Addis Ababa University

School of Graduate Studies

DEVELOPING A FORCASTING MODEL FOR CEREAL, COFFEE, PULSES AND OIL SEEDS: BOX-JENKINS APPROACH

By

Habtamu Adane

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Habtamu Adane Legas

Approved by the Board of Examiners:

Alemayehu Geda
Advisor — **Signature**

Fantu Guta
Examiner — **Signature**

Alebel Bayrau
Examiner — **Signature**

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ACRONYMS

ACF	Auto Correlation Function
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
BOP	Balance Of Payments
CSA	Central Statistics Authority
GDP	Gross Domestic Product
HIPC	Highly Indebted Poor Countries
ICOR	Inceremntal Capital Output Ratio
IFIs	Internaitonal Financial Institutions
IMF	International Monetary Fund
MAE	Mean Absolute Error
MA	Moving Average
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
MTEF	Medium Term Expenditure Framework
NBE	National Bank of Ethiopia
NLS	Non-Linear least Square
PACF	Partial Auto Correlation Function
PRSP	Poverty Reduction Strategy Papers
RMSE	Root Mean Square Error
RMSS	Root Mean Square Statistics
SSR	Smallest Sum of Squared Residuals
VAR	Vector Auto Regressive

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Abstract

This study tries to identify the macroforecasting gap created between Ethiopian government and some international organizations like IMF. The former uses informal methods(un officialized) and the later uses model based forecasting methods growth oriented financial programing model to predict rate of growth. The other(major) concern of the study was in developing a forecasting model for cereal, coffee, pulses and oilseeds using Box-Jenkins (univariate ARIMA) methodology. Following the four procedures of identification,estimation, diagnostic checking and forecasting,we get ARIMA(2,1,2), ARIMA(2,1,4), ARIMA(0,1,4) and ARIMA(0,1,4) as the data congruent forecasting models for cereal, coffee, pulses and oilseeds respectively.

CHAPTER ONE
INTRODUCTION

1.1 Back ground of the study

Macroeconomic forecasting in some form has a long history. For instance,the ancient Egyptians foretold harvests (highest contributor of their GDP) from the level reached by the Nile in the flood season,the Oracles of Delphi and Nostradamus (1500s) are early examples of often ambiguous forecasters, in the 17th century Sir William Petty discerned a seven-year business cycle, suggesting a basis for systematic economic forecasts. In the USA a forecasting industry was developed around 1910-1930 eventhough much of it was wiped out by the Great Depression — which it failed to foresee! (Diebold, 1997). Then, official forecasts came to effect following World War II in the Scandinavian countries, and the practice spread to the UK in the early 1950s and most other advanced economies by the 1960s (Pagan,1987).

Even though many observers interpret the failure of the early models as indicative of a bleak future for macroeconomic forecasting, they left a useful legacy of lasting contributions from which macroeconomic forecasting will continue to benefit: they spurred the development of powerful identification and estimation theory, computational and simulation techniques, comprehensive machine readable macroeconomic databases, and much else(Diebold,1997). Moreover, past failures do not necessarily imply a bleak future: we learn from our mistakes. Just as macroeconomic has benefited from rethinking since the 1970s, so too will macro economic forecasting (Jacques et al., 2006).

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Recent advances in information technology makes it possible to access in real time, at reasonable cost, thousands of economic time series for major developed economies. This raises the prospects of a new frontier in macro economic forecasting , in which a very large number of time series are used to forecast a few key economic quantities, like production and inflation(chatfield,1988). Similarily, Challen and Hagger (1983) noted "Nowadays, macro-econometric systems are in use in virtually every country of the world, market economy and command economy, developed and developing. The variety of contemporary macro-econometric systems is thus immense".

Though much delayed compared to the efforts made in other countries, constructing a macro-econometric model for Ethiopia has also been of interest for many stakeholders for a long time. Despite some efforts at individual and institutional levels and mainly in the context of some partial academic research, however, no serious attempt at government level has been pursued and officially disclosed (EEPRI, 2009). And it is not new to observe differences between projections disclosed by government officials and some international organizations like IMF supposed to use the same sources of data.

The study concerns identifications of this gap and developing a forecasting model for selected crop varieties-cereals, coffee, oil seeds and pulses as these crops constitue more than 75% of the crop production. In addition the crop subsector is the major constituent of the agricultural sector which accounts more than 60% of the total agricultural production which is the main stay of the country's economy. More over, the government has adopted an agricultural led industrialization strategy.

1.2 Statement of the Problem

It is irrefutable that the scarcity of sound forecasting frame works weakens budgeting and planning processes in Africa, which may be due to lack of required expertise, lack of data, which both associated with massive financial requirements, constitute an obstacle to the development of forecasting frame works in Africa. That was why macro economic forecasting in Africa has been highly dependent on the developed world economic patterns, which were not true representation of local realities (Jacques Kibambe and Charlotte Du Toit, 2006).

But recently, there is a growing need to draw short to medium term planning in most African countries. This need is becoming increasingly important since African countries are working with international financial institutions in the context of poverty reduction programs that may take three to five years. Without such forecasts, preparation of the resource envelope of a country through what is known as a 'medium term expenditure frame work' or annual budgets would be a difficult, if not impossible task (Alemayehu and Daniel, 2005).

Like that of other less developing countries, the Ethiopian government always disclosed the growth of economy including its major contributor, the agriculture sector. But much of the macro economic analysis in Ethiopia suffers from lack of accurate sources of data and inconsistency across different sources (Alemayehu, 1996). In addition there appears great disparity between the projections made by the authorized government officials and some international organizations like IMF supposed to use the same sources of data. Example, for the year 2010, the growth rate projection made by Ethiopian government was 10.2% and that of IMF was around 6.5%.

The purpose of the research is to

- identify the disparity
- develop a neutral, low cost, forecasting frame work
- focus on major crop varities of the agricultural sector as agriculture stimulates series of economic linkages with the rest of the economy

1.3 Objectives of the study

1.3.1 General objective of the study:

In the light of the above statements, this study has the objective of examining the forecasing gap created between Ethiopian government and international organizations and developing an appropriate forecasting model for four major crop varities.

1.3.2 Specific objectives of the study:

The specific objectives of the study are

- To identify the problem(gap)
- To develop a forecasting model for cereal, coffee, pulses and oilseeds
- To forecast the production of these crops
- To show policy implications that are in line with the results of the study

1.4 Significance of the study

The paper will have relevance in policy planning and providing a coherent narrative about the economic outlook of the major crop varities and making appropriate decisions.

1.5 Data Sources

The secondary data for this study were collceted from National bank of Ethiopia(NBE),Central Statistics Authority(CSA) and Ethiopian Economic Association CD-ROM.

1.6 Scope and Limitation of the study

Modeling of macro aggregates is not a simple thing. It includes many sectors of the economy. But the concern of this study is limited only to four crop varities as modeling of the whole economy needs much energy and time. To model the sectors we use production data starting from 1970 to 2008.

CHAPTER TWO

MACRO MODELS AND GROWTH FORECASTING IN AFRICA

In the African forecasting frame work, and other developing countries in general, the two gap model and its variants are widely used for forecasting the investment requirements to achieve a targeted level of growth rate (ESPA_ECA, 2005). This approach of macro modeling is quite common in many countries as it had been the basis for determining the aid requirement of countries (Alemayehu and Daniel, 2005). It also offers the gap between the available domestic resource and the desired investment level to achieve the targeted growth rate (Ibid). The coming sections discuss the basis for this approach, the World Bank and IMF approaches in computing the resource requirements of African countries, and the strength and weaknesses of the aforementioned approaches and suggest to a new approach.

2.1The Gap Approach

The analysis of the role of foreign capital inflow in economic development interms of the two gap-saving gap and trade gap-was fashionable among development economists during the 1960s, 1970s and 1980s(Matongela,2004;Easterly,2003).

The basic notion underlying the 'two-gap analysis' is that there are at least two independent resource constraints on the growth of an underdeveloped economy. The first of these is the savings constraint where growth of the economy is limited by the availability of savings for investment and the second is that of trade constraint which implies that growth of an economy is limited by the availability of foreign exchange for importing specific commodities required for current production and investment(Thirwall,1983; Mantogela,2004).

In addition, Alemayehu and Daniel (2005) and ESPD-ECA(2005) talked off the two-gap model as a simple Harrod-Domar growth model with flows of external assistance,where the impact of external resources on the growth of an economy can be judged by their contribution to the mobilization and allocation of all productive resources(Chenery et al.,1966).

There fore,the essential point of the model is that growth is related to three types of resources: the supply of skills and organizational ability, the supply of domestic savings and supply of imported commodities and services(Alemayehu and Daniel,2005; Chenery et al.,1966).

More recently, there has been an increasing interest in the fiscal constraint and inflation gap as possible third and fourth gaps respectively, limiting the growth prospects of the highly indebted group of developing countries (Bacha, 1990;Taylor Lance, 1990). The third gap was introduced by noting that private investment may be crowded in or crowded out by public investment through complementarities between the sorts of projects that these two sectors undertake. But, public investment has been drastically cut back after the terms-of-trade and debt shocks that hit many developing countries in the 1980s, because public revenue from export taxes has declined while foreign debt with its associated payments burden has increased substantially. This is set out in various forms by Bacha (1990), Ros (1992) and Taylor (1993). The fourth gap or inflationary gap describes a macroeconomic condition that shows the distance between the current level of real gross domestic product(GDP) and full employment (long run equilibrium) real GDP. The inflationary gap is so named because the relative increase in real GDP causes an economy to increase its consumption, which causes prices to rise in the long run(Investopedia home dictionary).

With respect to the two gap model which matters most developing countries even though the fiscal and inflation constraints are not ruled out(Matongela,2004),Alemayehu and Daniel (2005) divided the constraints to growth in to three phases. In phase I growth is limited by the ability to invest and the saving gap determines the capital inflow. Phase I ends when investment reaches the level adequate to sustain the target growth rate. In phase II growth is set by the target and capital inflow is required to fill the saving gap. The tapering off the capital inflow in this phase requires exports to grow faster than imports. But, this is found to be difficult for most developing countries and this new set of restriction, which is binding in this event, is Phase III. Using this model the authors concluded that although its impact varies in different phases, foreign economic assistance is generally productive either in supplementing domestic saving or relieving foreign exchange constraints (see Box 1).

Box 1: Theoretical Specification of a Two Gap Model

To project GDP, major macro variables as well as internal and external gaps a simple growth model, specified along the Harrod-Domar line, could be estimated using national income data. The Harrod-Domar equation is given by

$$g=\left(\frac{1}{k}\right)\frac{I}{Y} = \frac{\Delta Y}{Y}=\left(\frac{1}{k}\right)\frac{\Delta K}{Y} \qquad [1]$$

Where: g is the growth rate, k the incremental capital-output ratio (ICOR) and I/Y the investment (I) to GDP (Y) ratio. Based on the projection of I/Y it is straightforward to project GDP.

According to the 'two gap' model, capital is the key constraint to growth. In the context of such discussion equation [1] may be written into:

$$Y_{t+1}-Y_t=\frac{1}{k}I_t \qquad [2]$$

Since,

$$Y_{t+1}=(1+g)Y_t \qquad [3]$$

Then, $Y_{t+1}-Y_t=gY_t$ [4]

If the target rate of growth is specified as 'g', then it will be straightforward to estimate the desired level of investment (I*) required. This is given by,

$$I_t^* = gkY_t \qquad [5]$$

Desired level of saving (S*) and imports (M*) are given by the following equations,

$$S_t^* = \alpha_o + \alpha_1 Y_t \qquad [6]$$

$$M_t^* = \beta_o + \beta_1 Y_t \qquad [7]$$

The level of exports are also given by,

$$X_t = (1+\varepsilon)X_{t-1} \qquad [8]$$

Where: ε is an exogenously given value of export growth rate.

Based on equations [5] to [8] it is possible to compute the *ex ante* saving (I*- S*) and trade (M*-X) gaps.

In this version of the 'two gap' model the desired level of investment (and hence the target growth) is always met. This requires, however, that external finance (aid, A) need to bridge the larger of the two gaps,

$$A = \max\ \{I^* - S^*, M^* - X^*\} \qquad [9]$$

It is also easy to compute the *ex post* level of the two gaps by computing saving and imports as,

$$S_t = I_t - A_t \qquad [10]$$

$$M_t = X_t + A \qquad [11]$$

Extracted from Alemayehu and Daniel (2005)

2.2 The World Bank's Revised Minimum Standard Model(RMSM)

Following the stunning success of the Marshall plan in the reconstruction of post-war Europe, the World Bank shifted attention towards the provision of long-term finance for growth and development in developing countries. The Bank, until recently, mainly provided funding for specific investment projects, although its policy agenda has changed significantly since the later period of the 1970s (Jerome,2004).

The main analytical tool of the World Bank in macroeconomic management is the Revised Minimum Standard Model (RMSM), which was designed in 1973 based on contributions by *Chenery* and *Strout* to set up a consistent approach to projections among countries and facilitate comparisons among beneficiaries (Addison, 1989). It is an extension of the Harrod-Domar growth model discussed above that relates investment, imports and savings with output (Ibid).

RMSM is generally an accounting framework, linking the national accounts and BOP, with particular emphasis paid to the foreign financing gap and projections of foreign borrowing (Khan, *et al.*, 1990). The model highlights the importance of the relationship among savings, foreign capital flux, investment and growth. It has evolved over time and as at 1992, it had about 425 variables (Mills and Nallari, 1992: 105).

The frameworks initially used by the Bank in their 'empty' framework are aggregated by the following identities (Tarp, 1993; Sen, 1999; Murinda, 1993):

$Y = C + I + (X - Z)$ Production and expenditure balance (1)

$Y = C + S$ Income - savings balance (2)

$I - S = Z - X$ Savings and trade gaps (3)

From these identities, income is used either for savings or consumption. Investment must be sourced either from domestic savings or inflow of foreign capital (imports). Domestic savings is needed to finance targeted level of investment. Given that most developing countries experience low levels of domestic savings (Hussain, 2000; Easterly, 1997), imports should be larger than exports with a high proportion of imports constituting investment goods or intermediate inputs in the production process. The identity also implies that foreign resources need to be injected in the economy for financing of investment projects. Financing of capital inflows could be from foreign reserves. However, if foreign reserves are limited, as is often the case in most developing countries, then foreign borrowing is utilized to finance the gap (Grcic, 2005; Easterly, 1997).

This is expressed by the following identity:

$S - I = \Delta NFA + \Delta R$, ... (4)

Where,

ΔNFA is the additional foreign borrowing by the public and private sector ΔNFB. The two gap growth model is derived from the following identities. In a closed economy, real output Y is determined by savings and investments.

Thus:

$Y = C + I$.. (5)

In equilibrium, ex-ante investment is equal to ex-ante savings while saving is a function of real income:

$I = sY$ .... (6)

Where,

I = Investment

s = Marginal propensity to save

Since I is equal to ΔK, the rate of capital accumulation is given by:

$g = \Delta K/K = s/k$ where $k = K/Y$ (7)

Assuming k is constant, the growth in real output ($\Delta Y/Y$) will be the same as the growth in capital stock.

Thus,

$$g = \Delta K/K = \Delta Y/Y = s/k \qquad (8)$$

Equation [8] basically relates to the Harrod-Domar equation, which indicates that the rate of growth is determined by the savings rate and the capital-output ratio. The identity implies that growth in developing countries could be generated by targeting savings and translating these savings into effective investment. The growth rate also depends on the efficiency of investment which is measured by the incremental capital-output ratio (ICOR) or k. From Equation [8], given the level of savings and investments, the rate of economic growth can be determined. The identity is used by the Bank as a planning tool to establish how much investment and savings is needed to attain a targeted level of growth, which is expressed as:

$$\Delta Y^* = I/k \qquad (9)$$

Where,

ΔY^* = target level of growth.

Since developing countries face savings constraint, then the required level of foreign borrowing to finance inflow of capital can be determined from the equation:

$$S - I = \Delta NFA + \Delta R \qquad (10)$$

Where,

$\Delta NFA = \Delta NFB$,

Thus, the additional foreign borrowing required to finance capital inflows is given by:

$$\Delta NFB = k\,\Delta Y^* - sY + \Delta R = (\Delta R - sY\text{-}1) + (k - S)\,\Delta Y^* \qquad (11)$$

Furthermore, given the trade gap experienced by these countries, the additional foreign borrowing by the private and public sector to close the trade gap is given as (Tarp, 1993):

$$\Delta NFB = m1\,k\,\Delta y^* + m2\,y - X + \Delta R \qquad (12)$$

$$= (\Delta R - X + m2\,y\text{-}1\,) + (m1 + m2\,)\,\Delta y^*.$$

Tarp (1993) highlights four main equations which forms the core of RMSM:

$$\Delta Y = \Delta Y^* \qquad (13)$$

$$I = k\,\Delta Y^* \qquad (14)$$

$$X = X^* \qquad (15)$$

$$Z = mY \qquad (16)$$

According to Alemayehu and Daniel (2005),ESPD-ECA(2005) and Jerome(2004), the Bank programming and projections primarily focus on real rather than monetary variables. The projections on investment and savings are generally a planning aid to target the level of growth in the economy. Given the savings constraint of most developing countries, foreign financing is estimated to finance investment level that is consistent in achieving the targeted level of economic growth. It is this frame work which is currently in use in many African countries though critics doubt the realism of this frame work(Alemayehu and Daniel,2005). OECD (2003) noted that the focus on real variables completely occludes the monetary side of the economy. There is no public finance, hence no link between government deficit and potential inflation which may result when the government deficit is financed through money creation. Qualitative results may differ, depending on the choice of the closure. Furthermore, the supply is not modeled. The standard RMSM also relies on neoclassical equations assuming that equilibria solve instantly through flexible prices, without modeling any of the structural rigidity that is crucial in developing countries.

2.3 The International Monetary Fund (IMF) Financial Programming Model

The IMF approach to economic stabilization (generally referred to as financial programming) is based on the models designed in the 1950s and 1960s by J. J. Polak. The theoretical foundations of financial programming have remained largely unchanged in the last 40 years. The model is utilized by the IMF in line with its mandate of ensuring a stable world economy in financing temporary balance of payments (BOP) disequilibria (World Bank, 1997). It has constituted the backbone of analysis of IMF conditionality, the policy actions that a borrowing country agrees to implement as a precondition for receiving IMF credit (Polak, 1997).

Financial programming is an accounting framework that integrates a system of accounts, including national income and expenditure, current and capital accounts of the BOP, accounts of the central bank, the banking system and the government (Grcic, 2005). These accounts are all integrated into the flow of funds account and the monetary survey of the central bank. Consequently, the basic structure of the IMF programs is built on a financial analysis that ensures consistency between the impact of proposed policy measures and the desired BOP outcome (IMF, 1987).

The financial programming framework links the financial sector with the BOP as illustrated by the following identities (Bolnick, 1990; W.S.Ho, 2005):

$Y = GDP - NF$ (1)

$$GDP = C + I + (X - Z) \qquad (2)$$

$$DA = C + I \qquad (3)$$

$$CA = X - Z - NF \qquad (4)$$

Where,

Y = national income,

DA = domestic absorption,

CA = the balance on current account of BOP, and

NF = net factor payments to abroad.

The substitution of [2-4] into [1] gives the following identity;

$$Y = C + I + (X-Z) - NF \Rightarrow Y = C + I + (X-Z)-NF \Rightarrow Y = DA + CA,$$

Thus,

$$CA = Y - DA \qquad (5)$$

This implies that the current account deficit is equal to the difference between national income and domestic absorption. By implication, the current account shows a surplus if income is greater than domestic absorption and a deficit in the reverse case. Thus, a current account deficit can be reduced by a decline in absorption (relative to income) or by an increase in income (relative to absorption). Similarly, a change in reserves will be equal to the current account balance plus any net inflows of foreign capital (ΔFI) (W.S.Ho, 2005; Polak, 1997).

$$\Delta R = CA + \Delta FI \qquad (6)$$

Where,

ΔR = the change in net foreign assets of the banking system, and

ΔFI = the change in the net inflow of foreign capital.

Combining equations [5] and [6], one obtains,

$$\Delta R = Y - DA + \Delta FI \qquad (7)$$

Equation (7) indicates the excess of domestic absorption over income not financed entirely by foreign borrowing, leading to a rundown of net foreign assets. Since the stock of such assets is limited in developing countries, the financing of domestic absorption in this manner is greatly limited. Demand management policies directly influence domestic absorption and thereby the internal balance which refers to the conformity between aggregate expenditure (equal to absorption plus exports minus imports) and potential output at stable prices.

From the monetary balance identity:

$$\Delta M = \Delta R + \Delta DC \qquad (8)$$

Equation (8) shows a balance sheet relationship for the banking system, where the change in domestic money stock is equal to the sum of changes in foreign and domestic assets. It also assumes that money demand is a function of income, prices and the opportunity costs of holding money, which takes the form:

$$\Delta M\mu = f(\Delta Y, \Delta P) \qquad (9)$$

Rearranging to relate the change in nominal money ($M\mu$) to changes in nominal income (ΔY):

$$\Delta M\mu = k\,\Delta Y, \qquad (10)$$

Where,

k = the inverse of the income velocity of money.

Equilibrium condition in the money market is:

$$\Delta M\mu = \Delta M \qquad (11)$$

Hence, equations [9], [10] and [11] can be combined to relate the change in net foreign assets, in which BOP is given by the difference between the change in money stock (equal to $\Delta M\mu$) and the change in domestic credit (Tarp, 1993; Polak, 1997).

$$\Delta R = \Delta M - \Delta DC = f(\Delta y, \Delta P, \ldots) - \Delta DC \qquad (12)$$

Thus, a change in net foreign assets will be positive (BOP surplus) to the extent that the change in the total money stock exceeds the change in domestic credit. Real income is treated as exogenous (Polak, 1997). In the design of the IMF programs, the implications of policies for both output and the price level are analyzed carefully and output and inflation targets are major factors in deciding upon the policy package (W.S.Ho, 2005).

Equation [5] indicates the gap between income and domestic absorption, which is equal to the current account. The current account must be matched by the change in net foreign assets which is also equal to the difference between the change in the money supply and the change in domestic credit from the balance of the banking system (Polak, 1997).

Combining the equation gives:

$$CA + \Delta FI = \Delta M - \Delta DC \qquad (13)$$

Substituting equation [6] into the equation gives:

$$Y - DA + \Delta FI = \Delta M - \Delta DC \qquad (14)$$

Given the overall financial programming framework, the relationship between changes in net foreign assets and changes in domestic credit can be used in the design of a financial program. The IMF uses expenditure switching or/and expenditure reducing policies to bring about a favorable BOP outcome.

Devaluation is the main policy instrument to initiate expenditure switching policies, to change the composition of foreign and domestic expenditure between foreign and domestic goods (Jerome, 2004). In addition, fund uses growth oriented finanical programing model developed by chand (1989) to calculate the expected growth rate, which relates expected growth, ICOR and investment level like used by the bank.

But the fund models rely on simplifying assumptions which has earned its severe criticisms, given the influence of the IMF policy advice in the developing economies (Taylor 1983, and Tarp 1993). Balance of payment sustainability is not an objective in its own right, and the focus on monetary issues precludes the modeling of the material balance. The choice of the closure rule depends on assumptions that may not reflect the real world occurrence. For instance, government deficit and revenue are exogenous, leading public consumption to adjust. Such an assumption outlines the IMF emphasis on expenditure cuts rather than revenue increase. Furthermore, the model relies on neoclassical equations assuming that equilibria solve instantly through flexible prices, without any of the structural rigidities that are crucial in developing countries.

2.4 Limitations of the ICOR based models

Though the ICOR and gap based approaches are the building blocks of the international financial institutions macro framework for African countries, this approach has serious limitations. Easterly (1997) discussed the theoretical and empirical failures of the approach. According to Easterly, first, as the inventor of the model, Domar, admitted, the proportionality assumption of production capacity and capital stock is unrealistic. Second, the purpose of Domar's work was to comment upon the debate on business cycle as opposed to derive empirically meaningful growth rates. Third, by assuming that output is only proportional to the stock of capital the approach imposes that human capital does not contribute for growth.

On the empirical ground, Easterly (1997) showed that the basic link that aid promotes investment has a very weak empirical support. It is only on 19% of his sample countries that aid has a positive and significant effect on investment while it has a negative and significant coefficient on

41% of the same sample. Moreover, the regression result of the two gap model is not satisfactory. While the mis_specified model that suppresses the constant produces an ICOR value of 5.35, the model with the constant gave an unrealistic ICOR value ranging from 26 to 277. The basic assumption that investment is important for short run growth is not also empirically supported. In a nutshell, notwithstanding the wide use of the ICOR based models in many developing countries including many in Africa, they are flawed both theoretically and empirically. This necessitates a different modeling framework that can capture the salient features of the economies under consideration.

2.5 PRSP and MTEF

At their September 1999 annual meetings, the Bank and Fund lined up behind a proposal that "country-owned" poverty reduction strategies should form the basis for all Bank and Fund concessional lending. These strategies would take the form of papers called Poverty Reduction Strategy Papers. Hence was born the PRSP process (Levinsohn, 2002).

The process was essentially a way to implement a set of principles the Bank had earlier adopted. These principles were called the Comprehensive Development Framework or Medium Term Expenditure Framework. The relationship between the Comprehensive Development Framework and the PRSP process is confusing, but it is probably appropriate to think of the Framework as the destination and the PRSP as the route selected.

In time, the plan is that every country receiving what is called HIPC (highly indebted poor country) relief and all countries making use of the IMF's Poverty Reduction and Growth Facility will need to author a PRSP that must then be approved by the boards of the Bank and Fund (World Bank, 2002).The expectation is that eventually about 70 low-income countries will be expected to prepare PRSPs. Clearly, the process is going to be pervasive and will not be restricted to only the most troubled or very poorest economies.

The Bank and Fund have gone to some pains to emphasize that there is not a single template for a PRSP. Rather, each nation's PRSP is expected to follow the following five principles (World Bank, 2001):

PRSP's should be:

- Country-driven and owned, based on broad based participatory processes for formulation, implementation and outcome-based monitoring
- Results-oriented, focusing on outcomes that would benefit the poor
- Comprehensive in scope, recognizing the multidimensional nature of the causes of poverty and measures to attack it
- Partnership-oriented, providing a basis for the active, coordinated participation of development partners (bilateral, multilateral, non-governmental) in supporting country strategies
- based on a medium and long term perspective for poverty reduction, recognizing that sustained poverty reduction cannot be achieved overnight.

A medium-term expenditure framework (MTEF) or some times called Comprehensive Development Framework consists of a top-down estimate of aggregate resources available for public expenditure consistent with macro-economic stability; bottom-up estimates of the cost of carrying out policies, both existing and new; and a framework that reconciles these costs with aggregate resources. It is called "medium-term" because it provides data on a prospective basis, for the budget year (n+1) and for following years (n+2 and n+3) (Levinsohn, 2002).

MTEF is a rolling process repeated every year and aims at reducing the imbalance between what is affordable and what is demanded by line ministries (World Bank, 1999). MTEF does this by bringing together policy-making, planning, and budgeting early in the budgeting cycle, with adjustments taking place through policy changes. It involves building domestic macro-economic and sector modeling capacity. Also, even if the whole of the Government's budgeting system is not working well, each sector is better off managing itself with a medium-term perspective. A ccording to Holves and Evans (2003) a well implemented MTEF should:

(i) link the Government's priorities with a budget within a sustainable spending envelope;

(ii) highlight the tradeoffs between the competing objectives of the Government;

(iii) links budgets with the policy choices made, and

(iv) improve outcomes by increasing transparency, accountability, and the predictability of funding

According to Manuel(2005),seven major requirements must be considered for MTEF implementation:

- Good Macro-economic Policies: Good macro-economic analysis and forecasts are needed as a basis for a MTEF.
- Adaptable Fiscal Policy and Instruments: The MTEF approach is based on a strong link between macro-economic policy and fiscal policy. Plans for future expenditure must be based on reasonable estimates of prospective resources.
- Reprioritization and Reallocation: Behind the move to MTEF is a conviction that the annual budget by itself is a poor mechanism for shifting resources from lower-to higher priority use. A major function of an MTEF is to provide a better mechanism for aligning
- Budgetary Discipline: Budget allocations must be based on a hard aggregate budget constraint derived from what is affordable, and line ministries must live with their budget allocations.

- Institutional Conformity and Absence of Bias: An MTEF requires a supportive institutional base; that is to say, one in which the various actors use the MTEF as a framework within which are taken expenditure decisions. In particular, political decision makers must accept the MTEF as the means by which resources are allocated.
- Appropriate Parameters: Designing an MTEF requires that its parameters be set. These parameters are the definition of aggregate expenditure to be used, the relationship between the sectoral breakdown and the organizational structure of government, the content of expenditure envelopes, the appropriate price basis for estimating future expenditures, the mechanism for its coordination with the annual budget process, and the degree to which it is to be flexed for different scenarios.
- Transparency: Fiscal transparency and policy transparency improve the accountability of actors engaged in the MTEF process. Fiscal transparency means being open to the public about the structure and functions of government, fiscal policy intentions, public sector accounts, and fiscal projections. Policy transparency means being open to the public about what Government intentions are in a particular policy area, which outcomes are to be achieved, and the costs of achieving these outcomes. Also, transparency means reporting actual performance with quality of outputs and results achieved.

It is highly probable that for years to come, policy making and preparation of budget in most African countries (including Ethiopia) will thus be based on the preparation of PRSPs. This in turn will be closely tied with the preparation of the Medium Term Expenditure Framework (MTEF) which is considered as a vehicle for realization of the former. Both the realization of PRSP and the use of MTEF require an overall macroeconomic framework that ensures consistency in defining the aggregate resource envelop and how it is going to be spent. It also needs forecasting of major macro variables three to four years ahead.

2.6 Macro forecasting practice in Ethiopia

In the aforementioned sections, we have seen the two gap model and its variants are widely used in macro forecasting in Africa and other developing countries. In the case of Ethiopia there are two responsible institutions to prepare macro forecasting for the country: the ministry of finance and economic development(MoFED) and the National Bank of Ethiopia(NBE). The former is concerned with the fiscal frame work where as the later with the monetary part.

The researcher has tried to get the forecasting methods of these two institutions and the results are the Ministry of Finance and Economic Development used informal methods of forecasting / doesn't have formal ways of forecasting techniques. The national bank of Ethiopia(NBE) is yet preparing a macro forecasting frame work and does not have an officialized one.

Another body that is responsible in collecting, organizing, analysing and estimating various data sets in the country including the agriculture sector is the Central Statistics Authority. It used design based method to forecast future agricultural production. It does not have model based forecasting frame work. Given the focus of this study on Agriculture,which constitutes a significant part of the GDP and where forecast is the most difficult one, we will focus on that in the rest of this section.

According to the central statistics publication report 2009 the following formulas are used to estimate total area of land under specific crop,production and yield of specific crop in stratum.

1. Estimating total area of land under specific crop:

To estimate total area under specific crop

$$\hat{A}h = \sum_{i=1}^{n_h} W_{hi} \sum_{j=1}^{h_{hi}} a_{hij} = \sum_{i=1}^{n_h} W_{hi}\, a_{hi} \qquad \textbf{(1)}$$

In which $W_{hi} = \frac{M_h\, H_{hi}}{n_h m_{hi}\, h_{hi}}$

Where:

h represents the stratum

n_h is the total number of sample EAs(Enumerating Areas) successfully covered in the hth stratum

M_h is the measure of size of the hth stratum as obtained from the sampling frame.

m_{hi} is the measure of size of the ith sample EA in the hth stratum obtained from the sampling frame

H_{hi} is the total number of agricultural house holds of the ith sample EA in the hth stratum

h_{hi} is the number of sample agricultural house holds successfully covered in the ith sample EA in the hth stratum

a_{hij} is the value of area for agricultural house holds j, in the ith EA in the hth stratum under a specific crop

a_{hi} is the sample total area under specific crop for EA i in stratum h

$\hat{A}h$ estimate of total area under specific crop in stratum h

2. Estimating total production under specific crop

$$\hat{p}h = \sum_{i-1}^{n_h} w_{hi}\, p_{hi} \qquad (2)$$

In which $p_{hi} = a_{hi} * \bar{Y}_{hi}$

Where, $\bar{Y}_{hi}=\frac{y_{hi}}{16C_{hi}}$ is average yield per square meter of a specific crop in the i^th EA in the h^th stratum

$\hat{p}h$ is estimate of total quantity of production of a specific crop in the h^th statum

y_{hi} is sample total quantity of production of a specific crop defined area of land for crop cutting of a crop in the i^th EA in the h^th stratum

p_{hi} is estimate of total quantity of production under specific crop for EA i in statum h

C_{hi} is the number of crop cutting of a specific crop in the i^th EA in the h^th statum

3. Estimating yield of a specific crop in a stratum h:

$$\bar{Y}_{h}=\frac{\hat{p}h}{\hat{A}h} \qquad (3)$$

4. Sampling Variance of Estimation

Sampling variance for the estimate of stratum total of area, production and yield for a specific crop are estimated by the following formulas. That is the dispersion of the estimate of the stratum total of area, production and yield for each crop from the average estimated value.

$$var(\hat{A}h) = (1-fh)\frac{n_h}{n_{h-1}}\sum_{i=1}^{n_h}\left(\hat{A}hi-\frac{\hat{A}h}{\hat{n}h}\right)^2+fh\sum_{i=1}^{n_h}(1-f_{hi})\left(\frac{h_{hi}}{h_{hi}-1}\right)\sum_{j=1}^{h_{hi}}\left(\hat{A}hij-\frac{\hat{A}hi}{h_{hi}}\right)2$$

$$var(\hat{p}h) = (1-fh)\frac{n_h}{n_{h-1}}\sum_{i=1}^{n_h}\left(\hat{p}hi-\frac{\hat{p}h}{\hat{n}h}\right)^2+fh\sum_{i=1}^{n_h}(1-f_{hi})\left(\frac{h_{hi}}{h_{hi}-1}\right)\sum_{j=1}^{h_{hi}}\left(\hat{p}hij-\frac{\hat{p}hi}{h_{hi}}\right)2$$

$$var(\hat{y}h) = \frac{1}{\hat{A}h2}\left[var(\hat{p}h)+\hat{y}h2var(\hat{A}h)-2\hat{y}hcov(\hat{p}h,\hat{A}h)\right] \qquad (4)$$

Where:

$$cov(\hat{p}h,\hat{A}h) = (1 - fh)\frac{n_h}{n_{h-1}}\sum_{i=1}^{n_h}\left(\hat{A}hi - \frac{\hat{A}h}{\hat{n}h}\right)\left(\hat{p}hi - \frac{\hat{p}h}{\hat{n}h}\right)$$

$$+ fh\sum_{i=1}^{n_h}(1 - f_{hi})\left(\frac{h_{hi}}{h_{hi} - 1}\right)\sum_{j=1}^{h_{hi}}\left(\hat{A}hij - \frac{\hat{A}hi}{\hat{n}hi}\right)\left(\hat{p}hij - \frac{\hat{p}hi}{h_{hi}}\right)$$

Where,

fh = average first stage probability of selection of Eas(Enumerating Areas) with in stratum h

$f_{hi=}\frac{h_{hi}}{h_{hi}}$ =average second stage probability of selection with in the ith sample EA in statum h.

$\hat{A}hi, \hat{p}hi$ are weighted total area and production, respectively of a specific crop in the ith EA and hth stratum

$\hat{A}hij, \hat{p}hij$ are weighted total area and production respectively from j^{th} agricultural house hold in the i^{th} EA and hth statum under a specific crop

Since all strata are independent, the total variance at regional and country level is computed by aggregating the result obtained at Zone/special Wereda level,i.e.

$var(\hat{A})$=$\sum_h^L var(\hat{A}h)$,$var(\hat{p})$= $var(\hat{p}h)$ and $var(\hat{y})$= $\sum_h^L(\hat{y}h)$ (5)

Where, L is the number of strata (zone/special wereda).

In estimating the sample variance by the above formula, selection of EAs within a startum is assumed to be within replacement. By so doing the variance estimate may be slightly over estimated but it greatly simplifies the estimation procedure.

5. Coefficient of variation(cv) of estimate

Coeffcient of variation (which measures the lack of uniformity in estimating among strata) in percentage of estimate of stratum total area, production and yield for a specific crop are given by:

$$cv(\hat{A}h) = \frac{\sqrt{var\,(\hat{A}h)}}{\hat{A}h}*100,\ cv(\hat{p}h)=\frac{\sqrt{var\,(\hat{p}h)}}{\hat{p}h}*100, v(\hat{y}h) = \frac{\sqrt{var\,(\hat{y}h)}}{\hat{y}h}*100 \quad (6)$$

6. Niety-five percent confidence interval(CI) of stratum total of area:

$$\hat{A}h \pm 1.96 * SE(\hat{A}h) \quad (7)$$

Where, $SE(\hat{A}h) = \sqrt{var(\hat{A}h)}$ is standard error of the estimate of the statum total of area.

Estimates of standard error and confidence interval for the other estimates can also be calculated by adopting the above formulas.

As can be seen from above, the formulas the authority used are naive in nature(simple averages) and could help only to decide whether or not the improvement in changing from simple methods to a sophisticated model is worth the time and cost, or could only be used as a bench mark. There fore, we should not stick to it to forecast future agricultural production as this method will not change direction (up or down) until after the actual data has shown the change. That is, predicitng future values using the information today couldn't be reliable as the above formulas contain only current information/lacks information or has little information set.

To sum up, it is the two gap model and its derivatives that is widely used in predicting the resource requirements of most developing and African countries. But it doesn't imply that all African countries used it properly or do have their own model to forecast the resource requirements except some countries like south Africa and Kenya(Alemayehu and Daniel,2005).

This arises from lack of skilled man power, low remuneration for professioanls who want to work in the respective ministry and other responsible bodies (Kibambe and Du Toit,2006), over time complexity of models developed by world Bank and IMF which are difficult to understand for unskilled experts(Mills and Nallari,1992). Even though in some countries there are weldefined macro forecasting models by intellectuals working in different institutions, there is unwillingness of the responsible organizations to apply these models. They prefer to use informal ways of forecasting different macro aggregates which creates disparity in the projections made by these countries and international organizations like IMF. This applies to Ethiopia as well because we always observe the problem mentioned. For instance, if we see the projections in 2009 for 2010, the government's report showed more than 10% growth in the Economy while the IMF showed 6.5%. This arises from the fact that IMF uses growth oriented models of financial programing which are related to two gap model and its derivative in forecasting(Chand,1989) while the responsible government officials use informal/designed based forecasting methods.

CHAPTER THREE

LITERATURE REVIEW

This chapter deals with the theoretical works related to types of forecasting techniques and empirical works that are related to univariate ARIMA (Box- Jenkins) forecasting technique in the first and second part of the chapter respectively.

3.1 Theoretical Literature

3.1.1 Univariate Forecasting Techiniques

A time series is a set of data connected in time with a definite ordering given by the sequence in which the observations occurred. The time ordering of the data matters a great deal since the moments of the distribution of a time-series variable often change through time.

A univariate time series model describes the behaviour of a variable interms of its own past values. These forecasting techinques are summarized in the sections to come.

3.1.1.1. Naive Forecasts

Naive forecasting is a quantitative tool that uses only historical data of the variable being forecasted in the analysis. It provides a convenient way to generate quick and easy forecasts for short time horizon, i.e., a month, a quarter, at most a year ahead. This method has minimal data requirement and is easy to implement since generally it requires only simple arithmetic to generate the forecast (Diebold, 1998). Moreover, Moore(1969) identified as if this method establishes the minimum level of accuracy that a set of forecasts should have.

This implies, its forecast will miss turning points as it is based only on recent actual values of the variable. Hence, the forecast will not change direction (up or down) until after the actual data has shown this change. The naive method generally expects the data to have no trend and if a trend is present in the data it will usually treat the trend as a linear one.

The forecast for the time series containing trend are generated according to the following formula:

$$\hat{x}_{t+1} = x_t + (x_t - x_{t-1}) \qquad (3.1)$$

This method helps to decide whether or not the improvement in changing from simple to sophisticated models is worth the time and cost as the forecasters should perform at least as well as the simplest time series models from which predictions could have been derived (Nelson,1972,1984). There fore, from 1970s on most researchers used it as an appropriate bench mark for time series models like ARIMA and VARs(Holden,1995). From this, we can infer that it should not be used as a separate forecasting model.

3.1.1.2. Exponential Smoothing

Exponential smoothing is a simple technique used to smooth and forecast a time series without the necessity of fiting a parametric model. It is based on a recursive computing scheme, where the forecasts are updated for each new incoming observation. Exponential smoothing is sometimes considered as a naive prediction method. Yet it is often used in practice where it shows good performance (Makridakis et al., 1998; Kotsialos et al., 2005). In this method the forecasted values are the weighted averages of past observations with heavier weights given to recent values and exponentially decreasing weights to earlier values. This technique has been successfully employed in practice to predict future values of many types of time series, such as price, sales, or inventory data. Exponential smoothing methods under some circumstances may be more complicated forecasting techniques. At the same time, on average it produces more reliable results than the naive forecast (Chatifeld, 1988).

The most basic method of exponential smoothing is the single exponential smoothing with one parameter. According to Eviews technical documentation, this method is appropriate for series that move randomly above and below a constant mean with no trend or seasonal pattern. The smoothed series $\hat{y}t$ of y_t is computed recursively by evaluating:

$$\hat{y}_t = \alpha y_t + (1-\alpha)\, y_{t-1} \qquad (3.2)$$

Where $0 \leq \alpha \leq 1$ is the damping or smoothing factor. The smaller is α, the smoother is the $\hat{y}t$ series. By repeated substitution, the recursion can be rewritten as:

$$\hat{y}_t = \alpha \sum_{s=0}^{t-1} (1-\alpha)^s\, y_{t-s} \qquad (3.3)$$

This shows why this method is called exponential smoothing –the forecast y is a weighted average of past values of $\hat{y}_t$, where weights decline exponentially with time. The forecasts from single smoothing are constant for all future observations. This constant is given by $\hat{y}_{t+k} = \hat{y}_t$ for all K>0 and where t is the end of the estimation sample.

To start the recursion, we need an initial value for $\hat{y}_t$ and a value for α. Eviews uses the mean of the initial observations of y_t to start the recursion or it can also estimate α minimizing the sum of squares of one-step forecast errors.

The other type of exponential smoothing is Holt-Winters non seasonal algorithm with two parameters. According to Fildes(1992),this method is appropriate for series with a linear time trend and no seasonal variation.

The smoothed series is given by

$$\hat{y}_{t+k} = a + b_k \tag{3.4}$$

Where a and b are the permanent component and trend.

These two coefficients are defined by the following recursions:

$$a_t = \alpha y_t + (1 - \alpha)(a_{t-1} + b_{t-1}) \tag{3.5}$$

$$b_t = \beta(a_t - a_{t-1}) + 1 - \beta b_{t-1} \tag{3.6}$$

Where 0<α; β,γ<1 are the damping factors. This is an exponential smoothing method with two parameters.

Forecasts are computed by:

$$\hat{y}_{t+k} = a_t + b_{tk} \tag{3.7}$$

These forecasts lie on a linear trend with intercept $a(t)$ and slope $b(t)$.

Finally, Holt-Winters additive algorithm with three parameters is often being utilized for series with a linear time trend and additive seasonal variation. The smoothed series is given by:

$$\hat{y}_{t+k} = a + b_k + c_{t+k} \tag{3.8}$$

Where a is a permanent component (intercept), b is a trend, and ct is additive seasonal factor.

These three coefficients are defined by the following recursions:

$$\begin{aligned} a_t &= \alpha y_t + (1 - \alpha)(a_{t-1} + b_{t-1}) \\ b_t &= \beta(a_t - a_{t-1}) + 1 - \beta b_{t-1} \\ c_t(t) &= \gamma(y_t - a_{t-1}) - \gamma ct_{(t-s)} \end{aligned} \tag{3.9}$$

Where 0<α; β, γ<1 are the damping factors and s is the seasonal frequency.

Forecasts are computed by:

$$\hat{y}_{t+k} = a_t + b_{tk} + c_{t+k-s} \tag{3.10}$$

Where the seasonal factors are used from last s estimates and t is a total number of observations in the sample. This method could be incorporated in ARIMA model which is to be discussed in the section to come.

3.1.1.3. ARIMA (BOX-JENKINS) PROCEDURE

According to Makridakis (1997), autoregressive (AR) models were first introduced by Yule in 1926 and subsequently supplemented by Slutsky, who in 1937 presented moving average (MA) process. Wold in 1938 combined both AR and MA and showed that ARMA processes can be used to model a large class of stationary time series. In other words, a time series y can be modeled as a combination of past y_t values and/or past u_t,

$$y_t = a_o + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_p y_{t-p} - u_1 b_{t-1} - b_2 u_{t-2} - \cdots - b_q u_{t-q} + u_t$$

(3.11)

$ut \approx \text{WN}\,(0,\delta^2)$

For autoregressive process (AR), current observation depends on the lagged observations which are also known as a *stochastic difference equation,* while moving average process (MA) observes random variable dependent on the lagged unobservable shocks (pankratz, 1983).

The implementation of the theoretical framework introduced by Wold became possible only in the late 1960s when the first computers, capable of performing all necessary calculations, appeared. In 1970, Box and Jenkins published a landmark book on time series analysis and forecasting and popularized the use of the ARIMA method.

They introduced the guidelines for making time series stationary; suggested autocorrelation and partial autocorrelation as a tool for determining the appropriate values of p and q; proposed to check the residuals for white noise to determine whether the model is adequate or not. This methodology became known as Box-Jenkins or ARIMA approach, where 'I' stands for 'integrated,' signifying that time series might need to be differenced to become stationary(Makridakis,1997; El-Mefleh,1999). This methodology consists of four steps: identification, estimation, diagnostic checking and forecasting.

Generally the frame work for Box_Jenkins approach could be shown as follows:

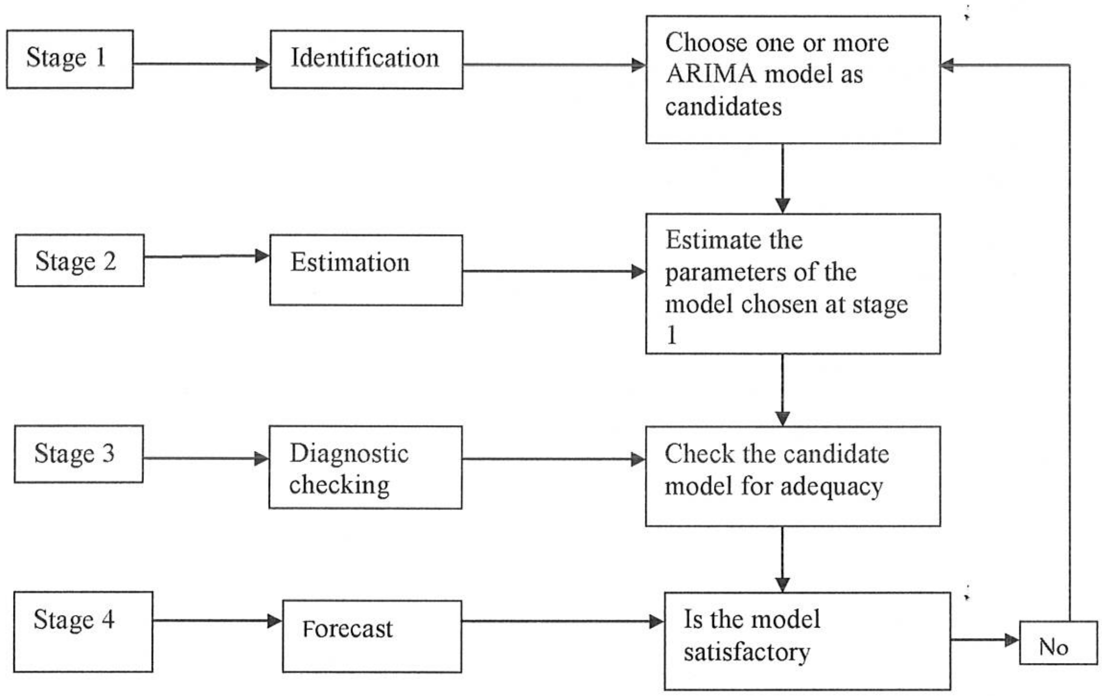


Fig 3.1: Box -Jenkins procedure

In the model identification stage, we use our judgment, the graphic representation and autocorrelation, as well as partial autocorrelations to identify a class of models representing the data.

Given a set of time series data, one can calculate the mean, variance, autocorrelation function (ACF), and partial autocorrelation function (PACF) of the time series. This calculation enables one to look at the estimated ACF and PACF which gives one an idea about the correlation between observations, indicating the sub-group of models to be entertained. This process is done by looking at the cutoffs in the AC and PACF. Judge (1985) points out that when the PACF has a cutoff at p while the ACF tails off, it gives us an autoregressive of order p (AR (p)). If the ACF has a cutoff at q while the PACF tapers off, it gives a moving-average of order q (MA (q)). However, when both ACF and PACF tail off, it suggests the use of the autoregressive moving-average of order p and q (ARMA (p, q)). Sometimes the ACF doesn't die out quickly, which may suggest that our stochastic process is non-stationary. This situation suggests the use of the ARIMA (p, d, q) to difference the data (d) times, once or twice, until stationarity is obtained.

Differencing is a relatively simple operation that involves calculating successive changes in the values of a data series, which helps to change the mean virtually to zero.

The autocorrelation coefficient (rk) of the time series is calculated for each set of order pairs as described in Chatfield (1985) in the following manner:

$$r_k = \sum_{t=1}^{n-k}(z_t - \bar{z})(z_{t+k} - \bar{z}) / \sum_{t=1}^{n}(z_t - \bar{z})^2 \qquad (3.12)$$

$$r_k = \sum_{t=1}^{n-k} wtw_{t+k} / \sum_{t=1}^{n-k} w_t{}^2$$

Where $w_t = z_t - \bar{z}$ and $-1 < r_k < +1$

Then if r_k = +1 it indicates a perfect positive correlation.

If r_k = -1 it indicates a perfect negative correlation.

If r_k = 0 it indicates no correlation at all.

By dividing the auto covariance, or what is called the Yule Walker equation, by the variance, we accomplish a standardized AC so their value is ensured to be between plus and minus one. When the mean is stationary, the estimated ACF drops out quickly to zero, otherwise the estimated ACF drop slowly toward zero.

The estimation of the PACF (Lii) does not deal only with pairs as does the ACF, but more than two variables at once. This is true except for the first PACF since no $w's$ fall between w_t and w_{t+1}: thus, we have$L11 = r1$. Pankratz (1983) stated that the best way to calculate the PACF is by the use of least-square regression technique to the following equations:

$wt + 1 = L11\, wt + ut + 1$ to calculate $L11$ for lag one.

$wt + 2 = L21\, wt + 1 + L22\, wt + ut + 2$ to calculate $L22$ for lag 2.

$wt + 3 = L31\, wt + 2 + L32\, wt + 1 + L33\, wt + ut + 3$ to calculate $L33$ for lag 3.

The above process continues until we estimate all the PACF.

Two statistical inferences could be used during the identification stage. One inference constitutes the AC coefficients; the other is the PAC coefficients. Bartlett's approximation helps to test the AC coeffcients to compute the standard error of the estimated AC s (rk) defined as:

$s(rk) = n^{-.5} (1 + 2 \sum_{j=1}^{k-1} rj^2)^{.5}$ for j = 1, 2, ... n. (3.13)

Bartlett's approximation has been used by Box and Jenkins (1976), Anderson (1980), and Pankratz (1983). To calculate the standard error, the Ling and Roberts (1980) method of calculating the standard error of AC at lag j could be used, which decreases as j increases:

SE (j) = $((n - j)/n\,(n + 2))^{.5}$ (3.14)

where n is the number of observations.

After calculating the standard error of the AC, we test for the null hypothesis that the autocorrelation coefficient $rk = 0$ for all k by calculating the t-statistics: $t_r = r_k / \sum r_k$

If the calculated t-statistics are more than those in the table, we reject the null hypothesis. Sometimes the calculated t-statistics for the estimated AC coefficients have an absolute value greater than 1.6 for the first five lags. This situation indicates the series may not be stationary and needs differencing (Pankratz, 1983).

The other statistical inference used in the identification stage is the test for the significance of the PAC coefficients. This test is easily done, since the standard error of the PAC coefficients is the same for all coefficients which are equal to $n^{-.5}$. We then use the standard error of the PAC coefficient to test for the null hypothesis that $Lkk = 0$ for all k. The null hypothesis is rejected if the calculated t-statistics are larger than those of the t-value of the table (Anderson, 1980).

Another important concept that we have to know in the Box-Jenkins identification stage is stationarity of the variables or the variables should have to be stationary to use this procedure. Greenberg and Webster (1983), Box (1976), Anderson (1976), Judge (1985), Chatfield (1985), and Pankratz (1983) point out that for the process to be strictly stationary, the joint distribution function describing the process must be invariant with respect to time,

Where

$$F\ (z_t, \ldots, z_{t+k}) = F(z_{t+s}, \ldots, z_{t+s+k}) \qquad (3.15)$$

for all s and all k.

This strong stationarity condition implies that the mean, variance, and covariance are constant. However, in economic applications only weak stationarity (second-order stationarity) is required where the mean and the variance are constant and

$E(z_t) = E(z_s) <$ infinity for all s and all t.

$E(z_t, z_{t+k}) = E(z_{t+s}, z_{t+s+k}) <$ infinity for all s, t, and k.

$Var(z_t) <$ infinity (3.16)

Most economic data increase over time, which makes the mean of the economic time series change over time, producing a non-stationary time series. This situation necessitates the transformation of a non-stationary time series to a stationary one by using the differencing principle which in most cases we do not need to use more than once to achieve stationarity. When stationarity is achieved after differencing, the mean become constant but the variance is the same as before. Pankratz (1983) warned about differencing the data more than necessary to achieve a stationary mean, because it not only creates an artificial pattern in the data but also tends to reduce the forecast accuracy in practice. One determines the number of times of differencing required by first examining the data visually to see if it has a trend and then by checking the estimated coefficient of the ARIMA model at the estimation stage to see if the coefficients satisfy the stationarity condition. The first difference is needed most frequently if the level of the variable changes over time; a second difference is needed only if the level and slope change over time. In most cases concerning economic data, not only the mean changes over time, but also the variance changes. Such a series must be transformed to have a constant variance. One obtains a constant mean by differencing once, but since the variance does not change, it is necessary to use a logarithmic transformation to reach a stationary variance.

After choosing one or more candidate models in the identification stage of Box-Jenkins procedure we go for estimation of the models.

According to Pankratz(1983),estimation of the ARIMA parameters is carried out by using an iterative nonlinear least-squares procedure, which gives the value of the coefficients, and produces the smallest sum of the square residuals (SSR). The nonlinear least square estimation can be accomplished in three different ways: (1) the grid search method, which tries all possible values of the coefficient to find the smallest SSR, (2) the algorithmic approach, which converges quickly to the least square residual, (3) Marquardt's compromise, which is the most efficient method of estimation. Marquardt's method is a combination of two nonlinear least square procedures. These two nonlinear procedures are the Gauss-Newton linearization and the Gradient method.

The Marquardt method works by taking the initial values for the coefficients from the identification stage, and then by selecting a corrected new coefficient to produce the smallest some of residuals (SSR). This process of correcting the coefficients continues until the processes achieve the smallest SSR possible.

To evaluate the estimated ARIMA model, one has to consider parsimony, stationarity, invertibility, and coefficient quality. Box and Jenkins (1976), Anderson (1980), and Pankratz (1983) emphasize the principle of parsimony, where they use the smallest number of coefficients to fit the available data adequately, because parsimonious models generally produce better forecasts. Through parsimony we also avoid coefficient near-redundancy.

A good autoregressive model of order p (AR (p)) has to be stationary, and a good moving average model of order q (MA (q)) has to be invertible. Invertibility and stationarity will give a constant mean, variance, and covariance.

Anderson (1976), Chatfield (1984), and Judge (1985) pointed out that by using what is called Wold's decomposition it is possible to show that the AR and MA processes are equivalent, thus causing one to expect that whenever a low-order-model of one type adequately explains a series, so should a higher-order-model of the other. This expectation is valid only if the sum of the coefficients is less than one. Nevertheless, the principle of parsimony requires the model builder to choose the low-order-model, where the smallest possible number of parameters is employed for adequate representation.

Finally, quality of the coefficients has to meet two requirements. They must be statistically significant, and the correlation between the coefficients must be less than 0.9(Pankratz, 1983). The estimated ARIMA model has to have a significant t-statistic for each coefficient of the estimated model. The correlation matrix measures the correlation between the estimated coefficients. The coefficients of the ARIMA model are correlated. However, if the absolute correlation coefficient between the two estimated ARIMA coefficients is 0.9 or more, such a coefficient value may suggest that the estimated coefficients are unstable and of poor quality. Under this condition the estimate could be inappropriate for future time periods, unless the behavior of future observations is the same as the behavior of a given realization.

After the model has been identified and the parameters have been estimated, the diagnostic checks should be applied to the model to see if the model is adequate. According to Pankratz(1983), four major criteria will be used to check each model for inadequacies so that any necessary revisions needed may be made. First, we need to check the independence of the random shock. An adequate model has statistically independent random shock. This condition is necessary because if the random shocks are correlated, then there is an autocorrelation pattern in the data that has not been captured in the model, and one should search for another model that satisfies the independence assumption of the residual. The way to test for independence in the residual shock is to test the estimate of the residual of the model at the estimation stage and then to look at the residual ACF to be sure that it has insignificant t-statistical autocorrelation coefficients. This important evidence demonstrates that it is not possible to improve upon the model. The residual ACF is calculated in the following way:

$$rk(a)= \sum_{T=1}^{n-k}(at-\bar{a})\,(at+k-\ \bar{a})/\sum_{t=1}^{n}(at-\bar{a})^2 \qquad (3.17)$$

The second check is the use of the over fit model. This method is appropriate if the initial ACF and PACF do not clearly give us the appropriate model. This method adds another coefficient to the model to see whether the t-statistics for the added coefficient are or are not significant. If the t-statistics are significant, one has to revise the model. Also one should avoid redundancy in the model by not adding one factor simultaneously to the p and the q of ARIMA model, because that would lead to extreme parameter instability. If the values of both the estimated parameters and variance are not significantly different between the two models, then the over fit model is not justified. When the parameters are not significantly different between the perceived correct one and the over fit model, but have significantly different variances, then one takes the estimate with the lower variance.

The third check is performed by evaluating the forecasting performance of the model. This is done by using the residual mean square statistics (RMSS) which is equal to

RMSS = $(\sum_{t=1}^{n} {a_t}^2)^{.5/n}$, where n is the number of the observation used in the estimation.

Schofield, Satchell, Chatterji, and Whiteley (1986) advocated the use of the RMSS in time series analyses as a measure of the goodness of fit of a model rather than the more familiar R-square statistic. It is appropriate because one could have an equal R-square for two models even though they have different RMSS's which is due to the different variability of the residuals. Since the

RMSS is not standardized, one cannot compare RMSS across different variables. Nevertheless, it is helpful when it is used as a comparison across different models for a given variable.

The fourth check is another statistical test called Chi square test (Q) or Box-Pierce test, which is based upon the autocorrelation function of the residual in the following manner:

$$Q = n(n + 2) \sum_{k=1}^{k} (n - k)^{-1} r_k^{\,2}(a) \quad \text{for small sample} \tag{3.18}$$

$$Q = n \sum_{k=1}^{k} r_k^{\,2}(\mathrm{a}) \qquad \text{for large sample.}$$

Where Q is distributed as Chi square with k-m degrees of freedom, k is the number of residual autocorrelations, n is the number of observations used to estimate the model, m is the number of the parameters estimated in ARIMA model. Chi-square is a device to test for a joint null hypothesis on the correlations among the random shocks, where the null hypothesis is

$$r_1(a) = r_2(a) = \cdots = r_k(a) = 0 \tag{3.19}$$

If the residual AC's as a set are significantly different from zero, then the random shocks of the estimated model are probably correlated and one has to revise the model. The rejection of the null hypothesis implies that the residual contains systematic information not incorporated in the model.

Nazem (1988) and Andersen (1984) mentioned that the Box-Pierce statistics have been criticized because its distribution may not be a Chi square distribution. On the other hand, Greenberg (1983) and Pankratz (1983) recommend other diagnostic checks such as the examination of the residual plot to see if it shows any pattern that can be accommodated.

After the estimated time series model has been scrutinized through all diagnostic checks, the model will be used for forecasting.

3.1.2 Forecasting with Regression

In addition to the univariate forecasting, forecasting with regression is the other popular method of forecasting. The regression can take a single or multi equation format, where the choice depends on the problem at hand and the feasibility for forecasting. In this section, forecasting using single equation and multi equation forecasting models will be discussed.

3.1.2.1 Single Equation Forecasting Models

The single equation model is the very basic forecasting frame work. The models can be

$$y_t = \alpha + \beta x_t + \varepsilon_t \qquad (3.20)$$

Where y is the endogenous variable, x is the exogenous variable and ε_t is the random error term. The simple model can be estimated by OLS or two stage least squares if we have an endogenous regressor. The equation can also be reformulated in to an error correction format if there is non stationarity in the variables. Once the coefficients of the model are obtained, the future values of the endogenous variable(y) can be forecasted. The problem in this approach is that inorder to obtain the forecasted value of the endogenous variable,we have to supply the future values of the exogenous(x) which inturn necessitates forecasting the x values. In such a case that exogenous variables can be forecasted in a univariate frame work like ARIMA model as mentioned in the section above. The forecasted values of the exogenous variable from the univariate model can then be used, along with the estimated coefficients, to compute the forecasted values of the endogenous variable(Alemayehu et al.,2009).

The task of forecasting the exogenous variable in a univariate frame work inorder to forecast the values of the endogenous variable can be avoided if our interest is to forecast only one period ahead. In this case the above equation could be re-specified using lagged value of the exogenous variable as a regressor:

$$y_t = \alpha + \beta x_{t-1} + \varepsilon_t \qquad (3.21)$$

In this formulation a one period ahead value of the endogenous variable can be forecasted using the current value of the exogenous variable.

3.1.2.2 Multiple Equation Forecasting Models

Multiple equation forecasting models can take two forms-structural equations forecasting model and vector autoregression models(Alemayehu et al.,2009). In the first case, we can have a set of individual structural equations that describe some behavioral relationshps. These individual equations can be estimated using single equation information estimation techniques(SEIE), limited information relating to the whole system(LISE), and full information estimation relating to the whole system techinque(FISE)(Challen and Hagger,1983). OLS, distributive lag class of models and ARIMA models can be classified as the single equation information technique,while 2SLS, instrumental variable estimation and limited information maximum likelihood(LIML) methods are classified as limited information relating to the whole system; and 3SLS and full information maximum likelihood (FIML) estimation techniques can be categorized as full information relating to the whole system (Alemayehu et al.,2009).

As their name indicates,the main difference of these techniques is on the information content of the estimator. The other important distinction of these methods is that single equation and limited information estimation techniques involve estimation of the stochastic equations one at a time while in the full information estimation all the stochastic equations are estimated simultaneously.

Once the individual equations are estimated, the next step is to solve the model,i.e, solving for the value of the endogenous variables given the values of exogenous variables. This enables us to examine the fit of the model to the historical data since the fit of the individual equations does not guarantee a good fit in the system or in the complete. According to Challen and Hagger(1983), ít is possible that every stochastic equation of the system performs adequately on the basis of the individual equation evaluation procedures but that the system as a whole gives a poor representation of the real economy in which the historical time paths of the endogenous variables were generated'. This may be the result of a more complex dynamic structure in the model as a whole than any of the individual equation it is composed of (Oshikoya,1990).

Thus ,with-in-sample tracking performance of the whole system should be examined based on the standard statistical tools such as MSE,RMSE and Theil's index.

This method requires a sound theoretical specification,consistent accounting frame work and closure rules. Then we proceed to VAR forecasting technique.

VAR is the multivariate counterpart of the univariate autoregression frame work. As opposed to the univariate model, VAR allows for cross variable dynamics. The VAR model is also important when we are not sure about the endogenous-exogenous classification(i.e,.the theoretical relationships of the variables. In this approach all the variables are treated as endogenous(Verbeek,2004).A first order VAR would be given by:

$$y_t = \delta_1 + \theta_{11} y_{t-1} + \theta_{12} x_{t-1} + \varepsilon_{1t}$$

$$x_t = \delta_2 + \theta_{21} y_{t-1} + \theta_{22} x_{t-1} + \varepsilon_{2t} \qquad (3.22)$$

Where $\varepsilon 1t$ and $\varepsilon 2t$ are two white noise processes(independent of the history of Y and X) that may be correlated. If, for example, $\theta 12 \neq 0$ it means that the history of X helps explaining Y. The systems above can be written as

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix} + \begin{pmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \quad (3.23)$$

Or,with appropriate definitions,as

$\vec{y}_t = \delta + \Theta_1 \vec{y}_{t-1} + \vec{\varepsilon}_t$

Where $\vec{y}_t = \delta + \Theta_1 \vec{y}_{t-1} + \cdots + \Theta_p \vec{y}_{t-p} + \vec{\varepsilon}_t$

Where each Θj is a k×k matrix and $\vec{\varepsilon} t$ a k-dimensional vector of white noise terms with covariance matrix $\sum$. As in the univariate case, we can use the lag operator to define a matrix lag polynomial

$\Theta(L) = I_k - \Theta 1 \ldots - \Theta_p L^p$,

Where I_k is the k-dimensional identity matrix, so that we can write the VAR as

$\Theta(L)\vec{y}t = \delta + \vec{\varepsilon}t$

The matrix lag polynomial is a k×k matrix where each element corresponds to a p-th order polynomial in L. Extensions to vectorial ARMA(VARMA) models can be obtained by premultiplying $\vec{\varepsilon}$t with a (matrix) lag polynomial.

The VAR model implies univariate ARMA models for each of its components. The advantages of considering the components simultaneously include that the model may be more parsimonious and includes fewer lags, and that more accurate forecasting is possible, because the information set is extended to also include the history of the other variables. From a different perspective, Sims(1980) has advocated the use of VAR models instead of structural simultaneous equations models because the distinction between endogenous and exogenous variable does not have to be made a priori, and 'arbitrary' constraints to ensure identification are not required(Canova,1995).

Having seen the different types of forecasting techinques, lets compare the univariate forecasting techinques so that we can have an idea of the better one for the intended purpose.

Advantages and disadvantages of forecasting techniques(summary of univariate forecasting techinques)

Model and author	Strength	weakness
Naive (Makridakis,1998;Wheelwright and Hyndman,1998;Newbold and Buss,1994;Diebold,1998)	-Inexpensive to develop, store data and operate, Easiest method, low cost, work well when random errors are small, develop quick and easy forecasts for short time horizon, used as a bench mark for sophisticated models	-results in highly variable forecast if the random errors are large, does not consider any possible casual relation ships that underlie the forecasted variable, miss turning points
Exponential smoothing(Winter,1960; Chow,1965; Peng et al., 2008; Whybark,1972)	- data storage and computing requirements are minimal,simple, intuitive and easily understood, to some extent controls for random error	- not applicable when trend exists, the level of time series should fluctuate about a constant level or change slowly over time
ARIMA(Newbold and Granger,1974; Reid,1975; Dacrymple,1978; Chatifled,1978; Chatfield and Prothero,1973;Brown,1959; Pankratz,1983)	-Optimality and comprehensiveness of the family of models, flexible, provide short run forecaste for large data precisely, logical and statistically accurate, extract a great deal of information from the historical time series data and it is parsimonious	-identification is difficult and time consuming, requires a great number of data, no simple method of adjustment of parameters of ARIMA models when new information is attracted, a model has to be almost fully reconstructed

According to Brown(1959), ARIMA models are generalizations of the exponential smoothing techniques. And they are generally good for forecasting even though regression and VAR approaches incorporate both forecasting and analysis(Pankratz,1983). There fore, there seems to be a general agreement among knowldgeable professionals that properly built Univariate Box-Jenkins models can handle a wide variety of situations and provide more accurate short term forecasts than any other standard single-series techniques, this suffices the objective of the paper.

3.2 Empirical Literature on Box- Jenkins (ARIMA) Methodology

There are several studies concerning forecasting and modeling using Box-Jenkins (ARIMA) techniques.

The models help to forecast the production of sugar cane crop in Pakistan for the years 1989-90 onwards. This enables the policy makers to foresee the future requirements of sugar cane, imports and/or export of sugar cane there by enabling them to take appropriate measures in this regard. The forecasts would thus help save much of the precious resources of their country, which otherwise may be wasted. (muhammad et al.,(1992). In addition, Granger and Newbold (1972) showed that Box-Jenkins methodology gives better forecasts than both Holt_Winters and step wise auto regression.

From forecasting shrimp and frozen food export earnings of Bangladesh using ARIMA model by Haque et al.,(2006), Box-Jenkins type autoregressive integrated moving average(ARIMA) and deterministic type growth models are examined to identify the best forecasting models for shrimp and frozen food export earning of Bangladesh. Among the deterministic type models, the quadratic model is best for both the series. The study also revealed that the ARIMA model is more efficient for short term forecasting than the quadratic model

Cleary and Levenbash(1982), Anderson(1980), Pankratz(1983) showed that the Box-Jenkins approach is a powerful and flexible method for short term forecasting as ARIMA models place more emphasis on the recent past and where structural shifts occur gradually, rather than suddenly. This makes the ARIMA models especially valuable when we are dealing with economic time series data. This emphasis on the recent past makes long term forecasts less reliable due to accumulation of error terms.

Hamid et al. (1987), Muhammad (1989) and Younis (1995) used ARIMA models forecasting wheat area and production in Pakistan. They all got ARIMA as best to see the prospects for continued growth in the area and yield of wheat and others in Pakistan.

Similarily,Qureshi et al. (1992) used this method to see the contribution of area and yield to total production of wheat and maize in Pakistan where they got more than 100% increase in total wheat production that can be attributed yield enhancement.

M.Sabry and H.Abd(2002) concluded that the ARIMA model is the best forecasting method especially for the average monthly and weekly daily traffic volume on comparison between regression and ARIMA models in forecasting Traffic volume. The study showed that the Box-Jenkins (1994) is the method providing best forecasts for the majority of the series tested.

Rangsan et al., (2006) used ARIMA model for forecasting three types of oil palm price by considering the minimum of mean absolute percentage error (MAPE). The results of forecasting were ARIMA model for forecasting farm price of oil palm is ARIMA(2,1,0), for whole sale price of oil palm ARIMA(1,0,1) and for pure oil price is ARIMA(3,0,0) or AR(3).

According to Ion Dobre and Andria(2008) on modeling the evolution of unemployment rate using the Box-Jenkins methodology during the period 1998-2007 monthly data, the most adequate model for the unemployment rate is ARIMA(2,1,2). Using the model, they forecasted the values of unemployment rate for January and February and got 4.06% for January 2008.

Nadeem Saeed et al., (2000) tried to see use of ARIMA models in forecasting of wheat production in Pakistan. The paper described an empirical study of modeling and forecasting time series data of wheat production in Pakistan. The Box-Jenkins ARIMA methodology has been used for forecasting. The diagnostic checking has shown that ARIMA (2, 2, 1) is appropriate.

The forecasts from 1998-99 to 2012-13 are calculated based on the selected model. Those forecasts would be helpful for the policy makers to foresee ahead of time the future requirements of grain storage import and/or export and adopt appropriate measures in this regard.

Indira Rajarama and Arindam Datta(2003) on univariate forecasting of state level agriculture: the drought of 2002 has brought home the critical need for a short-term forecasting model for agriculture sector at sub-national level, as good and bad agricultural years are not synchronous across states. So that the paper attempted forecasting through the fitting of univariate ARIMA models to past agricultural out comes for five states.

Ibrahim and Totsuki (1976) proved the Box-Jenkins method to be relatively easy to apply and extremely efficient in forecasting GNP. With a single logarithmic transformation, adequate models for all the series investigated were identified. The forecasting performance of these models relative to econometric and naive models was remarkable. Sample period simulations showed that the Box-Jenkins approach out performed each of the two econometric and the two naive models were used as bases for comparison. However, Green's mechanical constant adjustment improved the OBE model enough to put it on part with the Box-Jenkins approach. For post sample forecasts, the relative performance of the Box-Jenkins model is even better. It outperformed each of the two naive models as well as the two econometric models with and without Green's mechanical constant adjustment. This confirms earlier studies while indicated that the Box-Jenkins approach is more robust than econometric models.

From application of time series modeling to some major economic variables(El-mefleh,2000) : the auto regressive integrated moving average (ARIMA) forecasting models for key Qatari economic variables were developed, estimated and then used for ex-post and ex-ante forecasts.

The percentage forecast inaccuracy (PFI) method has been used to measure the precision of the models equal forecasts. The major findings of the paper are that ARIMA models

- Appear highly successful in forecasting government consumption and final consumption
- Are moderately successful in forecasting three years out of six years of GDP
- Are poor in forecasting(under forecast) capital formation, imports, and exports due to substantial increase in the price of oil and increase their forecasts inaccuracy as the time span for forecast increased from one year to two years to three years.

From forecasting with vector auto regressions versus univariate ARIMA process: an empirical example with U.S HOG prices by John A.Brandt and David A.Bossler (1984)

Out of sample quarterly forecasts of hog prices were generated over 1976-82 periods via VAR and univariate ARIMA process. The results indicated no improvement in forecasting ability by the more complex VAR procedure based on several measures of performance.

M.Yasee et al.(2005), from modeling and forecasting the sugar cane yield data during the period 1947-2000, the most appropriate model for the study is ARIMA(2,1,2). Forecasting was also done up to 2008-2009. For comparison purpose, first three forecast values from 1999-2000 to 2000-2001 are compared with actual values. Forecast values are very close to the actual values.

According to Al-Abdulrazaq Bashier and Bataineh Talal(2007) entitled as foreign direct investment inflow in Jordan using univariate ARIMA model:

The study was an attempt to build a univariate time series model to forecast the FDI inflows in to Jordan over the period 2004-2005. The study employees Box-Jenkins methodology of building ARIMA model to achieve the goals of the study. An annual sample time series data for the FDI in Jordan was utilized over the period 1976-2003. The data were collected from the central bank of Jordan publications. The accuracy of the selected models was tested by performing different diagnostic tests to ensure the accuracy of the obtained results. Results of the study show that ARIMA model provides a better model for forecasting FDI in Jordan. The Empirical results of ARIMA model have shown that FDI following an increasing trend over the forecast period 2004-2005. The empirical results indicate the expected impact of FDI inflows on different macro economic variables in Jordan Economy.

From Rune Jansen Hagen (2002) in forecasting daily mean ambient air pollutants (O3,No, No2 and Co) concentration at an urban traffic site(ITO) of Delhi, India using ARIMA,suitable variance stabilizing transformation has been applied to each time series in order to make them covariance stationary in a consistent way. A combination of different information criteria, namely ,AIC(Akakie Information Criterion),HIC(Hannan_Quinn Information Criterion),BIC(Ba-yesian Information Criterion), and FPE(Final prediction Error) in addition to ACF(autocorrelation function) and PACF(Partial autocorrelation function) inspection, has been tried out to get suitable orders of autoregressive(p) and moving average(q) parameters for the ARMA(p,q)/ARIMA(p,d,q) models. Forecasting performance of the selected ARMA (p,q)/ARIMA(p,d,q) models has been evaluated on the basis of MAPE(mean absolute error) and RMSE(root mean square error) indicators.

For 20 out of sample, one step (i.e., one day) ahead MAPE for Co, Co2, No, and O3 have been found to be 13.6, 12.1, 21.8 and 24.1% respectively. Given the stochastic nature of air pollutants data and in the light of earlier reported studies regarding air pollutants forecasts, the forecasting performance of the present approach is satisfactory and the suggested forecasting procedure can be effectively utilized for short term air quality for warning purposes.

Makridakis and Hibon(1979) concluded, after a careful comparison of various forecasting techniques, that Box-Jenkins has the better performance of being able to accommodate structural changes. In addition, Naylor et al., (1972) also reported that Box-Jenkins results were significantly better in all cases; they provide better forecasts by a factor of almost two to one. The same conclusion was drawn by other researchers like Mabret(1975),Clearry and Fryk(1974), Cooper and Nelson(1975) and McWhorter(1975).

According to Chris Chatfield (1997) of Forecasting in the 1990s, univariate ARIMA forecasting methods are still far more in practice than alternatives.

Nelson (1973) reported that the one quarter a head sample –period predictions of 14 variables by these time series models are almost equally comparable with the corresponding predictions by the Federal Reserve board –MIT_Penn(FMP) model. In the case of post-sample predictions, the simple time series models outperform the FMP model for many variables in terms of mean square errors criteria.

Makridakis(1998) found that ARIMA model is a powerful method to generate accurate forecasts in the short-run without involving economic theory. This conclusion was also shared by Sabia(1977),Baula(1980),Nachane(1981),Bowersux(1981), Ibrahim and Otsuki(1982), Armstrong(1983),Mentzer(1984), Fildes(1984),Salkar(1989),Poonam and Gupta(1990), Diebold and Rude Busch(1991), Fildes(1992), Mentzer(1995), Fildes(1998), Sethi(1999), Razzaque and RuhueAmin(2000),Naresh(2003),Gupta(2002),Afzal(2002),Gupta(2003),Gupta(2004),Armstrong (2005),Armstrong(2006),Taylor(2006) and Gupta(2006).

In addition, Priestley (1981),Hippel and Mchead(1994) used univariate Box-Jenkins modeling techniques in forecasting the short term behavior of Salinity in the day.

Paul (1998) worked with 'modeling and forecasting of Energy consumption in Bangladesh' by applying Box-Jenkins methodology or ARIMA methodology and found that the data were non-stationary. After making the data stationary, he selected three ARIMA models on the basis of smaller AIC and BIC and finally selected the best ARIMA model based on minimum values of AME,RMSE,SE(δ) and MAPE and made forecast by this model.

Hela Uddin (1998) showed that economic and environmental trend from 1996 to 2003 by using the time series from 1975 to 1995. He examined the stationarity of time series data and found that they were non stationary. The data were made stationary by transforming them and constructed ARIMA model and forecasting was performed based on the model.

Pindyck and Rubinfeld(1976) discussed about the properties of stationary and non-stationary time series, the correlation function and developed the methods by which time series models were specified, estimated and used for forecasting. They also showed how some non-stationary time series models could be differenced once or many times to produce a stationary time series that enabled to develop a general integrated auto regressive moving average (ARIMA) model. By using the data from 1960 to 1967, they forecast the U.S hog production over a two year horizon, using ARIMA models.

Darmodar N.Gudjrati(1995) examined the U.S GDP time series for the quarterly periods of 1970 to 1991. He found that U.S GDP was non-stationary on the basis of ACF and PACF. After making the first difference, it was stationary. He also applied four-step Box-Jenkins or ARIMA methodology: identification, estimation, diagnostic checking and forecasting to the U.S GDP data. Using the above mentioned data, forecasting was made for the first quarter of 1992

Wei and Abraham(1981) stated , in terms of forecasting aggregates, there is no guarantee that the forecast based on component series is more efficient than the forecast from a single univariate series.

Out of sample quarterly of hog prices were generated over the period 1976-1982 via VAR and a univariate ARIMA process. The results indicated no improvement in forecasting ability by the more complex VAR procedure based on several measures of performance.

Stocken and Glass man (1987) and Litterman (1986) got ARIMA models frequently out perform more sophisticated structural models in terms of short –run forecasting ability. The ARIMA forecasting technique will not only provide a bench mark by which other forecasting techniques may be appraised, but will also provide an input in to forecasting in its own right.

Landsman and Damodaran (1989) presented evidence that ARIMA parameter estimator improves forecast accuracy relative to other methods under the MSE loss criterion. Similarly, Boudreault et al.,(1977), Salia et al.,(1979), Mendelssohn(1981), Fagarty et al.,(1986), Mendelssohn and Cury (1987),Jeffries et al.,(1989) and Stergiou et al.,(1977) used the Univariate Auto regressive Integrated Moving Average(ARIMA) models in forecasting Fishery dynamics.

The empirical literatures show how much the model is versatile so that we could use in forecasting of the four major crop varities. Empirical works on the case of Ethiopia using this model in forecasting economic variables are not available.

CHAPTER FOUR

ARIMA PROCESS AND SHORT TERM FORECASTING

In this chapter we are going to see a brief description of short term forecasting model which will help us developing a forecasting model for the crop varieties selected for the study.

It is known that agriculture is the mainstay of the Ethiopian economy. It accounts for the lion's share of the total GDP; is the main source of foreign currency earnings and in employment creation, provides raw materials for both the industry and service sectors, generates foreign currency for the importation of essential inputs and feeds the fast growing population (MoFED 2008). For instance, during the period, 1970-2001/02, the average share of agricultural output to total GDP was 54.1%.

Despite the dominance over the years, however, the size of the agriculture sector in terms of its contribution to GDP has been steadily declining in recent years. To cite an example, during the period 2009, the share of agricultural output to total GDP was only 43.8%. The major reasons forwarded (as observed in many countries) for the structural transformation of the economy which leads to the decline in the share of the sector as the economy grows include the fact that (1) the income elasticity of demand for food items is very small (inelastic); and (2) the possibility of substantial expansion of agricultural production with a constant or declining farm labor force [J. Mellor, 1976].

Nevertheless, due to the fact that currently more than 80% of the total populations earn their livelihood from the sector and the bulk of the country's exports originate from the same sector; its role in the performance of the economy is still central. For instance, in 2007/08, the share of agricultural export to total value of exports was 72.8%. In addition, what makes the role of the agriculture sector in Ethiopia more important is the fact that current government has adopted an Agricultural Development Led Industrialization (ADLI) strategy, which takes agriculture as the engine of economic growth.

Therefore, understanding the dynamics of the sector, at least the major ones- cereal, coffee, pulses and oilseeds(their description given below) is indespensable to understand the over all growth of the economy and design an appropriate policy for it, as agriculture has both forward and back ward linkages with other sectors.

Cereals are the major food crops both interms of the area they are planted and volume of production obtained. They are produced in larger volume compared with other crops because they are the principal staple crops. According to 2008 CSA report, out of the total grain crop area, 78.23% was covered under cereal, which brought 84.69% of the total production.

Pulses are also among the various crops produced in all the regions of the country after cereals. Pulses grow in 2008 covered 14.14% of the grain crop area and 11.48% of the grain production (CSA,2008). By the same year, the contribution of oilseeds to the crop subsector was 3.83%. when we come to coffee, it is the most important tradable commodity in the Ethiopian Economy. There has always been excessive dependence on the commodity as the major export item in the country's history. More than 60% of the total foreign exchange comes from the export of this commodity. There fore developing a forecasting model for these crop varities is logical.

4.1 Short Term Forecasting

Here in forecasting the production of these four crops we are going to use univariate Arima(Box-Jenkins) procedure. As described in the sections herein before, it begins with the specification of the model. This requires a decision as to the degree of homogenity in the time series, i.e., how many times the time series must be differenced before a stationary series results. The decision is made by looking at the autocorrealtion functions for the time series and its differences. After the degree of homogenity has been specified, the orders of the moving average and the autoregressive parts of the model must be determined. In other words, values for p and q must be chosen for the ARMA model that will be used to represent the differenced series. One can get some guidance on the choice of p and q from examination of the total and partial autocorrelation functions, but often the correct choice will not be clear and several alternative specifications must be estimated.

Once a model (or a group of models) has been specified, it must then be estimated. If the number of observations in the time series is large relative to the order of the model, this estimation process involves a straightforward non linear regression. In such cases, problems associated with the initialization of the time series can be ignored when performing the estimation(Pindyck and Rubinfeld,1998).

After the model has been estimated, one must then perform a diagnostic check on it. This usually involves looking at the the autocorrelation function of the residuals from the estimated model(i.e., the series determined by subtracting the actual series from the estimated series).

A simple chi-square test can be performed to determine whether or not the residuals are themselves uncorrelated.

Once a time series has been estimated and its original specification has been checked, it can be used for forecasting. The following sections talk about how we can use the general ARIMA model

$\emptyset(B)y_t = \theta(B)\varepsilon_t$ *(1)*

to obtain a forecast of y_t for the period T +l(that is, l periods ahead, with $l \geq 1$). We denote this forecast by $\hat{y}_T(l)$, and call it the origin-T forecast for lead time l.

4.1.1 Minimum Mean Square Error Forecast

Our objective in forecasting is to predict future values of a time series subject to as little error as possible. For this reason we consider the optimum forecast to be that forecast which has the minimum square forecast error. Since the forecast error is a random variable, we minimize the expected value. Thus we wish to choose our forecast $\hat{y}_T(l)$ so that $E[e^2_T(l)] = E\{[y_{T+1} - \hat{y}_T(l)]^2\}$ is minimized((Pindyck and Rubinfeld,1981). This forecast is given by the conditional expectation of y_{T+l}, that is , by

$\hat{y}_T(l) = E(y_{T+l}|Y_T, Y_{T-1}, \ldots\ldots, Y_1)$

This could be derived by writing equation (1) as

$y_t = \emptyset(B)^{-1}\,\theta(B)\varepsilon_t = \psi(B)\,\varepsilon_t = \sum_{j=0}^{\infty} \Psi_j\,\varepsilon_{T-j}$ (2)

That means we expressed the ARIMA model as a purely moving average process of infinite order(Verbeek,2004).

Then, $y_{T+1} = \psi_0\ \varepsilon_{T+l} + \Psi_1\,\varepsilon_{T+l-1} + \ldots + \Psi_l\,\varepsilon_T + \Psi_{l+1}\,\varepsilon_{T-1} + \ldots$

$= \psi_0\ \varepsilon_{T+l} + \Psi_1\,\varepsilon_{T+l-1} + \ldots + \Psi_{l-1}\varepsilon_{T+1} + \sum_{j=0}^{\infty} \Psi_{l+j}\,\varepsilon_{T-j}$ (3)

The above equation is composed of two parts with the second beginning with the term $\psi_l \, \varepsilon_T$, and thus describing information up to and including time period T. Of course the forecast $\hat{y}_T(l)$ can be based only on information available up to time T. Our objective is to compare this forecast with the actual value y_{T+1} as expressed in equation (3). To do so, we write the forecast as a weighted sum of those error terms which we can estimate, namely, $e_t, e_{t-1}, \ldots$ Then, the desired forecast is

$$\hat{y}_T(l) = \sum_{j=0}^{\infty} \psi_{l^*+j} \, \varepsilon_{T-j} \tag{4}$$

Where the weights ψ_{l^*+j} are to be chosen optimally so as to minimize the mean square forecast error. We can now write an expression for the forecast error, $\varepsilon_T(l)$ using equations(3) and (4)

$$\varepsilon_T(l) = y_{T+l} - \hat{y}_T(l) = \psi_0 \, \varepsilon_{T+l} + \psi_1 \, \varepsilon_{T+l-1} + \ldots + \psi_{l-1} \, \varepsilon_{T+1} \sum_{j=0}^{\infty} (\psi_{l+j} - \psi_{l+j}^*) \varepsilon_{T-j}; \tag{5}$$

Since by assumption $E(\varepsilon_i \varepsilon_j) = 0$ for $i \neq j$, the mean square forecast error is

$$E[e^2_T(l)] = (\psi_0^{\ 2} + \psi_1^{\ 2} + \cdots + \psi_{l-1}^{\ 2}) \delta\varepsilon^2 + \sum_{j=0}^{\infty} (\psi_{l+j} - \psi_{l+j}^{\ *})^2 \, \delta\varepsilon^2 \tag{6}$$

Clearly this expression is minimized by setting the 'optimum' weights $\psi_{l+j}^{\ *}$ equal to the true weights (ψ_{l+j}, for j=0,1, . . .) . But then our optimum forecast $\hat{y}_T(l)$ is just the conditional expectation of y_{T+l}. This can be seen taking the conditional expectation of y_{T+l} in equation(3). The expected values of $\varepsilon_{T+l}, \ldots, \varepsilon_{T+1}$ are all 0, while the expected values of $\varepsilon_T, \varepsilon_{T-1}, \ldots$, are just the actual observed errors, i.e,. the residuals from the estimated equation. Thus we have

$$\hat{y}_T(l) = \sum_{j=0}^{\infty} \psi_{l+j} \, \hat{\varepsilon}_{T-j} = E(y_{T+l} | y_T, \ldots, y_1) \tag{7}$$

This provides the basic principle for calculating forecasts from our ARIMA models. Now we apply this principle to the actual computation of forecasts.

4.1.2 Computing a Forecast

The actual computation of the forecast $\hat{y}_T(l)$ can be done recursively using the estimated ARIMA model. This involves first computing a forecast one period ahead, using this forecast to compute a forecast two periods ahead, and continuing until the l-period forecast has been reached.

Let us write the ARIMA(p,d,q) model as

$$y_t = \emptyset_1 y_{t-1} + \ldots + \emptyset_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} \ldots - \theta_q \varepsilon_{t-q} + \delta \qquad (8)$$

To compute the forecast $\hat{y}_T(l)$, we begin by computing the one period forecast of y_t, $\hat{y}_T(1)$. To do so, we write equation (8) with the time period modified:

$$y_{t+1} = \emptyset_1 y_t + \ldots + \emptyset_p y_{t-p+1} + \varepsilon_{t+1} - \theta_1 \varepsilon_t \ldots - \theta_q \varepsilon_{t-q+1} + \delta \qquad (9)$$

we then calculate our forcasts $\hat{y}_t(1)$ by taking the conditional expected value of Y_{t+1} in equation (9):

$$\hat{y}_t(1) = E(y_{t+1} \mid y_t, \ldots) = \emptyset_1 y_t + \ldots + \emptyset_p y_{t-p+1} - \theta_1 \hat{\varepsilon}_t \ldots - \theta_q \hat{\varepsilon}_{t-q+1} + \delta \qquad (10$$

Where the $\hat{\varepsilon}_t$, $\hat{\varepsilon}_{t-1}$, etc., are observed residuals with the expected value of $\hat{\varepsilon}_{t+1}=0$.

Now using the one period forecast $\hat{y}_t(1)$, we can obtain the two period forecast $\hat{y}_t(2)$:

$$\hat{y}_t(2) = E(y_{t+2} \mid y_t, \ldots)$$

$$= \emptyset_1 \hat{y}_t(1) + \emptyset_2 yt + \ldots + \emptyset_p y_{t-p+2} - \theta_2 \hat{\varepsilon}_t \ldots - \theta_q \hat{\varepsilon}_{t-q+2} + \delta \qquad (11)$$

The two period forecast is then used to produce the three- period forecast, and so on, until the l-period forecast $\hat{w}_t(l)$ is reached:

$$\hat{y}t(l) = \emptyset_1 \hat{y}_t(l-1) + \ldots + \emptyset_l y_t + \ldots + \emptyset_p y_{t-p+l} - \theta_l \hat{\varepsilon}_t \ldots - \theta_q \hat{\varepsilon}_{t-q+l} + \delta \qquad (12)$$

Here if l> p and l >q, then the forecast will be

$$\hat{y}t(l) = \emptyset_1 \hat{y}_t(l-1) + \ldots + \emptyset_p \hat{y}t(l-p) \qquad (13)$$

4.1.3 The Forecast Error

As we saw above if we express the ARIMA model as a purely moving average process of infinite order, the forecast error l periods a head is given by

$e_T(l)=y_{t+1}-\hat{y}_t(l)=\psi_0\ \varepsilon_{T+l}+\psi_1\ \varepsilon_{T+l-1}+\ldots+\psi_{l-1}\ \varepsilon_{T+1}$ (14)

This helps to know the forecasting ability of a given model. There are also statistics which are derived from forecast error and helps to prefer a model from sets of tentative models: Root mean squared error, mean absolute error, mean absolute percentage error and Theils inequality coefficient.

The measure that is most often used is the root mean error(RMSE). The RMSE for the variable yt is defined as

$$\text{RMSE}=\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}t-\text{Yt})^2} \qquad (15)$$

Where Yt = Actual value

$\hat{y}$t = forecasted value of Yt

T= number of periods in the forecast

Another forecast error statistics is the mean absolute error which is defined as

$\text{MAE}=\frac{\sum_{t=1}^{T}|\hat{y}t-\text{Yt}|}{\text{T}}$ and also mean absolute percentage error, $\text{MAPE}=100\ \frac{\sum_{t=1}^{T}|\hat{y}t-\text{Yt}|/\text{Yt}}{\text{T}}$. (16).

RMSE and MAE are dependent of on the scale of the dependent variables

The last type of summary statistics to evaluate the forecasting ability of a model is Theil U statistics.Theils U statistics calculates the ratio of the RMSE of the chosen model to the RMSE of the 'naive'(i.e., assuming the value in the next period is the same as the value; in this period-no change in the dependent variable) forecasting model. Thus, a value of one for the Theil statistic indicates that, on average, the RMSE of the chosen model is the same as the ' naive' model(Pindyck and Rubinfeld,1998).

A Theil statistic in excess of one would lead one to reconsider the model as the simple 'naive' model performs better on average. A Theil statistic less than one does not lead to automatic acceptance of the model, but does indicate that, on average, it performs better than the 'naive' model. The advantage of the Theil statistic is that it is 'unitless' as it compares the RMSE of the chosen model to that of the 'naive' forecast model(Meyler et al.,1998).

It could be calculated as

$$u = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}t - Yt)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}t)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Yt)^2}} \qquad (17)$$

CHAPTER FIVE

EMPIRICAL ANALYSIS

In this chapter we are going to see the emprical results in developing forecasting models for cereal, coffee, oil seeds and pulses. To use ARIMA model for this purpose, we need to have stationary variables. So that the first step should have to be checking stationarity of the variables(identification stage of Box-Jenkins procedure).

The first variable to be discussed here is cereal production(TCER).

To see the nature of this variable lets start with time series plot of it. The series should be plotted against time to assess whether any structural breaks, outliers or data errors occur. If so one may need to consider use of intervention or dummy variables. This step may also reveal whether there is significant seasonal pattern in the time series(Alemayehu et al.,2009).

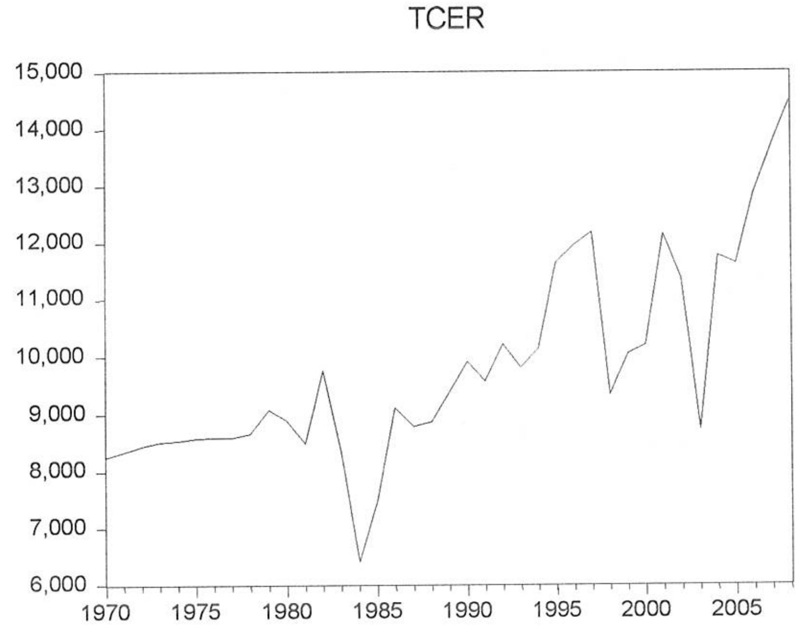


Fig 5.1 Time series plot of tcer

From the plot, we can see that the production varies considerably. The series wanders tell us that it is not staionary. In other words, the short term mean level is not constant but varies over the course of the series. It has also been observed from the plot that the short term variation also inceases or decreases with time. So it is non stationary.

Another way to examine the properties of a time series is to plot its autocorrelogram, which plots the autocorrelations between differing lag lengths of the time series.

Date: 03/16/10 Time: 03:29
Sample: 1970 2008
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |***** |	. |***** |	1	0.694	0.694	20.285	0.000
. |**** |	. | . |	2	0.492	0.020	30.754	0.000
. |*** |	. |*. |	3	0.404	0.108	38.021	0.000
. |*** |	. |*. |	4	0.389	0.129	44.931	0.000
. |** |	. | . |	5	0.340	0.002	50.379	0.000
. |** |	. |*. |	6	0.337	0.113	55.887	0.000
. |** |	. | . |	7	0.291	-0.030	60.130	0.000
. |*. |	.*| . |	8	0.169	-0.157	61.600	0.000
. |*. |	. |*. |	9	0.203	0.202	63.798	0.000
. |*. |	. | . |	10	0.213	-0.031	66.292	0.000
. |** |	. |*. |	11	0.228	0.074	69.256	0.000
. |*. |	.*| . |	12	0.136	-0.133	70.357	0.000
. |*. |	. | . |	13	0.087	-0.040	70.818	0.000
. | . |	. | . |	14	0.052	0.015	70.993	0.000
. | . |	.*| . |	15	-0.003	-0.132	70.994	0.000
.*| . |	.*| . |	16	-0.094	-0.177	71.609	0.000

Fig 5.2 Correlogram of tcer

From the estimated autocorrelations, we find that it dies out slowly confirming that the series is non-stationary. The signifiance p values also show us that the autocorrelation is different from zero / or non stationary.

Thirdly, we can check the stationarity of the variable using Augmented Dickey Fuller unit root - one of the powerful tools for testing a series(or the first or second difference of a series) for the presence of a unit root(Eviews 6).

Null Hypothesis: TCER has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.219976	0.6558
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

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

Table 5.1 Augmented Dickey Fuller unit root test on tcer

The Augmented Dickey-Fuller test also shows acceptance of the null of unit root or nonstationary of the series.

All the above tests show us that the variable tcer is unit root so that needs medicine to make the error term white noise. This could be done by differencing.

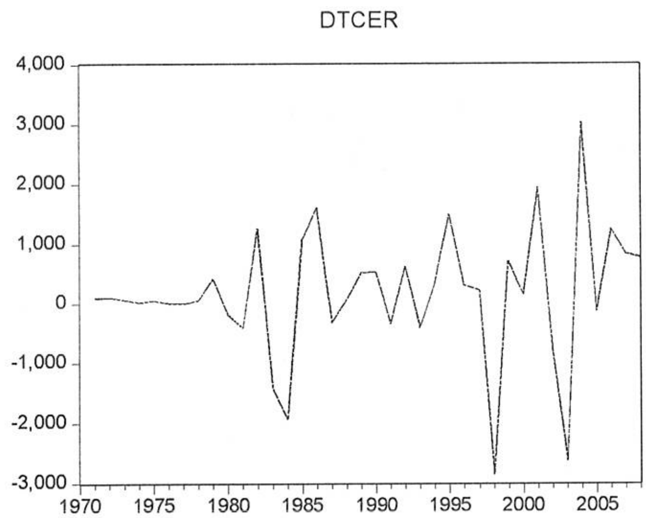


Fig 5.3- time series plot of DTCER

From the plot of the differenced series in the estimation period, we see that the mean of the differenced series is about zero from the beginning to the end and the variance does not noticeably change indicating that the series has attained the stationary.

Date: 03/16/10 Time: 03:45
Sample: 1970 2008
Included observations: 38

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.200	-0.200	1.6435	0.200
**| . |	**| . |	2	-0.218	-0.269	3.6552	0.161
.*| . |	.*| . |	3	-0.067	-0.197	3.8475	0.278
. | . |	.*| . |	4	0.057	-0.085	3.9934	0.407
. |*. |	. |*. |	5	0.189	0.139	5.6336	0.344
.*| . |	.*| . |	6	-0.170	-0.103	7.0056	0.320
. |*. |	. |*. |	7	0.098	0.142	7.4784	0.381
**| . |	**| . |	8	-0.208	-0.217	9.6803	0.288
. |*. |	. | . |	9	0.083	0.011	10.044	0.347
. | . |	.*| . |	10	0.044	-0.072	10.150	0.427
. | . |	. | . |	11	-0.050	-0.029	10.292	0.504
. | . |	.*| . |	12	-0.054	-0.143	10.465	0.575
.*| . |	. | . |	13	-0.074	-0.050	10.802	0.627
. |*. |	.*| . |	14	0.117	-0.067	11.670	0.633
. |*. |	. |** |	15	0.145	0.229	13.050	0.598
. | . |	. | . |	16	-0.050	-0.002	13.222	0.656

Fig 5.4- Correlogram of dtcer

The correlogram also shows the first difference of cereal production is stationary. And finally, the Dickey Fuller unit root test is applied to the difference of the variable, and gives a significant p-value or rejection of the null of unit root(table 5.2).

Null Hypothesis: DTCER has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.227137	0.0000
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

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

Table 5.2 Augmented Dickey-Fuller unit root of dtcer

After getting the variable stationary, the next step is to identify the order of AR and MA terms. This could be known by carefully observing the correlogram of the difference of this variable and then objective penality criteria(information criterion). Based on the information criteria we selected three tentative forecasting models: ARIMA(1,1,2),ARIMA(2,1,2) and ARIMA(2,1,0). The best model out of these three will be selected based on Theils inequality coefficient as it is the preffered one to evaluate the forecasting ability of amodel(Alemayehu et al.,2009). Based on that, the congruent model for the given data set is ARIMA(2,1,2). Then, the model is estimated using non-linear least square(NLS) estimation techinique, known as "Marquardt's Compromise' which is applicable to all univariate ARIMA models. Table (5.3) shows the estimation of congruent model selected for the series.

Dependent Variable: DTCER
Method: Least Squares
Date: 03/20/10 Time: 02:47
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments
Convergence achieved after 41 iterations
MA Backcast: 1971 1972

	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.052465	0.118578	8.875690	0.0000
AR(2)	-0.800636	0.124685	-6.421260	0.0000
MA(1)	-1.306922	0.073525	-17.77524	0.0000
MA(2)	0.941730	0.057921	16.25875	0.0000

R-squared	0.153830	Mean dependent var	168.0278
Adjusted R-squared	0.074501	S.D. dependent var	1152.277
S.E. of regression	1108.523	Akaike info criterion	16.96388
Sum squared resid	39322347	Schwarz criterion	17.13983
Log likelihood	-301.3499	Hannan-Quinn criter.	17.02529
Durbin-Watson stat	2.107457		

Inverted AR Roots	.53+.72i	.53-.72i
Inverted MA Roots	.65-.72i	.65+.72i

Table 5.3: Estimation of dtcer

After estimation of the model the next step is diagnostic checking. That is if the model is good for forecasting. That means we have to check the residual for white noise . This could be checked by observing the stationary of the residual series. That is we can use either the Augmented Dickey-Fuller unit root test of the residual or the plot of the autocorrelations of the residual(table5.4 and fig 5.6 respectively). The actual, fitted and residual graphs also help us to know how well the model fits(fig 5.5).

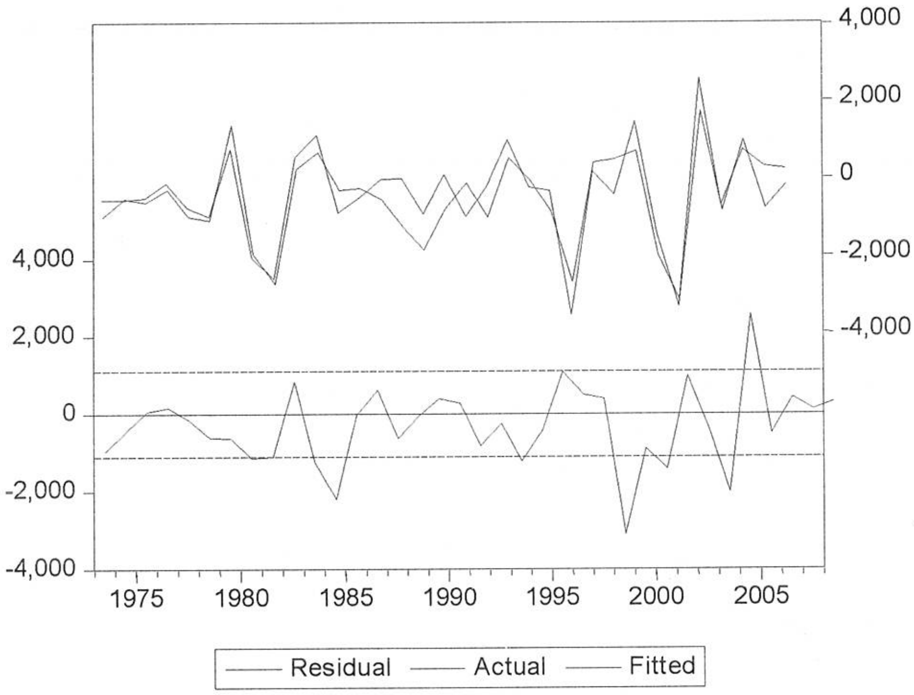


Fig 5.5 Actual, fitted and residual graph dcer

The actual and fitted graph shows us that the model is wel fit. The residual plot also shows as if it is a constant and revolves between given standard deviations.

Null Hypothesis: RESID01 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.381704	0.0000
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

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

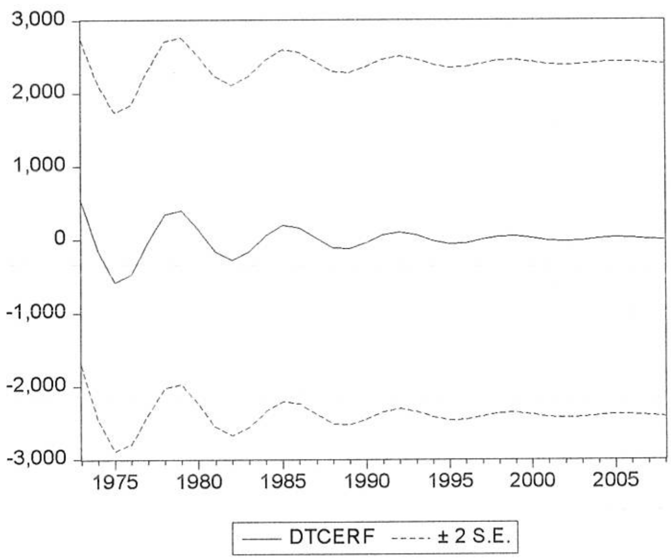
Table 5.4 Augmented Dickey-Fuller unit root test of the residual

Date: 03/03/10 Time: 04:47
Sample: 1970 2008
Included observations: 36

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.104	-0.104	0.4211	0.516
.*| . |	.*| . |	2	-0.116	-0.129	0.9670	0.617
.*| . |	.*| . |	3	-0.068	-0.098	1.1584	0.763
. | . |	.*| . |	4	-0.034	-0.072	1.2076	0.877
. | . |	. | . |	5	0.071	0.038	1.4310	0.921
.*| . |	.*| . |	6	-0.187	-0.202	3.0283	0.805
. |*. |	. |*. |	7	0.133	0.098	3.8584	0.796
.*| . |	**| . |	8	-0.178	-0.218	5.4011	0.714
. | . |	. | . |	9	0.043	0.014	5.4933	0.789
. | . |	. | . |	10	0.017	-0.054	5.5093	0.855
. | . |	. | . |	11	-0.035	-0.032	5.5780	0.900
. | . |	.*| . |	12	-0.051	-0.151	5.7275	0.929
.*| . |	. | . |	13	-0.067	-0.038	5.9926	0.946
. |*. |	. | . |	14	0.104	-0.051	6.6677	0.947
. |*. |	. |*. |	15	0.113	0.159	7.4924	0.943
. | . |	.*| . |	16	-0.036	-0.093	7.5818	0.960

fig 5.6 Correlogram of the residual

From the ACF and PACF plots of the residuals, we observe that the ACF and PACF are randomly distributed. All the Box-Ljung Q statistics for the ACF are not statistically significant at any lag. All these findings further confirm that the residuals are white noise. In addition, the value of DW statistics which is 2.107457, indicates the absence of first order autocorrelation in the residuals. The conclusion from this diagnostic checking is that the model is adequate for forecasting of cereal production.



Forecast: DTCERF
Actual: DTCER
Forecast sample: 1970 2008
Adjusted sample: 1973 2008
Included observations: 36

Root Mean Squared Error	1159.367
Mean Absolute Error	848.2011
Mean Abs. Percent Error	348.7432
Theil Inequality Coefficient	0.861380
Bias Proportion	0.022757
Variance Proportion	0.655776
Covariance Proportion	0.321467

Fig 5.7 forecast ARIMA(2,1,2)

After checking the independentness of the residuals, we can proceed to forecasting of wheat production from 2003 to 2013(Appendix,A), that is both with in and out of sample forecasts. The forecast results show replication of historical values. From the forecast result, in 2013, the maximum and minimum cereal production expected will be 161,079,000 and 103,722,100 quintals respectively with the 2008 production level 144,960,000 quintals. This shows us that there is not as such significant change in the production of cereals compared to the 2008 result.

Just like we did for cereal, we followed the same procedure for the rest of the series. Fig 5.8 and 5.9, 5.15 and 5.16, 5.22 and 5.23 are the time series plots and auto correlations and table 5.5,5.9 and 5.13 respectively of pulse, coffee and oil seeds indicate that the given time series are not stationary. As the series are not stationary, given time series are made stationary by taking differences. After taking first differences, the time series plots and autocorrelations in fig.5.10 and 5.11,5.17 and 5.18, 5.24 and 5.25 and Augmented Dickey-Fuller unit root test in table 5.6, 5.10 and 5.14 are put with the order above. The figures and tables revealed that the first differenced time series are stationary.

After checking the variables for stationary we select the values of p and q. Based on Information criteria we tentatively select Arima(0,1,4),Arima(0,1,3) and Arima(0,1,5) for pulse; Arima(0,1,1),Arima(0,1,2) and arima(2,1,4) for Coffee; Arima(4,1,2), Arima(0,1,4) and Arima(1,1,4) for oilseeds. Then based on Theils inequality coefficient we selected Arima(0,1,4),Arima(2,1,4) and Arima(0,1,4) for pulse, coffee and oil seeds respectively as the data congruent models. The estimation results are shown in table 5.7,5.11 and 5.15 for pulse, coffee and oilseeds respectively.

After estimation of the model, we go for diagnostic checking. That is if the model for each series is good for forecasting. From the autocorrelation plots and Augmented Dickey-Fuller unit root test of the residuals, we observe that all the Box-Ljung Q statistics for the autocorrelation functions statistically insignificant at any lag and also acceptance of the null of Augmented Dickey-Fuller unit root test. This implies us that the models are good for forecasting. There fore, we can use these models for forecasting of the production of these crops. We tried to show the forecast results till 2013 (Appendix B to D). The maximum and minimum amount expected to be produced for each crop is (22174820,151329590),(33586600,18412210) and (22174820,15329590) quintals for pulses, coffee and oilseeds respectively where the 2008 production was 19650000,26020000 and 6560000 quintals with the previous order.

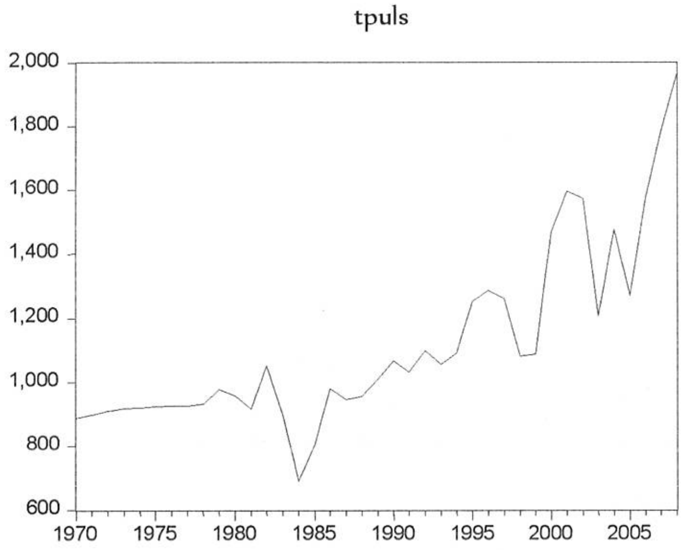


Fig 5.8- time series plot of tpuls

Date: 03/19/10 Time: 03:28
Sample: 1970 2008
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |***** |	. |***** |	1	0.744	0.744	23.314	0.000
. |**** |	. | . |	2	0.558	0.010	36.786	0.000
. |*** |	. | . |	3	0.447	0.064	45.668	0.000
. |**** |	. |** |	4	0.496	0.315	56.894	0.000
. |*** |	. | . |	5	0.460	-0.061	66.837	0.000
. |**** |	. |** |	6	0.499	0.250	78.903	0.000
. |*** |	.*| . |	7	0.396	-0.193	86.720	0.000
. |** |	**| . |	8	0.244	-0.241	89.787	0.000
. |*. |	. | . |	9	0.137	0.032	90.793	0.000
. |*. |	.*| . |	10	0.145	-0.067	91.955	0.000
. |*. |	. | . |	11	0.147	0.026	93.197	0.000
. |*. |	.*| . |	12	0.098	-0.093	93.765	0.000
. | . |	. | . |	13	0.040	-0.012	93.862	0.000
. | . |	. | . |	14	-0.011	0.059	93.870	0.000
.*| . |	.*| . |	15	-0.074	-0.111	94.231	0.000
.*| . |	.*| . |	16	-0.145	-0.123	95.688	0.000

Fig 5.9. correlogram for tpuls

Null Hypothesis: TPULS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.187586	0.9315
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

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

Table 5.5 Augmented Dickey-Fuller unit root test of tpuls

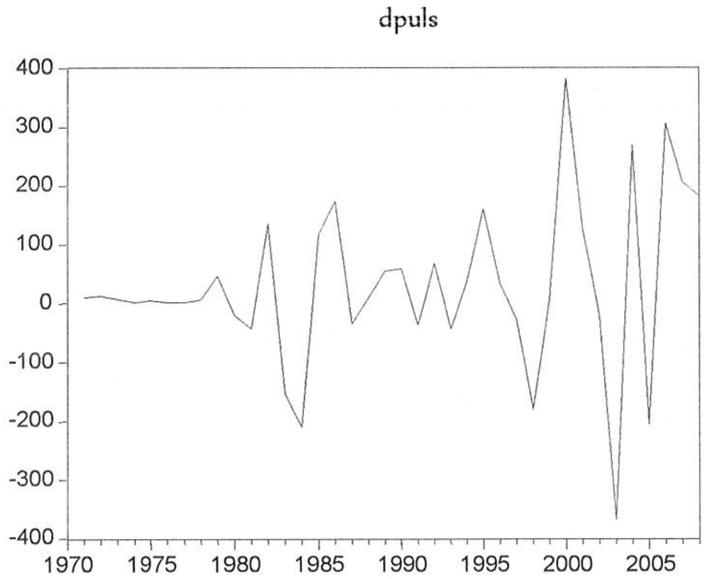


Fig. 5.10 Time series plot of dpuls

Null Hypothesis: DPULS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.510239	0.0000
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

*MacKinnon (1996) one-sided p-values

Table 5.6Augmented Dickey-Fuller unit root test of dpuls

Date: 03/19/10 Time: 03:31
Sample: 1970 2008
Included observations: 38

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.108	-0.108	0.4786	0.489
.*| . |	.*| . |	2	-0.095	-0.108	0.8574	0.651
**| . |	***| . |	3	-0.314	-0.345	5.1491	0.161
. |*. |	. | . |	4	0.086	-0.016	5.4833	0.241
. | . |	.*| . |	5	-0.017	-0.099	5.4964	0.358
. |*. |	. | . |	6	0.133	0.022	6.3418	0.386
. |*. |	. |*. |	7	0.138	0.201	7.2693	0.401
.*| . |	. | . |	8	-0.067	-0.028	7.4953	0.484
. | . |	. |*. |	9	-0.033	0.078	7.5527	0.580
. | . |	. |*. |	10	0.007	0.119	7.5554	0.672
. | . |	. | . |	11	-0.028	-0.065	7.6011	0.749
. | . |	. | . |	12	0.025	0.060	7.6366	0.813
. | . |	.*| . |	13	-0.065	-0.102	7.8974	0.850
. |*. |	. | . |	14	0.134	0.068	9.0266	0.829
. |*. |	. |*. |	15	0.084	0.169	9.4904	0.851
.*| . |	.*| . |	16	-0.099	-0.157	10.173	0.857

Fig 5.11 correlogram of dpuls

Dependent Variable: DPULS
Method: Least Squares
Date: 03/06/10 Time: 08:08
Sample (adjusted): 1971 2008
Included observations: 38 after adjustments
Convergence achieved after 14 iterations
MA Backcast: 1967 1970

	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.299812	0.093922	-3.192126	0.0030
MA(2)	-0.389170	0.093541	-4.160405	0.0002
MA(3)	-0.363792	0.075719	-4.804491	0.0000
MA(4)	0.827803	0.081974	10.09833	0.0000

R-squared	0.359402	Mean dependent var	28.34211
Adjusted R-squared	0.302878	S.D. dependent var	143.4986
S.E. of regression	119.8125	Akaike info criterion	12.50903
Sum squared resid	488070.9	Schwarz criterion	12.68141
Log likelihood	-233.6716	Hannan-Quinn criter.	12.57036
Durbin-Watson stat	1.703419		

Inverted MA Roots	.82-.45i	.82+.45i	-.67-.70i	-.67+.70i

Table 5.7 ARIMA(0,1,4) estimation of dpuls

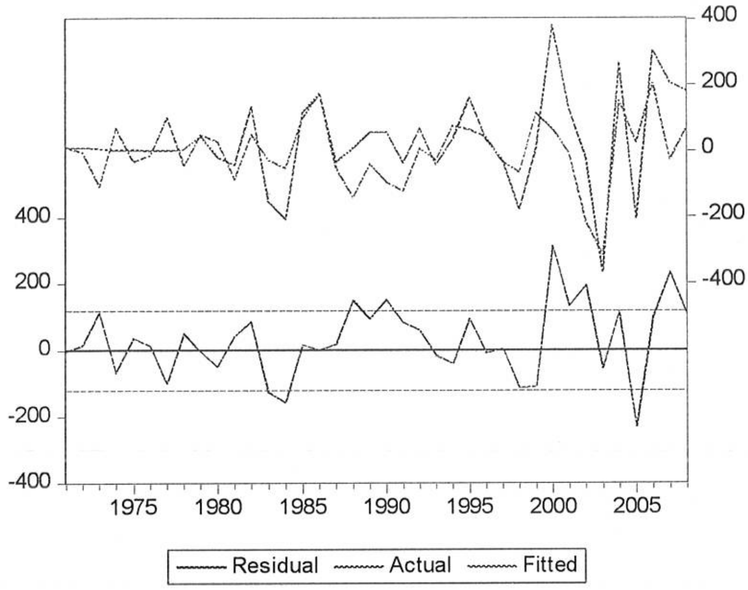


Fig 5.12: residual, actual and fitted graph

Null Hypothesis: RESID01 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.468606	0.0001
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

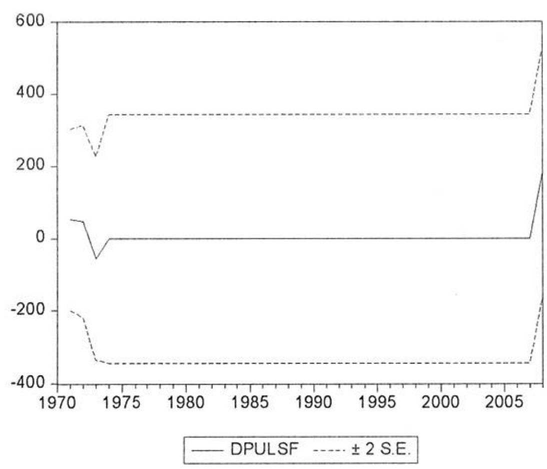
*MacKinnon (1996) one-sided p-values.

Table 5.8 Augmented Dickey-Fuller unit root test of residual

Date: 03/19/10 Time: 05:27
Sample: 1970 2008
Included observations: 38

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. | . |</td><td>. | . |</td><td>1</td><td>0.071</td><td>0.071</td><td>0.2086</td><td>0.648</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>2</td><td>-0.018</td><td>-0.024</td><td>0.2231</td><td>0.894</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>3</td><td>-0.168</td><td>-0.166</td><td>1.4456</td><td>0.695</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>4</td><td>-0.110</td><td>-0.090</td><td>1.9855</td><td>0.738</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>5</td><td>-0.111</td><td>-0.108</td><td>2.5486</td><td>0.769</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>6</td><td>0.115</td><td>0.101</td><td>3.1796</td><td>0.786</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>7</td><td>0.165</td><td>0.125</td><td>4.5157</td><td>0.719</td></tr>
<tr><td>.*| . |</td><td>**| . |</td><td>8</td><td>-0.154</td><td>-0.224</td><td>5.7104</td><td>0.680</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>9</td><td>-0.032</td><td>0.006</td><td>5.7645</td><td>0.763</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>10</td><td>0.001</td><td>0.060</td><td>5.7645</td><td>0.835</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>11</td><td>-0.018</td><td>-0.034</td><td>5.7833</td><td>0.887</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>12</td><td>0.161</td><td>0.171</td><td>7.2909</td><td>0.838</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>13</td><td>0.014</td><td>-0.092</td><td>7.3031</td><td>0.886</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>14</td><td>0.016</td><td>0.032</td><td>7.3196</td><td>0.922</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>15</td><td>0.011</td><td>0.150</td><td>7.3279</td><td>0.948</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>16</td><td>-0.072</td><td>-0.149</td><td>7.6883</td><td>0.958</td></tr>
</table>

Fig 5.13 correlogram of residual



Forecast: DPULSF
Actual: DPULS
Forecast sample: 1970 2008
Included observations: 38

Root Mean Squared Error	141.9633
Mean Absolute Error	96.91865
Mean Abs. Percent Error	131.5015
Theil Inequality Coefficient	0.800803
Bias Proportion	0.024892
Variance Proportion	0.592448
Covariance Proportion	0.382660

Fig 5.14 ARIMA(0,1,4) forecast of dpuls

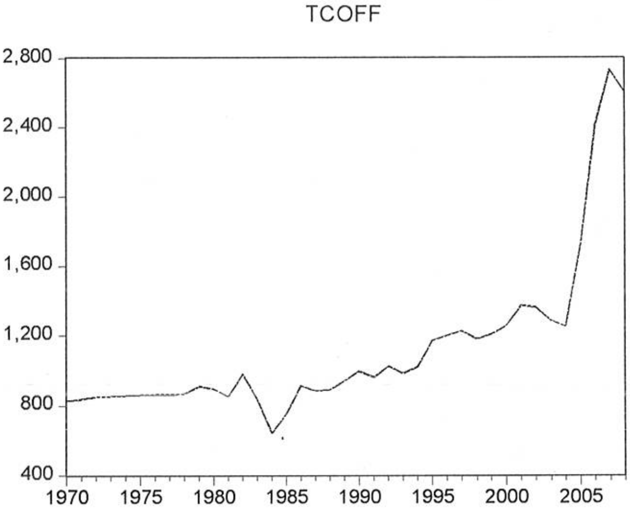


Fig 5.15 time series plot of tcoff

Date: 03/16/10 Time: 04:14
Sample: 1970 2008
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |******|	. |******|	1	0.810	0.810	27.603	0.000
. |**** |	**| . |	2	0.539	-0.339	40.179	0.000
. |** |	. |*. |	3	0.334	0.076	45.123	0.000
. |** |	. |*. |	4	0.262	0.188	48.250	0.000
. |** |	. | . |	5	0.263	0.032	51.492	0.000
. |** |	.*| . |	6	0.246	-0.067	54.422	0.000
. |*. |	. | . |	7	0.205	0.036	56.518	0.000
. |*. |	. | . |	8	0.160	0.022	57.834	0.000
. |*. |	. | . |	9	0.140	0.030	58.872	0.000
. |*. |	. | . |	10	0.126	-0.033	59.744	0.000
. |*. |	. | . |	11	0.100	-0.027	60.313	0.000
. | . |	. | . |	12	0.052	-0.047	60.475	0.000
. | . |	. | . |	13	0.011	0.009	60.483	0.000
. | . |	.*| . |	14	-0.029	-0.082	60.537	0.000
. | . |	. | . |	15	-0.053	0.001	60.721	0.000
.*| . |	. | . |	16	-0.073	-0.041	61.089	0.000

Fig 5.16 correlogram of tcoff

Null Hypothesis: TCOFF has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.462129	1.0000
Test critical values:	1% level	-3.626784	
	5% level	-2.945842	
	10% level	-2.611531	

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

Table 5.9 Augmented Dickey-Fuller unit root test of Tcoff

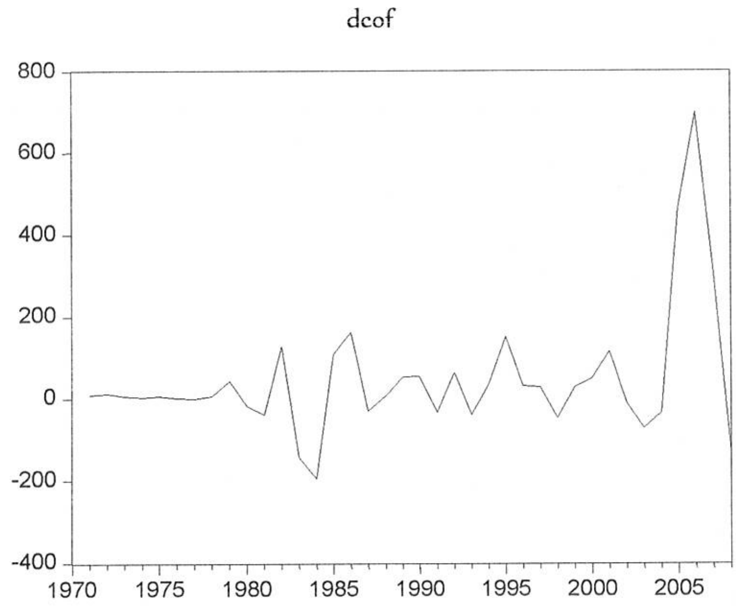


Fig 5.17- time series plot of dcof

Date: 03/16/10 Time: 04:21
Sample: 1970 2008
Included observations: 38

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |*** |	. |*** |	1	0.441	0.441	8.0009	0.005
.*| . |	***| . |	2	-0.171	-0.454	9.2339	0.010
.*| . |	. |*. |	3	-0.180	0.204	10.637	0.014
. | . |	. | . |	4	0.035	-0.038	10.691	0.030
. |*. |	. | . |	5	0.076	-0.004	10.958	0.052
. | . |	. |*. |	6	0.070	0.118	11.193	0.083
. | . |	.*| . |	7	-0.025	-0.166	11.225	0.129
.*| . |	. | . |	8	-0.084	0.070	11.579	0.171
. | . |	. | . |	9	-0.004	0.025	11.579	0.238
. |*. |	. | . |	10	0.113	0.053	12.271	0.267
. | . |	. | . |	11	0.067	-0.022	12.524	0.326
. | . |	. | . |	12	-0.015	0.026	12.537	0.404
. | . |	. | . |	13	-0.049	-0.039	12.681	0.473
. | . |	. | . |	14	-0.034	-0.005	12.754	0.546
. | . |	. | . |	15	0.010	0.026	12.760	0.621
. | . |	.*| . |	16	0.001	-0.087	12.760	0.690

Fig 5.18 correlogram of dcof

Null Hypothesis: DCOF has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.551470	0.0000
Test critical values:	1% level	-3.626784	
	5% level	-2.945842	
	10% level	-2.611531	

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

Table 5.10 Augmented Dickey-Fuller unit root test of dcof

Dependent Variable: DCOF
Method: Least Squares
Date: 03/03/10 Time: 03:04
Sample (adjusted): 1973 2008
Included observations: 36 after adjustments
Convergence achieved after 21 iterations
MA Backcast: 1969 1972

	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.814618	0.071177	11.44488	0.0000
AR(2)	-0.998913	0.095212	-10.49142	0.0000
MA(1)	0.022061	0.184778	0.119394	0.9058
MA(2)	0.305069	0.121647	2.507831	0.0178
MA(3)	0.668832	0.171170	3.907406	0.0005
MA(4)	-0.487884	0.198589	-2.456753	0.0200

R-squared	0.433333	Mean dependent var	48.69444
Adjusted R-squared	0.338889	S.D. dependent var	162.0740
S.E. of regression	131.7804	Akaike info criterion	12.75116
Sum squared resid	520982.0	Schwarz criterion	13.01508
Log likelihood	-223.5209	Hannan-Quinn criter.	12.84328
Durbin-Watson stat	2.119757		

Inverted AR Roots	.41-.91i	.41+.91i		
Inverted MA Roots	.51	.22+.97i	.22-.97i	-.97

Table 5.11 ARIMA(2,1,4) estimation of dcof

Null Hypothesis: RESID04 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.649432	0.0000
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

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

Table 5.12 Augmented Dickey-Fuller unit root test of residual for dcof

Date: 03/03/10 Time: 03:09
Sample: 1970 2008
Included observations: 36

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>1</td><td>-0.144</td><td>-0.144</td><td>0.8124</td><td>0.367</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>2</td><td>0.160</td><td>0.142</td><td>1.8374</td><td>0.399</td></tr>
<tr><td>**| . |</td><td>**| . |</td><td>3</td><td>-0.241</td><td>-0.210</td><td>4.2525</td><td>0.235</td></tr>
<tr><td>. |** |</td><td>. |** |</td><td>4</td><td>0.276</td><td>0.223</td><td>7.5103</td><td>0.111</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>5</td><td>-0.163</td><td>-0.076</td><td>8.6808</td><td>0.122</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>6</td><td>0.090</td><td>-0.030</td><td>9.0479</td><td>0.171</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>7</td><td>-0.002</td><td>0.147</td><td>9.0482</td><td>0.249</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>8</td><td>-0.011</td><td>-0.142</td><td>9.0539</td><td>0.338</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>9</td><td>0.034</td><td>0.107</td><td>9.1132</td><td>0.427</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>10</td><td>-0.044</td><td>-0.035</td><td>9.2150</td><td>0.512</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>11</td><td>0.119</td><td>0.052</td><td>9.9884</td><td>0.531</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>12</td><td>-0.122</td><td>-0.027</td><td>10.831</td><td>0.543</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>13</td><td>0.170</td><td>0.082</td><td>12.546</td><td>0.483</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>14</td><td>-0.241</td><td>-0.172</td><td>16.156</td><td>0.304</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>15</td><td>0.098</td><td>-0.014</td><td>16.786</td><td>0.332</td></tr>
<tr><td>.*| . |</td><td>. |*. |</td><td>16</td><td>-0.066</td><td>0.095</td><td>17.086</td><td>0.380</td></tr>
</table>

Fig 5.19 correlogram of residual for dcof

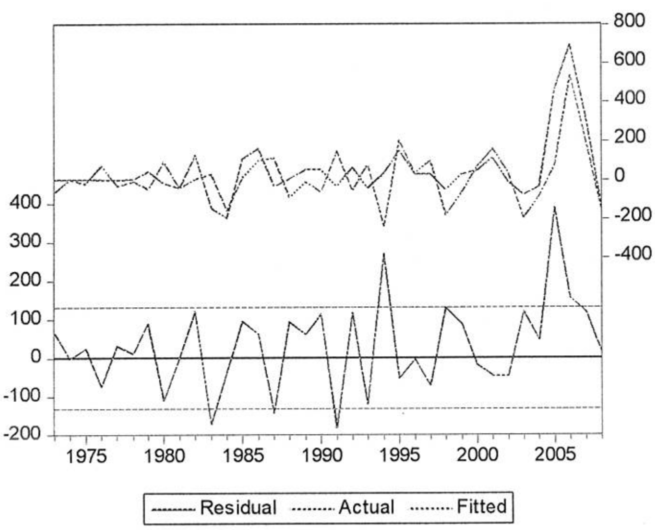
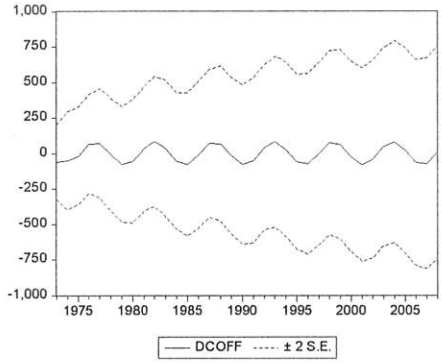


Fig 5.20 residual, actual and fitted graph



Forecast: DCOFF
Actual: DCOF
Forecast sample: 1970 2008
Adjusted sample: 1973 2008
Included observations: 36

Root Mean Squared Error	190.4454
Mean Absolute Error	126.4996
Mean Abs. Percent Error	464.0221
Theil Inequality Coefficient	0.850056
Bias Proportion	0.074628
Variance Proportion	0.292093
Covariance Proportion	0.633280

Fig 5.21 ARIMA(2,1,4) forecast of dcof

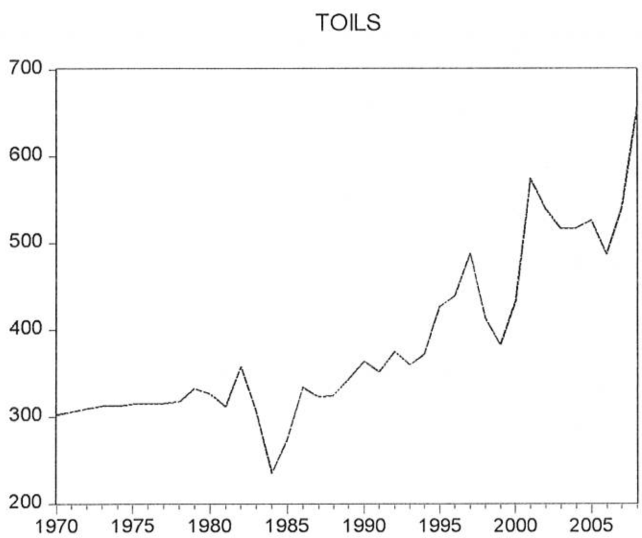


Fig 5.22 time series plot of toils

Date: 03/16/10 Time: 04:26
Sample: 1970 2008
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |******|	. |******|	1	0.787	0.787	26.071	0.000
. |***** |	. |*. |	2	0.650	0.079	44.318	0.000
. |***** |	. |** |	3	0.630	0.255	61.923	0.000
. |**** |	. | . |	4	0.599	0.066	78.307	0.000
. |**** |	. | . |	5	0.538	0.003	91.929	0.000
. |**** |	. | . |	6	0.497	0.033	103.92	0.000
. |*** |	.*| . |	7	0.420	-0.123	112.75	0.000
. |** |	**| . |	8	0.256	-0.318	116.14	0.000
. |*. |	. | . |	9	0.191	0.002	118.09	0.000
. |*. |	. | . |	10	0.183	0.023	119.94	0.000
. |*. |	. |*. |	11	0.162	0.087	121.43	0.000
. | . |	.*| . |	12	0.061	-0.130	121.65	0.000
. | . |	. | . |	13	0.007	0.033	121.65	0.000
. | . |	.*| . |	14	-0.051	-0.078	121.82	0.000
.*| . |	. | . |	15	-0.088	0.043	122.34	0.000
.*| . |	**| . |	16	-0.161	-0.249	124.13	0.000

Fig 5.23 correlogram of toils

Null Hypothesis: TOILS has a unit root
Exogenous: Constant
Lag Length: 5 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.140749	0.9999
Test critical values:	1% level	-3.646342	
	5% level	-2.954021	
	10% level	-2.615817	

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

Table 5.13- Augmented Dickey_Fuller unit root test of toils

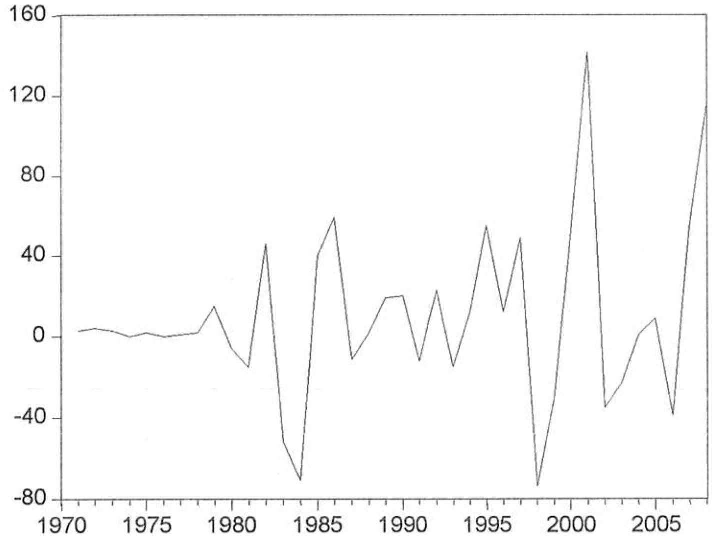


Fig 5.24- time series plot of doil

Date: 03/16/10 Time: 04:32
Sample: 1970 2008
Included observations: 38

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.032	0.032	0.0432	0.835
***| . |	***| . |	2	-0.419	-0.420	7.4383	0.024
.*| . |	.*| . |	3	-0.129	-0.117	8.1610	0.043
. |*. |	.|. |	4	0.159	-0.014	9.2909	0.054
.*| . |	**| . |	5	-0.131	-0.287	10.080	0.073
.|. |	. |*. |	6	0.060	0.139	10.251	0.114
. |** |	. |*. |	7	0.271	0.171	13.855	0.054
.|. |	.|. |	8	0.025	0.041	13.886	0.085
.*| . |	. |*. |	9	-0.104	0.213	14.449	0.107
.*| . |	.|. |	10	-0.083	-0.047	14.824	0.139
.|. |	. |*. |	11	0.060	0.116	15.029	0.181
.|. |	.|. |	12	-0.018	0.006	15.048	0.239
.|. |	.*| . |	13	-0.027	-0.104	15.093	0.302
.|. |	.|. |	14	-0.011	-0.053	15.101	0.371
. |** |	. |*. |	15	0.248	0.211	19.171	0.206
.|. |	.*| . |	16	-0.026	-0.109	19.216	0.258

Fig 5.25 correlogram of doil

Null Hypothesis: DOILS has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.104175	0.0000
Test critical values:	1% level	-3.626784	
	5% level	-2.945842	
	10% level	-2.611531	

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

Table 5.14 Augmented Dickey-Fuller unit root test of doil

Dependent Variable: DOIL
Method: Least Squares
Date: 03/19/10 Time: 03:14
Sample (adjusted): 1971 2008
Included observations: 38 after adjustments
Convergence achieved after 15 iterations
MA Backcast: 1967 1970

	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.212877	0.123286	-1.726697	0.0933
MA(2)	-0.624711	0.122597	-5.095648	0.0000
MA(3)	-0.081657	0.128535	-0.635293	0.5295
MA(4)	0.683130	0.126511	5.399783	0.0000

R-squared	0.322457	Mean dependent var	9.289474
Adjusted R-squared	0.262674	S.D. dependent var	42.92980
S.E. of regression	36.86283	Akaike info criterion	10.15159
Sum squared resid	46201.53	Schwarz criterion	10.32396
Log likelihood	-188.8801	Hannan-Quinn criter.	10.21292
Durbin-Watson stat	1.602644		

Inverted MA Roots	.81+.45i	.81-.45i	-.70-.55i	-.70+.55i

Table 5.15 ARIMA (0,1,4) estimation result of doil

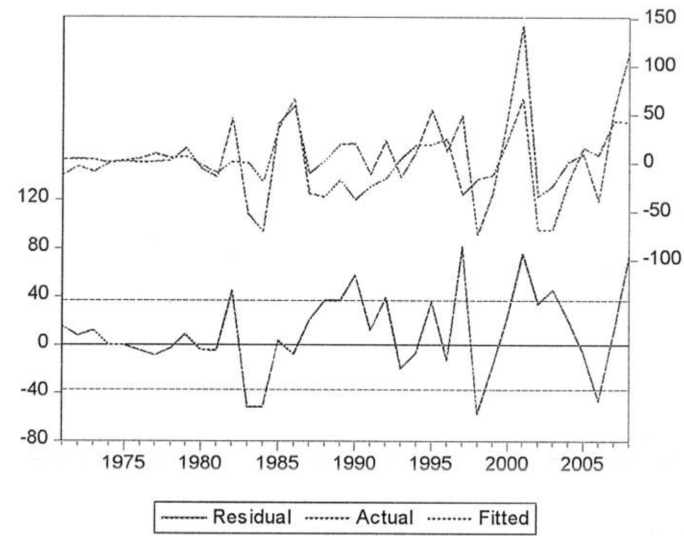


Fig 5.26 residual, actual and fiited graph of doil

Null Hypothesis: RESID02 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.199367	0.0001
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

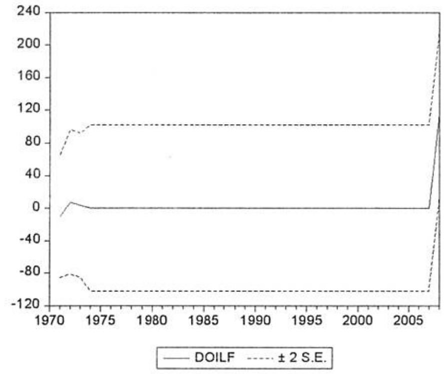
*MacKinnon (1996) one-sided p-values.

Table 5.16 Augmented Dickey-Fuller unit root test of residual of doil

Date: 03/19/10 Time: 03:19
Sample: 1970 2008
Included observations: 38

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.072</td><td>0.072</td><td>0.2105</td><td>0.646</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>-0.029</td><td>-0.035</td><td>0.2468</td><td>0.884</td></tr>
<tr><td>.*|. |</td><td>.*|. |</td><td>3</td><td>-0.124</td><td>-0.121</td><td>0.9197</td><td>0.821</td></tr>
<tr><td>.*|. |</td><td>.*|. |</td><td>4</td><td>-0.139</td><td>-0.125</td><td>1.7827</td><td>0.776</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.033</td><td>-0.025</td><td>1.8344</td><td>0.872</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>-0.016</td><td>-0.036</td><td>1.8460</td><td>0.933</td></tr>
<tr><td>.|*. |</td><td>.|*. |</td><td>7</td><td>0.187</td><td>0.163</td><td>3.5546</td><td>0.829</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>0.038</td><td>-0.006</td><td>3.6278</td><td>0.889</td></tr>
<tr><td>.*|. |</td><td>.*|. |</td><td>9</td><td>-0.137</td><td>-0.150</td><td>4.6124</td><td>0.867</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>-0.034</td><td>0.014</td><td>4.6753</td><td>0.912</td></tr>
<tr><td>.|. |</td><td>.|*. |</td><td>11</td><td>0.052</td><td>0.100</td><td>4.8282</td><td>0.939</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>0.041</td><td>0.016</td><td>4.9263</td><td>0.960</td></tr>
<tr><td>.|*. |</td><td>.|*. |</td><td>13</td><td>0.107</td><td>0.089</td><td>5.6259</td><td>0.959</td></tr>
<tr><td>.*|. |</td><td>.*|. |</td><td>14</td><td>-0.067</td><td>-0.113</td><td>5.9105</td><td>0.969</td></tr>
<tr><td>.|*. |</td><td>.|*. |</td><td>15</td><td>0.116</td><td>0.149</td><td>6.7949</td><td>0.963</td></tr>
<tr><td>.*|. |</td><td>.|. |</td><td>16</td><td>-0.094</td><td>-0.037</td><td>7.4078</td><td>0.965</td></tr>
</table>

Fig 5.27- correlogram of residual of doil



Forecast: DOILF
Actual: DOIL
Forecast sample: 1970 2008
Included observations: 38

Root Mean Squared Error	39.19898
Mean Absolute Error	26.63789
Mean Abs. Percent Error	97.74582
Theil Inequality Coefficient	0.630851
Bias Proportion	0.025474
Variance Proportion	0.369850
Covariance Proportion	0.604675

Fig 5.28 ARIMA (0,1,4) forecast of doil

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

This paper has tried to identify the sources of the disparity created between projections disclosed by Ethiopian government and international organizations like IMF. The results show us that the responsible government institutions used either informal methods(MoFED) or designed based (simple average) methods (CSA) or don't have an officialized one(NBE), while the later one uses formal models which are related to two gap models and its derivatives(like growth oriented financial programing model developed by Chaned ,1989) to forecast rate of growth. For this lack of well developed macro forecasting model lack of remuneration, lack of coordination/ or lack of willingness to work with research organizations or academic institutions(Kibambe and Du Toit,2006), lack of interest to apply the models already developed by intellectuals or reluctancy to adjust (for dynamicity) are the major ones observed in the course of the study.

Even though the choice of an appropriate forecasting procedure depends on a variety of considerations, most literatures show us that model based forecasting methods are better than simple observation methods(Chatfiel,1988; Newbold and Granger,1974; Reid,1975; Chatfield and Prothero, 1973; Ibrahim and Totsuki,1976). Newbold(1984) also strengthned this idea in his theorem stating that if you think you can get good forecasts 'by eye', then any sensible objective forecasting procedure will also give good forecasts.

The other objective of the study was to develop a forecasting model for major crop sectors using Box-Jenkins methodology(univariate ARIMA technique). To develop the model we followed the four basic procedures of identification, estimation, diagnostic checking and forecasting.

Following the four procedures we get the forecasting models for cereal, coffee, pulses, and oil seeds as ARIMA(2,1,2),ARIMA(2,1,4), ARIMA(0,1,4) and ARIMA(0,1,4) respectively. Using these models we tried to forecast the production of the crops under study. The forecasting result show us that the expected growth rate is not as such intutive except for coffee production which is relatively better than others. It seems the expected growth of these crops couldn't cope with the population growth rate(3% according to African Development indicator report 2008). Especially for cereal production which is the main grain crop and covers about 85% of the total production (CSA, 2008) is wandering too much or it is unstable. Pulses and oil seeds seem to grow at a constant rate(1%). There fore, it is worth-noting that as the objective of the paper was limited to forecasting, the results didn't tell us the causes for the trends the crop varities experienced. Hence, this paper could inspire other researchers to use other sophisticated methods and develop models that could tell us the causes for the variation . More over this paper could help researchers to develop the model for the total economy.

Finally, to solve the gap created in forecasting, the responsible bodies for macroforecasting should develop the habit of working with research organizations and academic institutions, should be independent and give their ear to out siders,payment system should be revisited as these two bodies are the main pilars to take major policies for the country.

In addition, for the crop varities to grow with the population growth rate the government should devise balanced policy for the cultivation of these major crops and should be checked out by the government. Incentive should be provided to the farmers for cultivation of these crops. Also, the government should import high yielding varieties from other countries for avering any crisis to come,the government should supply fertilizers to small farmers at lowest possible price as it is one of the major inputs to be affected by changes in international price,Irrigation system should be improved to make the production of the crops rain independent and even to produce more than once a year which could avoid uncertainity,the responsive bodies should arrange training courses for farmers in groups, the experts should demonstrate the use of modern implements, seeds, fertilizers and pesticides,the government should enhance the purchase price of products to give incentive to the farmers for more out put and make easy access for farmers to the market.

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Appendices

Appendix A
Forecast result for cereal

year	Forecast	UCL	LCL
2003	10650.88	13354.25	8685.4
2004	10732.93	13375.42	8759.36
2005	10815.61	13402.14	8973.17
2006	10798.92	13321.10	8824.73
2007	10982.88	13891.43	9175.42
2008	11867.48	14649.61	9237.47
2009	13931.21	16395.16	11622.54
2010	12766.97	15654.48	10108.51
2011	13097.25	16038.22	10388.01
2012	12779.13	15731.15	10065.92
2013	13120.87	16107.9	10372.21

Appendix B
Forecast result for pulse

Year	Forecast	UCL	LCL
2003	1552.4	1735.02	1289.14
2004	1499.7	1728.4	1264.7
2005	1484.7	16871.74	1259.47
2006	1487.23	1695.69	1262.9
2007	1497.41	1703.15	1279.31
2008	1504.73	1724.83	1281.6
2009	1613.769	1851.096	1376.442
2010	1602.071	1900.138	1304.005
2011	1764.519	2071.016	1458.021
2012	1851.307	2159.496	1543.118
2013	1875.221	2217.482	1532.959

Appendix C

Forecast result for coffee

Year	Forecast	UCL	LCL
2003	1207.015	1401.371	1187.752
2004	1221.229	1416.946	1193.253
2005	1234.855	1531.436	1203.415
2006	1749.392	1869.243	1465.310
2007	1863.336	1945.375	1527.247
2008	2078.194	2527.936	1883.625
2009	2409.082	2659.571	2158.593
2010	2341.291	2853.62	1828.963
2011	2377.011	3038.41	1715.612
2012	2471.771	3194.369	1749.173
2013	2599.94	3358.66	1841.221

Appendix D.

forecast result for oilseeds

Year	Forecast	UCL	LCL
2003	503.742	623.7406	413.284
2004	505.361	631.4925	417.649
2005	513.391	637.0372	422.482
2006	521.472	653.3841	437.571
2007	497.638	595.8362	389.296
2008	548.274	639.5438	438.475
2009	637.9169	709.9547	565.879
2010	573.7798	664.1821	483.3775
2011	578.3316	669.3591	487.304
2012	628.0062	719.0589	536.9535
2013	635.838	736.5785	535.0974

APPENDIX E. Data set(in ten thousands of quintals)

year	TCER	TCOFF	TOILS	TPULS
1970	8250	829	303	888
1971	8341	838	306	898
1972	8447	849	310	910
1973	8511	855	313	917
1974	8530	857	313	919
1975	8580	862	315	924
1976	8590	863	315	925
1977	8594	863	316	926
1978	8653	869	318	932
1979	9077	912	333	978
1980	8896	894	327	958
1981	8492	853	312	915
1982	9761	981	358	1051
1983	8339	838	306	898
1984	6400	643	235	689
1985	7481	752	275	806
1986	9103	914	334	980
1987	8787	883	323	946
1988	8863	890	325	955
1989	9380	942	344	1010
1990	9914	996	364	1068
1991	9573	962	352	1031
1992	10207	1025	375	1099
1993	9805	985	360	1056
1994	10136	1018	372	1092
1995	11636	1169	427	1253
1996	11950	1200	439	1287
1997	12180	1228	488	1260
1998	9332	1180	414	1081
1999	10042	1208	383	1087
2000	10193	1257	432	1469
2001	12145	1372	574	1596
2002	11352	1360	539	1575
2003	8725	1286	516	1207
2004	11755	1251	517	1476
2005	11624	1716	526	1271
2006	12879	2414	487	1577
2007	13717	2734	541	1783
2008	14496	2602	656	1965

DECLARATION

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

The examiners' comments have been duly incorporated.

Declared by:

Name: Habtamu Adane

Signature: ____________________

Date: 24/06/2010

Confirmed by advisor:

Name: Alemayehu Geda

Signature: ____________________

Date: 24/06/2010

Place and date of submission:

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