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ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

FORECASTING MODEL OF INFLATIONARY PROCESS IN ETHIOPIA

BY

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JULY 2008

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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 Applied Statistics

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Acknowledgements

First of all, I would like to offer my great thanks to almighty God and for His Mother Saint Mary who helped me through out my life and to accomplish the graduate study program.

My deepest and warmest thanks goes to my Brother Fikru Cherinet who built my life in academic education on behalf of my Father.

I give my special thanks to my advisor Olusanya Elisa Olubusoye (Dr.) for his guidance and support during my study.

My special thanks are also goes to Yordanos who allowed me to use her lap top for my work. My special thanks also extended to all staff members of Statistics department and all my friends who contributed to my graduate study program.

Abstract

The primary focus of monetary policy both in Ethiopia and elsewhere, has traditionally been the maintenance of a low and stable rate of aggregate price inflation as defined by commonly accepted measures such as the consumer price index. The control of inflation is one of the problems facing a government wishing to encourage rapid economic development. The aim of this study is to investigate the nature of inflation in Ethiopia and construct a model that can be used to forecast future values. The exponential smoothing method was employed and the forecasting performance of winter (additive) method was found to be better. Two alternative approaches to model identification were considered, the Box-Jenkins methodology and penalty function criteria. For Ethiopian monthly inflation data covering the period 1997:08 to 2006:06 various possible ARMA models were fitted. The comparative performance of these ARMA models were checked and verified by using Akaike Information Criteria, Schwartz Criteria, Root mean square percentage error, Mean absolute error and Mean absolute percentage error.

CHAPTER ONE

1. INTRODUCTION

The primary focus of monetary policy both in Ethiopia and elsewhere, has traditionally been the maintenance of a low and stable rate of aggregate price inflation as defined by commonly accepted measures such as the consumer price index. The underlying justification for this objective is the wide spread consensus supported by numerous economic studies, that inflation is costly so far as it undermines real, wealth-enhancing, economic activity.

There are a number of approaches available for modeling and forecasting economic time series. One approach, which includes only the time series being forecast, is known as univariate modeling. 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). Some times traditional methods of time series analysis can better perform, especially in short term forecasting than scientific time series models. To see this, exponential smoothing method which is one of traditional method in time series analysis is employed. On the other hand this study will focuses on the ARIMA models. An alternative approach is multivariate time series forecasting. Multivariate may consist of single equation models with exogenous explanatory variables or alternatively may include structural or non-structural system of equations. In practice the formal econometric models outlined above are often supplemented by subjective 'off-model' inputs. Such information may include survey data gathered from liaising with retailers and manufacturing enterprises. Thus inflation forecasting is an art rather than a hard science combining formal econometric techniques with forecasters' experience and expertise (Aidan Meyler et al, 1998).

Inflation has often been defined as "too much money chasing too few goods". This, however, is more an explanation of inflation than a definition, attributing the cause of inflation to monetary growth relative to the out put of goods and services. What is inflation? It is a persistent rise in the general level of prices and reduction in value of money. In other words, it is the rate at which prices are increasing. It can be measured monthly, quarterly, or annually.

Inflation can cause a variety of problems for the economy. If our price is rising more quickly than those of our competitors abroad, then we will rapidly become uncompetitive and our exports will fall. Inflation will also cause problems domestically as wages try to keep up and those on fixed income suffer. People's savings will also fall in value. Therefore, the control of inflation is one of the problems facing a government wishing to encourage rapid economic development. The fight against illiteracy, the reform of bureaucratic practices, endemic diseases, the substitution of competitive for monopolistic trade practices, the encouragement of the widespread spirit of entrepreneurship, and the creation of an adequate amount of social capital, may be important prerequisites for rapid growth. However, attacks on these problems are likely to be more feasible in atmosphere of financial stability: a rapid inflation will make the failure of such attacks much more likely (Greame S.Dorrance, 2008).

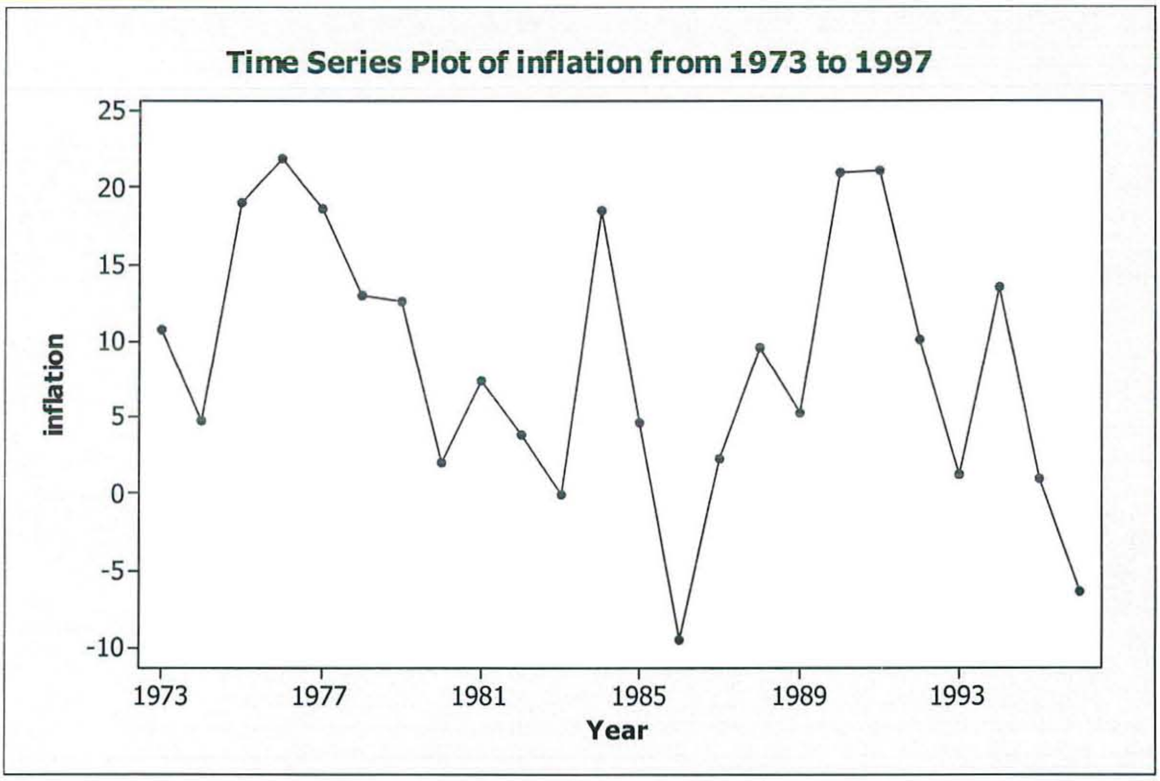
The question frequently asked is this. Who are the gainers and who are the losers in a drastic inflation? First among the gainers are the small proportions of speculators who either have capital or can borrow capital and are lucky enough to select the tangible things which come through with least loss. Then there are the prime producers of things to sell who owe more money than is owned to them. Chief among the sufferers are the salary workers and the wage earners. The reason is that the cost of food, clothing and the other necessities of life rise in price much faster than do the salaries and wages (M.A.Linton, 2008). According to Greame S.Dorrance (2008), therefore, modeling and forecasting inflation is necessary for a number of reasons. Firstly, it is important from the point of view of poverty alleviation and social justice. Secondly, 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.

During the past three decades, dramatic changes in the inflationary environment have stimulated a wealth studies on the relative accuracy of alternative models of inflation forecasts. Moreover, there has been much work on examining and evaluating different methodologies in forecasting inflation. One approach is associated with the work of Aidan Meyler, Goeff Kenny and Terry Quinn (1998) can be seen, which outlined ARIMA time series models for forecasting Irish inflation. It considered two alternative approaches which suggest that ARIMA forecast has outperformed. Muhammad Abdul Salam et al (2006), implemented ARIMA time series models for forecasting Pakistan's inflation. On the bases of in-sample and out-of-sample forecast the model has sufficient predictive powers. So keeping in view the above studies and literature, we have made an attempt to outline the practical steps which need to be undertaken to use Autoregressive integrated moving average (ARIMA) time series models for modeling and forecasting inflation in Ethiopia.

1.1. Inflation in Ethiopia: A brief History

As there was no index number used to measure inflation at country level until the period 2001. In fact, as Table1 (appendix B) indicates, the average rate of inflation in the period, 1974/75-1988/89 as measured by Addis Ababa retail price index (RPI) was 7.8 percent. However, in 1990/91 the inflation jumped to 20.9 percent. The period between 1974/75 and 1976/77 were characterized by high rate of domestic inflation which resulted from excess demand for goods and raw materials which were in short supply during that time. During this period, the rate of inflation rose from 4.7 percent per annum in 1974/75 to 21.9 percent in 1976/77. This was mainly due to significant increase in food prices which account for 57.4 percent of the weight. To handle the accelerating rate of inflation, the government introduced a system of price controls on domestic goods and maximum profit margin for certain imported goods. The inflationary pressure was reduced during 1977/78-1983/84 period. The annual rate of increase in retail price index (RPI) declined from 21.9 percent in 1976/77 to 1.9 percent in 1980/81 and dropped further to negative 0.2 percent per annum in 1983/84, triggered by the decline in food prices. During 1990/91 and 1991/92 inflation rate was above 20.0 percent per annum. This was mainly the result of the civil war and the consequent severe foreign exchange constraint which led to the closure of some industries and the operation of some below capacity due to lack of imported raw materials and spare parts. In late September 1992, the Transitional government of Ethiopia adopted a policy package which, according to its beliefs and hopes, is capable of relocating the economy from the inflationary depression on the trajectory of high growth in an environment of stable prices and suitable balance of payments. The post 1991 regime is one in which all prices are decontrolled and market determined. During 1990/91-1991/92 the annual inflation rate averaged about 20.0 percent, due to supply bottle necks and major macro-economic imbalances. During 1995/96-1997/98 the rate of inflation was significantly decelerating. In 1996/1997 it was negative 6.4 percent, a result of higher agricultural output whose supply lowered the price of food. We can summarize the above discussion by the following graph.

Figure 1: Graph of inflation rate from 1973 to 1997



The inflation rate based on the Addis Ababa retail price had been reported as it stood at single digit (less than 7.5 percent) for the past several years. However, it started to increase in 2002/3. The inflation rate based on the general consumer price at country level, which was 6.8 percent in 2004, has been increasing steadily and reached 15.8 percent in 2006/7 (see table 2 of appendix B). We can see from table 2 (of appendix B) that, the country level of overall inflation rate (annual change based on 12 months moving average) stood at 12.3% in June 2006. This rate is

5.5% percentage point higher than the corresponding annual average rate of 6.8%at June 2005. Even though it is difficult to compare the inflationary process displayed in tables 1 and 2, since the former one is calculated based on the Addis Ababa retail price index while the latter is calculated based on the general consumer price index at country level, it is clear that recently, especially since the last two years inflation is exponentially rising in Ethiopia. In other words, the spiral inflation rate observed in the Ethiopian economy has been talking point among the public as well as government officials for quite some time now. The much talked about millennium and the increasing cost of living remains a priority agenda.

1.2. Statement of the problem

Inflation is a controversial issue. Among other things the controversy mainly arises from the different view regarding the causes, consequences and control of inflation. Inflation has a wide range of impact on social and political system of a country. As cited in the work of Habtamu (2000), Kotwal (1987) explained this as "Apart from partially, theoretical interest, the significance of inflation as an important area of economic and social research arises from its impact on the distribution of income and wealth among different social groups, individuals on the rate of economic growth in a country, and on the stability of a given political and economic system." Therefore, to reduce the impact of inflation on the smooth operation of the economy, it is essential to know the process that generates inflation, the way in which it perpetuates itself, the condition which leads to it and the means by which it can be managed. Inflation is considered to be a major economic problem and thus fighting inflation and maintaining stable prices is the main objective of monetary authorities. The negative consequences of inflation are well known. Inflation can result in a decrease in the purchasing power of the national currency leading to the aggravation of social conditions and living standards. High prices can also lead to uncertainty making domestic and foreign investors reluctant to invest in the economy. If investors expect rapid change in basic economic relations, they will be hesitant to commit themselves for long periods. The expectation of rising prices will therefore be likely to bias investment decisions toward the purchase of fixed assets with relatively short lives. For these reasons, an inflationary economy may be expected to evolve along lines where long-term industrial and social investment is discouraged, and where resources flow more readily to those fields in which returns may be achieved most quickly. Moreover, inflation prices worsen the country's terms of trade by making domestic goods expensive on regional and world market. In other words, if inflation is high in an economy there are three main problems it can cause:

People on a fixed income (e.g. pensioners, students) will be worse off in real terms due to higher prices and equal income as before; this will lead to a reduction in the purchasing power of their income. This has a great effect on the GDP of a country.

Rising inflation can encourage trade unions to demand higher wages, as wages have to be adjusted to keep up with inflation. In the case of collective bargaining the wages will be set as a factor of price expectations (Pe). Price expectations will be higher when inflation has an upward trend. This can cause a wage spiral. Also if strikes occur in an important industry which has a comparative advantage the nation may see a decrease in productivity and suffer.

If inflation is relatively higher in one country, and that country maintains fixed exchange rates with other countries, then the country's exports will become more expensive for other countries to purchase, creating a deficit on its current account.

To develop an effective monitory policy, central banks should possess information on the economic situation in the country, the behavior and interrelationships of major macro economic indicators. Such information should enable the central bank to react in a proper way to shocks the economy is subject to. Thus studying inflationary processes is an important issue for researchers all around the world and hence, in Ethiopia. Even- though few in Ethiopia, there exists a number of empirical studies on inflation modeling and forecasting in other developing countries. These studies show that inflation is a country-specific phenomenon and its determinants differ across countries. Therefore, an effective monetary policy depends largely on the ability to develop a reliable model that could help understand the ongoing economic processes and predict future developments. This requires conducting research based on the data of a particular country that take in to account the specific socio-economic context of that country. In past studies of inflation in Ethiopia that we have seen, the emphasis has been on testing economic theory and on empirical analysis. The studies have not been subjected to rigorous modeling and forecast evaluation techniques for forecasting purposes. In this regard, this study is important since it is aimed to fill this gap.

1.3. Objectives of the study

The general objective of this study is to investigate the nature of inflation in Ethiopia and to construct or fit model that is used to forecast inflation in the country

1.3.1 Specific objectives

- To shed light on inflationary processes in Ethiopia;
- To fit or construct stochastic models which are capable of describing practically occurring situations and to forecast inflation in Ethiopia.

1.4 Significance of the study

The results could be an important step forward studying inflation process in the economy and could serve as a motivation and bases for further investigations by researchers, economists, and policy makers.

1.5 Organization of the paper

The strategy and format of this thesis is as follows: the second chapter will be concerned with literature review; the third chapter presents the data and methodology. Under this chapter theories of methods to be employed are discussed with the results obtained from the analysis of the series. Conclusion follows in chapter four.

1.6 Limitation of the Study

A lengthy time series data is required for univariate time series forecasting. It is usually recommended that at least 50 observations be available. The data used for this study has satisfied the minimal sample size requirement. But, the inflation data after December, 2006 are not used for this study due to unavailability. The possible sources, like Ethiopian Central statistics authority, Ministry of finance and economic development and others were visited to get data, but, we couldn't found data for the said period. But, most people are arguing that in Ethiopia since the last two years the inflation rate is increasing exponentially which make us to expect some structural break of the inflationary process. So the absence of data on these periods will have impacts on the results of this study. Not only this, but also there is a difference in the inflation data of the same period that have been computed on the same base year by the

Ethiopian Statistical authority and Ministry of finance and economic development which can generate some doubts about the reliability of the data used. For one and other reasons (like absence of data on key variables , shortage of time etc…), multivariate forecasting methods were not employed for the purpose of comparison of their forecasting performance with that of univariate forecasting method, as there are arguments about which of the methods to be used and this makes the scope of this study narrow. The other thing is using the selected model, for the period whose observations have not found, we do not forecast since data for the last two years were not included in the model construction and this may reduce the forecasting power of the selected model.

CHAPTER TWO

LITERATURE REVIEW

There were numerous attempts to model inflation in developed countries as well as 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 authors present stylized facts about inflation behavior in developing countries, focusing primarily on the relationship between the exchange rate regime and the sources of inflation. They employed Vector autoregressions (VAR's) method in which they focused particularly on the relationship between the exchange rate regime and the sources of inflation. Using annual data from 1964 to 1998 for 53 developing countries, they found that money growth and exchange rate changes –factors typically related to fiscal influences- are far more important in countries with floating exchange rate regimes than in those with fixed exchange rates. Instead inertial factors dominate the inflation process in developing countries with fixed exchange rate regimes.

Another important study of inflationary processes was accomplished by Fischer, Sahay, and Végh (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. Abu Hassan Shaari Mohd Nor (2006), studied the varying volatility dynamic of inflation rates in Malaysia for the period from August 1980 to December 2004. The researcher used generalized autoregressive conditional heteroschedasticity (GARCH) and the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) models to capture the stochastic variation and asymmetries in the economic instruments. An in sample evaluation of the sub periods volatility are done using both models. According to the results obtained the EGARCH model gives better estimates of sub-periods volatility.

A-M.M Abdel-Rahman, a case study of a less developed economy (1970-1994): attempted to study the determinants of the inflation process in Sudan during the past two decades, using ARCH model in which the results obtained generally validate the conjecture that the inflation witnessed in Sudan is really a hybrid of monetary demand, structural supply and expectational origins. Payne (2002) explores the inflationary dynamics in Croatia using vector autoregression over the period January 1992-December 1999. The VAR incorporate four variables: broad money supply, the retail price index, nominal wage per employee and the nominal effective exchange rate. The model results suggest that wage increases and currency depreciation are positively correlated with inflation rates. Quite surprisingly, no evidence of inflation inertia was found, although the data sample covers the period of hyperinflation. William R. Bell (1993) compared seasonal ARIMA models as presented in Box and Jenkins (1970) models with ARIMA component (structural) models as presented in Harvey (1989). Both are augmented appropriate with the same regression variables to account for calendar effects, level shifts, and additive outliers. The models are compared on a set of 40 Census Bureau monthly time series in regard to fit using AIC and related statistics. Bell and Puch (1990) made similar comparisons of ARIMA models with the basic structural model (BSM). The paper extended the previous work by also considering ARIMA component models with trigonometric seasonal components. For the 40 time series considered, AIC and the other model comparison statistics express a strong overall preference for the ARIMA models over the ARIMA component models.

By building on Payne's model, Botric and Cota (2006), model Croatian inflation dynamics using a structural vector autoregression model. They found that terms of trade and balance of payment shocks have the strongest impact on prices. The authors found justification for such a result in a Croatia being a small open economy with high import dependency and uncompetitive economic structure. In order to construct those findings, the authors also re-estimated Payne's model. While Payne's conclusion on the influence of wages and currency depreciation on prices still holds in the newly estimated four variable VAR, a positive correlation between broad money and prices and some inflation inertia also emerged.

Fountas, S., Karanasos. M., Karanassou, M.(2000), Vincent M.Nwani, Joseph Tchokote and Isitua K.Obiora, Karanasos, M., Karanassou, M., Fountas, S.,(2004), Kontonikas, A. (2004), Fountas, S., Ioannidis, A., Karanasos, M., (2004), Berument, H., Metin-Ozcan.,K. & Neyapti, B., (2001), Nas, T. F. and Perry, M. J. (2000), Valdovinos, C.M., (2001) and A.Kontonikas (2004), examined the relationship between inflation and inflation uncertainty. Stiliano Fountas Karanasos, and Marika karanassov (2000), employed a GARCH model that allows for simultaneous feedback between the conditional mean and variance of inflation. Their result shows that there is strong evidence in favor of a positive bi-directional relationship between inflation and inflation uncertainty in agreement with the prediction of economic theory. Similarly, Kontonikas A. (2004) examined the relationship between inflation-uncertainty and the impact of inflation targeting using British data over the period 1972-2002. Uncertainty is proxied using the conditional volatility from symmetric, asymmetric, and component GARCH-M models of inflation. The results indicate a positive relationship between past inflation and current uncertainty. Kontonikas (2004) analyze the relationship between inflation and inflation uncertainty in the United Kingdom from 1973 to 2003 with monthly and quarterly data. Different types of GARCH-Mean (M)-Level (L) models that allow for simultaneous feedback between the conditional mean and variance of inflation are used to test the relationship and they find positive relationship between past inflation and uncertainty about future inflation. Similarly, Karanasos, Karanassou and Fountas (2004) apply the same method in the US inflation rate using monthly data for the period February 1960 to December 1999. They find strong bidirectional relationship between inflation and inflation uncertainty. On the other hand, Fountas, Ioannidis and Karanasos (2004) use quarterly data from 1960Q01 to 1999Q02 in six European Union countries and Valdovinos (2001) applies monthly data covering period of January 1965-December 1999 in Paraguay with two-step approach to estimate. Once the measure of inflation uncertainty is obtained, they use Granger Causality methods to test whether higher average inflation causes inflation uncertainty or vice versa. Valdovinos (2001) shows that in Paraguay, higher levels of inflation have been accompanied by more inflation uncertainty.

Berument, Metin-Ozcan and Neyapti (2001) use an EGARCH method to model inflation uncertainty in Turkey from 1986M01 to 2000M12. They pointed out that the effects on inflation uncertainty of positive shocks to inflation are greater than negative shocks to inflation. In contrast, Nas and Perry (2000) employ the two-step approach to investigate the link between inflation and inflation uncertainty in Turkey from January 1960 to March 1998. The results show strong statistical support that inflation significantly raised inflation uncertainty over the full sample period from January 1980 to December 2004. Vincent M.Nwani, Joseph Tchokote and Isitua K.Obiora, examined the empirical relationship between inflation, inflation uncertainty and information targeting over time (1970-2002) using the Nigerian consumer price index. Uncertainty was measured using the generalized autoregressive conditional heteroscedasticity (AR GARCH) model. Their results suggest that there exists a positive relationship between the trend inflation and the measure of uncertainty. This relationship breakdown, however, when the time series data are sorted in ascending order of trend inflation and disaggregated in to low and high inflation sub periods.

Modeling and forecasting inflation in developing countries the case of economies in central Asia, Asel ISAKOVA (2007), studied some important macroeconomic developments in the countries of central Asia with a particular emphasis on the Kyrgyz Republic. The study focuses on the inflation behavior in Kyrgyzstan and the main factors that influence price changes in the country. A simple mark-up model based on the basic concept of the Phillips curve which reconciles the effects of "demand-pull" and "cost-push" inflation theories was employed by the author. The results obtained in estimation were interpreted in the most prudent manner due to complexity of the economic transformation process. The models were also used for predicting inflation, and, in fact, the absolute forecast error was small enough to conclude that the specifications derived have predictive power.

Charles S.Bos, Siem Jan Koopman and Marius Ooms (2007), discussed and implemented exact maximum likelihood estimation for stationary ARFMA models with stochastic volatility using Monte Carlo methods, in which they investigated changes in the time series characteristics of post war U.S. inflation. In a model-based analysis the conditional mean of inflation is specified by a long memory autoregressive fractionally integrated moving average process and the conditional variance is modeled by stochastic volatility process. Using monthly data set of core inflation for which they consider different sub samples of varying size, they found remarkable changes in the variance, in the order of integration, in the short memory characteristics and the volatility, based on the new modeling framework and the associated estimation technique. In his study on the determinants of inflation in Ukraine, the author, Lissovolik (2003), studies the factors of inflation in Ukraine during the period from 1993 to 2002, the so-called "transition period". The most relevant stylized facts important for modeling inflation behavior in Ukraine appear to be domestic financial instability, external disequilibria, seasonality of the economy, and allowance for an increase in administered prices. The resulting equation of an inflation model is a version of a long-term markup of prices over wages, the exchange rate, administrative prices, short-term factors and dummy variables. S.M.Husnain BOKHARI and Mete FERIDUN (2006) are concerned with Modeling and forecasting inflation in Pakistan. For this purpose they implemented ARIMA models, in which 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). Aidan M., Goeff Kenny and Terry Q. (1998) outlined autoregressive integrated moving average (ARIMA) time series models for forecasting Irish inflation. It 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. Terry Q. et al (1999) described how inflation analysis and forecasting has been carried out with particular emphasis on recent research and the new challenges facing the central Bank of Pakistan following the launch of the euro on January 1999. The eclectic approach to inflation forecasting has been adopted in the Bank which combines judgments and a range of formal approaches (including structural models, time series methods like ARIMA). According to the author, the emphasis on particular methodologies has evolved over time but in all cases judgment has played a central role. Muhammad Abdus Salam, Shazia Salam, Meta Feridun (2006), focused on the practical steps which need to be undertaken to use autoregressive integrated moving average (ARIMA) time series models for forecasting Pakistan's inflation. On the basis of in-sample and out-of sample forecast the model has sufficient predictive powers and the findings are well in line with those of other studies.

With the case of Ethiopia very few scholars have made study on the factors explaining the inflation experience of the country. With this regard the work of Habtamu (2000) can be cited. He studied "The causes of low inflation in Ethiopia" for the period ranging from 1962 to 1997. His analytic technique used involves estimations of a model that incorporates both the monetarist and structuralism variables of inflation. His finding was expectation of inflation, real income; per-capita food production and money supply were found to be significant with their theoretically postulated sign. According to the investigation of the study, the degree of monetization has no any role to play in the inflation spiral of the study; the degree of monetization has partly contributed to the prevalent of low inflation in the country.

Yohannis (2000) studied about the dynamics of inflation in Ethiopia in which he arrived at the conclusion that inflation in Ethiopia is basically structural. Monetary factors play limited role. Exchange rates have not played any role in determining inflation both in short and long run. Inflation inertia on the other hand, has significant effect on the price level in the long run.

CHAPTER THREE

3. DATA AND METHODOLOGY WITH DISCUSSION

3.1 The Data Issues

According to Box and Jenkins (1976), time series is a collection of observations made sequential in time and encountered in a variety of fields. Time series which arise in practice include economic time series, physical time series, marketing time series and demographic time series.

One special features of time series is, the successive observations are usually not independent. When successive observations are dependent future values may be predicted from past observations (Box and Jenkins, 1976).

Financial time series are often available at a higher frequency than macro-economic time series and many high-frequency financial time series have been shown to exhibit the property of 'long memory' (the presence of statistically significant correlations between observations that are a large distance apart) .

In most of developing countries like Ethiopia, economic processes are highly unstable and volatile. Moreover, the macro economic data on developing countries can be unreliable due to measurement error, imperfect methods of measuring and so on (Asel Isakova, 2007). Nonetheless, for the purpose of this study, the inflation series used is monthly data from August, 1997 to December, 2006. They were collected from the Central Statistics authority (CSA) and Ethiopian Economic Association (EEA).

3.2 Forecasting Using Exponential Smoothing Methods

There are many possible ways to forecast a time series. The main emphasis of forecasting techniques will be on the methods explicitly based on time series models such as ARIMA and transfer function models. Various adhoc methods, including those using moving averages and weighted smoothing, had been in use long before model-based forecasting methods were widely accepted. Some traditional forecasting methods were developed based on statistical theory, while most others were developed mainly based on empirical experiences. These methods share a similar characteristic. That is, the forecasts are based essentially on smoothing (averaging) past values of a time series using some type of weighting scheme. For example, naive, averaging, and smoothing. Naive methods are employed assuming that recent periods are the best predictors of the future. Averaging methods are developed based on an average of weighted observations. Smoothing methods are based on averaging past values of a series in a decreasing (exponential) manner. The last method will be our primary focus of this section. Some measures of the accuracy of fitted time series models such as mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean squared deviation (MSD) are employed. Since MSD is always computed using the same denominator, n, regardless of the model, we can compare MSD values across models. These measures of accuracies are measured as discussed in section 3.3.9 of this study.

3.2.1 Simple Exponential Smoothing

Let the time series be denoted by $Y_1, Y_2, \ldots, Y_n$. Suppose we want to forecast the next value of our time series Y_{t+1} that is yet to be observed with forecast for Y_t denoted by F_t. Then the forecast F_{t+1} is based on weighting the most recent observation Y_t with a weight value α and weighting the most recent forecast F_t with a weight of $(1-\alpha)$ where α is a smoothing constant /weight between 0 and 1. Thus, the forecast for the period t+1 is given by

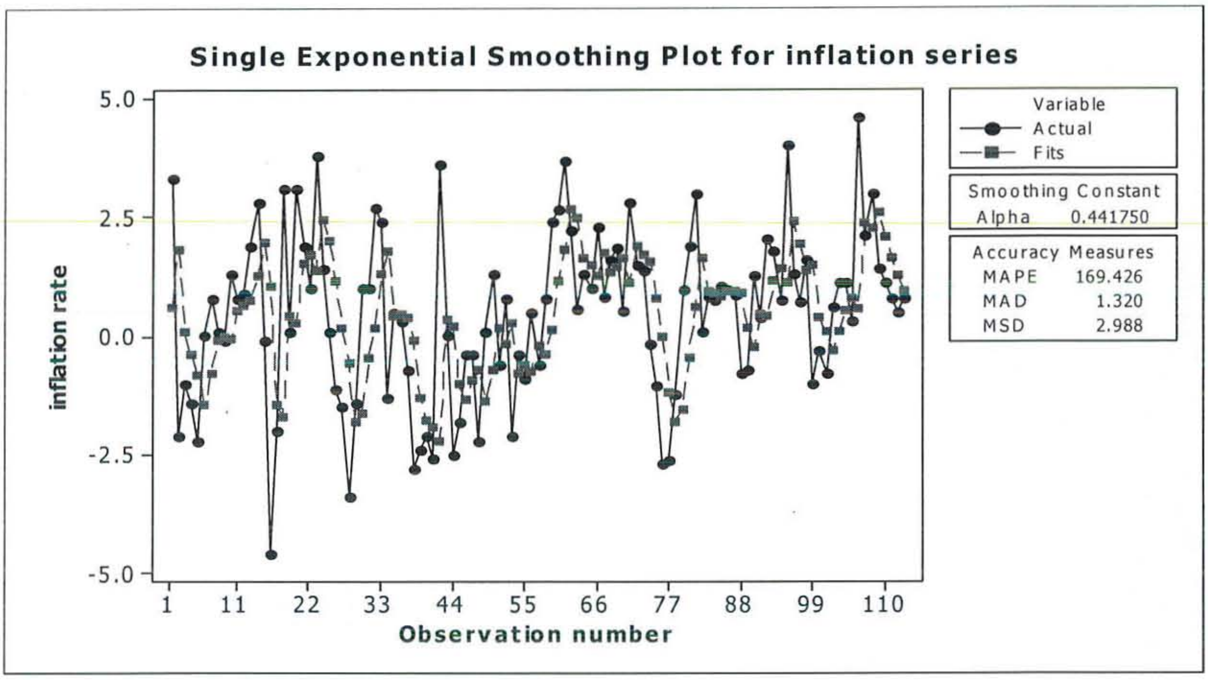
$$F_{t+1} = F_t + \alpha (Y_t - F_t). \quad \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Note that the choice of the value of α has considerable impact on the forecast. A large value of α (say 0.9) gives very little smoothing in the forecast, where as a small value of α (say 0.1) gives considerable smoothing. Alternatively, one can choose α from a grid of values 0.1, 0.2, ..., 0.9 and choose the value that yields the smallest MSE value. By default, MINITAB and Eveiws, estimates the damping parameters of the smoothing model to minimize the sum of squared forecast errors.

If you expand the above model recursively then F_{t+1} will come out to be a function of α, past value of Y_t and F_t. Therefore, knowing the values of α and past value of Y_t our point of concern relates to how to initializing the value of F_t. One method of initialization is to use the first observed value Y_1 as the first forecast ($F_1 = Y_1$) and then proceed. Another possibility would be to average the first four or five values in the data set and use these as the first forecast. Many softwares take this in to account by default.

From Figure 2 below, Single exponential smoothing plot for inflation series, the actual plot and the forecast plot seems cloth to each other. The accuracy measures are also relatively smaller than the other traditional methods of forecasting except for winter's (additive) Method (see table 3).

Figure 2: Single exponential smoothing plot for inflation series

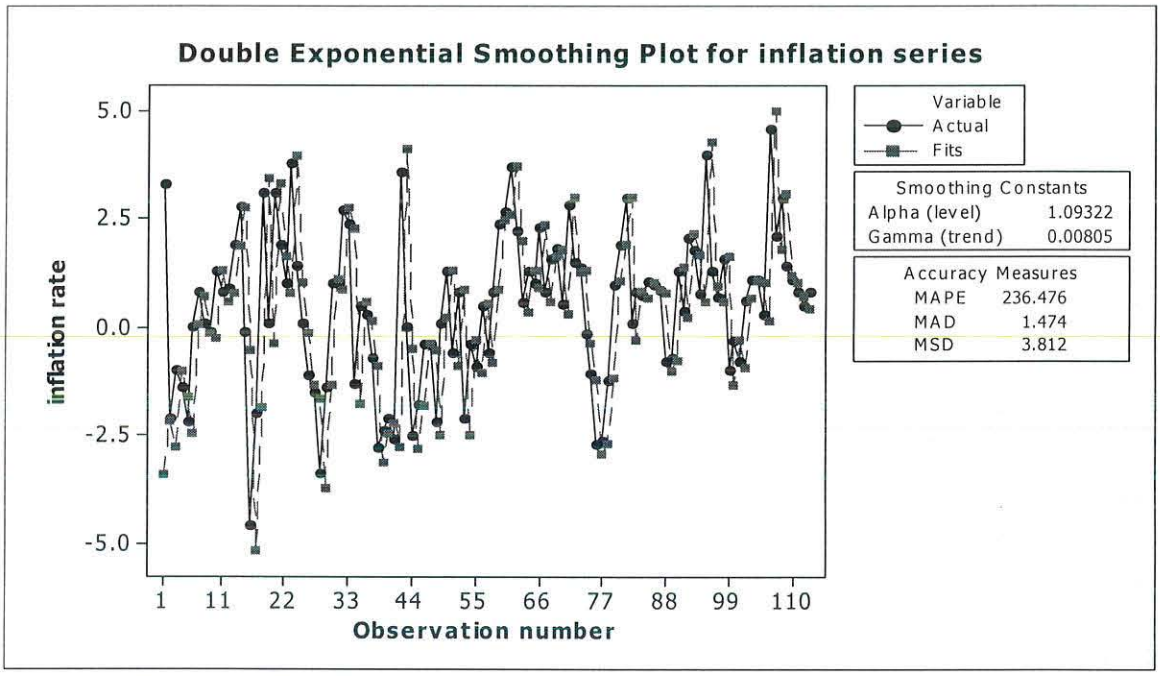


3.2.2 Holt's Double Exponential Smoothing

This is to allow data to forecast with trend. The forecast for Holt's linear exponential smoothing is found by having two more equations to simple exponential smoothing to deal with – one for level and one for trend. The smoothing parameters (weights) α and β can be chosen from a grid of values (say each combination of α= 0.1, 0.2, …, 0.9 and β=0.1, 0.2, …, 0.9) and then select the combination of α and β which correspond to the lowest MSE.

From figure 3 we visualize that the actual and the fitted plots seems to be very close to each other. But, when we see the values of measures of accuracies they all are large when compared with that of single exponential smoothing and Holt-Winters Additive Seasonal. The inflation series is observed under data examination in which we visualize that there is no trend in the series. But as we have discussed above double exponential smoothing allow data to forecast with trend. Here, the high values for the measures of accuracies may be due to the absence of trend in the series.

Figure 3: Double exponential smoothing plot for inflation series



3.2.3 Winters Triple Exponential smoothing

This method is recommended when seasonality exists in the time series data. This method is based on three smoothing equations – one for the level, one for the trend and one for the seasonality. In fact there are two types of Winter's exponential smoothing depending on whether seasonality is modeled in an additive or multiplicative way.

From figure 4 we can see that the actual and the fitted plots are highly apart from each other indicating that, multiplicative seasonality model is poor in forecasting the series in a sense that mean absolute percentage error (MAPE), Mean absolute deviation (MAD) and Mean squared deviation (MSD) are large. This may indicate that the seasonal component in the series is additive.

Figure 4: Winter's (multiplicative) Method plot for inflation series

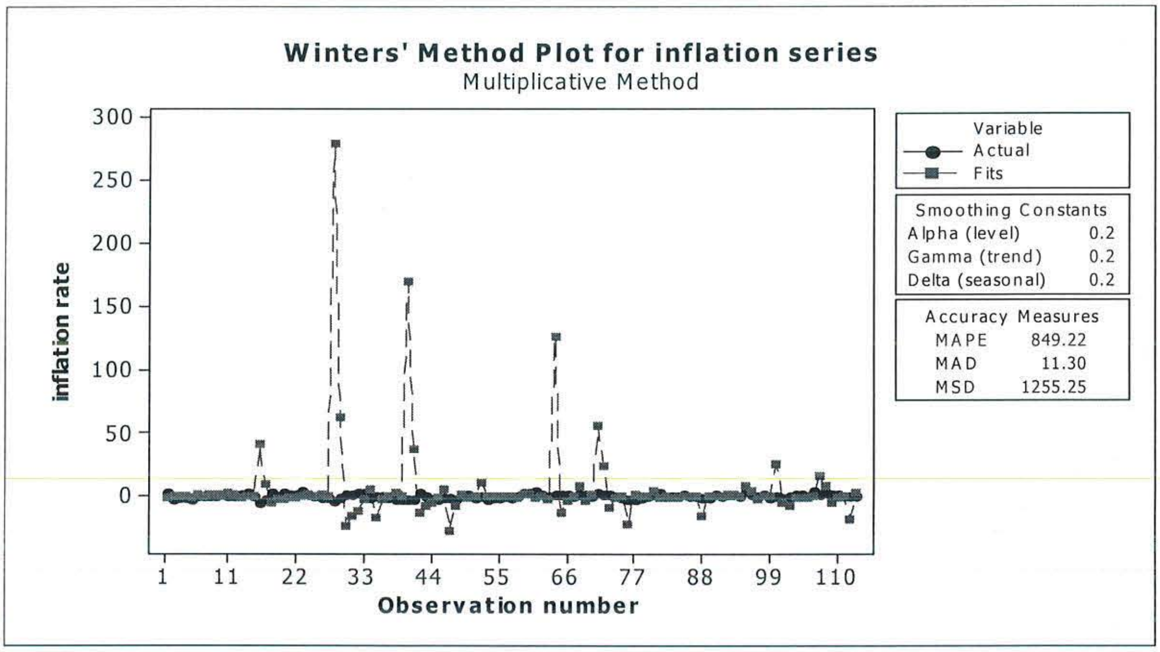
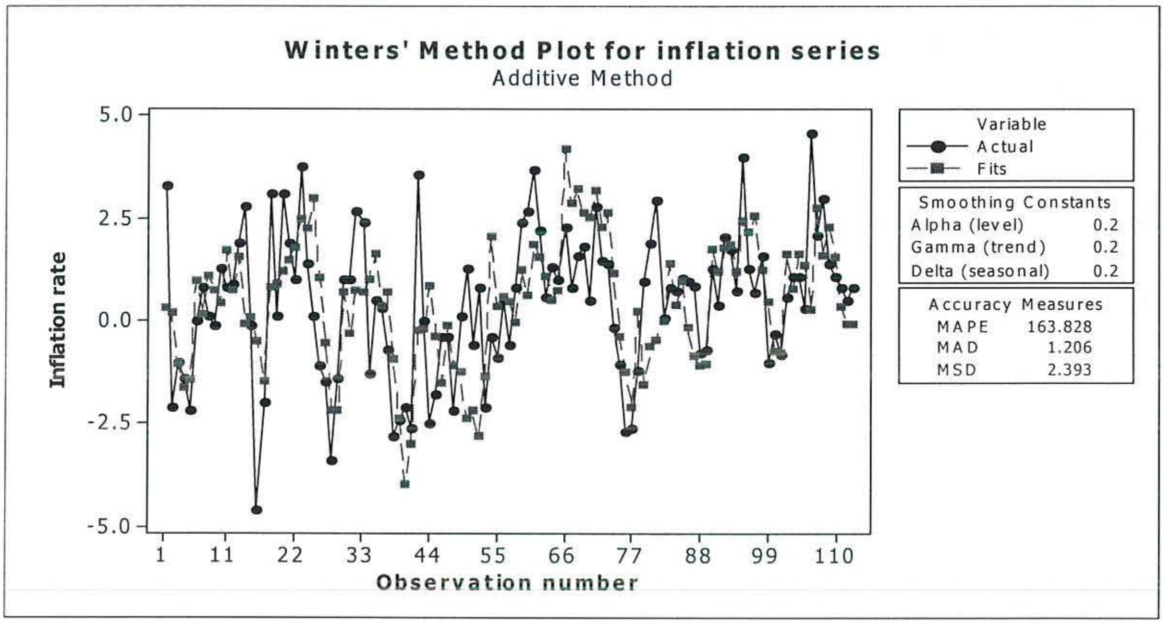


Figure 5 below depicts that, Winter's (additive) Method of forecasting inflation series is better than both single exponential smoothing, double exponential smoothing and Winter's (multiplicative) Method. All the measures of accuracy for Winter's (additive) Method are smaller than the other three traditional forecasting methods.

Figure 5: Winter's (additive) Method plot for inflation series



We can summarize the above discussion by the following table 3

Table 3: Summary of Exponential Smoothing Results

Model	Mean absolute deviation (MAD)	Mean absolute percentage deviation (MAPD)	Mean square deviation (MSD)
Single Exponential	1.320	169.426	2.988
Double Exponential	1.474	236.476	3.812
Holt-Winters No Seasonal	11.30	849.22	1255.25
Holt-Winters Additive Seasonal	1.206	163.828	2.393

As we can see from this table, Holt-Winters Additive Seasonal method is better forecasting method since the errors for this method are small when compared to others.

Now, it is important to see some of the scientific models that are used in forecasting inflation rate in this study.

3.3 An introduction to ARIMA Modeling

One objective of analyzing economic data is to predict the future values of certain variables in which we are interested. One approach to obtain forecasts is to set up an econometric model, estimate its parameters from the available data, and then use this model to predict future values of the variables of interest. An alternative approach that has proved quite successful, especially for short-term forecasting, is to use only the past values of a particular variable to predict its future values. This method does not utilize economic knowledge we may have about the process that has generated the values for the particular variable under investigation. Rather, it is assumed that the data are generated by a stochastic process and a model is constructed for this stochastic process. The reader may find that, by not using the knowledge about the economic structure, we neglect available information and thus make inefficient use of the data. In this regard, Rechad H. and Robert S. (2003) argue that, at first sight it would not seem very sensible for economist to pay much attention to univariate analysis. After all, economic theory is rich in suggestions for relationships between variables. Thus, attempting to explain and forecast a series using only information about the history of that series would appear to be an inefficient procedure, because it ignores the potential information in related series. On the other hand, some people argue that, this will be true, if economic models were indeed correct and if observed data were generated by precisely the models economists have provided to explain economic phenomena. Unfortunately, this is not the case. Rather, economic models are at best rough approximation to reality. This claim is to some extent confirmed by the fact that time series models that use only the information from a set of observations on a single variable have provided forecasts that are superior to the corresponding predictions from econometric models that is the case when a series is modeled only in terms of its own past values and some disturbance, (Judge G., Carter H., GriffthE. s, Helmut L. and Tsoung-chao L., 1982). Following this argument, in this study the inflation series is modeled only in terms of its own past values and some disturbance term to estimate the parameters of such a model using the method of least squares and to use the obtained model to forecast future values of inflation.

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). The main advantage of ARIMA forecasting is that it requires data on the time series in question only. First, this feature is advantageous if one is forecasting a large number of time series. Second, this avoids the problem that occurs some times with multivariate models. For example, consider a model including wages, prices and money. It is possible that a consistent money series is only available for a shorter period of time than the other two series, restricting the time period over which the model can be estimated. Third, with multivariate models, timelines of data can be a problem. If one constructs a large structural model containing variables which are only published with a long lag, such as wage data, then forecast using this model are conditional forecasts based on forecasts of the unavailable observations, adding an additional source of forecast uncertainty.

Some disadvantages of ARIMA forecasting are:

- Some of the traditional model identification techniques are subjective and the reliability of the chosen model can depend on the skill and experience of the forecaster (although this criticism often applies to other modeling approaches as well).
- It is not embedded within any underlying theoretical model or structural relationships. The economic significance of the chosen model is therefore not clear. Furthermore, it is not possible to run policy simulations with ARIMA models, unlike the structural models.
- ARIMA models are essentially 'backward looking'. As such, they are generally poor at predicting turning points, unless the turning point represents a return to a long-run equilibrium.

However, ARIMA models have proven themselves to be relatively robust (healthy) especially when generating short-run inflation forecasts. ARIMA models frequently outperform (do better than) more sophisticated structural models in terms of short-run forecasting ability.

Therefore, the ARIMA forecasting technique outlined in this paper will not only provide a benchmark by which other forecasting techniques may be appraised, but will also provide an input in to forecasting in its own right.

Appendix A presents a description of ARIMA models and some of their theoretical properties. A general notation for a multiplicative seasonal ARIMA models is ARIMA (p, d, q)(P, D, Q), where p denotes the number of autoregressive terms, q denotes the number of moving average terms, and d denotes the number of times a series must be differenced to induce stationarity. P denotes the number of seasonal autoregressive components, Q denotes the number of seasonal moving average terms and D denotes the number of seasonal differences required to induce stationarity.

This may be written as

$$\phi(B)\Phi(B)\Delta^{d}\Delta_{s}^{D}Y_{t}=\theta(B)\Theta(B)a_{t}\ldots\ldots\ldots\ldots\ldots(2)$$

Where,

$\Delta^{d}\Delta_{s}^{D}Y_{t}$ is a stationary series

Δ^{d} = (1-B) ^{d} represents the number of regular differences and

Δ_{s}^{D} = (1-B^{s}) ^{D} represents the number of seasonal differences and required to induce stationarity inY_t

s is the seasonal span (hence for quarterly data s=4 and for monthly data s=12),

B is the backshift operator;

$\phi(B) = 1-\phi_{1}B-\phi_{2}B^{2},\ldots,\phi_{p}B^{p}$

$\theta(B) = 1+\theta_{1}B+\theta_{2}B^{2}+,\ldots,+\theta_{q}\theta^{q}$ is a q-order polynomial in the backshift operator.

$\Phi(B) = 1 + \Phi_{1}B+\Phi_{2}B^{2}+\ldots+\Phi_{P}B^{P}$, and

$\Theta(B) =1 + \Theta_{1s}B^{1s}+\Theta_{2s}B^{2s} +\ldots+\Theta_{Qs}B^{Qs}$

As shown in appendix A, any non-deterministic stationary process can be approximated by an ARIMA process. The problem lies in ensuring the series is stationary and in determining the order of p and q that adequately describes the time series being examined. It is these issues which are examined in the next section.

3.3.1 ARIMA Modeling and Forecasting

This section outlines a general ARIMA modeling and forecasting strategy. It is important to note, however, that ARIMA modeling process is not a simple sequential one, but can involve iterative loops depending on results obtained at the diagnostic and forecasting stages. The first step is to collect and examine graphically and statistically the data to be forecast. The second step is to test whether the data are stationary or if differencing is required. Once the data are made stationary one should seek to identify and estimate the correct ARMA model. Two alternative approaches to model identification are considered-the Box-Jenkins methodology and penalty function criteria. It is important that any identified model be subject to a battery of diagnostic checks (usually based on checking the residuals) and sensitivity analysis. For example, the estimated parameters should be relatively robust with respect to time frame chosen. Should the diagnostic checks indicate problems with the specified model, one should return to the model identification stage. Once a model has been chosen, the models should then be used to forecast the time series, preferably using out-of-sample data to evaluate the forecasting performance of the model. One common pitfall or drawback of ARIMA modeling is to over fit the model at the identification stage, which examines the in-sample explanatory performance of the model but may lead to poor out-of-sample predictive power relative to a more parsimonious model. Thus if the model with a large number of AR and MA lags yields poor forecasting performance, it may be optimal to return to the model identification stage and consider a more parsimonious model.

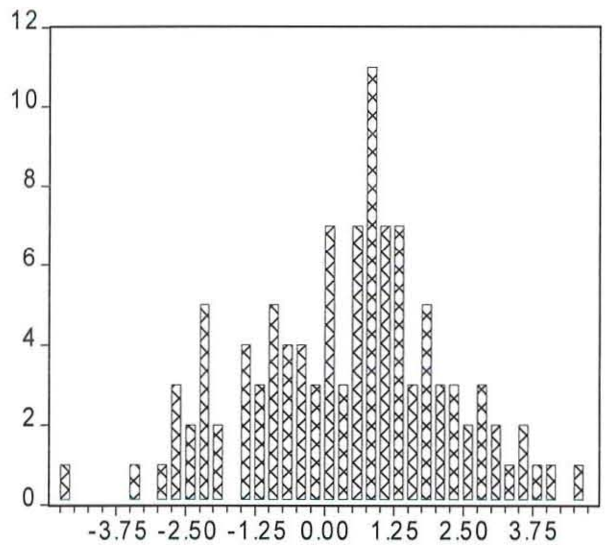
3.3.2 Data Examination

A lengthy time series of data is required for univariate time series forecasting. It is usually recommended that at least 50 observations be available. Using either Box-Jenkins or objective penalty function methods can be problematic if too few observations are available. Unfortunately, even if a long time series is available, it is possible that the series contains a structural break which may necessitate only examining a sub-section of the entire data series, or alternatively using intervention analysis or dummy variables. Thus, there may be the conflict between the need for sufficient degrees of freedom for statistical robustness and having a shorter data sample to avoid structural breaks. The series should also satisfy the assumption of normality. Jarque-Bera test statistic is a statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$JB = \frac{N-k}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where, S is skewness, K is kurtosis and k represent the number of estimated coefficients used to create the series. Under the null hypothesis of normal distribution, the JB statistic is distributed as Chi-square with 2 degrees of freedom. The reported Probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null—a small probability value leads to the rejection of the null hypothesis of a normal distribution. As we can see from Table 4 of normality test, the probability value is large and this leads us not to reject the null hypothesis of a normal distribution. The same conclusion can be derived from the graph of normality test given in the appendix (Figure 6 of appendix B).

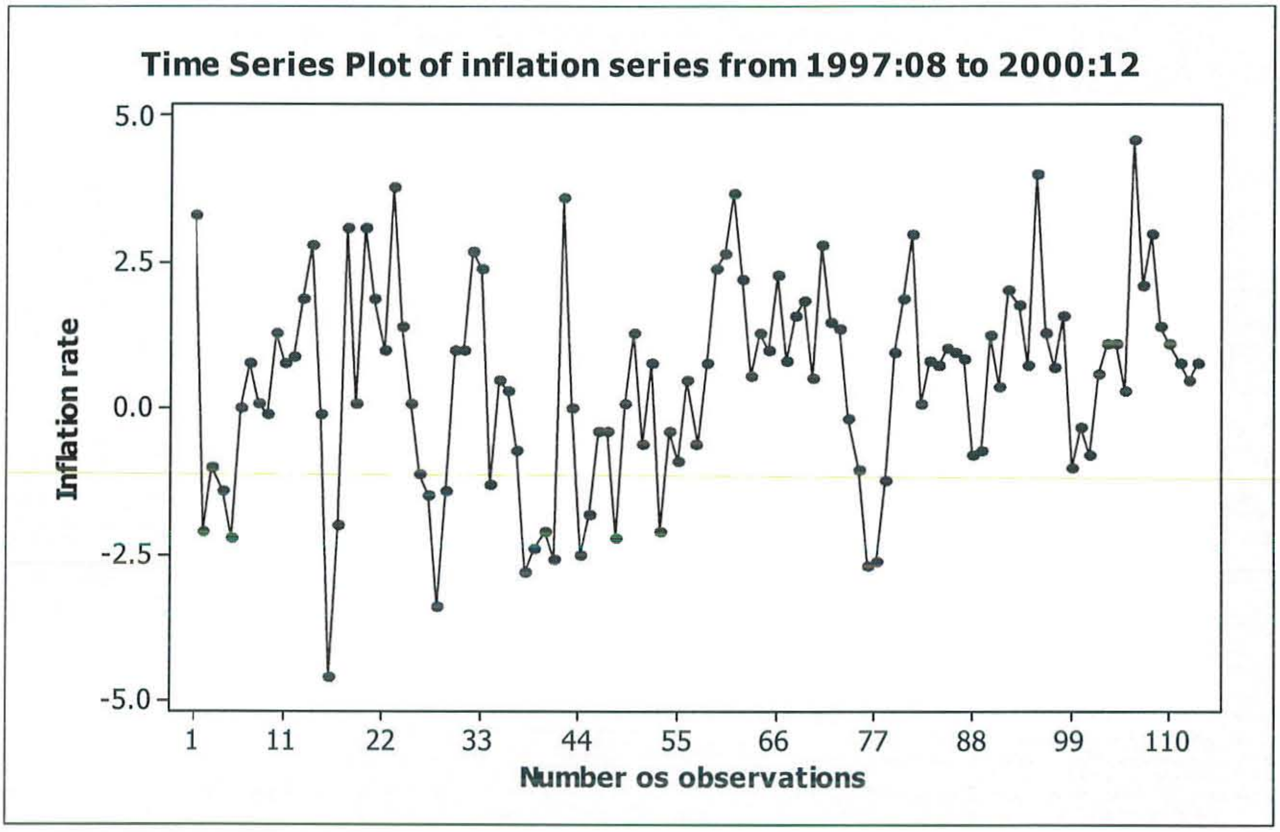
Table 4: Normality test for the inflation series



Series: P	
Sample 1997:08 2006:06	
Observations 107	
Mean	0.430187
Median	0.700000
Maximum	4.600000
Minimum	-4.600000
Std. Dev.	1.777384
Skewness	-0.175103
Kurtosis	2.831884
Jarque-Bera	0.672795
Probability	0.714339

Graphically examining the data is important. The series should be plotted against time to asses whether any structural breaks, outliers or data errors occur. If so any one may need to consider use of intervention or dummy variables. This step may also reveal whether there is significant seasonal pattern in the time series.

Figure 7: Plot of inflation rate



When we see the plot of the inflation series in levels for the period August 1997 to December 2006 that is shown above in figure 7, visual inspection does not give any strong indication of nonstationarity rather, since there is more violent oscillation; it appears to reflect a more pronounced seasonal pattern and this is confirmed by formal tests.

Table 5: Correlogram of inflation series for the sample period

Sample: 1997:07 2006:06
Included observations: 107

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |*** |	. |*** |	1	0.412	0.412	18.660	0.000
. |* |	. |. |	2	0.162	-0.009	21.573	0.000
. |. |	. |. |	3	0.059	-0.006	21.961	0.000
.*|. |	.*|. |	4	-0.124	-0.175	23.698	0.000
.*|. |	. |. |	5	-0.114	-0.001	25.174	0.000
.*|. |	. |. |	6	-0.114	-0.054	26.670	0.000
.*|. |	. |. |	7	-0.076	0.008	27.347	0.000
. |. |	. |. |	8	-0.053	-0.040	27.674	0.001
. |* |	. |* |	9	0.098	0.156	28.818	0.001
. |** |	. |* |	10	0.229	0.153	35.100	0.000
. |** |	. |. |	11	0.212	0.056	40.547	0.000
. |** |	. |* |	12	0.266	0.142	49.236	0.000
. |* |	.*|. |	13	0.101	-0.078	50.491	0.000
. |. |	. |. |	14	-0.037	-0.046	50.667	0.000
**|. |	**|. |	15	-0.227	-0.229	57.224	0.000
**|. |	.*|. |	16	-0.291	-0.087	68.080	0.000
.*|. |	. |* |	17	-0.148	0.068	70.907	0.000
**|. |	.*|. |	18	-0.195	-0.131	75.908	0.000
. |. |	. |* |	19	0.017	0.144	75.948	0.000
.*|. |	**|. |	20	-0.090	-0.284	77.034	0.000
.*|. |	. |. |	21	-0.085	-0.038	78.020	0.000
. |* |	. |. |	22	0.081	0.008	78.911	0.000
. |. |	. |. |	23	0.062	0.012	79.442	0.000
. |* |	. |. |	24	0.087	0.055	80.500	0.000
. |. |	. |. |	25	0.004	0.009	80.502	0.000
.*|. |	. |. |	26	-0.063	0.042	81.077	0.000
.*|. |	. |. |	27	-0.094	0.043	82.367	0.000
.*|. |	. |* |	28	-0.072	0.072	83.140	0.000
. |* |	. |* |	29	0.076	0.133	83.997	0.000
.*|. |	**|. |	30	-0.099	-0.194	85.484	0.000
. |. |	. |. |	31	-0.017	0.030	85.530	0.000
. |. |	. |. |	32	0.015	0.009	85.564	0.000
.*|. |	.*|. |	33	-0.079	-0.120	86.553	0.000
. |. |	. |. |	34	-0.011	-0.010	86.574	0.000
. |. |	. |. |	35	0.060	0.063	87.165	0.000
. |* |	. |. |	36	0.157	0.029	91.213	0.000

Another way to examine the properties of a time series is to plot its autocorrelogram. The autocorrelogram plots the autocorrelation between differencing lag lengths of the time series. Plotting the autocorrelogram is a useful aid for determining the stationarity of a time series, and is also important input into Box-Jenkins model identification. The theoretical autocorrelogram for different orders of AR, MA and ARMA models are outlined in section dealing with model identification. If a time series is stationary, then its autocorrelogram should decay quite rapidly from its initial value of unity at zero lag. If the time series is nonstationary then the correlogram will only die out gradually over time. Table 5 shows the correlogram which tells the similar story. That is, the autocorrelogram of the inflation series appears stationary although there seems to be some evidence for the existence of seasonal behavior.

Although the autocorrelogram gives some indication as to whether a series is stationary or nonstationary, in more recent years a vast array of formal tests for stationarity with known statistical properties have been developed.

3.3.3 Testing for Stationarity

The time series under consideration must be stationary before one can attempt to identify a suitable ARIMA model (Gujarati, 1995). For AR or ARMA models to be stationary it is necessary that the modulus of the roots of the AR polynomial be greater than unity, and for the MA part to be invertible it is also necessary that the roots of the MA polynomial lie outside the unit circle.

The original Dickey-Fuller test considered the model $X_t = \rho X_{t-1} + \varepsilon_t$ .... (4)

If the series contains a unit root, then $\rho = 1$. The standard t-distribution cannot be used to test if $\rho = 1$, the Dickey-Fuller distribution should be used instead. However, should ε_t be autocorrelated, the Dickey-Fuller distribution is no longer valid either. In this case, an alternative model should be estimated, where lags of the series are added until the series e_t displays no evidence of autocorrelation. More recently, MacKinnon has implemented a much larger set of simulations than those tabulated by Dickey and Fuller. In addition, MacKinnon estimates the response surface using the simulation results, permitting the calculation of Dickey-Fuller critical values for any sample size and for any number of right-hand variables. EViews reports these MacKinnon critical values for unit root tests. We have to decide whether to include other exogenous variables in the test regression like, constant, a constant and a linear time trend, or neither in the test regression. Our decision here is important since the asymptotic distribution of the t-statistic under the null hypothesis depends on our assumptions regarding these deterministic terms.

- If we include a constant in the test regression, the t-statistic has a nonstandard distribution if the underlying process contains a unit root with a zero constant.
- If we include a constant and linear trend in the test regression, the t-statistic has a nonstandard distribution if the underlying process contains a unit root with a zero linear trend.

The asymptotic distribution changes when these assumptions are not satisfied. For example, if we include a constant in the test regression and if the underlying process contains a unit root with a nonzero constant, then the t-statistic has an asymptotic standard normal distribution under the null hypothesis of a unit root. There still remains the problem of whether to include a constant, a constant and a linear trend, or neither in the test regression. One approach would be to run the test with both a constant and a linear trend since the other two cases are just special cases of this more general specification. However, including irrelevant regressors in the regression reduces the power of the test, possibly concluding that there is a unit root when, in fact, there is none. If the series seems to contain a trend, we should include both a constant and trend in the test regression. If the series does not exhibit any trend and has a nonzero mean, we should only include a constant in the regression, while if the series seems to be fluctuating around a zero mean, we should include neither a constant nor a trend in the test regression.

An augmented Dickey-Fuller test gives the result shown below in Table 6. As we can see from the result of the test, the unit root hypothesis is rejected in all the three conditions (i.e. ADF Test WOI, WI and WIT) of the test statistics indicating that, inflation series is stationary in level (with out differencing).

Table 6: Augmented Dickey-Fuller Unit root test

ADF Test Statistic	-3.997134	1% Critical Value*	-2.5860
WOI		5% Critical Value	-1.9432
		10% Critical Value	-1.6174
WI	-4.487269	1% Critical Value*	-3.4952
		5% Critical Value	-2.8897
		10% Critical Value	-2.5816
WIT	-4.672142	1% Critical Value*	-4.0503
		5% Critical Value	-3.4539
		10% Critical Value	-3.1523

WOI = with out intercept, WI = with intercept, and WIT = with intercept and trend

**MacKinnon critical values for rejection of hypothesis of a unit root.*

3.3.4 Model Identification and Estimation

Having determined the stationarity of the series, the next step is to find an appropriate ARMA form to model the stationary series. There are two main approaches to identification of ARMA models in the literature. The traditional method utilizes the Box-Jenkins procedure, in which an iterative process of model identification, model estimation and model evaluation is followed. The Box-Jenkins procedure is a quasi-formal approach with model identification relying on subjective assessment of plots of autocorrelograms and partial autocorrelograms of the series. Objective measures of model stability, in particular the penalty function criteria, have been used instead of the traditional Box-Jenkins procedure. However these objective measures are not without problems either. In order to estimate the parameters, we use the method of Ordinary Least Squares.

3.3.5 Box-Jenkins Methodology

The Box-Jenkins methodology essentially involves examining plots of the sample autocorrelogram and partial autocorrelogram and inferring from patterns observed in these functions the correct form of ARMA model to select. The Box-Jenkins methodology is not only about model identification but is, in fact, an iterative approach incorporating model estimation and diagnostic checking in addition to model identification. Theoretically Box-Jenkins model identification is relatively easy if one has a pure AR or a pure MA process. However, in the case of mixed ARMA models (especially of higher order) it can be difficult to interpret sample ACFs and PACFs, and Box-Jenkins identification becomes a highly subjective exercise depending on the skill and experience of the forecaster.

3.3.5.1 Pure AR Process

The autocorrelations of pure AR(p) processes should decay gradually at increasing lag length. Hence, using an autocorrelogram it is not possible to differentiate between a pure AR(3) model or pure AR(4) model. However, the partial autocorrelations of a pure AR(p) process do display distinctive features. The partial autocorrelogram should die out after p lags. Thus, the partial autocorrelogram of a pure AR(3) process would die out after 3 lags, whereas the partial autocorrelogram of a pure AR(4) process would die out after 4 lags.

Hence, for a pure AR(p) process the theoretical ACF and PACF are as follows:

ACF (i) $\neq 0$ for all i

PACF (i) $\neq$ 0 for all i= 1, …, p

PACF (i) = 0 for all i > p, where i denotes the number of lags.

3.3.5.2 Pure MA Process

The behavior of correlograms and partial autocorrelograms for pure MA(q) is the inverse of that for pure AR(p) processes. The autocorrelogram of a pure MA(q) process should die out after q lags. The partial autocorrelogram of a pure MA process, on the other hand, only decays slowly over time (similar to autocorrelogram of a pure AR process). Thus, it should be impossible to distinguish between the PACF of an MA(3) and MA(4) process, where as the ACF of the MA(3) process should decay to zero after 3 lags and the MA(4) process after 4 lags.

Hence, for a pure MA(q) process the theoretical ACF and PACF are as follows:

ACF(i) $\neq 0$ for all i= 1, …, q

ACF(i) = 0 for all i > q

PACF(i) $\neq$ 0 for all i

Thus if one has either a pure AR or MA process model identification should be relatively straightforward in theory.

3.3.5.3 Mixed ARMA Process

Unfortunately, model identification is greatly complicated for mixed (i.e, ARMA) processes. The patterns of sample autocorrelations and partial autocorrelations of high order ARMA models are notoriously difficult to interpret. Thus, model identification using the Box-Jenkins procedures will be an iterative process (Box and Jenkins 1976).

3.3.6 Objective Model Application

Because of the highly subjective nature of the Box-Jenkins methodology, time series analysts have sought alternative objective methods for identifying ARMA models. Penalty function statistics, such as Akaike Information Criteria (AIC), Schwarz Criteria (SC) or Bayesian Information Criteria (BIC), etc can be employed.

These statistics take the form minimizing the residual sum of squares plus a penalty term which incorporates the number of estimated parameter coefficients to factor in model parsimony.

These statistics take the form

$$\text{AIC} = \log\left(\frac{rss}{n}\right) + \left(2 * \frac{k}{n}\right) \quad \text{.........................(5) and}$$

$$\text{BIC} = \log\left(\frac{rss}{n}\right) + \left(\log(n) * \frac{k}{n}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

where, k = number of coefficients estimated (1 + p +q +P +Q),

rss = residual sum of squares,

n= number of observations

The BIC is strongly consistent whereas AIC will usually result in an over parameterized model; that is a model with too many AR or MA terms (Aidan M., Goeff K. and Terry Q., 1998). Thus, in practice, using the objective model selection criteria involves estimating a range of models and the one with the lowest information criterion is selected.

As we can see from the Table 5 of correlogram of the sample inflation series, the autocorrelation coefficients decline and then rise to a relative peak at lag 12 before declining substantially at higher lags, and the partial autocorrelations show a positive spike at lag 1 and a negative spike at lag 13. These patterns suggest an AR(1)*SAR(12) as a first approximation to the series. Although many models can be fitted to a set of data, not all of the parameter estimates may be necessary (statistically significant). As in regression analysis, the test of significance for the constant and coefficients is the t-test. Good modeling practice requires that we retain only those terms whose coefficients are significantly different from zero. Terms whose t-ratios are not significant should be dropped and the model recalculated with the remaining terms. As we can see in the following equation 7 except constant term, the coefficients of the variables in model AR(1)*SAR(12) are significant at 5% level of significance.

$$p_t = 0.505593 + 0.41109\,\text{p}_{t-1} + 0.234259\,\text{p}_{t-12} \quad \ldots\ldots\ldots(7)$$

P-value = (0.1712) (0.0000) (0.0256), SSE=232.9165

R-square =0.233352, adjusted R-square=0.216503, AIC=3.809092, SC=3.890261

That is, the model should be fitted by dropping constant term as shown in Table 8 of appendix B. About 21.7 percent of the variation in inflation at some period time t is explained by its first lag and seasonally differenced variables and the sum of square residual for this model is 237.5316.

An alternative model that can be fitted based on the correlogram of the sampled inflation series is AR(1)* SMA(12) or

$$p_t = 0.387521 + 0.388603\,p_{t-1} + 0.28489\,\varepsilon_{t-12} \;\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

P-value = (0.2199) (0.0000) (0.0049), SSE=253.9752

R-square = 0.222248, adjusted R-square=0.207146, AIC=3.768278, SC=3.843658

For this estimated model, we can observe that likewise the model 7 we have seen above, except for the constant term the coefficients of the random variables included in the model are significantly different from zero indicating that the model should have no constant term (see Table 10 in the appendix B) . The sum of squared residual is 253.9752 which is some how large when compared with the model 7 we have seen above. The adjusted coefficient of determination is almost equal with that of AR(1)*SAR(12) model. The other possible model that we can fit based on correlogram of the sample of inflation series is MA(1)*SMA(12) or

$$p_t = 0.427161 + 0.464864\,\varepsilon_{t-1} - 0.28489\,\varepsilon_{t-12} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

P-value = (0.1518) (0.0000) (0.0005), SSE=254.8212

R-square = 0.239030, adjusted R-square=0.224396, AIC=3.761685, SC=3.836624

As we can see from equation 9 above the constant term is not significant. That is, the model should be fitted with out intercept as shown in Table 12 in the appendix B and its square of residual error is 259.7657, which is larger than the two model discussed above and the adjusted coefficient of determination is not differ that much from those models.

$$p_t = 0.432377 + 0.475576\,p_{t-1} - 0.455752\,p_{t-12} + -0.880107\,\varepsilon_{t-12} \;\ldots\ldots\ldots(10)$$

P-value = (0.2226) (0.0000) (0.0005) (0.0000), SSE=187.8660

R-square =0.383282, adjusted R-square = 0.362725, AIC =3.612753, SC=3.720978

Similarly, when we see AR(1) SAR(12) SMA(12) or equation 10, the model should be fitted with out constant term as shown in (Table 13 in appendix B), its squared sum of square 190.3449 is relatively smaller than the above three models and the adjusted coefficient of determination of this model (0.362725) is relatively large.

Still we can see that AR(1) MA(10)*SAR(12)*SMA(12) with constant term which can be written as equation 5 could be best model since its coefficient of determination is relatively large, the coefficients of all variables in the model are highly significant, and the sum of squared residual for this model is quite small (see Table 14 in appendix B).

$$p_t = 0.884350 + 0.47162\,\mathrm{p}_{t-1} + 0.723590\,\mathrm{p}_{t-12} + 0.209258\,\varepsilon_{t-10} - 0.843693\,\varepsilon_{t-12} \cdots (11)$$

P-value = (0.0405) (0.0000) (0.000) (0.0003) (0.0000), SSE=134.4478

R-square = 0.557463, adjusted R-square=0.537574, AIC=3.302141, SC=3.437423

Note that, all the above models are specified using the information from the correlogram of the inflation series in the sample period (i.e Box-Jenkins procedure). That is, the correlogram simply reduce the number of trials made but not perfectly indicate the most appropriate order of ARIMA. After identifying the tentative models, we have to assess each of them using the diagnostic tests as discussed under model diagnostics.

3.3.6.1 Advantages of objective penalty Function criteria

- Objective measures with no subjective interpretation
- Results are readily reproducible and verifiable
- BIC is asymptotically consistent

3.3.6.2 Disadvantages of objective penalty Function criteria

- Need to calculate a wide range of models. This can be computationally expensive.
- Sometimes there is little to choose between competing models.

3.3.7 Model diagnostics

The fourth step will be the formal assessment of each of the time series models. This will involve a rigorous assessment of the diagnostic test for each of the competing models. As different models may perform reasonably similarly, a number of alternative formulations may have to be retained at this stage to be further assessed at the forecasting stage. There are a number of diagnostic tools available for insuring a satisfactory model is arrived at. Plotting the residuals of the estimated model is a useful diagnostic check. This should indicate any outliers that may affect parameter estimates and also point towards any possible autocorrelation or heteroscedasticity problems. A second check of model suitability which we used is to plot the autocorrelation of the residuals. If the model is correctly specified the residuals should be white noise. Therefore, the plot of autocorrelogram should immediately die out from one lag on. A good way to check the adequacy of over all Box-Jenkins models is to analyze the residuals. If the residuals are truly random, the autocorrelations and the partial autocorrelations calculated using the residuals should be statistically equal to zero. If they are not, this is an indication that we have not fitted the correct model to the data (Atricia E. Caynor R. Kirkpatrick C., 1994).

The last two columns reported in the correlogram are the Ljung-Box Q-statistics and their p-values. The Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k and is computed as

$$Q_{LR} = T(T+2)\sum_{j=1}^{k}\left(\frac{r_j^{2}}{T-j}\right) \qquad \text{................(12)}$$

where r_j is the j-th autocorrelation and T is the number of observations. If the series is not based upon the results of ARIMA estimation, then under the null hypothesis, Q is asymptotically distributed as a Chi-square with degrees of freedom equal to the number of autocorrelations. If the series represents the residuals from ARIMA estimation, the appropriate degrees of freedom should be adjusted to represent the number of autocorrelations less the number of AR and MA terms previously estimated. The Q-statistic is often used as a test of whether the series is white noise. Therefore, it is important to test for serial correlation in residuals because if the residuals are correlated then this will likely result in the squared residuals also being correlated indicating that the model fitted is not good (Kunist M.). The residual of the above models (i.e AR(1)*SAR(12), AR(1)*SMA(12), MA(1)*SMA(12), AR(1)*SAR(12)*SMA(12)) and C AR(1) MA(10)*SAR(12)*SMA(12) are tasted for randomness and the result of the test shows that the residuals are white noise (i.e the p-value of Q-statistics are all large) indicating that there is no problem with the fitted models (see Tables 15-19 of appendix B). Once we have tested the reliability of models, the next task is selecting the most appropriate model from these models using the penalty criteria. Using the objective model selection criteria, AR(1)*SAR(12)*SMA(12) the model with the lowest information criterion (i.e both Akaike information criterian (3.302141) and Schwarz criterian(3.437423) are the smallest when compared with that of the other models, and is selected as the best model as indicated in table 7. So, the proposed model is given as:

$$p_t = 0.884350 + 0.47162\,p_{t-1} + 0.723590\,p_{t-12} + 0.209258\,\varepsilon_{t-10} - 0.843693\,\varepsilon_{t-12}.$$

This model is assumed to be the best univariate model fitted for the inflation process in Ethiopia for the period 1997:08 through 2006:06. The above model is selected on the bases of its overall forecasting performance and it meets the entire prerequisites which are well in line and support the model regarding its robustness, forecasting evaluation and its forecasting accuracy is concerned. The supporting statistics like R-squared, Adjusted R-squared, sum of squared residual, Q-statistics, Akaike information criterion, Schwarz criterion, Root Mean Squared Error, Mean Absolute Error, Mean Abs. Percent Error, Theil Inequality Coefficient and others have out performed as compared to other models as indicated in the following table.

Table 7: Model evaluation and Measures of forecast accuracy

Model	R-squared	Adjusted R-squared	Sum of squared error	Akaike info. criterion	Schwarz criterion	Root mean squared error	Mean absolute error	Mean absolute percentage error	U-statistic
1	0.233352	0.2165	232.916	3.80909	3.89026	1.19104	1.06180	93.64885	0.612918
2	0.22224	0.2071	253.975	3.76827	3.84365	1.27571	1.14805	102.1329	0.665211
3	0.23903	0.2243	254.821	3.76168	3.83662	1.65853	1.39464	116.4418	0.707092
4	0.38328	0.3627	187.366	3.61275	3.72097	1.62287	1.49328	141.6078	0.784854
5	0.55746	0.5375	134.447	3.30214	3.43742	0.65023	0.50637	35.57699	0.263795

where, ***1= AR(1)*SAR(12) ,2= AR(1)*SMA(12), 3= MA(1)*SMA(12),***

4= AR(1)*SAR(12)*SMA(12), 5=AR(1)MA(10)*SAR(12)*SMA(12).

Having this positive behavior of the model, the model has also outperform as for as the forecasting power of the model is concerned. This predictive power of the model indicates that actual and predicted values have high level of close match.

3.3.8 Forecasting Univariate Time Series

In applied macro economics and financial econometrics, often the main reason for estimating an econometric model is so that the estimated model can be used to compute forecasts of the series. While any type of econometric model can be used to compute forecasts (eg. Multivariate regression model, Auto regressive Distributed Lag model, it is the univariate time series models such as AR and ARMA models that have proved to be the most popular. The forecasting theory for univariate time series models has long been established (Box and Jenkins, 1970) and univariate Box-Jenkins methods have continued to be popular with econometricians. Out of a number of reasons why univariate forecasting methods in particular deserve consideration is, they are quick and inexpensive to apply and may well produce forecasts of sufficient quality for the purposes of at hand (Rechad Harris and Robert Sollis , 2003).

3.3.9 Forecast Evaluation and Forecast Accuracy Criteria

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. One approach is to estimate the model recursively and forecast ahead a specific number of observations. For this purpose, we have a time series with data from August, 1997 to December, 2006 and we wish to forecast six steps ahead 2006:07 through 2006:12. This can be used to calculate statistics such as mean error (ME), mean absolute error (MAE), root mean square error (RMSE), and Theil's coefficients. The RMSE will always be at least as large as the MAE. They will only be equal if all errors are exactly the same. Theil's U statistics calculates the ratio of the RMSE of the chosen model to the RMSE of the 'naïve' (i.e assuming the value in the next period is the same as the value in this period – no change in the dependent variable) forecasting model. That is, the idea of Theil's coefficients was to evaluate a forecast against the background of a simple or primitive forecast. If a forecasting procedure is to be taken seriously, it should at least beat the simple benchmark. Unfortunately, it is not always clear which benchmark to use. Theil used mainly random-walk or no-change forecasts, while other researchers use autoregressive prediction or exponential smoothers instead (Robert M.Kunist, 2007). Thus, a value of one for the Theil statistic indicates that, on average, the RMSE of the chosen model is the same as the 'naïve' model. A Theil statistic in excess of one would lead one to reconsider the model as the simple 'naïve' model performs better, on average. On the other hand a Theil statistic less than one does not lead to automatic acceptance of the model, but does indicate that, on average, it performs better than the 'naïve' model. Theil statistic is that it is 'unitless' as it compares the RMSE of the chosen model to that of the 'naïve' forecast model. The ME, MAE, and RMSE all vary depending on the dimension (or scale of measurement) of the dependent variable. The Theil statistic also provides a quick comparison with 'no change' model and, as such, is a measure of one-step ahead forecasts of the additional forecasting information the model provides beyond a random walk model. The accuracy of forecasting model depends on how close the forecast values are to the actual values. In practice, we define the difference between the actual and the forecast values as the forecast error,

$$a_t = (Y_t - \hat{Y}_t) \qquad \text{..................(13)}$$

where,

a_t is forecast error, Y_t is the actual value and $\hat{Y}_t$ is the forecasted value.

- The mean absolute error

$$\text{MAE} = \frac{\sum_{t=1}^{n} |a_t|}{n} \qquad \text{..................(14)}$$

- The mean of the absolute percentage error

$$\text{MAPE} = \frac{\sum_{t=1}^{n} \frac{|a_t|}{Y_t}}{n} \qquad \text{.................(15)}$$

where a_t is the forecast error in time period t;

Y_t is the actual value in time period t;

n is the number of forecast observations in the estimation period

- The mean square error

$$\text{MSE} = \frac{\sum_{t=1}^{n} a_t^2}{n} \quad \text{..........................(16)}$$

- The root mean squared error (standard error

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} a_t^2}{n}} \quad \text{........................(17)}$$

where,

a_t is the forecast error in time period t;

n equals the number of out-of-sample observations retained for forecast evaluation allowing for the forecast step,

Because these statistics give a measure of the forecasting error, the decision of which one to use depends on the makeup of the data. That is, if there are only one or two errors, these will be magnified by using MSE and RMSE (since all the errors are squared); thus the MAE should be used. When all the errors are similar in magnitude, the statistic used is the MSE. The proper MAE or MSE (or RMSE) can then be employed to select the best forecasting model by simply choosing the model that yields the smallest MAE or MSE (or RMSE).

Theil,s inequality coefficient compares the accuracy of a forecast model to that of a naïve model, which simply uses the actual value for the last time period (Y_t) as a forecast for $\hat{Y}_{t+1}$.

The formula for Theil's U is

$$\text{Theil,s U} = \frac{\sqrt{\frac{\sum_{t=1}^{n} a_t^2}{n}}}{\sqrt{\frac{a_t^{2N}}{n}}} = {RMSE}\Big/{RMSE^N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(18)$$

where,

n = the number of out-of-sample observations retained for forecast evaluation allowing for the forecast step, and

N denotes the naive model of no change in the modeled series from the last available observation.

Another method that can be used to measure the accuracy of a model is the graphical method. For the plot of the actual, fitted and residual over time, if a visual inspection reveals that the residuals are randomly distributed over time and when the actual and the fitted plots are close to each other, then we have a good model. AR(1)MA(10)*SAR(12)*SMA(12) model satisfies all the requirements as reported in Table 8 and figure 8 below. That is, empirically taking, we have examined that the various measures of forecasting errors, namely the root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) and Theil's U and other selection criteria for different models. The first two forecast error statistics depend on the scale of the dependent variable. These are used as relative measures to compare forecasts for the same series across different models, the smaller the error, the better the forecasting ability of that model accordingly. The remaining two statistics are scale invariant. The Theil inequality coefficient lies between zero and one, where zero indicates a perfect fit.

The Root squared error, Mean absolute error, Mean absolute percentage error and Theil inequality coefficient for this model are smaller than the other models. Figure 8 below depicts that the Actual, fitted, residual graph for this model which shows that the plot for the actual and the fitted series highly close to each other. Therefore, we can use this model to perform short term forecast.

Figure 8: Actual, fitted, residual graph for C AR(1) MA(10)*SAR(12)*SMA(12)

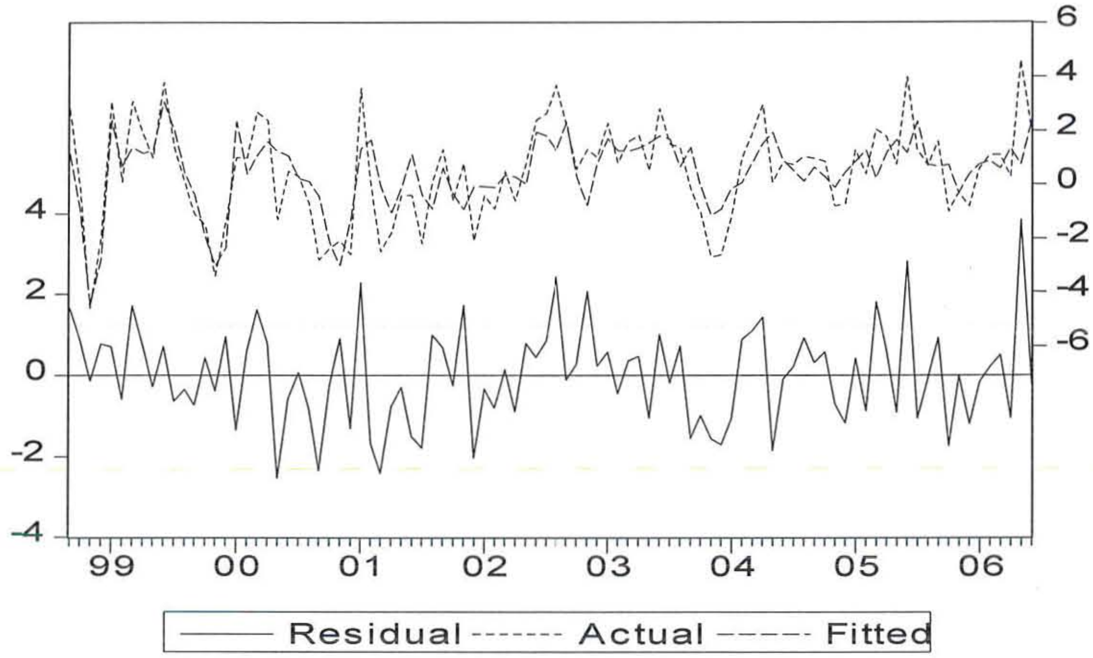


Table 8: Model evaluation and Measures of forecast accuracy

Model	Root mean squared error	Mean absolute error	Mean absolute percentage error	Theil inequality coefficient
AR(1)*SAR(12)	1.19104	1.061808	93.64885	0.612918
AR(1)*SMA(12)	1.275718	1.148051	102.1329	0.665211
MA(1)*SMA(12)	1.658533	1.394640	116.4418	0.707092
AR(1)*SAR(12)*SMA(12)	1.622875	1.493287	141.6078	0.784854
AR(1)MA(10)*SAR(12)*SMA(12)	0.650233	0.506377	35.57699	0.263795

CHAPTER FOUR

CONCLUSION

The aim of this study is to investigate the nature of inflation in Ethiopia and construct model that is used to forecast future values. First of all, we check for stationarity to see if we should construct a model in the levels of the series. To do so, the method of graphically examining the data was employed. That is, the series was plotted against time to assess whether any structural breaks, outliers or data errors occur. Inflation series was plotted against time and when we observed a plot of the inflation series in levels for the period 1997:08 to 2006:06. Visual inspection does not give any strong indication of nonstationarity. The correlogram of the series tells us similar story. An augmented Dickey-Fuller test statistic was used to justify the information from the graph and the correlogram. According to the result of this test statistics, the unit root hypothesis is rejected. Having determined the stationarity of the series, exponential smoothing approach and ARMA models were adopted to inflation forecasting. First, exponential method was employed of which Winter's (additive) method performs better in forecasting future values of inflation as indicated by values of measures of forecasting accuracy (see Table 3). Next, two main approaches namely the Box-Jenkins procedure and the penalty function criteria were used in identification of appropriate ARMA model. The Box-Jenkins procedure, which based on the autocorrelation function and partial autocorrelation function, to determine the order of p and q for ARMA model suggested AR(1)*SAR(12), AR(1)*SMA(12), MA(1)*SMA(12), AR(1)*SAR(12)*SMA(12)) and AR(1) MA(10)*SAR(12)*SMA(12) as tentative models to the inflation series and each of the models was assessed by diagnostic tests and found to satisfy the requirement (i.e the random errors of these models are found to be white noise) and of these, the penalty function criteria were employed to select the appropriate model. Accordingly AR(1)MA(10)*SAR(12)*SMA(12) is selected on the bases of its overall forecasting performance and it meets the entire prerequisites which are well in line and support the model regarding its robustness, forecasting evaluation and its forecasting accuracy is concerned. When we compare the values of forecasting accuracies, this model better performs than the exponential smoothing model.

APPENDIX A - A BRIEF OVERVIEW OF ARIMA MODELS

A general class of univariate models is the Autoregressive Integrated Moving Average (ARIMA) model. An ARIMA model represent current values of a time series in terms of past values of itself (the autoregressive component) and past values of the error term (the moving average terms). The integrated component refers to the number of times a series must be differenced to induce stationarity.

A.1. AR MODELS

A pure AR (p) process may be represented as follows, where X_t is modeled as lagged values of itself plus a 'white noise' error term.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + a_t = \sum_{i=1}^{p} \phi_i X_{t-i} + a_t \quad .... (A1)$$

This may be written alternatively as,

$$\phi \text{ (B) } X_t = a_t \quad ....(A2)$$

where ϕ (B) is a p-order polynomial in the backshift operator (i.e. $1-\phi_1 B-\phi_2 B^2 -... -\phi_p B^p$), and B is the backshift operator, such that $B^0 X_t = X_t$, $B^1 X_t = X_{t-1}$, $B^2 X_t = X_{t-2}$, ...

A useful way of gaining insight into univariate processes is to consider their autocorrelation and partial autocorrelation functions (ACF and PACF.

The ACF measures the ratio of the covariance between observation K lags apart and the geometric average of the variance of observation (i.e. the variance of the process if the process is stationary, as $V(X_t) = V(X_{t-k})$.

$$\rho_k = \frac{\text{cov}(X_t, X_{t-k})}{[V(X_t) \bullet V(X_{t-k})]^{1/2}} = \frac{\gamma_k}{\gamma_o} \quad ....(A3)$$

The sample autocorrelation function (SACF) may be calculated as follows;

$$r_k = \frac{\sum_{t=k+1}^{n}(X_t - \overline{X})(X_{t-k} - \overline{X})}{\sum_{t=1}^{n}(X_t - \overline{X})^{1/2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(A4)}$$

However, some of the observed autocorrelation between X_t and X_{t-k} could be due to both being correlated with intervening lags. The PACF seek to measure the autocorrelation between X_t and X_{t-k} correcting for the correlation with intervening lags. For example, consider an AR (1) process of the form $X_t = 0.8\, X_{t-1} + a_t$. The first order autocorrelation coefficient is 0.8. The autocorrelation coefficient for the second lag is 0.64 (i.e. 0.8 * 0.8), although the partial autocorrelation coefficient for the second lag is zero, as the process is an AR (1) process. In other words the autocorrelation between observation two lags apart is due only to the correlation between observation one lag apart which feeds through into the second lag. As the lag length increase the autocorrelation coefficient declines (at lag length K the autocorrelation coefficient is $(0.8)^K$).

The PACF is calculated as the partial regression coefficient, ϕ_{kk} , in the k^{th} order autoregression.

$$X_t = \phi_{k1} X_{t-1} + \phi_{k2} X_{t-2} + \ldots\ldots\ldots + \phi_{kk} X_{t-k} + a_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(A5)}$$

Thus for an AR (P) process $\phi_{kk} = 0\ \forall K > p$.

According to George G. Judge, R. Carter hill, Willium E. Griffths, Helmut Lutkepoh and Tsoung-chao lee (1982), Some general properties of the ACF and PACF for AR processes can be observed by considering a simple AR (1) process.

$$X_t = \phi_1 X_{t-1} + a_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(A6)}$$

Note that the AR (1) model can be written as an infinite length MA process, providing ϕ_1 less than unity. Denote the AR (1) series as,

$$(1 - \phi_1 B)X_t = a_t, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(A7)}$$

Where B is the backshift operator as before, which gives

$X_t = (1 - \phi_1 B)^{-1} a_t$ .... (A8),

Which upon expansion and providing $\phi_1 <$ unity yields

$X_t = a_t + \phi_1\ a_t + \phi_1^2 a_{t-2} + \phi_1^3 a_{t-3} + ...$, ... (A9)

This result holds more generally so that any finite order stationary AR process may be expressed as an infinite order MA process. This duality between AR and MA process is an important property which can often be exploited when attempting to identify ARMA models.

For the AR (1) process the value of the ACF at lag k is given by ϕ_1^k. The value of the autogressive coefficient can yield some insight into the underlying data generating process. For example, higher values of ϕ_1 indicate a higher degree of persistence in the series. A negative autoregressive component indicates a process which oscillates around its mean value.

For more general AR (p) models, the behavior of the process is determined by the solution to the p-order polynomial $(1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p)$, given by

$$\phi(B) = (1-g_1 B)(1-g_2 B)\ ...(1-g_p B) = 0 \qquad \text{(A10)}$$

For the process to be stationary it is a necessary and sufficient condition for the roots of the p-order polynomial to lie outside the unit circle, i.e. $\left|\frac{1}{g_i}\right| >$ unity $\forall i = 1....p$).

A.2. MA MODELS

A MA (q) process may be represented as follows, where X_t is modeled as the weighted average of a ' white noise ' series.

$$X_t = a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + ... + \theta_q a_{t-q} = \sum_{j=0}^{q} \theta_j a_{t-j} \quad ....(A11)$$

Or alternatively,

$X_t = \theta(B) a_t$ .... (A12) where, a_t is a 'white noise' series, $\theta(B)$ is a q-order polynomial in the backshift operator (i.e. $1+\theta_1 B+\theta_2 B^2+...+\theta_q B^q$), and

B is the backshift operator, $B^0\ a_t = a_t$, $B^1\ a_t = a_{t-1}$, $B^2\ a_t = a_{t-2}$, ...

Note that the expected value of X_t equals zero. Furthermore, the autocorrelation between X_t and X_{t+k} equals zero for k greater than q. Thus the order of the MA process, q, indicates the 'memory' of the process. All MA processes are stationary, regardless of the coefficient of the model. However, to ensure invertibility of the model (i.e. that the finite order MA process can be written in terms of a stationary infinite order AR process) the roots of the MA polynomial must lie outside the unit circle. MA models can be particularly useful for representing some economic time series as they can handle random shocks such as strikes weather patterns, etc..

A.3. ARMA MODELS

An ARMA (p, q) series may be represented as

$$X_t - \phi_1 X_{t-1} - \phi_2 X_{t-2} - ... - \phi_p X_{t-p} = a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + ... + \theta_q a_{t-q} \quad \text{.................(A13)}$$

Or alternatively

$$\sum_{i=0}^{p} \phi X_{t-i} = \sum_{j=0}^{q} \theta_j a_{t-j} \quad \text{............................ (A14)}$$

where ϕ_0 and $\theta_0 = 1$.

Or more compactly

$$\phi(B)X_t = \theta(B)a_t \quad \text{.................................. (A15)}$$

Using mixed ARMA models can be useful as it should usually be possible to represent a time series satisfactorily using fewer parameters than might be required with a pure AR or pure MA model.

A.4. SEASONAL ARMA MODELS

Seasonal data may be also modeled. The numbers of seasonal AR and MA terms are usually denoted by P and Q respectively. Thus, a general seasonal ARMA model may be represented as,

$$\phi(B)\Phi(B)X_t = \theta(B)\Theta(B)a_t \quad \text{.................................(A16)}$$

where,

$$\Phi(B) = 1 - \Phi_{1s}B^{1s} - \Phi_{2s}B^{2s} - \ldots - \Phi_{ps}B^{ps}$$

$$\Theta(B) = 1 + \Theta_{1s}B^{1s} + \Theta_{2s}B^{2s} + \ldots + \Theta_{Qs}B^{Qs}$$

s= the seasonal span, hence for quarterly data s=4 and for monthly data s=12.

A.5. ARIMA MODELS

The integrated component of an ARIMA model represents the number of times a time series must be differenced to induce stationarity. The general notation for ARIMA models is ARIMA (p, d, q)(P, D, Q), where p denotes the number of autoregressive terms, q denotes the number of moving average terms and d denotes the number of times a time series must be differenced to induce stationarity. P denotes the number of seasonal autoregressive components, Q denotes the number of seasonal moving average terms and D denotes the number of seasonal differences required to induce stationarity. This may be written as

$$\phi(B)\Phi(\mathrm{B})\Delta^{d}\Delta_{s}^{D}Y_{t} = \theta(\mathrm{B})\Theta(\mathrm{B})a_{t} \quad \text{...........................(A17)}$$

where,

X_t = $\Delta^d \Delta^D Y_t$ is a stationary series, and $\Delta^d = (1-B)^d$ represents the number of regular differences and $\Delta^D = (1-B^s)^D$ represents the number of seasonal differences required to induce stationarity in Y_t.

Two important properties of the parameters of ARIMA models are worth repeating. First, for an ARIMA processes to be stationary it is required that the modulus of the roots of the p-order AR polynomial be greater than unity (i.e $|1/g|$ > 1, $\forall$j=1, …, p).

Second for ARIMA model to be invertible (i.e, representable as a stationary infinite lag AR model) the roots of the q-order MA polynomial should be greater than unity (i.e $|1/g|$ > 1, $\forall$j=1, …, q).

APPENDIX B TABLES AND GRAPHS

Table1: Level of price index and inflation rates based on the retail price index for Addis Ababa

Ethiopian fiscal year Ending June 30	Average annual general index 1963=100	Inflation rate	Ethiopian fiscal year Ending June 30	Month	Average annual general index 1963=100	Inflation rate
1973/74	154.4	10.7	1988/89	June	501.8	9.6
1974/75	161.6	4.7	1989/90	June	527.7	5.2
1975/76	192.2	18.9	1990/91	June	638.0	20.9
1976/77	234.2	21.9	1991/92	June	771.9	21.0
1977/78	277.7	18.6	1992/93	June	849.0	10.0
1978/79	313.6	12.9	1993/94	June	858.9	1.2
1979/80	352.9	12.5	1994/95	June	973.6	13.4
1980/81	359.7	1.9	1995/96	June	982.6	0.9
1981/82	385.9	7.3	1996/97	June	919.5	-6.4
1982/83	400.7	3.8	1997/98	July	916.5	-6.3
1983/84	399.7	-0.2	1997/98	August	915.8	-5.7
1984/85	473.1	18.4	1997/98	September	914.6	-5.2
1985/86	495.0	4.6	1997/98	October	916.1	-4.5
1986/87	448.2	-9.5	1997/98	November	916.1	-4.0
1987/88	457.9	2.2	1997/98	December	914.8	-3.7

Source: Economic Association, (2000). "*Annual report on the Ethiopian Economy*", Vol.I

Table 2: The country level general inflation based on the consumer price index at the country level

Budget year	Month	Inflation rate
2001/2	June	4.7
2002/3	June	15.0
2003/4	June	8.6
2004/5	June	6.8
2005/6	June	12.3
2006/7	June	15.8

Source: Central statistics authority

Figure 6: Normality test

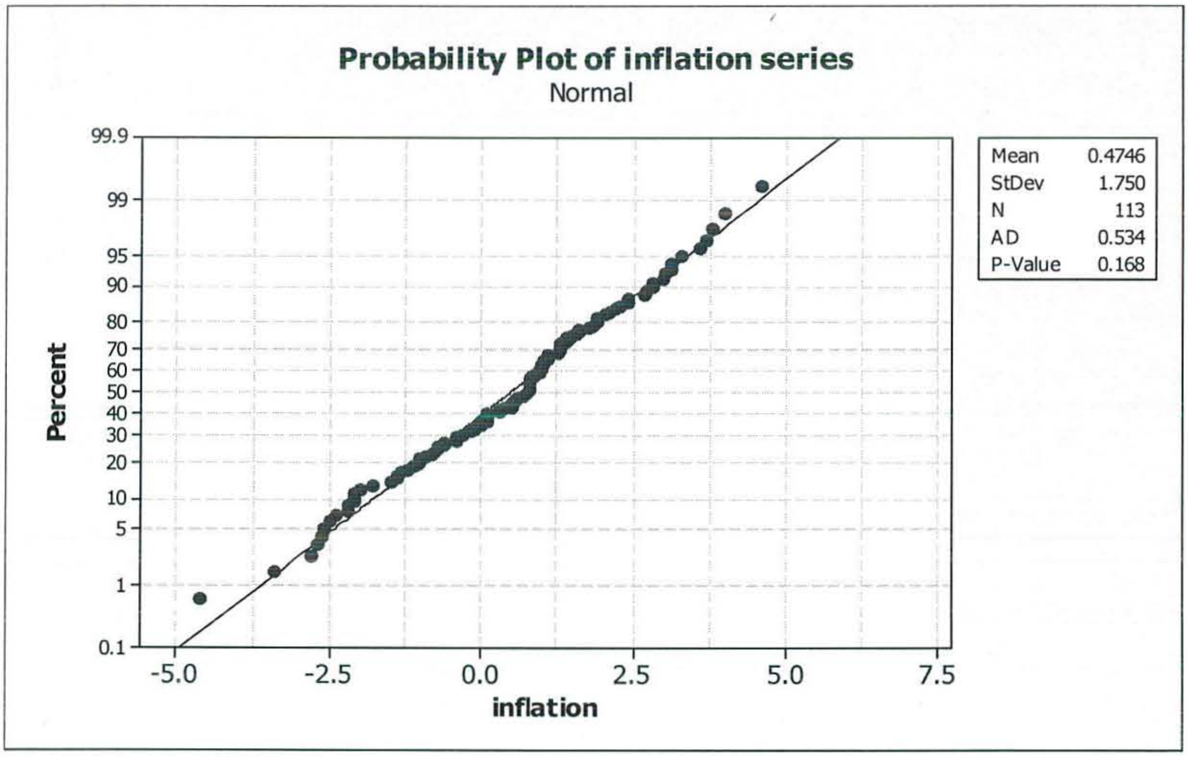


Table 7: Estimation of model AR(1)* SAR(12) with constant

Sample(adjusted): 1997:09 2006:06
Included observations: 94 after adjusting endpoints
Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.505593	0.366606	1.379117	0.1712
AR(1)	0.411099	0.096332	4.267549	0.0000
SAR(12)	0.234259	0.103213	2.269662	0.0256
R-squared	0.233352	Mean dependent var		
Adjusted R-squared	0.216503	S.D. dependent var		
S.E. of regression	1.599851	Akaike info criterion		
Sum squared resid	232.9165	Schwarz criterion		
Log likelihood	-176.0273	F-statistic		
Durbin-Watson stat	1.953370	Prob(F-statistic)		

Table 8: Estimation of model AR(1)* SAR(12) without constant

Sample(adjusted): 1997:09 2006:06
Included observations: 94 after adjusting endpoints
Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.437369	0.094781	4.614518	0.0000
SAR(12)	0.246827	0.103250	2.390581	0.0189
R-squared	0.218162	Mean dependent var		
Adjusted R-squared	0.209663	S.D. dependent var		
S.E. of regression	1.606818	Akaike info criterion		
Sum squared resid	237.5316	Schwarz criterion		
Log likelihood	-176.9495	F-statistic		
Durbin-Watson stat	1.966362	Prob(F-statistic)		

Table 9: Estimation of model AR(1)*SMA(12) with constant

Sample(adjusted): 1997:09 2006:06
Included observations: 106 after adjusting endpoints
Convergence achieved after 6 iterations
Backcast: 1996:09 1997:08

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.387521	0.313963	1.234287	0.2199
AR(1)	0.388603	0.090191	4.308669	0.0000
MA(12)	0.284089	0.098713	2.877935	0.0049
R-squared	0.222248	Mean dependent var		0.403113
Adjusted R-squared	0.207146	S.D. dependent var		1.763520
S.E. of regression	1.570280	Akaike info criterion		3.768278
Sum squared resid	253.9752	Schwarz criterion		3.843658
Log likelihood	-196.7187	F-statistic		14.71647
Durbin-Watson stat	1.850215	Prob(F-statistic)		0.000002

Table 10: Estimation of model AR(1)*SMA(12) without constant

Sample(adjusted): 1997:09 2006:06
Included observations: 106 after adjusting endpoints
Convergence achieved after 6 iterations
Backcast: 1996:09 1997:08

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.408214	0.088872	4.593281	0.0000
MA(12)	0.297040	0.097900	3.034127	0.0030
R-squared	0.211273	Mean dependent var		
Adjusted R-squared	0.203689	S.D. dependent var		
S.E. of regression	1.573699	Akaike info criterion		
Sum squared resid	257.5589	Schwarz criterion		
Log likelihood	-197.4614	F-statistic		
Durbin-Watson stat	1.862111	Prob(F-statistic)		

Table 11: Estimation of model MA(1)*SMA(12) with constant

Sample(adjusted): 1997:08 2006:06
Included observations: 107 after adjusting endpoints
Convergence achieved after 7 iterations
Backcast: 1996:07 1997:07

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.427161	0.295873	1.443729	0.1518
MA(1)	0.464864	0.085063	5.464946	0.0000
SMA(12)	0.337159	0.094203	3.579083	0.0005
R-squared	0.239030	Mean dependent var		
Adjusted R-squared	0.224396	S.D. dependent var		
S.E. of regression	1.565313	Akaike info criterion		
Sum squared resid	254.8212	Schwarz criterion		
Log likelihood	-198.2501	F-statistic		
Durbin-Watson stat	2.060218	Prob(F-statistic)		

Table 12: Estimation of model MA(1)*SMA(12) without constant

Sample(adjusted): 1997:08 2006:06
Included observations: 107 after adjusting endpoints
Convergence achieved after 7 iterations
Backcast: 1996:07 1997:07

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	0.484815	0.082616	5.868275	0.0000
SMA(12)	0.354357	0.093016	3.809623	0.0002

R-squared	0.224265	Mean dependent var	
Adjusted R-squared	0.216877	S.D. dependent var	
S.E. of regression	1.572882	Akaike info criterion	
Sum squared resid	259.7657	Schwarz criterion	
Log likelihood	-199.2783	F-statistic	
Durbin-Watson stat	2.060029	Prob(F-statistic)	

Table 13: Estimation of AR(1)*SAR(12)*SMA(12)

Sample(adjusted): 1997:09 2006:06
Included observations: 94 after adjusting endpoints
Convergence achieved after 10 iterations
Backcast: 1997:09 1998:08

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.497957	0.091016	5.471097	0.0000
SAR(12)	-0.444434	0.092935	-4.782221	0.0000
MA(12)	0.880384	0.026337	33.42779	0.0000

R-squared	0.373477	Mean dependent var	0.465213
Adjusted R-squared	0.359707	S.D. dependent var	1.807427
S.E. of regression	1.446272	Akaike info criterion	3.607250
Sum squared resid	190.3449	Schwarz criterion	3.688419
Log likelihood	-166.5407	F-statistic	27.12305
Durbin-Watson stat	1.967291	Prob(F-statistic)	0.000000

Table 14: Estimation of C AR(1) MA(10) *SAR(12)*SMA(12) (best model specification)

Sample(adjusted): 1997:09 2006:06
Included observations: 94 after adjusting endpoints
Convergence achieved after 11 iterations
Backcast: 1996:11 1997:08

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.884350	0.425339	2.079164	0.0405
AR(1)	0.447162	0.094337	4.740032	0.0000
SAR(12)	0.723590	0.052433	13.80040	0.0000
MA(10)	0.209258	0.055967	3.738937	0.0003
SMA(12)	-0.843693	0.039527	-21.34447	0.0000

R-squared	0.557463	Mean dependent var	
Adjusted R-squared	0.537574	S.D. dependent var	
S.E. of regression	1.229085	Akaike info criterion	
Sum squared resid	134.4478	Schwarz criterion	
Log likelihood	-150.2006	F-statistic	
Durbin-Watson stat	2.094453	Prob(F-statistic)	

Table15: Correlogram of residual of AR(1)*SAR(12)

Sample: 1997:09 2006:06
Included observations: 94
Q-statistic probabilities adjusted for 2 ARMA term(s)

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. | .</td><td>. | .</td><td>1</td><td>-0.019</td><td>-0.019</td><td>0.0338</td><td></td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>2</td><td>-0.069</td><td>-0.069</td><td>0.4970</td><td></td></tr>
<tr><td>. |*.</td><td>. |*.</td><td>3</td><td>0.104</td><td>0.102</td><td>1.5790</td><td>0.209</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>4</td><td>-0.072</td><td>-0.074</td><td>2.0973</td><td>0.350</td></tr>
<tr><td>. | .</td><td>. | .</td><td>5</td><td>-0.051</td><td>-0.039</td><td>2.3639</td><td>0.500</td></tr>
<tr><td>. | .</td><td>. | .</td><td>6</td><td>0.014</td><td>-0.007</td><td>2.3846</td><td>0.665</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>7</td><td>-0.092</td><td>-0.086</td><td>3.2691</td><td>0.659</td></tr>
<tr><td>. | .</td><td>. | .</td><td>8</td><td>-0.044</td><td>-0.043</td><td>3.4744</td><td>0.747</td></tr>
<tr><td>. |*.</td><td>. |*.</td><td>9</td><td>0.112</td><td>0.094</td><td>4.8075</td><td>0.683</td></tr>
<tr><td>. |*.</td><td>. |**</td><td>10</td><td>0.184</td><td>0.204</td><td>8.4603</td><td>0.390</td></tr>
<tr><td>. | .</td><td>. | .</td><td>11</td><td>0.005</td><td>0.024</td><td>8.4630</td><td>0.488</td></tr>
<tr><td>. | .</td><td>. | .</td><td>12</td><td>-0.004</td><td>-0.014</td><td>8.4644</td><td>0.584</td></tr>
<tr><td>. | .</td><td>. | .</td><td>13</td><td>-0.003</td><td>-0.034</td><td>8.4653</td><td>0.671</td></tr>
<tr><td>. | .</td><td>. | .</td><td>14</td><td>-0.016</td><td>0.005</td><td>8.4934</td><td>0.745</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>15</td><td>-0.094</td><td>-0.092</td><td>9.4939</td><td>0.735</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>16</td><td>-0.136</td><td>-0.133</td><td>11.619</td><td>0.637</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>17</td><td>-0.075</td><td>-0.058</td><td>12.270</td><td>0.658</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>18</td><td>-0.098</td><td>-0.104</td><td>13.419</td><td>0.642</td></tr>
<tr><td>. |*.</td><td>. |*.</td><td>19</td><td>0.192</td><td>0.173</td><td>17.863</td><td>0.398</td></tr>
<tr><td>.*| .</td><td>**| .</td><td>20</td><td>-0.125</td><td>-0.202</td><td>19.782</td><td>0.345</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>21</td><td>-0.085</td><td>-0.077</td><td>20.685</td><td>0.354</td></tr>
<tr><td>. | .</td><td>. | .</td><td>22</td><td>0.052</td><td>-0.042</td><td>21.023</td><td>0.396</td></tr>
<tr><td>. | .</td><td>. | .</td><td>23</td><td>-0.030</td><td>-0.011</td><td>21.140</td><td>0.450</td></tr>
<tr><td>. | .</td><td>. | .</td><td>24</td><td>-0.001</td><td>0.013</td><td>21.140</td><td>0.512</td></tr>
<tr><td>. | .</td><td>. | .</td><td>25</td><td>-0.011</td><td>-0.010</td><td>21.156</td><td>0.572</td></tr>
<tr><td>.*| .</td><td>. | .</td><td>26</td><td>-0.098</td><td>0.002</td><td>22.428</td><td>0.554</td></tr>
<tr><td>. | .</td><td>. | .</td><td>27</td><td>-0.010</td><td>0.017</td><td>22.440</td><td>0.610</td></tr>
<tr><td>. | .</td><td>. | .</td><td>28</td><td>0.030</td><td>0.009</td><td>22.560</td><td>0.658</td></tr>
<tr><td>. |**</td><td>. |**</td><td>29</td><td>0.199</td><td>0.197</td><td>28.044</td><td>0.409</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>30</td><td>-0.159</td><td>-0.132</td><td>31.599</td><td>0.291</td></tr>
<tr><td>. | .</td><td>. | .</td><td>31</td><td>0.000</td><td>0.032</td><td>31.599</td><td>0.338</td></tr>
<tr><td>. | .</td><td>. | .</td><td>32</td><td>0.057</td><td>-0.031</td><td>32.069</td><td>0.364</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>33</td><td>-0.077</td><td>-0.071</td><td>32.950</td><td>0.372</td></tr>
<tr><td>.*| .</td><td>.*| .</td><td>34</td><td>-0.064</td><td>-0.102</td><td>33.561</td><td>0.392</td></tr>
<tr><td>. | .</td><td>. | .</td><td>35</td><td>0.012</td><td>-0.002</td><td>33.581</td><td>0.439</td></tr>
<tr><td>. | .</td><td>. | .</td><td>36</td><td>0.019</td><td>0.038</td><td>33.640</td><td>0.485</td></tr>
</table>

Table 16: Correlogram of residual of MA(1)*SAR(12)

Sample: 1997:08 2006:06
Included observations: 95
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.004	-0.004	0.0013	
. |*. |	. |*. |	2	0.083	0.083	0.6854	
. |*. |	. |*. |	3	0.091	0.092	1.5193	0.218
. | . |	. | . |	4	-0.037	-0.044	1.6602	0.436
. | . |	. | . |	5	-0.039	-0.056	1.8154	0.612
. | . |	. | . |	6	0.017	0.015	1.8439	0.764
.*| . |	. | . |	7	-0.072	-0.057	2.3839	0.794
. | . |	. | . |	8	0.004	0.007	2.3854	0.881
. |*. |	. |*. |	9	0.106	0.113	3.5845	0.826
. |*. |	. |*. |	10	0.177	0.195	6.9620	0.541
. | . |	. | . |	11	0.013	-0.004	6.9820	0.639
. | . |	.*| . |	12	-0.027	-0.094	7.0602	0.720
. | . |	.*| . |	13	-0.041	-0.078	7.2509	0.778
. | . |	. | . |	14	-0.046	-0.025	7.4896	0.824
.*| . |	.*| . |	15	-0.116	-0.090	9.0523	0.769
.*| . |	.*| . |	16	-0.166	-0.158	12.252	0.586
.*| . |	. | . |	17	-0.063	-0.027	12.718	0.624
.*| . |	.*| . |	18	-0.150	-0.127	15.420	0.494
. |*. |	. |*. |	19	0.173	0.165	19.050	0.326
.*| . |	.*| . |	20	-0.142	-0.181	21.519	0.254
.*| . |	.*| . |	21	-0.071	-0.097	22.140	0.277
. | . |	. | . |	22	0.009	0.005	22.149	0.332
. | . |	. | . |	23	-0.046	0.010	22.415	0.376
. | . |	. | . |	24	-0.039	0.006	22.610	0.424
. | . |	. | . |	25	-0.023	-0.006	22.681	0.479
.*| . |	. | . |	26	-0.108	-0.009	24.234	0.448
. | . |	. | . |	27	0.017	0.046	24.273	0.504
. | . |	. | . |	28	-0.019	-0.036	24.322	0.558
. |** |	. |** |	29	0.213	0.197	30.663	0.285
.*| . |	.*| . |	30	-0.151	-0.149	33.906	0.204
. | . |	. | . |	31	0.018	-0.011	33.952	0.241
. | . |	. | . |	32	0.030	-0.028	34.085	0.277
.*| . |	.*| . |	33	-0.061	-0.087	34.638	0.298
.*| . |	.*| . |	34	-0.058	-0.088	35.144	0.321
. | . |	. | . |	35	0.010	0.013	35.160	0.366
. | . |	. | . |	36	0.027	0.042	35.271	0.408

Table 18: Correlogram of residual of AR(1)*SAR(12)*SMA(12) model

Sample: 1997:09 2006:06
Included observations: 94
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.008	-0.008	0.0061	
. | . |	. | . |	2	-0.013	-0.013	0.0223	
. | . |	. | . |	3	0.062	0.062	0.4094	
.*| . |	.*| . |	4	-0.145	-0.145	2.5189	0.112
. | . |	. | . |	5	-0.019	-0.018	2.5536	0.279
. | . |	. | . |	6	-0.024	-0.033	2.6138	0.455
. | . |	. | . |	7	-0.052	-0.035	2.8891	0.577
.*| . |	.*| . |	8	-0.089	-0.112	3.7183	0.591
. | . |	. | . |	9	0.007	0.002	3.7228	0.714
. |** |	. |** |	10	0.206	0.207	8.2797	0.309
. | . |	. | . |	11	0.013	0.014	8.2975	0.405
. | . |	. | . |	12	-0.007	-0.039	8.3032	0.504
. | . |	. | . |	13	-0.018	-0.052	8.3413	0.596
.*| . |	. | . |	14	-0.057	-0.004	8.7132	0.648
.*| . |	.*| . |	15	-0.070	-0.073	9.2750	0.679
.*| . |	.*| . |	16	-0.104	-0.121	10.515	0.651
. | . |	. | . |	17	-0.045	-0.036	10.749	0.706
.*| . |	.*| . |	18	-0.144	-0.114	13.204	0.587
. |*. |	. |*. |	19	0.100	0.096	14.409	0.568
. | . |	.*| . |	20	-0.039	-0.132	14.595	0.625
. | . |	.*| . |	21	-0.044	-0.064	14.831	0.674
. | . |	. | . |	22	0.040	-0.023	15.031	0.721
. | . |	. | . |	23	0.030	0.064	15.146	0.768
. | . |	. | . |	24	0.062	0.038	15.635	0.790
. | . |	. | . |	25	0.007	-0.010	15.642	0.833
. | . |	. | . |	26	-0.022	0.005	15.705	0.868
. | . |	. | . |	27	-0.053	-0.029	16.079	0.885
. | . |	. | . |	28	-0.033	0.007	16.228	0.908
. |*. |	. |*. |	29	0.162	0.114	19.867	0.798
.*| . |	.*| . |	30	-0.104	-0.104	21.395	0.767
. | . |	. |*. |	31	0.058	0.077	21.877	0.787
. | . |	.*| . |	32	-0.031	-0.088	22.019	0.819
.*| . |	.*| . |	33	-0.087	-0.082	23.147	0.809
. | . |	.*| . |	34	-0.010	-0.133	23.161	0.843
. | . |	. | . |	35	-0.010	-0.001	23.175	0.873
. |*. |	. |*. |	36	0.072	0.067	23.976	0.874

Table 17: Correlogram of residual of MA(1)*SMA(12)

Sample: 1997:08 2006:06
Included observations: 107
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*|. |	.*|. |	1	-0.060	-0.060	0.4015	
. |* |	. |* |	2	0.087	0.084	1.2492	
. |* |	. |* |	3	0.073	0.083	1.8396	0.175
. |. |	. |. |	4	-0.037	-0.036	1.9936	0.369
. |. |	. |. |	5	-0.006	-0.025	1.9983	0.573
. |. |	. |. |	6	-0.022	-0.024	2.0551	0.726
.*|. |	.*|. |	7	-0.064	-0.059	2.5339	0.771
. |. |	. |. |	8	-0.002	-0.004	2.5345	0.865
. |. |	. |. |	9	0.047	0.062	2.7983	0.903
. |* |	. |* |	10	0.140	0.159	5.1451	0.742
. |. |	. |. |	11	0.039	0.047	5.3292	0.805
.*|. |	.*|. |	12	-0.070	-0.109	5.9300	0.821
. |. |	.*|. |	13	-0.013	-0.064	5.9512	0.877
. |. |	. |. |	14	0.012	0.024	5.9702	0.918
.*|. |	.*|. |	15	-0.121	-0.093	7.8184	0.855
**|. |	**|. |	16	-0.217	-0.236	13.850	0.461
. |. |	. |. |	17	-0.002	0.002	13.850	0.537
**|. |	.*|. |	18	-0.213	-0.161	19.782	0.230
. |* |	. |* |	19	0.172	0.164	23.716	0.127
.*|. |	.*|. |	20	-0.139	-0.154	26.310	0.093
.*|. |	.*|. |	21	-0.079	-0.119	27.148	0.101
. |. |	. |. |	22	0.060	0.048	27.650	0.118
. |. |	. |. |	23	-0.029	0.007	27.768	0.147
. |* |	. |* |	24	0.087	0.092	28.822	0.150
. |. |	. |. |	25	-0.020	0.000	28.881	0.184
.*|. |	. |. |	26	-0.072	0.011	29.633	0.197
. |. |	. |. |	27	0.009	0.003	29.645	0.238
. |. |	. |. |	28	-0.040	-0.053	29.876	0.273
. |* |	. |** |	29	0.195	0.217	35.584	0.125
.*|. |	.*|. |	30	-0.134	-0.139	38.288	0.093
. |. |	. |. |	31	-0.011	-0.035	38.306	0.116
. |* |	. |. |	32	0.084	0.000	39.396	0.117
. |. |	.*|. |	33	-0.056	-0.132	39.895	0.131
. |. |	.*|. |	34	-0.025	-0.101	39.998	0.157
. |. |	. |. |	35	0.024	0.052	40.093	0.185
. |* |	. |. |	36	0.069	0.038	40.879	0.194

Table 19: Correlogram of residual of C AR(1) MA(10) SAR(12) SMA(12)

Sample: 1997:09 2006:06
Included observations: 94
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.057	-0.057	0.3207	
. | . |	. | . |	2	0.055	0.052	0.6172	
. |*. |	. |*. |	3	0.114	0.121	1.9146	
.*| . |	. | . |	4	-0.060	-0.050	2.2700	
. | . |	.*| . |	5	-0.044	-0.066	2.4696	0.116
. | . |	. | . |	6	-0.007	-0.020	2.4742	0.290
. | . |	. | . |	7	-0.025	-0.007	2.5395	0.468
. | . |	. | . |	8	0.020	0.030	2.5797	0.630
. |*. |	. |*. |	9	0.068	0.072	3.0705	0.689
. | . |	. |*. |	10	0.064	0.071	3.5095	0.743
. | . |	. | . |	11	0.006	-0.004	3.5140	0.834
. | . |	. | . |	12	0.019	-0.007	3.5524	0.895
.*| . |	.*| . |	13	-0.063	-0.072	3.9953	0.912
. | . |	. | . |	14	0.010	0.015	4.0063	0.947
.*| . |	.*| . |	15	-0.109	-0.094	5.3735	0.912
.*| . |	.*| . |	16	-0.144	-0.143	7.7669	0.803
.*| . |	.*| . |	17	-0.084	-0.107	8.5852	0.804
.*| . |	.*| . |	18	-0.181	-0.181	12.458	0.570
. |*. |	. |*. |	19	0.178	0.190	16.272	0.364
.*| . |	.*| . |	20	-0.102	-0.073	17.548	0.351
. | . |	. | . |	21	-0.013	-0.027	17.569	0.416
. | . |	. | . |	22	0.049	-0.016	17.869	0.464
. | . |	. | . |	23	-0.040	-0.014	18.068	0.518
.*| . |	.*| . |	24	-0.112	-0.099	19.683	0.478
. | . |	. | . |	25	-0.024	-0.019	19.760	0.537
.*| . |	. | . |	26	-0.064	-0.011	20.298	0.564
. | . |	. | . |	27	-0.019	0.030	20.346	0.621
.*| . |	.*| . |	28	-0.089	-0.120	21.418	0.614
. |*. |	. |*. |	29	0.145	0.122	24.342	0.500
.*| . |	**| . |	30	-0.172	-0.191	28.524	0.333
. |*. |	. |*. |	31	0.117	0.082	30.499	0.292
. | . |	. | . |	32	0.011	-0.030	30.516	0.339
. | . |	.*| . |	33	-0.040	-0.074	30.758	0.377
. | . |	. | . |	34	0.037	-0.007	30.962	0.417
. | . |	. | . |	35	0.005	0.018	30.966	0.468
. | . |	.*| . |	36	-0.057	-0.073	31.465	0.494

Figure 9: Actual, fitted, residual graph for AR(1)*SAR(12)

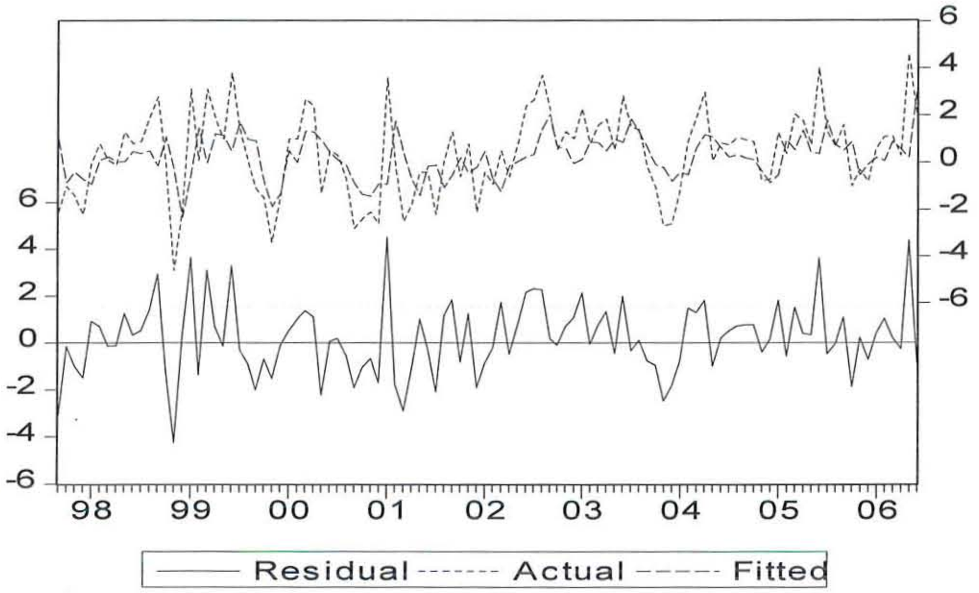


Figure 10: Actual, fitted, residual graph for AR(1)*SMA(12)

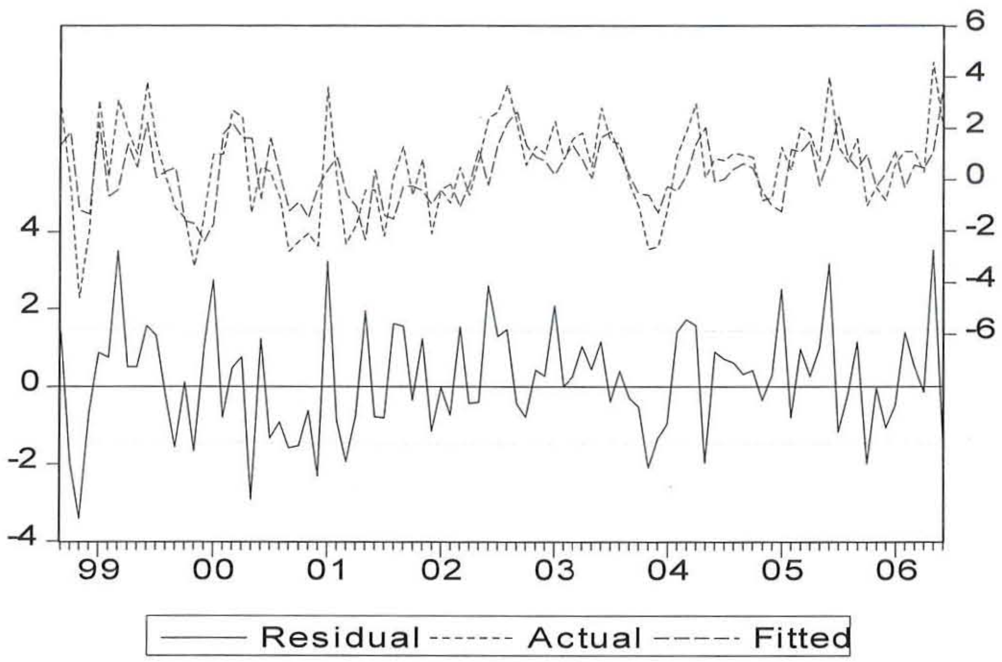


Figure 11: Actual, fitted, residual graph for MA(1)*SMA(12)

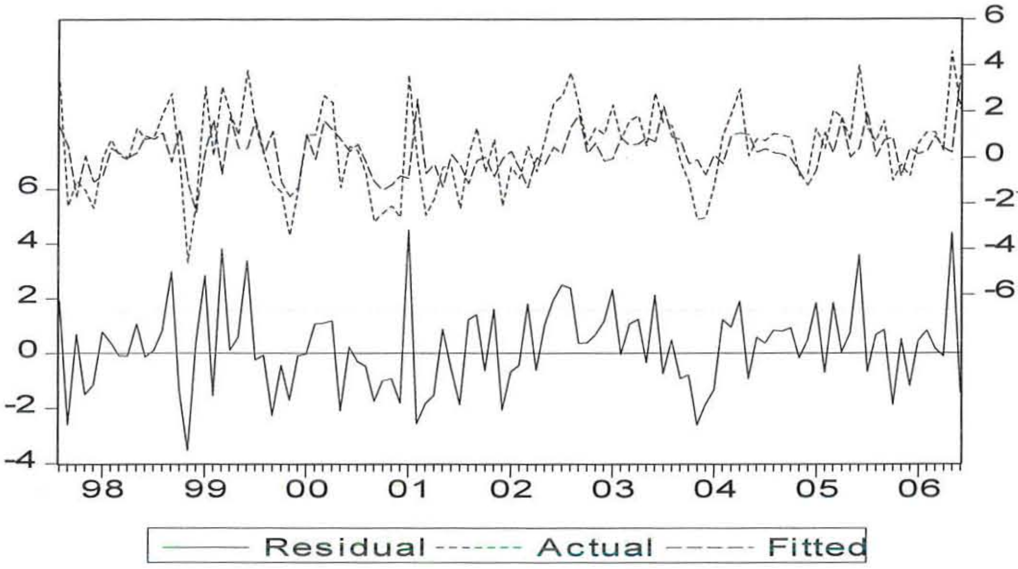
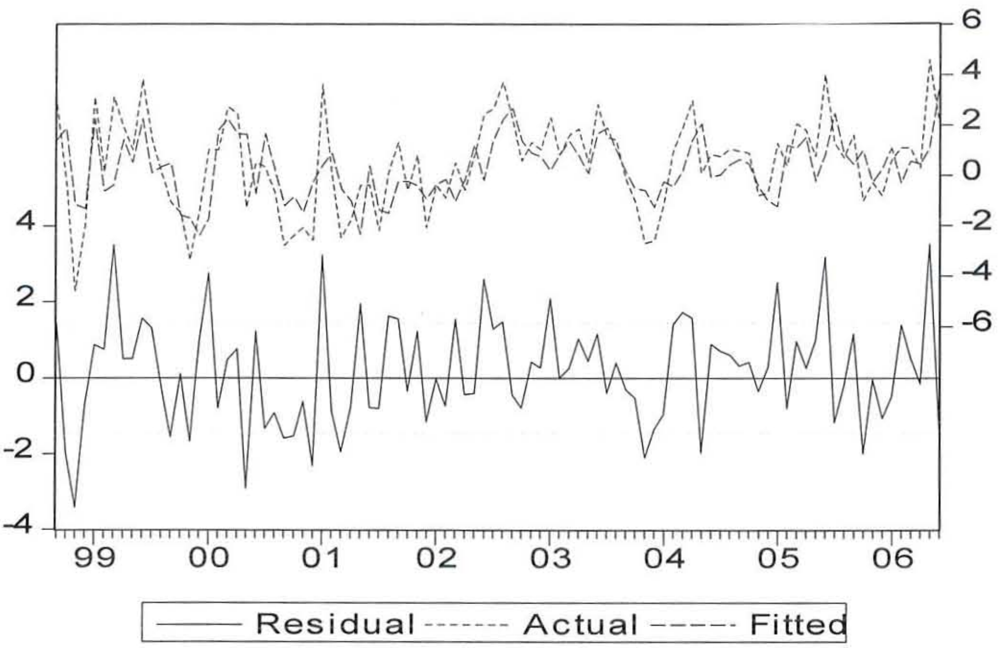


Figure12: Actual, fitted, residual graph for AR(1) *SAR(12)*SMA(12)



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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented in other university.

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

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