth of the country by keeping eyes on these factors. It can also be used as a basis for further studies in the same area or other related fields of study.

1.5 Limitation of the Study

This study assessed the contribution and impact of unemployment rate and inflation rate on economic growth in Ethiopia by using yearly data from 1983-2017. This study did not cover earlier periods because of the absence of complete data set of unemployment rate in ethiopia.

1.6 Organization of the Study

The study was organized into five chapters. Following the introductory chapter one, chapter two gives a review conceptual and emprical literature on the relationship between Economic growth indicator variables based on Real GDP growth, Inflation and Unemployment rate in Ethiopia. Chapter three discusses the methodology and sources of data used in the study. Chapter four deals result and discussion of the model estimation and interpretation of results. Finally, chapter five presents conclusions and recommendation of the study.

CHAPTER TWO

LITERATURE REVIEW

In this literature review there is an extensive body of conceptual and emprical literature up till date that has been researched and attempt to establish various relationships between economic growth and macroeconomic variables and these conceptual literature findings are mostly in e-books and textbooks and the empirical findings found in academic journals, articles, conferences, publications paper and unpublished paper.

2.1 Conceptual Literature

2.1.1 The Concept of Economic Growth

Economic growth is the most historic, challenging and important topics in macroeconomics. Standards of living within a country are measured by real GDP per capita. Capital stocks, inflation, employment, money supply, interest rate, exchange rate, financial market, monetary polciy and unemployment using advance in technology and improvement in the quality and level of literacy are among the principal indicators of economic growth. Economic Growth can be measured as the percentage change in GDP, specifically the percentage change of the real GDP where increments are adjusted for the effects of inflation (Douglas and Ian, 2017).

Economic growth is the process where by the real per capital income of once country increases over a long period of time, and is measured by the increase in the amount of goods and services produced in a country. A growing economy produces more goods and services in each successive time period. Thus in a wider perspective, it implies raising the standard of living of the people and reducing inequality of income distribution (Jhingan, 2013).

Economic growth which is always proxies by GDP often conceptualized as increase in output of an economy capacity to produce goods and services needed to improve the welfare of the country citizens. Growth is seen as a steady process which involves raising the level of output of goods and services in the economy. Growth is meaningful when the rate of growth is much higher than population growth because it has to lead to improvement in human welfare. Therefore, economy growth is seen as a steady process of increasing the productivity capacity of the economy and hence, of increasing national income,being characterized by higher rates of increase of per capita output and total factor productivity, especially labour productivity (Balami, 2006).

2.1.2 The Concept of Inflation

Inflation is a situation of a rising general price level of broad spectrum of goods and services over a long period of time. It is measured as the rate of increase in the general price level over a specific period of time. To the neo-classical and their followers at the University of Chicago, inflation is fundamentally a monetary phenomenon (Balami, 2006).

Inflation depends on the level of actual output (GDP) and the natural rate of unemployment. If GDP exceeds its potential and unemployment is below the natural rate of unemployment, then inflation will increase as suppliers increase their price and built in inflation which is often linked to the price/wage spiral because it involves workers trying to keep their wages up with prices and then employers passing higher costs on to consumers as higher prices as part of a vicious circle will worsen. On the other hand if the GDP falls below its potential level and unemployment is above the natural rate of unemployment, then inflation will decrease as suppliers reduce price as there will be excess capacity and this undermine built in inflation. The final case is when GDP is equal to its potential and unemployment rate is equal to NAIRU, then the inflation rate will not change as long as there is no supply shocks (Gokal and Hanif, 2004).

According to (Dernberg and McDougal, 1976) are more explicit when they wrote that the term inflation usually refers to a continuing rise in prices as measured by an index such as the consumer price index (CPI) or by implicit price deflator for gross national product. Keynes and his followers emphasize the increase in aggregate demand as the source of demand-pull inflation. Inflation can be conceptualized as persistence rise in the general price level of broad spectrum of goods and services over a long period as a result of cost-push. To them one tarists inflation is defined as too much money chasing too few goods.

2.1.3 The Concept of Unemployment

According to ILO definition Unemployment is a state of joblessness which occurs when people are without jobs and they actively sought work within the past four weeks. The unemployment is a measurement of the prevalence of unemployment and it is calculated as a percentage by dividing the number of unemployed individuals to individuals currently in the labour force. More than 200 million people globally are out of work,a high record, as almost two-third of advanced economies and half of developing economies experiencing a slow down in employment growth (Awad, 2009).

Unemployment, a phenomena of jobless, is an economic defect and affect a community structure and it is a key macroeconomic indicator that serves as primary diagnosis to test the health and growth of economic(Asif, 2013, Bean, 1998). Unemployment mostly regarded as foregone output because it deprives the government of necessary resource needed to develop the economy. The unemployment will not earn enough money and government loses revenue. Instead of government spend resource in different welfare to upkeep the unemployed. Therefore, it entails lost revenue to the government that it would have raised if more people had been working. When they face social Responsibility and lack finical resource, these unemployed people engages unwilling engage in underemployment contributing for the low income and saving, high health and dependency problem.

Ethiopia labour market is dominated by employment in agriculture sector (>80%) while this sector contributes less than 50% to the GDP (Admit et al., 2014). Despite these efforts, the economy is still unable to create equitable employment opportunities for the rapidly increasing labour force supply. Currently, people are massively migrating out of the country mainly because of unemployment(The Economist online, 2011). Hence unemployment is still one of the major problems in the country.

According to (Jhingan, 2013) finding unemployment can be conceived as the number of people who are unemployed in an economy, often given as percentage of the labour force. Unemployed is also defined as numbers of people who are willing and able to work as well make themselves available for work at the prevailing wage but no work for them. Therefore unemployment is a state of joblessness in the country.

2.2 Empirical Literature Review

According to (Li and Liu, 2012) conducted a study on the relationship among Chinese unemployment rate, economic growth and inflation; they employed Granger causality test, unit root, cointegration, VAR and VEC model. The study revealed that unemployment affects negatively on growth while inflation affects positively on growth in China. The study also revealed no causation between unemployment and inflation, but there is causation between unemployment and growth, while two-way causation existed between inflation and growth. Similarly a study conducted in Nigeria, for the impact of inflation on the economic growth and development of the Nigerian economy and conclude that inflation was negatively affect economic growth (Umaru and Zubairu, 2012a)

According to (Omoke and Ugwuanyi, 2010), founds the relationship between money, inflation and output by applying cointegration and Granger-causality test analysis. The findings revealed that no existence of a co-integrating vector in the series used. Money supply was seen to Granger cause both output and inflation. The results suggest that monetary policy can contribute towards price stability in Nigerian economy since the variation in price level is mainly caused by money supply. This shows that inflation in Nigeria is too much extent a monetary phenomenon. They find empirical support in context of the money-price-output hypothesis for Nigerian economy. M2 appears to have a strong causal effect on the real output as well as prices.

According to (Umaru and Zubairu, 2012b) study on the relationship between unemployment and inflation by applying OLS, ADF for unit root, Granger causality, Johansen co-integration, ARCH and GARCH techniques. The finding revealed that there is negative relationship between unemployment and inflation and no causation between unemployment and inflation; though they found that there is long-run relationship between the two phenomena in Nigeria.

According to (Muhammad et al., 2013) finding the effect of Unemployment and Inflation on Wages in Nigeria. The Ordinary Least Square Method initially used t-statistics shows that unemployment significantly affects wage rate, Durbin-Watson statistics which shows that the model is not spurious. The Unit Root Test results reveals that all variables are stationary on 1%, 5% and 10%.The Granger Causality Results shows that unemployment and inflation does not granger causes wage rate. This result indicates one-way causation flowing from unemployment to wage rate not inflation to wage rate. The unemployment has a positive effect on wage rate but on the other hand inflation cannot effect on wage rate.

According to (Jaradat, 2013) found the impact of unemployment and inflation on Jordanian GDP. Under his study he used the time series data from the year of 2000 to 2010. He collected the data from global bank database. He used the liner regression method through SPSS to estimate the relation between dependent and independent variables. His results indicates that when we increase 0.906% Inflation then GDP will increases by 1% on the other hand when Unemployment decreases 0.697% then GDP will increases by 1%. Overall results intimate that GDP and Unemployment have negative significant relationship but on the other hand GDP and Inflation have a strong positive significant relationship.

A study conducted by (Barro, 2013) on Inflation and Economic growth in 100 countries of the world including Ethiopia from 1960-1990, indicates that an increasing in average inflation by

10% are likely reduce the growth rate of real per capita GDP by 0.2 to 0.3% and falling the ratio of investment to real GDP by 0.4 to 0.6% per year. Similarly the study conducted by (Veiga et al., 2014) on Economic Growth and Inflation in African Economies on 15 Sub-Sahara Africa showed that a unit percentage rise in inflation will reduce the growth rate by 1.5% in the region. Not only this but also the study conducted by (Asmamaw, 2012) on relationship between Inflation and Economic Growth in Ethiopia have similar result. According to his study result, which was based on time series data from 1974-2011 applying VAR methodology, a unit percentage rise in inflation will reduce the GDP growth by 0.178% in log run.

According to (Ali and Kaushik, 2015) finding on the relationship between unemployment and economic growth in Ethiopia both the long-run and short run result shows that unemployment has negative impact on the economic growth by using cointegration and VAR model in the long-run estimating and VECM in the short-run estimating. Here also a study conducted by (Olana, 2014) states that there is long run strong inverse relationship between inflation and economic growth of real GDP in Ethiopia for the period of 1992-2012 by using one step cointegration approach. Similarly a study conducted by (Abis, 2014), found that there is positive long run and short run relationship between inflation and economic growth in the case of Ethiopia using Engle-Granger cointegration approach and Johansson cointegration approach.

The literature mentioned above shows that most of the sudy conducted by (Veiga et al., 2014, Umaru and Zubairu, 2012a, Asmamaw, 2012, Olana, 2014) inflation was negative effect on economic growth but some of the study conduted by (Li and Liu, 2012, Jaradat, 2013, Abis, 2014) inflation affects positively on economic growth while a study conducted by (Umaru and Zubairu, 2012b) there is negative relationship between unemployment and inflation on the other hand a study conducted by (Ali and Kaushik, 2015) there is negative realtion ship between Unemployement Rate and economic growth. So This study will fill the gaps and it will reduce the contradict findings.

CHAPTER THREE

DATA AND METHODOLOGY

3.1 Source of Data

The source of data is from sets of time series annual data on the economic growth indicators: real economic growth (RGDP), the inflation rate and unemployment rate was obtained from National Bank of Ethiopia, Central Statistical Agency and the world bank website statistical bulletin for the period of 1983 to 2017.

3.2 Study Variable

Economic growth is partially explained by its key indicators that are inflation, employment, unemployment, import-export, investment, interest rate, money supply, exchange rate and other macroeconmic variables. The study used the dependent variables of interest are Real GDP as a proxy of economic growth**,** Consumer price index (CPI) as a proxy of inflation and the Unemployment rate as a proxy of unemployment. The independent variable under this study is time and the lagged value of the dependent variable.

3.3 Method of Statistical Data Analysis

3.3.1 Basic Concepts of Multivariate Time Series Analysis

Time series is a sequence of observations taken sequentially in time. It is divided in to two major parts univariate and multivariate time series. Univariate time series analysis uses only the past history of the time series being forecast plus current and past random error terms for single data. Multivariate time series analysis is the study of statistical models and methods of analysis that describe the relationships among several time series. For many time series arising in practice, a more effective analysis may be obtained by considering individual series as components of a vector time series and analyzing the series jointly. We assume k time series variables, denoted as $\mathrm{y_{It}, y_{2t}, y_{3t}, \dots, y_{kt}}$ are of interest, and we let $\mathrm{Y_t = (y_{It}, y_{2t}, y_{3t}, \dots, y_{kt})}$ the time series vector at time t for $\mathrm{t} = 0, \pm 1, \pm 2, \dots$ Multivariate processes arise when several related time series are observed simultaneously over time. Multivariate time series processes are of interest in a variety of fields such as engineering, the physical sciences, business and economics and particularly the earth sciences (in meteorology and geophysics). Two main purposes for analyzing and modeling the vector of time series jointly are to gain an understanding of the dynamic relationships over time among the series and to improve accuracy of forecasts for individual series by utilizing the additional information available from the related series in the forecasts for each series (Box et al., 2008).

3.3.2 Stationarity and Testing of Statrionarity

Stationarity is a fundamental property underlying almost all time series statistical models. Time series is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed". In the time series literature, such a stochastic process is known as a weakly stationary or covariance stationary (Gujarati and Porter, 2003).

A time series process Y_t is strong stationary (or stationary) if the joint probability distribution of any set of k observation in the sequence $[Y_{t1}, Y_{t+1}, \dots, Y_{t+k}]$ is the same regardless of the origin, t, in the time scale. In the same way a time series process Y_t is weakly stationary or covariance stationary if the $E(Y_t)$ is finite and is the same for all values of t and if the covariance between any two observation (labeled their auto-covariance),$cov(Y_t, Y_{t-k})$, is finite function only of model parameters and their distance apart in time, k, but not the absolute location of either observation on the time scale (Greene, 2003). Therefore, the stochastic process Y_t is said to be stationary if:

I. $E(Y_t) = \mu, constant\ for\ all\ value\ of\ t$ [3.1]

II. $cov(Y_t, Y_{t-1}) = \Gamma j = E[(Y_t - \mu)(Y_t - \mu)^T\ ] = \Gamma^T_{-j}$,for all t and j= 0, 1, 2, [3.2]

From equation [3.1] all Y_t have the same finite mean vector μ and [3.2] requires that the autocovariances of the process do not depend on t but just on the time period j the two vectorsY_t and Y_{t-j} are apart. Therefore, a process is stationary if its first and second moments are time invariant. Frequently, if the two methods are not fulfilled then differencing may be needed to achieve stationarity. To test for stationarity of a series several procedures has been developed. The most popular ones are time plot and Unit root test such as ADF and PP test.

3.3.2.1 Time Plot

Regardless of which technique is used, the first step in any time series analysis is to construct a time plot of the data, and inspect the graph for any anomalies. A number of qualitative aspects are noticeable as you visually inspect the graph. A time plot of the data will typically suggest whether any differencing is needed to make the time series stationary. Before pursuing formal tests, it is always advisable to plot the time series under study. Such a plot gives an initial clue about the likely nature of the time series. For instance, if a line-graph of a time series shows an upward trend, then this suggests perhaps that the mean of the data has been changing. This may be a clue that the series is not stationary. Such an intuitive feel is the starting point of more formal tests of stationarity.

3.3.2.2 Unit Root Test

In most analysis, it is unknown whether the variables are integrated or stationary. Pre-tests for unit roots are often required in order to determine whether the series are stationary or not (Toda and Yamamoto, 1995). The following discussion outlines the basics features of unit root tests (Hamilton, 1994). Consider a simple AR (1) process:

$$Y_t = \rho Y_{t-1} + X_t{}' \delta + \varepsilon_t \quad [3.3]$$

Where X_t are optional exogenous regressors which may consist of constant or a constant and trend, ρ and δ are parameters to be estimated, and ε_t is assumed to be white noise. If $|\rho| \geq 1$, Y_t is a non-stationary series and the variance of Y_t increases with time. If $|\rho| \leq 1$, Y_t is a stationary series. Thus, the hypothesis of Stationarity can be evaluated by testing whether ρ is strictly lesst han one.

Hypothesis:

$$H_o\text{: The series are not stationary } (\rho\ = 1)$$

$$H_1\text{: The series are stationary } (\rho < 1)$$

3.3.2.2.1 Augmented Dickey-Fuller (ADF) Unit Roots Test

The most widely used and well established test for non-stationarity in a series is the (Dickey and Fuller, 1981). It is an extension of the (Dickey and Fuller, 1979) with the exception that the autocorrelation in a time series is removed prior to the testing for a unit root by the addition of extra lags of the dependent variable. The Augmented Dickey-Fuller (ADF) test depends on the standard Dickey-Fuller test and is conducted by estimating equation [3.3] after subtracting Y_{t-1} from both side of the equation then the following equation will be obtained:

$$\Delta Y_t = \alpha Y_{t-1} + X_t{}' \delta + \varepsilon_t \quad [3.4]$$

Where $\Delta Y_t = Y_t - Y_{t-1}\ and\ \alpha = \rho - 1$, the null and alternative hypotheses may be written as

$$H_o: \alpha = 0\ Vs\ \ H_1: \alpha < 0 \quad [3.5]$$

This hypothesis can be evaluated by using the conventional t-ratio of α as $t_\alpha = \frac{\hat{\alpha}}{se(\hat{\alpha})}$, Where $\hat{\alpha}$ is the estimate of α , and $se(\hat{\alpha})$ is the coefficient standard error.

According to (Dickey and Fuller, 1979) state that under the null hypothesis of a unit root, this statistic does not follow the conventional Student's t-distribution and they derive asymptotic results and simulate critical values for various test and sample sizes. (MacKinnon, 1991, MacKinnon, 1996) implements a much larger set of simulations than those tabulated by Dickey and Fuller. In addition, MacKinnon estimates response surfaces for the simulation results, permitting the calculation of Dickey-Fuller critical values and p-values for arbitrary sample sizes.

The simple Dickey-Fuller unit root test described above is valid only if the series is an AR (1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances ε_t is violated. The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR (p) process and adding lagged difference terms of the dependent variable y to the right-hand side of the test regression:

$$\Delta Y_t = \alpha Y_{t-1} + X_t{}'\delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \cdots + \beta_p \Delta Y_{t-p} + U_t \qquad [3.6]$$

This augmented specification is then used to test for the presence of a unit root. An important result obtained by (Fuller, 1976) is that the asymptotic distribution of the t-ratio for α is independent of the number of lagged first differences included in the ADF regression. Moreover, while the assumption that Y_t follows an autoregressive (AR) process may seem restrictive, (Said and Dickey, 1984) demonstrate that the ADF test is asymptotically valid in the presence of a moving average (MA) component, provided that sufficient lagged difference terms are included in the test regression.

3.3.2.2.2 The Phillips-Perron (PP) Unit root Test

(Phillips and Perron, 1988) propose an alternative (nonparametric) method of controlling for serial correlation when testing for a unit root. The PP method estimates the non-augmented DF test equation [3.5], and modifies the t -ratio of the α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_o}{f_o}\right)^{1/2} - \frac{T(f_o - \gamma_o)se(\hat{\alpha})}{2{f_o}^{1/2} s} \qquad [3.7]$$

Where $\hat{\alpha}$ is the estimate, t_α is the t-ratio of α, $se(\hat{\alpha})$ is coefficient standard error and s is the standard error of the test regression. In addition, γ_o is a consistent estimate of the error variance in [3.5] (calculated as $\frac{(T-K)s^2}{T}$, where k is the number of regressors). The remaining term, f_o, is an estimator of the residual spectrum at frequency zero. The asymptotic distribution of the PP modified t-ratio is the same as that of the ADF statistic.

3.3.3 Differencing

We know the problems associated with non-stationary time series, the practical question is what to do? To avoid the spurious regression problem that may arise from regressing a non-stationary time series on one or more non-stationary time series, we have to transform non-stationary time series to make them stationary. This procedure is known as differencing. Differencing is a technique commonly used to transform a time series from a non-stationary to stationary by subtracting each data Y_t in a series from its predecess or its lagged values Y_{t-1}. Hence, differrencing turns out to be a useful filtering procedure in the study of non-stationary time series. The set of observations $Y_t^{'}s$ that correspond to the initial time period (t) when the measurement was taken is described as a series at level (Gujarati, 2004).

Using the difference operator Δ, the first difference is defined by

$$\Delta Y_t = Y_t - Y_{t-1} \qquad [3.8]$$

Equation 3.8 also can be written as follow by using backshift operator B

$$\Delta Y_t = (1-B)Y_t, \ \ where \ \ B^k Y_t = Y_{t-k}, \quad k = 0,1,2, \ldots$$

In general the n^{th} order of differencing by using backshift is define as

$$\Delta^n Y_t = (1-B)^n Y_t \qquad [3.9]$$

3.3.4 Vector Autoregressive Model

Vector autoregressive models (VARs) were popularized in econometrics by (Sims, 1980) as a natural generalization of the univariate autoregressive models. A VAR is a systems regression model (i.e. there is more than one dependent variable) that can be considered a kind of hybrid between the univariate time-series models and the simultaneous equations models.

Le $Y_t = (Y_{It}, Y_{2t}, Y_{3t}, \ldots, Y_{nt})^{'}$denotes an (n×1) vector of time series variables. The basic p-lag vector autoregressive ($VAR(p)$) model has the form (Hamilton, 1994).

$$Y_t = C + A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \cdots + A_p Y_{t-p} + \varepsilon_t \qquad [3.10]$$

Where t= 1, 2, 3, …, T, π_i $are\ an(nxn)\ fixed\ coefficent\ of\ matrice$

$C = (c_{1,}c_2\,, c_{3,}, \dots, c_n)'$ is a fixed an (nx1) vector of intercept terms allowing for the possibility of a non-zero mean $E(Y_i)$ and $\boldsymbol{\varepsilon_t} = (\boldsymbol{\varepsilon_1}, \boldsymbol{\varepsilon_2}, \boldsymbol{\varepsilon_3}, \dots, \boldsymbol{\varepsilon_n})'$ is an (n×1) unobservable zero-mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix Σ, that is $E(\boldsymbol{\varepsilon_t}) = 0$ and $Cov(\boldsymbol{\varepsilon_t}, \boldsymbol{\varepsilon_s}') = 0$ for $\forall t \neq s$. The covariance matrix Σ is assumed to be nonsingular.

Let c_i denote the i^{th} element of the vector c and let A_{ij}^1 denotes the i^{th} row element and j^{th} column element of the matrix A_1.Then the first row of the vector system in equation (3.10) specifies as follows:

$$y_{1t} = c_1 + A_{11}^1 y_{1,t-1} + A_{12}^1 y_{2,t-1} + \cdots + A_{1n}^1 y_{n,t-1} + A_{11}^2 y_{1,t-2} + A_{12}^2 y_{2,t-2} + \cdots + A_{1n}^2 y_{n,t-2} + \cdots + A_{11}^p y_{1,t-p} + A_{12}^p y_{2,t-p} + \cdots + A_{1n}^p y_{n,t-p} + \varepsilon_{1t} \quad [3.11]$$

General the VAR(p) model equation have the form in this study is

$$\begin{bmatrix} UR_t \\ RGDP_t \\ CPI_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} A_{11}^1 & A_{12}^1 & A_{13}^1 \\ A_{21}^1 & A_{22}^1 & A_{23}^1 \\ A_{31}^1 & A_{32}^1 & A_{33}^1 \end{bmatrix} \begin{bmatrix} UR_{t-1} \\ RGDP_{t-1} \\ CPI_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} A_{11}^p & A_{12}^p & A_{13}^p \\ A_{21}^p & A_{22}^p & A_{23}^p \\ A_{31}^p & A_{32}^p & A_{33}^p \end{bmatrix} \begin{bmatrix} UR_{t-p} \\ RGDP_{t-p} \\ CPI_{t-p} \end{bmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix} \quad [3.12]$$

In lag operator notation, the $VAR(p)$ is written as follows

$$A(B)Y_t = c + \varepsilon_t \quad [3.13]$$

Where B is the lag or backshift operator and that

$$\pi(B) = I_n - A_1 B - A_2 B^2 - \cdots - A_p B^p \quad where \quad B^p Y_t = Y_{t-p}$$

The $VAR(p)$ is stable if the roots of $\det(I_n - A_1 B - A_2 B^2 - \cdots - A_p B^p) = 0$, lie outside the complex unit circle (have modulus greater than one) or equivalently, if the Eigen values of the companion matrix:

$$F = \begin{bmatrix} I_1 & 0 \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & 0 \cdots & \mathrm{I}_n \end{bmatrix} \quad [3.14]$$

have modulus less than one. Assuming that the process has been initialized in the infinite past, then a stable $VAR(p)$ process is stationary with time invariant means, variances, and auto-covariance.

If Y_t in equation (3.10) is covariance stationary (i.e if the covariance does not depend on t), then the unconditional mean is given by:

$$\mu = (I_n - A_1 - A_2 - \cdots - A_p)^{-1} C \qquad [3.15]$$

The mean-adjusted form of the $VAR(p)$ is then:

$$Y_t - \mu = A_1(Y_{t-1} - \mu) + A_2(Y_{t-2} - \mu) + A_3(Y_{t-3} - \mu) + \cdots + A_p\left(Y_{t-p} - \mu\right) + \varepsilon_t$$

The basic $VAR(p)$ model may be too restrictive to represent sufficiently the main characteristics of the data. In particular, other deterministic terms such as a linear time trend or seasonal dummy variables may be required to represent the data properly. Additionally, exogenous variables may be required as well. The general form of the VAR (p) model with deterministic terms and exogenous variables is given by:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \cdots + A_p Y_{t-p} + \beta D_t + G X_t + \varepsilon_t \qquad [3.16]$$

Where D_t represents an $(l\ x\ 1)$ matrix of deterministic components, X_t represents an $(m\ x\ 1)$ vector of exogenous variables, β and G are parameter matrices, and l and m are number of time trend and exogenous variables respectively.

3.3.4.1 Autocovariance and Autocorrelation for a VAR Process

An understanding of the autocovariances of a VAR process can be gained by considering the stationary VAR process where the mean is known form equation (3.13)

The mean-adjusted form of the $VAR(p)$is then:

$$Y_t - \mu = A(Y_{t-1} - \mu) + A_2(Y_{t-2} - \mu) + A_3(Y_{t-3} - \mu) + \cdots + A_p\left(Y_{t-p} - \mu\right) + \varepsilon_t$$

$$E[(Y_{t-h} - \mu)'(Y_t - \mu)] = \Gamma(h)$$

$$= E[A_1(Y_{t-1} - \mu) + A_2(Y_{t-2} - \mu) + \cdots + A_p\left(Y_{t-p} - \mu\right) + \varepsilon_t](Y_{t-h} - \mu)'$$

$$\Gamma(0) = A_1'\Gamma(1) + A_2'\Gamma(2) + \cdots + A_p'\Gamma(p) + \Sigma_\varepsilon \qquad [3.17]$$

Similarly for $h = 1,2,3, \ldots., p$

$$for\ h > 0, \quad \left.\begin{array}{c} \Gamma(1) - A_1'\Gamma(0) - A_2'\Gamma(1) - \cdots - A_p'\Gamma(p-1) = 0 \\ \Gamma(2) - A_1'\Gamma(1) - A_2'\Gamma(0) + A_3'\Gamma(1) - \cdots - A_p'\Gamma(p-2) = 0 \\ \vdots \\ \Gamma(p) - A_1'\Gamma(p-1) - A_2'\Gamma(p-2) - A_3'\Gamma(p-3) - \cdots - A_p'\Gamma(0) = 0 \end{array}\right\} \qquad [3.18]$$

Generally for $h > p,\ \Gamma(h) = -A_1'\Gamma(h-1) + A_2'\Gamma(h-2) + \cdots + A_p'\Gamma(h-p) = 0$

The equations (3.18) are known as the Yule-Walker equations and can be used to solve for the parameter matrices $A_1, \dots \dots \dots A_p$ in terms of $\Gamma(0), \Gamma(1) \dots \dots . . \Gamma(p)$ (Box et al., 2008).

The above equation can written as in matrix representation of Yule-Walker equation

$$\begin{bmatrix} \Gamma(1) \\ \Gamma(2) \\ \vdots \\ \Gamma(p) \end{bmatrix} = \begin{bmatrix} \pi_1' \\ \pi_2' \\ \vdots \\ \pi_p' \end{bmatrix} \begin{bmatrix} \Gamma(0) & \Gamma(1) & \Gamma(2) & \dots & \Gamma(p-1) \\ \Gamma(1) & \Gamma(0) & \Gamma(1) & \dots & \Gamma(p-2) \\ & & \vdots & & \\ \Gamma(p-1) & \Gamma(p-2) & \Gamma(p-3) & \dots & \Gamma(0) \end{bmatrix} \quad [3.19]$$

the value of is Σ_ε obtained from $\Gamma(0) - \sum_{i=1}^{p} \Gamma(i)$

Then the autocorrelations values of for $VAR(p)$ process are determined by the relation

$$\rho_h = D^{\frac{-1}{2}} \Gamma(h) D^{\frac{-1}{2}} \quad [3.20]$$

Where $D = \begin{bmatrix} \gamma_{11}(0) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \gamma_{kk}(0) \end{bmatrix}$ is a diagonal matrix with the autocovariances of the VAR process. The autocorrelations are generally easier to work with as compared to the autocovariances as they do not depend on the unit of measurement (Lütkepohl, 2005). The cross correlation functionbetween two individual time series is

$$r_{ij}(h) = \frac{\gamma_{ij}(h)}{\sqrt{\gamma_{ii}(0)}\sqrt{\gamma_{jj}(0)}} \; [where\ i, j = 1,2, \dots \dots \dots, k] \quad [3.21]$$

3.3.4.2 Estimating Order of VAR Model

The lag length for the VAR model may be determined using model selection criteria. The general approach is to fit VAR models with orders m = 0, ... , P_{max} and choose the value of m which minimizes some model selection criteria(Lütkepohl, 2005). The general form model selection criteria have the form

$$IC(p) = \log\left|\sum p\right| + c_T . \varphi(p, n) \quad [3.22]$$

Where $\hat{\Sigma}_p = T^{-1} \sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t'$, is the residual covariance matrix estimator for a model of order n, $\varphi(p, n)$ is a function of order n which penalizes large VAR orders and c_T is a sequence which may depend on the sample size and identifies the specific criterion. The term $\log|\hat{\Sigma}_p|$ is a non-increasing function of the order P while $\varphi(p, n)$ increases with P .The lag order is chosen which optimally balances these two forces.

The three most commonly used information criteria for selecting the lag order are the Akaike information criterion (AIC), Schwarz-Bayesian information criterion (SBIC), Hannan-Quin information criteria (HQIC):

$$\left.\begin{aligned} AIC(p) &= \log\left|\hat{\Sigma}_p\right| + \frac{2}{T} pn^2 \\ SBIC(p) &= log\,|\hat{\Sigma}_p| + \frac{log\,T}{T} pn^2 \\ HQIC(p) &= log\,|\,\hat{\Sigma}_p\,| + \frac{\log(lo\,g\,T)}{T} pn^2 \end{aligned}\right\} \quad [3.23]$$

In each case $\varphi(p,n) = pn^2$ is the number of VAR parameters in a model with order p and n is number of variables. Denoting by $\hat{p}(AIC),\ \hat{p}(SBIC)\ and\ \hat{p}(HQIC)$ the order selected by AIC, SBICand HQIC, respectively, the following relations hold for samples of fixed size T ≥ 16: (Lütkepohl, 2005).

$$\hat{p}(SBIC) \leq \hat{p}(HQIC) \leq \hat{p}(AIC) \quad [3.24]$$

The AIC criterion asymptotically overestimates the order with positive probability. On other hand, the HQIC and SBIC criteria are both consistent, that is, the order estimated with these criteria converges to the true VAR order p under quite general conditions if the true order (p) is less than or equal to p_{max}.

3.3.4.3 Estimation of Parameters VAR Model

The K-dimensional $VAR(p)$ model $Y_1, Y_2, \dots, Y_T$ where $Y_t = (Y_{1t}, Y_{2t}, \dots, Y_{kT})$, has the form from equation (3.10).From this equation the parameters are unknown and are required to be estimated. There are various methods of estimation that can be used, the most well-known being least squares estimation, Yule-Walker estimation and maximum likelihood estimation. If the VAR process has a known distribution and is assumed to be normally distributed, then maximum likelihood estimation can be used as an alternative procedure to least squares estimation. The main advantage of maximum likelihood estimation is that it is efficient asymptotically (Lütkepohl, 2005).

For a given sample of the endogenous variables $Y_1, Y_2, \dots, Y_T$ and sufficient pre-sample values $Y_0,\ Y_1, \dots, Y_{t-p+1}$ the coefficients of a VAR(p) process can be estimated efficiently by least squares applied separately to each of the equations. Because the disturbances are assumed to be normally distributed, the conditional density is multivariate normal distributed (Lütkepohl and Saikkonen, 1999, Sims, 1980, Watson, 1994):

$$[Y_t|Y_{t-1}, Y_{t-2}, \dots, Y_{T-p}] \sim MVN(\mathrm{A}Y_t, \Sigma_\mu)$$

The conditional density of the t^{th} observation by using maximum likelihood function

$$f(Y_t \middle| Y_{t-1}, Y_{t-2}, \dots, Y_{T-p})$$

$$= (2A\Sigma)^{-(\frac{Tm}{2})} \Sigma_\upsilon^{(-\frac{1}{2})} \exp\left[\frac{-1}{2}\sum_{t=1}^{T}(Y_t - \mathrm{A}Y_t)'\Sigma^{-1}(Y_t - \mathrm{A}Y_t)\right] \qquad [3.25]$$

The likelihood function is the product of each one of these densities function for $t = 1,2, \dots, T$. Then the log-likelihood function is the sum of the log of all these densities and thus it becomes:

$$l(A, \Sigma) = -\left(\frac{Tm}{2}\right)\log(2A) + \frac{T}{2}\log(\Sigma^{-1}) - \frac{1}{2}\sum_{t=1}^{T}(Y_t - \mathrm{A}Y_t)'\Sigma^{-1}(Y_t - \mathrm{A}Y_t) \qquad [3.26]$$

The estimated A or $(\widehat{\mathrm{A}})$, which maximizes the log-likelihood isthe ML estimator of the VAR coefficients which are determined by:

$$\widehat{\mathrm{A}} = \left[\sum_{t=1}^{T} Y_t Y_t^{'}\right]\left[\sum_{t=1}^{T} Y_t Y_t^{'}\right]^{-1} \qquad [3.27]$$

This means that the ML estimator of the VAR coefficients is equivalent to the OLS estimator of Y_{jt} *and* Y_t which is equivalent to the system multivariate estimator. The ML estimator for the variance is given as: $\widehat{\Sigma}_\upsilon = \frac{1}{T}\sum_{t=1}^{T}\hat{\upsilon}_t\hat{\upsilon}_t^{'}$

Where $\hat{\upsilon}_t = Y_t - \widehat{\mathrm{A}}Y_t$ and the (asymptotic) distribution of the coefficients of the j^{th} equation of the VAR model is: $\widehat{\mathrm{A}} \sim MVN(\mathrm{A}, \hat{\sigma}^2\left[\sum_{t=1}^{T} Y_t Y_t^{'}\right]^{-1})$

Where $\hat{\sigma}^2 = \frac{1}{T-mp-1}\sum_{t=1}^{T}\upsilon_{jt}^2$ that is, the coefficients' variance can be computed using equation-by-equation OLS estimation. Because the coefficients are asymptotically normal, significance tests for each coefficient can be applied by comparing the t-statistic with the normal distribution. The estimated values maximize the log-likelihood function and are the ML estimators of the VAR coefficients. Because the coefficients are asymptotically normal, significance tests for each coefficient can be applied by comparing the t-statistic with the normal distribution. The Wald statistics can be employed to test hypothesis that impose restrictions on the coefficients.

3.3.5 Cointegration Analysis

The procedure for cointegration involves determination of the existence of long run equilibrium relationship but it does not explain the direction of the causality of the variables. If the variables are not cointegrated, then long run equilibrium relationship does not exist hence only short run relationship can be carried out in such a case (Asteriou and Hall, 2007). In bivariate framework, two series can only be cointegrated if they are integrated of the same order, say order d. (Gujarati, 2004, Engle and Granger, 1987) considered two series, UR_t and CPI_t both with order of integration d and showed that a linear combination of both series was generally $I(d)$. However, if the linear combination of $I(d)$series is stationary, the series are said to be cointegrated, that is, if $UR_t \sim I(d)$ and $CPI_t \sim I(d)$ and $Z_t = CPI_t - \beta UR_t \; is \; I(0)$ then UR_t and CPI_t are said to be cointegrated.The relationship between the cointegrating time series variables is either single or multiple (Engle and Granger, 1987).

3.3.5.1 Johansen's Cointegration testing

According to (Johansen, 1991, Johansen, 1988) determining the number of cointegrating vectors is the VAR representation of Y_t. A vector autoregressive model of order p,VAR (p) is assumed that

$$Y_t = \mathrm{A}_1 Y_{t-1} + \mathrm{A}_2 Y_{t-2} + \cdots + \mathrm{A}_p Y_{t-p} + BX_t + \varepsilon_t \qquad [3.28]$$

Where $Y_t = (UR_t, RGDP_t, CPI_t)'$ is a k-vector of non-stationary I(1) variables(If a non-stationary series, Y_t must be differenced d times before it becomes stationary, then it is said to be integrated of order d. This would be written Y_t ~ I(d), X_t is a d-vector of deterministic variables, and ε_t is a vector of innovation. Then we can rewrite this equation as:

$$\Delta Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + BX_t + \varepsilon_t \qquad [3.29]$$

$$Where \; \pi = \sum_{i=1}^{p} \mathrm{A}_i - I \;\; and \;\; \Gamma_i = -\sum_{j=i+1}^{p} \mathrm{A}_j.$$

According to (Johansen, 1988) proposed two tests for estimating the number of cointegrating vectors: the Trace statistics and Maximum Eigen value. Trace statistics investigate the null hypothesis of r cointegrating relations against the alternative of n cointegrating relations, where n is the number of variables in the system for r = 0, 1, 2…n-1. Define $\widehat{\lambda_\iota}$, i=1, 2,…,k to be a complex modulus of eigenvalues of $\widehat{\Pi}$ and let them be ordered such that $\lambda_1 > \lambda_2 > \cdots > \lambda_n$.

The trace statistic computed as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \log[1 - \lambda_i] \qquad [3.30]$$

The Maximum Eigen value statistic tests the null hypothesis of r cointegrating relations against the alternative of $r + 1$ cointegrating relations for r = 0, 1, 2…n-1.

This test statistic is computed as:

$$\lambda_{max}(r, r+1) = -\mathrm{T} \log(1 - \lambda_{r+1}) \qquad [3.31]$$

Where λ_{r+1} is the $(r+1)^{th}$ ordered Eigen value of Π , and T is the sample size. The critical values tabulated by (Johansen and Juselius, 1990) will be used for these tests

3.3.6 Vector Error Correction Model

These models were used to measure the short-run effects of financial liberalization on Variables. The error correction modeling philosophy by (Granger, 1986) was used to produce short run forecasts and provide the short run dynamics necessary to obtain the long-run equilibrium. So that the reason for the error correction term is the same as with the standard error correction model, it measures any movement away from the long-run equilibrium.

A vector error correction (VEC) model is a restricted VAR designed for use with no stationary series that are known to be cointegrated. The VEC has cointegration relations built into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. When the variables are cointegrated, the corresponding error correction representations must be included in the system. By doing so, one can avoid misspecification and omission of the important constraints. Thus, the VAR in equation [3.28] can be reparametrized as a Vector Error Correction Model (VECM) form in (3.29): (Lütkepohl, 2005).

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + BX_t + \varepsilon_t \qquad [3.32]$$

Where $\Pi = \sum_{i=1}^{p} \mathrm{A}_i - I_n$ and $\Gamma_i = -\sum_{j=i+1}^{p} \mathrm{A}_j$, here I_n is identity marix

Granger's representation theorem state that if the coefficient matrix π has reduced rank $r < P$, then there exist P x r matrices α and β each with rank r such that $\pi = \alpha\beta'$ and $\beta' Y_t$ is I(0). Where r is the number of cointegrating relations (the cointegrating rank) and each column is the cointegrating vector. The elements of α are known as the adjustment parameters in the VEC model. It can be shown that for a given r, the maximum likelihood estimator of β defines the combination of Y_t that yields the r largest canonical correlations of ΔY_t with Y_{t-1} after correcting for lagged differences and deterministic variables when present

Generally, the following three conditions should be used in VECM:

- Condition 1: Rank$(\Pi) = 0$. this means that no cointegration being present in the model and any linear combination of the variables which is stationary does not exist. The nonstationarity for this model can be removed by taking differences or using a log root transformation. Thus the appropriate model which should be used is a VAR in first differences which does not involve any long run elements (Harris, 1995). The VECM model is not applicable because pure VAR model is utilized.
- Condition 2: Rank$(\Pi) = n$. The vector process Y_t contains no unit roots and it is $I(0)$ and Y_t is therefore stationary. As a result of this information have no guarantee for using the VECM model (Tsay, 2005). Y_t Should be studied directly and modeled in levels, not differences and there is no need for a VECM representation to be used. Here also pure VAR model is used.
- Condition 3: Rank$(\Pi) = r,\ 0 < r < n$. This is known as the partial non-stationary case where there are r distinct linear combinations of ΔY_t that are stationary (Mauricio, 2006). Pure VAR cannot be used and instead VECM will be the right model to be utilized.

3.3.7 Model Diagnostic Checking

Model checking is an obligatory activity to investigate validity and reliability of all inference procedures made by VARs and VECMs before one is going to use these models to forecast future patterns of series. Therefore a range of diagnostic tests is available for checking the model assumptions and properties formally. There are several tests for checking forecasting capability (adequacy) of these models.

3.3.7.1 Test of Residual Autocorrelation

3.3.7.1.1 Autocorrelation LM Test

Lagrange multiplier tests can be used to tests for residual autocorrelation in a VAR(p) process.

The Breusch–Godfrey test (1978) for h^{th}order residual autocorrelation LM assumes a VAR model is defined as $\mu_t = \beta_1\mu_{t-1} + \beta_2\mu_{t-2} + \cdots + \beta_h\mu_{t-h} + \nu_t$ of (Lütkepohl, 2005) in order to check the null and alternative hypothesis

H_o: $\beta_1 = \beta_2 = \cdots = \beta_h = 0$ (There is no serial correlation present in the model)

H_1: At least one of the β_j $j\epsilon[1,2,\ldots,h] \neq 0$

There are various methods which can be used in order to find a suitable Lagrange Multiplier test statistic and its critical values. According to (Brandt and Williams, 2007) proposed a step by step procedure by estimating an unrestricted as well as a restricted VAR model. The auxiliary model has the form

$$\hat{\mu}_t = A_1Y_{t-1} + \cdots + A_pY_{t-p} + \beta_1\mu_{t-1} + \cdots + \hat{\beta}_h\hat{\mu}_{t-h} + e_t \qquad [3.33]$$

an analogous of equation(3.33) VECM form is

$$\hat{\mu}_t = \alpha\hat{\beta}'Y_{t-1} + \Gamma_1\Delta Y_{t-1} + \cdots + \Gamma_{p-1}\Delta Y_{t-p+1} + \beta_1\mu_{t-1} + \cdots + \hat{\beta}_h\hat{\mu}_{t-h} + e_t \qquad [3.34]$$

Denoting the estimated residuals by $\hat{e}_t(t = 1,2,3,..,4)$, we obtain the following residual covariance matrix estimator from the auxiliary models: $\widehat{\Sigma}_e = \frac{1}{T}\sum_{t=1}^{T} e_t e_t'$.

Moreover, if we reestimate the relevant auxiliary model without the lagged residuals $\hat{e}_{t-i}$ (i=1,2,…,h), that is, impose the restrictions $\beta_1 = \beta_2 = \cdots = \beta_h = 0$ and denote the resulting residuals by $\hat{e}_t^R$, the corresponding covariance matrix estimator is $\widehat{\Sigma}_R = \frac{1}{T}\sum_{t=1}^{T} \upsilon_t^R \upsilon_t^{R'}$

The relevant LM test statistic is defined as

$$LM_h = T[k - tr(\widehat{\Sigma}_e\widehat{\Sigma}_R^{-1})] \qquad [3.35]$$

The value refers to the number of endogenous variables in the system. This LM statistic follows a $\chi^2(hk^2)$ distribution with the degrees of freedom, where is the number of restrictions placed on the parameters of the model in equation (3.35) under the null hypothesis that there is no residual correlation present.

A variant of the test statistic that adjusts the likelihood ratio in such a way that its distribution under H_o can be approximated well by an F-distribution was recommended by Edgerton & Shukur (1999). More precisely,for small samples, the following statistic well used for stationary full VAR processes without subset restrictions:

$$FLM_h = \left[\left(\frac{|\hat{\Sigma}_R|}{|\hat{\Sigma}_e|}\right)^{\frac{1}{s}} - 1\right]\frac{Ns - q}{Km}\ with \quad s = \left(\frac{K^2m^2 - 4}{K^2 + m^2 - 5}\right)^{\frac{1}{2}}, \qquad q = \frac{1}{2}Km - 1$$

$$and\ N = T - n - m - \frac{1}{2}(K - m + 1)$$

where n is the number of regressors in each equation of the original system and k is the number of estimated coefficients then $m = Kh$ is the number of additional regressors in the auxiliary system. Then the critical vlue of the F-distrbution is $F(hK^2, Ns - q)$.

3.3.7.1.2 Portmanteau Autocorrelation Test

The portmanteau test for residual autocorrelation checks the null hypothesis that all residual autocovariances are zero, that is:

$$H_o: E(\varepsilon_t\varepsilon_{t-j}^{'}) = 0 \quad Vs \quad H_1: E(\varepsilon_t\varepsilon_{t-j}^{'}) \neq 0, at\ least\ one\ j,\ \ i.e\ \ j = 1,2, \dots, h$$

The test statistic is based on the residual autocovariances and has the form:

$$Q_h = T\sum_{j=1}^{h} tr\left(\hat{\gamma}_j^{'}\hat{\gamma}_0^{'-1}\hat{\gamma}_j\hat{\gamma}_0^{-1}\right) \qquad [3.36]$$

$$\hat{\gamma}_j = T^{-1}\sum_{t=j+1}^{T} \varepsilon_t\varepsilon_{t-j}^{'} \qquad [3.37]$$

$\varepsilon_t{'}s$ are the estimated residuals. For unrestricted residuals stationary VAR(p) process the null distribution of $Q_h$and approximated by $\chi^2(n^2(h-p))$ distributed if T and h approaches infinity such that $h/T \longrightarrow 0$

Alternatively (especially in small samples), a modified statistic is used

$$Q_h{}^* = T^2\sum_{j=1}^{h}\frac{1}{T-j} tr\left(\hat{\gamma}_j^{'}\hat{\gamma}_0^{'-1}\hat{\gamma}_j\hat{\gamma}_0^{-1}\right), \qquad instead\ of\ the\ original\ version\ (3.36)$$

This statistic may have better small sample properties than the unadjusted version. The choice of h is important for the test performance. If h is chosen too small, the approximation to the null distribution may be very poor whereas a large h may result in a loss of power.

Therefore we conclude that the Brensch–Godfrey LM test is useful for testing for low order residual autocorrelation (small h) where as a portmanteau test is preferable for larger$h$.

3.3.7.2 Normality Test of the Residuals

(Lütkepohl, 1993) suggests using the multivariate generalization of (Jarque and Bera, 1987) test statistic $\frac{T}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$to test the multivariate normality of the μ_t where T is the number of observations,S is the sample skewness, and K is the sample kurtosis. This tests the skewness and kurtosis properties of the $\mu_t(3^{rd}\ and\ 4^{th}$ moments) against those of a multivariate normal distribution of the appropriate dimension.

$$H_o: E(\hat{\mu}_t^s)^3 = 0 \quad Vs \quad H_1: E(\hat{\mu}_t^s)^3 \neq 0\ for\ skewness$$

$$H_o: E(\hat{\mu}_t^s)^4 = 3 \quad Vs \quad H_1: E(\hat{\mu}_t^s)^4 \neq 3\ for\ kurtosis$$

It is possible that the first four moments of the u_t match the multivariate normal moments, and the u_t are still not normally distributed. It is hoped that most of the normal properties desired by the model fitter in the u_t are met by these four moments. This situation has an analog in linear regression. We assume that the errors are independent, but we can only test whether they are correlated. In linear regression, it is adequate to test the correlation of the residuals. If they are uncorrelated, that is enough independence for getting the variance calculations correct. We don't worry about the other forms of dependence.

From the Formulation of the Jarque-Bera test uses a mean adjusted form of the VAR (p) model

$$(Y_t - \mu) = \mathrm{A}_1(Y_{t-1} - \mu) + \cdots + \mathrm{A}_p\left(Y_{t-p} - \mu\right) + \mu_t \qquad [3.38]$$

Where μ_t white noise with mean zero and Σ_μ is nonsingular covariance matrix and $A, A_2, \ldots, \mathrm{A}_p$ are coefficient of matrix.

$$\hat{\mu}_t = (Y_t - \bar{Y}) - \hat{A}_1(Y_{t-1} - \bar{Y}) - \cdots - \hat{A}_p\left(Y_{t-p} - \bar{Y}\right), t = 1,2,\ldots,T \qquad [3.39]$$

where $\hat{\Sigma}_\mu$ is estimator of the covariance matrix of Σ_μ and $\hat{\mathrm{A}}_1,\ \hat{A}_2, \hat{\mathrm{A}}_p$ are estimator of coefficients $\mathrm{A}_1,\ A_2, \ldots,\ \mathrm{A}_p$ from the multivariate maximum likelihood estimation of VAR modal in the equation (3.38). Let $\hat{P}$ is the symmetric and idempotent matrix satisfying that $\hat{P}\hat{P}' = \hat{\Sigma}_\mu$ and $\underset{n\to\infty}{plim}(\hat{P} - p) = 0$ where $\hat{\Sigma}_\mu = \frac{1}{T-mp-1}\sum_{t=1}^{T}\hat{\mu}_t\hat{\mu}_t'$

Now we define the standardized residuals and their sample moments are:

$$\left.\begin{aligned}\hat{\mu}_t^s &= (\hat{\mu}_{1t}^s, \hat{\mu}_{2t}^s, \dots, \hat{\mu}_{kt}^s)' = \hat{P}^{-1}(\hat{\mu}_t - \bar{\hat{\mu}}_t).\\ \hat{b}_1 &= \left(\hat{b}_{11}, \dots, \hat{b}_{k1}\right)' with\ \hat{b}_{k1} = T^{-1}\sum_{t=1}^{T}(\hat{\mu}_{kt}^s)^3\\ \hat{b}_2 &= (\hat{b}_{12}, \dots, \hat{b}_{k2})' with\ \hat{b}_{k2} = T^{-1}\sum_{t=1}^{T}(\hat{\mu}_{kt}^s)^4\end{aligned}\right\} \qquad [3.40]$$

Therefore the test statistic can be computed as follows to test the Hypothesis:

$$for\ \ skewness\ \ test\ \ statistic\ \ \hat{\lambda}_s = \frac{T\hat{b}_1'\hat{b}_1}{6}$$

$$for\ \ kurtosis\ \ test\ \ statistics\quad \hat{\lambda}_k = \frac{T(\hat{b}_2 - 3)'(\hat{b}_2 - 3)}{24}$$

$$for\ \ joint\ \ test\ \ of\ \ the\ \ hypotesis\ \ test\ \ ststistic\ \ \hat{\lambda}_{ks} = \hat{\lambda}_s + \hat{\lambda}_k$$

The asymptotic distribution of the estimate is given as:

$$\left.\begin{aligned}\hat{\lambda}_s &\sim \chi^2(k)\\ \hat{\lambda}_k &\sim \chi^2(k)\\ \hat{\lambda}_{ks} &\sim \chi^2(2k)\end{aligned}\right\} \qquad [3.41]$$

3.3.8 Structural Vector Autoregressive Analysis

According to (Sims, 1981, Sims, 1986), (Bernanke, 1986) and (Shapiro and Watson, 1988) put forward a new class of econometric models that is now known as structural vector autoregressive (SVAR) or modified VAR. Instead of identifying the autoregressive coefficients, identification focuses on the errors of the system, which are interpreted as (linear combinations of) exogenous shocks. In the early applications of (Sargent, 1978) and(Sims, 1980) the innovations of the VAR were orthogonalized using a Choleski decomposition of the covariance matrix. A recursive structure was there by imposed on the instantaneous relations between the variables. So that the VAR model has many parameters and they may be difficult to interpret due to complex interactions and feedback between the variables in the model. As a result of the dynamic properties of a VAR (p) are often summarized using various types of structural analysis. Some of the structural analysis are: Granger Causality, Impose Response Function and Forecasting Error Variance Decomposition

3.3.8.1 Granger causality

In a regression analysis, we deal with the dependence of one variable on other variables, but it does not necessarily imply causation. In other words, the existence of a relationship between variables does not prove causality or direction of influence. The structure of the VAR model provides information about a variable's or a group of variables' forecasting ability for other variables. The following intuitive notion of a variable's forecasting ability is due to (Granger, 1969). If a variable, or group of variables, UR is found to be helpful for predicting another variable, or group of variables $RGDP$, then UR is said to Granger-cause $RGDP$; otherwise it is said to fail to Granger-cause $RGDP$. Formally, UR fails to Granger-cause $RGDP$. if for all s > 0 the MSE of a forecast of $RGDP(t+s)$ based on $(RGDP_t, RGDP_{(t-1)} \ldots\ldots)$ is the same as the MSE of a forecast $RGDP_{(t+s)}$based on $(RGDP_t, RGDP_{(t-1)} \ldots\ldots)$ and $(UR_t,\ UR_{(t-1)} \ldots\ldots)$. Clearly, the notion of Granger causality does not imply true causality. It only implies forecasting ability. If UR causes $RGDP$ and $RGDP$ also causes UR the process $(UR_t,\ RGDP_t)$ is called a feedback system.

For example, in a bivariate $VAR(p)$ model for $Y_t = (UR_t, RGDP_t)'$, $RGDP$ fails to Granger-cause UR if all of the $VAR(p)$ coefficient matrices $A_1, A_2, \ldots, A_p$ are lower triangular.

Therefore, the $VAR(p)$ model has the form for bivariate

$$\begin{pmatrix} UR_t \\ RGDP_t \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \end{pmatrix} + \begin{pmatrix} A_{11}^1 & 0 \\ A_{21}^1 & A_{22}^1 \end{pmatrix} \begin{pmatrix} UR_{t-1} \\ RGDP_{t-1} \end{pmatrix} + \cdots + \begin{pmatrix} A_{11}^p & 0 \\ A_{21}^p & A_{22}^p \end{pmatrix} \begin{pmatrix} UR_{t-p} \\ RGDP_{t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

So that all of the coefficients on lagged values of $RGDP_t$ is zero in the equation for UR_t. Similarly, UR_t fails to Granger-cause $RGDP_t$ if all of the coefficients on lagged values of UR_t are zero in the equation for $RGDP_t$. Granger non-causality may be tested using the Wald statistic. Therefore, the p linear coefficient restrictions implied by Granger non-causality may be tested using the Wald statistic. Notice that If $RGDP$ fails to Granger-cause UR and UR fails to Granger-cause $RGDP$, then the VAR coefficient matrices $A_1, A_2, \ldots, A_p$ are diagonal. Testing for Granger non-causality in general n variable $VAR(p)$ models follows the same logic used for bivariate models.

3.3.8.2 Impulse Response Functions

The impulse response test shows that the effects of an exogenous shock on the whole process over time (Sims et al., 1990). The idea is initially to look at the adjustment of the endogenous variables and to detect the dynamic relationships among contemporaneous values of the variables over time, after a hypothetical shock in time t. Impulse response function is an important tool in a VAR system in revealing the direction and magnitude at which one variable (especially the target variable) reacts to the change (shock) applied on the other exogenous variables in the system. Any covariance stationary $VAR(p)$ process as a Wolds representation by using the method of (Enders, 2008) having the form:

$$Y_t = \mu + \varepsilon_t + \psi_1\varepsilon_{t-1} + \Psi_2\varepsilon_{t-2} + \Psi_3\varepsilon_{t-3} + \cdots$$

where the (n × n) moving average matrices ψ_s are determined recursively.

$\psi_s = \sum_{j=1}^{p-1} \psi_{s-j} A_j$ It is tempting to interpret the$(i,j)^{th}$ element, ψ_{ij}^s , of the matrix ψ_s as the dynamic multiplier or impulse response. i.e ψ_{ij}^s represent the effects of unit shocks in the variables of the system

$$\frac{\partial Y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial Y_{i,t}}{\partial \varepsilon_{j,t-s}} = \psi_s, \quad i,j = 1,2,\dots,n$$

However, this interpretation is only possible if $var(\varepsilon_t) = \Sigma$ is a diagonal matrix so that the elements of ε_t are uncorrelated. One way to make the errors uncorrelated is to follow (Sims, 1980) and estimate the triangular structural VAR (p) model:

$$\left.\begin{aligned}
y_{1t} &= c_1 + \gamma'_{11}y_{t-1} + \gamma'_{12}y_{t-2} + \cdots + \gamma'_{1p}y_{t-p} + \eta_{1t}\\
y_{2t} &= c_2 + \beta_{21}y_{1t} + \gamma'_{21}y_{t-1} + \gamma'_{22}y_{t-2} + \cdots + \gamma'_{2p}y_{t-p} + \eta_{2t}\\
y_{3t} &= c_3 + \beta_{31}y_{1t} + \beta_{32}y_{2t} + \gamma'_{31}y_{t-1} + \gamma'_{32}y_{t-2} + \cdots + \gamma'_{3p}y_{t-p} + \eta_{3t}\\
&\;\;\vdots\\
y_{nt} &= c_n + \beta_{n1}y_{nt} + \cdots + \beta_{n,n-1}y_{n-1,t} + \gamma'_{n1}y_{t-1} + \gamma'_{n2}y_{t-2} + \cdots + \gamma'_{np}y_{t-p} + \eta_{nt}
\end{aligned}\right\} \qquad [3.42]$$

In matrix form, the triangular structural VAR(p) model is

$$Y_t = B^{-1}C + B^{-1}\Gamma_1 Y_{t-1} + B^{-1}\Gamma_2 Y_{t-2} + \cdots + B^{-1}\Gamma_p Y_{t-p} + B^{-1}\eta_t \qquad [3.43]$$

Where $C = (c_1, c_2, \dots c_n)^T$ and $\Gamma_i = (\gamma'_{1i}, \gamma'_{2i} \dots \gamma'_{ni})^T, i = 1,2,\dots,p$ and

$$B = \begin{bmatrix} 1 & 0 & 0 \;\dots\dots 0 & \\ -\beta_{21} & 1 & 0 \quad \cdots & 0 \\ & \vdots & \ddots & \vdots \\ -\beta_{n1} & -\beta_{n2} & \cdots & 1 \end{bmatrix}$$

is a lower triangular matrix with 1's along the diagonal. The algebra of least squares will ensure that the estimated covariance matrix of the error vector η_t is diagonal. The uncorrelated or orthogonal errors η_t are referred to as structural errors.The triangular structural model [3.42] imposes the recursive causal ordering.

$$UR \longrightarrow RGDP \longrightarrow CPI \ldots \longrightarrow \cdots$$

The ordering means that the contemporaneous values of the variables to the left of the arrow $\longrightarrow$ affect the contemporaneous values of the variables to the right of the arrow but not vice-versa. These contemporaneous effects are captured by the coefficients β_{ij} in [3.42]. For example, the ordering $UR \longrightarrow RGDP \longrightarrow CPI$ imposes the restrictions: UR_t affects $RGDP_t$ and CPI_t but $RGDP_t$ and CPI_t do not affect UR; $RGDP_t$ affects CPI but CPI_t does not affect $RGDP$.

Results from alternative orderings can always be compared to determine the sensitivity of results to the imposed ordering. Once a recursive ordering has been established, the Wold representation of Y_t based on the orthogonal errors η_t is given by

$$Y_t = \mu + \Theta_o\eta_t + \Theta_1\eta_{t-1} + \Theta_2\eta_{t-2} + \cdots$$

Where $\Theta_o = B^{-1}$ is a lower triangular matrices. The impulse responses to the orthogonal shocks η_{it} is defined as

$$IRF_{ij}(s) = \frac{\partial y_{t,t+s}}{\partial \eta_{jt}} = \frac{\partial y_{it}}{\partial \eta_{j,j+s}} = \theta_{ij}^{s}, i, j = 1, 2, \ldots, n \; and \; s > 0 \qquad [3.44]$$

θ_{ij}^{s} is the (i, j) th element of Θ_s. A plot of θ_{ij}^{s}, against s is called the orthogonal impulse response function (IRF) of y_i with respect to η_j. With n variables there are n^2 possible impulse response functions.

3.3.8.3 Forecast Error Variance Decompositions(FEVDs)

FEVDs is an alternative method of impulse responses function to receive a compact overview of the dynamic structures of VAR models. The FEVDs tells us the proportion of the movements in a sequence due to its own shocks versus shocks to the other variable and also it shows the portion of the variance in the forecast error for each variable due to innovations to all variables in the system (Enders, 2008). This method is also based on a vector moving average model and orthogonal error terms. So that FEVDs answers the question: what portion of the variance of the forecast error in predicting $Y_{i,T+h}$ is due to the structural shock η_j? Using the orthogonal shocks η_t the h-step ahead forecast error vector, with known VAR coefficients, may be expressed as

$$Y_{T+h} - Y_{T+h|T} = \sum_{s=0}^{h-1} \Theta_s \eta_{T+h-s}$$

For a particular variable $Y_{i,T+h}$this forecast error has the form

$$Y_{i,T+h} - Y_{i,T+h|T} = \sum_{s=0}^{h-1} \theta_{i1}^{s}\eta_{1,T+h-s} + \sum_{s=0}^{h-1} \theta_{i2}^{s}\eta_{2,T+h-s} + \cdots + \sum_{s=0}^{h-1} \theta_{in}^{s}\eta_{n,T+h-s} \qquad [3.45]$$

Since the structural errors are orthogonal, the variance of the h-step forecast error is

$$var(Y_{i,T+h} - Y_{i,T+h|T}) = var(\sum_{s=0}^{h-1} \theta_{i1}^{s}\eta_{1,T+h-s} + \cdots + \sum_{s=0}^{h-1} \theta_{in}^{s}\eta_{n,T+h-s})$$

$$= \sigma_{\eta 1}^{2} \sum_{s=0}^{h-1} (\theta_{i1}^{s})^2 + \cdots + \sigma_{\eta n}^{2} \sum_{s=0}^{h-1} (\theta_{in}^{s})^2 \qquad [3.46]$$

$where\ \sigma_{\eta j}^{2} = var(\eta_{jt})\ the\ portion\ of\ \ var(Y_{i,T+h} - Y_{i,T+h|T})$ due to shock η_j is then

$$FEVD_{ij}(h) = \frac{\sigma_{\eta j}^{2} \sum_{s=0}^{h-1} (\theta_{ij}^{s})^2}{\sigma_{\eta 1}^{2} \sum_{s=0}^{h-1} (\theta_{i1}^{s})^2 + \cdots + \sigma_{\eta n}^{2} \sum_{s=0}^{h-1} (\theta_{in}^{s})^2}, i.j = 1,2, \ldots, n \qquad [3.47]$$

In a VAR with n variables there will be $n^2\ FEVD_{ij}(h)$ values. It must be kept in mind that the FEVD in [3.49] depends on the recursive causal ordering used to identify the structural shocks η_j and is not unique. Different causal orderings will produce different FEVD values. Let us take a bivariat VAR models of $(RGDP_t = y_t, UR_t = z_t,)$ from equation [3.10] then If ε_{zt} shocks explain none of the forecast error variance of Y_t at all forecast horizons, we can say that the Y_t sequence is exogeneous. In this circumstance, Y_t evolves independently of the ε_{zt} shocks and the Z_t sequence. At the other extreme, ε_{zt} shocks could explain all of the forecast error variance in the Y_t sequence at all forecast horizons, so that Y_t would be entirely endogeneous. In applied research, it is typical for a variable to explain almost all of its forecast error variance at short horizons and smaller proportions at longer horizons. We would expect this pattern if ε_{zt} shocks had little contemporaneous effect on Y_t but acted to affect the Y_t sequence with a lag.

3.3.9 Forecasting

Forecasting is one of the main objectives of multivariate time series analysis for horizons $h \geq 1$ of an empirical $VAR(p)$process can be generated recursively according to (Box et al., 2008). Forecasting vector time series processes is completely analogous to forecastng univariate time series processes. Consider first the problem of forecasting future values of Y_t when the parameters A of the $VAR(p)$ process is assumed to be known and there are no deterministic terms or exogenous variables. The best linear predictor, in terms of minimum mean squared error (MSE),Y_{t+1} or 1-step forecast based on information available at time T is

$$Y_{T+1|T} = C + \mathrm{A}_1 Y_T + \cdots + \mathrm{A}_p Y_{T-p+1} \quad for T > P, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. [3.48]$$

Forecasts for longer horizons h (h-step forecasts) can be obtained using the chain-rule of forecasting

$$Y_{T+h|T} = C + \mathrm{A}_1 Y_{T+h-1|T} + \cdots + \mathrm{A}_p Y_{T+h-p|T} \qquad [3.49]$$

where $Y_{T+j|T} = Y_{T+j}\ for j \geq 0$. The h-step forecast errors may be expressed as

$$Y_{T+h} - Y_{T+h|T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s} \qquad [3.50]$$

Where the matrices Ψ_s are determined by recursive substitution $\Psi_s = \sum_{j=1}^{p-1} \Psi_{s-j} \mathrm{A}_j$,

With $\Psi_0 = \mathrm{I}_n$ and $\mathrm{A}_j = 0\ for j > p$. The forecasts are unbiased since all of the forecast errors have expectation zero, and the MSE matrix for $Y_{T+h|T}$ is

$$\Sigma(h) = MSE(Y_{T+h} - Y_{T+h|T}) = \sum_{s=0}^{h-1} \Psi_s \Psi_s' \qquad [3.51]$$

Now consider forecasting Y_{T+h} when the parameters of the VAR(p) process are estimated using multivariate least squares. The best linear predictor of Y_{T+h} is now

$$\hat{Y}_{T+h|T} = \hat{A}_1 \hat{Y}_{T+h-1|T} + \hat{\mathrm{A}}_2 \hat{Y}_{T+h-2|T} + \cdots + \hat{A}_p \hat{Y}_{T+h-p|T} \ldots\ldots\ldots$$

where $\hat{A}_j$ are the estimated parameter matrices. The h-step forecast error is given by

$$Y_{T+h} - \hat{Y}_{T+h|T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s} + \left(Y_{T+h} - \hat{Y}_{T+h|T}\right) \qquad [3.52]$$

and the term $(Y_{T+h} - \hat{Y}_{T+h|T})$captures the part of the forecast error due to estimating the parameters of the VAR. The MSE matrix of the h-step forecast is then

$$\hat{\Sigma}(\mathrm{h}) = \Sigma(h) + MSE(Y_{T+h} - \hat{Y}_{T+h|T})$$

In practice, the second term $MSE(Y_{T+h} - \hat{Y}_{T+h|T})$ is often ignored and $\hat{\Sigma}(\mathrm{h})$ is computed using [3.5] as $\hat{\Sigma}(\mathrm{h}) = \sum_{s=0}^{h-1} \hat{\Psi}_s \hat{\Sigma}\, \hat{\Psi}_s^{'}$ with $\hat{\Psi}_s = \sum_{j=1}^{s} \hat{\Psi}_{s-j} \hat{A}_j$ and $\hat{\Psi}_0 = I_k$

3.3.10 **Measures of Forecasting Accuracy**

The word accuracy refers to the goodness of fit, which intern refers to how well the forecasting model is able to reproduce the data that are already known. To the consumer of forecasts, it is the accuracy of the future forecast that is most important. If Y_t is the actual observation for the period t and F_t is the forecast for the sample period, then the error defined as $\nu_t = Y_t - F_t$.

Usually, F_t is calculated using data Y_t,…,Y_{t-1}.It is a one-step forecast because it is forecasting one period ahead of the last observation used in the calculation .Therefore ,we describe ν_t as a one-step forecast error. It is the difference between the observation Y_t and forecast made using all observations up to but not including Y_t. If there are observations and forecasts for T time periods, then there will be n error terms, and the following standard statistical measures can be defined:

$$Mean\ Error(ME) = \frac{1}{T}\sum_{t=1}^{T} \nu_t \qquad [3.53]$$

$$Mean\ Absolute\ Error(MAE) = \frac{1}{T}\sum_{t=1}^{T} |\nu_t| \qquad [3.54]$$

$$Mean\ Square\ Error(MSE) = \frac{1}{T}\sum_{t=1}^{T} (\nu_t)^2 \qquad [3.55]$$

Equation [3.53] used to compute the mean error for each period. Similarly equation (3.54) can be used to compute the averaged absolute the mean error. However, the ME is likely to be small since positive and negative errors tend to offset one another. In fact, the ME will only tell you if there is systematic under or over forecasting, called the forecasting bias. It does not give much indication as to the size of the typical errors.

Therefore, the MAE is defined by first making error positive by taking its absolute value, and then averaging the results. The idea behind the definition of MSE is similar. Here the errors are made positive by squaring each one, and then the squared errors are averaged. The MSE has advantage of being more interpretable and is easier to explain to non-specialist.

Each of these statistics deals with measures of accuracy whose size depends on the scale of the data. Therefore, they do not facilitate comparison across different time series and for different time intervals. To make comparisons we need to work with relative or percentage error measures. First let us define a relative or percentage error as

$$PE_t = \left(\frac{Y_t - F_t}{Y_t}\right) X100\ \% \qquad [3.56]$$

Then the following two relative measures are frequently used:

$$Mean\ percentage\ Error(MPE) = \frac{1}{T}\sum_{t=1}^{T} PE_t \qquad [3.57]$$

$$Mean\ percentage\ Absolute\ Error(MPAE) = \frac{1}{T}\sum_{t=1}^{T} |PE_t| \qquad [3.58]$$

Equation [3.56] can be used to compute the percentage error for any time period. In similar manner equation (3.57) used to compute the averaged mean percentage error. However, as with the ME, the MPE is likely to be small since positive and negative PEs tends to offset one another. Hence the MAPE is defined using absolute values of PE in equation [3.58]. Alternatively, Theil's U statistic can be used as a measure of forecasting accuracy. Theil's U can be estimated or calculated as:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n} {F_t}^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n} {Y_t}^2}} \qquad [3.59]$$

From equation (3.59) the scaling values of U always lies between 0 and 1. If U=0 then $Y_t = F_t$ for all forecasts and it gives a perfect fit; if U = 1 the predictive performance is not good.

CHAPTER FOUR

RESULT AND DISICUSSION

The study is based on the yearly time series data observed from 1983 to 2017. The total number of observation is 35. In this chapter the results of the VAR model specifications used for forecasting economic growth indicators under this study would be presented. The discussion begins by describing the data set and the results from the model selection procedure. Then, results will be interpreted and discussed. Data analysis was performed by using STATA 14 and Eviews 8 statistical software.

4.1 Descriptive Analysis

In the empirical analysis, three aggregate series namely, the Inflation of good and services measured as consumer price index (CPI), RGDP growth and Unemployment rate (UR) were used (as shown Figure 4.1). The descriptive statistics displayed in Table 4.2 shows economic growth increased from its minimum value of 101.803 in 1984 to its maximum value 794.734 in 2017 measured as real GDP. The inflation of goods and services as percent of GDP increased from their minimum values of 13.438 in 1983 to its maximum value of 246.357 in 2017. Similarly the Unemployment rate is decreased from its maximum value 48.56 in 1984 to its minimum value 4.98 in 2013. Here also Skewness test indicates that approximately not symmetric except unemployment variable but kurtosis test values show that approximately the variables are mesokurtic. The Jarque Bera statistic is also calculated to check for normality by stating the null hypothesis as all the variables are individually normal distribution and the alternative hypothesis states that the variables are not individualy normal distribution. Therefore the null hypothesis of normal distribution for all variables is not rejected at 5% significance level.

Table 4.1: Summary Result of the series using Eviews software

Variable	Obs	Mean	Median	Max.	Min.	Std.Dev.	Skewness	kurosis	Jarque-Bera
RGDP	35	307.593	198.321	794.734	101.803	210.604	0.984	2.7214	5.762(0.0561)
UR	35	28.969	29.95	48.56	4.98	9.039	-0.40352	3.126	0.973 (0.615)
CPI	35	84.676	72.215	246.357	13.438	63.955	0.978	3.3.161	5.616(0.060)

4.2 Stationarity Test

4.2.1 Time plot

The time series under consideration should be checked for stationary before one can attempt to fit a suitable model. That is, variables have to be tested for the presence of unit root(s) there by the order of integration of each series is determined. Figure 4.1 suggests that the series of the endogenous variables display a non stationary behavior.

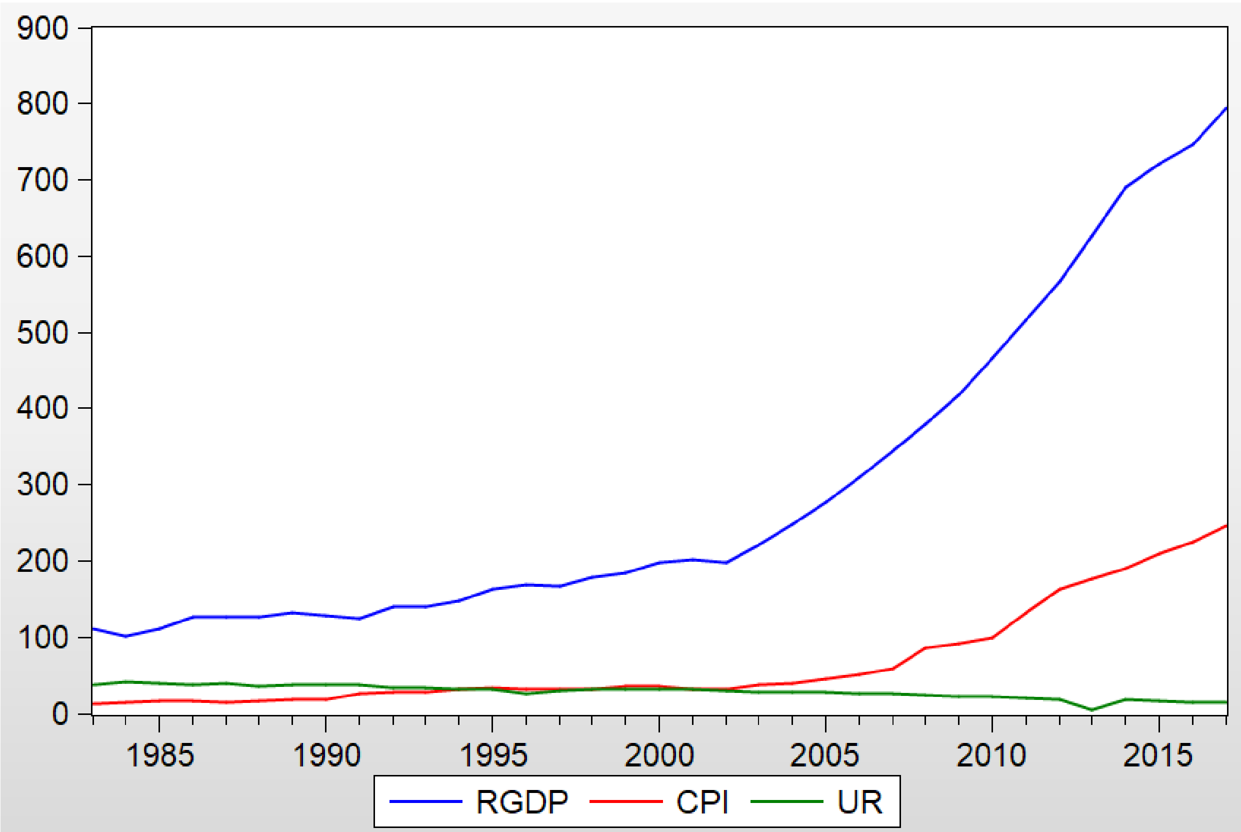

Figure 4.1: Time series plot of RGDP, CPI and UR (at level)

Figure 4.2 shows that the economic growth indicator variables individualy have stationary of time series behavior after 1st difference to fitting time series model but it is not indicate that all the economic growth indicator variables are strictly stationary.

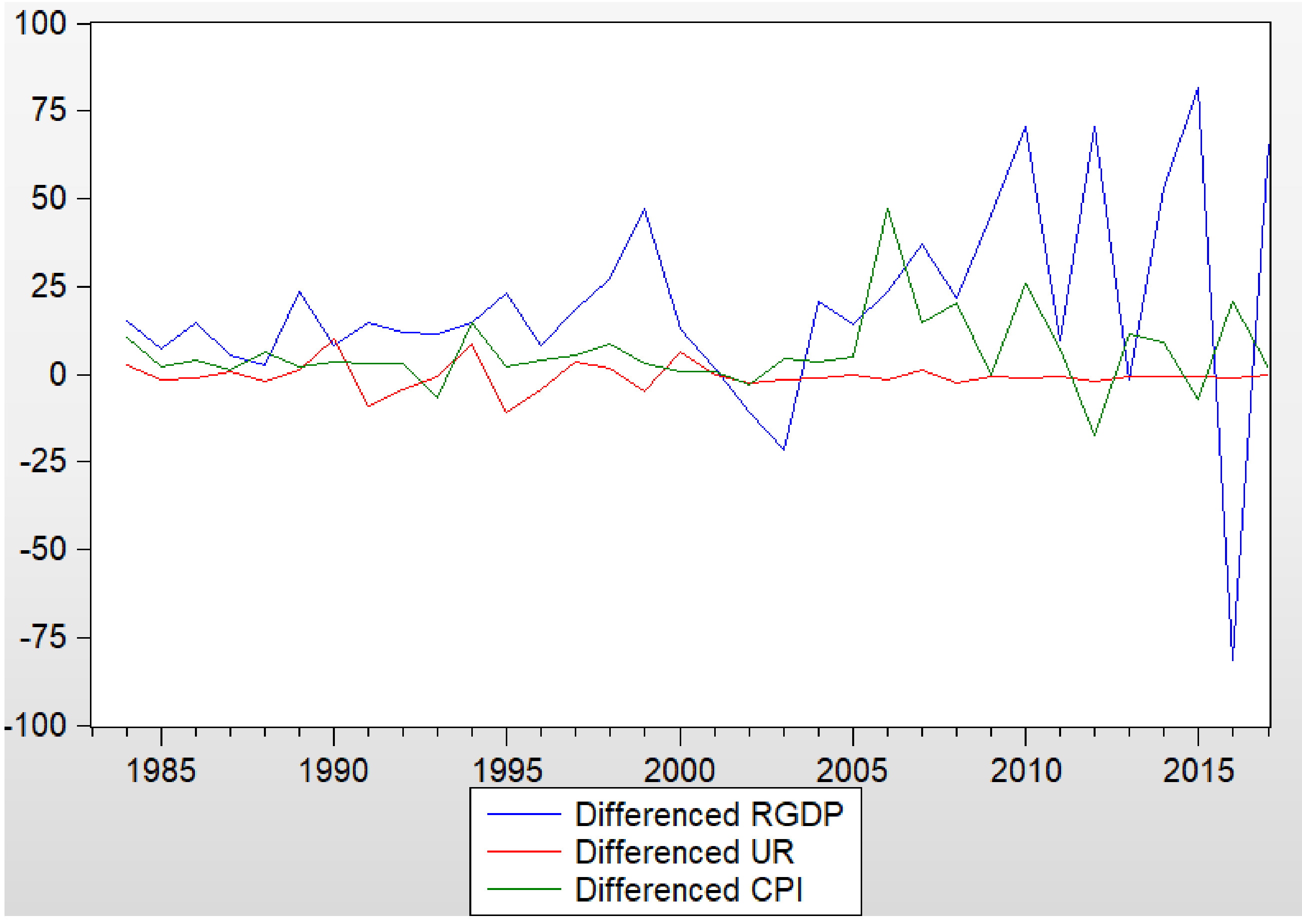

Figure 4.2:Time series plot of RGDP, CPI and UR (after first deference)

4.2.2 Unit Root Tests

Before we apply different techniques of multivariate time series analysis, we need to check for the stationarity of each variable under study since many of the methods assume that the data is stationary with respect to the mean and variances. The ADF and PP tests differ mainly in how they treat serial correlation in the test regressions. ADF tests use a parametric autoregressive structure to capture serial correlation while PP tests use non-parametric corrections based on estimates of the long-run variance of the differences Δy_t. Unit root test is the starting point of the analysis of time series variables. Accordingly, ADF and PP unit root test is used to see if the variables have unit root or not. Under this study passed the test and found to have unit root at level both without trend and with trend lnUR, lnRGDP and lnCPI are non-stationary at 5% level of significance based on MacKinnon approximate p-value (1991) and at 5% level of critical value which is given in the table 4.2.

Table 4.2:Unit root test for stationary at level

Series	Level with Intercept		Level with Intercept and trend		Level wit out Intercept and trend	
	Test statistic		Test statistic		Test statistic	
	ADF	PP	ADF	PP	ADF	PP
LnRGDP	1.458464	1.41673	-2.885198	-1.353212	2.16019	4.506506
LnCPI	0.394525	0.414235	-1.59804	-1.684039	3.00368	2.866446
LnUR	0.013735	-0.60358	-2.86771	-3.31323	-1.993077	-2.224926
5% critical value	-2.963972	-2.951125	-3.568379	-3.5514	-1.952473	-1.95100
Conclusion	Not Stationary		Not Stationary		Not Stationary	

The results in Table 4.3 indicate that the null hypothesis of unit root is rejected for the first differences of the three variables with intercept, with intercept and trend and also without intercept and trend using ADF and PP test. This implies that the three variable of economic growth indicators time series are integrated of degree one $I(1)$. Therefore, the ADF and PP test based on Table 4.2 and table 4.3 shows that all series are non-stationary at levels and stationary at the first differences respectively.

Table 4.3: ADF and PP unit Root test for stationary at first Difference

Series	1st difference with Intercept		1st difference with Intercept and trend		1st difference without Intercept and trend	
	Test statistic		Test statistic		Test statistic	
	ADF	PP	ADF	PP	ADF	PP
lnRGDP	-2.970876	-3.286389	-3.723707	-3.873740	-2.821443	-3.189887
LnCPI	-3.587932	-3.988768	-3.948106	-4.261776	-2.198564	-2.749980
LnUR	-5.718451	-9.963177	-5.622503	-9.792457	-5.545834	-9.391147
5% critical value	-2.9591		-3.5614		-1.9521	
Conclusion	Stationary		Stationary		Stationary	

4.3 VAR Model Specification

4.3.1 Cross- Correlation Matrix

Based on the cross-correlation matrix presented in Table 4.4, we observe that there exists high positive cross-correlation between RGDP and CPI upto third order pre-detrmined(lagged) values, in the same manner UR and CPI have high negative cross-correlation upto the third lagged values. On the other hand UR and RGDP have low negative correlation. Here the negative cross-correlation indicates that one variable value increase the other variable value is decreased and the positive cross-correlation shows that simultaneously as one variable increase the other variable also increase in the same manner that have correlated variables.

Table 4.4:Cross-Correlation Matrix of the variables

CCM at lag:0			
	RGDP	CPI	UR
RGDP	1	0.988	-0.916
CPI	0.988	1	-0.887
UR	-0.916	-0.887	1
Simplified matrix			
CCM at lag:1			
	+	+	-
	+	+	-
	-	-	+
CCM at lag:2			
	+	+	-
	+	+	-
	-	-	+
CCM at lag:3			
	+	.	-
	+	.	-
	.	.	+
CCM at lag:4			
	.	.	.
	.	.	.
	.	.	.
CCM at lag:5			
	.	.	.
	.	.	.
	.	.	.
CCM at lag:6			
	.	.	.
	.	.	.
	.	.	.

4.3.2 Test of Cross-Correlation Matrix

A basic test in multivariate time series analysis is to detect the existence of linear dynamic dependence in the data. This amounts to testing the null hypothesis $H_0: \rho_1 = \rho_2 = \cdots = \rho_m = 0$ versus the alternative hypothesis $H_0: \rho_i = 0$ for some i satisfying $1 \leq i \leq m$, where m is a positive integer. The *Portmanteau test* of univariate time series has been generalized to the multivariate. The p-values of the $Q_k(m)$ statistic for the economic growrh indicator variables of three-dimensional white noise series. For this economic growth indicator variables from Table 4.5, as expected, all p-values are greater than 0.05, confirming that the series has no zero Cross-Correlation Matrixs. This indicates all the economic growth indicator variables have linearly dynamic dependency upto the second pre-determined(lagged) values of variables

Table 4.5:Ljung-Box Statistics

Lag	M	Q(m)	P-value
1	1	0.111	0.742
2	2	10.775	0.076
3	3	10.930	0.010
4	4	14.062	0.012
5	5	14.095	0.023
6	6	14.988	0.026
7	7	15.220	0.037
8	8	15.220	0.068
9	9	15.225	0.089
10	10	15.941	0.101

4.3.3 Estimating Order of the VAR

Specifying the lag length has strong implications for subsequent modeling choices. For determining the appropriate lag length for the VAR model the AIC, SBIC and HQIC were used. By using the pre-lag order estimation technique in Eviews 8 and STATA-14 using four maximum number of lags (i.e $P_{max} = 4$), the suggested model is VAR (2) in all model selection criteria since it has the minimum AIC, SBIC and HQIC as shown table 4.5 reports lag-order selection statistics are given.

Table 4.6:VAR lag order selection results

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	10.28454	NA	0.000125	-0.469970	-0.331197	-0.424734
1	105.7221	166.2461*	4.77e-07*	-5.046587	-4.491495	-4.865641
2	109.0439	5.143416	7.01e-07	-5.680251*	-4.708840*	-5.363595*
3	113.4573	5.979440	9.89e-07	-5.384341	-3.996611	-4.931976
4	120.6959	8.406097	1.22e-06	-5.270701	-3.466653	-4.682626

*indicates lag order selected by the criterion

From Table 4.5 we can observe that VAR (2) is selected by the criterion and VAR (2) is the best since it has the minimum AIC, SBIC and HQIC. Accordingly this output, we can use the VAR (2) model for prediction and forecasting purposes.Therefore, the VAR model to be estimated is:

$$\begin{bmatrix} UR_t \\ RGDP_t \\ CPI_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} A_{11}^1 & A_{12}^1 & A_{13}^1 \\ A_{21}^1 & A_{22}^1 & A_{23}^1 \\ A_{31}^1 & A_{32}^1 & A_{33}^1 \end{bmatrix} \begin{bmatrix} UR_{t-1} \\ RGDP_{t-1} \\ CPI_{t-1} \end{bmatrix} + \begin{bmatrix} A_{11}^2 & A_{12}^2 & A_{13}^2 \\ A_{21}^2 & A_{22}^2 & A_{23}^2 \\ A_{31}^2 & A_{32}^2 & A_{33}^2 \end{bmatrix} \begin{bmatrix} UR_{t-2} \\ RGDP_{t-2} \\ CPI_{t-2} \end{bmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix} \tag{4.1}$$

4.3.4 Lag exclusion test

To check whether the chosen lag is optimal, Wald lag exclusion test is used. Given that VAR modeling requires uniform lag length for each variable, the result in Table 4.7 shows that second lag is significant for all variables at 5 percent level of significance. That is, the value in the square brackets indicates probability value for the corresponding chi-square statistics. Therefore; VAR (2) is found suitable for the data set and hence could be adopted.

Table 4.7: VAR Lag Exclusion Wald Tests

Chi-squared test statistics for lag exclusion:

Numbers in [ ] are p-values

	LNRGDP	LNCPI	LNUR	Joint
Lag 1	20.07607	21.56494	10.14866	52.73353
	[0.000164]	[8.03e-05]	[0.017344]	[3.28e-08]
Lag 2	3.133688	0.795671	0.866466	5.079051
	[0.001469]	[0.000502]	[0.003512]	[0.000363]
Df	3	3	3	9

4.3.5 Estimation of Parameters VAR Model

The K-dimensional $VAR(p)$ model $Y_1, Y_2, \dots, Y_T$ where $Y_t = (Y_{1t}, Y_{2t}, \dots, Y_{kT})$, has the form from equation (3.10).From this equation the parameters are unknown and are required to be estimated. There are various methods of estimation that can be used, the most well-known being least squares estimation, Yule-Walker estimation and maximum likelihood estimation. If the VAR process has a known distribution and is assumed to be normally distributed, then maximum likelihood estimation can be used as an alternative procedure to least squares estimation. The main advantage of maximum likelihood estimation is that it is efficient asymptotically (Lütkepohl, 2005).

The results of unrestricted VAR model fitted with significant estimated coefficients of $lnRGDP,$ lnCPI and $lnUR$ are presented in equation 4.2-4.4 below respectively

$$lnRGDP_t = 0.547 * lnRGDP_{t-1} + 0.266 * lnRGDP_{t-2} + 0.096 * lnCPI_{t-2} - 0.061 * UR_{t-2} + 0.503 \qquad (4.2)$$

$$lnCPI_t = -0.060 * lnRGDP_{t-2} + 0.812 * lnCPI_{t-1} - 0.130 * lnUR_{t-2} + 0.750 \qquad (4.3)$$

$$lnUR_t = -0.210 * lnRGDP_{t-2} - 0.392 * lnCPI_{t-1} + 0.087 * lnCPI_{t-1} + 0.492 * lnUR_{t-1} + 2.690 \qquad (4.4)$$

The fitted VAR model estimate ofReal GDP growth, when we considered as dependenat variable, is reported in equation (4.2). The estimated coefficient 0.547, 0.266, 0.096 and -0.061 of $lnRGDP_{t-1}, lnRGDP_{t-2}, lnCPI_{t-2}\ and\ lnUR_{t-2}$ respectively are significant at 5% level of significance. The overall statistically significant negative coefficient of $lnUR_{t-2}$ imply that the effect of a unit increase in total second per-determined of unemployment rate while keeping other factors constant results in reduction of 6% of current total Real GDP growth.

The overall statistically significant positive coefficient of $lnRGDP_{t-1}, lnRGDP_{t-2}$ and $lnCPI_{t-2}$ imply that the effect of a unit increase in first and second per-determined value of Real GDP growth and second per-determined value of inflation (consumer price index) while keeping other factors constant then results of current Real GDP growth is increased by 54.7%, 26.6% and 9.6% respectively. Based on the result of the fitted VAR model, in addition to its own one and two years lag effect of real economic growth, a significant impact of inflation of goods and services and unemployment rate in the past two years lag on current economic growth is detected in the study period. This shows that real economic growth of Ethiopia has a significant dynamic relationship with both consumer price index (inflation) and Unemployment rate during the study period. The Adjusted R-square value for this model is 0.99, indicating that 99% of the variation in the future Real GDP growth observation is explained

4.4 Cointegration Analysis

The procedure for cointegration involves determination of the existence of long run equilibrium relationship but it does not explain the direction of the causality of the variables. If the variables are not cointegrated, then long run equilibrium relationship does not exist hence only short run relationship can be carried out. Since the variables are integrated of order one, we proceed to test for Cointegration. Johansen(1995) Cointegration test is applied at the predetermined lag2. In these tests, Maximum Eigen value statistic or Trace statistic is compared to special critical values. The maximum Eigenvalue and trace tests proceed sequentially from the first hypothesis no Cointegration to an increasing number of Cointegration vectors.

Based on Johansen Cointegration tests natural logarithm of RGDP,CPI and UR are reported Table 4.8 by using the assumption Linear deterministic trend. Based on this output the trace statistic indicates that at least one Cointegration vector ($r \geq 1$) exists in the system at the 95 percent confidence level $12.8847 < 15.49471$ and its p-value (0.1191) is greater than at 5% level of significance. Inorder to cross check for identifying the specific number of Cointegration vectors, by using the maximal Eigenvalue statistic is further employed. This statistic confirms the existence of only one Cointegration relationship at the 95 percent confidence level $9.383115 < 14.2646$ and its p-value (0.2556) is greater than at 5% percent critical value. Based on

Johansen Cointegration test of cointegration the trace statistic and maximal Eigenvalue statistic the economic growth indicator variables are integrated at one $I(1)$. So that the pure VAR model cannot be used and instead VECM will be the right model to be utilized.

Table 4.8: Johansen Cointegration test results (By assumption: Linear deterministic trend)

Hypothesized Number of Cointegration vector	Eigenvalue	Trace Test			Maximum Eigenvalue Test		
		Test Statistic	5% Critical Value	Prob.**	Test Statistic	5% Critical Value	Prob.**
None *	0.51092	35.77206	29.79707	0.0091	22.88729	21.13162	0.0280
At most 1	0.25414	12.88477	15.49471	0.1191	9.383115	14.26460	0.2556
Atmost 2	0.10365	3.501658	3.841466	0.0613	3.501658	3.841466	0.0613

Normalized Cointegration Coefficients(standard error in parentheses) 1 Cointegrating Equation(s)

RGDP	CPI	UR
1.000000	-0.426357	1.081799
	(0.35642)	(0.76835)

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

From the Johansen Cointegration test table 4.8, it was determined that the rank of Cointegration matrix to be equal to one. Since we do not reject the null hypothesis for the trace test statistic value (12.885<15.495) and maximum Eigen value test statistic value (9.38<14.265) Consequently, the Cointegration vector is given by $\beta = (1, -0.426357,\ 1.081799)$.

The values correspond to the cointegrating coefficients of natural logarthim RGDP (normalized to one), CPI, and UR, respectively. Thus, the vector above can be expressed as follows:

$$lnRGDP_t = 0.426 * lnCPI_t - 1.082 * lnUR_t + \varepsilon_t \qquad [4.5]$$

Based on the cointgrarting vector equation 4.3 the current RGDP of economic growth is increased by 0.426 as a unit increasenig of the current inflation of good and service or Consumer

Price Index as in Ethiopia. Similarly the for a unit increase of unemployment rate, the current RGDP of economic growth of Ethiopia is decreased by more than one.

4.5 Vector Error Correction Model

Having concluded that variables in the VAR model appeared to be cointegrated, we proceed to estimate the short run behavior and the adjustment to the long run models, which is represented by VECM. The VEC model has the following structure:

$$\Delta Y_t = \alpha\beta Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + BX_t + \varepsilon_t \qquad [4.6]$$

Where β is the cointegrating vector. The responses of lnCPI, lnRGDP and lnUR to short-term output movements are captured by the Γ_i coefficient matrices. The α coefficient vector reveals the speed of adjustment to the equilibrium, which measures the deviation from the long-run relationship among economic growth indicator variables.

Coefficient estimates of the VEC model are presented in Table A2 in appendix, this table consists of two parts; the first part contains the detail of the Cointegration vector which is derived by normalizing the real GDP growth. The results indicate that, the long run coefficients of consumer price index (inflation) has a positive long run relationship with real GDP growth which is coincide with (Abis, 2014) findings in Ethiopia and the coefficient of unemployment has negative long run relationship with real GDP growth similar with (Ali and Kaushik, 2015) findings in Ethiopia. The long run equation is given as follows:

$$lnRGDP_t = 0.426 * lnCPI_t - 1.082 * lnUR_t + 7.150 \qquad [4.7]$$

The second part of the Table A2 contains the coefficients of the error correction terms (cointEq1) for the cointegration vector. These coefficients are called the adjustment coefficients. This measures the short-run adjustments of the deviations of the endogenous variables from their long- run values.

Based on the Table A2 in appendix shows all adjustment coefficients have a negative sign (-0.173123, -0.053138, -0.113562) and significant with large t-values. The figures in this row identify the fraction of the long-term gap that is closed in each period (annually). The first equation, i.e. the RGDP equation 4.8 shows that the remaining long-term RGDP gap closes by about 17.31% percent in each period, while the gaps in the CPI and UR equations close by 5.31% and 11.35% percent, respectively in equation 4.9 and 4.10.

Finally, using the error correction term as another independent variable in the unrestricted VAR model we can estimate the following Vector Error Correction Model: The results of VECM model fitted with significant estimated coefficients of $lnRGDP,$ lnCPI and $lnUR$ are presented in equation 4.8-4.10 respectively in Appendix-A from tableA3-5

Model for Real GDP growth:

$$\Delta lnRGDP_t = -0.173 * [lnRGDP_{t-1} - 0.426 * lnCPI_{t-1} + 1.082 * lnUR_{t-1} - 7.150] - 0.203 * \Delta lnRGDP_{t-1} + 0.264 * \Delta lnCPI_{t-1} - 0.025 * \Delta lnUR_{t-2} + 0.083 \qquad [4.8]$$

Model for consumer Price index:

$$\Delta lnCPI_t = -0.053 * [lnRGDP_{t-1} - 0.426 * lnCPI_{t-1} + 1.082 * lnUR_{t-1} - 7.150] + 0.007 * \Delta lnRGDP_{t-1} + 0.135 * \Delta lnCPI_{t-2} - 0.018 * \Delta lnUR_{t-2} + 0.076 \qquad [4.9]$$

Model for unemployment:

$$\Delta lnUR_t = -0.114 * [lnRGDP_{t-1} - 0.426 * lnCPI_{t-1} + 0.1.082 * lnUR_{t-1} - 7.150] - 0.252 * \Delta lnRGDP_{t-2} - 0.058 * \Delta lnCPI_{t-2} - 0.465 * \Delta lnUR_{t-2} - 0.035 \qquad 4.10$$

Where: 'Δ' stands for first difference (D), the value in the bracket is the error correction term and the coefficients of error correction term are called adjustment coefficients.

Based on VECM of the Real GDP growth mode under equation 4.8, the coefficient of Cointegrated vector (-0.173) is negative and significant by using OLS estimation method in appendix-A and Wald test statistic at 5% level of significance. Its shows that the speeds of adjustment towards long run at equilibrium causality. Under this model there is long run causality from the two independent variables CPI and UR to RGDP. It implies that CPI and UR have influence on the dependent variable of RGDP growth in long run causality. To find the short run causality among variables by using Wald test statistic to the coefficient of CPI. In this model Wald statistic of the coefficient of CPI indicates that there is positive short run causality running from CPI to GDP since p-value is less than 5% level of significance. This result is similar to (Li and Liu, 2012, Jaradat, 2013, Abis, 2014) findings in China, Jordanian and Ethiopia respectively. Similarly there is negatively short run causality running from UR to RGDP based on OLS estimation of the model and Wald test of the coefficient of UR in the RGDP growth model and the result is similar with (Ali and Kaushik, 2015) findings in Ethiopia.

Based on equation 4.9 and 4.10 models, the estimated coefficients are statistically significant at 5% level of significance using OLS estimation method in appendix-A. This results indicates that there is negatively short run causality between Unemployment rate and Consumer Price Index (inflation) in Ethiopia which is similar to (Umaru and Zubairu, 2012b) findings in Nigeria.

Here also based on the fitted VECM model estimate of $\Delta lnRGDP_t$, when we considered as dependenat variable, is reported in equation(4.8). The estimated coefficient -0.203, 0.264 and -0.025 of $\Delta lnRGDP_{t-1}, \Delta lnCPI_{t-1}$ *and* $\Delta lnUR_{t-2}$ respectively are significant at 5% level of significance. The over all statistically significant negative coefficient of $\Delta lnRGDP_{t-1}$ and $lnUR_{t-2}$ imply that the effect of a unit increase in total $\Delta lnRGDP_{t-1}$ and $\Delta lnUR_{t-2}$while keeping other factors constant results in reduction of 20.3% and 2.5% of current total $\Delta lnRGDP_t$ respectively.

The over all statistically significant positive coefficient of $\Delta lnCPI_{t-2}$ imply that the effect of a unit increase in total $\Delta lnCPI_{t-2}$ while keeping other factors constant results in 26.4% increment of current total $\Delta lnRGDP_t$. Based on the result of the fitted VECM model, in addition to its own one years pre-determined effect of real economic growth, a significant impact inflation of goods and services and unemployment rate in the past two years lag on current economic growth is detected in the study period. This shows that real economic growth of Ethiopia has a significant dynamic relationship with both consumer price index (inflation) and unempoyment rate during the study period. The Adjusted R-square value for this model is 0.69 in TableA3 from Appendix-A, indicating that 69% of the variation in the future $lnRGDP_t$ observation is explained. Similarly, for the fitted VECM of equation 4.9 the current inflation of good and survice positively affected by its own past second pre-determined (lagged) values and past first lagged values of Real GDP and from equation 4.10 the current unemployment rate is negatively affected by it own past two lagged values and past two lagged values of Real GDP and inflation of good and services.

4.6 Model checking

In order to ascertain whether the model provides an appropriate representation, a test for misspecification should be performed. Once a VECM-model has been estimated, it is pivotal interest to see whether the residuals obey the model's assumptions. That is, we should check for the absence of serial correlation and heteroskedasticity and see if the error process is multivariate normally distributed. The Breusch-Godfrey test for serial correlation with p-values less than 5% indicate the presence of serial correlation. A further characterization of our model includes VECM residual normality test using the Orthogonal Cholesky test method for the null hypothesis states that VECM residuals are multivariate normal with p-values less than 5% indicate non-normality.

4.6.1 Test of Residual Autocorrelation

Based on Table 4.9 shows the portmanteau Q-statistic and Lagrange Multiplier (LM) test for VEC model residual serial correlation. These tests are used to test for the overall significance of the residual autocorrelations up to $lag2$. Both results suggest that there is no obvious residual autocorrelation problem up to $lag2$ because all p-values are larger than the 0.05 level of significance. The model is also checked for heteroscedasticity. Residual heteroscedasticity White test (X^2= 73.73082 , P-value=0.7809) indicates that there is no heteroscedasticity in the system.

Table 4.9: Test of residual autocorrelation for Portmanteau and Lagrange Multiplier

	Portmanteau Q-statistic		LM-test statistic	
Lags	Value	P-Value	Value	P-Value(Prob)
1	1.821534	NA^*	6.362235	0.7032
2	4.942794	NA^*	9.728661	0.3729
* The test is valid only for lags larger than the VAR lag order.				
Probs from chi-square with 9 df				
Heteroskedasticity				
Chi-sq	Df	Prob*		
73.73082	84	0.7809		

4.6.2 Testing of Normality

Multivariate version of the Jarque Bera tests is used to test the normality of the residuals. It compares the 3^{rd} and 4^{th} moments (skewness and kurtosis) to those from a normal distribution. Under the testing of normality the null hypothesis states that residuals are multivariate normally distributed and the alternative hypothesis states that residual are not multivariate normally distributed. Based on the Table 4.10 results and figureB1 in appendix-B shows that the Vector Error Correction Model estimated residual are univariate and multivariate normal because all p-values of the Jarque Bera, Skewness and Kurtosis are greater than at 5% level of significance. Due to this we do not reject the null hypothesis.

Table 4.10: Vector Error Correction Model Normality test of Residual

Component	Jarque Bera			Skewness			Kurtosis		
	Test statistic	Df	Prob	Test statistic	Df	Prob	Test statistic	Df	Prob
ΔCPI	1.409993	2	0.4941	0.117481	1	0.7318	1.292512	1	0.2556
$\Delta RGDP$	1.485189	2	0.4759	1.478840	1	0.2240	0.006349	1	0.9365
ΔUR	0.769329	2	0.6807	0.541155	1	0.4620	0.228173	1	0.6329
Jointly	3.664511	6	0.7220	2.137476	3	0.5444	1.527035	3	0.6760

4.7 Structural Vector Autoregressive Analysis

4.7.1 Granger-Causality Test

Granger causality test is considered a useful technique for determining whether one time series is good for forecasting the other. The concept of granger causality test is explored when the coefficients of the lagged of the other variables is not zero. Table 4.11 presents the pair-wise Granger-causality tests which were obtained with two lag for each variable.

Table 4.11: Pair-wise Granger-causality tests

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
lnCPI does not Granger Cause lnRGDP	33	4.59156	0.0189
ln RGDP does not Granger Cause lnCPI		2.24945	0.1242
lnUR does not Granger Cause lnRGDP	33	5.52781	0.0095
RGDP does not Granger Cause lnUR		1.33773	0.2787
lnUR does not Granger Cause lnCPI	33	5.13160	0.0126
lnCPI does not Granger Cause lnUR		0.37098	0.6934

Based on the Table 4.10 Pairwise Granger-causality tests CPI is granger cause for RGDP but the reverse is not true. the result also shows that, UR is granger cause for RGDP and UR is granger cause for CPI but the reverse is not true depending upon the their p-value for this study.

Based the results, we can conclude that Granger causality runs unidirectionally from CPI and UR to RGDP. This indicates that the change in consumer price index (inflation) and unemployment leads to changes to real GDP growth. This study finding is similar to (Li and Liu,2012) findings in China. Furthermore, the result shows that the Granger causality runs unidirectionally from UR to CPI which implies that past values of Unemployment leads to change the current Inflation which is contradicate (Li and Liu,2012) findings in China and also (Umaru and Zubairu, 2012b) findings in Nigeria no granger causality between unemployment and inflation .

4.7.2 Impulse Response Function

Impulse responses function trace out the responsiveness of the variables in the VAR to shocks to each of the variables. Therefore, for each variable a unit shock is applied to the error and the effects upon the VAR system over time are noted. Thus, if there are n variables in a system, a total of n^2 impulse responses could be generated. A standard decomposition is used in order to identify the short run effects of shocks on the levels of the endogenous variables in the VAR (2).

The x-axis from figure 4.3 and figureB2 and B3 in Appendix B gives the time horizon or the duration of the shock while the y-axis gives the direction and intensity of the impulse or the percent variation in the dependent variable away from its baseline level. In our case there are 9 potential impulse response functions. The combined graphs of these IRF functions are given in Fig.4.3 and figureB2 and B3 in Appendix B with the Cholesky ordering lnRGDP, lnCPI and lnUR.

Figure 4.3 shows the responses of lnRGDP, lnCPI and lnUR to Cholesky a one standard deviation innovation in lnRGDP. The result indicates Real GDP growth innovations have a positive impact on consumer price index. This implies that consumer price index positively affects Real GDP growth. It exhibits a decline trend initially and reaches 0.03 and it stabilizes at around 3 year time horizon. Furthermore, UR is also affected by Cholesky a one standard deviation change of Real GDP growth.

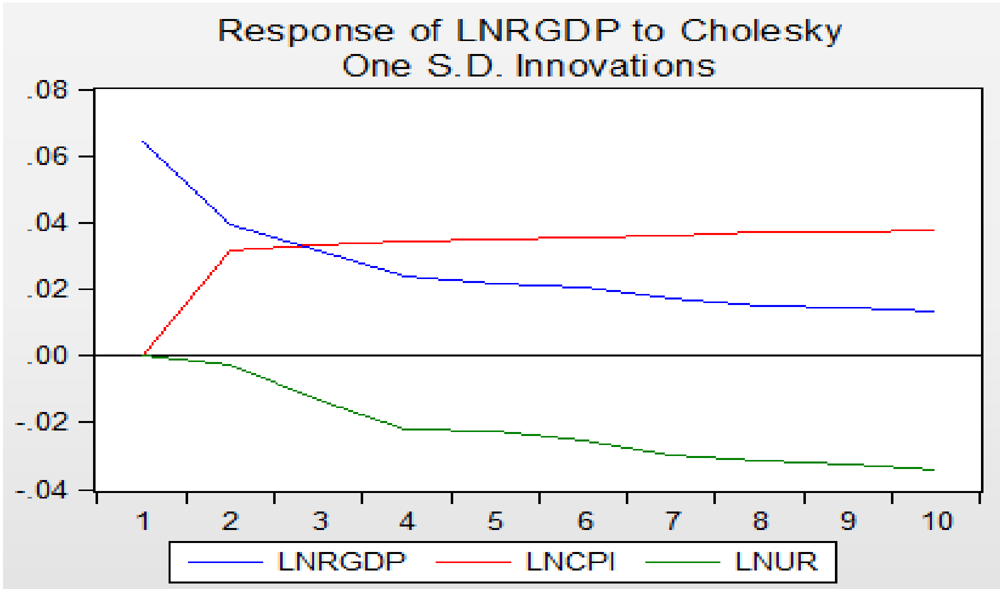

Figure 4.3: Graph of Impulse Response Function of lnRGDP

Similarly, FigureB2 in Appendix-B shows the responses of lnRGDP, lnCPI and lnUR to Cholesky a one standard deviation innovation in lnCPI. The result indicates CPI innovations have a negative impact on Unemployment rate. This implies that unemployment rate negatively affects consumer price index (inflation). It exhibits a decline trend initially 0.095 to 0.084 and it stabilizes at around 4 year time horizon.

4.7.3 Forecast Error Variance Decompositions

FEVDs are an alternative method of impulse responses function to receive a compact overview of the dynamic structures of VAR models. The FEVDs tells us the proportion of the movements in a sequence due to its own shocks versus shocks to the other variable and also it shows the portion of the variance in the forecast error for each variable due to innovations to all variables in the system (Enders, 2008)

The variance decomposition analysis result of RGDP in Figure 4.4 and table-A6(I) from Appendix-A shows that, at the first horizon, variation of RGDP is explained only by its own shock (innovation). In the second year 84.70 % of the variability in the RGDP fluctuations is explained by its own innovations and the remaining 15.20% is explained by CPI innovations. The proportion decreases dramatically and CPI and UR shocks increase as the contribution of RGDP shock decreases. They crossed each other at around 8 year time horizon which has equal contribution almost 42% each and after that, when CPI innovation increase, and RGDP growth own shock innovation will decrease and also the remaining 18% is explained by UR innovations at this horizon.

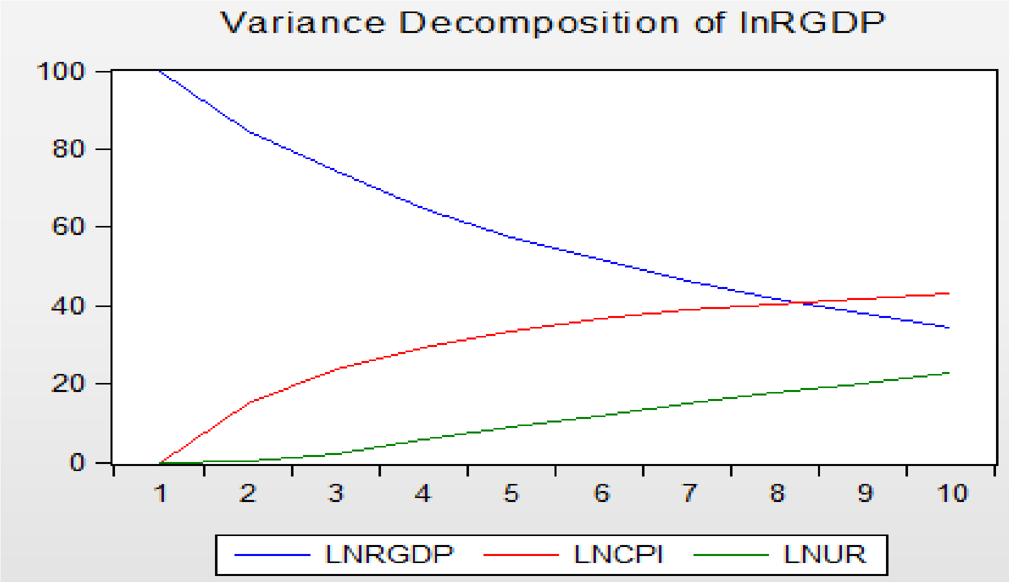

Figure 4.4: Variance Decomposition of lnRGDP

Similarly from tableA6(II) in appendix-A and figureB4 variance decomposition of lnCPI in Appendix-B the variation of CPI is explained only by its own shock (innovation) and the impact of RGDP and UR innovations are almost insignificant. Here also the variation of UR is explained only by its own shock (innovation) and the impact of RGDP and CPI innovations are almost insignificant.

4.8 FORECAST

Forecasting is one of the main objectives of multivariate time series analysis for horizons $h \geq 1$ of an empirical $VAR(p)$process can be generated recursively according to (Box et al., 2008). Forecasting vector time series processes is completely analogous to forecastng univariate time series processes.

4.8.1 Evaluation of forecaseting accuracy

The mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and Theil U statistics were used to assess the forecasting performance. The RMSE and MAE statistics are scale-dependent measures, but allow a comparison between the actual and forecast values. The Theil-U statistics is independent of the scale of the variables and is constructed to lie between zero and one, zero indicating a perfect fit. In evaluating the performance of the forecasting models, the lower the RMSE, MAE, MAPE and Theil-U statistic are better the forecasting accuracy.

Table 4.12: Measuring Forecasting Accuracy

Forecast sample :			
Measure of accuracy	Endogenous Variables		
	lnGDP	lnCPI	LnUR
Root mean square error	0.066167	0.110364	0.101157
Mean absolute error	0.054695	0.083514	0.084258
Mean absolute percentage error	0.997604	1.765751	2.536835
Theil-U statistic	0.005897	0.11781	0.015269
Bias proportion	0.004604	0.007753	0.032288

For the VAR (2) model in Table 4.12, the MAPE in forecasting lnRGDP, lnCPI and lnUR are 0.998, 1.766 and 2.537 respectively and the bias proportion of forecasting in lnRGDP, lnCPI and lnUR are 0.0046, 0.0078 and 0.0322 respectively. These computed values indicates that the average percentage error and bias proportion for each of the equations used to forecast in the study variables is less than 5%. The Theil-U statistic is also close to zero, indicating that the difference between the actual values and the predicted values are very small. The graph of the predicted values together with the actual observations for lnRGDP,lnCPI and lnUR is given in Figure 4.5 and figure-B6 amd B7 from Appendix-B respectively.

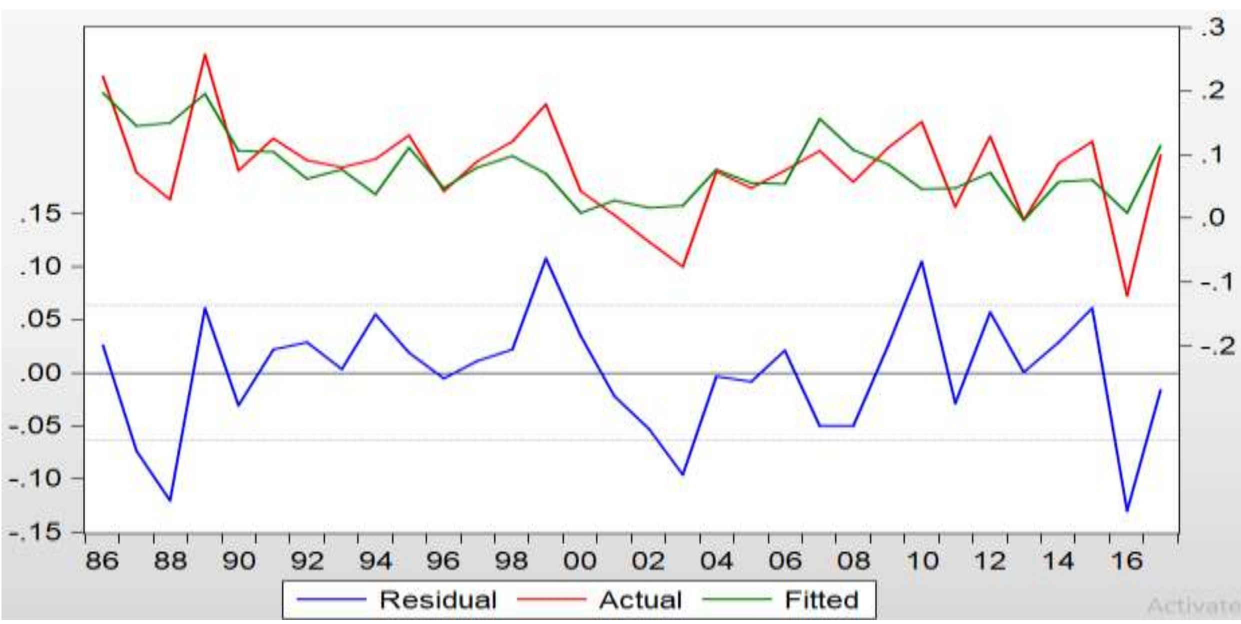

Figure 4.5: Graph of Actual, Fitted and Residual plot of lnRGDP growth

4.9 Out of Sample Forecasting Analysis

Out of sample forecasted values for the series under study, using the vector autoregressive model of the Vector Error Correction Model are presented in Table 4.13.

Table 4.13: Out of Sample Forecasting natural logarithms of variables Results

Year	Endogenous Variables		
	lnRGDP (USD Billion Dolar)	lnCPI (USD Billion Dolar)	lnUR (in Percentage)
2018	6.763184	5.569874	2.679625
2019	6.830626	5.634412	2.621807
2020	6.889151	5.68136	2.566304
2021	6.948364	5.734793	2.544317
2022	7.05155	5.76707	2.479124

Based on table 4.14 presents the predicted annual Real GDP growth is increased from 795.7 in 2017 to 865.39 in 2018 and the trend in increasing. Similarly the annual Consumer Price Index (inflation) also has increasing trend from 2017 to 2022 but the Unemployment has an decresing trend from 2017 to 2022.

Table 4.14:Out of Sample Forecasting VECM Results

Year	Endogenous Variables		
	RGDP (USD Billion Dolar)	CPI (USD Billion Dolar)	UR (in Percentage)
2018	865.3932	262.402	14.5796
2019	925.7702	279.8943	13.76057
2020	981.5677	293.3481	13.01762
2021	1041.445	309.4489	12.73453
2022	1154.647	319.5999	11.93081

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The main objective of this study is to investigate the nature of the relationship of macroeconomic variables, namely unemployment, consumer price index (inflation) of goods and services, and real economic growth in the context of Ethiopia. We tested if whether unemployment, inflation and real GDP growth are cointegrated using Johansson approach and the test suggests that there is long run relationship between unemployment rate and inflation of goods services and economic growth in case of Ethiopia. The VECM is appropriate than VAR model infers that the current real economic growth of Ethiopia measured as rate of real GDP is significantly affected by past first lagged values of its own, inflation of goods and services and past two lagged values of unemployment rate. The effect is negative for lags of Unemployment and its own lags and positive for inflation. Similarly, the current inflation of good and services is also positively affected by its own past two lagged values and past first lagged values of Real GDP, while negatively affected by past second lagged values of unemployment rate. unemployment is negatively affected by its own past two lagged values and past second lagged values of inflation of good and services and Real GDP growth.

Based on the empirical results of pairwise Granger causality test, the study found statistically evidence to conclude that there was direct causality from CPI and UR to RGDP economic growth of Ethiopia. The impulse response function analysis show that shock to RGDP leads to negative response from Unemployment which dies out after four years horizons, while the shock to RGDP from inflation of goods and services produces continuous positive responses. The result also signifies that Ethiopian economic growth moderately benefits from inflation of good and surivces after three year horizon because of the feasibility improving of Real GDP growth increases paralle with the consumer prce index increseases in Ethiopia and this increment of economic growth promotes the employment of labour force. The FEVDs test results shows that most of the variance in each variable is attributable by own shocks but at long horizons of RGDP growth shocks accounts almost half of variance of inflation of goods and services and by UR. The analysis also shows that shocks to inflation of goods and services lead to a significant response in real economic growth. The trend of forecasting using the VECM, the RGDP and CPI is an increasing trend and the Unemployment has a decreasing trend in the future five years head forecasting.

5.2 RECOMMENDATION

From the empirical findings the following recommendations are drawn.

- This study reveals that unemployment has a short run and long run impact on economic growth in Ethioipia, so that the government and non-govermental organization shoud be control unemployment by crearting different samall enterprise led industrialization strategy for Youth Ethiopia.
- The government and non-govermental organization shoud be control Youth Unemployment for sustainable economic growth by crearting different Job opportunity for Youths
- The scope of the analysis in this study has been limited to the relationship among the three economic growth indicators. In order to overcome this limitation and provide a more nuanced analysis, it might be profitable for future researchers to consider and incorporating the influence of factors such as foreign direct investment,real wages, interest rate and money supply on economic growth.

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Appendex-A

Table A1: Vector Autoregressive estimates results

Vector Autoregression Estimates
Sample (adjusted): 1985 2017
Included observations: 33 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	LNRGDP	LNCPI	LNUR
LNRGDP(-1)	0.547214	0.081714	0.267166
	(0.17456)	(0.25790)	(0.28961)
	[3.13487]	[0.31684]	[0.92250]
LNRGDP(-2)	0.226032	-0.060015	-0.209617
	(0.14351)	(0.21203)	(0.23810)
	[1.57501]	[-0.28304]	[-0.88037]
LNCPI(-1)	0.306857	0.811882	-0.391850
	(0.12297)	(0.18168)	(0.20402)
	[2.49543]	[4.46873]	[-1.92068]
LNCPI(-2)	-0.096493	0.094455	0.086863
	(0.13929)	(0.20580)	(0.23111)
	[-0.69273]	[0.45896]	[0.37586]
LNUR(-1)	- 0.021943	0.016642	0.491585
	(0.11633)	(0.17187)	(0.19300)
	[-0.18863]	[0.09683]	[2.54705]
LNUR(-2)	-0.061430	-0.129803	0.014146
	(0.11341)	(0.16756)	(0.18816)
	[-0.54167]	[-0.77468]	[0.07518]
C	0.502997	0.749996	2.690325
	(0.62049)	(0.91675)	(1.02946)
	[0.81065]	[0.81810]	[2.61334]
R-squared	0.993899	0.980251	0.905419
Adj. R-squared	0.992490	0.975694	0.883593
Sum sq. resids	0.100391	0.219144	0.276340
S.E. equation	0.062138	0.091808	0.103094
F-statistic	705.8749	215.0890	41.48282
Log likelihood	48.79573	35.91480	32.08844
Akaike AIC	-2.533075	-1.752412	-1.520511
Schwarz SC	-2.215634	-1.434971	-1.203070
Mean dependent	5.527676	4.617407	3.320039
S.D. dependent	0.717057	0.588870	0.302166

Determinant resid covariance (dof adj.)	3.40E-07
Determinant resid covariance	1.66E-07
Log likelihood	117.0830
Akaike information criterion	-5.823215
Schwarz criterion	-4.870892

Table A2: Vector Error Correction Estimates output

Vector Error Correction Estimates
Sample (adjusted): 1986 2017
Included observations: 32 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
LNRGDP(-1)	1.000000		
LNCPI(-1)	-0.426357		
	(0.35642)		
	[-1.19622]		
LNUR(-1)	1.081799		
	(0.76835)		
	[1.40796]		
C	-7.149715		
Error Correction:	**D(LNRGDP)**	**D(LNCPI)**	**D(LNUR)**
CointEq1	-0.173123	-0.053138	-0.113562
	(0.06005)	(0.08927)	(0.09285)
	[-2.88290]	[-0.59523]	[-1.22306]
D(LNRGDP(-1))	-0.203269	0.007317	0.326069
	(0.17110)	(0.25436)	(0.26456)
	[-1.18799]	[0.02876]	[1.23251]
D(LNRGDP(-2))	-0.074688	-0.155762	-0.251566
	(0.17663)	(0.26257)	(0.27310)
	[-0.42286]	[-0.59321]	[-0.92115]
D(LNCPI(-1))	0.264324	-0.155844	-0.230644
	(0.14157)	(0.21046)	(0.21890)
	[1.86704]	[-0.74048]	[-1.05365]
D(LNCPI(-2))	0.121631	0.134523	-0.053877
	(0.13996)	(0.20807)	(0.21641)
	[0.86904]	[0.64654]	[-0.24896]
D(LNUR(-1))	0.160361	0.153390	-0.276103
	(0.11954)	(0.17772)	(0.18484)
	[1.34143]	[0.86312]	[-1.49375]
D(LNUR(-2))	- 0.025013	-0.017857	-0.465480
	(0.10905)	(0.16212)	(0.16862)
	[-0.22936]	[-0.11015]	[-2.76058]
C	0.082818	0.075669	-0.034740
	(0.02869)	(0.04265)	(0.04436)
	[2.88688]	[1.77432]	[-0.78320]
R-squared	0.451496	0.071465	0.425534
Adj. R-squared	0.291515	-0.199358	0.257982
Sum sq. resids	0.098884	0.218530	0.236401
S.E. equation	0.064188	0.095422	0.099247

F-statistic	2.822193	0.263880	2.539706
Log likelihood	47.06672	34.37904	33.12134
Akaike AIC	-2.441670	-1.648690	-1.570084
Schwarz SC	-2.075236	-1.282256	-1.203650
Mean dependent	0.077930	0.057274	-0.029356
S.D. dependent	0.076259	0.087132	0.115216

Determinant resid covariance (dof adj.)	3.62E-07
Determinant resid covariance	1.53E-07
Log likelihood	114.9031
Akaike information criterion	-5.493947
Schwarz criterion	-4.257232

TableA3: Least squares estimator of lnRGDP

Dependent Variable: D(LNRGDP)
Method: Least Squares
Date: 04/30/18 Time: 09:28
Sample (adjusted): 1986 2017
Included observations: 32 after adjustments
D(LNRGDP) = C(1)*(LNRGDP(-1) - 0.426356916935*LNCPI(-1) + 1.08179853164*LNUR(-1) - 7.14971499823) + C(2)*D(LNRGDP(-1)) + C(3)*D(LNRGDP(-2)) + C(4)*D(LNCPI(-1)) + C(5)*D(LNCPI(-2)) + C(6) *D(LNUR(-1)) + C(7)*D(LNUR(-2)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.173123	0.060052	-2.882902	0.0082
C(2)	-0.203269	0.171103	-1.187991	0.0245
C(3)	-0.074688	0.176627	-0.422859	0.6762
C(4)	0.264324	0.141574	1.867042	0.0074
C(5)	0.121631	0.139961	0.869037	0.3934
C(6)	-0.160361	0.119545	1.341428	0.0192
C(7)	0.025013	0.109053	0.229365	0.8205
C(8)	0.082818	0.028688	2.886882	0.0081

R-squared	0.751496	Mean dependent var	0.077930
Adjusted R-squared	0.691515	S.D. dependent var	0.076259
S.E. of regression	0.064188	Akaike info criterion	-2.441670
Sum squared resid	0.098884	Schwarz criterion	-2.075236
Log likelihood	47.06672	Hannan-Quinn criter.	-2.320207
F-statistic	2.822193	Durbin-Watson stat	1.891682
Prob(F-statistic)	0.027032		

TableA4: Least squares estimator of CPI

Dependent Variable: D(LNCPI)
Method: Least Squares
Sample (adjusted): 1986 2017
Included observations: 32 after adjustments
D(LNCPI) = C(9)*(LNRGDP(-1) - 0.426356916935*LNCPI(-1) + 1.08179853164*LNUR(-1) - 7.14971499823) + C(10)*D(LNRGDP(-1)) + C(11)*D(LNRGDP(-2)) + C(12)*D(LNCPI(-1)) + C(13)*D(LNCPI(-2)) + C(14)*D(LNUR(-1)) + C(15)*D(LNUR(-2)) + C(16)

	Coefficient	Std. Error	t-Statistic	Prob.
C(9)	-0.053138	0.089273	-0.595233	0.0043
C(10)	0.007317	0.254361	0.028765	0.0973
C(11)	-0.155762	0.262574	-0.593212	0.5586
C(12)	-0.155844	0.210463	-0.740479	0.4662
C(13)	0.134523	0.208066	0.646541	0.0241
C(14)	0.153390	0.177715	0.863122	0.3966
C(15)	-0.017857	0.162118	-0.110149	0.0132
C(16)	0.075669	0.042647	1.774319	0.0087

R-squared	0.701465	Mean dependent var	0.057274
Adjusted R-squared	0.599358	S.D. dependent var	0.087132
S.E. of regression	0.095422	Akaike info criterion	-1.648690
Sum squared resid	0.218530	Schwarz criterion	-1.282256
Log likelihood	34.37904	Hannan-Quinn criter.	-1.527227
F-statistic	0.263880	Durbin-Watson stat	2.097392
Prob(F-statistic)	0.002102		

TableA5: Least squares estimator of UR

Dependent Variable: D(LNUR)
Method: Least Squares
Date: 04/30/18 Time: 09:33
Sample (adjusted): 1986 2017
Included observations: 32 after adjustments
D(LNUR) = C(17)*(LNRGDP(-1) - 0.426356916935*LNCPI(-1) + 1.08179853164*LNUR(-1) - 7.14971499823) + C(18)*D(LNRGDP(-1)) + C(19)*D(LNRGDP(-2)) + C(20)*D(LNCPI(-1)) + C(21)*D(LNCPI(-2)) + C(22)*D(LNUR(-1)) + C(23)*D(LNUR(-2)) + C(24)

	Coefficient	Std. Error	t-Statistic	Prob.
C(17)	-0.113562	0.092851	-1.223057	0.0232
C(18)	0.326069	0.264557	1.232507	0.2627
C(19)	-0.251566	0.273099	-0.921154	0.0361
C(20)	-0.230644	0.218900	-1.053650	0.8025
C(21)	-0.053877	0.216406	-0.248963	0.0055
C(22)	-0.276103	0.184839	-1.493747	0.1483
C(23)	-0.465480	0.168617	-2.760575	0.0109
C(24)	-0.034740	0.044356	-0.783202	0.0412

R-squared	0.425534	Mean dependent var	-0.029356
Adjusted R-squared	0.257982	S.D. dependent var	0.115216
S.E. of regression	0.099247	Akaike info criterion	-1.570084
Sum squared resid	0.236401	Schwarz criterion	-1.203650
Log likelihood	33.12134	Hannan-Quinn criter.	-1.448621
F-statistic	2.539706	Durbin-Watson stat	2.085475
Prob(F-statistic)	0.041684		

Table A6: Variance decomposition results

I-Variance Decomposition of LNRGDP:

Period	S.E.	LNRGDP	LNCPI	LNUR
1	0.064188	100.0000	0.000000	0.000000
2	0.081790	84.69960	15.19582	0.104576
3	0.094571	74.35166	23.57744	2.070898
4	0.105730	64.64079	29.44218	5.917033
5	0.115699	57.57004	33.59855	8.831416
6	0.125243	51.77068	36.64735	11.58197
7	0.134803	46.36103	38.84539	14.79358
8	0.144106	41.69098	40.54792	17.76110
9	0.153021	37.84365	41.88357	20.27278
10	0.161770	34.52047	42.87302	22.60652

II-Variance Decomposition of LNCPI:

Period	S.E.	LNRGDP	LNCPI	LNUR
1	0.095422	0.058678	99.94132	0.000000
2	0.127594	0.198697	99.25606	0.545248
3	0.160376	1.096127	98.52667	0.377202
4	0.184633	1.661219	97.95996	0.378823
5	0.206949	1.937961	97.75556	0.306481
6	0.226457	2.060229	97.67557	0.264201
7	0.244986	2.251375	97.47766	0.270966
8	0.262208	2.414004	97.31588	0.270115
9	0.278336	2.522479	97.21590	0.261619
10	0.293623	2.621672	97.11347	0.264856

III- Variance Decomposition of LNUR:

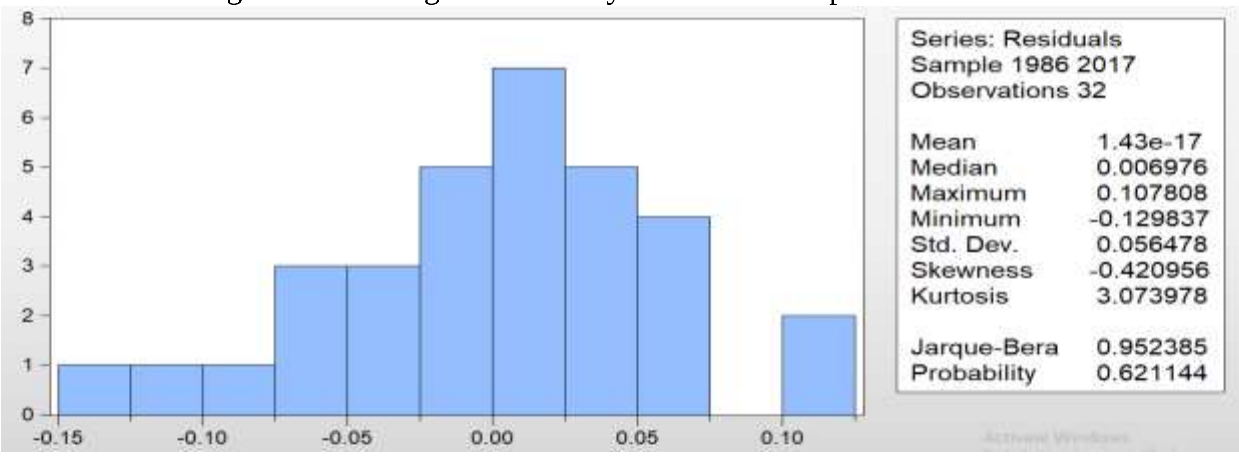
Period	S.E.	LNRGDP	LNCPI	LNUR
1	0.099247	0.070020	1.950908	97.97907
2	0.116509	1.198791	2.019209	96.78200
3	0.119143	4.016205	1.931387	94.05241
4	0.127826	4.651376	1.679707	93.66892
5	0.139098	3.944285	1.472577	94.58314
6	0.143753	4.181250	1.391751	94.42700
7	0.148365	5.009364	1.306584	93.68405
8	0.154583	5.134932	1.206844	93.65822
9	0.159785	5.263450	1.134142	93.60241
10	0.164058	5.708165	1.076179	93.21566

Cholesky Ordering: LNRGDP LNCPI LNUR

Appendix-B

Figure B1: Histogram normality test for the residuals for VEC model

FigureB1.1: histogram normalitytest for residual plot for lnRGDP



FigureB1.2: histogram normality test for residual plot for lnCPI

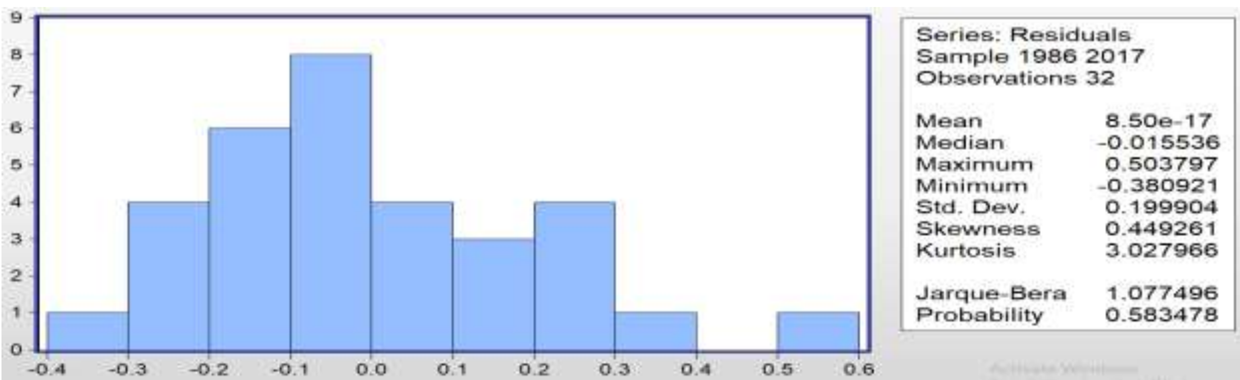


Figure B1.3: histogram normality test for residual plot for lnUR

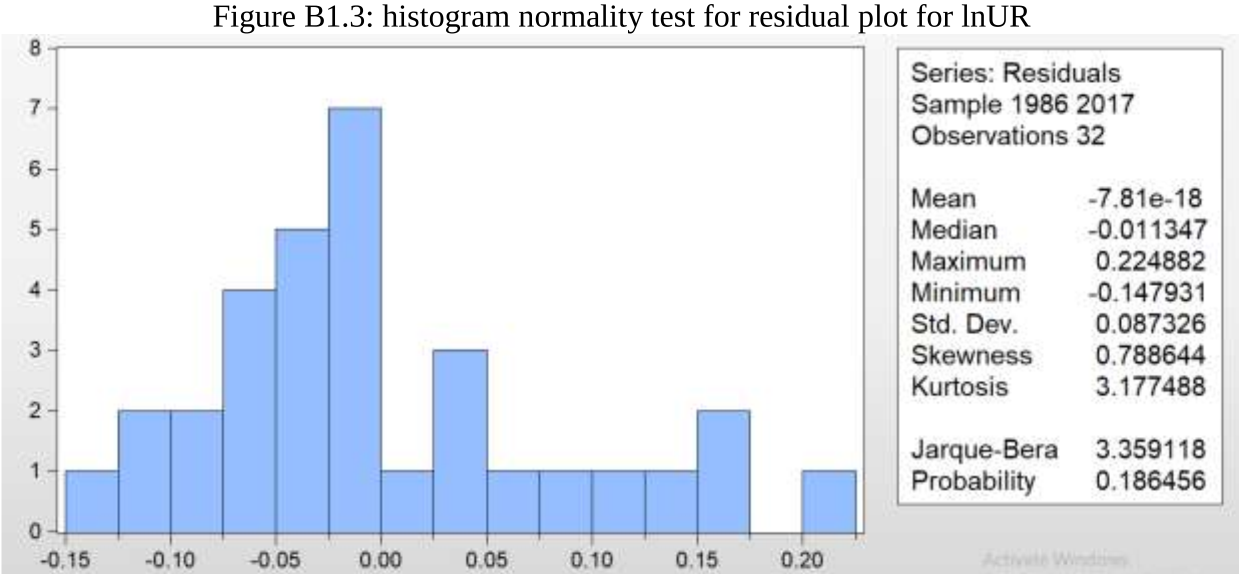


Figure B2: Graph of Impulse Response Function of lnCPI

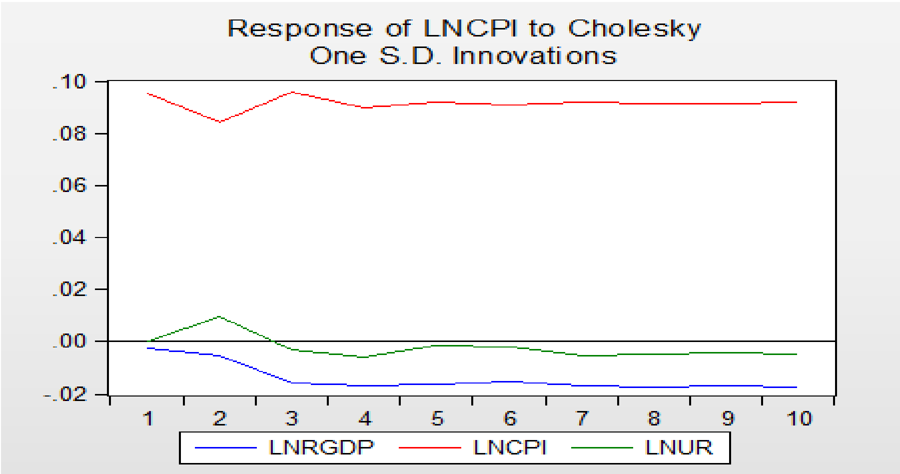


Figure B3: Graph of Impulse Response Function of lnUR

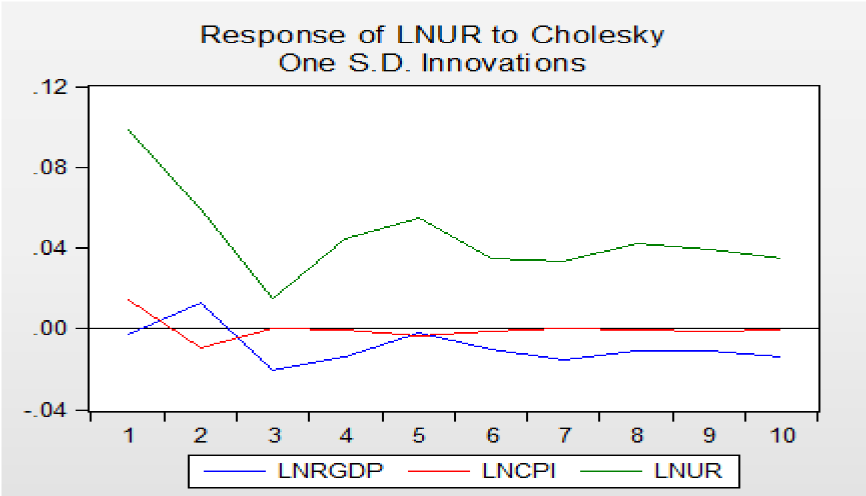


Figure B4: Variance Decomposition of lnCPI

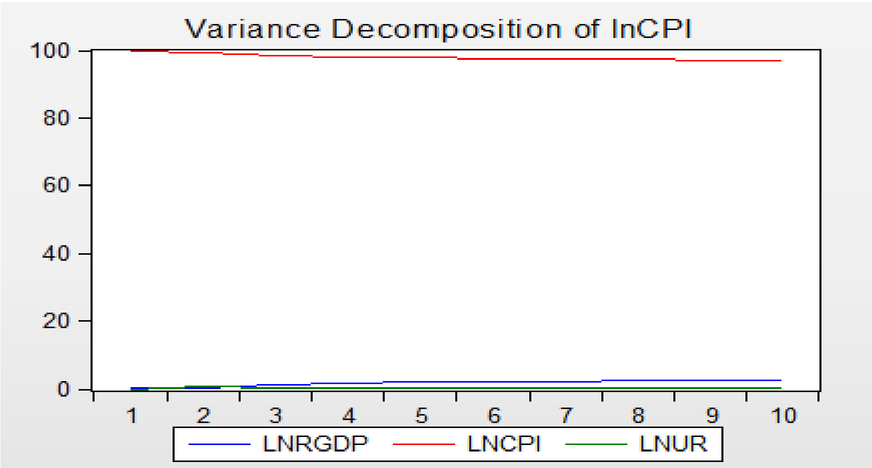


Figure B5: Variance Decomposition of lnUR

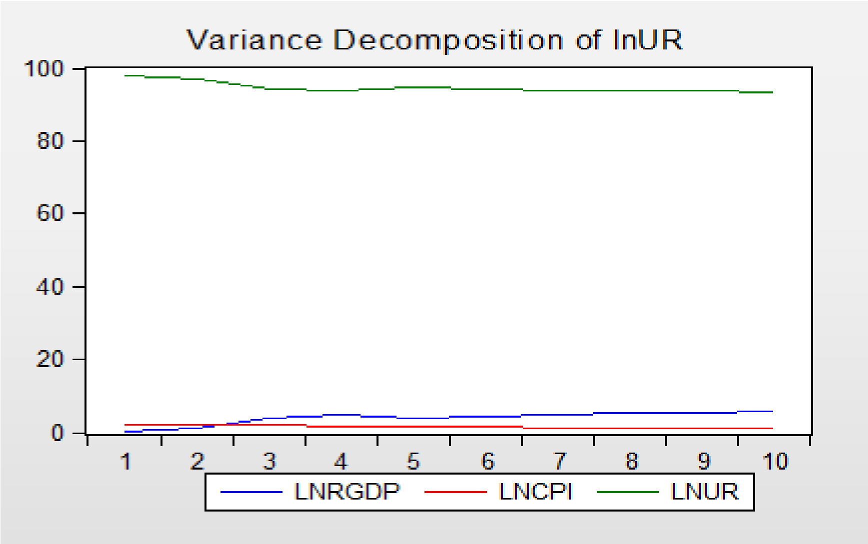


Figure B6: Graph of Actual, Fitted and Residual plot of lnCPI (inflation)

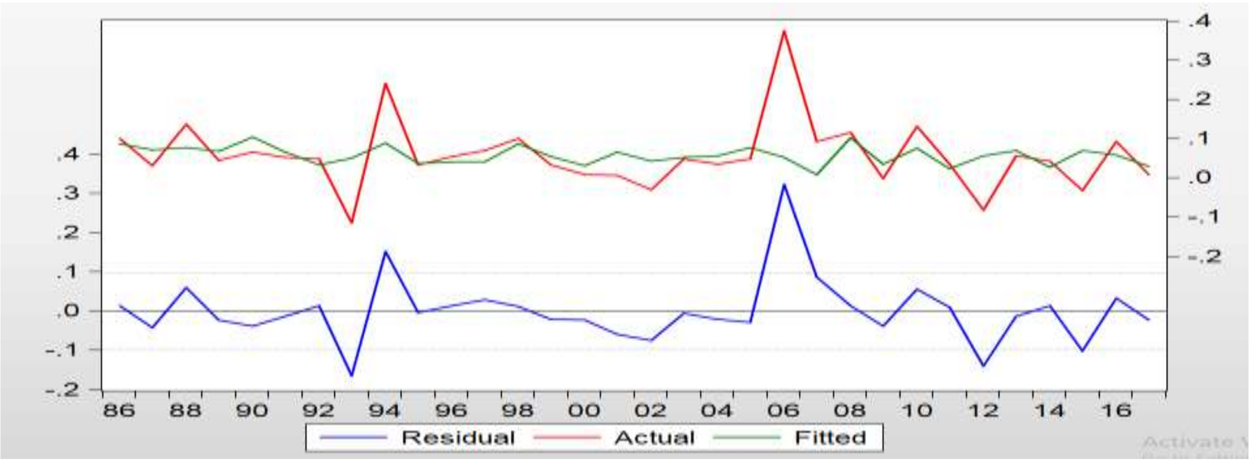


Figure B7: Graph of the Actual, Fitted and Residual plot of lnUR