UNIVERSITY OF NAIROBI

SCHOOL OF MATHEMATICS

Modeling Inflation in Kenya Using ARIMA and VAR Models

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This research project is submitted to the School of Mathematics of the University of Nairobi in partial fulfillment of the requirement for the degree of Masters of Science in Social Statistics.

DECLARATION

This project as presented in this report is my original work and has not been presented for any other university award.

Candidate: Gathingi Virginia Wairimu **Reg. No:** I56/80898/2012

Signature:.. **Date:** ....

Declaration by the Supervisor

This project has been submitted for the partial fulfillment of the requirements of the degree of Master of Science in Social Statistics with my approval as the supervisor.

Dr. John Ndiritu

Signature: .... **Date:** ....

DEDICATION

This Project is dedicated to the memory of my Mother of whom I owe my every bit of existence. Her love, sacrifices, words of encouragement and to make me believe that I can be anything I wanted to be," You are powerful beyond measure", kept me going….still keeps me going.

To the memory of my Grandmother; for her inspiration and contribution to my life.

Even though you are both not here, your spirits walks with me. You are always in my heart.

Rest in Peace.

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Table of Contents

ABBREVIATIONS

CPI	Consumer Price Index
PPI	Producer Price Index
KNBS	Kenya National Bureau of Statistics
ARIMA	Auto regressive Integrated Moving Average
VAR	Vector Autoregressive
AR	Autoregressive
MA	Moving Average
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
OLS	Ordinary Least Square
ADF	Augmented Dickey-Fuller
VECM	Vector Error Corrected Model
CBK	Central Bank of Kenya
AIC	Akaike Information Criteria
AICc	Corrected Akaike Information Criteria
BIC	Bayesian Information Criteria
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MPE	Mean Percentage Error
MAPE	Mean Absolute Percentage Error

ABSTRACT

Inflation is an important indicator of economic activity and is used by decision makers to plan economic policies. This paper is based on modeling inflation over the period 2005-2013 using two auto regressive models; Autoregressive Integrated Moving Average (ARIMA) model and the Vector Autoregression (VAR) model. ARIMA model is used to fit historical CPI time series expressed in terms of past values of itself plus current and lagged values of error term resulting to the model (1,1,0). Data for the last six months is used to evaluate the performance of the prediction. VAR model is used to investigate the effect of money supply, Murban oil prices and exchange rate on inflation rate over the same period. Unit root test (Augmented Dickey- Fuller test) has been exploited to check the integration order of the variables. A cointegration analysis with the four variables is employed. Study adopted Johansen test. Findings indicated that both trace test and max Eigen value static showed that individual variables are cointegrated with inflation at 5% significant level. This led to estimation of a Vector Error Correction Model (VECM). Findings showed that there is no long run causality running from the independent variables to inflation. In addition, money supply and exchange rate has no short run causality whereas a four lag Murban oil price had short run causality to inflation.

KEY WORDS:ARIMAmodel, VAR model, Inflation

CHAPTER ONE: INTRODUCTION

1.1 Background

Inflation is the time value of money. It is defined as the persistent increase in the level of general prices of goods and services and fall in the purchasing value of money over a given period of time. Prices of goods and services may increase when people have more money than the goods and services available so that the prices of goods and services are put under pressure to rise. Also, the cost of producing goods and services may increase due to increases in the cost of raw materials, bad weather, increase in the wages, increase in government taxation, increase in international oil prices or other factors that affect the supply and production of goods and services. This increases the prices of final goods and services produced.

There are many measures of inflation although all seek to show the price change in living costs. They include;

- Consumer Price Index (CPI); this is the most common index and measures the changes in prices of essential household basket from a consumer perspective.
- Price Producer Index (PPI); the index measures the changes in prices from a producers' perspective.
- Employment Cost Index (EPI); this index tracks changes in the labor market cost hence measuring inflation of wages, and employer-paid benefits.
- Gross Domestic Product Deflator (GDP-Deflator); measures the change in level of prices of all new domestically produced, final goods and services in an economy.
- International Price Program (IPP); tracks price changes in the foreign trade sector.

In Kenya, the most often cited measure of inflation is the change in the consumer price index. CPI as defined by KNBS is a measure of the weighted aggregate change in retail prices paid by consumers for a given basket of goods and services. The inflation basis in Kenya has changed from 1997=100 to 2009=100 as well as the area of coverage which now reflects better on the current households spending in different income groups. The new basket introduced in February 2010 is based on household budget survey data collected in 2005/06 that reflects significant changes in consumer spending habits in Kenya that have since developed. This led Kenya to adopt the geometric mean for the calculation of its inflation rate to match international best practice and new spending trends. The basket has twelve groups of goods and services which includes; Food and non-alcoholic beverages, Alcoholic beverages, Tobacco & Narcotics, Clothing and footwear, Housing, water, electricity, gas and other fuels, Furnishings, Household Equipment and Routine Household Maintenance, Health, Transport, Communications, Recreation & Culture, Education, Restaurant & Hotel, and Miscellaneous goods and services. Each group consists of several sub groups, and then in every sub group there are several items. Currently, the CPI is computed using a hybrid method; geometric average which measures the general trend at elementary level and arithmetic averaging at the higher level.

Given that $\boldsymbol{I}_t$ is the index at time t, $\boldsymbol{P}_{ti}$ is the price of the i^{th} commodity at time$t$, $\boldsymbol{P}_{oi}$ is the base period and $\boldsymbol{W}_i$ is its weight. The $\boldsymbol{i}_{th}$ commodity weight at the base period is expressed as;

$$W_{0i} = \left[\frac{p_{0i}q_{0i}}{\sum_{i=1}^{n} p_{0i}q_{0i}}\right]$$

This implies that the index at a time t is given by:

$$I_t = \sum_{i=1}^{n} W_{0i} * \left[\frac{p_{ti}}{p_{0i}}\right].$$ This is the Laspeyres formula.

High inflation reduces the value of money and thereby loss of purchasing power. This makes future prices less predictable. Sensible spending and saving plans are harder to make since inflation causes changes in price and discourages saving if the rate of return does not reflect the increase in level of prices. In terms of investment, businesses do not venture into long term productive investments as they are not sure whether the prices will continue rising or will drop at a future date. This causes misallocation of resources by encouraging speculative rather than productive investments. Inflated prices makes domestic goods and services expensive in the world markets worsening the country’s terms of trade.

Inflation creates winners and losers though it harms more than helps. Borrowers benefit from a general increase in prices or a reduction in purchasing power. In addition, producers experience higher profits when consumer prices increases in the short run. This occurs when consumer prices rise while wages paid to employees remain relatively stable allowing producers to benefit for a time until wages adjust to reflect the higher prices consumers are paying. Lenders and savers earn interest rates that assume some rate of inflation, and when the actual rate exceeds the expected rate, they both lose. Inflation is seen as a regressive form of taxation with the most vulnerable being the poor and fixed income earners.

Kenya has experienced large swings in inflation since independence. The 1990s were characterized by rising inflation, as well as economic growth slowdown, rapid rise in money growth and interest rates, and depreciation of the currency. The 2000s were most affected by post-election violence followed by the worst drought in 60 years and global economic meltdown in 2008. The effect was increased food insecurity, sharp oil price fluctuations, weak shilling, expanding current account deficit and a slow economic growth. Overall inflation accelerated from 2 percent in April 2007 to a high of 18.70 percent by May 2008 before falling back around 3 percent in October 2010. At the end of 2011, overall inflation had rose to19.72 percent as food and oil prices escalated. The shilling sank to a record low against the dollar of Kes 105prompting the CBK to raise interest rates to tame inflationary pressures. The CBK resolute to deal with inflation yielded positively as the rates trended as low as 3.20 per cent and an average of 6.99 per cent recorded by December 2012. By the end of 2013, overall inflation stood at 7.15 per cent resulting to lower interest rates and a stronger shilling against the hard currencies. Below is a chart capturing the quarterly inflation rates trend for the past nine years.

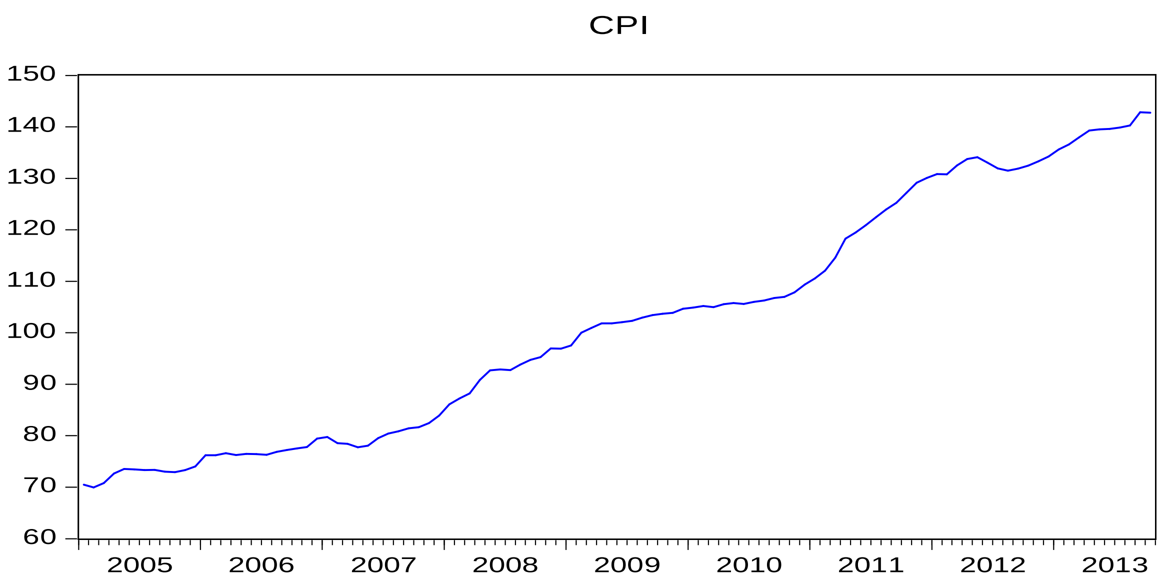


Figure 1 : Kenya Inflation 2005-2013

1.2 Research problem

The purpose of this study is to model inflation using univariate and multivariate time series. Forecasts of inflation are important because they affect many economic decisions. Without knowing future inflation rates, it would be difficult for lenders to price loans, which would limit credit and investments in turn have a negative impact on the economy. Investors need good inflation forecasts, since the returns to stocks and bonds depend on what happens to inflation. Businesses need inflation forecasts to price their goods and plan production. Homeowners' decisions about refinancing mortgage loans also depend on what they think will happen to inflation. Modeling inflation is important from the point of view of poverty alleviation and social justice.

1.3 Research questions

- Can historical inflation data be used to model inflation?
- Do money supply, oil prices and exchange rate determine inflation in the long and short term dynamics?
- Is there any directional causality of the variables to inflation?

1.4 Objectives

The main objective is to establish a univariate and multivariate time series model to forecast inflation. The time series estimates dynamic causal effects and correlation over time. Specific objective are:

- To analyze the determinants and dynamics of inflation in Kenya.
- To develop time series models for inflation in Kenya
- Test the causality of the determinants to inflation

1.5 Study Justification

The study is significance to policy makers as it guides them in formulating macroeconomic policies by providing them with a long term perspective of inflation. Optimal policy will depend on optimal inflation forecasts. CPI uses include;

- As the main estimator of the rate of inflation. The percentage change of the CPI over a one-year period is what is usually referred to as the rate of inflation.

- A macroeconomic indicator. The CPI is used for general economic/social analysis and policy formulation particularly since it conveys important information about indirect tax revenue.
- As a tool in wage negotiation and indexation. CPI is used to adjust taxes and to determine, among other things, wage levels in the event of trade disputes, social security benefits, public service remuneration and pensions.
- As a deflator of expenditure. The prevailing CPI can be used to establish the real/constant value by deflating nominal values (previous cost) of goods and services.

Forecasting inflation generally improves financial planning in both the corporate and private sectors. Inflation affects actual cost of expenses and stock valuations on the corporate level. Forecasting changes can therefore help investors understand risks and hedge investments. Forecasting inflation is important for banking sector in order to keep their investments profitable. Inflation can cause the bank's return on fixed rate loans to decrease, sometimes making the loan unprofitable. Forecasting inflation can therefore help banks achieve their operating capital requirements.

In corporate world, forecasting inflation can help businesses prepare for accurately calculating expenditures. Being prepared for inflationary shifts can lead companies to stock raw materials at a cheaper price, avoiding price increases in periods of inflation. Forecasting inflation can also prepare businesses for potential needs in wage shifts, signaling necessary adjustments in human resources. For individuals it is important to account for potential inflation to avoid a declining purchasing power. It helps in choosing optimal refinancing periods and appropriate mortgage rate decisions. Forecasting inflation can give investors information about whether or not to invest in the bond market, as fixed rate bonds lose value in periods of inflation. Portfolio diversification can also help counter the effects of inflation. Persons, who live off their retirement or their savings account, rely on their balance and on current interest rates. Inflation can push prices up, making currency today worth less in the future and rendering their fixed income less valuable.

1.6 Outline

The following chapter two gives a brief theoretical review of earlier studies done on inflation in Kenya and similar countries. Chapter three, gives the theoretical methodology to be used in this case ARIMA and VAR models as well as data validation tests to be carried out. Stationarity test will be applied to the data to determine the appropriate analysis. In the VAR model, level of integration and cointegration will be tested for the variables of interest using the ADF and Johansen test respectively. A VEC model will then be developed. In chapter four, results from data analysis are formulated, the parsimonious models will be given and diagnostic test carried out for their validity. The resulting two models will be compared for their predictability model. Finally in chapter five, summaries, conclusions and discussion arising from the results will be drawn.

CHAPTER TWO: LITERATURE REVIEW

Forecasting inflation is one of the most important, but difficult exercises in macroeconomics with many different approaches having been suggested. Focus has been given to modeling Kenya's inflation using various determinants in previous researches as the case of Durevall & Ndungu (2001). The authors explains that there are several external shocks that affect inflation and hence finding a stable and parsimonious model that describes Kenya inflation is a major challenge. The findings showed that in the long run inflation emanated from movements in the exchange rate, foreign prices and terms of trade. The error correction term for the monetary sector did not enter the model, but money supply and the interest rate influenced inflation in the short run. Inflation inertia was found to be an important determinant of inflation up until 1993. The dynamics of inflation were also influenced by food supply constraints, proxied by maize-price inflation. These findings indicate that the exchange rate is likely to be a more efficient nominal anchor than money supply, and that inflation could be made more stable by policies that secure the supply of maize during droughts.

Okafor & Shaibu (2013) empirically developed a univariate autoregressive moving average model for Nigerian inflation and analyzed their forecasting performance for data between 1982-2010. The study showed that ARIMA (2,2,3) tracked the actual inflation appropriately. The conclusion drawn was that Nigerian inflation is largely expectations-driven. In addition it showed that ARIMA models can explain Nigeria inflation dynamics successfully and help to predict future prices.

In a study to forecast Bangladesh's inflation, Faisal (2001) applied a Box Jenkins ARIMA time series model. One year forecasting was done for consumer price index of Bangladesh using a structure for ARIMA forecasting model where a time series was expressed in terms of past values of itself plus current and lagged values of a 'white noise' error term were drawn up. Validity of the model was tested using standard statistical techniques and the best model was proposed on the basis of various diagnostic and selection & evaluation criteria. The study found many disadvantages of ARIMA model as it neglected the inclusion of explanatory variables and conducted the forecasts only on past values of the dependent variable in combination with present and past moving average terms. So incorporating the judgmental elements with the selected ARIMA model can enhance the predictability of model for forecasting consumer price index of Kenya and better assist the policymakers.

Loungani & Swagel (2001) drew facts about inflation in 53 developing countries in Africa, Asia, the Mediterranean and South America between 1964-1998. The study focused on the relationship between the exchange rate regime and the sources of inflation. The findings indicated that the sources of inflation were quite diverse in African and Asian countries, which tended to have low to moderate rates of average inflation with the inertial component being the most important source. The study showed that the differences in the relative importance of sources of inflation across regions corresponded to differences in the exchange rate regime. The contribution of the fiscal component of inflation, money growth and exchange rate changes was far more important in countries with floating exchange rate regimes than in those with fixed exchange rates, where inertial factors dominated the inflationary process.

Durevall & Sjo (2012) assessed the main drivers of inflation in Ethiopia and Kenya by developing single-equation error correction models for the CPI in each country. The study took into account a number of potential sources of the recent surge in inflation, which included excess money supply, exchange rates, food and non-food world prices, world energy prices and domestic agricultural supply shocks. The findings showed that inflation rates in both Ethiopia and Kenya were driven by similar factors and evidence of substantial inflation inertia. World food prices and exchange rates had a long run impact, while money growth and agricultural supply shocks had short to-medium run effects.

A brief done by African Development Bank investigated dynamics of inflation in Ethiopia, Kenya, Tanzania and Uganda. The note established that growth in money supply accounted for 40 percent and one third of short-run inflation in Ethiopia and Uganda respectively. In Kenya and Tanzania oil prices were the main driver of short-run inflation accounting for one fifth and one quarter respectively. Money growth was also noted to have made a significant contribution to the recent increases in Kenya and Tanzania. Further the study explored other possible causes of inflation and the following were cited: Exchange rate; Depreciation of exchange rate contributed between 11 percent in Ethiopia, 38 percent Uganda and close to 17 percent of the observed inflation in 2011. Velocity of money was noted to be a key indicator of the pace of monetary transactions, and in turn helps in contextualizing the prevailing inflationary developments. M-PESA effects in Kenya; the increase in the velocity of money induced by M-Pesa activities may have in turn propagated self-fulfilling inflation expectations and complicated monetary policy implementation. Effects of informal trade in Ethiopia; the price effects generated by rising demand for agricultural commodities in the face of supply shocks placed a high premium on Ethiopia's inflation (AfDB, 2011).

Research by Mohanty & Marc (2011) examined the factors that affect inflation in emerging markets economies in 1990s in Africa, Asia and South America. Output gap, excess money supply and wages were seen to have significance influence on inflation. Shocks to food prices emerged as the most common inflation determinants in all EMEs followed by the exchange rate while inflation and oil price shocks were weakly associated particularly with regard to the degree of monetary accommodation or to rigidities in the adjustment of domestic oil prices. In some countries, monetary policy did not accommodate these shocks.

Andrle, et al. (2013) sought to forecast and analyze monetary policies in low income countries using food and non-food inflation dynamics. The findings showed that while imported food price shocks had been an important source of inflation, both in 2008 and more recently, accommodating monetary policy had also played a role, most notably through its effect on the nominal exchange rate. The model correctly predicted that a policy tightening was required, although the actual interest rate increase was larger

A study by Kennedy & Bernard (2012) established the major determinants of inflation in Ghana using econometric analysis. Two broad theories were applied; the excess–demand theories which argue that excess demand for goods and services over supply in an economy is the main source of inflation, and the cost-push theories in which a host of non-monetary supply oriented factors influencing the price level in the economy were considered. The study showed that the growth rate of real GDP and the growth of money supply are the main determinants of inflation in Ghana both in the short-run and the long-run, with money supply being the key determinant.

A research by Sumaila & Laryea (2001) on the determinants of inflation in Tanzania established that in the short-run, output and monetary factors are the main determinants of inflation in Tanzania. However, in the long-run, parallel exchange rate also influences inflation in addition to output and money. The study evidenced that inflation was engineered more by monetary factors that real factors implicating that Tanzania inflation is a monetary phenomenon.

Kenya has seen large swings in prices to which the CBK attributed to supply shocks and currency depreciations. Guided by these potential sources, this paper tries to improve previous studies by using oil prices and exchange rate to account for the supply shocks. Oil accounts for a huge chunk of the total imports in Kenya of about 25%. Secondly, we use more current data as other recent studies has concentrated on periods ending in 1990s. Thirdly, the inflation basis in Kenya has since changed as well as the area of coverage which now reflects better on the current households spending in different income groups which led Kenya to adopt the geometric mean for the calculation from arithmetic averaging.

CHAPTER THREE: METHODOLOGY

3.1 Empirical analysis

Different sources can cause inflation simultaneously. Previous studies on inflation in Kenya have shown that some key factors that affect the rate of inflation are money growth, supply shocks and exchange rate movements. To derive the inflation equation we analyze the impact of the relevant explanatory factors in this study.

Price of goods is assumed to be determined by money market equilibrium. Money supply is increased by velocity of circulation- changes in the way people hold money and the government has tried to control this through tightening and loosening of the monetary policy. Money supply is generally expected to grow at the same rate as the real output so as to maintain the price level. If money supply grows faster than real output it causes inflation, this is in the case where aggregate demand increases while aggregate supply remains static. In the period under review periods where money supply has grown are characterized with high pricing index leading to the assumption that an increase in money supply will result to increase inflation.

Oil prices account for the influence of supply shocks since it is a major input in the economy. Oil is used from the production level to transportation of goods hence has effect on the cost of the end products. Inflation is assumed to follow the same direction as the changes in oil prices and can help in elaborating short term movements in inflation. During the period under review, for instance in 2008 and 2011 oil prices were trending high which corresponded with high inflation rate.

Exchange rate, another variable in this study is assumed to influence inflation through its effect on net exports. Kenya embraces the free floating exchange rate system where demand and supply forces of market determine the daily value of one currency against another. The exchange rate affects the prices of directly imported goods as well as and indirectly through the local goods that are under competitive pressure from imported goods. As illustrated by our data, exchange rate in mid 2011 hit highs of Kes 105 in turn skyrocketing general prices of goods and services.

In this study we use a combination of these theories based on the assumptions discussed above and develop a model for inflation such that;

$$\Pi_t = f(\underset{+}{M2_t}, \underset{+}{P_t}, \underset{+}{E_t})$$

where an increase in Money supply$(M2)$, Murban oil prices (P) and Exchange rate (E) leads to an increase in inflation(Π) in period t.

3.2 Data

The study researches on inflation monthly data based on CPI, which have been collected for the period from 2005:1-2013:12 sourced from the KNBS and CBK data bank. The VARmodel includes Money supply, exchange rate and Murban crude oil monthly average prices. R, SPSS, EViews and Excel are the main statistical software's for analysis and estimation employed in this study $\Pi, M2, P\ and\ E$ will be used in this study to denote Inflation, money supply, Oil Prices and Exchange rate respectively.

Inflation

The inflation is based on Kenya CPI time series monthly data from 2005-2013.CPI is a measure of the weighted aggregate change in retail prices paid by consumers for a given basket of goods and services.

Money supply

Money and quasi money comprise the sum of currency outside banks, demand deposits other than those of the central government, and the time, savings, and foreign currency deposits of resident sectors other than the central government. Which can also be defined as M2= M1 + short-term time deposits in banks. M2 is a broader money classification than M1, because it includes assets that are highly liquid but not cash.

Murban Oil Prices

Oil prices included in this study is the actual monthly average (FOB) prices (US$) for Murban crude oil imported into Kenya from Abu Dhabi National Oil Company (ADNOC). The price applicable for each loading is the daily average for the month in which crude oil is loaded. Oil importation accounts for about 25% of all imported goods in Kenya. Data is sourced from the Petroleum Institute of East Africa.

Exchange Rate

The exchange rate used in this research refers to the price unit of the US dollar rate in Kenya Shilling.

3.3 ARIMA Models

The Box-Jenkins (ARIMA) model is in theory the most general class of models for forecasting time series and was first popularized by Box and Jenkins (1970). $ARIMA\ (p, d, q)$ completely ignores independent variables and assumes that past values of the series plus previous error terms contain information for the purposes of forecasting. The integers refer to the Autoregressive (AR), Integrated (I) and Moving Average (MA) parts of the data set respectively. The models are applied in some cases on data which show evidence of non-stationarity which can be stationarized by transformations such as differencing and logging. The model takes into account historical data and decomposes it into AR process, where there is a memory of past events; an integrated process, which accounts for stationarity, making it easier to forecast; and a MA of the forecast errors, such that the longer the historical data, the more accurate the forecasts will be, as it learns over time. The ARIMA models are applicable only to a stationary data series, where the mean, the variance, and the autocorrelation function remain constant through time.

Autoregressive process AR expresses a dependent variable as a function of past values of the dependent variable. A p_{th}-order process is of the form:

$$y_t = \alpha + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + \emptyset_p y_{t-p} + \varepsilon_t$$

Where;$Y_t$is the stationary depended variable being forecasted at time t. $y_{t-1}, y_{t-2}, \cdots\cdots, y_{t-p}$is the response variable at time lags $t-1, t-2 \ldots\ldots t-p$respectively.$\alpha = \mu(1 - \emptyset_1 - \cdots\cdots - \emptyset_p)$. $\emptyset_1, \emptyset_2, \ldots\ldots\ldots \emptyset_p$ are the coefficients to be estimated. ε_t is the error term at time t with mean zero and a constant variance. Using the backshift operator we can write the $AR(p)$ model as;

$$(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots\cdots - \emptyset_2 B^2) y_t = \emptyset(B) y_t = \varepsilon_t$$

The moving average model of order $MA(q)$ is defined as;

$$y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots\cdots + \theta_q \varepsilon_{t-q}$$

Where;q is the number of lags in the moving average and $\theta_1, \theta_2, \ldots\ldots\ldots \theta_q$ are parameters to be estimated. The moving average operator is given by;

$$\theta(B) = \theta_1 B + \theta_2 B^2 + \cdots\cdots + \theta_q B^q$$

To create an ARMA model, we begin with an econometric equation with no independent variables $Y_t = \beta_0 + \varepsilon_t$ and add to it both the AR process and the MA process.

$$y_t = \beta_0 + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots\cdots + \emptyset_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots\cdots + \theta_q \varepsilon_{t-q}$$

$\beta_0 + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots\cdots + \emptyset_p y_{t-p}$ is the AR(p), and $\theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots\cdots + \theta_q \varepsilon_{t-q}$ is the MA(q) process. Where the $\emptyset_s$ and θ_s are the coefficients of the autoregressive and moving average processes respectively.

The integrated ARMA or ARIMA model is a broadening class of ARMA model which includes a differencing term. A process is said to be $ARIMA\ (p, d, q)$ if

$$\nabla^d y_t = (1 - \mathrm{B})^d y_t$$

is an $ARMA\ (p, q)$. The is generally written as;

$$\emptyset(B)(1 - \mathrm{B})^d y_t = \theta(1 - \mathrm{B})\varepsilon_t$$

A first- differenced inflation series is of the form:

$$CPI_t = (\nabla CPI_t) = CPI_t - CPI_{t-1} = \Delta CPI_t - \Delta CPI_{t-1}$$

Thus the $ARIMA\ (p, 1, q)$model may be specified as:

$$CPI_t = \beta_0 + \emptyset_1 CPI_{t-1} + \emptyset_2 CPI_{t-2} + \cdots\cdots + \emptyset_p CPI_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots\cdots + \theta_q \varepsilon_{t-q}$$

Where CPI_t, is the differenced inflation series of order 1 , and $\emptyset, \beta, and\ \theta$ are the parameters to be estimated. Shumnay & Stoffer (2011)

The equation must assume stationarity before applying to a time series. In case of non-stationarity successive differences are taken until the series is stationary. In practice the differences are rarely more than two.

The aim of this methodology is to find the most appropriate $ARIMA\ (p, d, q)$ model and to use it for forecasting. It uses an iterative six-stage scheme:

i. A priori identification of the differentiation order d (or choice of another transformation);

ii. A priori identification of the orders *p* and *q*;

iii. Estimation of the parameters ($\emptyset$, β, and θ ,δ^2 = Var ϵ_t);

iv. Validation;

v. Choice of a model;

vi. Prediction.

3.3.1 Data Validation

For the data to be tested using time series models, it has to be stationary. If the raw data is found to be on stationary it has to go through some transformation first. The statistical summaries as well as distribution of the time series will be tested by means of coefficient of skewness and kurtosis, normal probability plots and test of normality, to check presence of typical stylized facts.

3.3.2 Test stationarity of the time series data

To model the series we check the structure of the data in order to obtain some preliminary knowledge about the stationarity of the series; whether there exist a trend or a seasonal pattern. A time series is said to a stationary if both the mean and the variance are constant over time. A time plot of the data is suggested to determine whether any differencing is needed before performing formal tests. If the data is non-stationary, we do a logarithm transformation or take the first (or higher) order difference of the data series which may lead to a stationary time series. This process will be repeated until the data exhibit no apparent deviations from stationarity. The times of differencing of the data is indicated by the parameter *d* in the ARIMA (*p,d,q)* model.

Then an Augmented Dickey-Fuller Test (ADF Test) is used to determine the stationarity of the data.

Augmented Dickey-Fuller Test (ADF Test)

The ADF test is used to test for unit root. The testing procedure for the ADF test is the same as for the Dickey–Fuller test but it is applied to the model. A random walk with drift and trend is represented as;

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t$$

whereα is a constant, $\beta$the coefficient on a time trend and p the lag order of the autoregressive process. Imposing the constraints$\alpha = 0$ and $\beta = 0$corresponds to modeling a random walk and using the constraint $\beta = 0$ corresponds to modelling a random walk with a drift.

The test statistics , value is calculated as follows:

$$\tau = \frac{\hat{\gamma}}{\sigma_{\hat{\gamma}}}$$

Where:$\hat{\gamma}$ is the estimated coefficient and $\sigma_{\hat{\gamma}}$ is the standard error in the coefficient estimate

The null-hypothesis for an ADF test: $H_0: \gamma = 0$ vs $H_1: \gamma < 0$

Where H_0: is the null hypothesis (has unit root) and H_1: Does not have unit root. The test statistics value τ is compared to the relevant critical value for the Dickey Fuller Test. If the test statistic is less than the critical value, we reject the null hypothesis and conclude that no unit-root is present. The ADF Test does not directly test for stationarity, but indirectly through the existence (or absence) of a unit-root. Decision rule:

If t* > ADF critical value, ==> not reject null hypothesis, i.e., unit root exists.

If t* < ADF critical value, ==> reject null hypothesis, i.e., unit root does not exist.

Using the usual 5% threshold, differencing is required if the p-value is greater than 0.05.

Correlograms

In addition to graphical testing of stationarity, formal testing schemes by means of autocorrelation function (ACF), partial autocorrelation functions (PACF) are applied. The correlograms examines the time series data by plotting the ACF and PACF in order to try and get the functional form of the data. ACF represents the degree of persistence over respective lags of variables; correlation between two values of the same variable at time X_i and X_{i+k}. PACF measures the amount of correlation between two variables which is not explained by their mutual correlations with a specified set of other variables. ACF will be used to identify the order of MA process while PACF will identify the order of AR model. Primary distinguishing characteristics of theoretical ACF‘s and PACF’s for stationary processes is as tabulated below;

Table 1: Distinguishing characteristics of ACF and PACF for stationary processes

Process	**ACF**	**PACF**
AR	Tails off towards zero (exponential decay or damped sine wave)	Cuts off to zero (after lag p)
MA	Cuts off to zero (after lag q)	Tails off towards zero (exponential decay or damped sine wave)

If the original or differenced series comes out to be non-stationary some appropriate transformations will be made for achieving stationarity, otherwise we will proceed to next phase where preliminary values of p and q are chosen.

3.3.3 Estimation and order selection

Once the model order has been identified (i.e., the values of p, d and q), we need to estimate the parameters $\emptyset, \beta, and\ \theta.$ Box Jenkins method will be implemented by observing the autocorrelation of the time series. Therefore, ACF and PACF are core in providing ways to identify ARIMA model. There are three rules to identify ARIMA (p,d,q) model:

- If ACF graph cut off after lag n and PACF dies down we identify MA(q) resulting to ARIMA(0, d, n) model.
- If ACF dies down and PACF cut off after lag n, we identify AR(p) resulting to ARIMA (n, d, 0) model.
- If ACF and PACF die down that is mixed ARIMA model, then differencing is needed.

In fitting ARIMA model, the idea of parsimony is important in which the model should have as small parameters as possible yet still be capable of explaining the series (p and q should be 2 or less). The more the parameters, the greater noise that can be introduced into the model and hence, the greater standard deviation. In addition, the following methods Maximum likelihood estimation (MLE), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are also applied;

Maximum likelihood estimation

The maximum likelihood estimation (MLE) will be used to estimate the ARIMA model. This technique finds the values of the parameters which maximize the probability of obtaining the data that we have observed. For ARIMA models, MLE is very similar to the least square estimates. In a standard Gaussian, the likelihood function is;

$$logL = -\frac{T}{2}log(2\pi) - \frac{T}{2}log\delta^2 - \frac{1}{2\delta^2}\sum_{t=1}^{T}{\varepsilon_t}^2$$

Where is T is the time $t = 1, \dots, T$ of the historical data, ε_t and δ is the error and constant variance respectively. The log likelihood reports the logarithm of the probability of the observed data coming from the estimated model. We choose the model where the log likelihood is maximal.

Information Criteria

Akaike's Information Criterion (AIC) is useful for determining the order of an ARIMA model. It is used to compare competing models fit to the same series. It can be written as;

$$AIC = -2lnL + 2\mathrm{N}$$

where L is the likelihood of the data, The term in Nis the number of parameters in the model (including $\sigma 2$, the variance of the residuals).The original definition AIC adds a linear penalty term for the number of free parameters, but the AICc adds a second term to factor in to the sample size, making it more suitable for smaller sample sizes.

The Bayesian Information Criterion (BIC) can be written as

$$BIC = AIC + \mathrm{N}log(T), \quad \mathrm{N}: is\ the\ number\ of\ fitted\ model\ parameters$$

The BIC generally penalizes free parameters more strongly than does the AIC, though it depends on the size of n and the relative magnitude of n and k. Good models are obtained by minimizing either the AIC, AICc or BIC and maximizing log likelihood. Our preference is to use the AICc and the parsimonious model with the lowest AICc and largest log likelihood will be selected.

3.3.4 Parameter Estimation

To estimate the parameters, we run the selected model(s) as guided by the log likelihood, standard error and AICc values. The result will provide the estimate of each element of the model. The parameters with the least standard error in Root Mean Square Error (RMSE), Root Mean Square Percent Error (RMSPE), and Mean Absolute Error (MAE) will be selected. The full model equation will be indicated.

3.3.5 Model diagnostic checking

Estimated model(s) will be considered most appropriate if it typically simulate historical behavior as well as constitute white-noise innovations. Historical behavior will be tested by ACF and PACF of estimated series and choose the one which best describes the temporal dependence in the inflation series i.e., the model(s) whose residuals show no significant lags. White-noise innovations will be tested by a battery of diagnostic tests based on estimated residuals as well as by over-fitting. The Ljung-Box test will also be used to verify whether the autocorrelation of a time series are different from zero. If the result rejects the hypothesis, this means the data is independent and uncorrelated; otherwise, there still remains serial correlation in the series and the model needs modification.

The Ljung Box Test

The standard portmanteau test for checking that the data is a realization of a strong white noise is that of Ljung and Box (1978). It involves computing the statistic

$$Q(m) := n(n+2)\sum_{j=1}^{m} \hat{\rho}_j^{\,2} \Big/ (n-j)$$

and rejecting the strong white noise hypothesis if $Q(m)$ is greater than the $(1-\alpha)$quantile of $x^2{}_m$. n is the sample size, $\hat{\rho}_j$ is the sample auto correlation at lag j and m is the lag order that needs to be specified. This is one-side (i.e. one-tail) test, so the computed p-value should be compared with the whole significance level(α). In practice, the selection of m may affect the performance of the $Q(m)$statistic. Several values of m are often used. Simulation studies suggest that the choice of $m \approx ln(T)$ provides better power performance. The null hypothesis is given by: The data are independently distributed (i.e. the correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process). The alternative hypothesis is: The data are not independently distributed. If the Ljung-Box statistic of the model is not significantly different from 0 we fail to reject the null hypothesis of no remaining significant autocorrelation in the residuals of the model and conclude that the model seems adequate in capturing the correlation information in the time series. i.e.

$$If\ Q \leq X^2{}_{\alpha}(m-p-q), the\ H_0\ is\ not\ rejected;$$
$$if\ \ Q > X^2{}_{\alpha}(m-p-q), the\ H_0\ is\ rejected.$$

The best fitting model(s) will then go under various residual and normality tests and only qualifying model(s) will be selected and reserved for forecasting purpose.

3.3.6 Forecasting

Forecasting performance of the various types of ARIMA models will be compared by computing statistics like AIC, Root Mean Square Error (RMSE), Root Mean Square Percent Error (RMSPE), Mean Absolute Error (MAE). The smaller the statistics, the better the model. On the basis of these aforementioned selection & evaluation criteria concluding remarks have been drawn. Lastly, we perform a diagnostic check to ensure the chosen model best fits. Here we compare the predicted values with true values and check the relative error. The Ljung-Box statistic, also known as the modified Box-Pierce statistic, provides an indication of whether the model is correctly specified. A significance value less than 0.05 implies that there is structure in the observed series which is not accounted for by the model. Plotting the residuals of the estimated model is a useful diagnostic check through checking the white noise requirement of residuals. The ACF and PACF of residuals for forecasted CPI series will be in examined until the residuals cannot be used to improve the forecast. Final Estimates of Parameters of the selected model will be tabulated.

3.4 VAR Model

The Vector Autoregression (VAR) model, proposed by Sims (1980), is one of the most successful, flexible, and easy to use models for analysis of multivariate time series. It is applied to grasp the mutual influence among multiple time series.VAR models extend the univariate autoregressive (AR) model to dynamic multivariate time series by allowing for more than one evolving variable. All variables in a VAR model are treated symmetrically in a structural sense; each variable has an equation explaining its evolution based on its own lags and the lags of the other model variables (Enders, 2003).

Let $Y_t = (y_{it}, y_{2t}, \cdots\cdots, y_{nt})'$ denote an $(n \times 1)$ vestor of time series variable (inflation, money supply, oil prices and exchange rate). A VAR model with p lags can be expressed as follows;

$$Y_t = c + \Psi_1 Y_{t-1} + \Psi_2 Y_{t-2} + \cdots\cdots + \Psi_p Y_{t-p} + \epsilon_{t,} \qquad t = 1, \cdots\cdots, T$$

Where Ψ_i is a $(n \times n)$ coeeficient matrix,$\epsilon_{t,}$ is an $(n \times 1)$ unobservable zero mean white noise vector process, and c is an $(n \times 1)$ vector of constants (intercept).

Estimates $\Psi_i$of contain information on short run adjustments while c contain information on long run adjustments in changes in Y_t

3.4.1 Data Validation

We first check for stationarity for all the data sets. If the data is stationary, then we have an unrestricted VAR, if it's not stationary then the data needs to be modified to allow consistency in estimation of the relationships among the series. This can be done through log or differencing which then prompts for a cointegration test to check relationships among the variables. If the results show that there is cointegration then we have to use Vector Error Correction Model (VECM). VEC model is a special case of VAR for variables that are stationary in their differences. If there is no cointegration then we use unrestricted VAR. Before estimating VAR/VECM we determine the VAR/VECM model. We should also conduct the impulse function and variance decomposition to analyze the dynamic property of the model before conducting stability test on the model.

3.4.2 Testing the stationarity of time series

Sim, et al (1990) Suggest that non-stationary time series are still feasible in VAR modeling. But in practice, using the non-stationary time series in VAR modeling is problematic with regards to statistical inference since the standard statistical tests used for inference are based on the condition that all of the series used must be stationary. If we have a non-stationary time series it is not a good idea to regress one on the other. Even if they are independent, the vast majority of the points will be significantly correlated to one another. If we fit an OLS, the parameter beta will look statistically significant even though they are independent (spurious regression.) we try to avoid regressing processes which are I(1) (non-stationary) on one another.

3.4.3 Cointegration

Macroeconomic time series are typically non-stationary, as established by Nelson & Plosser, (1982). When traditional regression analysis is used on two non-stationary time series, a spurious regression may result Granger & Newbold (1974). Testing for cointegration is necessary step to check if you are modeling empirically meaningful relationships. If variables have different trends processes, they cannot stay in fixed long-run relation to each other, implying that you cannot model the long-run, and there is usually no valid base for inference based on standard distributions. If you do not find cointegration it is necessary to continue to work with variables in differences instead. In a nutshell, cointegration assumes a common stochastic non-stationary (i.e. I ((1)) process underlying two or more processes X and Y.

$X_t = \gamma_0 + \gamma_1 Z_t + \varepsilon_t \sim I(1)$, $\quad Y_t = \delta_0 + \delta_1 Z_t + \eta_t \sim I(1)$, $\quad Z_t \sim I(0)$, $\varepsilon_t . \eta_t \sim I(0)$

η, ε are stationary process $I(0)$ with zero mean, but they can be serially correlated.

Although X_t and Y_t are both non-stationary$I(1)$, there exists a linear combination of them, which is stationary; $\delta_1 X \sim \gamma_1 Y_t(0)$. In other words, the regression of Y and X yields stationary residuals $\{\varepsilon\}$.

In general, given a set of non-stationary (of type I(1)) time series variables ,$\{X_{1,t}, X_{2,t} \cdots\cdots, X_{k,t}\}$ there exists a linear combination consisting of all variables with a vector β, such that:

$$\beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots\cdots + \beta_k X_{k,t} \sim I(0)$$

Where$\beta_j \neq 0, j = 1,2, \cdots\cdots, k$ .If this is the case, then the X's are cointegrated to the order of . $C, I(1,1)$. The Johansen test has two forms: the trace test and the maximum Eigen value test. Both forms/tests address the cointegration presence hypothesis, but each asks very different questions.

Trace Test

The trace test examines the number of linear combinations (i.e. K) to be equal to a given value (K_0), and the alternative hypothesis for K to be greater than K_0

$$H_0: K = K_0 \quad Vs\ H_1: K > K_0$$

To test for the existence of cointegration using the trace test, we set $K_0 = 0$ (no cointegration), and examine whether the null hypothesis can be rejected. If this is the case, then we conclude that there is at least one cointegration relationship. In this case, we need to reject the null hypothesis to establish the presence of cointegration between the variables.

Maximum Eigen value Test

With the maximum Eigen value test, we ask the same central question as the Johansen test. The difference, however, is an alternate hypothesis:

$$H_0: K = K_0 \quad Vs\ H_1: K = K_0 + 1$$

So, starting with $K_0 = 0$ and rejecting the null hypothesis implies that there is only one possible combination of the non-stationary variables to yield a stationary process. If we have more than one, the test may be less powerful than the trace test for the same K_0 values. A special case for using the maximum Eigen value test is when $K_0 = m - 1$,where rejecting the null hypothesis implies the existence of m possible linear combinations. This is impossible, unless all input time series variables are stationary $I(0)$ to start with.

3.4.4 Model Identification

It is known that the more the lags there are, the less the degrees of freedom are. When we determine the number of lags, we choose the one with the minimum AIC and SC value. If the AIC and SC value are not minimized using the same model, we instead apply a likelihood-ratio (LR) test Johansen (1995). The LR-statistic can be expressed as follows:

$$LR = -2\left(\log L_{(k)} - logL_{(k+1)}\right) \sim x^2(n^2)$$

Where *k* is the lag order, *L* is the maximized likelihood of the model and *n* is the number of variables. If $\leq x^2{}_a$, we do not reject the null hypothesis that all the elements in the coefficient matrix are zero. Then we can reduce the lag order until the null hypothesis is rejected.

3.4.5 Estimation of parameters and the model diagnostics

Although the structure of the VAR model looks very complex, the estimation of the parameters is not difficult. The most common methods are the Maximum Likelihood Estimator (MLE) and the Ordinary Least Square Estimator (OLS). In this study, we use the OLS method to estimate the parameters. Similar as ARIMA modeling, a Q test is applied to test whether the residuals of the VAR models are white noise. Serial correlation and heteroscedasticity are tested as well.

Impulse Response Function

Impulse response identifies the responsiveness of the dependent variables when a shock is put into the error term. We apply a unit shock to VECM to see the response of all variables of the VAR system. Our VAR system model is given by;

$$\Pi = C_1 + C_2 * M2 + C_3 * P_{t-1} + C_4 * E_{t-1} + U_1$$

A change or shock in U_1 (residual) is expected to bring a change in inflation i.e. it will change money supply, oil prices and exchange rate.

Variance decomposition

The variance decomposition helps in interpretation of a VAR model once it has been fitted. It indicates the amount of information each variable contributes to the other variables in the auto-regression. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables.

3.5 Model Comparison

For the purpose of finding a model with the better forecasting capability we will compare the performance of the two models. The percentage errors and mean absolute percentage errors (MAPE) are used to evaluate the performance of different autoregressive models. MAPE can be expressed as follows;

$$MAPE = \left[{}^{1}/_{n} \sum_{i=1}^{n} abs(\widehat{y_t} - y_t)/y_t)_t \right] * 100\%$$

where $\widehat{y_t}$ is the predicted value and y_t is the actual value, and n indicated the number of fitted points.The model with the least error is selected.

CHAPTER FOUR: RESULTS

4.1 ARIMA Model

This chapter displays the empirical results from the modeling of inflation using ARIMA and VAR models respectively.

4.1.1 Data Description

In the first model, we only take the CPI data to model ARIMA. Table 2 shows CPI's descriptive statistics. CPI data has a non-normal distribution according to kurtosis and Q-Q plot.

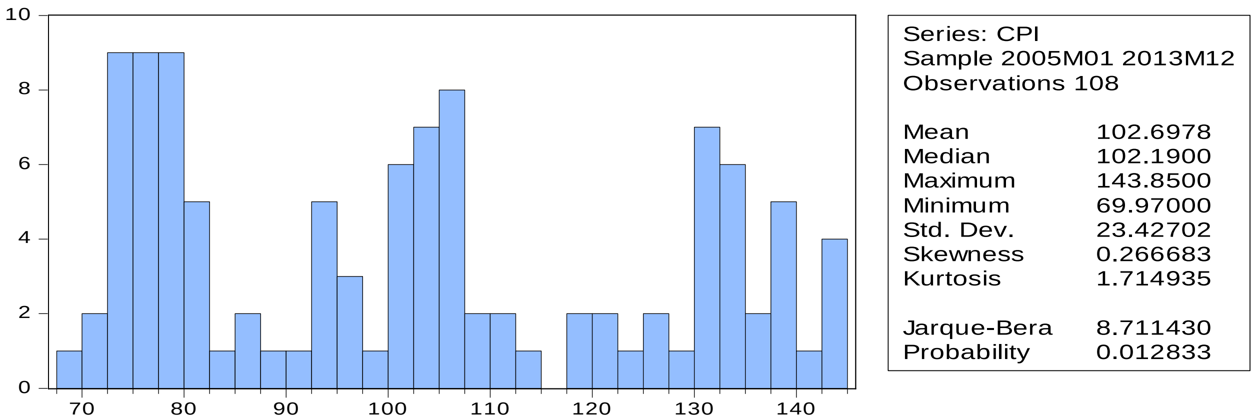
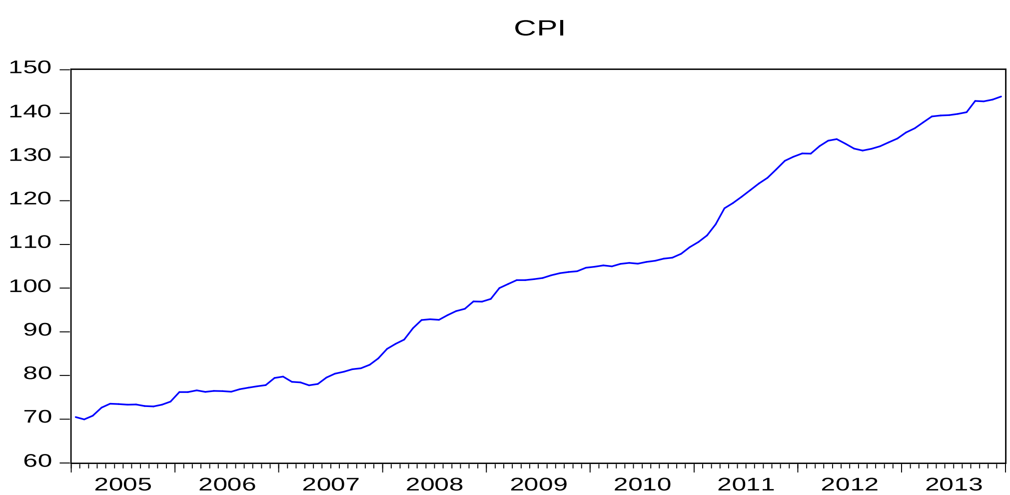


Figure : Descriptive Statistics for the inflation series

The data is not stationary since it does not display a particular state of statistical equilibrium evidencing that the variance changes with time. Performing a log transformation still produces a non-stationary process in which case we should difference the series before proceeding.



Running the autocorrelation and partial autocorrelation functions will also tell us tell us about the type of transformation requires. Below are the ACF and PACF for the CPI data before differencing is performed. The graph on the left shows the ACF decaying slowly suggesting non stationarity behavior. The autocorrelations are significant for a large number of lags but perhaps the autocorrelations at lags 2 and above are merely due to the propagation of the autocorrelation at lag 1.

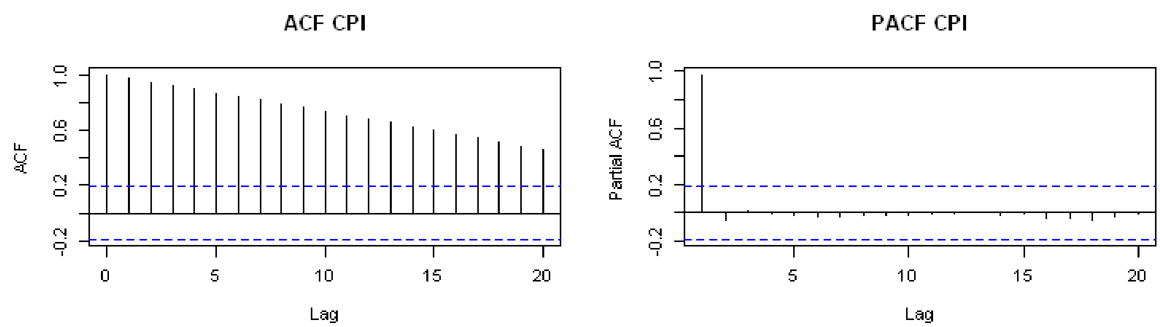


Figure : ACF and PACF for inflation series

The corresponding PACF plot has a significant spike only at lag 1 and then cuts off, meaning that all the higher-order autocorrelations are effectively explained by the lag-1 autocorrelation. The non-stationarity is of the order one as only the first-lagged bar is significantly higher than the cut-off line i.e. the first lag PACF is above the critical limit. This indicates the presence of non-stationarity and suggests first order differencing as the remedy. If a time series is stationary then its autocorrelogram should decay quite rapidly from its initial value of unity at zero lag.

4.1.2 Unit Root Test for CPI Series

Test for unity we use the ADF test for unit test hypothesis;

H_o: the CPI has unit root (non-stationary) Vs H_1: CPI data has no unit root (stationary).

CPI		**No Differencing**		**Difference=1**	
		t-Statistics	**Prob**	**t-Statistics**	**Prob**
ADF Test		-2.098457	0.5404	-6.407853	0.0000
Test Critical values	1%	-4.04			
	5%	-3.45			
	10%	-3.15			

Table : ADF test for stationarity

The test produces a Dickey-Fuller statistics greater than the critical value at all levels; the p-value is greater than 0.05 hence we fail to reject the null hypothesis and conclude the data is non-stationary. Further differencing by one, the p-value for the ADF statistics is greater at $\propto = 0.01$, 0,05 & 0.1 thus we reject null hypothesis and conclude that the data is has weak stationarity after first differencing.

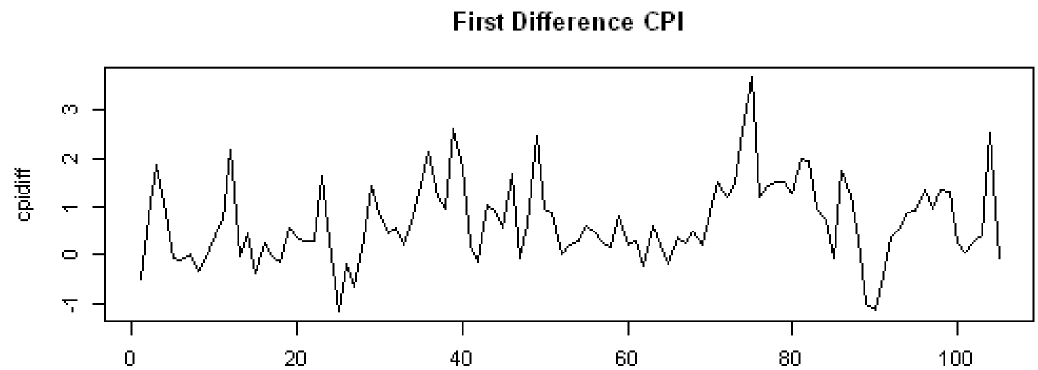


Figure : CPI series first difference

4.1.3 Model Identification, Estimation and Interpretation

ARIMA models are univariate models that consist of an autoregressive polynomial, an order of integration (*d*), and a moving average polynomial. Since CPI became stationary after first order difference (ADF test) the model that we are looking at is ARIMA (*p*, 1, q). We have to identify the model, estimate suitable parameters, perform diagnostics for residuals and finally forecast the inflation series.

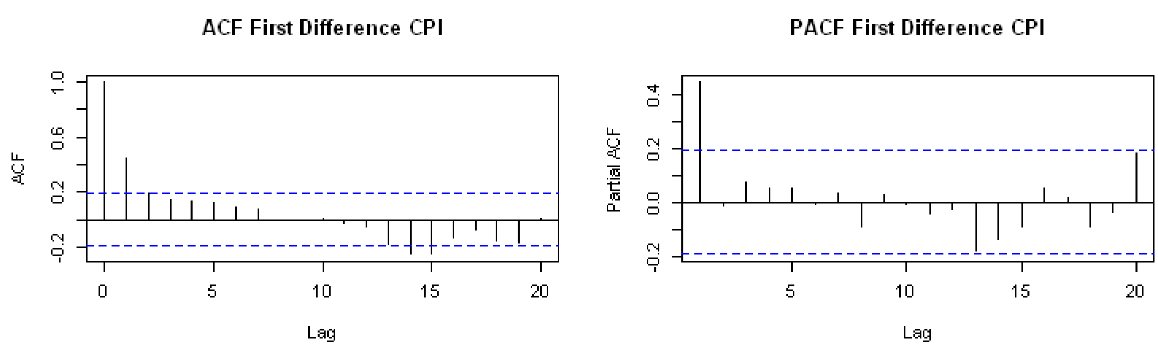


Figure : ACF and PACF First Difference for CPI series

From Figure : ACF and PACF First Difference for CPI series above, lags of ACF and PACF were generated generally displaying small autocorrelations, making it close to a white noise. The

ACF tails off towards zero (exponential decay or damped sine wave) and PACF died out slowly after lag 1(AR). Thus, the *p* and *q* values for the ARIMA (*p*, 1, *q*) model are set at 1 and 0 respectively. So, we temporarily set our ARIMA model to be ARIMA (1, 1, 0). The ACF at lag 1 is significant and positive while PACF cuts off sharply with one significant spike. Thus the differenced series displays a non-seasonal MA (1) and AR (1) signatures. This therefore suggests the possibility of the following combinations of ARIMA: ARIMA(1,1,0), ARIMA(1,1,1), ARIMA(1,1,3) to ARIMA (1,1,2).From these possible ARIMA combinations, the AIC, log likelihood and BIC criteria were used to select the most desirable ARIMA model. The results of all the ARIMA combinations are presented in Table 3 below.

Variable	**ARIMA(1,1,0)**	**ARIMA(1,1,1)**	**ARIMA(1,1,2)**	**ARIMA(1,1,3)**
S.E	0.5656	0.5647	0.5594	0.5594
Log likelihood	-117.55	-117.47	-117	-117
AIC	241.1	242.94	243.99	245.99
AICc	241.34	243.34	244.6	246.85
BIC	249.06	253.56	257.26	261.91
BIC	258.85	262.76	265.62	262.79

Table : Results for ARIMA Combinations

From the tabulation above, ARIMA (1, 1, 0) has the smallest AIC value of 241.1. Evaluating the set errors, the same model has the smallest error. We therefore conclude that ARIMA (1,1,0,) is the best model from the combination.

4.1.4 Parameter Estimation

After identifying the models we estimate the parameter coefficients. It is evidenced that ARIMA (1,1,0) is the better model as the coefficients has the smallest standard error. The parsimonious model is given by;

Let $\pi^*{}_t$ denote the first difference inflation series, so that the equation of the first order CPI series becomes:

$$ARIMA\ (1{,}1{,}0)\colon \Pi^*{}_t = \beta_0 + \emptyset_1 \Pi_{t-1} + \epsilon_t$$

More specifically;

$$\widehat{\Pi^*}_t = 0.6729 + 0.4555\pi_{t-1}$$

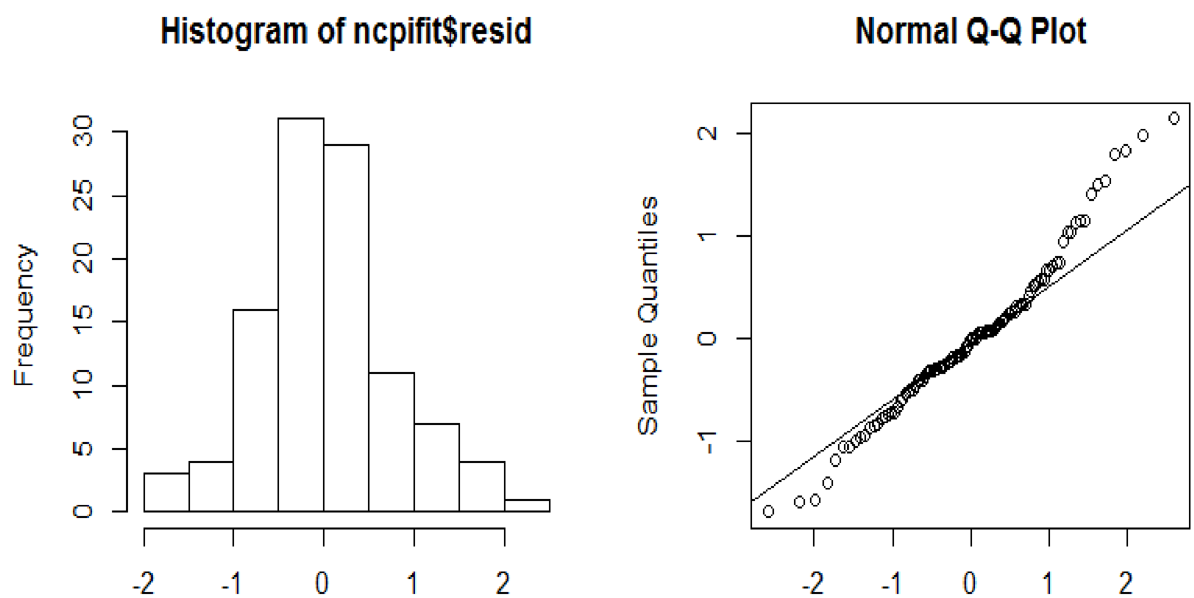
This is an autoregressive integrated model $AR(1)$.

4.1.5 Diagnostic checking

The procedure involves analyzing the residuals as well as model comparisons. If the model fits well the standardized residuals should have an independent identically distributed sequence with zero mean and variance one. We inspect the time plot (plots for normality) for any obvious deviations from this assumption, analyze ACF and PACF diagrams and the Ljung Box result. We investigate normality by plotting a histogram of the residuals and a QQ plot.

Figure : Histogram and Q-Q Plot for ARIMA (1,1,0)

The figure 6 above illustrates the residual from ARIMA (1, 1, 0) tested for normality using the histogram, Q-Q plot and box plot. The Q-Q plot is relatively normal save for a few outliers at the tails, the tests indicate that the model residuals are normally distributed.



We test for randomness by inspecting the autocorrelations of the residual for any patterns or large values. The ACF and PACF of the standardized residuals in the Figure 8 below show no significant lags and they immediately die out from lag one on hence the selected model is appropriate to represent the series.

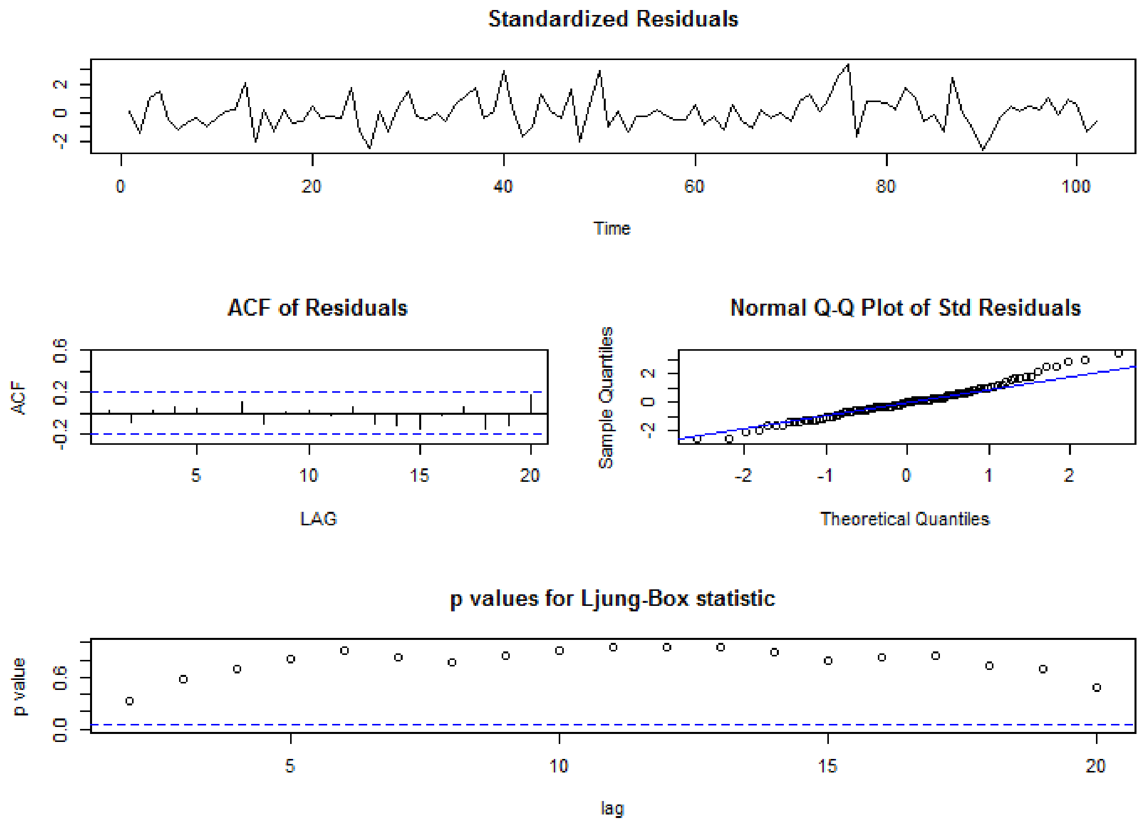


Figure : ACF and PACF for ARIMA (1,1,0) Residuals

In addition, Ljung-Box test also provides a different way to double check the model by verifying whether the autocorrelations of a time series are different from 0. In other words, if the result fails to rejects the hypothesis, this means the data is independent and uncorrelated; otherwise, there still remains serial correlation in the series and the model needs modification. The hypothesis to test at 95% confidence level is;

H_0: The model is a good fit Vs H_1: The model is not a good fit.

Box Ljung Test

Lags	**4**	**8**	**12**	**16**	**20**
X-squared	0.6914	2.401	2.793	9.6927	17.9453
p-value	0.9524	0.9662	0.9968	0.8822	0.591

Table : Results for Box Ljung Test for ARIMA (1,1,0)

At $\propto = 0.05$, the Ljung statistics for ARIMA (1,1,0) tested at different lags is not significantly different from zero with the associated p-values. We fail to reject the null hypothesis that the autocorrelation is different from zero and conclude that the model is good fit. The Q-statistic p-value for this model appears to fit the data well hence fail to reject the Box Pierce null. This means the data is independent and uncorrelated. The Jarque–Bera test statistics 5.1724 (p-value= 0.0753) indicate the presence of normality (no excess skewness and kurtosis) in the residuals.

4.1.6 Forecasting

Forecasting the inflation series will be done using ARIMA (1,1,0) model. The duration of forecasts is from 2013:07 to 2013:12.

Month	CPI Actual	ARIMA Predicted	% variance
Jul-13	139.87	139.96	-0.06
Aug-13	140.29	140.47	-0.13
Sep-13	142.82	141.06	1.25
Oct-13	142.75	141.69	0.75
Nov-13	143.14	139.67	2.49
Dec-13	143.85	140.33	2.51

Table : Forecasted Inflation

4.2 VAR Modeling

In the first VAR model, we take the CPI as the dependent variable. The VAR model will contain four variables, Money supply, Murban oil Prices and exchange rate.

A preliminary data analysis is conducted to display the summary statistics as well as a corresponding time series plotsΠ, $M2$, P and E .

Statistics	Π	$M2$	P	E
Mean	100.3788	875003.1	83.27647	77.31039
Median	101.4000	786910.0	76.80000	76.75500
Maximum	139.5900	1547882.	137.3500	99.83000
Minimum	69.97000	428711.0	42.10000	62.03000
Std. Dev.	21.98960	339122.6	24.99200	7.740460
Skewness	0.315397	0.408211	0.229291	0.276804

Kurtosis	1.782997	1.891869	1.826718	3.100043
Jarque-Bera	7.985741	8.051628	6.744276	1.345080
Probability	0.018447	0.017849	0.034316	0.510410
Sum	10238.64	89250312	8494.200	7885.660
Sum Sq. Dev.	48837.78	1.16E+13	63084.63	6051.387
Observations	102	102	102	102

Table : Descriptive Statistics for independent variables

We set up a VAR model such that inflation data against the independent variable and then test for cointegration. We also test if there is any long and short run causality relationship between inflation and each of the independent variable.

4.2.1 Testing the stationarity

As shown in the Figure below all the independent time series are non- stationary. We therefore do the differencing for each series. Inflation(Π), Money supply $(M2)$, Oil prices (P) and Exchange rate(E).

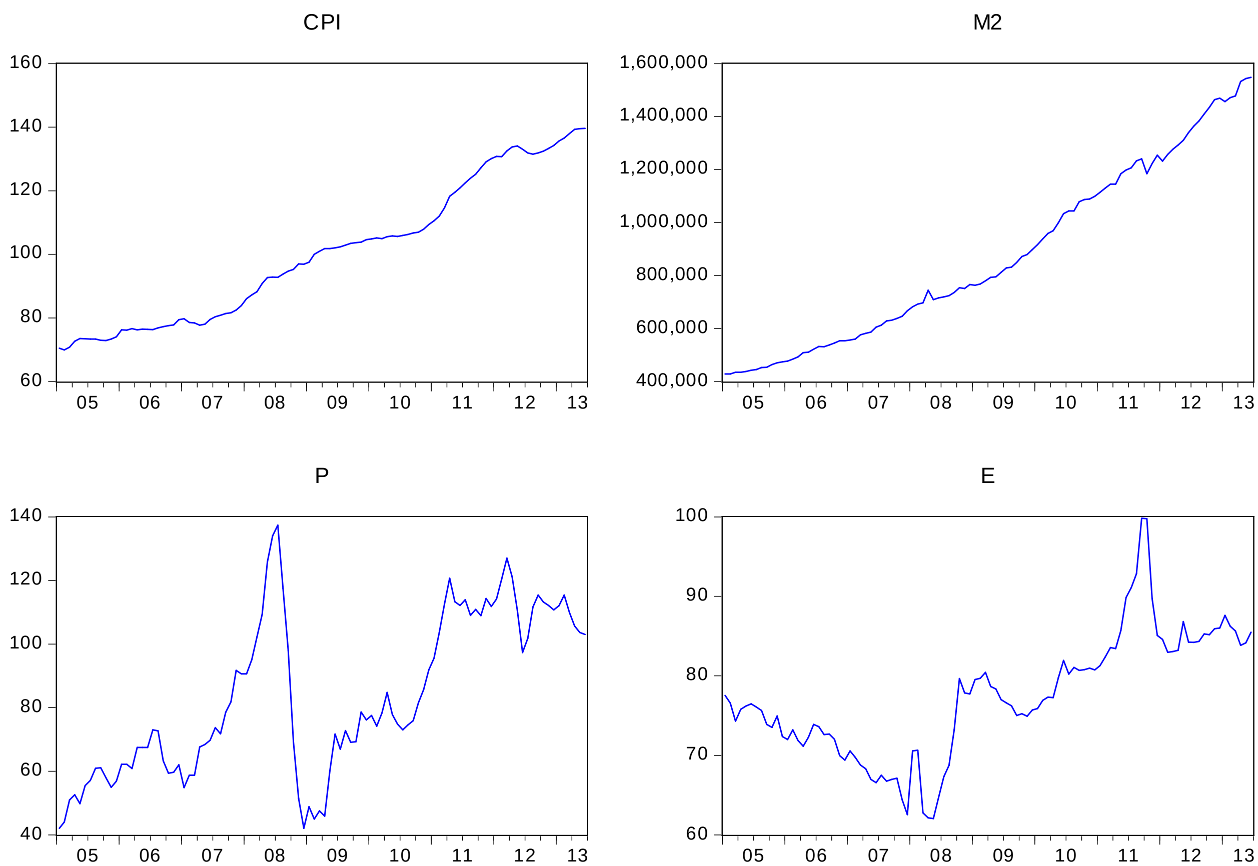


Figure : Time plot of the raw series of independent variables

After the first order differencing we apply the ADF unit root for each series. The results as shown below indicate that all the series are stationary.

Intermediate ADF test results

Series	Prob.	Lag	Max Lag	Obs
D(Π)	0.0000	0	12	100
D(M2)	0.0000	1	12	99
D(P)	0.0000	0	12	100
D(E)	0.0000	1	12	99

Table : ADF test for the series

Stationarity is emphasized by the time plot of the first differenced series below.

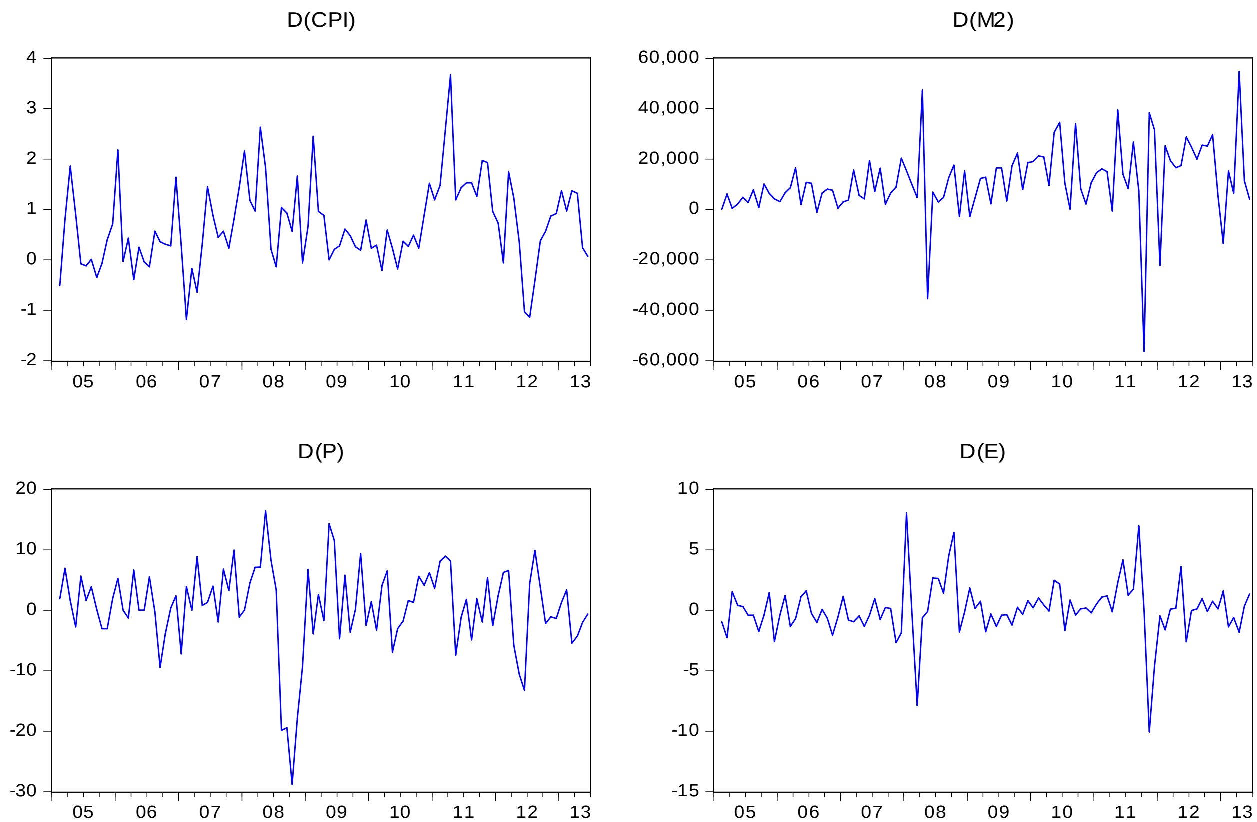


Figure : Plot of First Differencing of the independent variables

4.2.2 Test for Cointegration

To avoid spurious regression, testing for cointegration is a necessary step to check if we are modeling empirically meaningful relationships. We run a cointegration test with the null hypothesis being no cointegration. The number of lags in the VAR is based on the evidence provided by AIC. The cointegration test amongst inflation(Π), Money supply $(M2)$, Oil prices $(P)$and Exchange rate (E)include four lags in the VAR.

Table : Cointegration Test

Hypothesized No. of CE (s)	None	At most 1	At most 2	At most 3
Eigen value	0.314199	0.126905	0.077136	0.055912
Trace Statistics	**63.1166**	26.53139	13.36745	**5.580963**
95% Critical Value	47.85613	29.79707	15.49471	3.841466
Prob.**	0.001	0.1136	0.102	0.0182
Max-Eigen Statistic	**36.58521**	13.16393	7.78649	**5.580963**
95% Critical Value	27.58434	21.13162	14.2646	3.841466
Prob.**	0.0027	0.4373	0.4008	0.0182

The results above indicates that there exists one cointegrating equation for both the Trace and Maximum Eigen value tests hence we reject the null hypothesis. This implies that there exists a long run relationship between inflation and the independent variables. This is the long run cointegrated model. The coefficients for the variables are long run coefficients. The coefficients show that when Money supply $(M2)$ and Exchange rate(E) goes down inflation goes up and vice versa and while oil prices (P)go up, inflation goes up and vice versa. The normalized cointegrating relation assuming one cointegrating relation r = 1 is given by;

$$D(\Pi) = -5.51059E - 05M2 + 0.3221P - 0.2071E - 63.6219$$

We can therefore proceed and run a Vector Error Corrected Model to establish the short run dynamics and estimate the parameters.

4.2.3 Model identification and parameter estimation

We determine the optima number of lags is 4 guided by the AIC and SIC minimum rules. The estimated VAR model of first differences and with 4 lags can be expressed as follows;

$$
\begin{aligned}
D(\Pi) = C(1) * (\, \Pi(-1) - 5.50578945919e - 05 * M2(-1) + 0.32214876861 \\
* P(-1) - 0.20709860277 * E(-1) - 63.621883326\,) + C(2) * D(\Pi(-1)) \\
+ C(3) * D(\Pi(-2)) + C(4) * D(\Pi(-3)) + C(5) * D(\Pi(-4)) + C(6) \\
* D(M2(-1)) + C(7) * D(M2(-2)) + C(8) * D(M2(-3)) + C(9) \\
* D(M2(-4)) + C(10) * D(P(-1)) + C(11) * D(P(-2)) + C(12) \\
* D(P(-3)) + C(13) * D(P(-4)) + C(14) * D(E(-1)) + C(15) \\
* D(E(-2)) + C(16) * D(E(-3)) + C(17) * D(E(-4)) + C(18)
\end{aligned}
$$

From here we can derive the residual of the cointegrating equation when CPI is the dependent variable as shown in Table 9. C(1)- the error correction term, is the speed of adjustment towards long run equilibrium. For long run causality to be established C(1) must be significant and the sign must be negative. The results indicate that it is not significant or negative; therefore there is no long run equilibrium between the independent variables money supply, oil prices and exchange rate and inflation. Meaning the independent variables have no influence on the dependent variable in the long run.

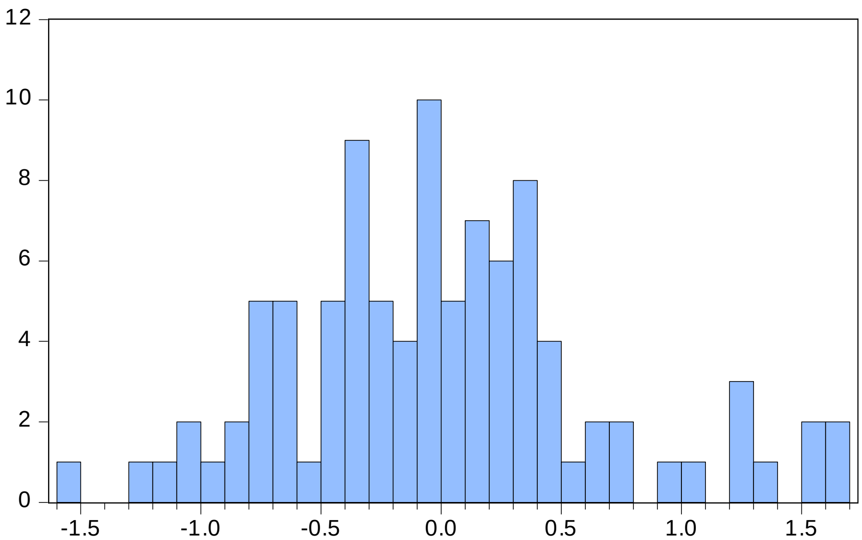
We find that lagged CPI and oil prices are important since they are significant. First lag of inflation has a significant coefficient at 5% level with 47% of the previous period inflation feeding into current inflation. The ECM term is significant suggesting a long run relationship between inflation and the independent variables.

We then test for short run causality i.e. whether the variables have a short run causality or not by checking against the cointegrating coefficients using the use Wald statistics. The null hypothesis is that C()=0 meaning that there is no short run causality running from each independent variable to inflation.

The results are shown in Table 11, 12 and 13. Running the Wald statistics for the money supply, the p-value 60% which is larger than 5%, we fail to reject null hypothesis meaning the c's are zero thence no short run causality from money supply to inflation. Testing for short run causality from oil prices to inflation, the test shows that there is short run causality between Murban oil prices and inflation. We reject the null hypothesis since the p-value is less than 5%. Finally we test for short run causality from exchange rate to inflation. We fail to reject the null hypothesis and conclude that there is to short run causality from the exchange rate to inflation.

4.2.4 Diagnostic check

We check if our model where inflation is the dependent variable has any statistical error or not. R-squared is 34% which is not significant. Performing a residual diagnostic, we check serial correlation, R-squared (79%) is greater than 5% meaning we fail to reject null hence no serial correlation which is a good sign. Testing for heteroscedasticity results to a p-value of 21% indicating that the model has no heteroscedasticity. Test for normality, the Jarque Bera statistics indicated that the p-value is greater than 5% hence we cannot reject the null hypothesis.



Series: Residuals
Sample 2005M06 2013M06
Observations 97

Mean	4.38e-17
Median	-0.030168
Maximum	1.682610
Minimum	-1.500443
Std. Dev.	0.656526
Skewness	0.492880
Kurtosis	3.328706
Jarque-Bera	4.364066
Probability	0.112812

Figure : VAR model Normality test

The kurtosis is close to 3 indicating normality. This means that the residual of this model is normally distributed which is desirable. It is therefore reasonable to consider that our VAR model is valid. Stability test shows that our dependent variable is stable as shown by Figure 11.

Impulse Response Function

Impulse response identifies the responsiveness of the dependent variables when a shock is put into the error term. We apply a unit shock to VECM to see the response of all variables of the VAR system. A change or shock in U_1 (residual) is expected to bring a change in inflation i.e. it will change $M2, P\ and\ E$. Our VAR system model is given by

$$\Pi = C_1 + C_2 * M2_{t-1} + C_3 * P_{t-1} + C_4 * E_{t-1} + U_1$$

When we give one standard deviation positive shock to CPI, CPI increases. If we give one positive standard deviation shock to money supply, CPI is initially constant and then increases positively after four periods. One standard deviation shock to oil prices, inflation reacts positively before becoming steady after three periods. One standard deviation shock on exchange rate, CPI reacts positively before becoming steady in the fifth period. The change is as shown in Figure 12 with a ±2 standard errors indicating that the parameters are quite stable as Figure 13 demonstrates.

Variance decomposition

The variance decomposition shows the variance forecast error. In the short run, for instance two months, the impulse or shock to CPI account for 97.54% variation of the fluctuation in CPI (own shock). As shown in Table 14, shock to money supply in 6 periods is 0.89%, exchange rate is 3.70%. Shock on CPI cause 91.93% fluctuation to CPI variance and decreases in the long run. Shocks applied on money supply, oil prices and exchange rate increases in the long run.

4.2.5 Forecasting

Since the model is free from serial correlations, heteroscedasticity and the residuals are normally distributed then we can use the selected model to forecast. We shall be forecasting beyond our model data i.e. from 2013:07 to 2013:12. We apply the model to forecast inflation, Figure 15 and Figure 16 shows the graphs of the forecasted series.

The forecasted series is as tabulated below;

Actual CPI	VAR Forecasted	%Error VAR
139.87	139.59	0.20
140.29	140.14	0.10
142.82	141.40	1.01
142.75	142.71	0.02
143.14	143.51	(0.26)
143.85	144.20	(0.24)

Table 15: VAR Forecasted series

4.3 Model comparison

Finally we compare the ARIMA and VAR model prediction accuracy, the model with the smallest errors has the better forecasting ability. In this case VAR model has the least error of 0.23% mean absolute percentage hence the better model in forecasting inflation.

Variable	ARIMA(1,1,0)	VAR
RMSE	0.7449339	0.578614
MAE	0.5598324	0.34123
MAPE	0.5744717	0.239519

Table 16: Comparison of ARIMA and VAR models

CHAPTER FIVE: CONCLUSION

This study analyses the determinants of inflation in Kenya using ARIMA and VAR model where the forecasting power of historical inflation data and the determinants of inflation are investigated.

In ARIMA model we use historical consumer pricing data to model inflation for the period 2005:01-2013:06. ARIMA model (1, 1, 0) resulted as the best model. The study shows that despite the exclusion of explanatory variables there is evidence of substantial inflation inertia concurring with Durevall & Sjo (2012) findings. This is also evidence by the hypothesis that if the level of inflation is determined by inertia then the parameters on lagged inflation should sum to unity. Parameters of the selected lagged parsimonious model in this study sum approximately to unity.

In the vector autoregressive model we examine effects of money supply, oil prices and exchange rate, on consumer price inflation using a vector error correction model. We used the VEC model because the time series are all stationary after first differencing and are cointegrated. A cointegration framework exhibit a long run relationship where a gain in money supply and exchange rate result to a drop in inflation and a gain in oil prices result to a gain in inflation rate. Change in exchange rate and money supply affect inflation negatively while change in oil prices have positive effect on inflation.

There is no long run equilibrium between the independent variables and inflation. The absence of relation over a long span of time between supply shocks factors i.e. exchange rate and oil prices is because the prices are determined by factors that affect demand and supply of the foreign exchange and oil. These findings are consistent with evidence presented by of Durevall & Ndungu (2001).

Testing for causality shows that there is no long run causality running from money supply, oil prices and exchange rate variables to inflation. However, short run causality was established from Murban oil prices to inflation. In our model oil prices are likely to be an efficient nominal anchor since it affects the level of prices in the short run. Reasonably, oil prices solely accounts for the largest share in Kenya's imported good at about 25% and is key to production of goods and services thus it can capture the influence of supply shocks. It is therefore seen that imported inflation influences domestic inflation. Money supply also failed to show long run effect on inflation implying that money growth does not determine prices as often perceived.

In the VAR model, lagged values of inflation are seen to be significant with a large coefficient of 0.47 confirming the results of the ARIMA model with a significant coefficient of 0.46, that inflation inertia substantially exist.

These results confirm broadly previous findings that money supply, oil prices and exchange rate are important determinants of inflation. In addition, lags of historical CPI price can be used to forecast inflation. Finally, the study shows that the basic determinants of inflation include its own lagged series and oil prices.

The selected models can enhance the predictability of model for forecasting consumer price index of Kenya and better assist the policymakers. Further analysis using additional specifications of inflation expectations such as output gap, real GDP, employment rate data which are more current in Kenya would be useful.

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APPENDIX:

Table : Error Correction Model

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.012493	0.010292	1.213899	0.2284
C(2)	0.468921	0.114888	4.081564	0.0001
C(3)	-0.038296	0.121943	-0.314050	0.7543
C(4)	0.006128	0.123336	0.049684	0.9605
C(5)	-0.066804	0.119084	-0.560984	0.5764
C(6)	3.68E-06	6.15E-06	0.597801	0.5517
C(7)	-2.82E-06	6.15E-06	-0.458692	0.6477
C(8)	-8.11E-06	6.50E-06	-1.246752	0.2162
C(9)	-1.76E-06	7.19E-06	-0.244323	0.8076
C(10)	0.039338	0.015034	2.616610	0.0106
C(11)	0.007770	0.014290	0.543774	0.5881
C(12)	-0.023041	0.014576	-1.580777	0.1179
C(13)	0.010282	0.013384	0.768228	0.4446
C(14)	0.048273	0.039471	1.223004	0.2250
C(15)	0.059745	0.042176	1.416553	0.1605
C(16)	0.057551	0.042288	1.360908	0.1774
C(17)	0.031853	0.040093	0.794459	0.4293
C(18)	0.486842	0.232237	2.096320	0.0393

R-squared	0.382160	Mean dependent var	0.680928
Adjusted R-squared	0.249207	S.D. dependent var	0.835246
S.E. of regression	0.723726	Akaike info criterion	2.357064
Sum squared resid	41.37859	Schwarz criterion	2.834845
Log likelihood	-96.31759	Hannan-Quinn criterion.	2.550255
F-statistic	2.874405	Durbin-Watson stat	2.022850
Prob(F-statistic)	0.000807		

Table : Vector Error Correction Estimates

Cointegrating Eq:	CointEq1			
Π(-1)	1.000000			
$M2$(-1)	-5.51E-05 (1.3E-05) [-4.36361]			
P(-1)	0.322149 (0.11109) [2.89995]			
$E(-1)$	-0.207099 (0.34088) [-0.60755]			
C	-63.62188			
Error Correction:	**D(CPI)**	**D(M2)**	**D(OPM)**	**D(USD)**
CointEq1	0.012493 (0.01029) [1.21390]	408.5419 (184.496) [2.21437]	-0.390086 (0.07563) [-5.15774]	0.000593 (0.03091) [0.01918]
D(Π(-1))	0.468921 (0.11489) [4.08156]	-545.8486 (2059.49) [-0.26504]	0.161838 (0.84425) [0.19169]	0.203988 (0.34503) [0.59122]
D(Π(-2))	-0.038296 (0.12194) [-0.31405]	-1577.622 (2185.95) [-0.72171]	0.838605 (0.89610) [0.93584]	0.126866 (0.36622) [0.34642]
D(Π(-3))	0.006128 (0.12334) [0.04968]	171.1023 (2210.93) [0.07739]	2.450007 (0.90634) [2.70320]	-0.423511 (0.37040) [-1.14338]
D(Π(-4))	-0.066804 (0.11908) [-0.56098]	-2520.609 (2134.71) [-1.18077]	1.541546 (0.87509) [1.76158]	0.433245 (0.35763) [1.21142]
D($M2$(-1))	3.68E-06 (6.2E-06) [0.59780]	-0.178737 (0.11028) [-1.62075]	6.69E-05 (4.5E-05) [1.48005]	3.12E-05 (1.8E-05) [1.69100]

D($M2$(-2))	-2.82E-06	0.051060	0.000111	2.57E-05
	(6.1E-06)	(0.11021)	(4.5E-05)	(1.8E-05)
	[-0.45869]	[0.46330]	[2.45599]	[1.39259]
D($M2$(-3))	-8.11E-06	0.237477	0.000196	1.25E-05
	(6.5E-06)	(0.11659)	(4.8E-05)	(2.0E-05)
	[-1.24675]	[2.03682]	[4.09041]	[0.63974]
D($M2$(-4))	-1.76E-06	0.026275	7.50E-05	-4.22E-06
	(7.2E-06)	(0.12882)	(5.3E-05)	(2.2E-05)
	[-0.24432]	[0.20397]	[1.41947]	[-0.19569]
D(P(-1))	0.039338	-348.3832	0.215392	-0.065755
	(0.01503)	(269.501)	(0.11048)	(0.04515)
	[2.61661]	[-1.29270]	[1.94964]	[-1.45635]
D(P(-2))	0.007770	104.3744	0.139799	0.060997
	(0.01429)	(256.155)	(0.10501)	(0.04291)
	[0.54377]	[0.40747]	[1.33133]	[1.42137]
D(P(-3))	-0.023041	392.2412	-0.056469	-0.003913
	(0.01458)	(261.290)	(0.10711)	(0.04377)
	[-1.58078]	[1.50117]	[-0.52719]	[-0.08938]
D(P(-4))	0.010282	-322.3348	-0.061820	0.002183
	(0.01338)	(239.925)	(0.09835)	(0.04020)
	[0.76823]	[-1.34348]	[-0.62855]	[0.05432]
D(E(-1))	0.048273	-2104.018	-0.762826	0.251623
	(0.03947)	(707.554)	(0.29005)	(0.11854)
	[1.22300]	[-2.97365]	[-2.62998]	[2.12271]
D(E(-2))	0.059745	834.0537	-0.635904	-0.296636
	(0.04218)	(756.055)	(0.30993)	(0.12666)
	[1.41655]	[1.10317]	[-2.05175]	[-2.34191]
D(E(-3))	0.057551	819.8811	-0.565618	0.187456
	(0.04229)	(758.067)	(0.31076)	(0.12700)
	[1.36091]	[1.08154]	[-1.82013]	[1.47602]
D(E(-4))	0.031853	-1065.814	-0.151225	-0.119229
	(0.04009)	(718.718)	(0.29463)	(0.12041)
	[0.79446]	[-1.48294]	[-0.51328]	[-0.99020]
C	0.486842	13369.14	-7.775256	-0.868513
	(0.23224)	(4163.10)	(1.70660)	(0.69746)

	[2.09632]	[3.21135]	[-4.55600]	[-1.24526]
R-squared	0.382160	0.341761	0.536219	0.272856
Adj. R-squared	0.249207	0.200114	0.436418	0.116382
Sum sq. resids	41.37859	1.33E+10	2234.474	373.2047
S.E. equation	0.723726	12973.59	5.318316	2.173502
F-statistic	2.874405	2.412772	5.372885	1.743782
Log likelihood	-96.31759	-1046.337	-289.7840	-202.9867
Akaike AIC	2.357064	21.94509	6.346061	4.556427
Schwarz SC	2.834845	22.42287	6.823843	5.034209
Mean dependent	0.680928	11446.75	0.548454	0.095876
S.D. dependent	0.835246	14505.95	7.084279	2.312213
Determinant resid covariance (dof adj.)		9.46E+09		
Determinant resid covariance		4.16E+09		
Log likelihood		-1624.803		
Akaike information criterion		35.06810		
Schwarz criterion		37.08540		

The null hypothesis for the Wald Test is given by C()=0.

c(2)=c(3)=C(4)=C(5)

Wald Test:

Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	5.137257	(3, 79)	0.0027
Chi-square	15.41177	3	0.0015

Wald Test:

Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	0.628031	(3, 79)	0.5990
Chi-square	1.884094	3	0.5968

Table : Money Supply Wald Test

Wald Test:

Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	0.628031	(3, 79)	0.5990
Chi-square	1.884094	3	0.5968

Table : Murban oil prices Wald Test

Wald Test:

Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	2.586236	(3, 79)	0.0589
Chi-square	7.758708	3	0.0513

Table : Exchange rate Wald Test

Wald Test:

Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	0.118047	(3, 79)	0.9493
Chi-square	0.354140	3	0.9495

Figure : Stability test

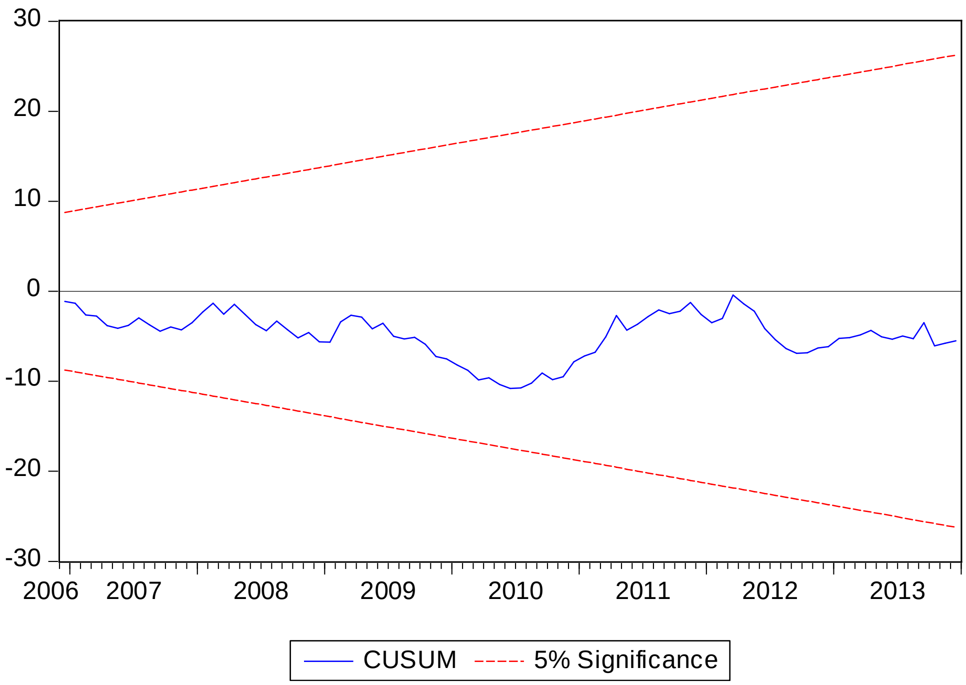


Figure : Impulse Response Function

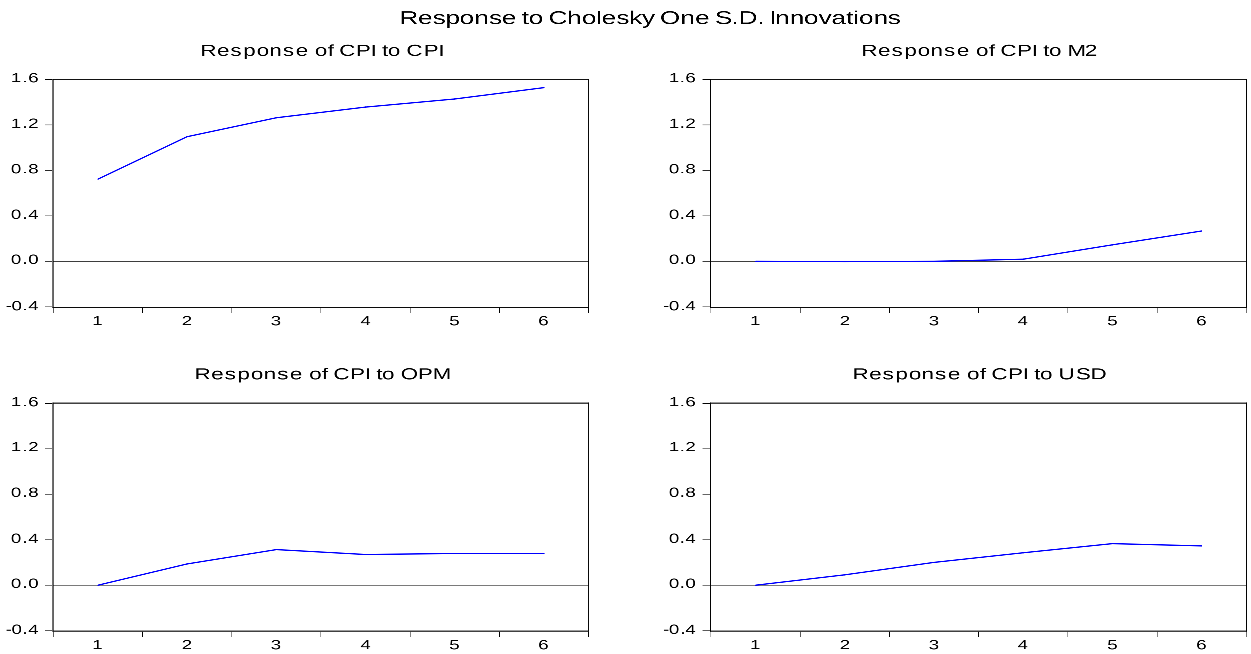


Figure : Recursive Estimates

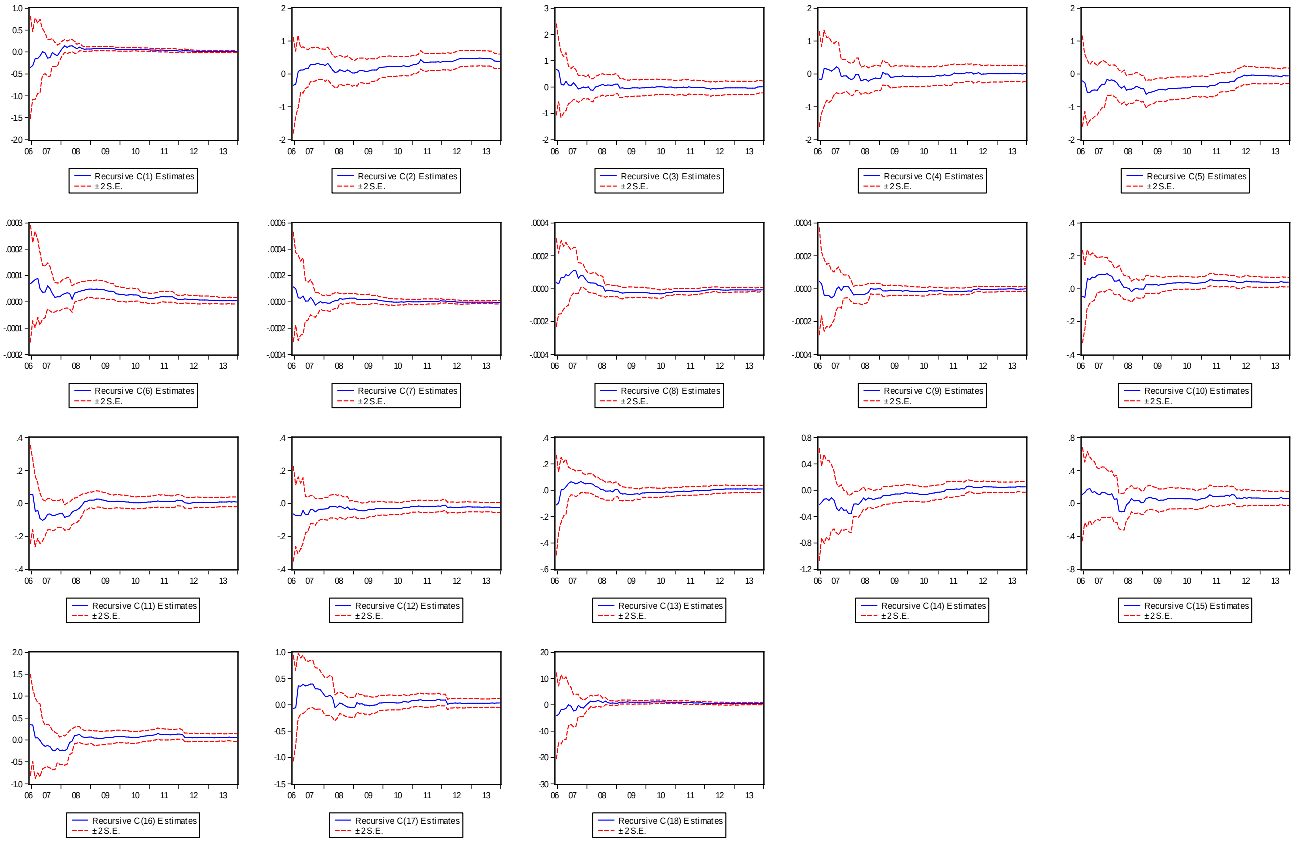


Table : Variance Decomposition

Variance Decomposition of CPI:

Period	S.E.	π	m	p	f
1	0.723726	100.0000	0.000000	0.000000	0.000000
2	1.329677	97.54023	0.000472	1.983510	0.475792
3	1.871115	94.80444	0.000244	3.799050	1.396270
4	2.344393	93.87268	0.005983	3.747816	2.373524
5	2.787354	92.68117	0.274556	3.650574	3.393704
6	3.220798	91.92677	0.890376	3.486795	3.696063

Figure : Variance Decomposition Chart

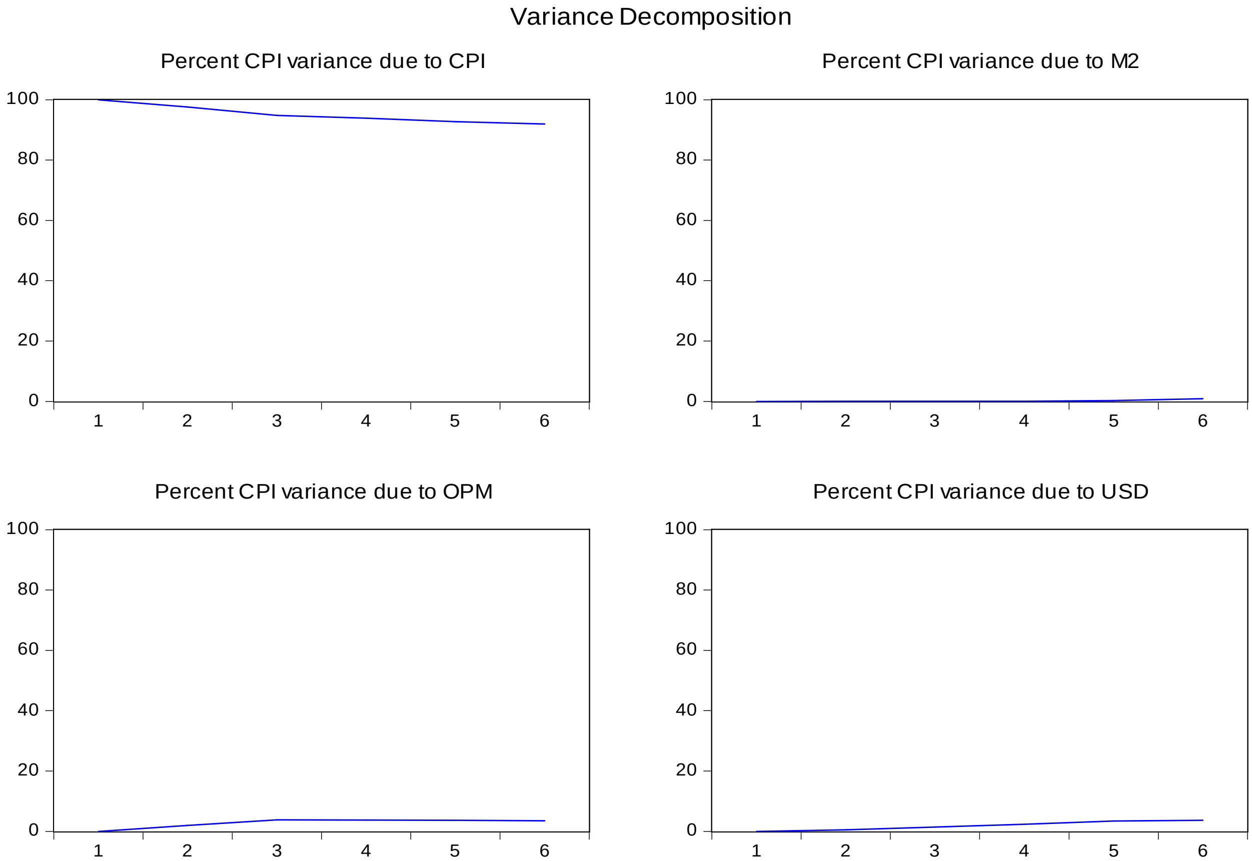
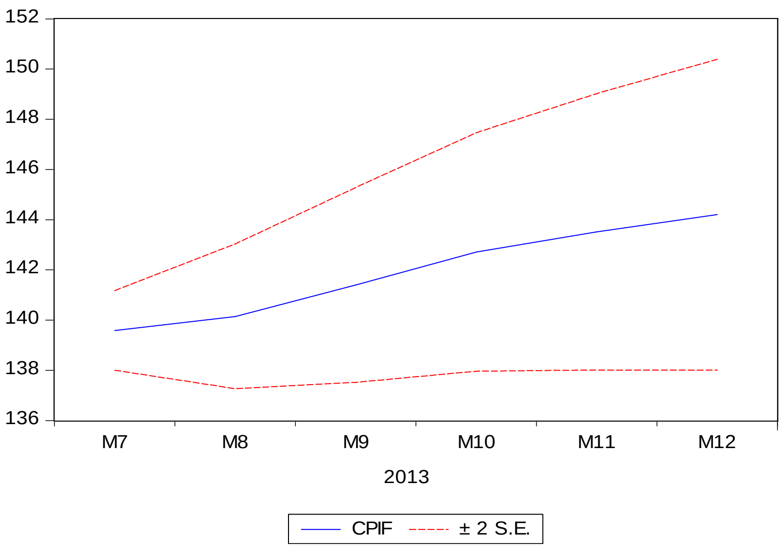


Figure : Forecasted series Statistics



Forecast: CPIF
Actual: CPI
Forecast sample: 2013M07 2013M12
Included observations: 6

Root Mean Squared Error	0.630959
Mean Absolute Error	0.435340
Mean Abs. Percent Error	0.305437
Theil Inequality Coefficient	0.002221
Bias Proportion	0.094798
Variance Proportion	0.105339
Covariance Proportion	0.799863

Figure : Actual, Fitted, Residual Graph

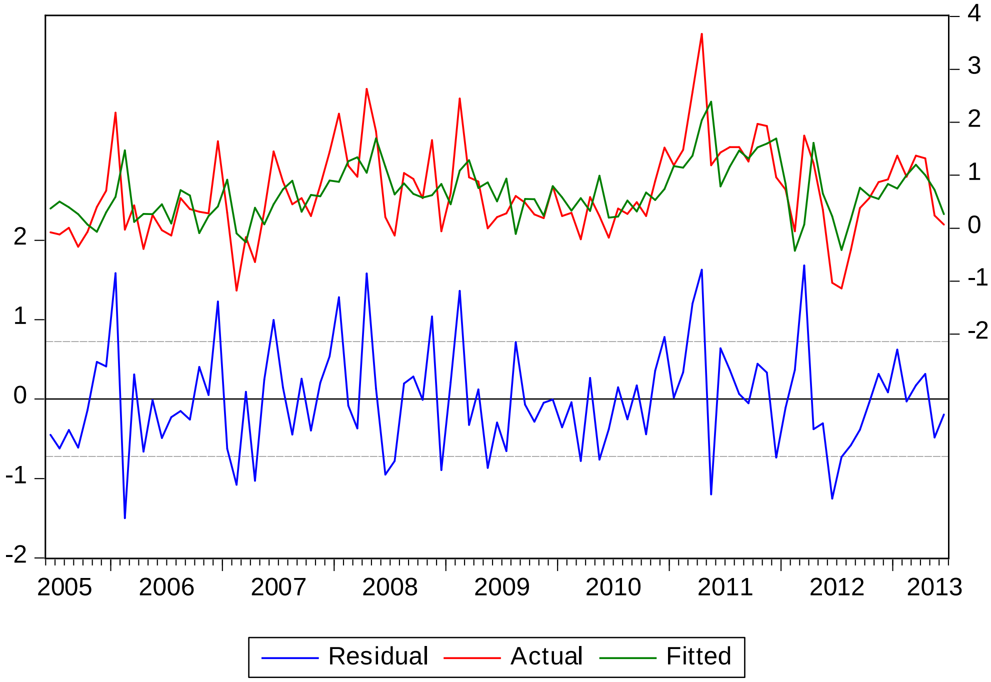
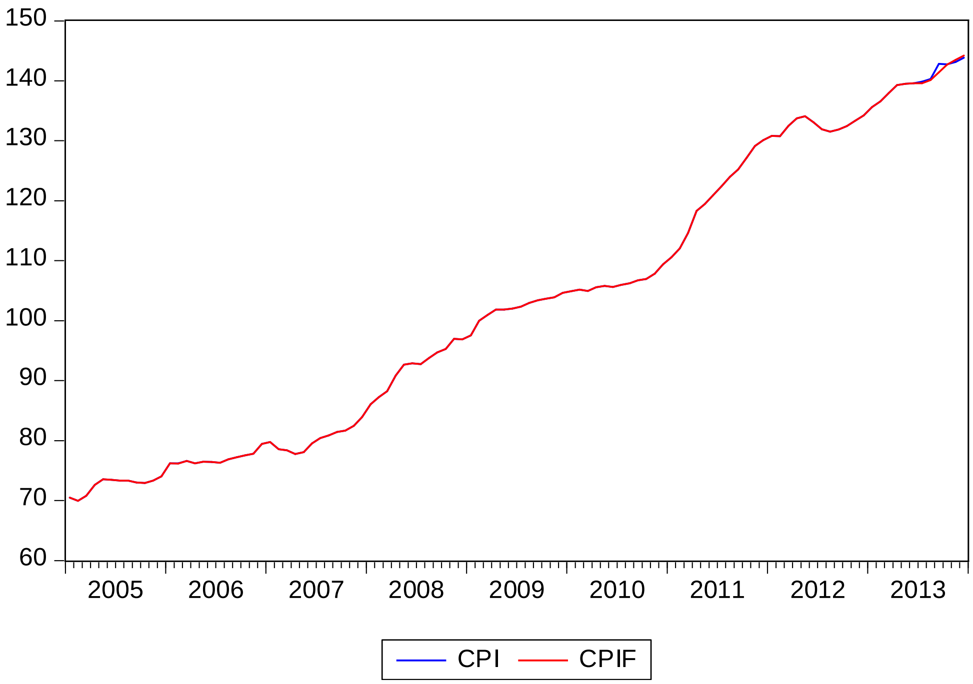
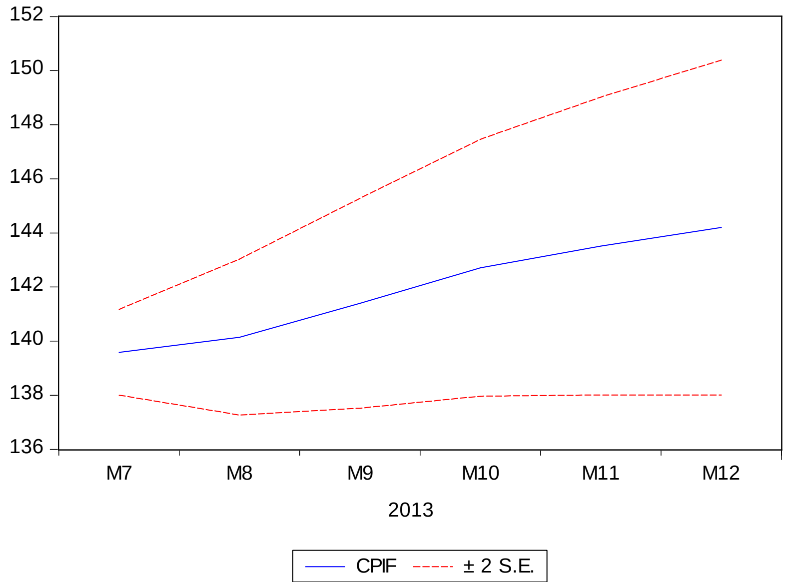


Figure : Line plot of Actual and Forecasted Inflation series





Forecast: CPIF	
Actual: CPI	
Forecast sample: 2013M07 2013M12	
Included observations: 6	
Root Mean Squared Error	0.630959
Mean Absolute Error	0.435340
Mean Abs. Percent Error	0.305437
Theil Inequality Coefficient	0.002221
Bias Proportion	0.094798
Variance Proportion	0.105339
Covariance Proportion	0.799863