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Inflation-Economic Growth relationship in Ethiopia: A Multivariate Time Series Analysis

By

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This is to certify that the thesis prepared by Olana Angesa, entitled: Inflation-Economic Growth relationship in Ethiopia: A Multivariate Time Series Analysis and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Statistics (Applied Statistics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ACRONYMS

ADB	Africa Development Bank
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
CPI	Consumer Price Index
CSAE	Central Statistical Agency of Ethiopia
DF	Dickey-Fuller
ECM	Error Correction Model
FEVD	Forecast Error Variance Decomposition
GDP	Gross Domestic Product
GTP	Growth and Transformation Plan
HQIC	Hannan-Quin Information Criteria
IMF	International Monetary Fund
IRF	Impulse Response Function
LM	Lagrange Multiplier
LS	Least Square
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Percentage Absolute Error

ME	Mean Error
ML	Maximum Likelihood
MPE	Mean Percentage Error
MSE	Mean Square Error
PE	Percentage Error
PP	Phillips and Perron
RGDP	Real Gross Domestic Product
RMSE	Root Mean Squared Error
SBIC	Schwarz Bayesian Information Criterion
SVAR	Structural Vector Autoregressive
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
WEO	World Economic Outlook

Abstract

Ethiopia is one of countries in Sub Saharan African with moderate economic growth in recent years. The aim of this study was to examine the relationship between inflation rate and economic growth in Ethiopia. The methodology employed in this study is the vector error correction model (VECM). The series considered are consumer price index (as a proxy for inflation rate), real GDP (constant 2005 USD) (as a measure of economic growth) and openness. Annual data on inflation rate, openness and real GDP for the period from 1992 to 2012 are obtained from the World Economic Outlook (WEO) database of the International Monetary Fund (IMF). A stationarity test was carried out using the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) tests. The null hypothesis of a unit root was not rejected for all series under consideration implying that the series are all non-stationary in levels. The first differences of all series, however, were found to be stationary. For the period spanning from 1992 to 2012, there was one co-integrating relationship between openness, inflation rate and economic growth. The estimated long run model shows that there exists strong inverse long-run relationship between inflation rate and economic growth. The estimated coefficient of the error correction term (0.0143) shows that about 1.43% of the short run disequilibrium in real GDP will be adjusted within a year. In the short run, one time lagged inflation rate has a significant negative impact on the current real GDP whereas two time lagged openness has a significant positive impact. The impulse response functions reveal that inflation rate and openness innovations have a positive impact on real GDP. The results of Granger causality test show that a unidirectional causality was running from economic growth to inflation.

CHAPTER ONE

Introduction

1.1 Background of the study

One of the most difficult issues that monetary authorities in many developing economies have to deal with is the management of a stable price environment. This involves managing inflation and openness in order to avoid uncertainties associated with them. Countries with high average inflation also tend to have inflation rates that change greatly from year to year. Inflation rate has strong implication on macroeconomic stability. Noble Laureate Engle (1983, as cited in Eden 2012) argued "When inflation is unpredictable, risk adverse economic agents will incur loss, even if prices and quantities are perfectly flexible in all markets".

Inflation uncertainty is considered as one of the major costs of inflation since it not only distorts decisions regarding future saving and investment due to lower predictability of the real value of future nominal payments, but it also extends the adverse affects of these distortions to the efficiency of resource allocation and the level of real activity (Fischer, 1981; Golob and Holland, 1993).

Ethiopia is one of countries in Sub Saharan African with moderate economic growth in recent years. Despite a series of setbacks that have kept it among Africa's poorest nations, government statistics indicate double digit growth for the past several years. International Monetary Fund (IMF) projection however shows that the country's economic growth rate is around 5 percent in 2012. The IMF lowers the forecast over the coming years, citing faster inflation and restrictions on bank lending as major causes. The World Bank in its part indicated that the country's growth rate was 7.2 percent in 2011. According to African Development Bank, the main driving force for the recent growth of the country is improvement in agricultural sector due to favorable climatic condition and improved supply of fertilizers. The growth base is also broadening with increasing contributions of service and manufacturing sector to GDP. Even if there is a dispute on the statistics by how much the country is growing, it is obvious that the country is in a good sign of economic progress (ADB, 2010).

Ethiopia's economy is based on agriculture, which accounts for 42 percent of GDP and 80 percent of employment. The country's five year Growth and Transformation Plan (GTP) unveiled in October 2010 presents the government led effort to achieve the country's ambitious development goal. Ethiopia's GTP over 2010-2015 emphasizes agricultural transformation and industrial development as drivers of growth. The economy continued to progress over the past six years. Moreover, growth has continued to be broad-based with industry, services and agriculture sectors gradually progressing. The agricultural sector grew by 6.4 percent as a result of the good weather in 2011. The expansion in agriculture production has been driven by increases in the area of land cultivated and favorable weather conditions in cereal growing areas, rather than major improvements in productivity. Given the current technological conditions and the structure of production, pushing the production frontier further is difficult due to the already existing pressures on the land (ADB, 2010).

The agricultural sector continues to face major challenges. It is extremely vulnerable to weather shocks due to dependency on rainfall, weak marketing infrastructure, limited use of improved farming practices, and rising cost of key agricultural inputs. There has been a general decline in per capital food production as high population growth rates have contributed to a decline in farm size. However, the potential for growth in agriculture is huge, especially considering that less than 15 percent of the arable land is cultivated while productivity is still among the lowest in sub-Saharan Africa.

The contribution of the service sector to the country's GDP grew in the last five years. This impressive growth in services was driven by the rapid expansion in financial intermediation, public administration and retail business activities. These services sub-sectors grew by more than 10 percentage point in GDP share during the past five years. The services sector is expected to continue to grow rapidly, though at a slower pace than in previous years. The progress of industrial sector performance in 2011 was driven by gradual expansion of mining and manufacturing subsectors.

Although Ethiopia's industrial base is still relatively small, the growth prospects of this sector is significant, as new industries are coming on stream and new projects are planned in other areas including steel, chemicals and pharmaceuticals. This momentum is expected to continue given the priority accorded to industrialization, both for exports and import substitution, in the government's plan.

Ethiopia's overall growth prospects are good, with public investment in infrastructure, transformation of agriculture and non-traditional exports are expected to continue driving growth. However, several risks to growth prospects exist, among them high inflation, slowdown in the global economy, and recurrence of drought.

The country's economic progress is accompanied by sustained inflationary problems. The level of overall inflation rate (annual change based on 12 months moving average) rose by 32.0 percent in July 2012 as compared to the one observed in a similar period a year ago. The country level food inflation increased by 39.2 percent as compared to the one observed a year ago.

The country level non-food inflation rate increased by 21.5 percent in July 2012 as compared to the one observed in July 2011. The 12 months moving average inflation rate shows the longer term inflationary situation in the country (CSAE, 2012).

Instead of stimulating economic growth, inflationary pressure in Ethiopia seems to be on the verge of distorting the allocation of resources and is likely to be a deterrent to undertaking productive investments (http://www.studymode.com/essays/Inflation-40260655.html). People who are living on a fixed income are those who suffer greatly from this sustained inflation.

There are different empirical studies on the possible sources of this inflationary situation in the country. The major sources of inflation discussed in the literature are increase in money supply unwarranted by the level of output growth, the nature of investment in the country, the widening of the national deficit and ways of financing it, the inefficiency within government controlled organizations, soaring of oil prices and others (Geda et.al, 2008). In contrast, the government argues that the inflation is due to rapid economic expansion that has happened in the country. They also indicate oil prices and increase in world food prices as the possible sources of the inflation.

Despite the recent economic growth, the country still faces some structural weaknesses that present significant challenges in the medium term. Its growth performance and considerable development gains are challenged by macroeconomic problem of high inflation. Pressures on prices and the balance of payment heightened as a result of the global food and economic crisis. Ethiopia's economy is highly vulnerable to exogenous shocks by virtue of its dependence on primary commodities and rain fed agriculture. It has experienced major exogenous shocks during the past five to seven years. These are notably droughts and adverse terms of trade in commodities like coffee and fuel (ADB, 2010).

1.2 Statement of the Problem

Inflation that raises the price level in a country creates financial problems in raising the prices of commodities, services, and other factors. It is, therefore, found that inflation is one of the major reasons of raising the price level of different commodities. Not surprisingly, there has been considerable debate on the existence and nature of the inflation and growth relationship. While few doubt that very high inflation is bad for growth, there have been mixed empirical studies as to their precise relationship.

The traditional Keynesian aggregate supply-aggregate demand (AS-AD) framework postulated a positive relationship between inflation and growth where, as growth increased, so did inflation. Tobin (1965) framework also shows that a higher inflation rate permanently raises the level of output. Quite simply, the Tobin effect suggests that inflation causes individuals to substitute out of money and into interest earning assets, which leads to greater capital intensity and promotes economic growth.

In the 1970s, however, the validity of the positive relationship was questioned. Inflation rates were somewhat modest in most countries before the 1970s, and then started to get high afterwards. For instance, Dewan and Hussein (2001) found in a sample of 41 middle-income developing countries that inflation was negatively correlated to growth. In another study, Cooley and Hansen (1989) show that the level of output permanently falls as the inflation rate increases.

In light of the above, it appears that the direction and causal relationship between economic growth and inflation are worth investigating. Is the empirical inflation-growth relationship primarily a long-run relationship, a short-run relationship, both or none? Literatures on the issue of inflation and economic growth in Ethiopia are few probably due to the fact that there was low inflation experience in the country before some years. Most of the papers focus on the source and impacts of the current rampant inflation in the country. However, methodologies of most of the studies are theoretical description with individual argumentations.

1.3 Objectives of the study

1.3.1 General objective

The overall objective of this study is to examine the relationship between economic growth and inflation for the period 1992-2012 in Ethiopia using a vector error correction model.

1.3.2 Specific objectives

- To examine the short-run and long-run relationship between inflation and real gross domestic product.
- To investigate the direction of causality between inflation and economic growth.
- To examine the response of each variable to the impulses of other variables.

1.4 Significance of the study

This study is very important to macroeconomists, financial analysts, and policy makers in understanding the responsiveness of real GDP to the change in general price level and thus come up with the relevant policies. It is necessary to policy makers to clear doubt as many studies on the relationship between inflation and economic growth remain inconclusive-several empirical studies confirm the existence of either a positive or negative relationship between these two macroeconomic variables.

Thus, the study is useful to find out the impact of certain macro-economic factors like inflation and openness on economic growth of Ethiopia 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

Due to lack and incompleteness of data on key macroeconomic variables, the analysis in this study is limited only to real GDP, inflation rate and openness of the economy.

CHAPTER TWO

Literature review

There have been extensive theoretical and empirical researches that examine the relationship between inflation and economic growth both in the context of developed and developing countries. Sarel (1995) mentioned that inflation rates were somewhat modest in most countries before the 1970s, and then started to get high afterwards. Most empirical studies conducted before the 1970s show an evidence of a positive relationship between inflation and economic growth, and a negative relationship between the two beyond that time period due to the severe inflation hike.

Mallik and Chowdhury (2001) examined the short-run and long-run dynamics of the relationship between inflation and economic growth for four South Asian countries (Bangladesh, India, Pakistan, and Sri Lanka) using data for the periods: Bangladesh 1974-1997; India 1961-1997; Pakistan 1957-1997; Sri Lanka 1966-1997. The periods of analysis were determined by data availability. Applying co-integration and error correction models to annual data, they found that the relationship between inflation and economic growth is positive and statistically significant for all four countries at the five percent level. Moreover, the sensitivity of growth to changes in inflation rates is smaller than that of inflation to changes in growth rates. These results have important policy implications, that is, although moderate inflation promotes economic growth, faster economic growth absorbs into inflation by overheating the economy.

Barro (1996) analyses the effect of inflation and other variables such as fertility, democracy and others on economic growth for a period of 30 years in England. He uses linear regression model in which other determinants of growth are held constant. To estimate the effect of inflation on economic growth without looking at the endogeneity problem of inflation, he includes inflation as an explanatory variable over each period along with other determinants of economic growth. The result indicates that there is a negative relationship between inflation and growth (p-value=0.004). One problem arising from the above conclusion is that the regression may not show causation from inflation to growth. Inflation is an endogenous variable that my respond to growth and other variables related to growth. For example an inverse relationship between inflation and growth may arise if an exogenous falling down of growth rate tended to generate higher inflation rate. He uses instrumental variables like independence of the central bank, lagged inflation and prior colonial status to avoid this problem. The result is statistically significant and strengthens the negative relationship between inflation and growth. Thus, there is some reason to believe that the relation reflects causation from higher long term inflation to reduced growth.

Ahmed and Mortaza (2005) empirically explored the relationship between inflation and economic growth in Bangladesh using annual data on real GDP and CPI for the period 1980 to 2005, and utilizing co-integration and error correction models. The empirical evidence demonstrate that there exists a statistically significant (p-value <0.001) long-run negative relationship between inflation and economic growth for the country.

Chimobi (2010) tried to see the relationship between inflation and economic growth in Nigeria for the period 1970-2005. Consumer Price Index (CPI) and Gross Domestic Product (GDP) were taken as a proxy for inflation and economic growth, respectively. To ascertain the relationship between the two variables, Johansen's cointegration test was carried out. However, the result obtained from this estimate fails to find a cointegration relationship or long run relationship during the investigating period.

Saaed (2007) explored the relationship between inflation and economic growth in the context of Kuwait using annual data set on real GDP and CPI for the period of 1985 to 2005 using co-integration and error correction models. The estimated coefficients of the error correction term (long-run effects) and lagged values of the series (short-run effects) are calculated. The empirical results show the existence of a statistically significant (p-value < 0.05) negative short-run and long-run relationships between CPI and RGDP in Kuwait. This also implies there is a negative short-run and long-run relationship between inflation and economic growth in the country.

Erbaykal and Okuyan (2008) examined the relationship between inflation and economic growth in Turkey using data covering the periods 1987-2006. The existence of a long run relationship (cointegration relationship) between the two series was detected following the test result. The causality relationship between the two series was examined in the framework of the causality test developed by Toda and Yamamoto (1995). Whereas no causality relationship was found from economic growth to inflation, a causality relationship was found from inflation to economic growth.

Faria and Carneiro (2001) investigated the relationship between inflation and economic growth in Brazil which has been experiencing persistent high inflation until recently. Analyzing a bivariate time series model (i.e. vector auto regression) with annual data for the period from 1980 to 1995, they found that there is a negative relationship between inflation and economic growth in the short-run. However, inflation does not affect economic growth in the long-run.

Tabi and Ondoa (2001) study the link between economic growth, inflation and money in circulation. They analyze the major importance of monetary variables on economic growth in Cameroon. Using data from 1960-2007, they constructed VAR model to identify the possible link between the variables mentioned above. The result shows that money in circulation causes growth and growth causes inflation. The interesting conclusion is that increase in money in circulation does not necessarily induce an increase in general price level.

Gokal and Hanif (2004) examined the relationship between growth and inflation, specifically on the context of Fiji. The primary objective of the study was to determine any possible causal relationship between inflation and economic growth. The data set consisted of 34 years of annual observations (from 1970-2003) and the variables included are average annual CPI, CPI growth rates and real GDP growth rate. To find the causality between the two variables, granger causality techniques have been employed. The results concluded that there is a weak negative correlation between inflation and economic growth. The granger causality test further confirmed that a unidirectional causality exists from growth to inflation. These results are consistent with most of the previous empirical findings and the theories of inflation and growth.

Omisakin et al, (2009) examine the empirical econometric evidence of both casual and long-run interrelationship among foreign direct investment, trade openness and economic growth in Nigeria. The study covers the periods from 1970 to 2006. The study employs more robust econometric procedures by employing the Toda Yamamoto non-causality test and the autoregressive distributed lag technique to cointegration. The Toda Yamamoto non-causality test reveals unidirectional causality running from foreign direct investment to output and trade openness to output. Having established a long-run relationship among the variables when their vector is normalized on output, the autoregressive distributed lag bounds testing procedure further suggests that both foreign direct investment and trade openness are positively related with economic growth.

Amarjit (2012), based upon quarterly time series data covering the period from 1996-97 to 2008-09 in India, analyzed the relationship between trade openness and economic growth within the framework of vector error correction model (VECM) using the Johansen technique of cointegration and the block exogeneity Wald test. The study found that there is unidirectional causality running from trade openness to GDP for India. The two time lagged coefficient of trade openness is positive and statistically significant-an indication that higher trade openness has a positive impact on GDP.

Oluwaseyi and Adejoke (2013) examined the effect of trade openness and financial investment on economic growth in Nigeria from 1960 to 2011. Estimates from the reported dynamic regression model indicated that trade openness and foreign investment exert positive and negative effect on economic growth, respectively.

Teshome (2011) explains the relationship between inflation and economic growth in Ethiopia using descriptive analysis, even though the method he applies for the analysis is open to critique. Accordingly, he states that it is difficult to specify the exact relationship between inflation and growth. However, one must study the structure of government spending and the nature of economic growth. By comparing the rate of inflation and economic growth of Ethiopia to that of Sub Saharan Africa, he explains how inflation affects economic growth through time. Using statistical comparison of the rate of inflation and economic growth, he tries to figure out the relation between them from 2004 to 2010. Accordingly, inflation affects economic growth nonlinearly in the country. From 2004 to 2006 inflation and economic growth have a positive relationship, while from 2006-2008 they have a negative relationship. Despite the variation in the magnitude between 2008 and 2010, he states that inflation and economic growth have positive relationship.

Durevall, Loening and Birru (2010) develop error correction terms that measure deviations from equilibrium in the money market, external sector, and agricultural market to evaluate the impact on inflation of excess money supply, changes in food and non-food world prices, and domestic agricultural supply shocks in Ethiopia. Their primary purpose is to show the determinants of the current rampant inflation in the country. Since Ethiopia is a developing country with large agriculture sector dominance, it is crucial to give due emphasis to food inflation. The result shows that overall inflation in Ethiopia is closely associated with agriculture and food in the economy, and that the international food crisis had a strong impact on domestic food prices in the long run but, an agricultural supply shock affects food inflation in short run. The evolution of money supply does not affect food prices directly, though money supply growth significantly affects non-food price inflation in the short run.

Geda and Tafere (2008) state that the Ethiopian economy has been characterized by erratic nature of output growth as the economy has been highly dependent on fortune of nature and external shocks. Since agriculture accounted for over 50 percent of GDP for most of the recent past, whenever weather conditions turned to be unfavorable, agricultural production contracted and GDP followed suit. With this systematic relationship between GDP (output) and rainfall there followed a systematic price trend. Prices followed the inverse of output growth trend. During years of good rainfall, as output rises prices often dropped considerably. Even within any particular year prices have been lower during harvest periods. This co-movement appeared to have reversed in the post 2002 period. From 2003 onwards, output is on average reported to have grown by 11.8 percent per annum.

Despite this reported significant increase in output (especially in agriculture), prices continued to rise. Thus, during the same period the general price level has recorded an average annual rise of 12 percent. The 2007 budget year alone witnessed prices jump by 18.4 percent, the food inflation being 49 percent in August 2008. This co-movement that contradicts the pattern of negative co-movement in price and output growth has puzzled many and led many more to suspect the credibility of the stories of fast economic growth (and hence the official data) over the past five years.

Getachew (1996) in his study of inflation in Ethiopia used two models. In the first model, monetarists' model has been used using monthly data from July 1990/91 to February 1995. In the second model, a long run model (cointegration) was utilized using annual data from 1972/73 up to 1990/91. The results from the first model show that, in the short run, money stock has been a significant determinant of inflation in Ethiopia. The long run model shows that, in the long run, inflation in Ethiopia is determined by supply factors. His conclusion is supported by the findings of Yohannes (2000) in which money supply is the basic determinant of inflation in Ethiopia using monetarists, demand and supply side model and structuralism model. He also shows that inflation inertia and world inflation level affect the country's inflation in the short run. Yohannes argues that controlling inflation is not a feasible policy; instead the government should have to focus on solving the supply side problem of the economy.

Desta (2009) using the full-employment model argues that it is possible to assume that if a nation achieves full employment, economic growth is likely to precipitate an inflationary situation. Since the 10 percent increase in nominal GDP cannot keep pace with a 40 percent inflation rate, the acceleration of economic growth seems to be overstated. In fact, it is possible to assert that double digit inflation in Ethiopia is nothing but a clear sign of an unhealthy economy. The inflationary situation in a country could have a negative-structural-break effect on economic growth if the sustained increase in prices is more than 15 percent.

Finally, Loening and Takada (2008) study the dynamics of inflation in short run using error correction model fitted with monthly observations. The result shows that increased money supply and the nominal exchange rate significantly affect inflation in the short run and that monetary policy in Ethiopia triggers price inertia, which has large and persistent effects. A simulation suggests that monetary policy alone may be unfeasible to control inflation effectively.

CHAPTER THREE

DATA AND METHODOLOGY

3.1. Data

Annual data on inflation rate, openness and real GDP for the period from 1992 to 2012 are obtained from the World Economic Outlook (WEO) database of the International Monetary Fund (IMF).

Real GDP is GDP at purchasers' price and is the sum of gross value added by all resident producers in the economy plus any product taxes minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources.

Inflation Rate is the annual percentage change in consumer price index (CPI). A CPI measures changes in the prices of goods and services that households consume. Such changes affect the real purchasing power of consumers' incomes and their welfare. As the prices of different goods and services do not all change at the same rate, a price index can only reflect their average movement. A price index is typically assigned a value of unity, or 100, in some reference period and the values of the index for other periods of time are intended to indicate the average proportionate, or percentage, change in prices from this price reference period. CPI is expressed in averages of the year in the data.

Openness is frequently used to measure the importance of international transactions relative to domestic transactions. This indicator is calculated for each country as the sum of exports and imports of goods and services relative to GDP. This ratio is often called the trade openness ratio. The term "openness" may be somewhat misleading since a low ratio does not necessarily imply high (tariff or non-tariff) barriers to foreign trade, but may be due to factors such as size of the economy and geographic remoteness from potential trading partners.

3.2. Methodology

Time series is broadly defined as a sequence of data points measured typically at successive points in time spaced at uniform time intervals. It can be divided into two major parts: univariate and multivariate time series. The term "univariate time series" refers to a time series that consists of single (scalar) observations recorded sequentially over equal time increments. Autoregressive integrated moving average (ARIMA) modeling is a specific subset of univariate modeling in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of a 'white noise' error term (the moving average component).

On the other hand, multivariate time series analysis involves statistical analysis of more than one statistical outcome variable at a time. In design and analysis, the technique is used to perform studies across multiple dimensions while taking into account the effects of all variables on the responses of interest. Multivariate time series analysis is used when one wants to model and explain the interactions and relationships among a group of time series variables. This paper is concerned with modeling multivariate time series data. The method used in this study can be divided into two broad sections. The first section is concerned with the Vector Autoregressive (VAR) models for stationary and co-integrated variables. In this section model specification and parameter estimation are discussed. The second section deals with Structural Vector Autoregressive (SVAR) Analysis.

3.2.1. Vector autoregressive (VAR) models

Vector autoregression (VAR) model was introduced by Sims (1980) as a technique that could be used by macroeconomists to characterize the joint dynamic behavior of a collection of variables without requiring strong restrictions of the kind needed to identify underlying structural parameters. It has become a prevalent method of time-series modeling. Although estimating the equations of a VAR does not require strong identification assumptions, some of the most useful applications of the estimates, such as calculating impulse-response functions (IRFs) or variance decompositions do require identifying restrictions. A typical restriction takes the form of an assumption about the dynamic relationship between a pair of variables.

3.2.2. Stationary vector autoregression model

Let $Y_t = (Y_{1t}, Y_{2t}..., Y_{nt})'$ denote an (n×1) vector of time series variables. The resulting basic p-lag autoregressive model has the form:

$$Y_t = C + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + \varepsilon_t, t = 1,2,...,T \qquad [3.1]$$

where C denotes an n x 1 vector of constants and Π_j is an n x n matrix of autoregressive coefficients for j= 1, 2, . . . , p. The n x 1 vector ε_t is a vector generalization of white noise:

$E(\varepsilon_t) = 0$ and

$$E(\varepsilon_t \varepsilon_s) = \begin{cases} \Sigma \ \ if \ \ s = t \\ 0 \ \ if \ \ s \neq t \end{cases} \quad \text{[3.2]}$$

where Σ is an (n x n) positive definite symmetric matrix with sample variance of Y_{jt} along the diagonal and sample covariance between Y_{jt} and Y_{it} along off-diagonal where j is not equal to i.

Let C_i denote the i^{th} element of the vector C and $\Pi_{lm}(i)$ indicates the *(l, m)* element of Π_i . Then the i^{th} row of the vector system in [3.1] specifies that:

$$Y_{it} = C_i + \sum_{i=1}^{p} \Pi_{1m}(i) Y_{1,t-i} + \sum_{i=1}^{p} \Pi_{2m}(i) Y_{2,t-i} + ... + \sum_{i=1}^{p} \Pi_{pm}(i) Y_{p,t-i} + \varepsilon_{it} \quad \text{[3.3]}$$

Thus, a VAR system contains a set of n variables, each of which is expressed as a linear function of p lags of itself and of all of the other n-1 variables, plus an error term. It is possible to include exogenous variables such as seasonal dummies or time trends in a VAR.

Using lag operator notation, [3.1] can be written in the form:

$$\Pi(B) Y_t = C + \varepsilon_t \quad \text{[3.4]}$$

where $\Pi(B) = I_n - \Pi_1 B - \cdots - \Pi_p B^P$ is a matrix of polynomials in the lag operator and B is the lag (backward shift) operator. To simplify things for the present, we note that the p^{th} order VAR which given in [3.1] can be written as a first-order VAR as follows:

$$\begin{pmatrix} Y_t \\ Y_{t-1} \\ . \\ . \\ . \\ Y_{t-p+1} \end{pmatrix} = \begin{pmatrix} C \\ 0 \\ . \\ . \\ . \\ 0 \end{pmatrix} + \begin{pmatrix} \Pi_1 & \Pi_2 & . & . & . & \Pi_n \\ I_n & 0 & . & . & . & 0 \\ 0 & . & & & & . \\ & & . & & & . \\ & & & . & & . \\ 0 & 0 & & 0 & I_n & 0 \end{pmatrix} \begin{pmatrix} Y_{t-1} \\ Y_{t-2} \\ . \\ . \\ . \\ Y_{t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ 0 \\ . \\ . \\ . \\ 0 \end{pmatrix} \quad \text{[3.1 } i\text{]}$$

The VAR (p) is stable if the roots of $\left|I_n - \Pi_1 z - \cdots - \Pi_p z^P\right| = 0$ lie outside the unit circle or equivalently, if the eigenvalues of the matrix:

$$F = \begin{pmatrix} \Pi_1 & \Pi_2 & . & . & . & \Pi_n \\ I_n & 0 & . & . & . & 0 \\ 0 & . & & & & . \\ & & . & & & . \\ & & & . & & . \\ 0 & 0 & & 0 & I_n & 0 \end{pmatrix} \quad \text{..........(3.5)}$$

have modulus less than one or the system is covariance stationary if $\left|I_n - \Pi_1 z - \cdots - \Pi_p z^P\right| = 0$. 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 covariances.

If Y_t in [3.1] is covariance stationary, then the unconditional mean is given by:

$$\mu = (I_n - \Pi_1 B - ... - \Pi_p B^p)^{-1} C = (\Pi(B)^{-1})\ C$$

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

$$Y_t - \mu = \Pi_1 (Y_{t-1} - \mu) + \Pi_2 (Y_{t-2} - \mu) + ... + \Pi_p (Y_{t-p} - \mu) + \varepsilon_t \text{..........[3.6]}$$

A vector autoregression (VAR) expresses each variable as a linear function of its own past values, the past values of all other variables being considered, and a serially uncorrelated error term. It is a set of k time series regression in which the regressors are lagged values of all k series. When the number of lags in each of the equations is the same and is equal to p, the system of the equation is called a VAR (p). The general form of the VAR (p) model with deterministic terms and exogenous variables is given by:

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + \mathrm{A} D_t + G X_t + \varepsilon_t \text{..........[3.7]}$$

where D_t represents an $(l \times 1)$ vector of deterministic components, X_t represents an $m \times 1$ vector of exogenous variables, $\mathrm{A}_{l \times l}$ and $G_{m \times m}$ are parameter matrices, and l and m are number of time trend and exogenous variables, respectively.

3.2.3. Testing stationarity: unit root test

Before fitting a particular model to time series data, the series must be made stationary. A time series is said to be stationary when the mean and autocovariances of the series remain constant over time. In other words, the stochastic process Y_t is said to be stationary if:

$E(Y_t) = \mu$, constant for all value of t ………………………………………………….. [3.8]

$\text{cov}(Y_t, Y_{t-j}) = \Gamma_j$, for all t and j=0, 1, 2, …………………….. [3.9]

Equation [3.8] means that all Y_t have the same finite mean vector μ and [3.9] requires that the autocovariances of the process does not depend on t but just on the time period j that the two vectors Y_t and Y_{t-j} are apart. Therefore, a process is stationary if its first and second moments are time independent.

A time series variable Y_t is said to be integrated of order d, denoted by I (d) where d is an integer with d ≥ 1, if the stochastic trends can be removed by differencing the variable d times or time series are nonstationary in level and become stationary after dth difference. Using the differencing operator Δ which is defined as $\Delta^d Y_t = (1-B)^d Y_t$, the variable Y_t is I (d) if $\Delta^d Y_t$ is stationary, where B is the lag operator. A series is said to be integrated of order zero, denoted by I (0), if the series is stationary in level.

The stationarity of the series is tested by using statistical tests such as Augmented Dickey-Fuller (ADF) test due to Dickey and Fuller (1979, 1981) and the Phillip-Perron (PP) due to Phillips (1987) and Phillips and Perron (1988). The following discussion outlines the basic features of unit root tests Hamilton D. (1994).

Consider a simple AR (1) process:

$Y_t = \rho Y_{t-1} + X_t'\delta + \varepsilon_t$...[3.10]

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 |ρ| ≥ 1, Y_t is a non stationary series and the variance of Y_t increases with time. If |ρ|<1, Y_t is a stationary series. Thus, the hypothesis of stationarity can be evaluated by testing whether ρ is strictly less than one i.e. H_0: ρ=1 versus H_1: ρ<1.

3.2.3.1 Augmented Dickey-Fuller (ADF) test

The standard Dickey-Fuller test is conducted by estimating equation [3.10] after subtracting Y_{t-1} from both side of the equation:

$$\Delta Y_t = \alpha Y_{t-1} + X_t' \delta + \varepsilon_t \text{ ....[3.11]}$$

where $\alpha = \rho - 1$ and $\Delta Y_t = Y_t - Y_{t-1}$. The null and alternative hypotheses may be re-expressed as H_0: α=0 versus H_1: α<0 and evaluated using the conventional t-ratio:

$$t_\alpha = \frac{\hat{\alpha}}{s.e(\hat{\alpha})} \text{ ....[3.12]}$$

where $\hat{\alpha}$ is the estimate of α, and $s.e(\hat{\alpha})$ is the standard error of $\hat{\alpha}$.

Dickey and Fuller (1979) show 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, 1996) implements a much larger set of simulations than those tabulated by Dickey and Fuller (1979). In addition, MacKinnon (1991, 1996) 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 to the right-hand side of the test regression:

$$\Delta Y_t = \alpha Y_{t-1} + X_t' \delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \ldots + \beta_p \Delta Y_{t-p} + U_t \text{ ....[3.13]}$$

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.

3.2.3.2. The Phillips-Perron (PP) 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 and modifies the t -ratio of α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0} \right)^{\frac{1}{2}} - \frac{T(f_0 - \gamma_0)(s.e(\hat{\alpha}))}{2 f_0^{\frac{1}{2}} * s} \text{.....................................}[3.14]$$

where $\hat{\alpha}$ is the estimate of α, t_α is the t -ratio, $s.e$ ($\hat{\alpha}$) is the standard error of $\hat{\alpha}$ and s is the standard deviation of the test regression. In addition, γ_0 is a consistent estimate of the error variance in [3.11] (calculated as $(T-n)\frac{S^2}{T}$, where n is the number of regressors). The remaining term f_0 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.

3.2.4. Estimating the order of the VAR

The lag length for the VAR model may be determined using lag 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 Lutkepohl (2005). The general form of model selection criteria is:

$$C(m) = \ln\left|\hat{\sum}_m\right| + C_T . \varphi(m,n) \text{.....................................}[3.15]$$

where $\hat{\sum}_m = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$ is the residual covariance matrix estimator for a model of order m, $\varphi(m,n)$ is a function of order m which penalizes large VAR orders and C_T is a sequence which may depend on the sample size and identifies the specific criteria.

The term $\ln\left|\hat{\sum}_m\right|$ is a non-increasing function of the order m, while $\varphi(m,n)$ increases with order m. 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 (HQ) information criteria:

$$AIC(m) = \ln\left|\hat{\sum}_m\right| + \frac{2}{T}mn^2 \qquad [3.16]$$

$$SBIC(m) = \ln\left|\hat{\sum}_m\right| + \frac{\ln T}{T}mn^2 \qquad [3.17]$$

$$HQIC(m) = \ln\left|\hat{\sum}_m\right| + \frac{2\ln\ln T}{T}mn^2 \qquad [3.18]$$

In each case $\varphi(m,n) = mn^2$ is the number of VAR parameters in a model with order *m* and *n* is number of variables. The AIC criterion asymptotically overestimates the order. 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 $p_{\max}$.

3.2.5. Cointegration analysis and vector error correction model (VECM)

Two series Y_{1t} and Y_{2t} are said to be cointegrated if Y_{1t} and Y_{2t} have unit roots, but some linear combination of them is stationary. The variables in the VAR system may have a long-run equilibrium relationship to which any deviating variable is gradually pulled over time. The long-run equilibrium relationship is called the cointegrating vector. When there is a cointegrating vector, the VAR model should be augmented with an error correction term. In other words, pure VAR can be applied only when there is no cointegrating relationship among the variables in the VAR system. Hence, a prerequisite before running any VAR model is to run a cointegration test.

The role of cointegration is to link between the relations among a set of integrated (nonstationary) series and the long-term equilibrium. The presence of a cointegrating equation is interpreted as a long-run equilibrium relationship among the variables. If there is a set of n integrated variables of order one (I (1)), there may exist up to (n-1) independent linear relationships that are I (0). In general, there can be r ≤ n-1 linearly independent cointegrating vectors, which are gathered together into the (n x r) cointegrating matrix.

3.2.5.1 Testing for cointegration using Johansen's methodology

The starting point in Johansen's procedure (1988, 1991) in determining the number of cointegrating vectors is the VAR representation of Y_t. A vector autoregressive model of order p VAR (p) is assumed:

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \ldots + \Pi_p Y_{t-p} + \beta D_t + \varepsilon_t \quad [3.19]$$

where Y_t is an (n x 1) vector of non-stationary (I (1)) variables, D_t is a d-vector of deterministic components, and ε_t is a vector of innovations. When the variables of a VAR are cointegrated, we use a vector error-correction (VEC) model. A VEC for n variables might look like:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \beta D_t + \varepsilon_t \quad [3.20]$$

where $\Pi = \sum_{i=1}^{p} \Pi_i - \mathrm{I}$ and $\Gamma_i = -\sum_{j=i+1}^{p} \Pi_j$, i=1, 2, …, p-1.

Granger's representation theorem asserts that if the coefficient matrix *Π* has reduced rank r < n, then there exist n 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 and each column of *β* is a cointegrating vector. The elements of α are known as the adjustment parameters in the vector error correction (VEC) model. A vector error correction (VEC) model is a restricted VAR designed for use with nonstationary 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 $\Pi Y_{t-1} = \alpha\beta' Y_{t-1}$ 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 rank (Π) = 0, then there are no cointegrating variables, i.e., all rows (columns) of Π are linearly dependent and the system is nonstationary in level. When Π has full rank (rank (Π) = n), then Y_t has no unit root, i.e., Y_t is stationary in level.

Johansen (1988) proposed two tests for estimating the number of cointegrating vectors: the trace test and the maximum eigenvalue test. Trace statistic tests the null hypothesis of r cointegrating relations against the alternative of (r+1) cointegrating relations for r = 0, 1, 2…, n-1. Define $\hat{\lambda}_i$, i=1, 2, …, n to be a complex modulus of eigenvalues of $\hat{\Pi}$ and let they be ordered such that $\hat{\lambda}_1 > \hat{\lambda}_2 ... > \hat{\lambda}_n$. The trace statistic is computed as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \log\left[1 - \hat{\lambda}_i\right] \text{..........} [3.21]$$

The maximum eigenvalue statistic tests the null hypothesis of r cointegrating relations against the alternative of n cointegrating relations for r = 0, 1, 2…n-1 where n is the number of variables. This test statistic is computed as:

$$\lambda_{\max}(r, r+1) = -T \log\left(1 - \hat{\lambda}_{r+1}\right) \text{..........} [3.22]$$

where $\hat{\lambda}_{r+1}$ is the $(r+1)^{th}$ ordered eigenvalue of $\hat{\Pi}$, and T is the sample size. The asymptotic critical values tabulated by Johansen, S. and K. Juselius (1990) will be used for these tests.

3.2.6 Estimation of the vector error correction model

In order to estimate a vector error correction model without deterministic terms, subtracting Y_{t-1} from both side of equation (3.1) and rearranging terms gives the so-called error correction model form of the process:

$$\Delta Y_t = -\Pi Y_{t-1} + \beta_1 \Delta Y_{t-1} + ... + \beta_{p-1} \Delta Y_{t-p+1} + \varepsilon_t \text{..........} [3.23]$$

where $\Pi = I - \Pi_1 - ... - \Pi_p$ denote the n X n matrix of least squares coefficients for the n equation and $\beta_i = -\Pi_{i+1} - ... - \Pi_p$ for i= 1,2,…,p-1. In this representation of the process, all terms are stationary because ΔY_t and ε_t are stationary.

Hence, the term ΠY_{t-1} is the only one which includes I (1) variables and, consequently, ΠY_{t-1} must also be I (0). In other words, ΠY_{t-1} must contain the cointegrating relations of the system. It is also possible to obtain the Π_j parameter matrices from the coefficients of the error correction model as: $\Pi_i = \beta_i - \Pi + I$, $\Pi_i = \beta_i - \beta_{i-1}$ for i=2,3,…,p-1, and $\Pi_p = -\beta_{p-1}$. In deriving an estimator for the parameters of [3.23], we will use the following additional notation:

$$\Delta Y = [\Delta Y_1, \Delta Y_2, ..., \Delta Y_T]_{n\ x\ T}, Y = [Y_1, Y_2, ..., Y_T]_{n\ x\ T}, \mathrm{A} = [\mathrm{A}_1, \mathrm{A}_2, ..., \mathrm{A}_{p-1}]_{n\ x\ p-1}$$

$$X = [X_1, X_2, ..., X_T]_{p-1\ x\ T} \text{ with } X_{t-1} = \begin{bmatrix} \Delta Y_{t-1} \\ . \\ . \\ . \\ \Delta Y_{t-p+1} \end{bmatrix}_{p-1\ x\ 1} \text{ and } U = [u_1, u_2, ..., u_T]_{n\ x\ T}.$$

For t=2, 3, …, T, the error correction model in (3.23) can be written as:

$$\Delta Y + \Pi Y = \mathrm{A}X + U \text{..} [3.24]$$

If Π were known, the least square (LS) estimator of A would be:

$$\hat{\mathrm{A}} = (\Delta Y + \Pi Y)X'(XX')^{-1} \text{..} [3.25]$$

Substituting this estimator in [3.24] gives the multivariate regression model:

$$\Delta YM = -\Pi YM + \hat{U} \text{..} [3.26]$$

where $M = I - X'(XX')^{-1}X$. Now an estimator of Π can be obtained by a reduced rank regression. A feasible estimator of A is then obtained by replacing Π in [3.25] by $\hat{\Pi}$. If the process is normally distributed, the estimators obtained in this way are in fact ML estimators (Johansen (1988, 1991)).

Under general assumptions, the estimators of A and Π are asymptotically normal, that is,

$$\sqrt{T}(\hat{\mathrm{A}}-\mathrm{A}) \xrightarrow{d} N(0,\ \Sigma_{\hat{\mathrm{A}}}) \text{...}[3.27]$$

$$\sqrt{T}(\hat{\Pi}-\Pi) \xrightarrow{d} N(0,\ \Sigma_{\hat{\Pi}}) \text{...}[3.28].$$

The asymptotic distribution of $\hat{\mathrm{A}}$ is nonsingular, and hence, standard inference may be used. In contrast, $\Sigma_{\hat{\Pi}}$ in [3.28] has rank nr and is singular if r < n, where r is the number of cointegrated vectors.

3.2.7. Model checking

A wide range of procedures is available for checking the adequacy of VAR and VEC models. They should be applied before a model is used for specific purpose to ensure that it represents the data adequately.

3.2.7.1. Test of residual autocorrelation

3.2.7.1.1. Portmanteau autocorrelation test

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

$$H_0 : E(\varepsilon_t \varepsilon'_{t-j}) = 0, \quad j = 1,2,...,h \text{..}[3.29]$$

It is tested against the alternative that at least one auto covariance and, hence, one autocorrelation is nonzero. The test statistic is based on the residual autocovariances and has the form:

$$Q_h = T\sum_{j=1}^{h} tr\left(\hat{\gamma}'_j \hat{\gamma}_0'^{-1} \hat{\gamma}_j \hat{\gamma}_0^{-1}\right) \text{..}[3.30]$$

where $\hat{\gamma}_j = T^{-1}\sum_{t=j+1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}'_{t-j}$, tr(.) is the trace operator and the $\hat{\varepsilon}_t$'s are the estimated residuals. If $\hat{\varepsilon}_t$ are residuals from a stable VAR (*p*) process, Q_h has an approximate $\chi^2\left(n^2(h-p)\right)$ distribution under the null hypothesis, where T is the length of the series, h denotes the order of the autocorrelation, p is the maximum lag in the VAR model and n is the number of regressors. The limiting χ^2 distribution is strictly valid only if $\frac{h}{T} \to 0$ with growing sample size Edgerton and Shukur (1999).

Alternatively (especially in small samples), a modified statistic is given by:

$$Q^*_h = T^2 \sum_{j=1}^{h} \frac{1}{T-j} t_r \left(\hat{\gamma}'_j \hat{\gamma}_0'^{-1} \hat{\gamma}_j \hat{\gamma}_0^{-1} \right) \text{...[3.31]}$$

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 χ^2 approximation to the null distribution may be very poor whereas a large h may result in a loss of power.

3.2.7.1.2. Autocorrelation LM test

This test was developed by Breusch and Godfrey (1978). Assume a VAR model for the error u_t given by:

$$u_t = \mathrm{B}_1 u_{t-1} + ... + \mathrm{B}_h u_{t-h} + v_t \text{...[3.32]}$$

The quantity v_t denotes a vector of white noise error terms. To test for autocorrelation in u_t, the null and alternative hypotheses are:

$H_0 : \mathrm{B}_1 = \mathrm{B}_2 = ... = \mathrm{B}_h = 0$

$H_1 : \mathrm{B}_j \neq 0$ for at least one $j \leq h$

where $\mathrm{B}_1, \mathrm{B}_2, ..., \mathrm{B}_h$, represents coefficient matrix.

We use the Lagrange Multiplier method to perform the test. This method is very useful for finding optimal estimates under constraint conditions.

Under H_0, we only need to check the regular VAR model $u_t = v_t$. To determine the test statistic we begin with the auxiliary regression:

$$\hat{u} = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + ... + \Pi_p Y_{t-p} + \mathrm{B}_1 \hat{u}_{t-1} + \mathrm{B}_2 \hat{u}_{t-2} + ... + \mathrm{B}_h \hat{u}_{t-h} + \beta D_t + v_t \text{............................[3.33]}$$

where D_t represents an (l × 1) matrix of deterministic components, β is a parameter matrix of suitable dimension and v_t is an auxiliary error term.

The model is estimated by the same method as original model [3.32] with $\hat{u}_t$, $t \leq 0$, replaced by zero. Denoting the residuals from the estimated auxiliary model by $\hat{v}_t$ (t = 1, . . . , T), the residual covariance matrix estimator obtained from the auxiliary model is:

$$\hat{\Sigma}_v = \frac{1}{T}\sum_{t=1}^{T}\hat{v}_t\hat{v}_t'.$$

Moreover, re-estimating the relevant auxiliary model without the lagged residuals $\hat{u}_{t-i}$, that is, imposing the restriction $B_1 = B_2 = ... = B_h = 0$, and denoting the resulting residuals by $\hat{v}^R{}_t$, the corresponding covariance matrix estimator is:

$$\hat{\Sigma}_R = \frac{1}{T}\sum_{t=1}^{T}\hat{v}^R{}_t\hat{v}^{R'}{}_t.$$

The LM statistic is:

$$\lambda_{LM}(h) = T\{n - tr[(\hat{\Sigma}_R)^{-1}\hat{\Sigma}_v]\}.$$

This statistic has an asymptotic $\chi^2(hn^2)$ distribution under the null hypothesis.

3.2.7.1.3. Test of multivariate normality

The multivariate version of the Jarque Bera test is used to test the normality of the residual vector such that its components are independent and then check the compatibility of the third and fourth moments with those of a normal distribution. In a first step, the residual covariance matrix is estimated as: $\hat{\Sigma}_u = \frac{1}{T}\sum_{t=1}^{T}(\hat{u}_t - \bar{\hat{u}})(\hat{u}_t - \bar{\hat{u}})'$ and the square root of covariance matrix $((\hat{\Sigma}_u)^{\frac{1}{2}})$ is computed.

The tests for non-normality may be based on the skewness and kurtosis of the standardized residuals $(\hat{u}_t)^s = \{(\hat{u}_{1t})^s, ..., (\hat{u}_{nt})^s\}' = (\hat{\Sigma}_u)^{-\frac{1}{2}}(\hat{u}_t - \bar{\hat{u}})$:

$$b_1 = (b_{11},...,b_{1n})' \text{ with } b_{1n} = T^{-1}\sum_{t=1}^{T}((\hat{u}_{nt})^s)^3$$

$$b_2 = (b_{21},...,b_{2n})' \text{ with } b_{2n} = T^{-1}\sum_{t=1}^{T}((\hat{u}_{nt})^s)^4$$

Defining $s_3 = \frac{1}{6}T\hat{b}_1'\hat{b}_1$ and $s_4 = \frac{1}{24}T\left(\hat{b}_2 - \underset{\sim}{3}\right)'\left(\hat{b}_2 - \underset{\sim}{3}\right)$ where $\underset{\sim}{3} = (3,\ 3\ ,...,\ 3)'$ is an (n x 1) vector, a multivariate version of the Jarque-Bera statistic is:

$$JB_n = s_3 + s_4 .$$

The statistics s_3 and s_4 have $\chi^2(n)$ limiting distributions and JB_n has a $\chi^2(2n)$ asymptotic distribution if the normality null hypothesis holds. The latter statistic was proposed by Doornik and Hansen (1994).

3.2.8. Forecasting

Forecasting is one of the main objectives of multivariate time series analysis. The structure of equations (3.1) is designed to model how the values of the variables in period *t* are related to past values. This makes the VAR a natural for the task of forecasting the future paths of variables conditional on their past histories.

Suppose that we have a sample of observations on Y_t that ends in period *T*, and that we wish to forecast their values in *T* + 1, *T* + 2, etc. For period *T* + 1, our VAR is:

$$Y_{T+1/T} = C + \Pi_1 Y_T + ... + \Pi_p Y_{T-p+1},\ T \geq p \text{..}[3.34]$$

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

$$Y_{T+h/T} = C + \Pi_1 Y_{T+h-1/T} + ... + \Pi_p Y_{T+h-p/T} \text{..}[3.35]$$

where $Y_{T+j/T} = Y_{T+j}$ for j ≤ 0. The h-step-ahead forecast errors may be expressed as:

$$Y_{T+h} - Y_{T+h/T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s} \text{.........} [3.36]$$

where the matrices Ψ_s are determined by recursive substitution:

$$\Psi_s = \sum_{j=1}^{p} \Psi_{s-j} \Pi_j \text{.........} [3.37]$$

with $\Psi_0 = I_n$ and $\Pi_j = 0$ 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:

$$\Sigma(h) = MSE(Y_{T+h} - Y_{T+h/T}) = \sum_{s=0}^{h-1} \Psi_s \Sigma \Psi_s' \text{.........} [3.38]$$

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:

$$\hat{Y}_{T+h/T} = C + \hat{\Pi}_1 \hat{Y}_{T+h-1/T} + ... + \hat{\Pi}_p \hat{Y}_{T+h-p/T} \text{.........} [3.39]$$

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

$$Y_{T+h} - \hat{Y}_{T+h/T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s} + \left(Y_{T+h/T} - \hat{Y}_{T+h/T}\right) \text{.........} [3.40]$$

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

In practice, the second term $MSE\left(Y_{T+h} - \hat{Y}_{T+h/T}\right)$ is often ignored and $\hat{\Sigma}(h)$ is computed using [3.36] as:

$$\hat{\Sigma}(h) = \sum_{s=0}^{h-1} \hat{\Psi}_s \hat{\Sigma} \hat{\Psi}_s' \text{.........} [3.41]$$

where $\hat{\Psi}_s = \sum_{j-1}^{p} \hat{\Psi}_{s-j} \hat{\Pi}_j$

3.2.9. Measures of forecasting accuracy

In most forecasting situations, accuracy is treated as the overriding criterion for selecting a forecasting method. In many instances, 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.

If Y_t is the actual observation for the period t and F_t is the forecast for the sample period, then the error is defined as:

$$v_t = Y_t - F_t \qquad [3.42]$$

Usually F_t is calculated using data $Y_1, Y_2, ..., Y_{t-1}$. It is a one step-ahead forecast because it is forecasting one period ahead of the last observation used in the calculation. Therefore, we describe v_t as a one step-ahead forecast error. It is the difference between the observation Y_t and the 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 vectors of error terms, and the following standard statistical measures can be defined:

$$\text{Mean Error}(ME) = \frac{1}{T}\sum_{t=1}^{T} v_t \qquad [3.43]$$

$$\text{Mean Absolute Error}(MAE) = \frac{1}{T}\sum_{t=1}^{T} |v_t| \qquad [3.44]$$

$$\text{Mean Square Error}(MSE) = \frac{1}{T}\sum_{t=1}^{T} v_t^2 \qquad [3.45]$$

Equation [3.42] can be used to compute the error for each period. These can be averaged as in equation [3.43] to give 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 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.

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:

$$PE_t = \left(\frac{Y_t - F_t}{Y_t} \right) * 100 \qquad [3.46]$$

Then the following two relative measures are frequently used:

Mean Percentage Error (MPE) $= \frac{1}{T} \sum_{t=1}^{T} PE_t$ ....[3.47]

Mean Percentage Absolute Error (MPAE) $= \frac{1}{T} \sum_{t=1}^{T} \left| PE_t \right|$ ....[3.48]

Equation [3.46] can be used to compute the percentage error for any time period. These can be averaged as in equation [3.47] to give the 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_t in equation [3.47].

Alternatively, Theil's U statistic can be used as a measure of forecasting accuracy. Like MAPE statistic, high values suggest poor performance in the forecast. However, and unlike MAPE, the U-Theil corrects the performance scale that MPAE had. Theil's U can be estimated as:

$$U == \frac{\sqrt{\frac{1}{T} \sum_{t=1}^{T} (Y_t - F_t)^2}}{\sqrt{\frac{1}{T} \sum_{t=1}^{T} F_t^2} + \sqrt{\frac{1}{T} \sum_{t=1}^{T} Y_t^2}}$$

The scaling of U is such that it will always lie between 0 and 1. If U = 0, $Y_t = F_t$ for all forecasts and there is a perfect fit; if U = 1, the predictive performance is not good.

3.2.10. Structural vector autoregressive (SVAR) analysis

The general VAR (p) 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, the dynamic properties of a VAR (p) are often summarized using various types of structural analysis.

The three main types of structural analysis summaries are:

- Granger causality tests;
- Impulse response functions; and
- Forecast error variance decompositions.

The following sections give brief descriptions of these summary measures.

3.2.10.1. Granger causality test

One of the first, and undeniable, maxims that every econometrician or statistician is taught is that "correlation does not imply causality." Correlation or covariance is a symmetric, bivariate relationship; $\text{cov}(Y_{1t}, Y_{2t}) = \text{cov}(Y_{2t}, Y_{1t})$. We cannot, in general, infer anything about the existence or direction of causality between Y_1 and Y_2 by observing non-zero covariance. The following intuitive notion of a variable's forecasting ability is due to Granger (1969). Even if our statistical analysis is successful in establishing that the covariance is highly unlikely to have occurred by chance, such a relationship could occur because Y_1 causes Y_2, Y_2 causes Y_1, each causes the other, or because Y_1 and Y_2 are responding to some third variable without any causal relationship between them. However, Clive Granger defined the concept of Granger causality, which, under some controversial assumptions, can be used to shed light on the direction of possible causality between pairs of variables. The formal definition of Granger causality asks whether past values of Y_1 aid in the prediction of Y_2, conditional on having already accounted for the effects on Y_2 of past values of Y_2 (and perhaps of past values of other variables). If they do, the Y_1 is said to "Granger cause" Y_2.

The VAR is a natural framework for examining Granger causality. Consider the two-variable system in equations (3.3). The first equation models Y_1 as a linear function of its own past values, plus past values of Y_2. If Y_2 Granger causes Y_1 (which we write as), then some or all of the lagged Y_2 values have non-zero effects: lagged Y_2 affects Y_1. If Y_1 causes Y_2 and Y_2 also causes Y_1 the process $(Y'_{1t}, Y'_{2t})'$ is called a feedback system.

In a bivariate VAR (p) model for $Y_t = (Y_{1t}, Y_{2t})'$, Y_2 fails to Granger-cause Y_1 if all of the p VAR coefficient matrices $\Pi_1, \Pi_2, ..., \Pi_P$ are lower triangular. That is, the VAR (p) model has the form:

$$\begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \end{pmatrix} + \begin{pmatrix} \Pi_{11}^1 & 0 \\ \Pi_{21}^1 & \Pi_{22}^1 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + ... + \begin{pmatrix} \Pi_{11}^p & 0 \\ \Pi_{21}^p & \Pi_{22}^p \end{pmatrix} \begin{pmatrix} Y_{1,t-p} \\ Y_{2,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

so that all of the coefficients on lagged values of Y_2 is zero in the equation for Y_1. Similarly, Y_1 fails to Granger-cause Y_2 if all of the coefficients on lagged values of Y_1 are zero in the equation for Y_2.

The p linear coefficient restrictions implied by Granger non-causality may be tested using the Wald statistic. Notice that if Y_2 fails to Granger-cause Y_1 and Y_1 fails to Granger-cause Y_2, then the VAR coefficient matrices $\Pi_1, \Pi_2, ..., \Pi_P$ are diagonal. Testing for Granger non-causality in the general n variable VAR (p) models follows the same logic used for bivariate models.

3.2.10.2. Impulse response functions

Impulse responses trace out the response of current and future values of each of the variables to a one unit increase in the current value of one of the VAR errors, assuming that this error returns to zero in subsequent periods and that all other errors are equal to zero. More generally, an impulse response refers to the reaction of any dynamic system in response to some external change. According to Hamilton (1994), a VAR can be written in vector Moving Average (MA) form as follows:

$$Y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + ... + \Psi_p \varepsilon_{t-p} \quad [3.49]$$

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

$$\frac{\partial Y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial Y_{i,t}}{\partial \varepsilon_{j,t-s}} = \Psi_{ij}^s \quad \text{......[3.50]}$$

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) recursive VAR model and estimate the triangular structural VAR (p) model:

$$\left.\begin{aligned}
Y_{1t} &= C_1 + \gamma'_{11} Y_{t-1} + \ldots + \gamma'_{1p} Y_{t-p} + \eta_{1t} \\
Y_{2t} &= C_1 + \beta_{21} Y_{1t} + \gamma'_{21} Y_{t-1} + \ldots + \gamma'_{2p} Y_{t-p} + \eta_{2t} \\
Y_{3t} &= C_1 + \beta_{31} Y_{1t} + \beta_{32} Y_{2t} + \gamma'_{31} Y_{t-1} + \ldots + \gamma'_{3p} Y_{t-p} + \eta_{3t} \\
&. \\
&. \\
&. \\
Y_{nt} &= C_1 + \beta_{n1} Y_{1t} + \ldots + \beta_{n,n-1} Y_{n-1,t} + \gamma'_{n1} Y_{t-1} + \ldots + \gamma'_{np} Y_{t-p} + \eta_{nt}
\end{aligned}\right\} \quad \text{......[3.51]}$$

where γ_{ij} represents the structural parameters.

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

$$BY_t = C + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots + \Gamma_p Y_{t-p} + \eta_t \quad \text{......[3.52]}$$

$$\text{where} \quad B = \begin{pmatrix} 1 & 0 & 0 & . & . & . & 0 \\ -\beta_{21} & 1 & 0 & . & . & . & 0 \\ . & . & . & & & & . \\ . & . & & . & & & . \\ . & . & & & . & & . \\ -\beta_{n1} & -\beta_{n2} & -\beta_{n3} & . & . & . & 1 \end{pmatrix} \quad \text{......[3.53]}$$

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/orthogonal errors η_t are referred to as structural errors.

The triangular structural model [3.51] imposes the recursive causal ordering:

$Y_1 \to Y_2 \to ... \to Y_n$..[3.54]

For example, the ordering $Y_1 \to Y_2 \to Y_3$ imposes the restrictions: Y_{1t} affects Y_{2t} and Y_{3t} but Y_{2t} and Y_{3t} do not affect Y_1; Y_{2t} affects Y_{3t} but Y_{3t} does not affect Y_{2t}. Similarly, the ordering $Y_2 \to Y_3 \to Y_1$ imposes the restrictions: Y_{2t} affects $\mathbf{Y}_{3t}$ and $\mathbf{Y}_{1t}$ but Y_{3t} and Y_{1t} do not affect Y_2; Y_{3t} affects Y_{1t} but Y_{1t} does not affect Y_{3t}.

For a VAR (p) with n variables there are n! possible recursive causal orderings. Which ordering to use in practice depends on the context and whether prior theory can be used to justify a particular ordering. 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's representation of Y_t based on the orthogonal errors η_t is given by:

$$Y_t = \mu + \Theta_0 \eta_t + \Theta_1 \eta_{t-1} + ... + \Theta_p \eta_{t-p} \text{..[3.55]}$$

where $\Theta_0 = B^{-1}$ is a lower triangular matrix. The impulse responses to the orthogonal shocks η_{jt} are:

$$\frac{\partial Y_{i,t+s}}{\partial \eta_{j,t}} = \frac{\partial Y_{it}}{\partial \eta_{j,t-s}} = \theta_{ij}^s, \;\; i, j = 1,2,...,n; \;\; s > 0 \text{.......................................[3.56]}$$

where 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.

3.2.10.3. Forecast error variance decompositions

Forecast Error Decomposition indicates the amount of information each variable contributes to the other variables in the autoregression. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. The forecast error decomposition is the percentage of the variance of the error made in forecasting a variable due to a specific shock at a given horizon. The forecast error variance decomposition (FEVD) answers the question: what portion of the variance of the forecast error in predicting $Y_{i,T+h}$ is due to the structural shock ε_t? Using the orthogonal shocks ε_t, the h-step-ahead forecast error vector, with known VAR coefficients, may be expressed as:

$$Y_{T+h} - Y_{T+h/T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s}$$

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

$$Y_{T+h} - Y_{T+h/T} = \sum_{s=0}^{h-1} \Psi_{i1}^{s} \varepsilon_{1,T+h-s} + \ldots + \sum_{s=0}^{h-1} \Psi_{in}^{s} \varepsilon_{n,T+h-s}$$

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

$$Var\left(Y_{T+h} - Y_{T+h/T}\right) = \delta_{\varepsilon 1}^{2} \sum_{s=0}^{h-1} \left(\Psi_{i1}^{s}\right)^{2} + \ldots + \delta_{\varepsilon n}^{2} \sum_{s=0}^{h-1} \left(\Psi_{in}^{s}\right)^{2}$$

where $\delta_{\varepsilon j}^{2} = Var\left(\varepsilon_{jt}\right)$. The portion of $Var\left(Y_{T+h} - Y_{T+h/T}\right)$ due to shock ε_j is then:

$$FEVD_{i,j}(h) = \frac{\delta_{\varepsilon j}^{2} \sum_{s=0}^{h-1} \left(\Psi_{ij}^{s}\right)^{2}}{\delta_{\varepsilon 1}^{2} \sum_{s=0}^{h-1} \left(\Psi_{i1}^{2}\right) + \ldots + \delta_{\varepsilon n}^{2} \sum_{s=0}^{h-1} \left(\Psi_{in}^{s}\right)^{2}}, \quad i, j = 1,2,\ldots,n \text{..................[3.57]}$$

In a VAR with n variables there may be $n^2 FEVD_{i,j}(h)$ values. It must be kept in mind that the FEVD in [3.57] depends on the recursive causal ordering used to identify the structural shocks ε_t and is not unique. Different causal orderings may produce different FEVD values.

CHAPTER FOUR

Results and discussions

The empirical analysis is based on annual data set on real GDP (constant 2005 USD), openness and inflation rate for the period from 1992 to 2012 that was retrieved from the World Economic Outlook (WEO) database of the International Monetary Fund (IMF). In the empirical analyses, the relationship between inflation rate and economic growth has been considered. The discussion begins with descriptive analysis. Data analysis was performed using STATA 11 and Eviews 7.

4.1. Descriptive analysis

The descriptive statistics results show that real GDP grows at an average rate of 11.8 billion USD from 1992 to 2012 in Ethiopia. Moreover, the average inflation rate was 10.39% with maximum and minimum values of 34.19% and -5.76%, respectively. The standard deviations show that the spread of real GDP, openness and inflation rate from their corresponding means are 5.26×10^9, 0.112 and 10.980, respectively.

Table 4.1: Descriptive statistics of series: 1992 to 2012

	Real GDP Rea	Inflation rate	Openness
Mean	1.18×10^{10}	10.39097	0.368868
Median	9.66×10^9	9.875292	0.396142
Maximum	2.32×10^{10}	34.19253	0.510949
Minimum	5.76×10^9	-5.755372	0.108307
Std. Dev.	5.26×10^9	10.98005	0.112425
Observations	21	21	21

4.2. Unit root properties of individual series

The time series under consideration should be checked for stationarity before one attempts to fit a suitable model. That is, variables have to be tested for the presence of unit root(s) so that the orders of integration of each series are determined. The time series plots of the series under consideration are shown in Figure 4.1. From the figures we can see that real GDP and openness seem to have an increasing trend over time. Moreover, inflation rate shows a decreasing trend till 2001 and then increasing upward trend thereafter.

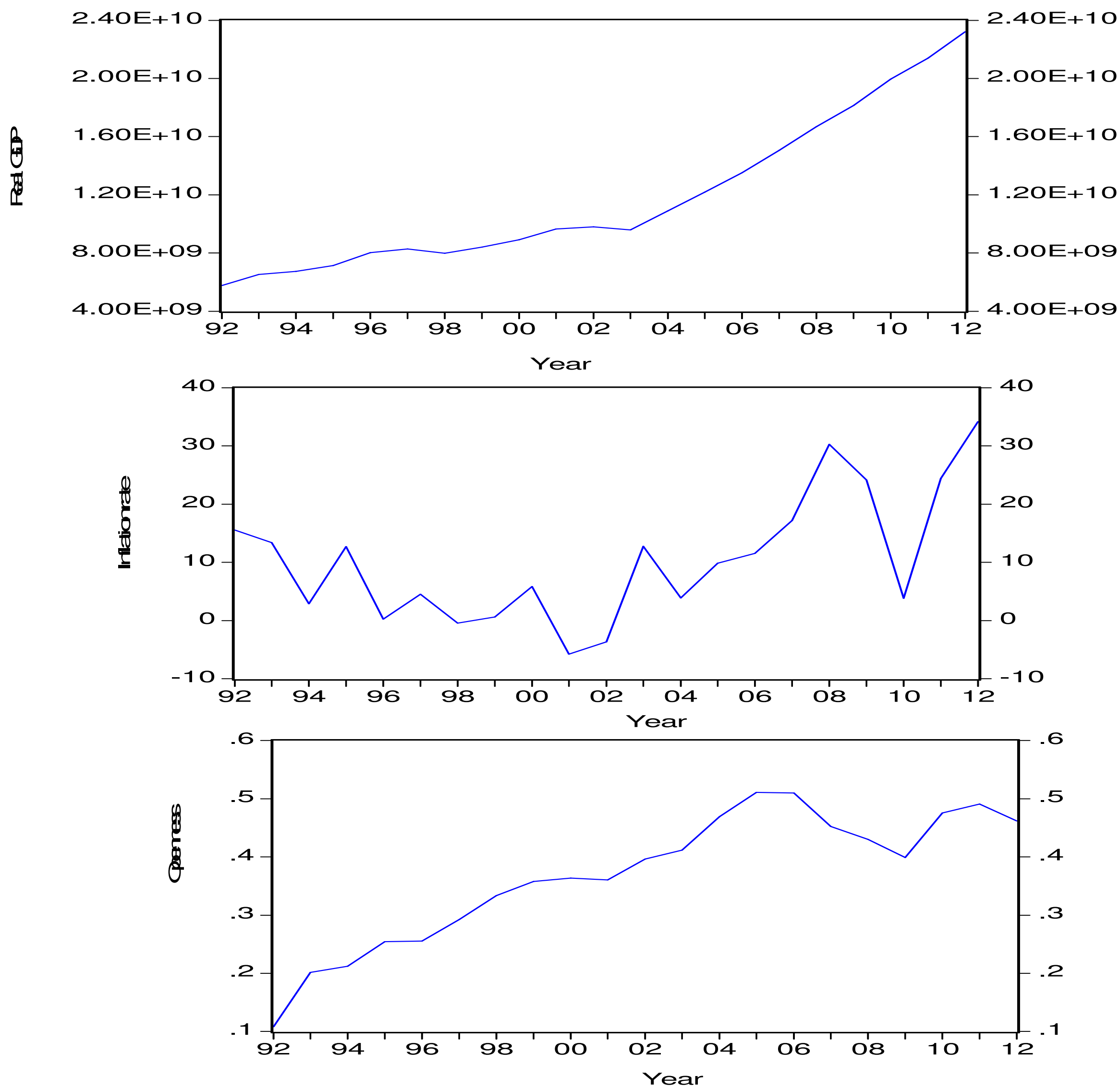

Figure 4.1 Time series plots of real GDP, inflation rate and openness

Figure 4.2 suggests that the first differenced series of the endogenous variables seem to have a stationary behavior.

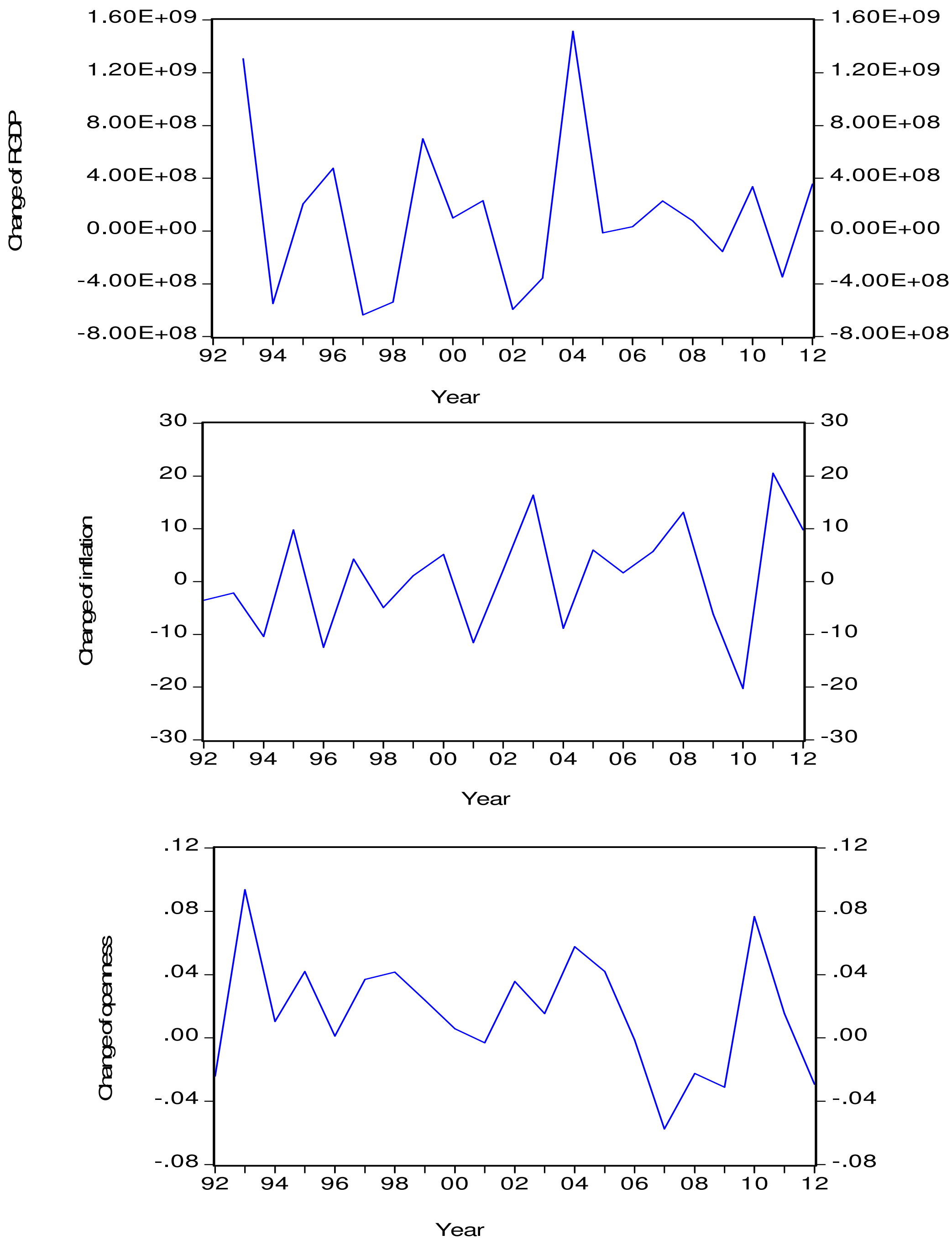

Figure 4.2 Time series plots of differenced series

However, the stationarity of the series have to be tested by using objective statistical tests such as Augmented Dickey-Fuller and a Phillips - Perron tests. The hypothesis to be tested is:

H_0: The series is non stationary against

H_1: The series is stationary

The results of ADF and PP tests, in level with intercept and trend and first difference with intercept and trend, for each of the three series are presented in Table 4.2. The critical values used for the tests are the MacKinnon (1996) critical values.

Table 4.2: Unit root test results

Series	**Level with Intercept and trend**				**First difference with Intercept and trend**			
	Test Statistic		**Prob.***		**Test Statistic**		**Prob.***	
	ADF	**PP**	**ADF**	**PP**	**ADF**	**PP**	**ADF**	**PP**
Real GDP	0.516	0.436	0.9985	0.9981	-3.568	-3.533	0.0577	0.0615
Inflation rate	-2.632	-2.394	0.2711	0.3714	-5.268	-15.566	0.0020	0.0000
Openness	-1.433	-1.433	0.8200	0.8200	-5.17	-4.330	0.0133	0.0132
Test critical values 1%	-4.468				-4.468			
5%	-3.645				-3.645			
10%	-3.261				-3.261			

*MacKinnon (1996) one-sided p-values.

According to the test results for the series in level with intercept and trend, we have no evidence to reject the null hypothesis. Therefore, the three series in level contain unit root, i.e., the series are not stationary. In order to determine the order of integration of the three time series, the same tests were applied to their first difference. The order of integration of a series is given by the number of times the series must be differenced in order to produce a stationary series. The result indicates that we reject the null hypothesis for the first differenced series with intercept and trend at the 1% level of significance for inflation rate, at 5% level for openness and at 10% level for real GDP. Thus, the series are all integrated of order one (I (1)).

4.3. VAR model specification

4.3.1. Specifying the order of the VAR

Specifying the lag length has strong implications for subsequent modeling choices. If we choose too few lags, autocorrelation of the error terms could lead to apparently significant and inefficient estimators, whereas if too many lags are chosen, it comes with the penalty of fewer degrees of freedom. For determining the appropriate lag length for the VAR model, the Akaike information criterion (AIC), Schwarz Bayesian information criterion (SBIC) and Hannan-Quinn information criterion (HQIC) were used. The lag length selection criteria are given in Table 4.3.

Table 4.3: VAR lag order selection results

Lag	Log L	AIC	SBIC	HQIC
0	-203.4708	14.67648	14.77164*	14.70558
1	-199.0577	14.64698	14.93245	14.73425
2	-193.7157	14.55112*	15.02691	14.69657*

* indicates lag order selected by the criterion

As can be seen from Table 4.3, among the three lag order selection criteria two of them attain their minimum at lag two. Thus, we choose two lags to be included in Johansen test of cointegration.

4.3.2 Cointegration analysis

Since real GDP, inflation rate and openness are integrated of the same order, we proceed to test for cointegration. Johansen (1995) cointegration test is applied at the predetermined lag two by assuming linear deterministic trend in data. In these tests, maximum eigenvalue and trace test statistics are compared to their corresponding special critical values. The trace test statistic proceed sequentially from the first hypothesis of no cointegration to an increasing number of cointegrating vectors whereas maximum eigenvalue test checks for r cointegrating relationships versus n cointegrating relationships, where n is the number of variables. The results of cointegration test for the series are given in Table 4.4.

Table 4.4: Johansen cointegration test results

Hypothesized No. of CE(s)	Eigenvalue	Trace Test			Maximum eigenvalue test		
		Statistic	5% critical value	Prob.**	Statistic	5% critical value	Prob.**
None *	0.752317	35.10697	29.79707	0.0111	29.30768	21.13162	0.0028
At most 1	0.214536	5.799288	15.49471	0.7191	5.071089	14.26460	0.7328
At most 2	0.034082	0.728200	3.841466	0.3935	0.728200	3.841466	0.3935

Normalized cointegrating coefficients (standard error in parentheses)

RGDP	IR	OP
1.000000	$5.88x10^9$	$4.53x10^{11}$
	$(1.0x10^9)$	$(8.4x10^{10})$

* denotes rejection of the null hypothesis, ** denotes MacKinnon-Haug-Michelis (1999) p-values.

The null hypothesis is that the number of cointegrating relationships is equal to r, which is given in the “Hypothesized No. of CE(s)” column of the output. The trace test indicates that at least one cointegrating vector ($r \geq 1$) exists in the system at the five percent significance level. In order to identify the specific number of cointegrating vectors, the maximum eigenvalue test is further employed. This test also confirms the existence of one cointegrating relationship at the one percent significance level. Therefore, there is one cointegrated vector in the system. From the Johansen cointegration test, the rank of the cointegration matrix was determined to be equal to one.

4.4 Vector error correction model (VECM) estimation

Having concluded that the variables in the VAR model appear to be cointegrated, we proceed to estimate the short run behavior and adjustment to the long run equilibrium, which is represented by vector error correction model (VECM). The estimated results of the vector error correction model are presented in Table 4.5.

Table 4.5 Estimated coefficients of Vector Error Correction Model

Cointegrating Eq:	CointEq1	Standard error	T-Statistics
$RGDP_t$	1.000000		
IR_t	5.88x10^{9}	1.0x10^{9}	5.60695
OP_t	4.53x10^{11}	8.4x10^{10}	5.38391
C	-2.28x10^{11}		
Error Correction:	$\Delta RGDP_t$	ΔIR_t	ΔOP_t
EC_{t-1}	0.014270	6.59x10^{-11}	3.70x10^{-13}
	(0.00250)	(9.6x10^{-11})	(3.0x10^{-13})
	[5.70132]	[0.68378]	[1.22200]
$\Delta RGDP_{t-1}$	-0.230590	-1.18x10^{-9}	-4.94x10^{-11}
	(0.19223)	(7.4x10^{-9})	(2.3x10^{-11})
	[-1.19958]	[-0.15921]	[-2.12436]
$\Delta RGDP_{t-2}$	-0.538208	-4.55x10^{-9}	-1.29x10^{-11}
	(0.21338)	(8.2x10^{-9})	(2.6x10^{-11})
	[-2.52233]	[-0.55446]	[-0.49755]
ΔIR_{t-1}	-53851638	-0.948964	-0.003630
	(1.7x10^{7})	(0.63877)	(0.00201)
	[-3.24497]	[-1.48560]	[-1.80691]
ΔIR_{t-2}	-17591516	-0.878752	-0.000301
	(1.5x10^{7})	(0.57923)	(0.00182)
	[-1.16899]	[-1.51709]	[-0.16546]
ΔOP_{t-1}	-4.71x10^{9}	-113.4481	-0.119399
	(3.0x10^{9})	(116.434)	(0.36614)
	[-1.55828]	[-0.97436]	[-0.32610]
ΔOP_{t-2}	5.20x109	54.28727	0.004564
	(1.6x10^{9})	(62.4268)	(0.19631)
	[3.20533]	[0.86961]	[0.02325]
C	1.36x10^{9}	6.399401	0.063744
	(2.6x10^{8})	(9.91665)	(0.03118)
	[5.28709]	[0.64532]	[2.04414]
R-squared	0.914379	0.381423	0.534893
Adj. R-squared	0.868275	0.048343	0.284451
F-statistic	19.83312	1.145139	2.135796

The system is then subjected to block exogeneity test. The results are displayed in Table 4.6. From the results we can see that real GDP is the only endogenous variable, while inflation rate and openness are weakly exogenous. Thus, there is no need to interpret the short-run equations corresponding to inflation rate and openness.

Table 4.6 VEC Granger Causality/Block Exogeneity Wald Tests results

VEC Granger Causality/Block Exogeneity Wald Tests			
Dependent variable: $\Delta RGDP_t$			
Excluded	Chi-sq	df	Prob.
ΔIR_t	17.63620	2	0.0001
ΔOP_t	12.88917	2	0.0016
All	26.17844	4	0.0000
Dependent variable: ΔIR_t			
Excluded	Chi-sq	df	Prob.
$\Delta RGDP_t$	0.314095	2	0.8547
ΔOP_t	1.737133	2	0.4196
All	1.861455	4	0.7612
Dependent variable: ΔOP_t			
Excluded	Chi-sq	df	Prob.
$\Delta RGDP_t$	4.552674	2	0.1027
ΔIR_t	8.754296	2	0.0126
All	9.118697	4	0.0582

4.5 Long run analysis

The cointegrating vector is given by:

$$\hat{\beta} = \left(1,\ 5.88\times10^{9},\ 4.53\times10^{11}\right)$$

The parameter estimates correspond to the cointegrating coefficients of real GDP (normalized to one) and inflation rate and openness, in that order. The estimated long run model is given by:

$$RGD\hat{P}_t = 2.28\times10^{11} - 5.88\times10^{9}\, I\hat{R}_t - 4.53\times10^{11}\, O\hat{P}_t$$

The estimated long run model given in the above equation shows that there exist a strong inverse long-run relationship between inflation rate and real GDP in Ethiopia. On average, a one percent increase in inflation rate leads to a decline in real GDP by 5.88 billion USD in the long-run. The result is consistent with the studies of Barro (1996), Ahmed and Mortaza (2005) and Saaed (2007), and inconsistent with the study of Chimobi (2010) in Nigeria. There is also an inverse relationship between openness and real GDP in the long-run. The result is inconsistent with the study of Omisakin et al. (2009) and Oluwaseyi and Adejoke (2013) in Nigeria and Amarjit (2012) in India.

4.6 Short-run analysis

Table 4.7 shows the matrix of short run coefficients. The estimated coefficient of the error correction term (0.0143) is statistically significant at the one percent level. This shows that about 1.43% of the short run disequilibrium in real GDP will be adjusted within a year (the same year). We can see from the results that, in the short run, two time lagged real GDP has a significant negative impact on the current real GDP. Furthermore, one time lagged inflation rate has negative impact on real GDP and the effect is significant at 5% level of significance. In other words, short-run changes in inflation rate affect economic growth negatively. This result is consistent with the study of Saaed (2007) in Kuwait and Faria and Carneiro (2001) in Brazil. Moreover, two time lagged openness has a significant positive impact on the real GDP in the short-run. The result is consistent with the study of Amarjit (2012) in India.

Table 4.7 Matrix of short run coefficients

Dependent Variable: $\Delta RGDP_t$

Independent variables	Coefficient	Std. Error	t-Statistic	Prob.
EC_{t-1}	0.014270	0.002503	5.701320	0.0001
$\Delta RGDP_{t-1}$	-0.230590	0.192226	-1.199576	0.2517
$\Delta RGDP_{t-2}$	-0.538208	0.213377	-2.522330	0.0255
ΔIR_{t-1}	-53851638	16595407	-3.244972	0.0064
ΔIR_{t-2}	-17591516	15048535	-1.168985	0.2634
ΔOP_{t-1}	-4.71×10^9	3.02×10^9	-1.558275	0.1432
ΔOP_{t-2}	5.20×10^9	1.62×10^9	3.205335	0.0069
C	1.36×10^9	2.58×10^8	5.287093	0.0001

R-squared	0.914379	Mean dependent var	8.05×10^8
Adjusted R-squared	0.868275	S.D. dependent var	7.21×10^8
S.E. of regression	2.62×10^8		
Sum squared resid	8.90×10^{17}		
Log likelihood	-431.7987		
F-statistic	19.83312		
Prob(F-statistic)	0.000006		

4.7. Model checking

In order to ascertain whether the model provides an adequate fit to the data or not, a test for misspecification should be performed.

4.7.1. Test of residual autocorrelation

Here we utilize VAR residual Portmanteau tests for autocorrelation and VAR residual serial correlation LM tests. The results of the two tests are illustrated in Tables 4.8. The test results show that the null hypothesis of no serial correlation in the residuals cannot be rejected.

Table 4.8: Test of residual autocorrelation

Lags	Q-Stat	Prob.	LM-Stat	Prob.
1	0.8110	0.368	11.83557	0.2227
2	1.1269	0.569	11.44415	0.2465
3	1.8515	0.604	11.88401	0.2199

4.7.2. Testing normality

Multivariate version of the Jarque Bera tests is used to test the normality of the residuals. It compares the skewness and kurtosis coefficients to those from a normal distribution. The null hypothesis is that the error terms in the model have skwness and kurtosis coefficients corresponding to a normal distribution. The results given in Table 4.9 show that the null hypothesis of multivariate normality of the residuals cannot be rejected for all tests considered.

Table 4.9: Normality test

Component	Skewness	Chi-sq	Prob.	Kurtosis	Chi-sq	Prob.	Jarque-Bera Test	Prob.
1	0.649097	1.474643	0.2246	2.171956	0.599950	0.4386	2.074593	0.3544
2	-0.482720	0.815564	0.3665	1.704265	1.469062	0.2255	2.284626	0.3191
3	-0.271081	0.257197	0.6121	1.084097	3.211848	0.0731	3.469045	0.1765
Joint		2.547405	0.4668		5.280860	0.1523	7.828265	0.2510

4.7.3. Lag exclusion test

To check whether the chosen lag is optimal or not, lag exclusion test is used. The results are given in Table 4.10. The values in the square brackets are probability values for the corresponding chi-square test statistics. The results show that jointly two lags of all endogenous variables are statistically significant. Therefore, restricted VAR (2) is found to be suitable for the data set, and hence, could be adopted.

Table 4.10: VAR lag Exclusion Wald Tests

	GDP_t	IR_t	OP_t	Joint
DLag 1	15.02514	3.943099	5.093343	32.74786
	[0.001795]	[0.267674]	[0.165088]	[0.000148]
DLag 2	16.26017	5.067885	0.395434	25.39424
	[0.001003]	[0.166893]	[0.941184]	[0.002565]
Df	3	3	3	9

4.8. Structural analysis

4.8.1. Granger causality test

The bivariate Granger causality tests were conducted to find out the direction of causality and possible feedback among the variables. The results given in Table 4.11 indicate that inflation rate does not Granger cause real GDP. Thus, past values of inflation rate cannot be used to predict the future values of real GDP. The result is consistent with the study of inconsistent with the study by Erbaykal and Okuyan (2008) in Turkey. However, the results show that real GDP Granger causes inflation rate at the 10% level of significance. Therefore, past values of real GDP can be used to predict the future values of inflation rate. The result is consistent with the study of Gokal and Hanif (2004) in Fiji and Tabi and Ondoa (2001) in Cameroon.

Table 4.11: Pair-wise Granger causality Wald tests

Null Hypothesis:	Obs	T-Statistic	Prob.
Inflation rate does not Granger Cause real GDP	21	1.22880	0.31883
Real GDP does not Granger Cause Inflation rate	21	3.50398	0.05469
Openness does not Granger Cause real GDP	21	0.95993	0.40391
real GDP does not Granger Cause Openness	21	0.25134	0.78077
Openness does not Granger Cause Inflation rate	21	1.56081	0.24031
Inflation rate does not Granger Cause Openness	21	2.36113	0.12632

4.8.2. Impulse response functions

The impulse response function of VAR is used to analyze the dynamic effects of the system when the endogenous variables received the impulse. Figure 4.3 shows the response of real GDP to Cholesky one standard deviation innovations in real GDP, inflation rate and openness. On the x-axis we have the time horizon or the duration of the shock while the y-axis gives the direction and intensity of the impulse. From the result we can see that real GDP innovations have a negative impact on real GDP. On the other hand, inflation rate and openness innovations have a positive impact on real GDP. The intensity is much higher for innovations in inflation rate.

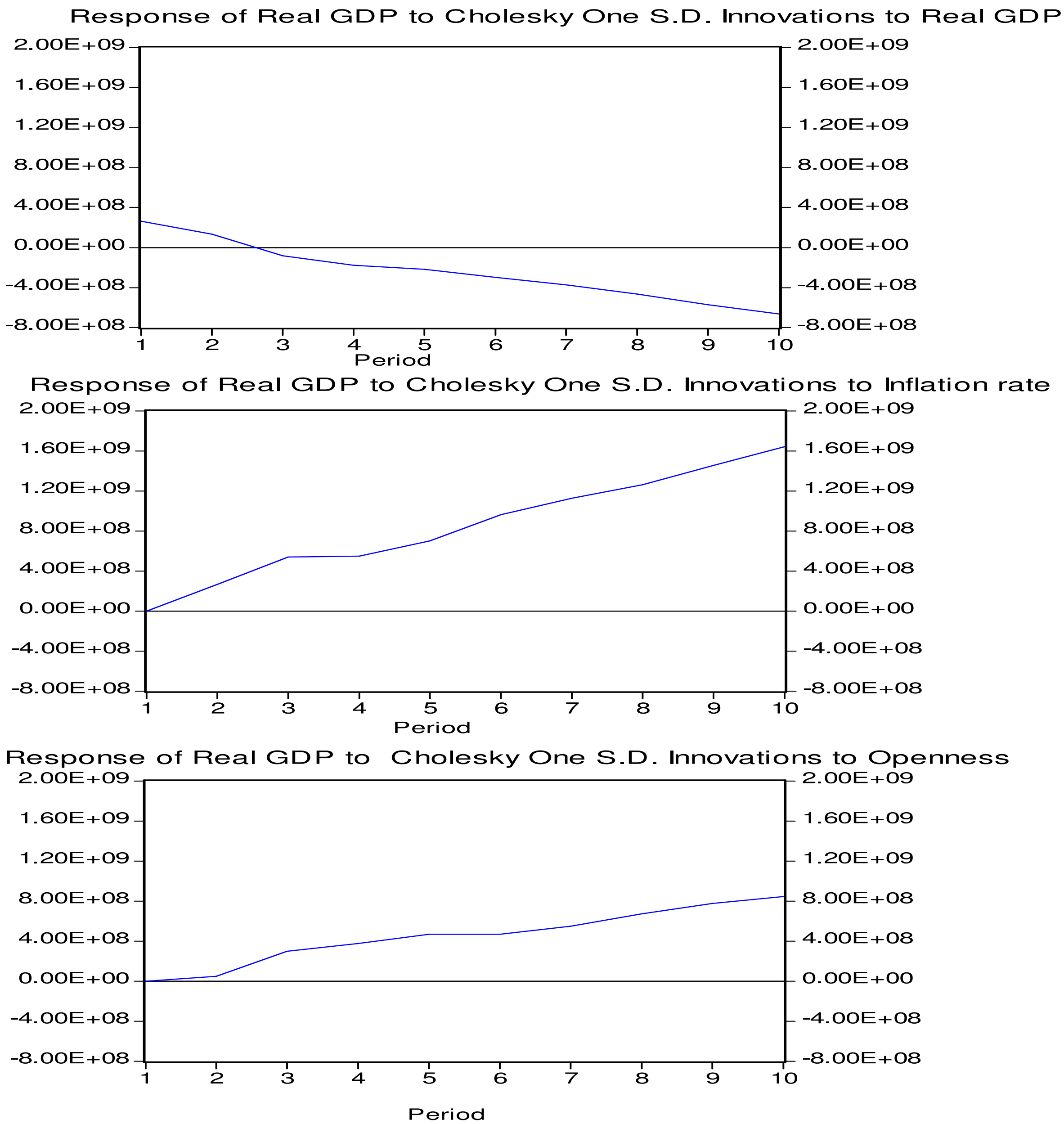

Figure 4.3: Response of real GDP to Cholesky one S.D. innovations

4.8.3. Forecast error variance decomposition

Variance decompositions offer a slightly different method for examining VAR system dynamics. The decomposition is used to understand the proportion of the fluctuation in a series explained by its own shocks versus shocks from other variables. In general, we expect a variable to explain almost all its forecast error variance at short horizons and smaller proportions at longer horizons. The results of the decomposition of real GDP are presented in Table A (in Annex) and Figure 4.4. The Cholesky ordering employed is real GDP to inflation rate to openness.

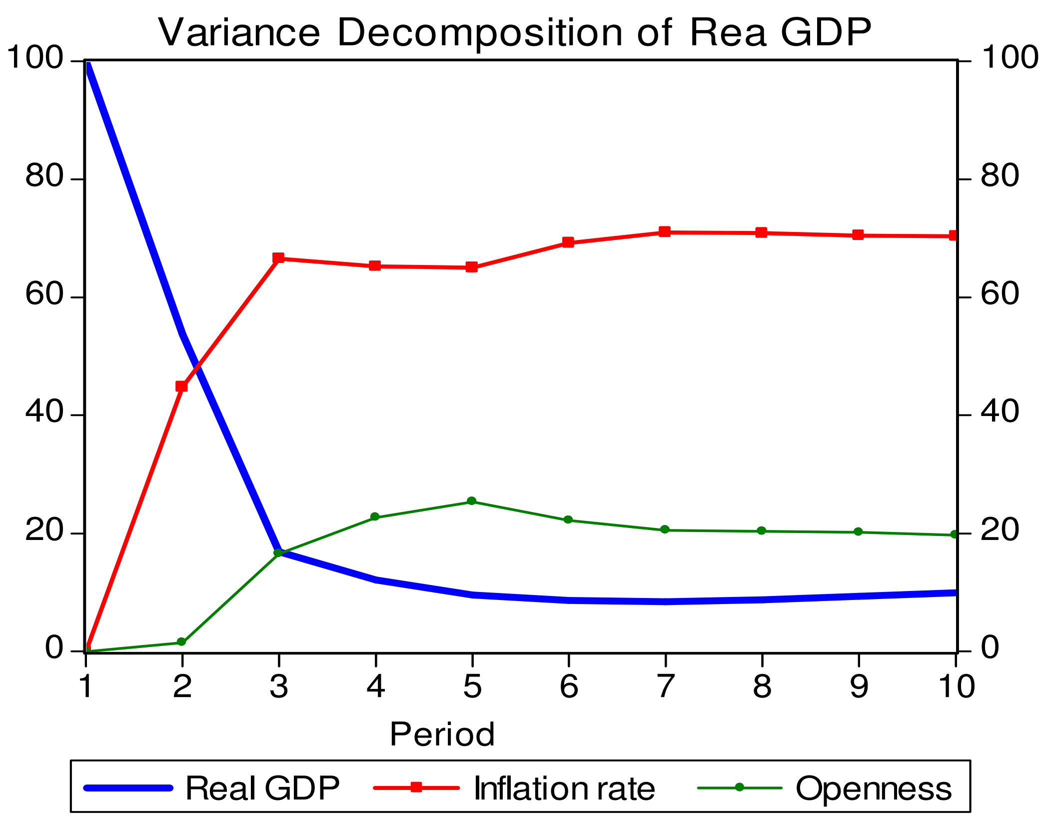

Figure 4.4: Variance Decomposition of real GDP

The variance decomposition analysis shows that, at the first horizon, variation of real GDP is explained only by its own shocks. In the second year, this figure drops to 53.7 percent; the remaining 44.8% and 1.5% of the variation in the real GDP is explained by inflation rate and openness innovations, respectively. The proportion decreases in subsequent years and reaches 9.92% by the tenth year, where much of the variation is accounted for by inflation rate innovations (about 70%).

4.9. Forecasting

One of the fundamental applications of time series analysis is forecasting. The discussions so far confirm that restricted vector autoregressive model of order two is a good fit model to describe the series. In this section we examine the forecasting accuracy of the fitted model and then make a forecast for 2013 to 2015.

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

To assess the out-of-sample forecasting ability of the model it is advisable to retain some observations at the end of the sample period which are not used to estimate the model. Therefore, using the data from 1992–2008 the estimates are derived and then the forecast is conducted for the period 2009–2012. Table 4.12 reports the forecasting accuracy statistics of the estimated model. The results indicate that the Theil-U statistic is close to zero and the mean absolute percent error is 1.96%. Thus, it appears that the estimated model for real GDP is good enough to describe the series.

Table 4.12: Forecasting Accuracy statistic

Forecast sample : 2009 to 2012	
Accuracy measure	Real GDP
Root Mean Squared Error	5.31
Mean Absolute Error	4.25
Mean Absolute percent error	1.96
Theil Inequality Coefficient	0.01

4.10 Post forecasting analysis

Out of sample forecasted values for real GDP using the error correction model are presented in Table 4.13. The results indicate that annual real GDP forecasts increase from 25.05 billion USD in 2013 to 28.36 billion USD in 2015 (constant 2005 USD).

Table 4.13: Forecasted annual real GDP from the VEC model

Forecast annual real GDP	
Year	Real GDP
2013	2.51×10^{10}
2014	2.67×10^{10}
2015	2.84×10^{10}

CHAPTER FIVE

Conclusions and Recommendations

5.1 Conclusion

This paper empirically explores the relationship between inflation and economic growth in the context of Ethiopia. A stationarity test was carried out using the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) tests. The null hypothesis of a unit root was not rejected for all series under consideration implying that the series are all non-stationary in level. Consequently, the first differenced series were considered for further analysis as the corresponding unit root tests indicated the absence of unit roots. Using annual data set on real GDP, openness and inflation for the period of 1992 to 2012, an empirical analysis has been made through the vector error correction model. For the period spanning from 1992 to 2012, there was one co-integrating relationship between inflation rate, openness and economic growth. The estimated results of the relationship between economic growth and inflation show that there exists a long-run and strong inverse relationship between inflation and real GDP in Ethiopia. The estimated long run model also shows that there exists a strong inverse long-run relationship between openness and economic growth for the country. The estimated coefficient of the error correction term (0.0143) was found to be statistically significant at the one percent level. This shows that about 1.43% of the short run disequilibrium in real GDP will be adjusted within the same year. In the short run, two time lagged real GDP has a significant positive impact on the current real GDP. Furthermore, one time lagged inflation rate has significant negative impact on real GDP. Moreover, two time lagged openness has a significant positive effect on real GDP. A further effort was made to check the causality relationships that exist between the variables by employing the VAR-Granger causality test. According to the results, a unidirectional causality was seen running from economic growth to inflation rate.

Impulse response analysis was also employed to study the dynamic relationship between the variables. The results of impulse response analysis indicate that real GDP innovations have a negative impact on real GDP whereas inflation rate and openness innovations have a positive impact on real GDP. Variance decomposition analysis was conducted in order to supplement the outcomes of impulse response analysis. The variance decomposition analysis shows that, at the first horizon, variation of real GDP is explained only by its own shocks. The proportion decreases in subsequent years and reaches 9.92% by the tenth year, where much of the variation is accounted for by inflation rate innovations.

5.2 Recommendations

From the empirical finding the following recommendations are drawn.

- As inflation has short-run and long-run negative impact on economic growth in Ethiopia, focus should be given to curb its surge.
- Further studies need to be done to investigate the influence of factors such as foreign direct investment, interest rate and money supply on economic growth.

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APPENDICES

Table A: Variance Decomposition of Real GDP

Variance Decomposition of Real GDP:				
Period	Standard error	Real GDP	Inflation rate	Openness
1	$2.62x10^8$	100.0000	0.000000	0.000000
2	$4.01x10^8$	53.72065	44.77752	1.501832
3	$7.41x10^8$	16.89353	66.51603	16.59044
4	$1.01x10^9$	12.08442	65.19506	22.72052
5	$1.34x10^9$	9.593508	65.05738	25.34911
6	$1.74x10^9$	8.612687	69.19141	22.19590
7	$2.17x10^9$	8.437033	71.00666	20.55630
8	$2.64x10^9$	8.779289	70.85211	20.36861
9	$3.17x10^9$	9.362803	70.45455	20.18265
10	$3.73x10^9$	9.922083	70.34201	19.73590
	Cholesky Ordering: Real GDP inflation rate openness			

Table B Estimated coefficient of VECM

Vector Error Correction Estimates

Cointegrating Eq:	CointEq1		
RGDP(-1)	1.000000		
INFL(-1)	$5.88x10^{9}$		
	$(1.0x10^{9})$		
	[5.60695]		
OPEN(-1)	$4.53x10^{11}$		
	$(8.4x10^{10})$		
	[5.38391]		
C	$-2.28x10^{11}$		
Error Correction:	D(RGDP)	D(INFL)	D(OPEN)
CointEq1	0.014270	$6.59x10^{-11}$	$3.70x10^{-13}$
	(0.00250)	$(9.6x10^{-11})$	$(3.0x10^{-13})$
	[5.70132]	[0.68378]	[1.22200]
D(RGDP(-1))	-0.230590	$-1.18x10^{-9}$	$-4.94x10^{-11}$
	(0.19223)	$(7.4x10^{-9})$	$(2.3x10^{-11})$
	[-1.19958]	[-0.15921]	[-2.12436]
D(RGDP(-2))	-0.538208	$-4.55x10^{-9}$	$-1.29x10^{-11}$
	(0.21338)	$(8.2x10^{-9})$	$(2.6x10^{-11})$
	[-2.52233]	[-0.55446]	[-0.49755]
D(INFL(-1))	-53851638	-0.948964	-0.003630
	$(1.7x10^{7})$	(0.63877)	(0.00201)
	[-3.24497]	[-1.48560]	[-1.80691]
D(INFL(-2))	-17591516	-0.878752	-0.000301
	$(1.5x10^{7})$	(0.57923)	(0.00182)
	[-1.16899]	[-1.51709]	[-0.16546]

D(OPEN(-1))	$-4.71x10^9$	-113.4481	-0.119399
	$(3.0x10^9)$	(116.434)	(0.36614)
	[-1.55828]	[-0.97436]	[-0.32610]
D(OPEN(-2))	$5.20x10^9$	54.28727	0.004564
	$(1.6x10^9)$	(62.4268)	(0.19631)
	[3.20533]	[0.86961]	[0.02325]
C	$1.36x10^9$	6.399401	0.063744
	$(2.6x10^8)$	(9.91665)	(0.03118)
	[5.28709]	[0.64532]	[2.04414]
R-squared	0.914379	0.381423	0.534893
Adj. R-squared	0.868275	0.048343	0.284451
Sum sq. resids	$8.90x10^{17}$	1319.029	0.013043
S.E. equation	$2.62Ex10^8$	10.07292	0.031675
F-statistic	19.83312	1.145139	2.135796
Log likelihood	-431.7987	-73.26906	47.73441
Akaike AIC	41.88559	7.739910	-3.784230
Schwarz SC	42.28350	8.137824	-3.386316
Mean dependent	$8.05x10^8$	0.719465	0.015681
S.D. dependent	$7.21x10^8$	10.32560	0.037446
Determinant resid covariance (dof adj.)		$5.08x10^{15}$	
Determinant resid covariance		$1.20x10^{15}$	
Log likelihood		-454.0014	
Akaike information criterion		45.80965	
Schwarz criterion		47.15261	