ADDIS ABABA UNIVERSITY
GRADUATE STUDIES PROGRAMME
DEPARTMENT OF STATISTICS

MULTIVARIATE TIME SERIES ANALYSIS OF INFLATION: *THE CASE OF ETHIOPIA*

BY:

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JUNE, 2011

ADDIS ABABA

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THE CASE OF ETHIOPIA

A Thesis submitted to the School of Graduate Studies of Addis Ababa University in partial fulfillment of the requirements for the Degree of Master of Science in Statistics.

By Seifu Neda

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June, 2011

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ACKNOWLEDGEMENT

First and for most, I would like to extend my unshared thanks to the almighty God for providing me the opportunity for what I have achieved and for his mercy.

My deepest gratitude goes to my thesis advisor Dr. Butte Gotu for his constructive advice and guidance in all phases of the study.

No words can suffice to express my feelings of gratitude to my brother Mr. Bereket Tolch for his generous assistance and provision of the Laptop computer throughout my research work.

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ACRONYMS

ADF	AUGMENTED DICKEY-FULLER
AIC	AKAIKE INFORMATION CRITERION
ARIMA	AUTOREGRESSIVE INTEGRATED MOVING AVERAGE
CPI	CONSUMER PRICE INDEX
CSA	CENTRAL STATISTICAL AGENCY
ECM	ERROR CORRECTION MODEL
FPI	FOOD PRICE INDEX
GDP	GROSS DOMESTIC PRODUCTION
HICE	HOUSEHOLD INCOME, CONSUMPTION AND EXPENDITURE
HICP	HARMONIZED INDEX OF CONSUMER PRICES
HQ	HANNAN-QUIN INFORMATION CRITERIA
IFPRI	INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
MAE	MEAN ABSOLUTE ERROR
MAPE	MEAN PERCENTAGE ABSOLUTE ERROR
MOFED	MINISTRY OF FINANCE AND ECONOMIC DEVELOPMENT
MPE	MEAN PERCENTAGE ERROR
MSE	MEAN SQUARE ERROR
NFPI	NONFOOD PRICE INDEX
PP	PHILLIPS AND PERRON
PPI	PRODUCER PRICE INDEX
RMSE	ROOT MEAN SQUARED ERROR
SC	SCHWARZ INFORMATION CRITERION
VAR	VECTOR AUTOREGRESSIVE
VECM	VECTOR ERROR CORRECTION MODEL

ABSTRACT

Inflation refers to a situation in which the economy's overall price level is rising. The inflation rate is the percentage change in the price level from the previous period. The measures of inflation are various price indices, such as a consumer price index (CPI), producer price index (PPI), or GDP deflator. However, inflation is usually defined as a change in the CPI over a year. The aim of this study is to fit a time series model for CPI and its components which can be used to forecast the rate of inflation in Ethiopia.

The data used are monthly observations from January 2000 to December 2010 of the Consumer Price Index (CPI), Food Price Index (FPI) and Non-food Price Index (NFPI). The vector autoregressive (VAR) model is employed for modeling.

The cointegration relations among the price indices were identified by applying Johansen's cointegration tests, while potential causal relations were examined by employing Granger's causality tests. Moreover, the short run interactions among the variables were determined through the application of impulse response analysis and variance decomposition.

The results of the research imply the existence of short term adjustments and long-term dynamics in the CPI, FPI and NFPI. Unit root test reveals that all the series are non stationary at level and stationary at first difference. The result of Johansen test indicates the existence of one cointegration relation between the variables. The final result shows that a Vector Error Correction (VEC) model of lag two with one cointegration equations best fits the data. The forecasting accuracy of this model was checked using RMSE, MAE, MAPE and Theil-U statistics. Finally, using the fitted model out-of-sample forecasts were produced for Ethiopian inflation rate.

Keywords: Inflation, Vector autoregressive**,** co-integration, Vector Error correction model and forecasting

1. INTRODUCTION

1.1. Background

Inflation can be defined as a sustained or continuous rise in the general price level or, alternatively, as a sustained or continuous fall in the value of money. Several things should be noted about this definition. First, inflation refers to the movement in the general level of prices. It does not refer to changes in one price relative to other prices. These changes are common even when the overall level of prices is stable. Second, the rise in the price level must be somewhat substantial and continue over a period longer than a day, week, or month. However, if the rise is a continuous drop instead, it is called deflation.

When the price level rises, each unit of currency buys fewer goods and services; consequently, inflation is also erosion in the purchasing power of money, a loss of real value in the internal medium of exchange and unit of account in the economy (Walgenbach et al., 1973).

There are many measures of inflation, because there are many different price indices relating to different sectors of the economy. Two widely known indices for which inflation rates are reported in many countries are the Consumer Price Index (CPI), which measures the rate of change in the prices of goods and services bought by the consumers, and the GDP deflator, which measures prices of locally-produced goods and services.

In Ethiopia raw inflation figures are reported monthly using the Consumer Price Index (CPI) by the Central Statistical Agency. The CPI is an estimation of the price changes for a typical basket of goods. In other words, the prices of everyday goods such as housing, food, education, clothing, etc., are compared from one month to the next and the difference represents the CPI. The CPI published by CSA composed of the weighted average of two sub indexes that reflect the development of prices of goods production in certain sectors of economy, namely food and non food prices.

Since the appropriate reaction of monetary policy to inflationary pressures depends among other things on the sources of inflation, it is useful to monitor, analyze and forecast sub indices of headline inflation that are defined according to the type of product contained in the overall consumer price index (CPI). The incorporation of information on developments in the sub indices helps to give a more detailed picture on the sources of inflation and the propagation of shocks to inflation across product categories and time.

There are a number of approaches available for modeling and forecasting inflation using time series. One approach, which includes only the time series being forecast, is known as univariate forecasting. 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). An alternative approach is multivariate time series forecasting. Multivariate models may consist of single equation models with exogenous explanatory variables or alternatively may include a structural or non-structural system of equations. In this investigation multiple time series approach is adopted.

1.2.Measures of inflation and Computation

A price index is a weighted average of the prices of a number of goods and services. Each price is weighted according to the economic importance of the commodity in question. Inflation rates are calculated from different price indices.

1.2.1. Price Indices

(i) The consumer price index (CPI) :

It is most widely used index to measure inflation. The index measures the cost of buying a standard basket of goods and services at different points of time. The standard basket is constituted to represent as closely as possible the consumption pattern of the population group in which case the inflation rate calculated is specific to the group and may include food and clothing, housing, fuel, entertainment and other common items of consumption in day to day life.

The formula for calculating price index is:

$$CPI = \frac{\text{Cost of basket in curret year}}{\text{Cost of basket in base year}} X100$$

(ii) Producer price index (PPI) :

It measures the general price level at the producer stage. These are generally the prices charged by the producers at the level of their first commercial transaction. These are of course the wholesale prices charged at the first link of the distribution chain. These prices are easy to obtain and monitor. The construction and interpretation of this index is broadly the same as that of the consumer price index.

(iii) GDP deflator(GDPF):

GDP is a measure of the income and expenditures of an economy. It is the total market value of all final goods and services produced within a country in a given period of time. GDP deflator is a measure of the price of all the goods and services included in Gross Domestic Product (GDP). The **GDP deflator** is defined as the ratio of nominal GDP to real GDP.

$$GDPD = \frac{\text{Nominal GDP}}{\text{Real } GDP} X\,100$$

Note that the Nominal GDP values the production of goods and services at current prices whereas Real GDP values the production of goods and services at constant prices.

1.2.2. Computation of Inflation Rate

Inflation rate (π) is the percentage change in the price index with respect to last period. It can be computed using the following formula:

$$\pi_t = \frac{(\text{price level}_t) - (\text{price level}_{t-1})}{(\text{price level}_{t-1})} X100$$

Where: t = given year, and price level can be either CPI or GDP deflator.

1.2.3. Using CPI as a measure of inflation

In this study consumer price index (CPI) is used to study the rate of inflation in Ethiopia. Since it is published every month, the CPI is the most important inflation indicator in Ethiopia. The index is calculated in relation to a base period 2006 where it was set to 100. The following Laspeyres formula is used to calculate the current period t Ethiopian CPI.

$$CPI_t = \frac{\sum W_i \left(\frac{P_t}{p_o} \right)}{\sum W_i} \times 100$$

where;

P_t is the price of commodity i in the current period t, P_o is the price of the commodity i in the reference period and W_i is the weight associated with commodity i.

The reasons to use the CPI to measure the rate of inflation in this study are:

- It is simple for calculation
- It has large Population Coverage-it covers almost all areas of the country.
- It includes many products and services
- It is commonly used measure of inflation in Ethiopia

1.3. Overview of Inflation in Ethiopia

Ethiopia is one of Africa's largest countries with an estimated population of 77 million people in 2008. According to the government data, about 38 percent of the population lived below the official poverty line in 2005, but it is likely that a larger proportion experiences extended periods of poverty due to shocks (Bigsten and Shimeles, 2008). Evidence on the welfare impacts of high food inflation on the rural population is somewhat inconclusive, but there is evidence of a significant negative impact on the urban population (Loening and Oseni, 2008).

Ethiopia's economy has grown very rapidly during the last seven years: according to official data, GDP growth averaged 11.3 percent between 2003/04 and 2009/10.The agriculture, industry and service sectors' annual average month in this period was 10.3 percent, 10.2 percent and 13 percent, respectively. In this period a slight structural change is observed in economy. The agricultural sector's share of GDP is decreasing and that of service sector is increasing. The industry sector's share is more or less constant. The GDP deflator (annual percentage change) decreased to 1.7 percent in 2009/10(MOFED, 2010).

Table 1.1: GDP deflator (base Year: 2006)

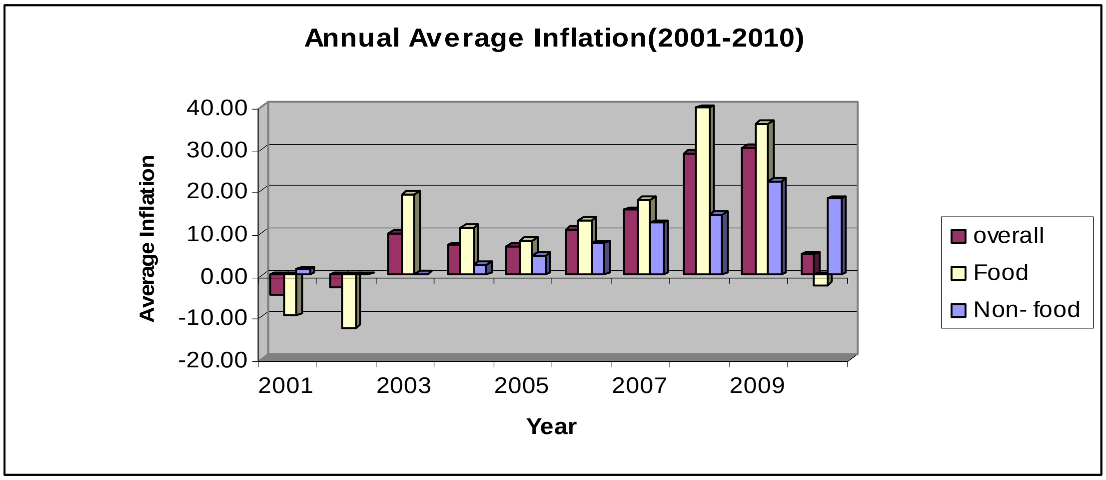
Year	GDP Deflator
1998/99	0.7
1999/00	6.9
2000/01	5.8
2001/02	3.6
2002/03	12.8
2003/04	3.9
2004/05	9.9
2005/06	11.6
2006/07	17.2
2007/08	30.3
2008/09	24.1
2009/10*	1.7
2010/11**	6
*estimate;**forecast	

Source: National Economic Accounts Directorate, Ministry of Finance and Economic Development, November 2010, Addis Ababa

Ethiopia has a long history of high and variable inflation. According to Ethiopian Central Statistical Agency (CSA) data, annual average inflation rate in 2002 was below zero. This occurs when the general price level of goods and services decreases. That is, the real value of money increases (one can buy more goods with the same amount). However, due to increasing food prices over the years 2004 to 2009, it reached all-time high levels in 2008 (39.78 percent) [Figure 1.1].Note that the "Annual Average" inflation considers price movement within the whole year but does not reflect the last price movements.

The country has not suffered from high inflation prior to 2004 and annual average inflation was only 5.2 percent during 1980/81-2003/04. The major hikes in the general price level occurred during war and drought times. The highest inflation episodes of 18.2, 21.1 and 15.5, respectively, occurred in 1984/85 due to severe drought, in 1991/92 at the peak of war, and in 2003 following drought (Loening *et al*., 2009).

Figure 1.1: Annual average inflation (2001-2010)



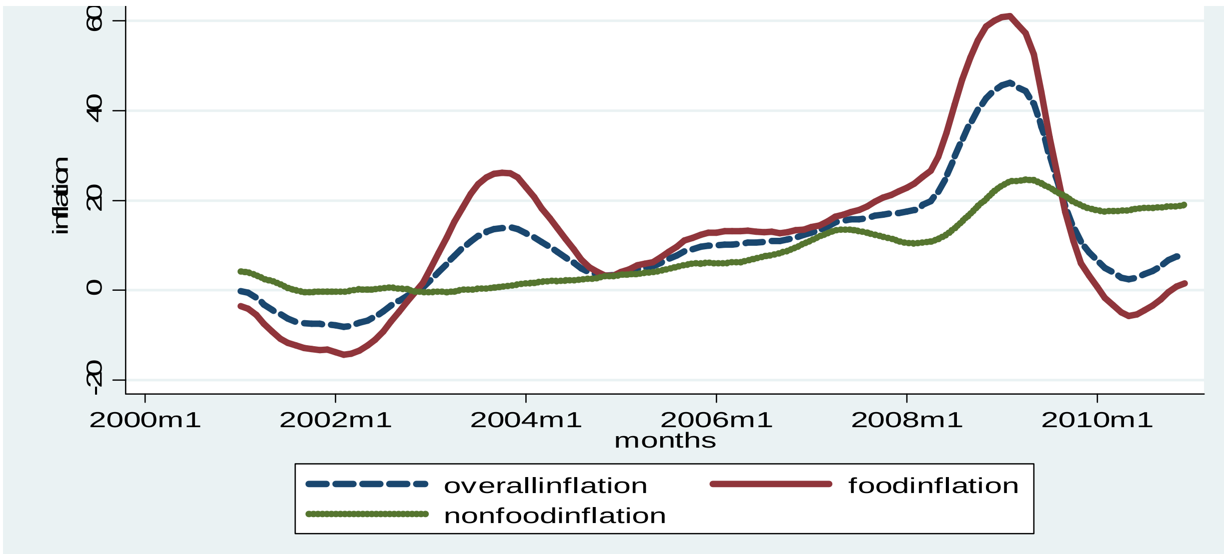
Source: Central Statistical Agency

At the national level, the overall inflation rate (annual change based on 12 months Moving Average) steadily increased from a mere 0.7 percent in December 2002 to 14.1 percent in 2003. In November 2004 this rate dropped to 3.2 percent and then after five years the rate rose to 46.1 percent by February 2009. In December 2010, overall inflation declined to 8.2 percent (CSA, 2010).[Figure 1.2]

In Ethiopia, the food inflation rates show a general trend of increasing over the years 2004 to 2009, reaching highest level in 2009. At the national level, the food inflation rate steadily increased from a mere 3.4 percent in 2004 to 13.6 percent in 2006 and rose further to 61.1 percent by February 2009. The rise in the food inflation rate was due to the rise in the prices of cereals, pulses, meat, oils and fats, milk and eggs, vegetables and fruits, spices (especially whole pepper and chili), potatoes and other tubers and stems, other food items, and food taken away from home (John *et al*., 2009).

The moving average inflation rate of non-food components has shown steady increase during the period 2002 to 2009 [Figure1.2].The inflation rate of non-food component recorded were below 20 percent before November 2008. In April and May 2009 it reached a peak of 24.6 percent. Generally, the Non-food Inflation increased at slower pace than Food inflation.

Figure 1.2: Movement of monthly inflation Rates: Overall, Food and Non-food inflation (December 2006 = 100)



Source: Central Statistical Agency (2002-2010)

1.4.Statement of the problem

Inflation is viewed as being undesirable because of some serious economic and social effects. Inflation impacts on income distribution making a random redistribution of real income. Those receiving fixed money incomes (e.g., pensioners, beneficiaries etc.) are usually disadvantaged because often their incomes are not adjusted upwards fast enough to compensate for the effects of continually rising prices. Their real incomes (i.e., the goods and services their incomes will buy) will fall. Individuals whose incomes rise more rapidly than the inflation rate will experience increasing real incomes. Generally, the pattern of income distribution tends to become more unequal than it was before inflation.

If the rate of inflation is high, individuals with money tend to buy real assets such as property, gold and antiques, which often increase in value faster than the rate of inflation. This group will gain by increasing the size of their share of the nation's wealth.

Inflation tends to increase spending and encourage borrowing at the expense of savings. If prices are rising quicker than incomes, individuals will tend to buy at current prices before goods and services become more expensive and less affordable. Some consumers may buy using higher levels of debt (i.e., borrowing) than otherwise might the case. Savings may be discouraged because with high inflation when the money saved is repaid, it can be worth much less than when it was lent and the real rate of interest may be low. As the real rate of interest rates fail to keep pace with inflation, the saver loses purchasing power, i.e., their ability to buy things falls. Rising prices are a boon to borrowers because the repayment of interest and the sum borrowed (i.e., the principal) is with lower valued money. Inflation reduces the real value of the amount they owe, as the sum repaid has less purchasing power. Of course, any gain by borrowers must be weighed against the interest they must pay.

Inflation in Ethiopia is measured by using consumer price index (CPI), which is composed of food and non food prices on monthly bases. Since food prices and the non food prices are the important sub indexes of the overall inflation, it is better to study independently to get a more detailed picture on the trend of inflation and to forecast country level inflation.

Previous research outputs on Ethiopia have used only the overall consumer price indexes to model and forecast the rate of inflation. However, the effect of the sub indices is not taken as a consideration independently. For detail picture of inflation it is necessary to study the sub indexes.

The aim of this research is to investigate inflation in Ethiopia by explicitly modeling food and non-food price index, as well as the general Consumer Price Index (CPI) by applying a vectoregressive (VAR) model.

1.5. Objectives of the Study

1.5.1. Main Objective

The main objective of this study is to fit a multivariate time series model for CPI and its components which can be used to forecast the rate of inflation in Ethiopia.

1.5.2. Specific Objectives

Specifically, this research aims:

- To study the trend of inflation in Ethiopia.
- To study the relationship between consumer price index, food and non-food price index.
- Forecast the sub components of overall inflation (food prices and non food prices) for Ethiopia

1.6. Significance of the Study

Modeling and forecasting inflation is necessary for a number of reasons. It is important from the point of view of poverty alleviation and social justice. In addition, inflation is a regressive form of taxation and among the most vulnerable to the inflation tax are the poor and fixed income groups. Inflation also causes relative price distortion as some prices adjust more slowly than others. Another form of distortion takes place during inflationary periods when absolute price changes are mistaken for relative price changes. These distortions cause efficiency losses and lower the productive base of the economy. Furthermore, inflation can discourage savings if the rate of return on savings does not reflect the increase in the level of prices. The uncertainty about future prices can also cause unexpected gains and losses in trade and industry and, thus, discourage long term contracts and investments channeling resources into speculation.

Therefore, this study will have the following purposes. First, the study acts as a case study in Ethiopian inflation for time periods from 2000-2010. This enables to have a look over the change of overall, food and non food inflation. Second, the study used to identify the long run and the short run relationship between the Consumer Price Index, food and non-food price index. This could be useful to monitor, analyze and forecast sub-indices of headline inflation. Third, the study incorporates consumer price index and its sub-indices in order to forecast inflation. This can be an alternative method to forecast inflation and it helps policy makers to take action in order to control inflation.

1.7.Limitation of the study

The main drawback of this study is that food and non- food prices are used as the determinant of inflation; other variables like money supply, wages and GDP are not included. The reason for excluding these variables from the study is difficult to obtain in monthly bases.

1.8.Organization of the study

The study is organized into five chapters. Following the introductory chapter, Chapter two gives a review of literature on inflation followed by Chapter three, which discusses the methodology and sources of data used in the study. Chapter four deals model estimation and interpretation of results. Finally, Chapter five presents conclusions of the study.

2. LITERATURE REVIEW

Several studies have investigated the relative accuracy of alternative inflation forecasting models. One approach has been to compare the accuracy of survey respondents' inflation forecasts relative to univariate time-series models. Another approach is the methodology associated with the work of Fama (1975, 1977) and extended by Fama and Gibbons (1982, 1984). This approach extracts from observed nominal interest rates the market's inherent expectation of inflation. Based on a univariate time-series modeling of the real interest rate, Fama and Gibbons (1984) conclude that the interest-rate model yields inflation forecasts with a lower error variance than a univariate model.

Meyler, *et al*. (1998) outlined autoregressive integrated moving average (ARIMA) time series models for forecasting Irish inflation. They considered two alternative approaches to the issue of identifying ARIMA models - the Box Jenkins approach and the objective penalty function methods. The emphasis is on forecast performance, which suggests that ARIMA forecast has outperformed.

Parallel investigation which is done by Kenny *et al* (1998) focused on the development of multiple time series models for forecasting Irish Inflation. The Bayesian approach to the estimation of vector autoregressive (VAR) models is employed. This allows the estimated models combine the evidence in the data with any prior information, which may also be available. A large selection of inflation indicators is assessed as potential candidates for inclusion in a VAR. The results confirm the significant improvement in forecasting performance, which can be obtained by the use of Bayesian techniques.

Golinelli and Orsi (2002) study the inflation processes in three new EU member countries: the Czech Republic, Hungary and Poland. All three countries possess a similar historico-economic background and similar economic context: they were administrative economies before and have undergone major systemic changes during the transition to a market economy. Investigating inflationary processes in these countries is of great importance because all countries experienced high inflation episodes during the years of transition, and price stabilization policies played an important role in their successful transition to a new economic system. The authors follow a methodology very close to that of Juselius (1992) in modeling inflation behavior in the countries under consideration. They use the multivariate VAR approach, grouping together those determinants that belong to main inflation theories: cost pushed inflation, foreign prices and exchange rates, and excess money. Further, a vector equilibrium correction model specification is used since it enables capturing short-term dynamics by including stationary variables and past imbalances, i.e. the "gaps" detected by previous cointegrated relationships.

Leheyda (2005) studied the determinants of inflation in Ukraine through applying cointegration analysis and error-correction modeling. A simple theoretical framework of inflation for a small open economy is being derived. The analysis is based upon three hypothesis of inflation determination: excess money supply, foreign inflation and cost-push inflation. Upon testing for the existence of the long-run cointegration relationships using the Johansen procedure for the sectoral VARs, a structural inflation function as an equilibrium error correction model was established. The long-run money demand, purchasing power parity and mark-up relationships were found, which may govern prices in the long run. In the short-run, inflation inertia, money supply, wages, exchange rate and real output as well as some exogenous shocks influence inflation dynamics.

Oomes and Ohnsorge (2005) are concerned with the problem of significant dollarization in transition economies, and its impact on the money demand and inflation. In particular, the authors study the case of Russia, and illustrate that all the measures of money aggregates that exclude foreign currency are negatively correlated with the nominal depreciation rate. This could suggest that foreign currency has been an important substitute for domestic money. The authors estimate an error correction model (ECM) for inflation in order to identify how the short-term dynamics of inflation are affected by deviations from the long-term money demand equation. They found that inflation does not react significantly to the excess supply of monetary aggregates that exclude foreign currency.

Reijer and Vlaar(2006) build two forecasting models to predict inflation Harmonised Index of Consumer Prices (HICP) for the Netherlands and for the euro area. The models provide point forecasts and prediction intervals for both the components of the HICP and the aggregated HICP –index itself. Both models are small-scale linear time series models allowing for long-run equilibrium relationships between HICP components and other variables, notably the hourly wage rate and the import or producer prices. The model for the Netherlands is used to generate the Dutch inflation projections for the eurosystem's Narrow Inflation Projection Exercise (NIPE). The recursive forecast errors for several forecast horizons are evaluated for all models, and are found to outperform a naive forecast and optimal AR models. Moreover, the same result holds for the Dutch NIPE projections, which have been provided quarterly since 1999. The aggregation method to predict total HICP inflation generally outperforms the direct method, except for long horizons in the case of the Netherlands.

Lack (2006) presented (VAR) models in order to forecast Swiss consumer price inflation. In the study in order to examine and improve the quality of the forecasting procedure, the author made several modifications and the results are compared with one another. Models specified with respect to levels of variables are superior to those specified with respect to differences in variables. Bank loans and the monetary aggregate are the most important variables for inflation forecasting. The optimized procedure reduces the root mean squared error (RMSE) of the inflation forecast to one third of the RMSE of a naive "no change" forecast.

Bokhari and Feridum (2006) empirical study is another investigation which aims at modeling and forecasting inflation in Pakistan. For this purpose a number of econometric approaches are implemented and their results are compared. In ARIMA models, adding additional lags for p and/or q necessarily reduced the sum of squares of the estimated residuals. Results further indicate that the VAR models do not perform better than the ARIMA (2, 1, 2) models and, the two factor model with ARIMA (2, 1, 2) slightly performs better than the ARIMA (2, 1, 2). Related investigation also done by Muhammad *et al.(*2006) and the main focus of the study was to forecast the monthly inflation on short-term basis.

Kiley (2008) examine the common trend in inflation for consumer prices and consumer prices excluding prices of food and energy in US. Both the personal consumption expenditure (PCE) indexes and the consumer price indexes (CPI) are examined. The statistical model employed is a bivariate integrated moving average process; this model extends a univariate model that fits the data on inflation very well. The bivariate model forecasts as well as the univariate models. The results suggest that the relationship between overall consumer prices, consumer prices excluding the prices of food and energy, and the common trend has changed significantly over time.

Vizek and Broz (2007) analyze inflation in Croatia in the period 1995-2006 using the cointegration approach. They find that mark-up and excess money are the most significant variables for explaining the short-run behaviour of inflation. Furthermore, output gap, nominal effective exchange rate, import prices, interest rates and narrow money are also found to be important in their influence on inflation.

Gabriel *et al.* (2004) applied factor models proposed by Stock and Watson (1999) and VAR and ARIMA models to generate 12-month out of sample forecasts of Austrian Harmonized Index of Consumer Prices (HICP) inflation and its sub-indices processed food, unprocessed food, energy, industrial goods and services price inflation. A sequential forecast model selection procedure tailored to this specific task is applied. It turns out that factor models possess the highest predictive accuracy for several sub-indices and that predictive accuracy can be further improved by combining the information contained in factor and VAR models for some indices. With respect to forecasting HICP inflation, analysis suggests to favor the aggregation of sub-indices forecasts. Furthermore, the sub-indices forecasts are used as a tool to give a more detailed picture of the determinants of HICP inflation from both an ex-ante and ex-post perspective.

Dejan (2007) made factor forecasts for the overall inflation and the subcomponents (energy inflation, industrial goods inflation, services inflation, processed food and the non-processed food inflation) for Slovenia. The forecasts of the factor model are compared to autoregressive (AR) and vector autoregressive (VAR) models in terms of the Root Mean Squared Error (RMSE). In addition, the factors were identified so as to give interpretation to the forecasts. Results show that the factor model is significantly better than the AR benchmark forecasts and is not worse from the VAR forecasts for all subcomponents and the headline inflation, which renders it a good tool for forecasting inflation in Slovenia.

There were numerous attempts to model inflation in developing countries. Among the studies on modeling inflation, the study by Loungani and Swagel (2001) is the one that could serve as a starting point for understanding inflation in developing countries. The author’s present stylized facts about inflation behavior in developing countries, focusing primarily on the relationship between the exchange rate regime and the sources of inflation. Another important study of inflationary processes was accomplished by Fischer *et al.* (2002) on the experiences of hyper and high inflations in various countries. The authors found that there is a very strong relationship between money growth and inflation both in the long and short run.

Callen and Chang (1999) found that the Reserve Bank of India (RBI) has moved away from a broad money target toward a “multiple indicators” approach to the conduct of monetary policy. In adopting such a framework, it is necessary to know which of the many potential indicators provide the most reliable and timely information on future developments in the target variable(s).This paper assesses which indicators provide the most useful information about future inflationary trends. It concludes that while the broad money target has been de emphasized, developments in the monetary aggregates remain an important indicator of future inflation. The exchange rate and import prices are also relevant, particularly for inflation in the manufacturing sector. Maintaining a reasonable degree of price stability while ensuring an adequate expansion of credit to assist economic growth have been the primary goals of monetary policy in India (Rangarajan, 1998). The concern with inflation emanates not only from the need to maintain overall macroeconomic stability, but also from the fact that inflation hits the poor particularly hard as they do not possess effective inflation hedges. One may say that Inflation is the single biggest enemy of the poor. Consequently, maintaining low inflation is seen as a necessary part of an effective anti-poverty strategy. By the standards of many developing countries, India has been reasonably successful in maintaining an acceptable rate of inflation. Since the early 1980s inflation has not exceeded 17 percent (measured by the year-one-year change in the monthly WPI and has averaged about 8 percent).

Laryea and Sumaila (2001) estimated a simple structural inflation equation using quarterly data to study the determinants of inflation in Tanzania. The model includes the usual suspects of inflationary process: money supply, output, exchange rate, lagged price level and foreign prices. Price is assumed to be a weighted sum of the prices of traded and non-traded goods. The price of traded goods is determined by exchange rate and foreign prices (PPP is assumed to hold). Non-traded price is assumed to be determined by money market equilibrium condition. Money demand is assumed a function of real income (output) and expected inflation. OLS regression was used after correcting for autocorrelation and heteroskedasticity to identifying long run relationships while error correction model was estimated for short run relationships.

Tadelle (2008) investigated the nature of inflation in Ethiopia and constructed a model that can be used to forecast future values. The exponential smoothing model was employed and the forecasting performance of winter (additive) models was found to be better. Two alternative approaches for model identification were considered, namely, the Box-Jenkins methodology and Penalty function criteria. For Ethiopian monthly inflation data covering the period 1997 to 2006 ARMA model was fitted. Taddele suggests SARIMA $(1, 0, 10)*(12, 0, 12)_{12}$ model using CPI for forecasting inflation in Ethiopia.

Kibrom (2008) has studied the “Sources of the Inflationary Experience in Ethiopia”. His study aims to understand the forces behind the recent inflationary process in Ethiopia. He used vector autoregressive (VAR) and single error correction models to estimate inflation dynamics. This estimated model enable to understand the short run and the long run price dynamics in Ethiopia between 1994/95 and 2007/08. The study reveals that the determinants of inflation for food and non-food are different, and depend on the time horizons under consideration.

Muche (2007) used structural vector autoregressive model (SVAR) with two variables- real output and CPI. He tried to study the effect of demand and a supply shock on real output and suggests that high inflation rate in Ethiopia is an outcome of demand and/or supply shocks. He argues that in the periods considered in the study inflation is mainly driven by demand factors.

Yohannes *et al.* (2009) used monthly data to estimate error correction models to identify the relative importance of several factors contributing to overall inflation, and its three major components, cereal prices, food prices and non-food prices. The main finding of the study indicates: in the long run, domestic food and non-food prices are determined by the exchange rate and international food and goods prices.

3. DATA AND METHODOLOGY

3.1.Data

A monthly data on inflation based on CPI, food price and non food price for the period from January, 2000 to December,2010 are obtained from the Ethiopian Central Statistics Agency (CSA) .The CPI's collected by CSA is divided in to two major groups that is food and non food indices. The non- food index includes; beverage, cigarettes and tobacco, clothing etc. On the other hand the food index includes; cereals, bread and prepared foods, meet, milk, vegetables etc.

Country level CPI aggregates the regional group indices and the contributions of the five relatively big regions in terms of the magnitude of the expenditure account for more than 95 percent .The regions considered are Oromia, Amhara, SNNP, Addis Ababa and Tigray.
The series considered are:

- Consumer Price Index (CPI)
- Food Price Index (FPI)
- Non- Food Price Index (NFPI)

3.2.Methodology

Time series is broadly defined as any series of measurements taken at different times. It can be divided in to two major parts univariate and multivariate time series. Univariate time series analysis uses only the past history of the time series being forecast plus current and past random error terms. 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 more than one time series data sets. Multivariate time series analysis is used when one wants to model and explain the interactions and co movements 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 variable. 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

The VAR model is one of the most successful, flexible, and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model.

In addition to data description and forecasting, the VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with impulse response functions and forecast error variance decompositions.

3.2.2. Stationary Vector Autoregression Model

Let $Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})^T$ denote an (n×1) vector of time series variables. The basic p-lag vector autoregressive (VAR (p)) model has the form (Hamilton,1994)

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t, t = 1, \ldots, T \quad \ldots\ldots\ldots\ldots\ldots\ldots [3.1]$$

where c denotes an n x 1 vector of constants and Π_j 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:

$$E(\varepsilon_t) = 0 \text{ and } E(\varepsilon_t \varepsilon_s') = \begin{cases} \Sigma & t = s \\ 0 & t \neq s \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots [3.2]$$

with Σ an (nxn) symmetric positive definite matrix.

Let c_i denote the i^{th} element of the vector c and let $\Pi_{ij}^{(1)}$ denote the row i, column *j* element of the matrix Π_1. Then the first row of the vector system in [3.1] specifies that

$$Y_{1t} = c_1 + \Pi_{11}^{(1)} Y_{1,t-1} + \Pi_{12}^{(1)} Y_{2,t-1} + \ldots + \Pi_{1n}^{(1)} Y_{n,t-1} + \Pi_{11}^{(2)} Y_{1,t-2} + \Pi_{12}^{(2)} Y_{2,t-2} + \ldots + \Pi_{1n}^{(2)} Y_{n,t-2}$$

$$+ \ldots + \Pi_{11}^{(p)} Y_{1,t-p} + \Pi_{12}^{(p)} Y_{2,t-p} + \ldots + \Pi_{1n}^{(p)} Y_{n,t-p} + \varepsilon_{1t} \quad \ldots\ldots\ldots\ldots[3.3]$$

Thus, a vector autoregression is a system in which each variable is regressed on a constant and *p* of its own lags as well as on *p* lags of each of the other variables in the *VAR*. Note that each regression has the same explanatory variables.

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

$$\Pi(L) Y_t = c + \varepsilon_t \quad \ldots\ldots\ldots\ldots[3.4]$$

Where $\Pi(L) = \mathbf{I}_n - \Pi_1 L - \ldots - \Pi_p L^p$. The VAR (p) is stable if the roots of

$$\det(I_n - \Pi_1 z - \cdots - \Pi_p Z^p) = 0 \quad \ldots\ldots\ldots\ldots[3.5]$$

lie outside the complex unit circle (have modulus greater than one), or, equivalently, if the eigen values of the companion matrix

$$F = \begin{pmatrix} \Pi_1 & \Pi_2 & \cdots & \Pi_n \\ I_n & 0 & \cdots & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & I_n & 0 \end{pmatrix} \quad \ldots\ldots\ldots\ldots[3.6]$$

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

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

$$\mu = (I_n - \Pi_1 - \cdots - \Pi_p)^{-1} c$$

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

$$Y_t - \mu = \Pi_1 (Y_{t-1} - \mu) + \Pi_2 (Y_{t-2} - \mu) + \cdots + \Pi_p(Yt{-}p - \mu) + \varepsilon_t \quad \ldots\ldots [3.7]$$

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

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \Phi D_t + GX_t + \varepsilon_t \ldots\ldots [3.8]$$

Where Dt represents an ($l \times 1$) matrix of deterministic components, X_t represents an $n \times 1$ vector of exogenous variables, and Φ and G are parameter matrices.

3.2.3. Testing Stationarity: Unit root test

Before fitting a particular model to time series data, the series must be made stationary. Stationarity occurs in a time series when the mean and autocovariances of the series remains constant over the time series. Therefore, the stochastic process Y_t is said to be stationary if:

i. $E(Y_t) = \boldsymbol{\mu}$, constant for all value of t ……[3.9]

ii. The $Cov(Y_t, Y_{t-j}) = \Gamma_{j=} E[(Y_t - \mu)(Y_{t-j} - \mu)^T] = \Gamma_{-j}^T$ for all t and j= 0,1,2,… …[3.10]

Condition [3.9] means that all Y_t have the same finite mean vector μ and [3.10] requires that the autocovariances of the process do not depend on t but just on the time period j the two vectors Y_t and Y_{t-j} are apart. Therefore, a process is stationary if its first and second moments are time invariant.

Frequently, differencing may be needed to achieve stationarity. To test for stationarity of a series several procedures has been developed. The most popular ones are 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 basics features of unit root tests (Hamilton, 1994).

Consider a simple AR (1) process:

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

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 assumed to be white noise. If |ρ|>1, y is a non stationary series and the variance of y increases with time and approaches infinity. If |ρ|<1, y is a stationary series. Thus, the hypothesis of (trend) stationarity can be evaluated by testing whether the absolute value ρ of is strictly less than one.

Hypothesis:

H_0: The series are not stationary (ρ=1)

H_1: The series are stationary (ρ<1)

3.2.3.1. Augmented Dickey-Fuller (ADF) Test

The standard Dickey-Fuller test is conducted by estimating equation [3.11] after subtracting y_{t-1} from both side of the equation

$$\Delta Y_t = \alpha Y_{t-1} + X_t'\delta + \varepsilon_t \text{ ....[3.12]}$$

Where α=ρ-1 and $\Delta Y_t = Y_t - Y_{t-1}$. The null and alternative hypotheses may be written as,

$$H_0\text{: } \alpha=0$$

$$H_1\text{: } \alpha<0 \text{ ....[3.13]}$$

and evaluated using the conventional t-ratio for α:

$$t_\alpha = \hat{\alpha} / (se(\hat{\alpha})) \text{ ....[3.14]}$$

Where $\hat{\alpha}$ is the estimate of α , and *se*($\hat{\alpha}$) is the coefficient standard error.

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. In addition, MacKinnon estimates response surfaces for the simulation results, permitting the calculation of Dickey-Fuller critical values and p-values for arbitrary sample sizes.

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

$$\Delta Y_t = \alpha Y_{t-1} + X_t'\delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + ... + \beta_p \Delta Y_{t-p} + U_t \text{............................[3.15]}$$

This augmented specification is then used to test [3.13] using the t -ratio [3.14]. An important result obtained by Fuller 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 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 [3.13], and modifies the t -ratio of the α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\hat{t}_\alpha = t_\alpha (\frac{\gamma_0}{f_0})^{1/2} - \frac{T(f_0 - \gamma_0)(se(\hat{\alpha}))}{2 f_0^{1/2} s} \text{..[3.16]}$$

where $\hat{\alpha}$ is the estimate, t_α is the t -ratio of α, $se(\hat{\alpha})$ is coefficient standard error and s is the standard error of the test regression. In addition, γ_0 is a consistent estimate of the error variance in [3.13] (calculated as $(T-k)s^2/T$, where k is the number of regressors). The remaining term, f_0 , is an estimator of the residual spectrum at frequency zero.

3.2.4. Estimating Order of the VAR

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

$$C(m) = \log|\hat{\Sigma}_m| + c_T \cdot \varphi(m,k) \quad \text{……………………………….[3.17]}$$

Where $\hat{\Sigma}_m = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$ is the residual covariance matrix estimator for a model of order m, φ(m,k) 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 criterion. The term $\log|\hat{\Sigma}_m|$ is a non-increasing function of the order m while φ(m,k) increases with 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 information criterion (SC), Hannan-Quin (HQ) information criteria:

$$AIC(m) = \log|\hat{\Sigma}_m| + \frac{2}{T}mk^2 \quad \text{……………..…………[3.18]}$$

$$SC(m) = \log|\hat{\Sigma}_m| + \frac{\log T}{T}mk^2 \quad \text{……………………[3.19]}$$

$$HQ(m) = \log|\hat{\Sigma}_m| + \frac{2\log\log T}{T}mk^2 \quad \text{…………….....[3.20]}$$

In each case φ(m,k) $=mk^2$ is the number of VAR parameters in a model with order *m* and *k* is number of variables. Denoting by $\hat{p}$ (AIC), $\hat{p}$ (SC) and $\hat{p}$ (HQ) the order selected by AIC,SC and HQ ,respectively ,the following relations hold for samples of fixed size T≥16:(Lutkepohl, 2005).

$$\hat{p}(SC) \leq \hat{p}(HQ) \leq \hat{p}(AIC)$$

Thus, among the three criteria AIC always suggests the largest order, SC chooses the smallest order and HQ is between .Of course, this does not preclude the possibility that all three criteria agree in their choice of VAR order. The HQ and SC criteria are both consistent, that is, the order estimated with these criteria converges in probability or almost surely to the true VAR order p under quit general conditions, if p_{max} exceeds the true order.

3.2.5. Cointegration Analysis

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 significant 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 (non-stationary) 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 k integrated variables of order one (I(1)), there may exist up to k-1 independent linear relationships that are I(0). In general, there can be $r \leq k-1$ linearly independent cointegrating vectors, which are gathered together into the k x r cointegrating matrix. Thus, each element in the r-dimensional vector is I(0), while each element in the k-dimensional vector is I(1) [Engle and Granger, 1987].

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. It is assumed a vector autoregressive model of order p and is expressed as follows:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + Bx_t + \varepsilon_t$$

where y_t is a k-vector of non-stationary I(1) variables(If a non-stationary series, y_t must be differenced d times before it becomes stationary, then it is said to be integrated of order d. This would be written $y_t \sim I(d)$), X_t is a d-vector of deterministic variables, and ε_t is a vector of innovations.

We may rewrite this VAR as,

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + Bx_t + \varepsilon_t \qquad [3.21]$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I, \ \Gamma_i = -\sum_{j=i+1}^{p} A_j \qquad [3.22]$$

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

Johansen (1988) proposed two tests for estimating the number of cointegrating vectors: the Trace statistics and Maximum Eigenvalue. Trace statistics investigate the null hypothesis of r cointegrating relations against the alternative of n cointegrating relations, where n is the number of variables in the system for r = 0, 1, 2…n-1. Define $\hat{\lambda}_i$,i=1,2,…,k to be a complex modulus of eigenvalues of $\hat{\Pi}$ and let them be ordered such that $\lambda_1 > \lambda_2 > \ldots > \lambda_n$. The trace statistic computed as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \log[1-\lambda_i] \qquad [3.23]$$

The Maximum Eigenvalue statistic tests the null hypothesis of r cointegrating relations against the alternative of r+1 cointegrating relations for r = 0, 1, 2…n-1. This test statistic is computed as:

$$\lambda_{\max}(r, r+1) = -T \log(1-\lambda_{r+1}) \qquad [3.24]$$

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

3.2.6. Vector Error Correction (VEC) Models

A vector error correction (VEC) model is a restricted VAR designed for use with non-stationary series that are known to be cointegrated. The VEC has cointegration relations built into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments.

When the variables are cointegrated, the corresponding error correction representations must be included in the system. By doing so, one can avoid misspecification and omission of the important constraints. Thus, the VAR in [3.21] can be reparametrized as a Vector Error Correction Model (VECM) form: (Hamelton, 1994.)

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + Bx_t + \varepsilon_t ....[3.25]$$

$$where\ : \Pi = -I_n + \sum_{i=1}^{p} A_i,\ \Gamma_i = -\sum_{j=i+1}^{p} A_j, \text{and } \mathrm{I_n} \text{ is an identidy matrix}$$

The above specification of VECM contains information on both the short and the long run adjustment to changes in y_t via estimating Γ and Π, respectively. Matrix Π can be decomposed as Π=αβ', where α is nxr matrix of speed of adjustments, and β is an nxr matrix of parameters which determines the cointegrating relationships matrix of long- run coefficients such that $\beta' y_{t-k}$ represent the multiple cointegration relationships. The columns of β are interpreted as long-run equilibrium relationships between variables. The matrix α determines the speed of adjustment towards this equilibrium. Values of α close to zero imply slow convergence and r,0≤r≤n is the rank of the matrix Π and represents the number of cointegrating vectors in the system which can be determined using the Johansen Maximum Likelihood method .

3.2.7. Model Checking

A wide range of procedures is available for checking the adequacy of VAR and VECMs. 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

Portmanteau autocorrelation test

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

$$H_0: E(\varepsilon_t \varepsilon'_{t-i}) = 0 \quad (i = 1,2,\ldots) \qquad [3.26]$$

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

$$Q_h = T\sum_{j=1}^{h} tr(\hat{\gamma}'_j \hat{\gamma}_0^{-1} \hat{\gamma}_j \hat{\gamma}_0^{-1}) \qquad [3.27]$$

where

$$\hat{\gamma}_j = T^{-1} \sum_{t=j+1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}'_{t-j} \qquad [3.28]$$

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

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

$$Q^*_h = T^2 \sum_{j=1}^{h} \frac{1}{T-j} tr(\hat{\gamma}'_j \hat{\gamma}_0^{-1} \hat{\gamma}_j \hat{\gamma}_0^{-1}) \qquad [3.29]$$

instead of the original version [3.27].

Autocorrelation LM Test

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

$$u_t = D_1 u_{t-1} + ... + D_h u_{t-h} + v_t \text{..}[3.30]$$

The quantity v_t denotes a white nose error term. Thus, to test autocorrelation in u_t, we test

$H_0 : D_1 = \ldots = D_h = 0$ against $H_1 : D_j \neq 0$ for at least one $j < h$

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 estimate the regular VAR model ($u_t = v_t$). So the constrained case estimates are simple. To determine the test statistic we begin with the auxiliary regression model

$$\hat{U} = BZ + D\hat{U} + E \text{..}[3.31]$$

where

$$\hat{U} = [\hat{u}_1 ... \hat{u}_T]$$
$$Z_t = [1^T \; y_t^T ... y_{t-p+1}^T]^T \text{..}[3.32]$$
$$Z = [Z_0 ... Z_{T-1}]$$
$$D = [D_1 ... D_h]$$

Define F_i such that

$$\hat{U} F_i \hat{U}^T = \sum_{t=i+1}^{T} \hat{u}_t \hat{u}^T{}_{t-i} \text{..}[3.33]$$

Then

$$F = [F_1 ... F_h]$$
$$\hat{U} = (I \otimes \hat{U}) F^T \text{..}[3.34]$$

This yields the least squares estimate of D

$$\hat{D} = \hat{U}\hat{U}^T [\hat{U}\hat{U}^T - \hat{U}Z^T (ZZ^T)^{-1} Z\hat{U}^T]^{-1} \text{..}[3.35]$$

The standard χ^2 test statistic for testing whether $D = 0$ (no autocorrelation) is

Under H_0 $\lambda_{LM}(h) = vec(\hat{D})^T ([\hat{U}\hat{U}^T - \hat{U}Z^T (ZZ^T)^{-1} Z\hat{U}^T] \otimes \hat{\Sigma}_u) vec(\hat{D}) \text{..}[3.36]$

$$\lambda_{LM}(h) \xrightarrow{d} \chi^2 (hk^2) \text{..}[3.37]$$

3.2.7.2. Normality of the Residuals

Lütkepohl (1993) suggests using the multivariate generalization of the Jarque-Bera test (Jarque & Bera 1987) to test the multivariate normality of the u_t. This tests the skewness and kurtosis properties of the u_t (3rd & 4th moments) against those of a multivariate normal distribution of the appropriate dimension.

$$H_0 : E(u_t^s)^3 = 0 \,(skewness) \quad and \quad E(u_t^s)^4 = 3 \,(kurtosis)$$
$$H_1 : E(u_t^s)^3 \neq 0 \quad or \quad E(u_t^s)^4 \neq 3$$

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

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

$$\hat{u}_t = (y_t - \bar{y}) - \hat{A}_1(y_{t-1} - \bar{y}) - \ldots - \hat{A}_p(y_{t-p} - \bar{y}) \quad [3.38]$$
$$\hat{\Sigma}_u = \frac{1}{T - kp - 1} \sum_{t=1}^{T} \hat{u}_t \hat{u}_t^T$$

Let $\hat{P}$ be the matrix satisfying $\hat{P}\hat{P}^T = \hat{\Sigma}_u$ such that plim($\hat{P} - P$)=0

Now we define the standardized residuals and their sample moments

$$\hat{w}_t = \hat{P}^{-1}\hat{u}_t$$

$$\hat{b}_1 = (\hat{b}_{11} \ldots \hat{b}_{k1}) \ni \hat{b}_{i1} = \frac{1}{T}\sum_{t=1}^{T} \hat{w}^3{}_{it} \quad [3.39]$$

$$\hat{b}_2 = (\hat{b}_{12} \ldots \hat{b}_{k2}) \ni \hat{b}_{i2} = \frac{1}{T}\sum_{t=1}^{T} \hat{w}^4{}_{it}$$

Finally our test statistics are

$$\lambda_S = T\hat{b}_1^T \hat{b}_1 / 6$$

$$\lambda_S = T(\hat{b}_2 - 3\underline{1})^T (\hat{b}_2 - 3\underline{1}) / 24 \quad [3.40]$$

$$\lambda_{SK} = \lambda_S + \lambda_K$$

The third and fourth moments of u_t should be 0 and 3.

Under the third moment assumption

$$\lambda_S \xrightarrow{d} \chi^2(k) \quad [3.41]$$

Under the fourth moment assumption

$$\lambda_k \xrightarrow{d} \chi^2(k) \quad [3.42]$$

Under both assumptions

$$\lambda_{Sk} \xrightarrow{d} \chi^2(2k) \quad [3.43]$$

3.2.8. Forecasting

Forecasting is one of the main objectives of multivariate time series analysis. Forecasting from a VAR model is similar to forecasting from a univariate models.

Consider first the problem of forecasting future values of Y_t when the parameters Π of the VAR (p) process are assumed to be known and there are no deterministic terms or exogenous variables. The best linear predictor, in terms of minimum mean squared error (MSE), of Y_{t+1}

or 1-step forecast based on information available at time T is

$$Y_{T+1|T} = c + \Pi_1 Y_T + \cdots + \Pi_p Y_{T-p+1} \ldots\ldots [3.44]$$

for $T \geq p$.

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

$$Y_{T+h|T} = c + \Pi_1 Y_{T+h-1|T} + \cdots + \Pi_p Y_{T+h-p|T} \ldots\ldots [3.45]$$

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

$$Y_{T+h} - Y_{T+h|T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s} \ldots\ldots [3.46]$$

Where the matrices Ψ_s are determined by recursive substitution

$$\Psi s = \sum_{j=1}^{p-1} \Psi_{s-j} \Pi_j \ldots\ldots [3.47]$$

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

$$\Sigma(h) = MSE(Y_{T+h} - Y_{T+h|T} = \sum_{s=0}^{h-1} \Psi_s \Sigma \Psi_s' \ldots\ldots [3.48]$$

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

$$\hat{Y}_{T+h|T} = \hat{\Pi}_1 \hat{Y}_{T+h-1|T} + \ldots + \hat{\Pi}_p \hat{Y}_{T+h-p|T} \ldots\ldots [3.49]$$

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

$$Y_{T+h} - \hat{Y}_{T+h|T} = \sum_{s=0}^{h-1} \psi_s \ \varepsilon_{T+h-s} + (Y_{T+h} - \hat{Y}_{T+h|T}) \ldots\ldots [3.50]$$

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

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

In practice, the second term MSE ($Y_{T+h} - \hat{Y}_{T+h|T}$) is often ignored and $\hat{\Sigma}(h)$ is computed using [3.48] as

$$\hat{\Sigma}(h) = \sum_{s=0}^{h-1} \hat{\Psi}_s \hat{\Sigma} \hat{\Psi}_s{}' \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.51]$$

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

Lütkepohl (1991) gives an approximation to MSE ($Y_{T+h} - \hat{Y}_{T+h|T}$) which may be interpreted as a finite sample correction to [3.51]

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. To the consumer of forecasts, it is the accuracy of the future forecast that is most important.

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

$$\upsilon_t = Y_t - F_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.52]$$

Usually, Ft is calculated using data $Y_1,\ldots,Y_{t-1}$.It is a one step forecast because it is forecasting one period ahead of the last observation used in the calculation .Therefore ,we describe υ_t as a one step forecast error. It is the difference between the observation Y_t and forecast made using all observations up to but not including Y_t.

If there are observations and forecasts for T time periods, then there will be n error terms, and the following standard statistical measures can be defined:

$$\textit{Mean Error}\ (ME) = \frac{1}{T}\sum_{t=1}^{T} \upsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.53]$$

$$\textit{Mean absolute Error}\ (MAE) = \frac{1}{T}\sum_{t=1}^{T} |\upsilon_t| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.54]$$

$$\textit{Mean Squared Error}\ (MSE) = \frac{1}{T}\sum_{t=1}^{T} \upsilon_t^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.55]$$

Equation [3.52] can be used to compute the error for each period. These can then be averaged as in equation [3.53] 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 you if there is systematic under-or over forecasting, called the forecasting bias. It does not give much indication as to the size of the typical errors.

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

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

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

Then the following two relative measures are frequently used:

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

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

Equation [3.56] can be used to compute the percentage error for any time period .These can be averaged as in equation [3.57] to give the mean percentage error. However, as with the ME, the MPE is likely to be small since positive and negative PEs tend to offset one another. Hence the MAPE is defined using absolute values of PE in equation [3.58].

Alternatively, Theil's U statistic can be used as a measure of forecasting accuracy. Like MAPE statistics, 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: $$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}F_t^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n}Y_t^2}}$$

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 tests

One of the main uses of VAR models is forecasting. The structure of the VAR model provides information about a variable's or a group of variables' forecasting ability for other variables. The following intuitive notion of a variable's forecasting ability is due to Granger (1969). If a variable, or group of variables, y_1 is found to be helpful for predicting another variable, or group of variables, y_2 then y_1 is said to Granger-cause y_2; otherwise it is said to fail to Granger-cause y_2. Formally, y_1 fails to Granger-cause y_2 if for all s > 0 the MSE of a forecast of $y_{2,t+s}$ based on ($y_{2,t}$, $y_{2,t-1}$, . . .) is the same as the MSE of a forecast of $y_{2,t+s}$ based on ($y_{2,t}$, $y_{2,t-1}$, . . .) and ($y_{1,t}$, $y_{1,t-1}$, . . .). Clearly, the notion of Granger causality does not imply true causality. It only implies forecasting ability. If y_1 causes y_2 and y_2 also causes y_1 the process $(y_{1t}', y_{2t}')'$ is called a feedback system.

For example, in a bivariate VAR (p) model for Yt = $(y_{1t}, y_{2t})'$, y_2 fails to Granger-cause y_1 if all of the p VAR coefficient matrices $\Pi_1, \ldots, \Pi_p$ are lower triangular.

That is, the VAR(p) model has the form

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & 0 \\ \pi_{21}^1 & \pi_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \ldots + \begin{pmatrix} \pi_{11}^p & 0 \\ \pi_{21}^p & \pi_{22}^p \end{pmatrix} \begin{pmatrix} y_{1t-p} \\ y_{2t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

So that all of the coefficients on lagged values of y_2 are 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 $\Pi_1, \ldots, \Pi_p$ are diagonal. Testing for Granger non-causality in general n variable VAR(p) models follows the same logic used for bivariate models.

3.2.10.2. Impulse Response Functions

Any covariance stationary VAR (p) process has a Wold representation of the form

$$Y_t = \mu + \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \cdots \text{ ....[3.59]}$$

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 Ys as the dynamic multiplier or impulse response

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial y_{i,t}}{\partial \varepsilon_{j,t-s}} = \psi_{ij}^s \qquad \text{i,j = 1, …, n ....[3.60]}$$

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

$$
\left.\begin{aligned}
y_{1t} &= c_1 + \gamma'_{11}Y_{t-1} + \cdots + \gamma'_{1p}Y_{t-p} + \eta_{1t} \\
y_{2t} &= c_1 + \beta_{21}y_{1t} + \gamma'_{21}Y_{t-1} + \cdots + \gamma'_{2p}Y_{t-p} + \eta_{2t} \\
y_{3t} &= c_1 + \beta_{31}y_{1t} + \beta_{32}y_{2t} + \gamma'_{31}Y_{t-1} + \cdots + \gamma'3pY_{t-p} + \eta_{3t} \\
&\vdots \\
y_{nt} &= c_1 + \beta_{n1}y_{1t} + \cdots + \beta_{n,n-1}y_{n-1,t} + \gamma'_{n1}Y_{t-1} + \cdots + \gamma'_{np}Y_{t-p} + \eta_{nt}
\end{aligned}\right\} \quad \ldots\ldots[3.61]
$$

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

$$
BY_t = c + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \cdots + \Gamma_p Y_{t-p} + \eta_t \quad \ldots\ldots[3.62]
$$

Where

$$
B = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ -\beta_{21} & 1 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -\beta_{n1} & -\beta_{n2} & \cdots & 1 \end{pmatrix} \quad \ldots\ldots[3.63]
$$

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 [3.61] imposes the recursive causal ordering

$$
y_1 \rightarrow y_2 \rightarrow \cdots \rightarrow y_n \quad \ldots\ldots[3.64]
$$

The ordering means that the contemporaneous values of the variables to the left of the arrow $\rightarrow$ affect the contemporaneous values of the variables to the right of the arrow but not vice-versa. These contemporaneous effects are captured by the coefficients β_{ij} in [3.61].For example, the ordering $y_1 \rightarrow y_2 \rightarrow y_3$ 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 $y_2 \rightarrow y_3 \rightarrow y_1$ imposes the restrictions: y_{2t} affects y_{3t} and 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 representation of Y_t based on the orthogonal errors η_t is given by

$$Yt = \mu + \Theta_0\eta_t + \Theta_1\eta_{t-1} + \Theta_2\eta_{t-2} + \cdots \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.64]$$

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

$$\frac{\partial y_{i,t+s}}{\partial \eta_{j,t}} = \frac{\partial y_{it}}{\partial \eta_{j,t-s}} = \theta_{ij}^{s}, \; i,j=1,\ldots n; \; s>0 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.65]$$

where θ_{ij}^{s} is the (i, j) th element of Θs. 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.

In practice, the orthogonal IRF [3.65] based on the triangular VAR (p) [3.61] may be computed directly from the parameters of the non triangular VAR (p) [3.1] as follows. First, decompose the residual covariance matrix Σ as

$$\Sigma = ADA' \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...[3.66]$$

where A is an invertible lower triangular matrix with 1's along the diagonal and D is a diagonal matrix with positive diagonal elements. Next, define the structural errors as

$$\eta_t = A^{-1}\varepsilon_t$$

These structural errors are orthogonal by construction since $var(\eta_t) = A^{-1}\Sigma A^{-1'} = A^{-1}ADA'A^{-1'} = D$. Finally, re-express the Wald representation [3.61] as

$$\begin{aligned} Y_t &= \mu + AA^{-1}\varepsilon_t + \Psi_1 AA^{-1}\varepsilon_{t-1} + \Psi_2 AA^{-1}\varepsilon_{t-2} + \cdots \\ &= \mu + \Theta_0\eta_t + \Theta_1\eta_{t-1} + \Theta_2\eta_{t-2} + \cdots \end{aligned}$$

where $\Theta_j = \Psi_j A$. Notice that the structural B matrix in [3.62] is equal to A^{-1}.

3.2.10.3. Forecast Error Variance Decompositions

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 η_j? Using the orthogonal shocks $\boldsymbol{\eta_t}$ the h-step ahead forecast error vector, with known VAR coefficients, may be expressed as

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

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

$$y_{i,T+h} - y_{i,T+h|T} = \sum_{s=0}^{h-1} \theta_{i1}^{s} \eta_{1,T+h-s} + \ldots + \sum_{s=0}^{h-1} \theta_{in}^{s} \eta_{n,T+h-s}$$

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

$$\text{var}(y_{i,T+h} - y_{i,T+h|T}) = \sigma_{\eta 1}^{2} \sum_{s=0}^{h-1} \left(\theta_{i1}^{s}\right)^{2} + \ldots + \sigma_{\eta n}^{2} \sum_{s=0}^{h-1} \left(\theta_{in}^{s}\right)^{2}$$

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

$$F\,EV\,D_{i,j}(h) = \frac{\sigma_{\eta j}^{2} \sum_{s=0}^{h-1} \left(\theta_{ij}^{s} \right)^{2}}{\sigma_{\eta 1}^{2} \sum_{s=0}^{h-1} \left(\theta_{i1}^{s} \right) + \ldots + \sigma_{\eta n}^{2} \sum_{s=0}^{h-1} \left(\theta_{in}^{s} \right)^{2}}, \quad i,j=1,\ldots,n \qquad \ldots\ldots\ldots\ldots[3.67]$$

In a VAR with n variables there will be n^2 F $EVD_{i,j}(h)$ values. It must be kept in mind that the FEVD in [3.67] depends on the recursive causal ordering used to identify the structural shocks η_t and is not unique. Different causal orderings will produce different FEVD values.

4. RESULTS AND DISCUSSION

The study is based on the monthly time series data observed from January 2000 to December 2010. The total number of observation is 132. In this chapter the results of the VAR model specifications used for forecasting inflation will be presented. The discussion begins by describing the data set and the results from the model selection procedure. Then, results will be interpreted and discussed. Finally, inflation will be predicted. Data analysis was performed by STATA10 and Eviews 5.

4.1.Descriptive Analysis

In the empirical analysis, three aggregate series namely, the general consumer price index (CPI), food price index (FPI), and non-food price index (NFPI) were used (Figure 4.1). Some descriptive statistics including the mean, the standard deviation, the coefficient of variation, minimum and maximum values of the series under study are presented in Table 4.1.The results show that the values of summary statistics are more or less similar except standard deviation which indicates relatively high dispersion for FPI.

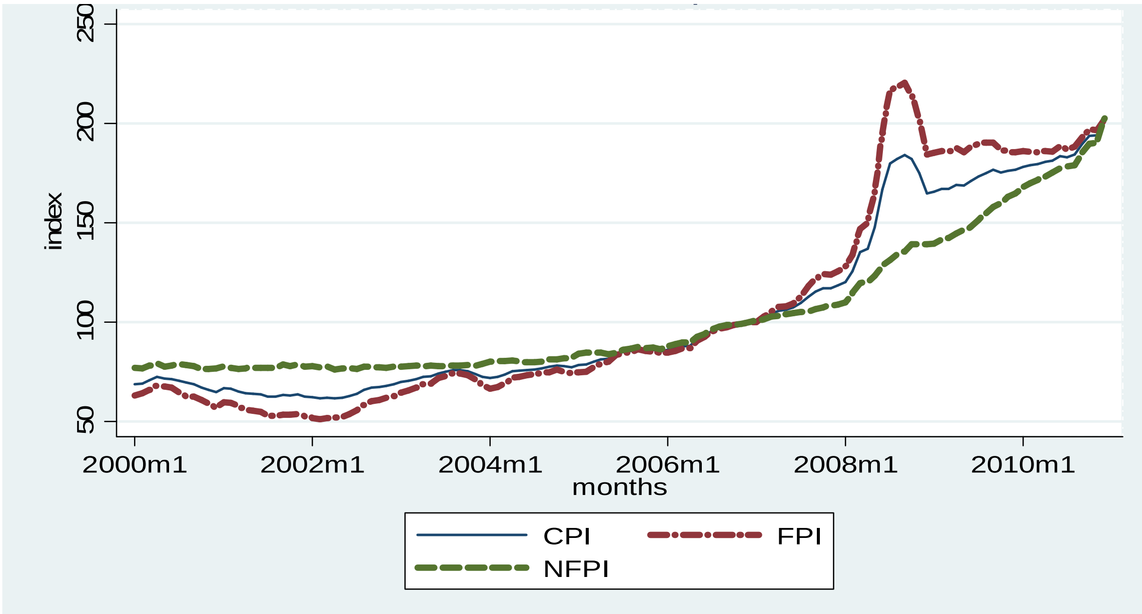
Table4.1: Descriptive Statistics of Series: 2000m1 to 2010m12

Series	Obs	Mean	Std. Dev.	Min	Max	CV
Food price Index	132	105.864	53.10999	51.2	220.6	0.50168
Non-food Index	132	103.242	34.00806	76.3	202.7	0.3294
Consumer Price Index	132	104.524	44.47867	61.7	202.4	0.42553

4.2.Unit Root Properties of Individual Series

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

Figure4. 1: Time series plot of FPI, NFPI and CPI



The stationarity of the series can be tested by using an Augmented Dickey-Fuller test and a Phillips and Perron test. The hypothesis to be tested is

H_o: the series is non stationary against

H_1: the series is stationary

The results of ADF and PP tests, with intercept but no trend, and with intercept and trend both at level and first difference for each series are presented in Table 4.2 and 4.3. The critical values used for the tests are the McKinnon (1991) critical values. Test results, presented in Table 4.1, indicate that the null hypothesis that the series in levels contain unit root could not be rejected for all the three series. That is, the respective p-values are greater than conventional significance levels α =0.05 and 0.01

Since the null hypothesis cannot be rejected, in order to determine the order of integration of the non stationary time series, the same tests were applied to their first differences (Figure 4.2). The order of integration is the number of unit roots that should be contained in the series so as to be stationary.

Table 4.2: Unit root test results (At level)

Series	Level with Intercept				Level with Intercept and trend			
	Test Statistic		Prob.*		Test Statistic		Prob.*	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
FPI	-0.23	0.13	0.93	0.96	-2.59	-2.04	0.287	0.571
NFPI	8.75	7.8	1.00	1.00	3.12	2.79	1.00	1.00
CPI	0.97	1.2	0.99	0.99	-1.62	-1.43	0.781	0.848
Critical Value (5%)	-2.88				-3.44			

*MacKinnon (1996) one-sided p-values

The results in table 4.3 indicate that the null hypothesis is rejected for the first differences of the three indices given that p-values less than 5% level of significance with intercept and trend in PP test. Similar result were also obtained from ADF test except D(FPI) is not significant at 5% level ,but it is significant at 10% level of significance. This implies that the three time series are integrated of degree one (I (1)).

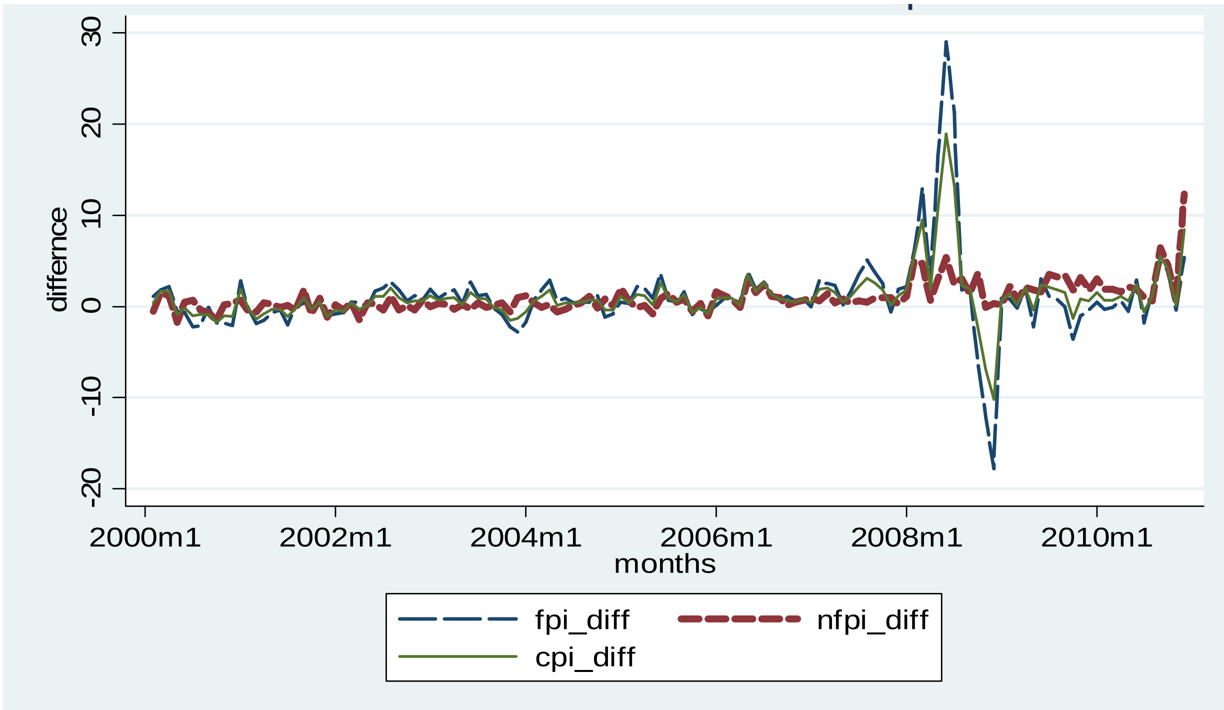
Therefore, the ADF and PP test shows that all series are non stationary in the levels, and stationary in the first difference.

Table 4.3: Unit root test results (after first difference)

Series	With Intercept				With Intercept and trend			
	Test Statistic		Prob.*		Test Statistic		Prob.*	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
D(FPI)	-5.25	-5.37	0.000	0.000	-5.34	-5.45	0.0001	0.0001
D(NFPI)	-0.98	-7.37	0.75	0.000	-3.44	-9.54	0.0506	0.000
D(CPI)	-5.11	-5.21	0.000	0.000	-5.48	-5.62	0.0001	0.000
Critical Value (5%)	-2.88				-3.44			

*MacKinnon (1996) one-sided p-value

Figure 4.2: Time series plot of FPI, NFPI and CPI (after first deference)



4.3.VAR Model Specification

4.3.1. Estimating for Order of the VAR

Specifying the lag length has strong implications for subsequent modeling choices. Choosing too few lags could lead to systematic variation in the residuals whereas if too many lags are chosen it comes with the penalty of fewer degrees of freedom (as adding another lag, adds p x p variables). For determining the appropriate lag length for the VAR model the Akaike information criterion (AIC), Schwarz information criterion (SC), Hannan-Quin(HQ) information criteria were used.

In Table 4.4, the lag length selection criterion is tabulated. The AIC, SC and HQ test suggest appropriate lag length for the VAR model is two (2).That is, the best fitting model is the one that minimize AIC or SC or HQ .

Table 4.4: VAR lag order selection results (Eviews 5 software)

Lag	AIC	SC	HQ
0	18.10153	18.16976	18.12925
1	6.874417	7.147347	6.985287
2	**6.291188***	**6.768816***	**6.485212***
3	6.388295	7.070621	6.665472
4	6.334326	7.221350	6.694656
5	6.387624	7.479346	6.831108
6	6.444070	7.740490	6.970707
7	6.525384	8.026502	7.135174
8	6.535768	8.241583	7.228710

*indicates lag order selected by the criterion

4.3.2. Cointegration analysis

Since the variables are integrated of order one, we proceed to test for co-integration. Johansen (1995) cointegration test is applied at the predetermined lag 2. In these tests, Maximum Eigenvalue statistic or Trace statistic is compared to special critical values. The maximum eigenvalue and trace tests proceed sequentially from the first hypothesis –no cointegration– to an increasing number of cointegrating vectors.

The results of Cointegration tests for *FPI, NFPI and CPI* are reported in Table 4.5. The trace statistic indicates that at least one cointegrating vector ($r \geq 1$) exists in the system at the 95 percent confidence level (estimated LR statistic, 42.59 > 29.79, 95 per cent critical value). In order to cross check for identifying the specific number of cointegrating vectors, the maximal eigenvalue statistic is further employed. This statistic confirms the existence of only one cointegrating relationship at the 95 per cent confidence level in this system (estimated LR statistic, 36.15 > 21.13, 95 per cent critical value).

Table4. 5: Johansen Cointegration test results (By assumption: Linear deterministic trend)

Number of Cointegrating vector	Eigenvalue	Trace Test			Maximum Eigenvalue Test		
		Statistic	0.05 Critical Value	Prob.**	Statistic	0.05 Critical Value	Prob.**
None *	0.244378	42.58801	29.79707	0.001	36.14758	21.13162	0.0002
At most 1	0.037482	6.440438	15.49471	0.6434	4.928085	14.2646	0.7509
At most 2	0.011655	1.512353	3.841466	0.2188	1.512353	3.841466	0.2188

Normalized cointegrating coefficients (standard error in parentheses)

CPI	FPI	NFPI
1.000000	-0.572110	-0.347224
	(0.01644)	(0.02652)

* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

From the Johansen cointegration test, it was determined that the rank of cointegration matrix to be equal to one. Consequently, the cointegrating vector is given by

$$\beta = (1,-0.57211,-0.347224)$$

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

$$CPI_t = 0.57211 FPI_t + 0.347224\ NFPI_t$$

4.4.Model Estimation

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

$$\Delta Y_t = \mu + \sum_{i=1}^{p} \Gamma_i \Delta Y_{t-i} + \alpha B X_{t-1} + \varepsilon_t ,$$

where BX_t is the error correction term given by $\beta' Y_t$ and β is the cointegrating vector. The responses of CPI, FPI and NFPI to short-term output movements are captured by the Γ_i coefficient matrices. The α coefficient vector reveals the speed of adjustment to the equilibrium, which measures the deviation from the long-run relationship between the price indexes.

Coefficient estimates of the VEC model are presented in Table A1 (appendix).This table consists of two parts; the first part contains the detail of the Cointegration vector which is derived by normalizing the consumer price index. The result indicate that ,the long run coefficients of consumer price index has a positive long run relationship with food price index and non-food price as expected in the theory. The log run equation is given as follows:

$$CPI_t = 8.08 + 0.57211 FPI_t + 0.347224\, NFPI_t$$

The value 0.572 suggests that a one unit increase in food price index induces, on average, an increase of about 0.57 units in consumer price index. Similarly, one unit increase in non-food price index leads to an increase of about 0.34 units in the CPI.

The second part of the Table A1 contains the coefficients of the error correction terms (cointEq1) for the cointegration vector. These coefficients are called the adjustment coefficients. This measures the short-run adjustments of the deviations of the endogenous variables from their long- run values.

The result in Table A1 shows all adjustment coefficients have a positive sign (0.35, 0.29, and 0.43) and are significant with large t-values. The figures in this row identify the fraction of the long-term gap that is closed in each period (months). The first equation, i.e. the CPI equation((Eq(i) below), shows that the remaining long-term CPI gap closes by about 35 percent in each period, while the gaps in the FPI and NFPI equations close by about 29 and 43 percent, respectively(Eq(ii) and Eq(iii)). These results imply that FPI and CPI take longer to achieve equilibrium after a shock.

Finally, using the error correction term as another independent variable in the unrestricted VAR model we can estimate the following Vector Error Correction Model.

Model of Overall consumer Price index:

$$\Delta CPI_t = 0.35*(CPI_{t-1} - 0.57*FPI_{t-1} - 0.35*NFPI_{t-1} - 8.08) - 1.89*\Delta CPI_{t-1}$$
$$- 1.52*\Delta CPI_{t-2} + 1.54*\Delta FPI_{t-1} + 0.84*\Delta FPI_{t-2} + 0.61*\Delta NFPI_{t-1}$$
$$+ 0.31*\Delta NFPI_{t-2} + 1.05 \ldots\ldots Eq(i)$$

Model of Food Price index:

$$\Delta FPI_t = 0.29*(CPI_{t-1} - 0.57*FPI_{t-1} - 0.35*NFPI_{t-1} - 8.08) - 3.11*\Delta CPI_{t-1}$$
$$-1.46*\Delta CPI_{t-2} + 2.52*\Delta FPI_{t-1} + 0.78*\Delta FPI_{t-2} + 1.13*\Delta NFPI_{t-1}$$
$$+ 0.04*\Delta NFPI_{t-2} + 1.04 \ldots\ldots Eq(ii)$$

Model of Non-Food Price index :

$$\Delta NFPI_t = 0.43*(CPI_{t-1} - 0.57*FPI_{t-1} - 0.35*NFPI_{t-1} - 8.08) + 0.68*\Delta CPI_{t-1}$$
$$- 1.41*\Delta CPI_{t-2} - 0.28*\Delta FPI_{t-1} + 0.79*\Delta FPI_{t-2} - 0.49*\Delta NFPI_{t-1}$$
$$+ 0.59*\Delta NFPI_{t-2} + 1.06 \ldots\ldots Eq(iii)$$

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

4.5.Model checking

In order to ascertain whether the model provides an appropriate representation, a test for misspecification should be performed.

4.5.1. Test of residual autocorrelation

Table 4.6 presents the results of the portmanteau Q-statistic and Lagrange Multiplier (LM) test for VEC model residual serial correlation. These tests are used to test for the overall significance of the residual autocorrelations up to lag 2. Both results suggest that there is no obvious residual autocorrelation problem up to lag2 because all *p*-values are larger than the 0.05 level of significance.

Table 4.6: Test of residual autocorrelation

	Q-Stat		Adj Q-Stat		LM-Stat	
Lags	Value	Prob.	Value	Prob.	Value	Prob.
1	0.627597	NA*	0.632500	NA*	15.96945	0.0675
2	4.697620	NA*	4.766618	NA*	15.24462	0.0844
*The test is valid only for lags larger than the VAR lag order.						

4.5.2. Testing Normality

Multivariate version of the Jarque Bera tests is used to test the normality of the residuals. It compares the 3rd and 4th moments (skewness and kurtosis) to those from a normal distribution. The test has null hypothesis indicating that the error term in the model has skwness and kurtosis corresponding to a normal distribution. The results in Table4.7 show that the null hypothesis has to be rejected. It might be the case that there is the presence of outlier in the model. Furthermore, failed Jarque-Bera test is a common phenomenon, which will not crucially distort final results.

Table4. 7: Normality test

Component	Jarque-Bera	Prob.	Skewness	prob.	Kurtosis	prob.
1	11.86488	0.0027	0.395411	0.0616	4.536162	0.0038
2	35.27649	0.0000	0.797182	0.0005	7.154341	0.0000
3	35.06530	0.0000	1.584777	0.0000	9.831389	0.2548
Joint	82.20667	0.0000	49.46681	0.0000	32.73985	0.0000

4.5.3. Lag exclusion test

To check whether the chosen lag is optimal, Wald lag exclusion test is used. Given that VAR modeling requires uniform lag length for each variable, the result in Table 4.8 shows that second lag is significant for all variables at 5 percent level of significance. That is, the value in the square brackets indicates probability value for the corresponding chi-square statistics. Therefore; VAR (2) is found suitable for the data set and hence could be adopted.

Table 4.8: VAR Lag Exclusion Wald Tests

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

Variable	FPI	NFPI	CPI	Joint
Lag 1	573.3280	99.87952	521.8284	681.2605
	[0.000000]*	[0.000000]*	[0.000000]*	[0.00000]*
Lag 2	91.63188	12.27600	82.15677	113.3686
	[0.000000]*	[0.006495]*	[0.000000]*	[0.00000]*
Df	3	3	3	9

*denotes rejection at 5% significance level.

4.6. Structural Analysis

4.6.1. Granger-Causality Test

Granger causality test is considered a useful technique for determining whether one time series is good for forecasting the other. The concept of granger causality test is explored when the coefficients of the lagged of the other variables is not zero. Table 4.9 presents results from the pair wise Granger-causality tests which were obtained with two lag for each variable.

Table 4.9:Pair-wise Granger-causality tests (Eviews 5 software)

Null Hypothesis:	Obs	F-Statistic	Probability
FPI does not Granger Cause CPI	130	4.21216	0.01697
CPI does not Granger Cause FPI		1.88335	0.15637
NFPI does not Granger Cause CPI	130	3.71978	0.02696
CPI does not Granger Cause NFPI		6.16563	0.00279
NFPI does not Granger Cause FPI	130	1.75564	0.17703
FPI does not Granger Cause NFPI		6.02432	0.00318

The result show that FPI granger cause CPI, while the converse is not true. This indicates that the change in FPI precedes the change in the CPI, and that the last information on the FPI provides important information to forecast future value of the CPI. In addition, the FPI granger cause NFPI but not true in opposite. Furthermore NFPI is ganger cause CPI and vice versa at 5% rejection level.

4.6.2. Impulse-Response Functions

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

Impulse responses are presented in Figures (A1-A4) (Appendix) with the Cholesky ordering CPI, FPI, and NFPI. The x-axis gives the time horizon or the duration of the shock whilst the y-axis gives the direction and intensity of the impulse or the percent variation in the dependent variable away from its base line level. Figure A1 shows the responses of CPI, FPI and NFPI with respect to one standard deviation innovation in CPI .The result indicates CPI innovations has a positive impact on FPI. It exhibits a rising trend initially and reaches 1.88 and it stabilizes at around 7 month time horizon. Moreover, the shocks of CPI have initially positive effect on NFPI and then become negative around 18 month time horizon.

Impulse responses for FPI in FigureA2 show that the effect of a one standard deviation shock to CPI is positive. It rises initially to 3.35, then rises to 7.62 and then stabilizes around 7-month time horizon. This figure also shows that FPI innovation has a positive effect on NFPI and its effect is smooth. It rises in the beginning, reaches 0.2, and then stabilizes. Finally, Figure A3 provides evidence that NFPI innovation has a positive effect on CPI and has a negative effect on FPI.

4.6.3. Forecast Error Variance Decomposition

Variance decompositions offer a slightly different method for examining VAR system dynamics. The decomposition 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 the endogenous variables of the model are presented in Table A5 and plotted in FigureA4-A6. These two results provide the percentage of the forecast error in each variable that could be attributed to innovations of the other variables, for different time period. The Cholesky ordering employed is CPI, FPI and NFPI.

The variance decomposition analysis result in table A5 (i) shows that, at the first horizon variation of CPI explained only by its own shock. In the second month 98.34 % of the variability in the CPI fluctuations is explained by its own innovations. The proportion decreases for the following months to 89.42% after10 months. FPI shocks increase the percentage as the contribution of CPI shock decreases and it reaches 10% after 8 months. The role of NFPI shocks is not significant in determining CPI.

The result in table A5(ii) shows that, in the first month, 94.72% of the variability of the FPI is explained by CPI shocks and its own effect is only 5.27%.After 10 months, the variability comes from CPI decreases to 82.04% and the FPI increase to 17.87%. The NFPI do not have significant variability to forecast FPI shocks.

The variance decomposition of NFPI in table A5(iii) shows that, the variability explain by its own fluctuations is less than 2.17 % over 20 months .However, the innovations of CPI is 35.07% and FPI is 62.74%. In the medium and the long-run periods, the percentage explained by innovations of CPI increases and the percentage explained by FPI innovations decline.

4.7.Forecasting

One of the fundamental applications of time series analysis or developing a time series model is forecasting. The previous discussion confirm that vector error correction model of order two is a good model to describe the series. In this section we examine the forecasting accuracy of the fitted model and then make a forecast for January 2011 to December 2013.

4.7.1. Evaluation of accuracy

The mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and Theil U statistics were used to assess the forecasting performance. The RMSE and MAE statistics are scale-dependent measures, but allow a comparison between the actual and forecast values. The Theil-U statistics is independent of the scale of the variables and is constructed to lie between zero and one, zero indicating a perfect fit. In evaluating the performance of the forecasting models, the lower the RMSE, MAE, MAPE and Theil-U statistic, 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 2000m1–2008m12 the estimates are derived and then the forecast is conducted for the period 2009m1–2010m12. Table 4.10 reports the forecasting accuracy statistics of the estimated model. The result indicates that the estimated models are good enough to describe the series. The RMSE, MAE, MAPE values are less than 5% and Theil-U statistics is close to zero, which indicates the difference between the actual value and the predicted value is very small. That is, the predictive powers of the models are better and suitable for n-step ahead forecasting.

Moreover, Figures A7, A8 and A9 show the (in sample) forecasts compared with the actual series over the period January 2000 to December 2010. One can observe from the figures that the forecast series are much closer to the actual series.

Table 4.10: Forecasting Accuracy statistic

Forecast sample :January 2009 to December 2010			
	Variables		
Accuracy measure	CPI	FPI	NFPI
Root Mean Squared Error	3.21	5.001	3.01
Mean Absolute Error	2.14	3.24	1.98
Mean Absolute percent error	1.19	1.72	1.25
Theil Inequality Coefficient	0.009	0.01	0.009

4.7.2. Post forecasting analysis

Post forecasted values for the CPI and its subcomponents, using the error correction model are presented in Table A6 of appendix. The result indicates the non-food price index has high increasing trend and reached 446.55 at the end of 2013.However, the food price index and consumer price index exhibit slow increment rates and will reach 279.02 and 350.93 in December 2013, respectively.

Using the forecasted result of these three indices we can compute predictable inflation rates. Accordingly, overall inflation rate (annual change based on 12 months Moving Average) will reach 17.82, 19.82 and 22.20 percent at the end of 2011, 2012 and 2013 respectively. Food inflation rate will rise from 8.2 in December 2010 to 12.75 after three years and has slight change compared to overall inflation. However, non-food inflation rate will increase to 32.12 percent in December 2013 from 19.1 percent in December 2010.

Table 4.11: Forecasted annual inflation rate from the VEC model

Forecasted Annual average Inflation rate			
Year	Food inflation	Non food inflation	Overall inflation
2011	7.31	22.92	13.58
2012	10.34	28.84	18.37
2013	12.05	30.87	20.92

Furthermore, Table 4.11 presents the predicted annual average inflation rate. The result indicates annual food inflation rate increases from -2.34 percent in 2010 to 7.31 in 2011 and then reaches 12.05 percent in 2013. Similarly, annual average overall and non-food inflation will increase to 30.87 and 20.92, respectively in 2013.

5. CONCLUSION

Inflation rate is one of the important indicators of economic well-being .Low inflation indicates positive effect on the economy while high inflation gives negative signals. Therefore the prediction of future rate of inflation in a given country helps to outline relevant policy measures.

The aim of this study is to fit a multivariate time series model for CPI and its components which can be used to forecast the rate of inflation in Ethiopia. The analysis was based on the monthly data from January 2000 to December 2010. The series used in this study are Consumer Price Index, Food Price Index and Non food Price Index. In the study vector autoregressive model (VAR) is used.

Over the time period considered, all the three series showed an increasing pattern, that is, there is the sign of non stationarity in each of the series. In order to examine the VAR model, the unit root tests (ADF and Phillips-Perron tests), identification of the number of lags and cointegration analyses were conducted. Unit root tests indicate that all indices are non stationary at level and are stationary at first difference at 5 percent significant level. The Johansen cointegration test suggests that there is at least one cointegration vector, which describes the long run relationship between CPI, FPI and NFPI. The appropriate number of lag identified was two. Furthermore, Granger causality test are applied to explore the long run relationships. The result indicates, in the long run FPI used to forecast CPI and NFPI, where as NFPI should not be used to forecast FPI, at 5 percent significance.

Impulse response function and Variance decomposition were also employed to study the dynamic relationship of the variables. The results of impulse response functions obtained by applying a standard Choleski decomposition indicate that a CPI innovation have a positive impact on FPI and have initially positive effect on NFPI and then becomes negative. In addition, FPI shocks have a positive effect on CPI and NFPI innovations. Furthermore, NFPI innovation has a positive effect on CPI and has a negative effect on FPI.

Variance decomposition analysis, conducted in order to supplement the outcomes of impulse response analysis, indicated similar results. It was observed that CPI is mainly explained by its own innovations and slightly by FPI shocks. While FPI is largely explained by CPI shocks, and its own effect is very limited. Moreover, the variability of NFPI explained by its own innovations is less than 3 % over 20 periods. This shows that, it is highly explained by FPI and NFPI shocks.

Finally, forecasting is made using vector error correction (VEC) model. The result of mean square error (MSE), mean absolute error (MAE) and Theil's U statistics indicate that the estimated model is good enough to describe the data set. Therefore, post forecasts are made for CPI as well as two sub-indices from January 2011 to 2013. The result indicates the non-food price index has high increasing trend whereas the food price index and consumer price index exhibit slow increment rates. Moreover, the inflation rates were also projected from the predicted price indices.

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7. APPENDICES

Table A1: Vector Error Correction Estimates

Vector Error Correction Estimates
Sample (adjusted): 2000M04 2010M12
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
CPI(-1)	1.000000		
FPI(-1)	-0.572110		
	(0.01644)		
	[-34.8007]		
NFPI(-1)	-0.347224		
	(0.02652)		
	[-13.0920]		
C	-8.080883		
Error Correction:	**D(CPI)**	**D(FPI)**	**D(NFPI)**
CointEq1	***0.350551***	***0.293719***	***0.430757***
	(0.11933)	(0.18213)	(0.06959)
	[2.93762]	[1.61265]	[6.18995]
D(CPI(-1))	-1.886088	-3.113442	0.675181
	(2.49008)	(3.80056)	(1.45212)
	[-0.75744]	[-0.81921]	[0.46496]
D(CPI(-2))	-1.522075	-1.456059	-1.406394
	(2.49998)	(3.81567)	(1.45789)
	[-0.60884]	[-0.38160]	[-0.96467]
D(FPI(-1))	1.543913	2.518886	-0.284526
	(1.43195)	(2.18556)	(0.83506)
	[1.07819]	[1.15251]	[-0.34072]
D(FPI(-2))	0.839291	0.782520	0.797547
	(1.44019)	(2.19814)	(0.83987)
	[0.58276]	[0.35599]	[0.94961]
D(NFPI(-1))	0.611060	1.133957	-0.493071
	(1.05174)	(1.60525)	(0.61334)
	[0.58100]	[0.70641]	[-0.80392]
D(NFPI(-2))	0.314152	0.041324	0.589455
	(1.05863)	(1.61576)	(0.61735)
	[0.29675]	[0.02558]	[0.95481]
C	1.049696	1.043538	1.059654
	(0.31635)	(0.48283)	(0.18448)
	[3.31818]	[2.16128]	[5.74395]
R-squared	0.435919	0.436117	0.440729

Adj. R-squared	0.403286	0.403496	0.408374
Sum sq. resids	614.3193	1431.078	208.9174
S.E. equation	2.253224	3.439054	1.313998
F-statistic	13.35830	13.36908	13.62186
Log likelihood	-283.7084	-338.2540	-214.1402
Akaike AIC	4.522610	5.368279	3.444035
Schwarz SC	4.699963	5.545632	3.621387
Mean dependent	1.019380	1.055039	0.965116
S.D. dependent	2.916898	4.452790	1.708328

Determinant resid covariance (dof adj.)	0.118799
Determinant resid covariance	0.098039
Log likelihood	-399.3350
Akaike information criterion	6.609846
Schwarz criterion	7.208411

Table A2: Least squares estimator of FPI

Dependent Variable: D(FPI)
Method: Least Squares
Sample (adjusted): 2000M04 2010M12
Included observations: 129 after adjustments
D(FPI) = C(9)*(CPI(-1) - 0.5721101532*FPI(-1) - 0.3472242489*NFPI(-1) - 8.080883) + C(10)*D(CPI(-1)) + C(11)*D(CPI(-2)) + C(12)*D(FPI(-1)) + C(13)*D(FPI(-2)) + C(14)*D(NFPI(-1)) + C(15)*D(NFPI(-2)) + C(16)

	Coefficient	Std. Error	t-Statistic	Prob.
C(9)	0.293719	0.182134	1.612654	0.1094
C(10)	-3.113442	3.800558	-0.819207	0.4143
C(11)	-1.456059	3.815667	-0.381600	0.7034
C(12)	2.518886	2.185562	1.152512	0.2514
C(13)	0.782520	2.198141	0.355992	0.7225
C(14)	1.133957	1.605249	0.706406	0.4813
C(15)	0.041324	1.615760	0.025575	0.9796
C(16)	1.043538	0.482834	2.161277	0.0326

R-squared	0.436117	Mean dependent var	1.055039
Adjusted R-squared	0.403496	S.D. dependent var	4.452790
S.E. of regression	3.439054	Akaike info criterion	5.368279
Sum squared resid	1431.078	Schwarz criterion	5.545632
Log likelihood	-338.2540	Durbin-Watson stat	1.885062

Table A3: Least squares estimator of NFPI

Dependent Variable: D(NFPI)
Method: Least Squares
Date: 04/13/11 Time: 10:04
Sample (adjusted): 2000M04 2010M12
Included observations: 129 after adjustments
D(NFPI) = C(17)*(CPI(-1) - 0.5721101532*FPI(-1) - 0.3472242489
*NFPI(-1) - 8.080883) + C(18)*D(CPI(-1)) + C(19)*D(CPI(-2)) +
C(20)*D(FPI(-1)) + C(21)*D(FPI(-2)) + C(22)*D(NFPI(-1)) + C(23)
*D(NFPI(-2)) + C(24)

	Coefficient	Std. Error	t-Statistic	Prob.
C(17)	0.430757	0.069590	6.189945	0.0000
C(18)	0.675181	1.452122	0.464962	0.6428
C(19)	-1.406394	1.457895	-0.964675	0.3366
C(20)	-0.284526	0.835062	-0.340725	0.7339
C(21)	0.797547	0.839869	0.949609	0.3442
C(22)	-0.493071	0.613336	-0.803917	0.4230
C(23)	0.589455	0.617351	0.954813	0.3416
C(24)	1.059654	0.184482	5.743947	0.0000

R-squared	0.440729	Mean dependent var	0.965116
Adjusted R-squared	0.408374	S.D. dependent var	1.708328
S.E. of regression	1.313998	Akaike info criterion	3.444035
Sum squared resid	208.9174	Schwarz criterion	3.621387
Log likelihood	-214.1402	Durbin-Watson stat	1.687343

Table A4: Least squares estimator of CPI

Dependent Variable: D(CPI)
Method: Least Squares
Date: 04/13/11 Time: 09:39
Sample (adjusted): 2000M04 2010M12
Included observations: 129 after adjustments
D(CPI) = C(1)*(CPI(-1) - 0.5721101532*FPI(-1) - 0.3472242489*NFPI(
-1) - 8.080883) + C(2)*D(CPI(-1)) + C(3)*D(CPI(-2)) + C(4)
*D(FPI(-1)) + C(5)*D(FPI(-2)) + C(6)*D(NFPI(-1)) + C(7)*D(NFPI(
-2)) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.350551	0.119332	2.937619	0.0040
C(2)	-1.886088	2.490077	-0.757441	0.4503
C(3)	-1.522075	2.499976	-0.608836	0.5438
C(4)	1.543913	1.431952	1.078188	0.2831
C(5)	0.839291	1.440194	0.582762	0.5611
C(6)	0.611060	1.051739	0.581000	0.5623
C(7)	0.314152	1.058625	0.296755	0.7672
C(8)	1.049696	0.316347	3.318184	0.0012

R-squared	0.435919	Mean dependent var	1.019380
Adjusted R-squared	0.403286	S.D. dependent var	2.916898
S.E. of regression	2.253224	Akaike info criterion	4.522610
Sum squared resid	614.3193	Schwarz criterion	4.699963
Log likelihood	-283.7084	Durbin-Watson stat	1.833313

Table A5: Variance decomposition results

Table A5(i) Variance Decomposition of CPI:

Period	S.E.	CPI	FPI	NFPI
1	2.253224	100.0000	0.000000	0.000000
2	4.343197	98.34036	1.611999	0.047637
3	6.270604	95.55680	4.324481	0.118715
4	7.996186	93.44508	6.434133	0.120785
7	12.14819	90.34376	9.568187	0.088057
8	13.29234	89.90711	10.01305	0.079846
9	14.35575	89.61560	10.31159	0.072805
10	15.35382	89.42355	10.50978	0.066667
15	19.68801	89.20956	10.74602	0.044422
20	23.37195	89.51401	10.45415	0.031836

Table A5(ii) Variance Decomposition of FPI:

Period	S.E.	CPI	FPI	NFPI
1	3.439054	94.72795	5.272050	0.000000
2	6.814377	93.25066	6.663270	0.086065
3	9.944591	89.59756	10.29243	0.110013
4	12.74228	87.07764	12.80043	0.121927
7	19.42777	83.34006	16.56461	0.095330
8	21.25250	82.76694	17.14333	0.089730
9	22.94022	82.35175	17.56307	0.085176
10	24.51644	82.04430	17.87429	0.081417
15	31.26027	81.30559	18.62580	0.068606
20	36.83471	81.11275	18.82743	0.059827

Table A5(iii) Variance Decomposition of NFPI:

Period	S.E.	CPI	FPI	NFPI
1	1.313998	35.07846	62.74806	2.173483
2	1.828412	47.60014	51.13398	1.265882
3	2.323416	55.27776	42.93145	1.790791
4	2.746675	61.15899	37.30544	1.535568
7	3.867066	70.18918	28.70637	1.104445
8	4.211549	71.81975	27.20311	0.977146
9	4.549048	73.08975	26.04686	0.863388
10	4.882078	74.10147	25.13621	0.762321
15	6.538582	77.01823	22.54759	0.434181
20	8.272925	78.24354	21.39162	0.364841

Cholsky Ordering: CPI FPI NFPI

TableA6: Forecasts from the VEC models.

	CPI and its sub components			12 months moving average			Inflation rate		
months	FPIF	NFPIF	CPIF	FPIFMA	NFPIFMA	CPIFMA	FIRF	NFIRF	OIRF
Jan-11	206.5482	205.305	206.0745	191.8874	183.1838	188.1479	*2.39(2.6)*	*19.26(19.4)*	*8.82(9.0)*
Feb-11	205.3208	209.7169	207.2572	193.5224	186.5102	190.511	*3.27(3.7)*	*19.56(19.6)*	*9.55(9.8)*
Mar-11	205.4429	213.4943	208.9528	195.176	189.993	192.957	*4.15(5.8)*	*19.95(20.0)*	*10.32(11.3)*
Apr-11	206.002	217.7252	211.084	196.8262	193.6951	195.489	*5.14*	*20.46*	*11.14*
May-11	207.2033	222.0307	213.6179	198.6181	197.581	198.1822	6.10	21.07	12.03
Jun-11	208.6826	226.5434	216.3989	200.2917	201.6846	200.9071	6.99	21.79	12.87
Jul-11	210.3553	231.1896	219.3481	202.2546	206.0921	203.9278	8.16	22.75	14.05
Aug-11	212.1206	235.9883	222.4154	204.2313	210.8495	207.1041	9.33	24.10	15.38
Sep-11	213.9506	240.9301	225.5812	205.9605	215.4853	210.0858	10.14	25.14	16.33
Oct-11	215.8246	246.0204	228.8358	207.5209	220.1703	212.9972	10.44	26.10	16.90
Nov-11	217.7366	251.2613	232.1766	209.274	225.2421	216.1785	10.85	27.32	17.69
Dec-11	219.6834	256.6571	235.6036	210.7392	229.7385	218.9455	10.81	27.59	17.82
Jan-12	221.6645	262.212	239.1184	211.9989	234.4808	221.6992	10.48	28.00	17.83
Feb-12	223.6802	267.9307	242.7231	213.5289	239.3319	224.6547	10.34	28.32	17.92
Mar-12	225.7312	273.8179	246.4202	215.2196	244.3589	227.7769	10.27	28.61	18.05
Apr-12	227.8183	279.8785	250.2123	217.0376	249.5383	231.0376	10.27	28.83	18.18
May-12	229.9427	286.1177	254.102	218.9326	254.8789	234.4113	10.23	29.00	18.28
Jun-12	232.1053	292.5406	258.0924	220.8844	260.3787	237.8858	10.28	29.10	18.41
Jul-12	234.3073	299.1526	262.1863	222.8804	266.0423	241.4556	10.20	29.09	18.40
Aug-12	236.5499	305.9592	266.3867	224.9162	271.8732	245.1199	10.13	28.94	18.36
Sep-12	238.8341	312.9663	270.6968	226.9898	277.8762	248.8795	10.21	28.95	18.47
Oct-12	241.1613	320.1795	275.1198	229.1012	284.0561	252.7365	10.40	29.02	18.66
Nov-12	243.5327	327.6051	279.6589	231.2509	290.4181	256.6934	10.50	28.94	18.74
Dec-12	245.9495	335.2491	284.3177	233.4398	296.9674	260.7529	10.77	29.26	19.09
Jan-13	248.4132	343.1181	289.0995	235.6688	303.7096	264.918	11.17	29.52	19.49
Feb-13	250.9251	351.2185	294.0081	237.9392	310.6503	269.1917	11.43	29.80	19.82
Mar-13	253.4866	359.5573	299.0471	240.2522	317.7952	273.5773	11.63	30.05	20.11
Apr-13	256.0991	368.1412	304.2203	242.6089	325.1504	278.078	11.78	30.30	20.36
May-13	258.7642	376.9776	309.5317	245.0107	332.7221	282.6971	11.91	30.54	20.60
Jun-13	261.4834	386.0739	314.9853	247.4589	340.5165	287.4382	12.03	30.78	20.83
Jul-13	264.2583	395.4376	320.5853	249.9548	348.5403	292.3048	12.15	31.01	21.06
Aug-13	267.0905	405.0766	326.336	252.4998	356.8001	297.3005	12.26	31.24	21.29
Sep-13	269.9816	414.9989	332.2418	255.0955	365.3028	302.4293	12.38	31.46	21.52
Oct-13	272.9335	425.2129	338.3072	257.7431	374.0556	307.6949	12.50	31.68	21.75
Nov-13	275.9479	435.7272	344.5369	260.4444	383.0657	313.1014	12.62	31.90	21.97
Dec-13	279.0266	446.5504	350.9358	263.2008	392.3409	318.6529	12.75	32.12	22.20

Note that: Values in the brackets indicates the actual inflation rates which is reported by CSA (March 2011). This indicates the fitted values are more close to the actual value.

Figure A1: Response of CPI to Cholesky one S.D. Innovations

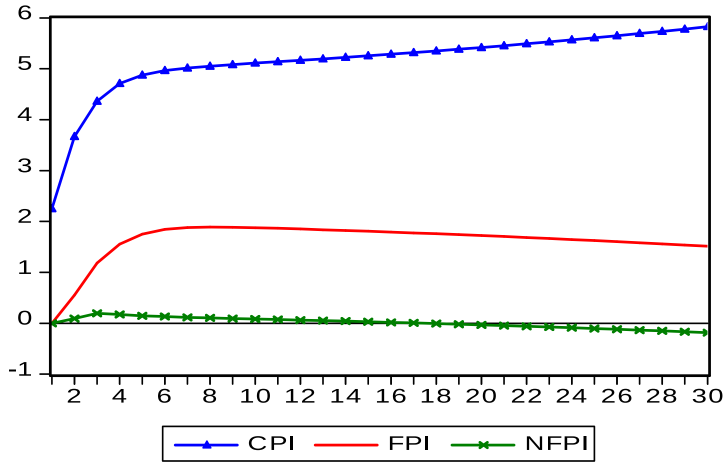


Figure A2: Response of FPI to Cholesky one S.D. Innovations

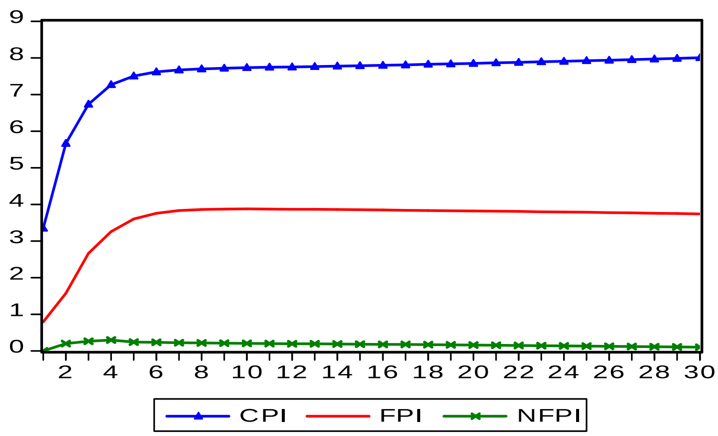


Figure A3: Response of NFPI to Cholesky one S.D. Innovations

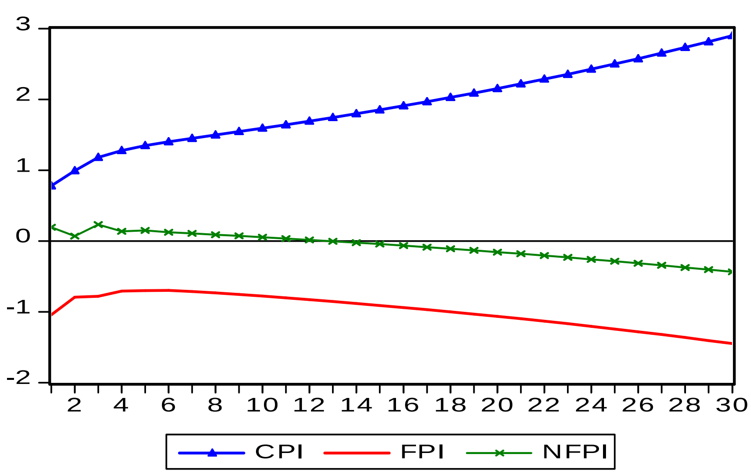


Figure A4: Variance Decomposition of CPI

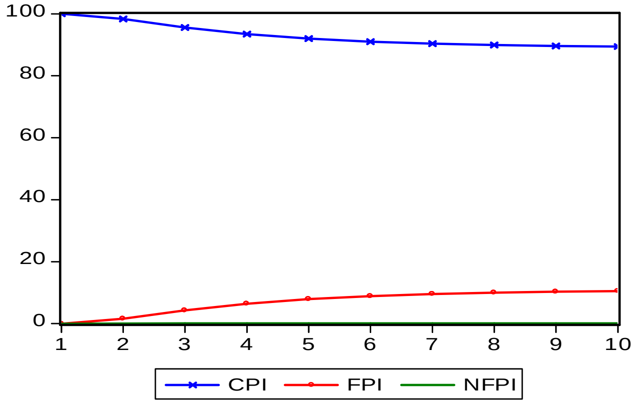


Figure A5: Variance Decomposition of FPI

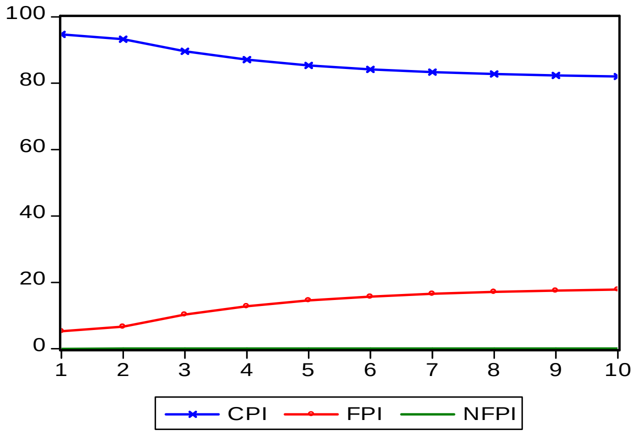
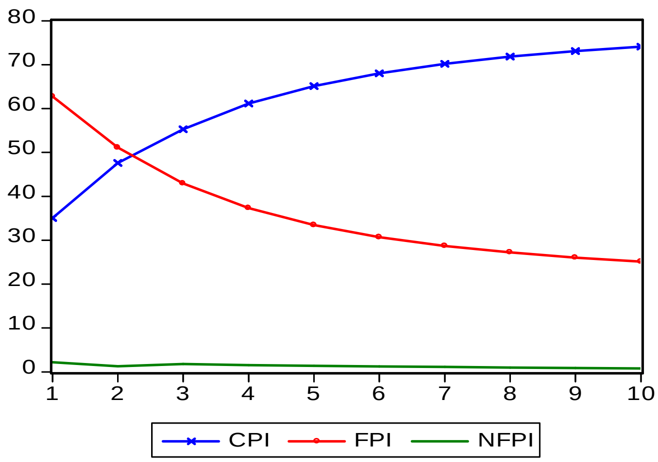
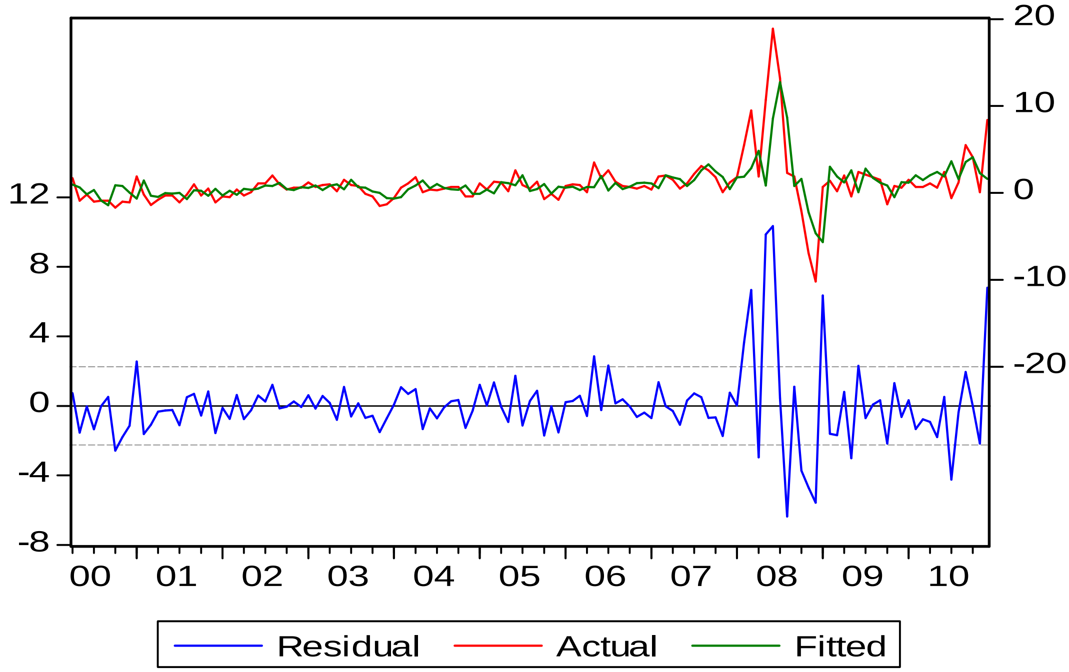


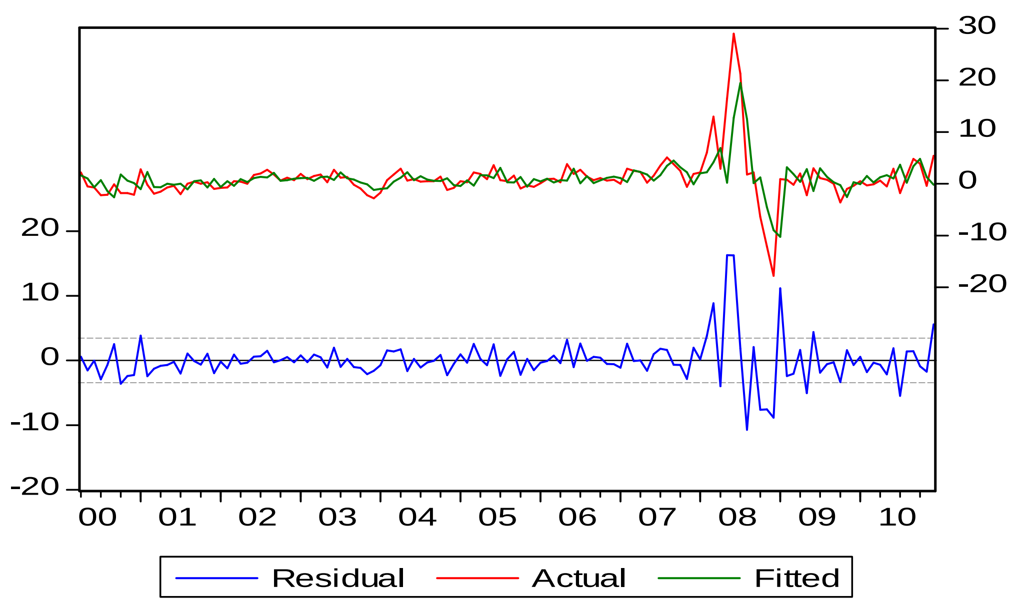
Figure A6: Variance Decomposition of NFPI



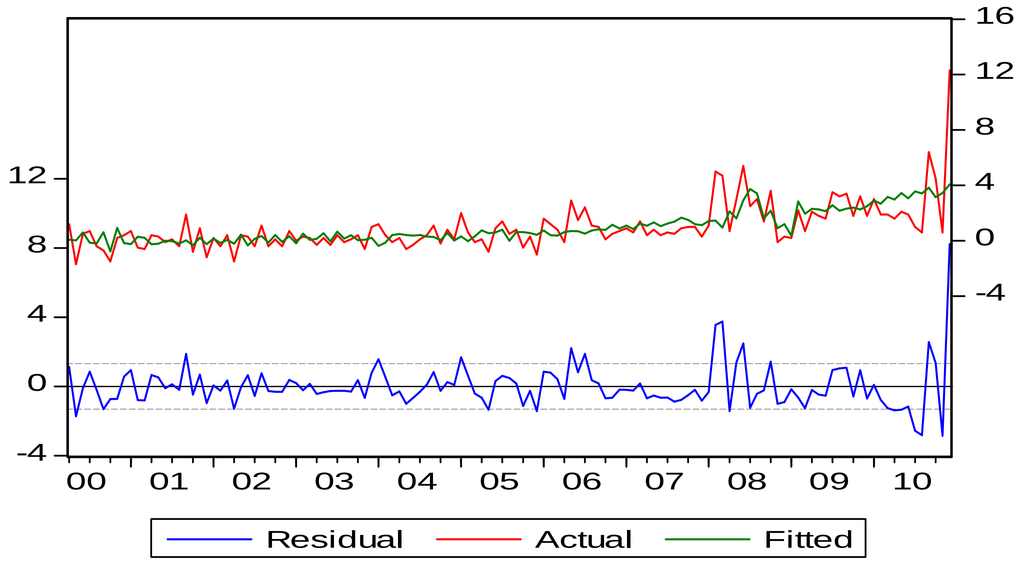
FigureA7: Graph of Actual, Fitted and Residual plot of Consumer price index



FigureA8: Graph of Actual, Fitted and Residual plot of Food price index

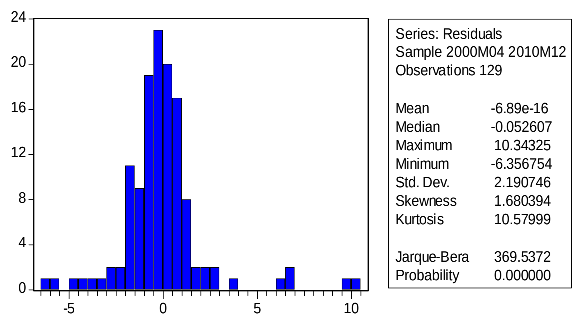


FigureA9: Graph of Actual, Fitted and Residual plot of Non food price index

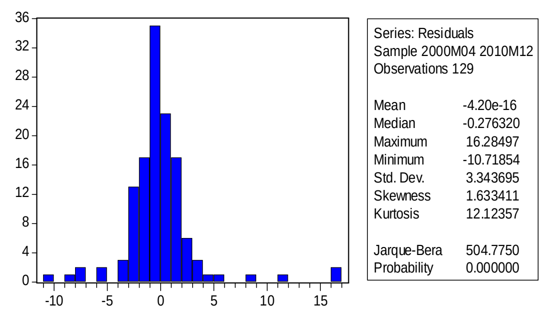


FigureA10: Histogram normality test for the residuals for VEC model

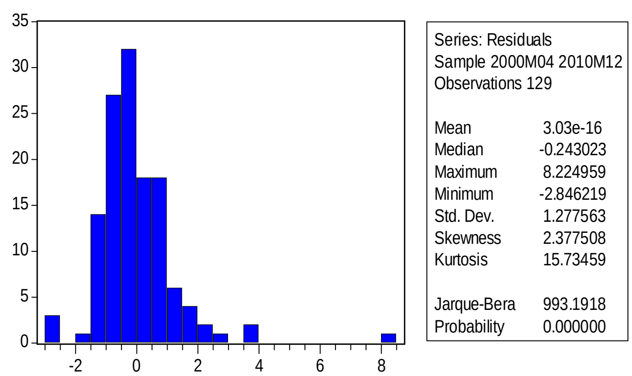
Consumer price Index



Food price index



Non food price index



DECLARATION

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

Declared by:

Name: ________________________________

Signature: _____________________________

Date: _________________________________

Confirmed by Advisor:

Name: ________________________________

Signature: _____________________________

Date: _________________________________