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MODELING AND FORECASTING CURRENCY IN CIRCULATION IN ETHIOPIA

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MODELING AND FORECASTING CURRENCY IN CIRCULATION IN ETHIOPIA

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This is to certify that the project paper Prepared by Getahun Semate, entitled: Modeling and forecasting currency in circulation in Ethiopia and submitted in partial fulfillment of the requirements for the Degree of Masters of Arts in Applied Economic Modeling and Forecasting (Financial Policy Analysis and Planning) compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ABSTRACT

Modeling and Forecasting Currency in Circulation in Ethiopia

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In the literature, Currency in circulation is typically estimated either by specifying a currency demand equation based on the theory of transaction and portfolio demand for money or univariate time series models. The first approach works well with low frequency data but faces limitations with high frequency data series. Using monthly and weekly data of currency in circulation form May 2007 to April 2014, the paper proposes an alternative approach in modeling the high frequency data series by using Multivariate time series (structural model and VAR) univariate time series(trend and ARIMA) Model. The four separate models were estimated with monthly, and two separate models with weekly time series, assembling tools for forecasting trend, seasonal patterns and cycles in individual series separately. Trend and seasonal effects were identified by regressing on trend and seasonal dummies while cyclical dynamics were captured by allowing for ARMA effect in the regression disturbances. The monthly and weekly models clearly identify both intra – month and inter-month variation of currency in circulation. The monthly trend model also indentified that Ethiopian New Year has significant positive impact on demand for currency in Ethiopia.

Finally model comparison result showed both monthly VAR, and trend models outperforms the structural and ARIMA models and trend model performs the weekly data wheel at 5% level of significance. In general this methodology may be used in forecasting currency in circulation with careful assessment of month to month and week to week current developments in the economy.

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SECTION ONE

1. Introduction

The National Bank of Ethiopia (NBE) is primarily committed to achieving and maintaining price and exchange rate stability. With this regard, NBE directly determines and implements monetary policy instruments in order to influence interest rates and manage liquidity in the money market. In other words, for NBE to effectively steer interest rates it should manage the conditions that equilibrate demand and supply in the market for bank reserves. In this respect, liquidity management based on accurate liquidity forecasts has crucial role in controlling the short-term interest rates in line with the main goal of achieving price stability. Among those variables used in forecasting Ethiopian Liquidity, currency in circulation is the one that strongly influences the liquidity of the Ethiopian banking system. Due to this the main motive of this paper is to construct an econometric model to forecast weekly and monthly currency in circulation (CiC).

To model and forecast currency in circulation, generally three types of approaches are followed. The first approach is through a standard currency demand equation based on the theory of transaction and portfolio demand for money. Such an equation could be estimated in isolation (Jadhav, 1994) or could be a part of a bigger macroeconomic model (Palanivel and Klein, 1999). Explanatory variables traditionally used in the equation are income or its proxy, price level and the opportunity cost of holding cash. The second approach is based on univariate time series models such as trend models and ARIMA model. The third approach is the multivariate time series models, VAR, for monthly series, all of these approaches have been applied extensively. (Hamilton, 1994)

Comparison analysis among the three models were made to evaluate their forecasting performance. While all these approaches work well at low frequency, application of similar approaches at high frequency becomes difficult. In the first and third approach, the estimates of income are not available beyond annual frequency. Due to the fact that this paper used the disaggregated income level obtained by interpolation techniques. As regards the second approach, although univariate time series models could theoretically(be applied to any frequency, the main problem at high frequency seems to be an appropriate specification of the intra-month variation which may change from month to month or year to year. The other problems are modelling the effects of a change of distance from specific dates from year to year, holidays and variations in lag effects (Anıl Talaslı, 2010).

1.2 About currency in circulation series

The CiC is one of the major autonomous liquidity factors in NB's balance sheet and it plays a major role in the context of NB's liquidity management, both in terms of absolute size and volatility. Therefore the series is an important factor in liquidity forecasting process. Since the volume of CiC is out of the control of the NBE, it cannot be determined exactly. Therefore, it is required to construct an econometric model in order to approximate the behavior of the series as accurately as possible.

For the purposes of this paper, CiC is defined as the volume of bank notes in circulation excluding the vault cash held by commercial banks. The CiC includes all banknotes in domestic currency that the economic agents demand for a specific moment for transaction or as a store of value. When currency is returned to banks (the volume of CiC diminishes), it is considered to be a part of banks' reserve with the NB, thus liquidity of the banking sector increases. Similarly, cash withdrawals from banks (the volume of CiC increases) leads to a decrease in the liquidity of the system.

As the series of CiC displays very significant seasonality; comprising daily, weekly, monthly, annual patterns and some calendar effects like public holidays, the modeling of daily series, which display seasonal patterns, is not simple.

1.3 Objective of the study

The main purpose of the study is to apply modern techniques in the area of modeling and forecasting time series to understand monthly and quarterly behavioral patterns and to develop a mini model suitable for short term forecasting of the CiC in Ethiopia

1.4 The specific objectives of the study include:

- To asses data pattern in time series ,trend ,seasonal ,cyclical and irregular time series pattern
- To evaluate the forecasting performance of the three econometric models
- To select the best model for short term forecasting CiC among the three model candidates which are structural model based on money demand function , univariate time series and multivariate time series models
- To examine the nature and the extent of intra-week and intra-month variation of the currency in circulation.

1.5 The significant of the study

The importance of this study includes:

- It provide clear understanding on seasonal adjustment, modeling and forecasting currency in circulation
- It give a view on formulation or developing a mini model on forecasting or currency in circulation
- It provide for the policy and decision maker to obtain policy oriented forecasted output and to forward critical decisions.
- It encourage others in further investigation depending up on this study

- It give know-how in model selection and comparison methods for forecasting any series

1.6 statement of the problem

CiC is one of the most important factors that absorb or supply bank reserves.' The short-term movements in this and other reserve factors which are outside the direct control of the National Bank Reserve System are capable of absorbing or adding substantial amounts to the reserves available to commercial banks. These fluctuations could be disturbing to the credit and money markets and might create mistaken impressions regarding the current posture of monetary policy. The NBE generally attempts to minimize these problems by offsetting the changes in these reserve factors through appropriate open market operations. In order to assist the System Open Market Account in determining and anticipating the need for such operations, reliable forecasts tools are important things and needs more attention. As far as my knowledge is concerned, analytical models help in systematizing the thought process of policy makers, and provide a transparent setting for policy formulation. Formalizing the methods of policy making through models also enhance the effectiveness of central bank operations as they help improve financial markets' understanding of the conduct of monetary policy and in conditioning market expectations that are so critical for transmission of monetary policy. It is, therefore, necessary for the central banks to reveal great deal about the methods, including, at least, the broad contours of forecasts, and the methods and internal models that they have historically done (Muller and Zelmer, 1999; Blinder et al, 2001).

1.7 Limitation of the study

1.7.1 Data limitation

Creating econometric models to forecast the demand and supply of liquidity requires certain data sets. One of the main setbacks for the creation of an econometric model to forecast these variables has been the timely availability of both liquidity variables and the structural drivers. Data interpolation has been used heavily within the proposed model because of the lack of high frequency data as well as a poor relationship between interest rates and liquidity. Given a lack of data on other economic and non-economic structural variables, there is a limited pool of structural series that can be included within the modeling process. Thus, it is strongly recommended that the liquidity forecasting team in tandem with the relevant ministries and data collectors/providers moves to strengthen this area of the liquidity forecasting process.

1.7.2 Method limitation

Since as it is clearly described in introduction section, in general, three types of statistical techniques are used in modeling and forecasting currency in circulation. One approach is the estimation through a standard currency demand function based on the theory of transactions and portfolio demand for money. Such an equation is estimated in isolation or as a part of a macro economic model. Explanatory variables commonly used in such an equation are income, price levels and interest rate to represent the opportunity cost of holding currency. These variables also used for estimating multivariate time series models. The other approach is based on univariate time series models. In the literature, the three approaches are used extensively in modeling annual and quarterly data series. However, the first approach is rarely used in modeling series with high frequencies *i.e.,* beyond quarterly data. This is mainly due to the non availability of income data with high frequencies. It is also difficult to find a proxy for income with frequencies beyond monthly data. Theoretically, univariate models could be applied to any frequency (*i.e.,* monthly, weekly or daily). Here also judgmental analysis on forecasting is not considered due to expert knowledge limitation

1.8 Organization of the study

In section one, the introductory part, statement of the problem, Significance of the study, objectives of the study and Limitations of the study are outlined. Section two consists of literature reviews which are deemed to be relevant with the research project. The data and methodology that are used to achieve the objectives of the study are outlined and discussed in section three. Section four presents the results obtained by applying the methods described in chapter three. In section five conclusions and recommendations are made based on the results obtained. Finally, the appendix contains the data used in this research project.

SECTION TWO

2. LITERATURE REVIEW

2.1 Theoretical Review

Currency in circulation (CiC) refers to notes and coins held outside banks and are the most liquid monetary aggregate. Currency in circulation, together with demand deposits is a component of narrow money, movements of which are of interest to policy makers. CiC dynamics are often considered as an indicator for monetization or demonetization of the economy. Two most relevant indicators showing the relative significance of CiC in any economy are (1) share of CiC in money supply and (2) ratio of CiC to nominal gross domestic product (Stavreski, 1998).

An increase (decrease) in currency demand reduces (increases) the availability of liquidity. In the short-run, the demand for currency is mainly affected by seasonal factors or exceptional events (such as retrospective pay increases), the patterns of which could be identified from historical data. Separate forecasts could also be obtained from the banking sector to improve the central bank's forecasts. In the long run, the demand for currency depends upon select macroeconomic variables (e.g., GDP, interest rates etc.), and such forecasts could possibly facilitate identifying shifts in the demand function over time (Stavreski, 1998).

To model and forecast currency in circulation, generally two types of approaches are followed. The first approach is through a standard currency demand equation based on the theory of transaction and portfolio demand for money. Such an equation could be estimated in isolation (Jadhav, 1994) or could be a part of a bigger macroeconomic model (Palanivel and Klein, 1999). Explanatory variables traditionally used in the equation are income or its proxy, price level and the opportunity cost of holding cash. The second approach is based on univariate time series models. For annual and quarterly series, both these approaches have been applied extensively.

While both approaches work well at low frequency, application of similar approaches at high frequency becomes difficult. In the first approach, the estimates of income are not available beyond quarterly frequency.

2.1.1Vector Autoregression (VAR) models as a device to study sources of business cycles

The instability of the world economy in the aftermath of the oil price shocks in the 1970's brought a renewed interest in the study of business cycles. By then, the use of large scale macroeconometric models for policy analysis, (that had dominated macroeconomic research in the post war period) had been highly criticised by Lucas, as their assumptions of invariant behavioural equations were shown to be inconsistent with dynamic maximising behaviour (see Lucas, 1976).

A group of economists referred to as the New Classical economists, set out to replace the Keynesians macroeconometric models, and argued instead for the use of classical market clearing models of economic fluctuations. One of the goals of the New Classical Economics was to reconcile business cycles with the postulates of dynamic competitive general equilibrium theory. More recently, a new branch of the classical models referred to as the Real Business Cycle (RBC) models have been developed, that emphasise real productivity shocks, as opposed to aggregated demand shocks, as a source of economic fluctuations (e.g. Kydland and Prescott, 1982).

While the new classical research agenda was developed in the 1970's, Keynes macroeconomics was in a state of confusion. Keynes had emphasised how shifts in aggregate demand could cause economic fluctuations. However, during the 1970s, aggregate supply seemed to dominate. When the large scale macroeconometric models failed to predict the 1970s turmoil, many of the models were abandoned, and internationally business cycles studies were put on the agenda. The response of a significant part of the economic profession has been to turn to the use of structural vector autoregression (VAR) models to analyse business cycles. At a first stage, all variables are modelled together as endogenous. The VAR models may not satisfy

Lucas's criteria for policy intervention, but are still useful to indicate the impact of policy actions that fall within the realm of historical experience. In particular, shifts in policy rules can be somewhat subsumed under stable policy rules (D.M.P.K, 2012).

Sims (1980) first introduced VAR models as an alternative to the large scale macro econometric models. Since then the methodology has gained widespread use in applied macroeconomic research. The methodology grew out of a dissatisfaction of the economic profession with the traditional large scale macroeconometric models working in the tradition of the Cowles commission, in which identification was achieved by excluding variables - most often lagged endogenous variables - without any theoretical or statistical justifications. The idea behind the traditional macroeconometric procedure was that variables could be classified as either endogenous or exogenous. The exogenous variables were determined outside the system and could therefore be treated independently of the other variables. Imposing exclusion restrictions on the lags of some variables was the practical way to deal with the problem. Sims (1980) questioned the idea of developing sophisticated econometric models identified via what he called incredible (non-justified) exclusion restrictions that were neither innocuous nor essential for the constructing of a model that could be used for policy analysis and forecasting.

According to Sims (1980), all variables appearing in the structural models could be argued to be endogenous.Economic theory place only weak restrictions on the reduced form coefficients and on which variables that should enter a reduced form model. Similar ideas had already been put forward by Liu (1960), but the proposed solution by Sims was new. Sims suggested that empirical research should use small-scale models identified via a small number of constraints.

At the first stage, the analyst's a priori knowledge should only be used to decide what variables should enter the reduced form. Thereafter, lag length of the autoregression, choice of deterministic components and appropriate treatment of the nonstationary components should be decided on. Once the model is dynamically well specified, the in-sample effects of a shock on the rest of the system can be assessed through the computation of impulse responses and variance decompositions. Economic hypothesis can be formulated and tested, and the historical dynamics of the data can be examined (D.M.P.K, 2012).

The VAR models have the advantage over traditional large-scale macroeconometric models in that the results are not hidden by a large and complicated structure (the "black box"), but are easily interpreted and available. Sims argued that VARs provide a more systematic approach to imposing restrictions and could lead one to capture empirical regularities which remain hidden to standard procedures. In contrast, the results from policy exercises on large scale macreconometric models are hard to compare and recreate, and can easily be amended by their users with judgmental ex-post decisions. Finally, the lack of consensus about the appropriate structural model to use has led many economists instead to favour the use of a VAR model to examine the effects of different policies (D.M.P.K, 2012).

However, VAR models have also been much criticised, although the criticism usually refers to particular applications and interpretations of empirical results, rather than the methodology itself. Before I discuss this further, I will explain in somewhat more detail how estimation and identification of VARs are performed.

2.1.1 Review on, ARIMA and Structural model

2.1.2 ARIMA model

AutoRegressive Integrated Moving Average (ARIMA) models intend to describe the current behavior of variables in terms of linear relationships with their past values. These models are also called Box-Jenkins (1984) models on the basis of these authors' pioneering work regarding time-series forecasting techniques. An ARIMA model can be decomposed in two parts. First, it has an Integrated (I) component (d), which represents the amount of differencing to be performed on the series to make it stationary. The second component of an ARIMA consists of an ARMA model for the series rendered stationary through differentiation. The ARMA component is further decomposed into AR and MA components. The autoregressive (AR) component captures the correlation between the current value of the time series and some of its past values. For example, AR(1) means that the current observation is correlated with its immediate past value at time *t-1*. The Moving Average (MA) component represents the duration of the influence of a random (unexplained) shock. For example, MA(1) means that a shock on the value of the series at time *t* is correlated with the shock at *t-1*. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PCF) are used to estimate the values of p and q, using the rules reported in Table 1. In the next section, we provide an example of a simple.

ARIMA models produce accurate forecasts based on the historical patterns of the time series data. ARIMA belongs to the class of linear models and can represent both stationary and non-stationary data. ARIMA models do not involve the dependent variable; instead they make use of information in the series to generate the series itself. Stationary series is the one which vary about a fixed value and non-stationary series do not vary about a fixed value (Box-Jenkins 1984). The seasonal ARIMA is represented as below:

ARIMA (p, d, q) (P, D, Q)

Where (p-auto regressive parameter, d-order of differencing, q-moving average parameter) is the regular model and P- seasonal auto regressive parameter, D-seasonal order of differencing, Q-seasonal moving average parameter.

Structural model based on money demand function

2.2 Empirical literature

In this section, different research findings on modeling and forecasting currency in circulation and related are reviewed.

R, Dheerasinghe(2005) modeled and forecast currency in circulation in Sri Lanka based on daily , monthly and quarterly frequency, The paper presents three models suitable for forecasting currency in circulation, based on monthly, weekly and daily data for the period of 1 January 2000 to 30 September 2005. The data for the period

1 October – 30 November 2005 were used for post sample validity tests. The forecasts produced by all three models accurately matches the shape of the monthly, weekly and daily oscillations, respectively, and capture the trend, seasonal and cyclical effects well. Post sample estimation error is very small and remained less than 1 per cent in all models. The forecasts based on the daily and monthly models performed very well, predicting very similar results, and were close to realized data when used within sample.

Modeling currency in circulation in India by Kaushik Bhattacharya and Himanshu Joshi, (2000). Focused on weekly and monthly data the findings clear evidence of trend and seasonality in currency in circulation. Earlier analyses of the average seasonal factors by Reddy (1998) and DESACS (2000) reveal that the currency demand in India typically follows a V-shape pattern. The demand for currency is high during April–June, bottoms out during July–September and picks up again during October–March. The high currency demand during April–June emanates from the realization of proceeds from the wheat harvest. The entire quantum of wheat procurement in India takes place during this period. On the other hand, the high transactions demand during October–March is because of festivals, rice procurement and pick-up in agro-based industrial activities. Further, both studies use the data pertaining to the last Friday of a month, estimating the monthly seasonal factors using standard X-11 or X-12 ARIMA.

Williams (1997), used three modeling approaches; structural model based on currency demand function , error correction model and univariate ARIMA model found out that the estimated SARMA(1,1,2) and ECM models have performed well in and out of sample, despite indications that on average both models tend to over-estimate the monthly currency demand changes. The results indicate that the ECM specification quality as a suitable model to predict future currency movements.

The performance of the models with respect to the percentage root mean square error (PRMSE), in deriving out-of–sample forecasts indicates that a necessary condition for generating reliable forecasts is relative stability of major economic variables.

Hence, both models have demonstrated superior performance during the out-of-sample period relative to the generated in-sample forecasts, during which economic upheavals of foreign exchange market instability and high inflation persisted. Further, the presence of clear January and December effects. These effects point to adjustments during these periods of base money management strategies to reduce the potential for ad hoc changes in base money and attendant inflation effects.

Examining the results of other studies , the conclusion is that where predicting future value movements is of essence, the pure time series analysis model (in this case the ARIMA representation) generally out-performs structural specifications. Theoretically, this conclusion is reasonable since structural models, although they facilitate other in-depth economic analysis, have noted deficiencies –variable definition problems, omitted variable problems, data frequency problems, to mention a few. However, despite the potential deficiencies in any structural specification, a statistical case is made for the superiority of this structural Error Correction Model specification. This model adequately captures, and explicitly models underlying structural parameters over the horizon, which should influence the public's demand for currency. Hence, the model dominates the extrapolative ARIMA specification. In spite of its superior performance relative to the ARMA representation, the problems of lagged data availability for variables of the ECM specification arises, and mitigates against relying on the model to generate the currency forecasts for the monthly base money management target. Hence there is scope for use of the ARMA model to generate such forecasts Williams (1997).

While the estimated error correction model highlights some structural relationships, the need to further investigate the presence of other adjustment processes is required. There is still scope for a possible re-examination and re-estimation of the money demand function using for instance a Vector Autoregressive Process (VAR), to determine and comprehensively analyze the existing economic relationships between currency demand and the range of macroeconomic variables. Additionally, as the financial sector evolves, there is the need for the money demand specification to the transformed to reflect these developments Williams (1997).

John Barry, Currency Department (*Vol 60 No.1, 1997)*, all together were worked under the title forecasting the demand for currency in circulation in New Zealand Central Banks**.** They used three models to find out the best forecasting models among the selected model candidates due to the Reserve Bank has found it difficult to forecast accurately the amount of notes and coins demanded by registered banks these models were structural model based on money demand function , error correction model and ARIMA model. They stated or summarized their results as follows.

Yevgen Zinovyev(2003),under his study " The money demand equation and macroeconamic forecasting " used monthly and weekly data .The main conclusion is that ARIMA , DVAR ,SVAR and SVEC can be used for short term forecasting. In shorts term period VECM do not give better forecasts than DVAR , and thus DVAR is more preferable as more parsimonious model that do not demand the presence of conintegration relationship between variables. In long term period VEC is expected to give more accurate forecasts as it takes into account the long term relationship between variables (but it cannot be checked now due to a small number of available observations). As VEC gives short run forecasts comparable with ones produced by DVAR, VEC is expected to have better overall forecast performance incorporating short-term and long-term forecasts.

SECTION THREE

3. DATA AND METHOD OF STATISTICAL DATA ANALYSIS

3.1 Data consideration

The study uses 6 year's quarterly, monthly and weekly currency in circulation data from January 2007 to April 2014. The data were obtained from NBE monitory directorate. The data for multivariate time series model includes GDP, CPI (inflation rate), interest rate, and CiC.

This paper focuses on the narrowest monetary aggregate, that of notes and coins, which forms the base of any monetary economy. While the primary objective rests with deriving an adequate time series model which best forecasts the monthly and weekly movements in the notes and coins in circulation, special attention is given to a time series model that incorporate the theoretical and economic relationships between currency demand and major economic variables. Thus the forecasting of monthly changes in the demand for Ethiopian notes and coins is carried out using two different methodological aproaches. The first technique utilizes time series analysis to model the monthly and weekly changes in currency demand. In the subsequent technique, a structural economic relationship is employed to provide an alternative forecasting methodology.

3.2 Model Techniques

In this study univariate time series models, will be covered to achieve the target of its objective in producing best forecasting mini model on currency in circulation. Then finally the study will reach the best model among the three model candidates by comparing their forecasting error values using analysis of variance (ANOVA) test.

3.2.1Trend model

If we look at the time series or any one of your time series, the first thing that stands out us is the obvious tendency of the series to grow (or, in some cases, to fall) over time. That is, it is immediately apparent from the time series plot that the average change in the series is positive (or, in some cases, negative). This tendency is the series's trend.

The simplest model of the time trend is the **linear trend model**

$$T_t = \beta_o + \beta_1 t\,,\quad t = 1\ldots \mathrm{T}$$

That is, the trend component is a straight line with intercept β_0 and slope β_1.

The intercept, as is often the case in econometric models, does not have a meaningful interpretation and its sign can be positive or negative, regardless of the trend's sign.

In some cases, a linear trend is inadequate to capture the trend of a time series. A natural generalization of the linear trend model is the***Polynomial trend model***

$$T_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \ldots + \beta_p t^p$$

Where p is a positive integer.

Note that

- The linear trend model is a special case of the polynomial trend model (p=1)
- For economic time series we almost never require p > 2. That is, if the linear trend model is not adequate, the **quadratic trend model** will usually work:

$$T_t = \beta_0 + \beta_1 t + \beta_2 t^2$$

The Log Linear Trend Model

Another alternative to the linear trend model is the **log linear trend model**, which is also called the **exponential trend model**:

$$T_t = \beta_0 \exp(\beta_1 t)$$

Or, taking natural logs on both sides,

$$\mathrm{Log}\,(T_t) = \log\,(\beta_0) + \beta_1 \mathrm{t}$$

So that the log of the trend component is linear.

Note that for the log linear trend model

$$\beta_1 = \log\ (T_t) - \log(T_{t-1}) = \%\ \text{change in T}$$

In the linear trend model the change in T is constant over time; in the quadratic trend model the change in T has a linear trend and in the log linear trend model the growth rate that is constant over time.

These differences can help to decide whether the linear, quadratic or log linear trend model is more appropriate for the data at hand.

However, in practice, as you will see when you look at your own data series, it is not always obvious by simply looking at the time series plot which form the trend model should take – linear, log linear, quadratic? Other?

Note that in all of these models, the trend is **deterministic**, i.e., perfectly forecastable. For instance, in the linear trend model, $\hat{T}_{T+h}, T$, the forecast of T_{T+h} made at time T is:

$$\hat{T}_{T+h,T} = \beta_0 + (T+h)\beta_1 = T_{T+h}$$

However, even if we correctly specify the shape of the trend (linear, quadratic, exponential), the parameters of the trend model are unknown. So, in practice, we will have to estimate these parameters, which will introduce errors (called sampling or estimation error) into our trend

3.2.2 ARIMA model

Lat first state the univariate Autoregressive Moving Average (ARMA) model, It is a time series methodology that uses past and current values of the dependent variable to produce forecasts of the variable. The technique generates that this identified correlation will continue into the future. In this way, it becomes possible to obtain good approximation of the behavior of a variable by a purely statistical approach.

Based on the Box-Jenkins (1976) modeling technique, ARMA methodology seeks to establish a parsimonious relationship, using as few parameters as possible. For example to forecast the values of a series y, using the ARMA technique, the general model specification for the series is expressed as

$$y_t = \left(a_1 L + a_2 L^2 + \cdots + a_p L^P\right) y_t + \left(1 + b_1 L + \cdots + b_q L^q\right) e_t$$

AR(P) MA(q)

Which can be expressed as

$$y_t = \sum_{i=1}^{p} (a_i L^P) y_t + \sum_{i}^{q} \left(b_i L^q\right) e_t + e_t$$

Where P and q = the number lags for autoregressive (AR) and moving average (MA) processes respectively;

e_t = an error process, with e_t ~N(0,1)

L =the lag operator on the processes; defined as $L^n y_t = y_{t-n}$ or $L y_t = y_{t-1}$

The specification is can be further extended to include explicit modeling of seasonal factors observed in the data. Apart from specifying seasonal dummy variables, the pure time series ARMA Specification is extended to the Seasonal Autoregressive Moving Average (SARMA). Detail definition of ARIMA models are stated as follows.

To determine the appropriate lag lengths of the processes, examination of the autocorrelation (ACF) and Partial autocorrelation (PACF) functions is necessary, as these functions give the relationship between data points, and indicates the memory of the data generation process. Perusal of these functions will facilitate an assessment of the additional information obtained from past values, resulting in testing and elimination of unnecessary or uninformative lags, to derive the final parsimonious SARMA model.

The main premise on which ARMA models is generated is the property of 'stationarity' in the series, which is defined as reversion of the series. to its mean regardless of short-term fluctuations in the variable. The significance of this property is that the series displays constant mean and time in-variant variance, which, with its absence, estimation would be impossible since the variance would be inestimable. One attractive feature of this technique is that it does not rely on any a priori specification of economic hypotheses, and the use of the technique itself circumvents the possible problems which may arise in estimating structural models , for example omitted variables, variable definition problems, multicollinearity, and other model sepecification issues.

The ARIMA-seasonal model

The standard ARIMA-model that is defined as above does not include the regular seasonal variation pattern, and therefore it is necessary in this context to define the so-called ARIMA- seasonal model. In the ARIMA model, differences between two succeeding observations are included, while there are in the ARIMA-seasonal model differences between two observations that have exactly the seasonal length between them. The seasonal length is I 4 for quarterly figures and twelve for monthly figures.

An ARIMA-seasonal model is denoted ARIMA(P,D,Q)$_S$, where P is the order of auto regression in the seasonal model, D is the order of differencing, Q is the order of the moving average in the seasonal model and S is the seasonal length.

A seasonal-ARIMA (P,D,Q) *S* model is given by

$$\left(1-\beta_1 L^S - \cdots - \beta_P L^{SP}\right)\left(1-L^S\right)^D y_t = \left(1-\phi_1 L^S - \cdots - \phi_Q L^{QS}\right)\varepsilon_t$$

Identification of ARIMA-models

When the ARIMA model has to be identified the first step is to determine how the time series should be transformed into a stationary series using differences. This order can be determined by the use of the so-called autocorrelation function.

We know that it holds that the correlation between two variables x and y is given by

$\frac{Cov(x,y)}{\sqrt{Var(x)Var(y)}}$, which is a number between -1 and 1.

If the autocorrelation function is graphed, it is denoted a correllogram.

The autocorrelations function (ACF) is a similar function calculated for elements of a time series y_t and y_{t-j}.

The autocorrelation function (where n is the number of observations) is therefore estimated as

$$\rho(j) = \frac{n-1\sum_{i=j+1}^{n}(y_t - \bar{y})(y_{t-j} - \bar{y})}{n-j-1\sum_{i=1}^{n}(y_t - \bar{y}\ )}$$

Where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_t$

The time series plot of ACF, PACF, and ADF test helps to identify the tentative model and the stationarity of the series. If the time series plot shows the data scattered horizontally around a constant mean, or equivalently, if the ACF of the time series is rapidly decreasing or if ADF t- statistics value is highly negative value, then the mean is stationary. If the time-series data is not stationary in the mean, it can often be converted to a stationary series by differencing of data. Then, if the ADF t-statistics value is highly negative value H_0 will reject, then, the data is stationary. Once a stationary series has been obtained, then identify the form of the model to be used by using the patterns of the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

Once a tentative model is selected we can select the best one by the information obtained from model selection criteria. In this study the researcher used full sample criteria. Full sample criteria do not rely on data splitting to obtain their fit statistics, but rather are based on the log likelihood on the data as a whole. Three full sample criteria I considered are those proposed by Akaike, Schwarz, and Allenby.

(1) Akaike. Akaike(1974) proposed an astonishingly simple model comparison criterion, based on an information theoretic rationale. This criterion uses a penalty term to penalize the log maximum likelihood for lack of parsimony. If In L is the log maximum likelihood, Akaike's criterion is computed as

$$A = \ln L - \text{(Number of parameter)}.$$

In the regression case, with v independent variables, there are $v+1$ total estimated regression coefficients, yielding:

$$A = \ln L - v - 1$$

(2) Schwarz. Schwarz (1978) criticized Akaike'sb criterion as being asymptotically nonoptimal and provided a simple alternative, based on a Bayesian argument. His mathematical results lead to a revised form of the penalty function, but again one which is simple computationally. His criterion is:

$$B = \ln L - \left[\frac{ln2}{2}.(numberofparametrs)\right]$$

(3) Allenby. A third full sample criterion has been proposed by Allenby (1990). Using an approximation based on a Bayesian approach, he arrives at the criterion

$$C = \ln L - \left[\frac{ln2}{2}.(numberofparametrs)\right]$$

Both Akaike's criterion and Schwarz's criterion often appear in slightly different form, multiplied by a numerical constant (usually – 1/2).

The model which has the smallest criterion values the best one and selective.

Controlling an ARIMA-model

First step in the model controlling phase is an examination of the estimated parameters of the model. It has to hold that the sum of the estimates in both the ordinary model and in the seasonal model each, seen numerically, has to be strictly less than 1. Empirically, this demand is often constrained to the sum being less than 0.9. If the sum of these parameter estimates exceeds this limit, this is equivalent to the fact that too many differences have been performed in the model.

Or Estimate the parameters for a tentative model that has been selected by using the Least Square Method.Reject H_0, when the corresponding P-value drops blew the preset significance level α (i.e. if P-value < α-value) so, the strong evidence that parameter is important.

The next step is an examination of the adequateness of the model in describing the variation of the data. The degree of explanation of the model is typically evaluated by a calculation of R^2. This is calculated by using the formulae

$$R^2 = \frac{\hat{\sigma}^2 - \hat{\sigma}_{res}{}^2}{\hat{\sigma}^2} = \frac{\text{Variace in the original series} - \text{ the residual variance}}{\text{Variance in the original series}}$$

R^2 Takes values between 0 and 1. This calculated fraction often takes values close to 1. The fraction gives an expression of the part of the variation in the dependent variable that can be explained by the regression. By adding variables in the regression model, even variables with no a priori explanatory power, the fraction R^2

will always increase. This has to be taken into account when an interpretation o R^2 is given.

And also there are other essential model accuracy diagnostic measures not only in ARIMA model but also the two models mentioned above. These accuracy diagnostic measures considered are MAPE (mean absolute percentage error), RMSE (the root mean square error),and MAE (Mean absolute error)

1- MAPE (mean absolute percentage error) measures accuracy of the fitted time series and is expressed as a percentage.

$$MAPE = \frac{\sum \left| (y_t - \hat{y}_t) / y_t \right|}{n} x100 \quad , \quad (y_t \neq 0)$$

.

2 –RMSE (the root mean square error), which is given bye

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (A_t - F_t)^2}{n}}$$

3-MAE (Mean absolute error), $MAE = \frac{\sum_{i=1}^{n} | A_t - F_t |}{n}$

Note: the lower the value of MAPE, MAD, MSD, MAE, and RMSR the best the fitted model

Another fundamental assumption in the model is that the residual term is a white noise process. This assumption can be examined by the use of the so-called Ljung-Box portmanteau test, which is a function of ACF defined as

$$Q_{LB} = n(n+2)\sum_{j=1}^{k} \frac{\rho^2{}_j}{n-j}$$

Where ρ_j is the estimated residual autocorrelation for lag j, n is the number of residuals and K is the number of lags in the estimation.

Q_{LB} is asymptotically χ^2 -distributed, the degrees of freedoms equaling k minus the number of estimated parameters in the model.

An estimated ARIMA-model is used for predictions. The ability of prediction of the model can be examined by comparing the values predicted by the model (on the basis of the observations in the prediction period) with the actual values in a previously defined period.

3.3.3 Structural Models

Structural models are derived from economic theory and use structural factors and lagged variables of the dependent variable to determine relationships that are used to predict future values of the dependent variable. The structural elements may be economic as well as non-economic factors, and the model construction may consist of several equations. However, there are weaknesses with the model that centre around requiring data history for dependent and independent variables, and the model may miss information and misjudge transition/structural change periods.

The Currency Demand Model

A standard money demand functions is estimated to perform a two- fold role:

1. To generate future period forecasts of the demand for local denominations of notes and coins;
2. To assess the policy implications by establishing and defining the short-run and long-run economic relationship(s) which exist between major economic variables and the demand for currency.

The model represents an eclectic combination of the transactions demand and the portfolio balance demand theoretical specifications. The trasactions demand for currency describes the need to hold cash balances to facilitate planned and less significantly, unexpected expenditure such as unplanned bills. The portfolio balance model emanates from the model reformulated (Tobin, 1958) from the speculative of Keynes' theory of money demand. In the two-asset approach, the individual allocates his portfolio between money, assumed to be interest free, and alternative assets with uncertain rates of return. Portfolio adjustments require relative adjustments in balances to attain maximal returns on existing resources. The motive for adjustment in the balances of currency relative to near liquid interest earning assets is assessed to determine the relative elasticity of adjustments.

Based on these traditional theories of money demand, the defined model with adaptations reflective of characteristics of developing economies like Ethiopia is as follows:

$$M_t = f(P_t, R_t, Y_t, \tau_t)$$

Where M_t = amounts of notes and coins demanded, and is in circulations' with the public at time t

p_t = Consumer price index at time t

R_t = A weighted average deposit rate for financial institutions' deposit instruments

Y_t = The exchange rate defined as $\$ET_Y$ =US$1

τ_t = Consumer imports selectively comprising of food and non-durable items

Assuming a semi-log demand function, with linear mathematical specification, the estimated model is

3.4.4Vector Auto Regression *(VAR*)

A VAR is a *n*-equation, *n*-variable linear model in which each variable is explained by its own lagged values plus current and past values of the remaining *n* - 1 variables; see Stock & Watson (2001). A mathematical representation of a *p*th-*order* vector auto regression, denoted *VAR*(*p*), is:

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-n} + \psi x_t + \varepsilon_t$$

Where y_t is the (*n x* 1) vector of endogenous variables, x_t is the vector of exogenous variables, Φ1 …Φ*p* and ψ are matrices of coefficients to be estimated, and ε_t is a vector of innovations which are i.i.d. N~(0; Σ). VAR models can be used for data description, forecasting, structural inference and policy analysis. They are a neutral way of observing interdependencies between variables since no structural assumptions – except the choice of the variables themselves and the lag length – are necessary. Therefore it can be regarded as a (economic-) theory-free way to capture dynamics in multiple time series. The same logic applies for forecasts made from VAR estimations.

Due to the large number of parameters to be estimated, however, VAR models are often inefficient and suffer from over-parameterization and a low number of degrees of freedom.

3.4.4(A) Stationary and Nonstationary Time Series – Unit Roots

According to Wooldridge (2006, p. 381) a strictly stationary process is one whose probability distributions are stable over time in the following sense: "if we take any collection of random variables in the sequence and then shift that sequence ahead *h* time periods, the joint probability distribution must remain unchanged"; i.e. for every collection of time indices $1 \leq t_1 < t_2 < \ldots < t_m$, the joint distribution of a stochastic process $(x_{t1}, x_{t2,} \ldots x_{tm})$ is the same as the joint distribution of $(x_{t1+h}, x_{t2+h}, \ldots, x_{tm+h})$ for all $h \geq 1$. When times series exhibit unit roots they are *nonstationary*, however.

The Augmented Dickey-Fuller (ADF) unit root tests shows strong evidence for unit root in the levels of our data. To determine the optimal lag length of the VAR, I use the lag selection criteria(AIC,SIC,and HQC).

ANOVA (analysis of variance)

The study also uses ANOVA test to compare each forecasting model performance using their forecasted error mean values applying one way ANOVA test.

Analysis of Variance (ANOVA) methodology is quite effective in determining if two or more group means differ due to chance, or if observed differences are indeed the result of true difference between phenomena. As useful as it may be to determine singular differences between multiple groups:

Suppose I have a treatment (in my case the three models are considered as treatment) or different level of a single factor that I wish to compare. The observed response from each of the treatments is random variable. The data would appear as in table 3-1. An entry in the table 3-1(e.g., y_{ij}) represents the j^{th} observation taken under the factor level or treatment i .there will be, in general, ***n*** observation under the i^{th} treatment.

Table 3-1 typical data for single-factor ANOVA

Treatment (level)	observation				total	average
1	y_{11}	y_{12}	$\cdots$	y_{1n}	$y_{1.}$	$\bar{y}_{1.}$
2	y_{21}	y_{22}	$\cdots$	y_{2n}	$y_{2.}$	$\bar{y}_{2.}$
$\vdots$	$\vdots$	$\vdots$	$\vdots \vdots \vdots$	$\vdots$	$\vdots$	$\vdots$
a	y_{a1}	y_{a2}	$\cdots$	y_{an}	y_{an}	$\bar{y}_{..}$

Source=Gomez,K.A.and Gomez, A.A.(1984) Statistical procedure for agricultural research

SECTION FOUR

4. StatisticalData Analysis

Theoretically, univariate models could be applied to any frequency (*i.e.*, monthly, weekly or daily). Nevertheless, the specification of these models with high frequency data is somewhat difficult due to certain factors which are common to any country. Some of these difficulties are discussed below.

• In any economy, intra-month or intra-week variations may change from week to week or month to month. For example, the second and third weeks of April are significantly different from any other month in a year due to the Sinhala/Tamil New Year festival effect in these two weeks in April. Similar differences are common within the months as well.

• Modeling the effect of a particular day in two different years, is rather difficult because of holidays and variations in lag effects. This problem is most pronounced in analyzing daily or weekly data series. For example, if weekly data are used, it is well known that demand for currency is high in the Christmas week and the week prior to the Christmas week. Univariate time series models will not be able to capture the effect of one or two extra days in weekly models. This nature of data will make it difficult to explain intra-month variations as well.

• The changing nature of the number of weeks belonging to a month makes it difficult to identify the fluctuations within a month.

• Countries almost universally follow the Gregorian calendar. Sri Lanka too follows the same calendar to set its weekends and all statistics are compiled according to this calendar. However, holidays do not follow the

Gregorian calendar, as they are based on the festivals and religious observances of different ethnic groups in the country, which do not necessarily follow the pattern of the Gregorian calendar. This makes it difficult to model high frequency time series.

• Currency in circulation displays a pronounced seasonality, with weekly, monthly and annual patterns. The monthly pattern of the currency in circulation may be determined by the payment of salary advances or salaries. The amount of the currency in circulation may increase on the weekend and decline afterwards.

Given these constraints, the paper attempts to identify the short term variations, as far as possible, in the currency in circulation in Ethiopia. To model the currency in circulation it is important to know the factors which affect its movement, especially its trend and seasonality. So this study performs seasonality test to indentify whether seasonal fluctuation in the data series using X-12 seasonal adjustment methodology and using dummy variable to capture seasonal factors like holydays.

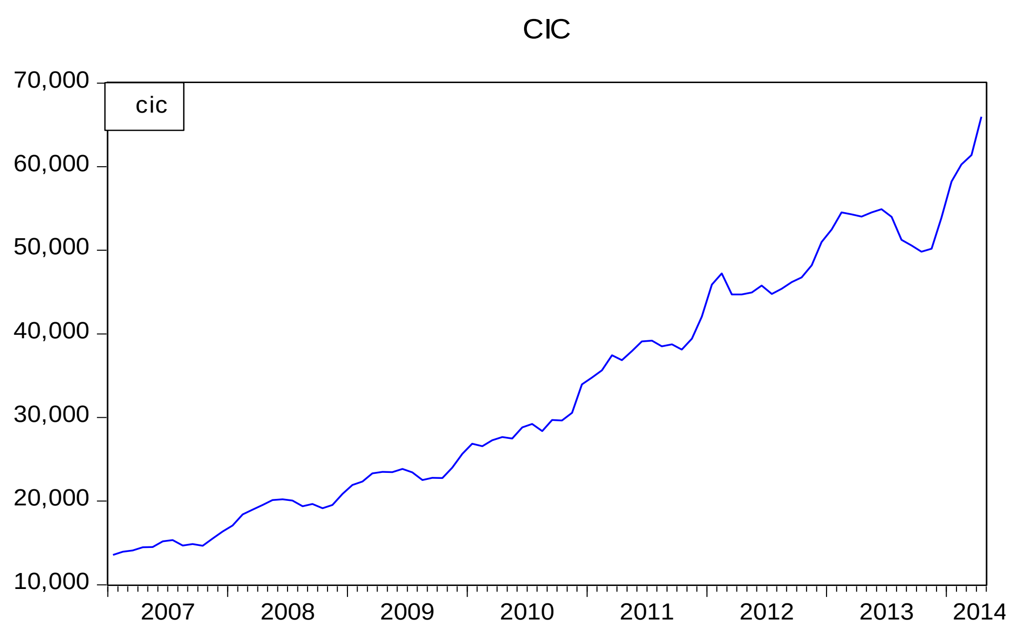


Figure: - 1

The above figure indicates the time series graph of currency in circulation from 2007 to 2014, this time series clearly shows that the series follows multiplicative time series pattern due to this, the study used multiplicative seasonal test and adjustment procedure.

4.1 Seasonality test

This helps us to identify whether there is seasonality effect or not in the data, if there is the adjustment will performed using the widely applicable and advanced technique X-12 ARIMA seasonal adjustment program. The test result for the three variables is shown the **table 1**below

Table 4.1: Combined Seasonality Test for currency in circulation

Observation =CIC			H_0: No signs of seasonality
Seasonality test	Statistic	Probability Level	Remarks
Stable Seasonality F-test	49.585**	.000	Stable seasonality present at the 0.1 % level
Moving Seasonality F-test	0.901	.000	No evidence of moving seasonality at the 5% level.
Kruskal-Wallis Chi-square Test	71.05	.000%	Identifiable seasonality present at the 0.1% level
Combined Measures:			
T1 = 7/F_Stable	0.14		
T2 = 3*F_Moving/F_Stable	0.054		
T = (T1 + T2)/2	0.097		
Combined Test of Identifiable Seasonality	T <1		PRESENT

The result from the seasonal adjustment procedure shows that the series is indeed suitable for seasonal adjustment. All the above test statistics have been tested; fail to indicate the suitability of seasonal adjustment.

4.2 Stationarity test

To perform forecasting, most techniques require the stationarity conditions to be satisfied.

- **First Order Stationary**

A time series is a first order stationary if expected value of X(t) remains same for all t. For example in economic time series, a process is first order stationary when we remove any kinds of trend by some mechanisms such as differencing.

- **Second Order Stationary**

A time series is a second order stationary if it is first order stationary and covariance between X(t) and X(s) is function of length (t-s) only. Again, in economic time series, a process is second order stationary when we stabilize also its variance by some kind of transformations, such as taking square root.

Table 4.2:First order Stationarity Test for Broad Money

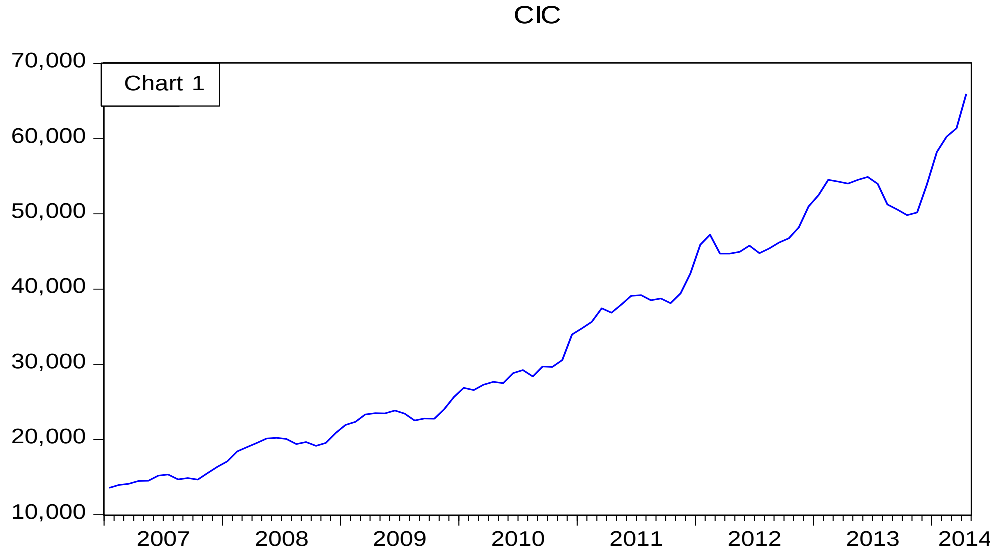
CIC at different transformation		CIC_SA		LOG(CIC_SA)		DLOG(CIC_SA)	
		t-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.
ADF t-statistic		1.04137	.996	-0.07785	0.9479	-8.504	.0000
Test critical value	1% level	-3.50326		-3.50387		-3.5083	
	5% level	-2.89551		-2.89358		-2.8955	
	10% level	-2.58495		-2.58393		-2.5849	

ADF test in the above table shows that the log series are I(1) or stationary at first difference of log series.

4.3Model Selection and Estimation on Trend models

It is empirically obvious that in many economic time series a trend exists. A trend is defined as slow, long run, evolution in the variable. It is produced by slowly evolving factors such as preferences, technologies, institutions and demographics.

Chart 1, shows monthly currency in circulation data patternin Ethiopia from 1 January 2007 to February 2014which the trend appears roughly curve linear.



4.3.1 Model estimation

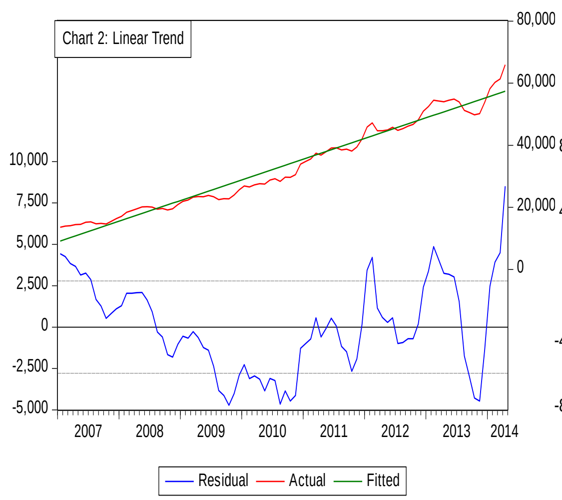
A simple linear function of time, equation 4, provides the description of the trend. The variable TIME is constructed artificially and is called the time trend or time dummy

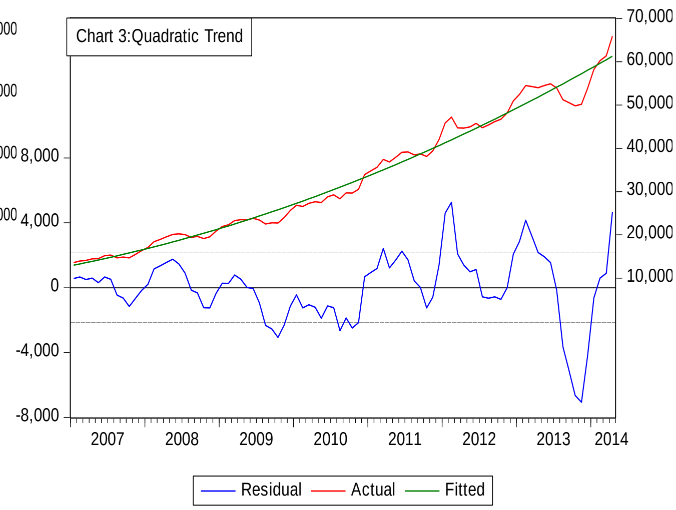
$$CIC_t = 9136.964 + 555.1782\,TIME_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$
$$(590.511) \qquad (11.72263)$$

Where sample size is 92 and TIME = (1, 2, …92)

Chart 2 which depicts currency in circulation, the fitted trend and residuals, shows a somewhat adequate representation. However, a deviation of actual broad money from the trend is apparent.

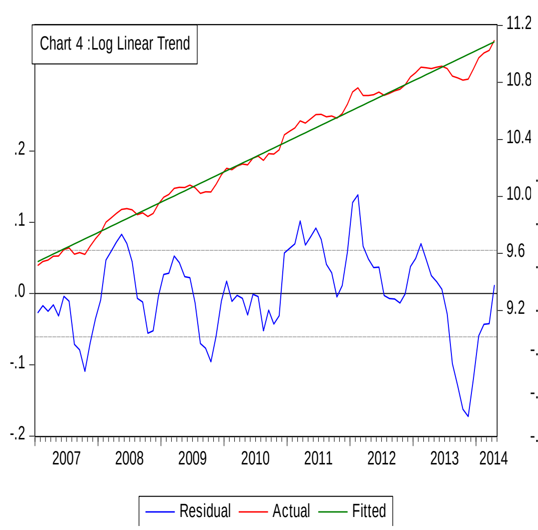
Therefore, quadratic trend model is used to capture the nonlinearities observed in the currency in circulation.

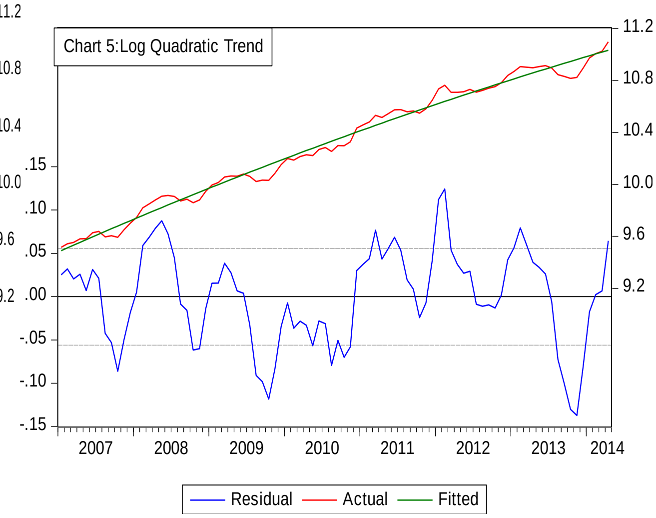




$$BM_t = 12998.01 + 285.8027\,TIME_t + 3.09627\,TIME^2_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.1$$
$$(669.882) \qquad (35.5897) \qquad (0.395808)$$

Chart 3 presents currency in circulation data with a superimposed quadratic trend. Although the quadratic trend fits the better than the linear trend, it is still appropriate to test other type of trend models as well.





In Chart 4, which shows the logarithm of currency in circulation, the trend appears to be approximately linear. In this data series, the trend appears to be non linear in levels but linear in logarithms, that is, it has a log linear trend. If the trend is characterized by constant growth at rate β_1, then the equation is

$$T_t = \beta_0 \, e^{\beta_1 TIME_t} \text{ ....}4.2$$

In logarithmic form

$$\text{Log }(\text{CiC}_t) = 9.542731 + 0.012848\text{TIME}_t$$
$$(0.017724) \qquad (0.000250)$$

$$\text{Log }(\text{CiC}_t) = 9.478809 + 0.022027\text{TIME}_t - 4.90\text{TIME}^2_t \qquad \text{……………………….}4.3$$
$$(0.012176) \quad (0.000647) \qquad (34.0517)$$

Table 4.3:Results of model selection criteriaon trend models

Model	Adj,R^2	AIC	SIC	HQC
Linear	0.962644	18.73036	18.78112	18.71235
Quadratic trend	0.978025	18.73036	18.78666	18.75304
Log linear	0.982299	-2.740767	-2.684463	-2.718083
Log Quadratic trend	0.992888	-3.620027	-3.535572	-3.58600

Note: - CiC is currency in circulation

Based on the selection criteria discussed in section 3, the above results suggests that the log linear and quadratic trend model in logs fits the data well, but the quadratic trend model performs better than in both within the sample and out of sample forecasts. As shown in Chart 5 and estimation results given in Equation 4.3, currency in circulation trends up wards and the trend appears nonlinear in spite of the fact that logarithms are used. The residual plot shows that the fitted trend increases at decreasing rat and quadratic terms are significant. The adjusted R^2 is 99 per cent, reflecting the fact that the trend is responsible for large part of the variation in the currency in circulation.

Table 4.4: Model accuracy diagnostics of the models

Models	Linear	Quadratic trend	Log linear	Log Quadratic trend
RMSE	2758.584	905.0392	0.037701	0.033865
MAE	2441.441	678.4595	0.031141	0.028409
MAPE	12.73444	3.042175	0.315208	0.0286077
TIC	0.053922	0.017645	0.001896	0.001703
Bias Proportion	0.000000	0.00000	0.000000	0.000000
Variance proportion	0.015786	0.001652	0.001519	0.001225
Covariance Proportion	0.984214	0.998348	0.998481	0.998775

The lower the value of, RMSE, MAE, MAPE, and Variance Proportion, the better fitted the model.

Since Durbin-Watson statistics suggests serial correlation in errors, I estimate the following model which is trend with AR(1)

$$LCiC\_SA = 9.1209 + 0.017655\ TIME + [AR(1) = 0.89365] \ldots\ldots 4.4$$

(0.0416) **(0.00057)**

$R^2 = 0.9901$ AIC = -4.8841 SCI =-4.8108 DW =1.7288

Where,

LCiC_SA = Log of Seasonally adjusted Currency in Circulation

TIME t = t = 1, 2, n-1, n (n = 88)

Equation 4.4 shows the results of regression on linear trend with AR (1). The adjusted R2 rises to almost 100 per cent and the standard error of the regression falls to 0.0142. The residual plot shows no seasonality as it is adjusted by the ARIMA X-12model, andit does not confirms the signal given by the DW statistic of serial correlation. The residual correlograms show that the partial auto correlations oscillate and decay slowly and they exceed the Bartlett standard errors frequently. The Ljung-Box test strongly rejects the white noise null at all displacements. The residual sample auto correlations cut off at displacement 1. These factors suggest that the AR(1)would provide a good approximation to the disturbance's Wolds representation.

Chart 6: Results of Sample ACF and Partial ACF

Correlogram of Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.034	0.034	0.1042	
		2	0.112	0.111	1.2665	
		3	0.088	0.082	2.0007	
		4	-0.083	-0.101	2.6495	0.104
		5	-0.066	-0.082	3.0678	0.216
		6	0.131	0.154	4.7455	0.191
		7	-0.036	-0.010	4.8716	0.301
		8	0.082	0.054	5.5471	0.353
		9	0.001	-0.039	5.5472	0.476
		10	0.037	0.049	5.6863	0.577
		11	0.018	0.026	5.7191	0.679
		12	0.001	-0.019	5.7191	0.768
		13	-0.063	-0.065	6.1371	0.804
		14	-0.141	-0.164	8.2935	0.687
		15	-0.127	-0.089	10.061	0.611
		16	-0.069	-0.033	10.593	0.645
		17	-0.186	-0.161	14.488	0.414
		18	0.024	0.018	14.553	0.484
		19	-0.068	-0.060	15.085	0.518
		20	0.013	0.058	15.104	0.588
		21	0.034	0.036	15.239	0.645
		22	-0.062	-0.060	15.705	0.677
		23	-0.038	0.007	15.883	0.724
		24	-0.054	-0.053	16.252	0.755
		25	-0.030	0.064	16.366	0.797
		26	-0.046	-0.063	16.639	0.827
		27	-0.089	-0.114	17.680	0.818
		28	0.019	0.009	17.727	0.854
		29	0.016	-0.000	17.761	0.884
		30	0.053	0.054	18.152	0.899
		31	0.130	0.035	20.529	0.844
		32	0.043	-0.000	20.790	0.867
		33	0.051	0.047	21.166	0.883
		34	0.056	0.031	21.625	0.894
		35	0.046	0.106	21.948	0.909
		36	-0.001	-0.060	21.948	0.929

A model with a linear trend, andAR(1) improved the R^2 to 99.8 per cent and Durbin-Watson statistic confirms that it is free of serial correlation. The standard error of the regression is as small as 0.03. The residual plot in Chart 6reveals no pattern and looks like white noise. The residual sample auto correlations and partial auto correlations display no patterns, and are mostly inside the Bartlett bands. The Ljung-Box statistics are also good for small and moderate displacements. The histogram and normality test applied to the test suggest that the residuals appear to be fairly well approximated by a normal distribution.

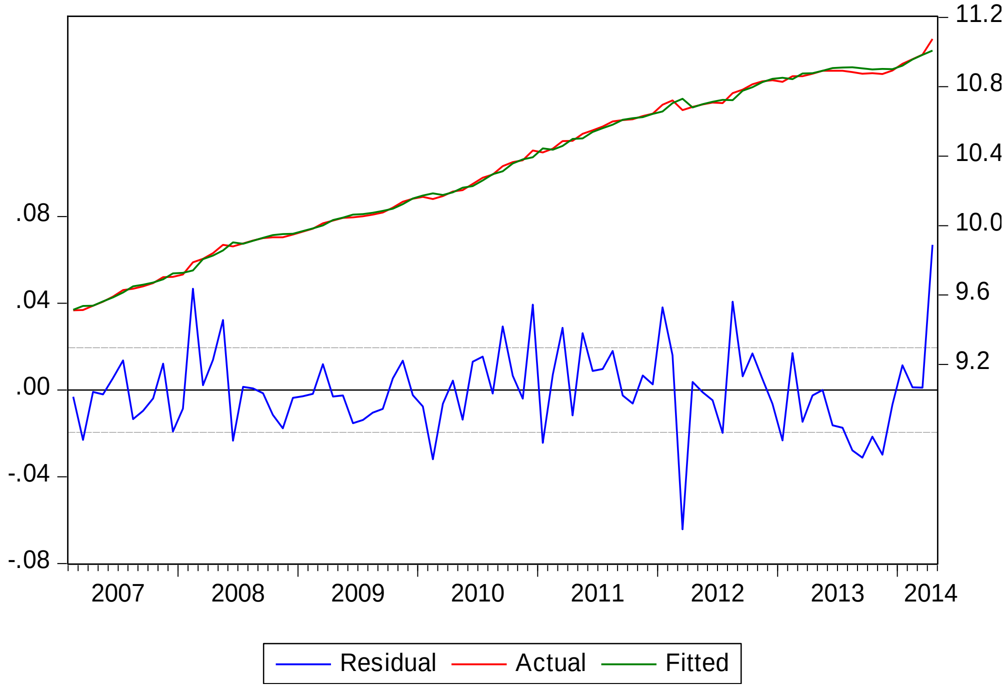


Fig.2

The model produced white noise residuals. The residual sample autocorrelations and partial auto correlations display no patterns and are mostly inside the confidence bands, while the histogram and normality test too performed well.

To select the model that produces an accurate estimate of the 1-step-ahead out of sample prediction error variance, it is necessary to penalize them in sample residual variance (the MSE) reflecting the degrees of freedom used. The model that minimizes the standard error of the regression or the model that maximizes adjusted R^2, are equivalent, and they do penalize for degrees of freedom used. Two very important such criteria currently used in the literature are Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC). Comparing the properties of all these criteria, recent literature suggests that MSE is inconsistent because it doesn't penalize for degrees of freedom. S^2 penalizes [What is S2 please] for degrees of freedom but not enough to use as a consistent model selection procedure. The AIC penalizes degrees of freedom more heavily than S2, but SIC, which penalizes degrees of freedom most heavily, is consistent than S^2 and AIC.
The AIC, although inconsistent, is asymptotically efficient, whereas SIC is not. Therefore, the literature suggests examining both AIC and SIC as model selecting criteria; although on many occasions they select the same model by producing minimum values. If these two criteria select different models, the use of the model selected by SIC is recommended. RupaDheerasinghe1(2005)

4.4 Model Estimation based on Structural Model

(i) Interpolation

Given the data constraints and their relatively low frequency, the desired monthly/weeklyfrequencies have to be generated through a mathematical interpolation technique. Within themonthly model, nominal GDP is interpolated using a simple yearly expected GDP for that particularmonth. The total GDP growth for that year is estimated and the nominal difference is divided by 12.This monthly nominal increase/decrease is then added to the previous month's annual GDP growth.

Within the weekly model, the monthly CPI and UCPI series as well as the government accounts data need to be interpolated into weekly data. The CPI history and forecast is based on converting the monthly consumer price index (CPI) rate into weekly data. The data are converted into weekly data by dividing the difference between monthly CPI rates by the number of weeks within the month in question. This weekly growth is then added to the previous week for the duration of the month.

The evolution in currency in circulation is generally determined by pressures that drive the population to hold currency rather than deposit it. A historical analysis of the development of the currency in circulation in Ethiopia reveals a strong statistical relationship with nominal gross domestic product, population growth, and the developments in the consumer price index. Seasonal drivers are also strong drivers of currency in circulation, such as the flow of remittance spending, tourist season, and yearly holidays. Other drivers of demand for currency are the levels of dollarization and technological and behavioural changes over time, including those that move general payments from cash to card transfers. Here the series is seasonally adjusted using the census X12 method option in E-views. The model is then based on the seasonally adjusted currency in circulation data. Once the seasonally adjusted series is forecast, it is converted back into the underlying series using the seasonal factors. An analysis of different types of forecasting methods revealed a strong case for using a time series econometric OLS-based technique, and a number of model tests reveal the following as the equation of best fit:

$$CiC = f(GDP, CPI, CiC(-1,-12))$$

This equation is based on one-year percentage change of the amount of cash circulating within theeconomy:

Table 4.5: Parameter Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.031088	0.009103	3.415323	0.0009
PCHY(CIC_SA(-1))	0.860787	0.041689	20.64783	0.0000
PCHY(CIC_SA(-12))	-0.123133	0.048390	-2.544623	0.0122
PCHY(GDP)	0.093684	0.042559	2.201291	0.0296
PCHY(CPI)	0.001441	0.000641	2.246295	0.0265

R-squared = 0.845396, Adjusted R-squared = 0.840199, Durbin-Watson stat=1.920538

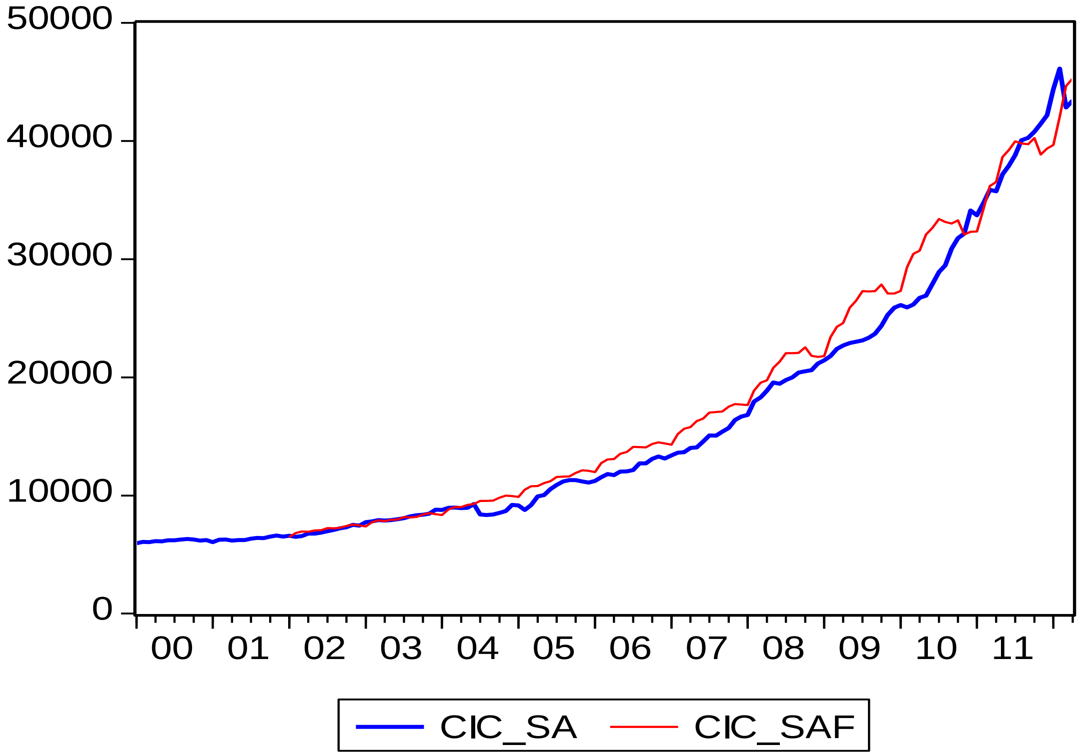
Where:

PCY = Year-on-Year Change
CIC_SA = Currency in Circulation seasonally adjusted
GDP = Nominal GDP
CPI = Headline inflation rate

The model estimation output above shows strong seasonal patterns within currency in circulation.

Nevertheless, both disaggregated GDP and CPI projections share a positive relationship with currency in circulation, with both significant at the 5% level. The in-sample forecast comparisonbelow shows the forecast tracking the actual currency in circulation exhibited over the period withfew deviations. Through in-sample testing between period 2007M1 and 2008M6, the forecastpercentage error was around 2.5%. This model improved the current model by minimizing forecasting evaluation criteria such as RMSR,MAE,MAPE Within the forecasting horizon 2002 to 2012, forexample the model increases R-Squared value from 78% to 84%, Durbin-Watson stat from 1.73 to 1.92 and the forecast percentage error form 3% to 2.5%

Chart 7: in Sample Forecast Result (2008 to 2012)

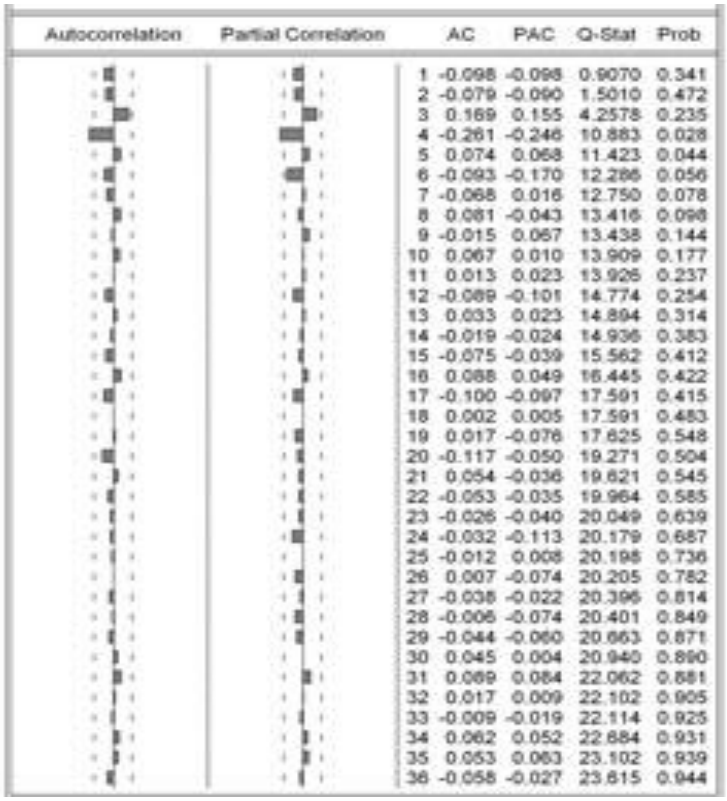


4.5:-Data Analysis using ARIMA model

4.5.1 Model Selection

In this section the study selects the temporal models by using the patterns of the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Then after form these model candidates the best one will be selected based on their model selection criteria as well as by observing model accuracy diagnostics of the residual correlogram. The lower the value of the model selection criteria and the residual correlogram falls within the confidence interval (if there is uncut off points), the best the model is selected.

Correlogram of d(Log(cic_sa))



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.098	-0.098	0.9070	0.341
		2	-0.079	-0.090	1.5010	0.472
		3	0.169	0.155	4.2578	0.235
		4	-0.261	-0.246	10.883	0.028
		5	0.074	0.068	11.423	0.044
		6	-0.093	-0.170	12.286	0.056
		7	-0.068	0.016	12.750	0.078
		8	0.081	-0.043	13.416	0.098
		9	-0.015	0.067	13.438	0.144
		10	0.067	0.010	13.909	0.177
		11	0.013	0.023	13.926	0.237
		12	-0.089	-0.101	14.774	0.254
		13	0.033	0.023	14.894	0.314
		14	-0.019	-0.024	14.936	0.383
		15	-0.075	-0.039	15.562	0.412
		16	0.088	0.049	16.445	0.422
		17	-0.100	-0.097	17.591	0.415
		18	0.002	0.005	17.591	0.483
		19	0.017	-0.076	17.625	0.548
		20	-0.117	-0.050	19.271	0.504
		21	0.054	-0.036	19.621	0.545
		22	-0.053	-0.035	19.964	0.585
		23	-0.026	-0.040	20.049	0.639
		24	-0.032	-0.113	20.179	0.687
		25	-0.012	0.008	20.198	0.736
		26	0.007	-0.074	20.205	0.782
		27	-0.038	-0.022	20.396	0.814
		28	-0.006	-0.074	20.401	0.849
		29	-0.044	-0.060	20.663	0.871
		30	0.045	0.004	20.940	0.890
		31	0.089	0.084	22.062	0.881
		32	0.017	0.009	22.102	0.905
		33	-0.009	-0.019	22.114	0.925
		34	0.062	0.052	22.684	0.931
		35	0.053	0.063	23.102	0.939
		36	-0.058	-0.027	23.615	0.944

Fig.3

By observing the ACF and PACF on the above figure the following tentative models were selected and the best one among them is selected based on model selection criteria as shown in table 4.6A below

Table 4.6A: Models for Currency in Circulation

	Without constant			With constant		
ARIMA model	AIC	SIC	HQC	AIC	SIC	HQC
0,1,1	The mod	el is insg	nificant	-4.439445	-4.311853	-4.41523
3 1 1	-4.43342	-4.37595	-4.41030	-4.474866	-4.388655	-4.44018
1,1,3	-5.03513	-4.97844	-5.01230	-5.019848	-4.934816	-4.98560
3,1,3	The mod	el is insg	nificant	-3.609299	-3.553374	-3.56371

From the result of the above table*AIC*suggests that you *should not* fit a constant. The best model of all those considered is theARIMA(1,1,3) without constant, and the second best is ARIMA (3,1,1) without constant. The model preferred by *AIC* is the one having smallest value, i.e., "furthest to the left on the number line". This means that if any of the *AIC* values is negative, we select the most negative one.

4.5.2A Model Estimation and Testing Adequacy of the Selected Model

In this section the study estimated the parameter for a selective model that has been selected and checked the adequacy of the selected model by using least square estimation results and by observing the collerogram of the residuals.The Least Square estimation result as show in the table 4.6B

CIC_SA=f(ARIMA(1,1,3))

The equation forecasts the monthly currency in circulation series, and the estimation results for the period January 2007 to April 2014 are presented below:

Table4.6B: MA(1) AR(3) Estimation Results

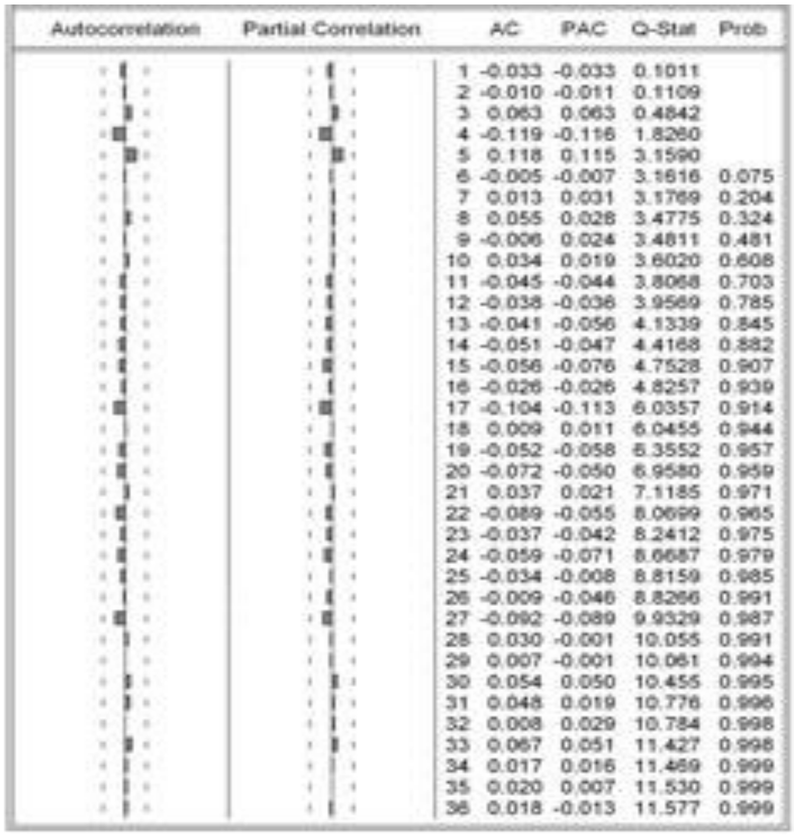
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.001791	0.000254	3944.248	0.0000
MA(3)	0.273276	0.110652	2.469679	0.0155

R-squared	0.998185	Mean dependent var	10.32218
Adjusted R-squared	0.998164	S.D. dependent var	0.450300
S.E. of regression	0.019296	Akaike info criterion	-5.035133
Sum squared resid	0.031648	Schwarz criterion	-4.978446
Log likelihood	221.0283	Hannan-Quinn criter.	-5.012307
Durbin-Watson stat	1.790463		

Inverted AR Roots	1.00		
	Estimated AR process is nonstationary		
Inverted MA Roots	.32+.56i	.32-.56i	-.65

Extensive testing found the above auto-regressive integrated moving average (ARIMA) model as the bestForecast model for currency in circulation among the selective candidates.

Correlogram of the Residuals



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.033	-0.033	0.1011	
		2	-0.010	-0.011	0.1109	
		3	0.063	0.063	0.4842	
		4	-0.119	-0.116	1.8260	
		5	0.118	0.115	3.1590	
		6	-0.005	-0.007	3.1616	0.075
		7	0.013	0.031	3.1769	0.204
		8	0.055	0.028	3.4775	0.324
		9	-0.006	0.024	3.4811	0.481
		10	0.034	0.019	3.6020	0.608
		11	-0.045	-0.044	3.8068	0.703
		12	-0.038	-0.036	3.9569	0.785
		13	-0.041	-0.056	4.1339	0.845
		14	-0.051	-0.047	4.4168	0.882
		15	-0.056	-0.076	4.7528	0.907
		16	-0.026	-0.026	4.8257	0.939
		17	-0.104	-0.113	6.0357	0.914
		18	0.009	0.011	6.0455	0.944
		19	-0.052	-0.058	6.3552	0.957
		20	-0.072	-0.050	6.9580	0.959
		21	0.037	0.021	7.1185	0.971
		22	-0.089	-0.055	8.0699	0.965
		23	-0.037	-0.042	8.2412	0.975
		24	-0.059	-0.071	8.6687	0.979
		25	-0.034	-0.008	8.8159	0.985
		26	-0.009	-0.046	8.8266	0.991
		27	-0.092	-0.089	9.9329	0.987
		28	0.030	-0.001	10.055	0.991
		29	0.007	-0.001	10.061	0.994
		30	0.054	0.050	10.455	0.995
		31	0.048	0.019	10.776	0.996
		32	0.008	0.029	10.784	0.998
		33	0.067	0.051	11.427	0.998
		34	0.017	0.016	11.469	0.999
		35	0.020	0.007	11.530	0.999
		36	0.018	-0.013	11.577	0.999

Fig.4

Further,RACF and RPACF in FIGURE.4 also reveals that there are no spikes or the residual autocorrelation are fall in the confidence interval. In general the selected model is adequate.

Model comparison based on model evaluation criteria

Table 4.7: Models Evaluation Criteria

Models	Trend model with ARMA	ARIMA model	VAR	Structural Model
RMSE	0.041094	0.090548	0.40211	0.052367
MAE	0.033511	0.083250	0.03201	0.041387
MAPE	0.337868	0.836927	0.3356	16.80432
TIC	0.002064	0.004519	0.00205	0.101161
Bias Proportion	0.000000	0.080182	-	0.01189
Variance proportion	0.004143	0.002490	-	0.047108
Covariance Proportion	0.995852	0.195681	-	0.940998

4.6. VAR estimation and model selection

4.6.1 Unit root test.

Null Hypothesis: D(LCIC_SA) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic based on SIC, MAXLAG=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.576188	0.0000
Test critical values:	1% level	-4.073859	
	5% level	-3.465548	
	10% level	-3.159372	

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

Null Hypothesis: D(LCPI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic based on SIC, MAXLAG=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.788741	0.0011
Test critical values:	1% level	-4.073859	
	5% level	-3.465548	
	10% level	-3.159372	

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

Null Hypothesis: D(LGDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 9 (Automatic based on SIC, MAXLAG=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.593187	0.0373
Test critical values:	1% level	-4.088713	
	5% level	-3.472558	
	10% level	-3.163450	

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

All the three variable are integrated of order one, I(1) at 5% level of significance(i.e., there is no unit root)

4.6.2 Lag selection criteria

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	131.9772	NA	7.04e-06	-3.350057	-3.258740	-3.313531
1	497.6797	693.4099	6.67e-10	-12.61506	-12.24979	-12.46895
2	535.6220	68.98602	3.15e-10	-13.36680	-12.72758*	-13.11112
3	540.7445	8.914586	3.49e-10	-13.26609	-12.35292	-12.90083
4	561.3381	34.23351	2.60e-10	-13.56722	-12.38010	-13.09239
5	580.5838	30.49320*	2.01e-10*	-13.83335*	-12.37227	-13.24893*
6	586.1269	8.350541	2.23e-10	-13.74356	-12.00853	-13.04956
7	591.4091	7.546060	2.50e-10	-13.64699	-11.63801	-12.84342

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

The above lag selection criteria result, among the five lag selection criteria four of them chooses the maximum lag to be 5. So I estimate the VAR model using five lag length (P=5).

4.6.3Residual correlograms.

The residuals correlograms from a VAR provide a summary of the autocorrelation properties of the estimated residuals. The aim is to find a model in which no residuals autocorrelations are significant. For the residuals to be considered white noise, they must each be uncorrelated with lags of themselves as well as lags of all other residuals (i.e.my aim to find a model in which the estimated residual auto-correlations lie inside the 95% confidence intervals). For the VAR(5) model, the correlograms are displayed in Figure 7. For a VAR model there is a set of estimated residuals from each equation, so in this case there are three sets of residuals, one from each of the equations for LCiC, LCPI and LGDP.

1. The top three correlograms in Figure 7 show the correlations between the residuals of the LCiC equation and lags of the LCiC residuals (i.e. Cor(LCiC,LCiC(-l))), lags of the LCPI residuals (i.e. Cor(LCiC,LCPI(-l))) and lags of the LGDP residuals (i.e.

Cor(LCiC, LGDP(-l))). There is a significant correlations between LCiC and LCPI at lag 5 and hence suggest the LCiC

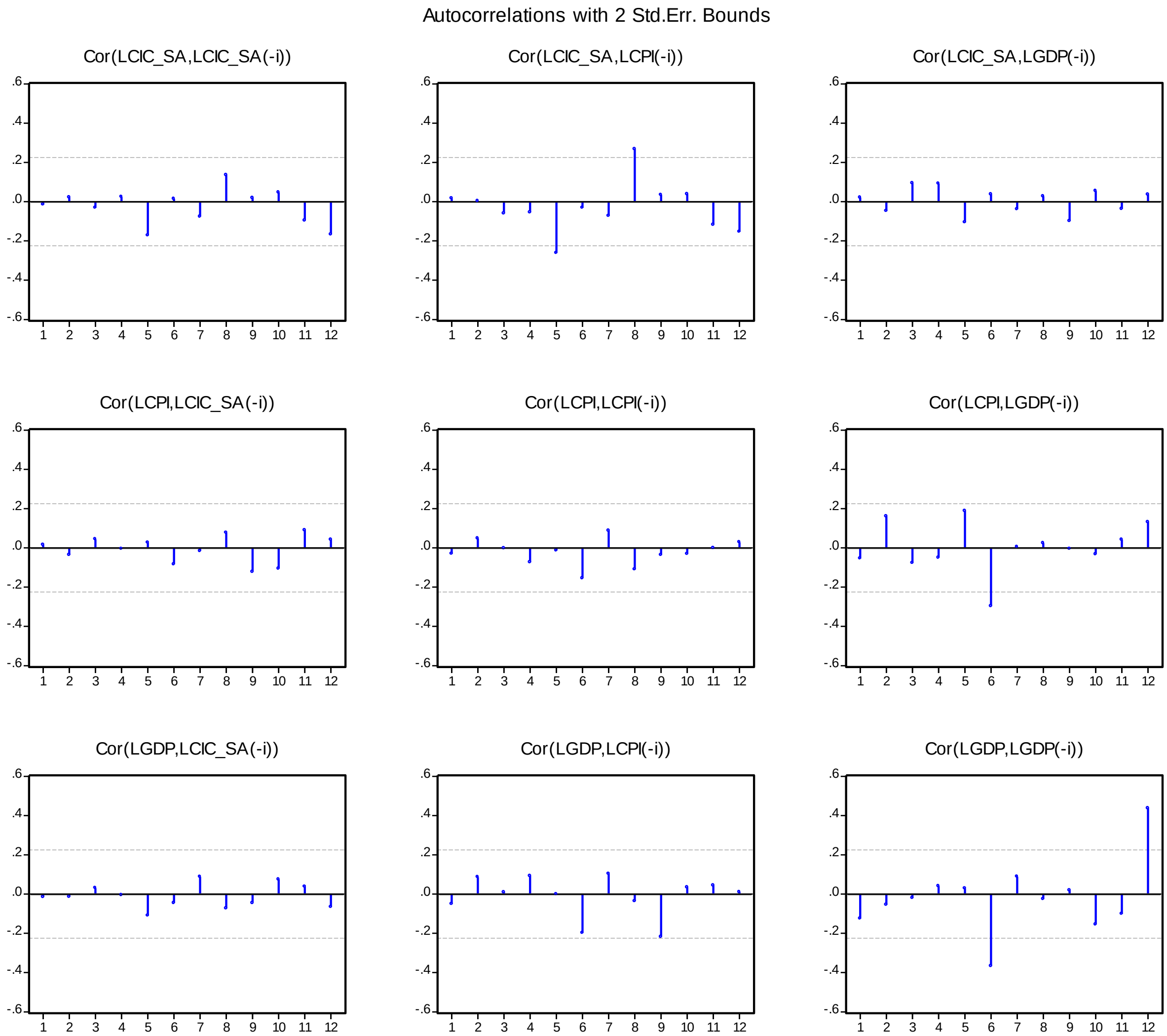


Fig.5

2. The second row of correlogram relates to the lCPI residuals. They have significant correlations with the LGDP residuals at lags 6.

3. In the third row of correlograms, the LGDP residuals show significant correlation with the its self at lag6 and lag 12.

This study turns out that a VAR with four lags is sufficient to remove the autocorrelation from the residuals of all of the equations. This finding, along with the evidence of the LR, FPE and AIC approaches, leads us to choose a VAR (4).

VAR Residual Serial Correlation LM Tests
H0: no serial correlation at lag order h

Lags	LM-Stat	Prob
1	6.399098	0.6994
2	10.53539	0.3089
3	5.631998	0.7761
4	5.104505	0.8251

Probs from chi-square with 9 df.

VAR Residual serial correlation LM test suggests that there is no serial correlation for the selected lag order because we cannot reject the null hypothesis which is no serial correlation at lag 4 at 5% level of significance.

4.6.4 VAR Estimation Results

The VAR estimation results are just the coe¢ cient estimates for each equation in the VAR.

Vector Autoregression Estimates
Standard errors in ( ) & t-statistics in [ ]

	LCIC_SA	LCPI	LGDP
LCIC_SA(-1)	0.962425	0.191065	0.018289
	(0.12514)	(0.11386)	(0.22998)
	[7.69080]	[1.67806]	[0.07952]
LCIC_SA(-2)	-0.033218	-0.169608	0.116759
	(0.17246)	(0.15691)	(0.31694)
	[-0.19262]	[-1.08092]	[0.36840]
LCIC_SA(-3)	0.216386	0.339219	-0.161857
	(0.16791)	(0.15278)	(0.30859)
	[1.28868]	[2.22034]	[-0.52451]
LCIC_SA(-4)	-0.276462	-0.274593	0.050337
	(0.17365)	(0.15800)	(0.31914)
	[-1.59203]	[-1.73791]	[0.15773]
LCPI(-1)	-0.183889	1.353363	0.174690
	(0.14041)	(0.12775)	(0.25804)
	[-1.30969]	[10.5937]	[0.67699]

LCPI(-2)	0.299568	-0.636592	-0.385921
	(0.23184)	(0.21095)	(0.42608)
	[1.29211]	[-3.01779]	[-0.90574]
LCPI(-3)	-0.241023	0.500962	0.495461
	(0.23707)	(0.21570)	(0.43569)
	[-1.01668]	[2.32248]	[1.13720]
LCPI(-4)	0.081742	-0.381708	-0.798796
	(0.22550)	(0.20517)	(0.41442)
	[0.36249]	[-1.86040]	[-1.92748]
LGDP(-1)	0.064807	0.117314	1.511740
	(0.05975)	(0.05437)	(0.10982)
	[1.08457]	[2.15778]	[13.7662]
LGDP(-2)	-0.112480	-0.066482	-0.624853
	(0.09013)	(0.08201)	(0.16564)
	[-1.24796]	[-0.81069]	[-3.77231]
LGDP(-3)	0.105582	-0.173195	-0.843199
	(0.08871)	(0.08072)	(0.16303)
	[1.19017]	[-2.14574]	[-5.17191]
LGDP(-4)	-0.048223	0.252355	1.308876
	(0.09172)	(0.08346)	(0.16857)
	[-0.52575]	[3.02382]	[7.76463]
R-squared	0.998351	0.998075	0.996683
Adj. R-squared	0.997959	0.997616	0.995893
Sum sq. resids	0.021668	0.017938	0.073185
S.E. equation	0.018546	0.016874	0.034083
F-statistic	2543.520	2177.194	1261.978
Log likelihood	211.8571	219.3193	163.7801
Akaike AIC	-4.958407	-5.147324	-3.741268
Schwarz SC	-4.478519	-4.667436	-3.261380
Mean dependent	10.32852	4.338785	11.53033
S.D. dependent	0.410504	0.345610	0.531848

Determinant resid covariance (dof adj.)	1.06E-10
Determinant resid covariance	5.40E-11
Log likelihood	597.5680
Akaike information criterion	-13.91311
Schwarz criterion	-12.47345

4.6.5 Stability Test

To perform forecasting in the series the model must satisfy stability criteria, so this study tests the stability criteria of the model and the result is depicted below. As the result showed, the model is stable because all modulus values are less than 1or all roots are not outside unit circle.

Roots of Characteristic Polynomial

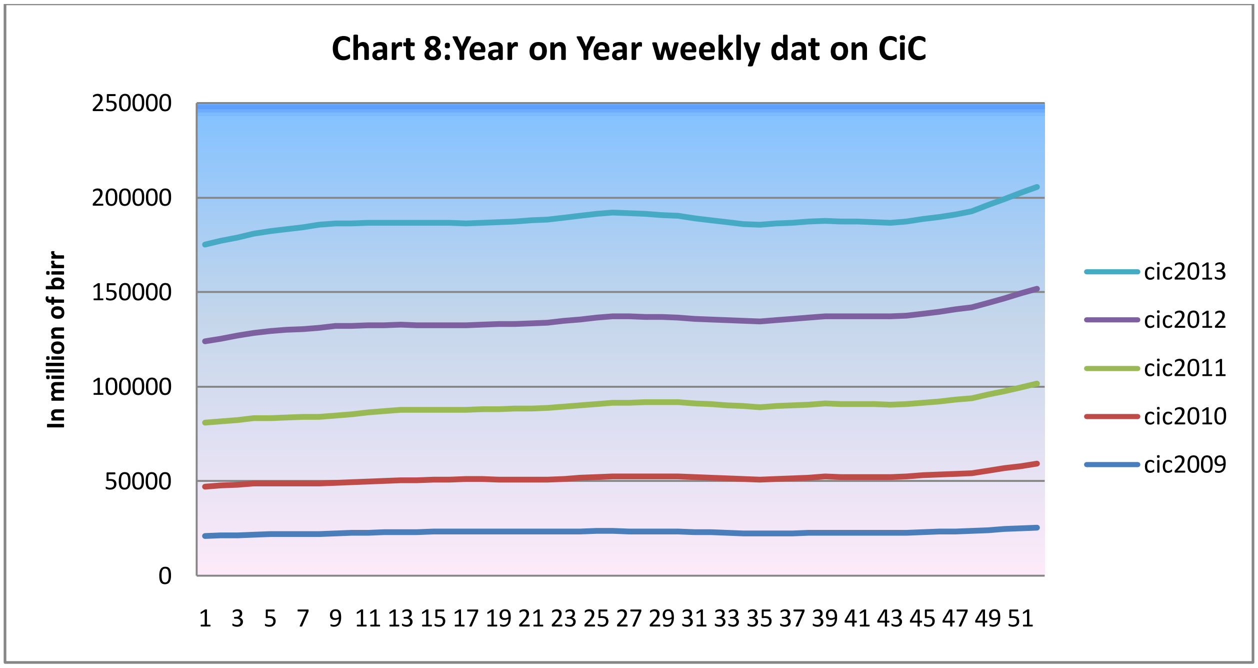
Root	Modulus
0.991938	0.991938
0.916450 - 0.175119i	0.933031
0.916450 + 0.175119i	0.933031
0.437703 - 0.810525i	0.921159
0.437703 + 0.810525i	0.921159
-0.914417	0.914417
0.796705 - 0.407406i	0.894829
0.796705 + 0.407406i	0.894829
-0.476576 - 0.597472i	0.764263
-0.476576 + 0.597472i	0.764263
-0.104194 - 0.628529i	0.637107
-0.104194 + 0.628529i	0.637107
0.402051 - 0.419099i	0.580766
0.402051 + 0.419099i	0.580766
-0.194271	0.194271

No root lies outside the unit circle.
VAR satisfies the stability condition.

4.7:-Weekly Model Estimation

4.7.1 Estimation of trend model

In this section data on currency in circulation are used by interpolating the monthly series to weekly series using linear –mach last method due to unavailability of full range of such weekly series until the data consistently updated. Chart 8 does not clearly indicate intra month seasonality in almost all months accept themonthaugust,and September. However, seasonality is not that evident in other months. Therefore, to examine the intra- month seasonality more intensively, the year over year line graphs of currency in circulation are examined. Chart 8 reveals that for all the years, the patterns are very similar, indicating no evidence of a structural break or change in seasonality during the period. The minor variations from year to year occur mostly due to (*a*) shift of the week. In order to examine intra-month seasonality in a systematic manner, seasonal dummies were included in the model. To represent the 5th week in some months, a 5th dummy variable was also included.



Weeks

The above chart indicates year on year weekly data on currency in circulation from bottom to top the value increases with the year specified

$$LCiC = 0.003316\ TIME + 9.7707\ D_1 + 9.7705\ D_2 + 9.7708\ D_3 + 9.7709\ D_4$$

(0.000426) (0.12879) (0.12878) (0.1288)(0.1287)

$$+9.7701\,D_5 + [AR(1) = 1.8357\,, AR(2) = -0.8436\,, MA(4) = -0.32146\,, MA(9) = -0.1672\,, MA(17) = -0.21505$$

(0.12879) (0.04532) (0.04588) (0.06138) (0.05886) (0.06589)

$$, MA(18) = -0.2236 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{4.8}$$

(0.06306)

$R^2 = 0.99965$ AIC = -8.3668 SCI = -8.2430 DW =2.02

In this model the impact of New Year and other public holidays was found insignificant. In the monthly model, the impact of the first variables is captured by seasonal dummies and was found significant.

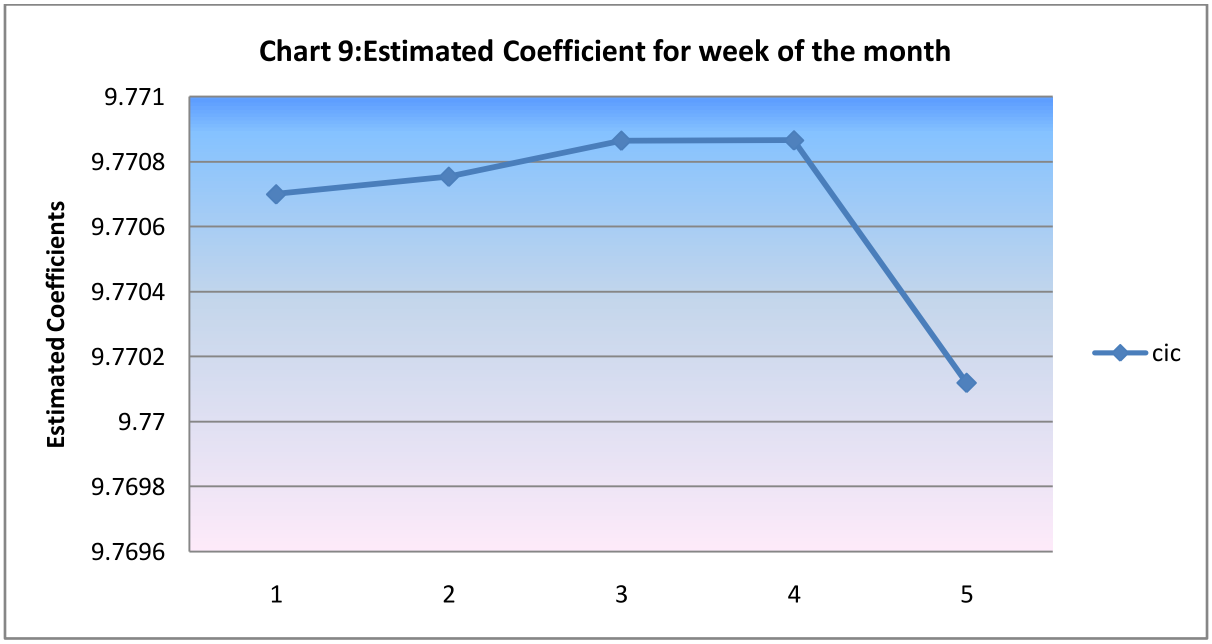
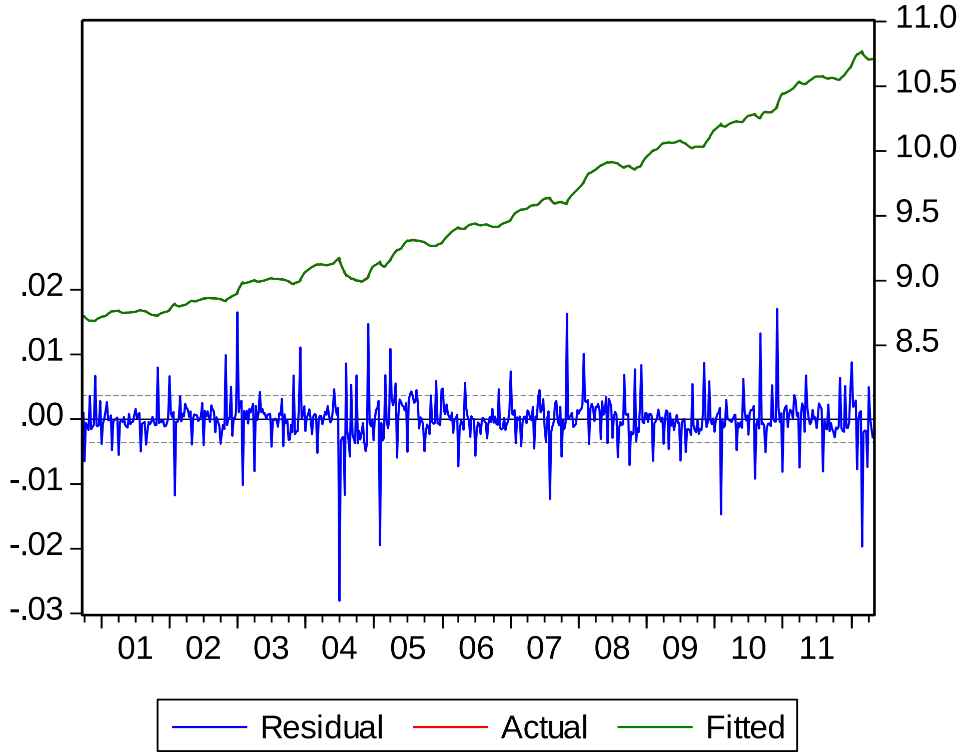


Chart 9, which presents estimated coefficients of seasonal dummies, indicates clear seasonality among weeks. Within each month, weekly currency clears seasonality among weeks. Within each month, weekly currency demand tends to increase during the second week and remains high in the fourth week and then tends to decline. However, the variations among the weeks are small in magnitude. Most of the payments to individuals are made during this time. The government pays salary advances to public school teachers and public servants around the 21Th to 31th of each month.This payment mechanism is likely to create a pronounced 'day of the month' effect in currency in circulation.

Chart 10: Results of the above model



4.8 Model comparison using ANOVA test

In this section the study compares the three best models based on monthly data and two model based on weekly series of currency in circulation in order to reach identify the best model among these model candidates based on their forecasting performance by using ANOVA test by setting the models as group models and their forecasting errors (absolute percentage error) are as treatment. The hypothesis is formulated as shown below in model

Ho: $\mu_{ARIMAFE} = \mu_{trendFE} = \mu_{SMFE} = \mu_{WTFE} = \mu_{VARFE} =$ *the five models forecasting error means are equal*

H1: at least one's model forecasting error mean is different.

If the null hypothesis is rejected, multiple comparison tests (analysis) will proceed (Multiple comparison procedure in ANOVA) by Post Hoc test. This helps us to identify whether there is a significant differences between each models or not in their forecasting performance.

Table 4.9: Analysis of variance result

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4520.662	4	1130.166	111.734	.000**
Within Groups	4197.648	415	10.115		
Total	8718.310	419			

* *. The mean difference is significant at the 0.05 level.

Table 4.7Shows strong evidence to reject H_0in favor H_1 because P-value is very small ($p < .000$) at 5% level of significance. Based on the result shown on the above table multiple comparison among the models were conducted related to their forecasting error mean in in order to arrive on the best forecasting model among the model candidates in these series. These model comparisons were performed based on their forecasting error mean by using Tukey HSD(honestly significant different) test of Post Hock. The multiple comparison (pair wise comparison) result of the models is shown in table 4.8 below.

Table 4.8B shows a significant forecasting error mean difference between monthly trend with ARMA model and ARIMA, and with VAR model, because there is sufficient evidence to reject H_0 in favor of H_1 at 5% level of significance ($p < 0.05$) and also the 95% CI's supports the conclusion, because it does not contain 0. But there is no significant forecasting error means difference between monthly trend with ARMA and structural model because there is no sufficient evidence to reject H_0 ($p >0.05$) at 5% level of significance. So based on percentage forecasting error mean difference resultmonthly Trend with AR(1) Model and structural model forecasts the data well for monthly series next to VAR model which outperforms the whole model.

Table 4.8B: Multiple Model Comparisons for Currency in Circulation

(I) MODEL	(J) MODEL	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
TREND MODEL WITH MA and AR	ARIMA Model	-5.18888*	.38081	.000	-6.2322	-4.1455
	Structural Model	.48994	.38081	.700	-.5534	1.5333
	Weekly Trend Model	-.38573	.38081	.849	-1.4291	.6576
	VAR	3.21214*	.38081	.000	2.1688	4.2555
ARIMA Model	TREND MODEL WITH MA and AR	5.18888*	.38081	.000	4.1455	6.2322
	Structural Model	5.67881*	.38081	.000	4.6355	6.7222
	Weekly Trend Model	4.80314*	.38081	.000	3.7598	5.8465
	VAR	8.40101*	.38081	.000	7.3577	9.4444
Structural Model	TREND MODEL WITH MA and AR	-.48994	.38081	.700	-1.5333	.5534
	ARIMA Model	-5.67881*	.38081	.000	-6.7222	-4.6355
	Weekly Trend Model	-.87567	.38081	.147	-1.9190	.1677
	VAR	2.72220*	.38081	.000	1.6789	3.7656
Weekly Trend Model	TREND MODEL WITH MA and AR	.38573	.38081	.849	-.6576	1.4291
	ARIMA Model	-4.80314*	.38081	.000	-5.8465	-3.7598
	Structural Model	.87567	.38081	.147	-.1677	1.9190
	VAR	3.59787*	.38081	.000	2.5545	4.6412
VAR	TREND MODEL WITH MA and AR	-3.21214*	.38081	.000	-4.2555	-2.1688
	ARIMA Model	-8.40101*	.38081	.000	-9.4444	-7.3577
	Structural Model	-2.72220*	.38081	.000	-3.7656	-1.6789
	Weekly Trend Model	-3.59787*	.38081	.000	-4.6412	-2.5545

*. The mean difference is significant at the 0.05 level.

SECTION FIVE

Conclusions

The paper presents two models suitable for forecasting currency in circulation, based on monthly, data for the period of 1January 2007 to April 2014. The forecasts produced by the VAR, trend and structural models accurately matches the shape of the monthly. Post sample estimation error is very small and remained less than 7 per cent in all models. The forecasts based on the weekly and monthly trend models performed very well, predicting very similar results, and were close to realized data when used within sample.

The models evidenced clear seasonality in April and December mainly associated with the Ethiopian New Year and Holly cross holiday. The models based on weekly and daily data clearly indicated high seasonal demand around the 3rdand 4thweek of the month.

The application of these models and their results may have important implications to researchers and policy makers. The NBE can particularly benefit by incorporating this method in disaggregating its annual monetary targets into monthly targets thereby smoothening the implementation of its monetary policy. Systematic projection of currency in circulation is always an important part of the liquidity forecasting mechanism of the Central Bank. Using these results, the demand for liquidity in specific months can be projected with lower error and therefore, subsequent injections or withdrawals through open market operations are likely to lead to better targeting of monetary aggregates.

Nevertheless, it is important to note that a central bank cannot depend purely or mechanically on forecasting models to predict currency in circulation to be used in liquidity management. As currency in circulation is subject to the influence of various unforeseen developments in the economy, including one off events such as the Tsunami, and the September 11th attack in the USA, close monitoring of day to day developments is extremely important. Even in developed economies, like the USA and

UK, central banks continuously develop and use time series and structural models to forecast currency demand, but review market conditions daily and do necessary adjustments manually tomake the assessment more realistic.

While the paper exposes some limitations of traditional techniques of estimating and forecasting currency in circulation at high frequency, the results reported in this paper may not be treated as final as many of the issues have remained unexplored. A future research agenda could be to examine the link between currency demanded and short-term interest rates at the Ethiopian money market.

Reference

Baumol, W.J., 1952: 'The Transaction Demand for Cash: An Inventory Theoretic Approach', *Quarterly Journal of Economics*, 66, 545–556.

Bhattacharya, K. and Joshi Himanshu M. (2001), “Modelling Currency in Circulation in India”, *Applied Economic Letters,* 8: 585-592.

Box, G and G Jenkins, (1970) *Time Series Analysis: Forecasting and control*, Holden-Day, San Francisco

Cabrero, G. Camba-Mendez, A. Hirsch, F. Nieto (2002) “Modelling the Daily Banknotes in the Context of the Liquidity Management of the European Central Bank”. European Central Bank Working Paper No. 142

Cassino, V. P. Misich and J. Barry, 1997: 'Forecasting the Demand of Currency', *Reserve Bank Bulletin, Reserve Bank of New Zealand*, 60, 27–33.

Chakravarty, S. (Chairman), 1985: Report of the Committee to Review the Working of the Monetary System, *Reserve Bank of India.*

Claney E. Williams (1997) alternative approaches to forecasting currency demand in the Jamaican economy.

Coleman, A and P Cruse, (1989) ‘An investigation of monetary targets in a New Zealand context 1981-1986’, *Discussion Paper G89/6*, Reserve Bank of New Zealand

Cuthbertson, K, (1991) ‘Modelling the demand for money’ in *Surveys in Monetary Economics*, Vol 1 (eds) Green C and D Llewellyn, Basil Blackwell, London

D. M.P. Krainz,(2011), Forecasting Performance of Three Econometric Models for the Eurozone and the USA

Department of Statistical Analysis and Computer Services (DESACS), Reserve Bank of India, 2000: 'Monthly Seasonal Factors of Selected Economic Time Series', *Reserve Bank of India Bulletin*, 1325–1345. Frances, P. H., 1996: Periodicity and Stochastic Trends in Economic Time Series, *Oxford University*

Diebold, F. X. (2004), Elements of forecasting, *third Edition, Thomson-South Western Publishers*, Canada.

Diebold, F and R Mariano, (1995) ‘Comparing predictive accuracy’, *Journal of Business and Economic Statistics*

Halil Güler and Anıl Talaslı, 2010: Modelling the Daily Currency in Circulationin Turkey* *Central Bank Review* ISSN 1303-0701

International Monetary Fund, 2000: 'Liquidity Forecasting', *Monetary and Exchange Affairs Department Operational Paper, MAE OP/00/7.*

Kaushik Bhattacharya and Himanshu Joshi, 200: Modelling Currency in Circulation in India

Pindyck, R and D Rubinfeld, (1981) *Econometric Models and Economic Forecasts,* McGraw-Hill, Singapore

Rao, D. C., T. R. Venkatachalam and A. Vasudevan, 1981: 'A Short Term Model to Forecast Monetary Aggregates: Some Interim Results', *RBI Occasional Papers,* 2, 113–140.

Rupa Dheerasinghe1, 2005: Modeling and Forecasting Currency in Circulation in Sri Lanka

Stavreski, Z. (1998) "Currency in Circulation" National Bank of Republic of Macedonia. Working PaperNo. 1.

Stock, J. H., & Watson, M. W. (2001, Fall). Vector Autoregressions. *Journal of Economic Perspectives* , pp. 15:101-115.

Tillers Ivars (2002), Time Series Modelling of the Daily Currency in Circulation, *University of Latvia.*

V. C, P. M, and J.B, *(1*997 *forecasting the demand for currency in circulation in New Zealand Central Banks Vol 60 No.1*