ADDIS ABABA UNIVERSITY
OFFICE OF GRADUATE STUDIES
DEPARTMENT OF STATISTICS

STATISTICAL ANALYSIS AND PREDICTION OF THE BALANCE OF TRADE IN ETHIOPIA USING ERROR CORRECTION AND ARIMA MODELS

BY

YIBELTAL AREGA

June, 2011
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Tables of Content

I List of tables

II List of figures

List of Acronyms

ACF	Akaike information criteria
ADF	Augmented dickey fuller
AR	Auto regressive
ARIMA	Auto regressive integrated moving average
ARMA	Auto regressive moving average
BIC	Schwarz Information Criterion
BT	Balance of trade
CSA	Central Statistical Agency
DF	Dickey-Fuller
ECM	Error correction model
ECT	Error correction term
FDI	Foreign direct investment
FINC	Foreign income
GDP	Gross domestic product
I(0)	Integrated of order zero
I(1)	Integrated of order one
IMF	International Monetary Fund
MA	Moving average
MAPE	Mean absolute percentage error
MoFED	Ministry of finance and economic development
NBE	National bank of Ethiopia
PACF	Partial auto correlation function
PP	Phillips- Perron
REERI	Real effective exchange rate index

RGDP	Real gross domestic product
SC	Schwarz Criterion
SSE	Sum of squares of errors
TIC	Theil's inequality
UNECA	United Nations Economic Commission for Afric
VAR	Vector auto regressive
VECM	Vector error correction model

Abstract

For a long period of time, Ethiopia has involved in foreign trade and experienced trade deficit several time in the past. This deficit can be largely explained by the unequal terms of trade between agricultural commodities (the country's major exports) and capital goods (the country's major imports).

The core objective behind this study is to explore the long run as well as the short run correlates of balance of trade with reference to Ethiopia by using Johansen cointegration approach and Error correction model (ECM), and to forecast the balance of trade through ARIMA model by using annual data from 1974/75 to 2009/10.

The Johansen multivariate co-integration procedure reveals that Ethiopia's trade balance and key determinants (such as real gross domestic product, real effective exchange rate index, debt and foreign income) are co-integrated, and thus share a long-run equilibrium relationship. The error correction model indicates that real gross domestic product has short run impact on the balance of trade in Ethiopia but other determinants such as real effective exchange rate index, debt and foreign income do not have short run effect on the balance of trade in Ethiopia, and that about 77.8 percent of shock (disequilibria) will be adjusted within the same year.

The value of balance of trade is forecasted by using ARIMA model. The result indicated that the deficit in the balance of trade is expected to rise from 2010/11 up to 2015/16.

Key words: Trade balance, Johansen cointegration approach, Error correction model, ARIMA.

1. INTRODUCTION

1.1. Background of the Study

When we compare one country to another we can see differences in economic structure and economic dependence. This economic dependence creates economic interrelationships among the countries in the real world. As a consequence, foreign trade comes into existence. In general this trade covers many countries in the world. Due to this we can say foreign trade is an international trade.

International trade consists of the export trade and import trade. According to demand and supply of international market structure, countries of the world create economic interrelationship. Actually the main benefit from increasing export is usually to increasing the capacity to import intermediate inputs and other goods and services which are necessary or helpful to faster economic development in the domestic market.

Ethiopia has tried to implement completely different trade strategies in the past, including a strategy of import replacement/protection for infant industries during the imperial period, a heavily state-managed trading system during the military government era, and a market-oriented liberalized approach supported by the international financial institutions in the most recent period. Each of these trade regimes incorporated the policy objective of diversifying Ethiopia's export palette to reduce dependence on coffee and other cash crops. Numerous trade-related technical assistance projects have already been implemented. Policies promoting exports have been adopted.

For a long period of time, Ethiopia has involved in foreign trade, that is, it imports and exports different types of goods and commodities. The major export commodities include coffee, gold, leather products, beeswax, fruit and vegetables, sugar, oilseeds, pulses, meat and meat product, live animals and chat.

Major import commodities are raw materials, semi-finished goods (i.e. chemical, fertilizer, textile material), fuel, crude petroleum, capital goods (i.e. transport, agricultural and industrial machineries, heavy road motor vehicles, air craft and others) and consumer good (i.e. durable and non durable). The country's top export trade partners are China, Germany, Netherlands and Saudi Arabia where as import partners are China, Saudi Arabia, India and Italy.

Ethiopia has experienced trade deficit[1] several time in the past. Ethiopia's trade deficit can be largely explained by the unequal terms of trade between agricultural commodities (the country's major exports) and capital goods (the country's major imports). It is projected to reach an all time high of USD 6.7 billion (NBE, 2007).

Though Ethiopia has made good progress in both exports and imports, import bill has grown relatively more as compared to the export bills. The increase in import bills is mainly attributed to the rising investment in the telecom, power and road infrastructure while the slow down in export receipts is mainly due to a weak improvement in commodity export prices according to industry observers (IMF,1999).

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[1] The difference between monetary value of export and import of out put of the economy is negative.

To overcome the unbalance of import and export bill, in 1992 the government began adopting significant reforms for foreign trade. The new foreign trade policies aimed at:

- Promoting private sector development.
- Providing adequate incentives for exporters.
- Replacing quantitative restrictions with tariffs.
- Encouraging export diversification and minimize illicit trade.
- Restructuring state-owned trading enterprises

Various measures have been taken to achieve these objectives since then. The exchange rate has been liberalized using the auction system. Licensing procedure, tariff structures, and foreign exchange retention procedures have been simplified. And private exporters have been given support services, including transport assistance, overseas market research, and training in marketing and packaging.

The deficit of Ethiopia's trade balance can be interpreted in to two ways. On the positive note, the fact that the value of imports is taken up by capital goods plus intermediate inputs is in fact an indication of growth domestic economy and expanding productive capacity of the country at an increasing rate. On a negative note, it can be seen as cause for alarm since such a wide and growing gap between the value of exports and imports of a country means that the country continues to need other sources of financing such as foreign aid and credit.

Trade deficits are not necessarily a policy “problem” in the sense that they require policy adjustments. In some cases, deficits may simply indicate a stronger growth performance in the deficit country than in its major trading partners. In a similar vein, they may reflect transient adverse terms-of-trade developments if prices for major export commodities fall while those for important imports rise. Such cyclical/transient deficits should however self-correct over the course of the business cycle.

Further, trade deficits are not necessarily indicative of a trade policy problem or by the same token a problem that can be solved by trade policy instruments alone. In general, high import taxes or barriers also act indirectly as a tax on exports; the net result is a lower trade share of GDP but there is no definitive implication for the balance of trade. The external balance is, in the long run, decided by other factors.

However, in the highly important medium term, a country’s policy mix can contribute to an external deficit by, in effect, taxing exports. For example, the use of the exchange rate as an external anchor for monetary policy can lead to an increase in the real effective exchange rate and widen trade deficits in a medium-term context. For a country like Ethiopia, which is counting on an export-led development strategy, getting the policy mix right is thus very important.

In any case, the fact still remains that Ethiopia is technically known as an "import compressed" economy, that is, an economy whose growth potential could artificially be limited by its inability to import what it needs for growth due to the gap between the value of exports and the imports demand (NBE, 2008/09).

1.2. Statement of the Problem

In the history of Ethiopia, foreign trade and exchange of goods had started at the ancient time. At the time of axumite empire there was a trade among neighbouring countries in the region of the Red Sea. This trade system has its own importance and considerable influence on the exchange of goods among countries around the region during that time. Starting from that time, Ethiopian governments tried to improve Ethiopia's balance of trade by encouraging exports and by curtailing imports.

All available data indicate that Ethiopia’s foreign trade balance has basically been in deficit since it began trade exchanges. For instance Negadras Gebrehiwot (1912) wrote that during that year, Ethiopia imported commodities through the port of Djibouti worth 7.77 million birr and collected 7.58 million birr from export. At that time the trade deficit was around 192,000 birr.

In 2008/09 the trade deficit widened to USD 6.3 billion from USD 5.3 billion in the preceding fiscal year due to an increase in import and a slow down in exports (NBE 2008/09).

In general, Ethiopia faced deficit for a long period of time. Thus, this study aims to forecast balance of trade in Ethiopia and to analyze the relationship between balance of trade and its determinants.

1.3. Objective of the Study

The general objective of this study is to analyze the relationship between balance of trade and selected macro economic variables in Ethiopia.

Specifically,

- Investigate the nature and fit a model for the balance of trade in Ethiopia.
- Forecast the balance of trade in Ethiopia by using ARIMA model.
- Explain the short-run and long-run dynamics explicitly by using error correction model.

1.4. Significance of the Study

The findings from this study will address the long run and short run relationship between selected macroeconomic variables and balance of trade in Ethiopia. And it can also serve as a reference to subsequent research works in the area of balance of trade in Ethiopia.

1.5. Limitation of the Study

Because of the lack of complete data, variables such as foreign direct investment (FDI), money supply, interest rate etc that are expected to affect the balance of trade are not considered in the study.

2. LITERATURE REVIEW

Numerous studies have been conducted on the issue of factors determining trade balance, both taking itself as a subject of study or by breaking down to its components, namely import and export. Alternative theories have different predictions about the factors underlying balance of trade dynamics and about the sign and magnitude of the relationship between trade balance fluctuations and the determinants. The following literatures examine the relationship between balance of trade with different macroeconomic variables in different countries from oldest to recent.

Bhagwati and Owrisrika (1974), after having an empirical study in 46 African countries which devalued their currencies, concluded that imports continued to grow after devaluation and in the majority of cases, the growth rate exceeds the pre-devaluation growth rate, that is, conditions that require the elasticity of export and import demand to be more than unity are not satisfied. This is because of the very strong demand for imported necessities and inelastic foreign demand for African exports. Thus, with relatively inelastic demand for exports and imports, devaluation has little or no effect in changing trade balance in the contest of African countries (UNECA, 1990).

Lizando and Montiel (1989) seem to agree on the positive effect of devaluation on the trade balance. According to them, the view that a properly administered devaluation will improve the trade balance is widely accepted. But there is much less consensus about possible effects of devaluation on output and employment. However, there is a huge body of literatures that indicates the effect of devaluation on trade balance to be insignificant. Ostray and Rose (1992) in their empirical work suggested that once the time series properties of the variables are properly taken into consideration in the estimation, there is little evidence that relative prices have a significant and predictable effect on trade. While Rose (1990), found that changes in real exchange rate do not have a significant effect on changes in the balance of trade of developing countries.

Also Baharumushah and Rashid (1999) examined the relationship between Malaysian export growth and income growth by including import in the system of equations by using the Johansen (1988) procedure and vector error correction model (VECM). Real exports were disaggregated in to manufacturing and agricultural exports. The result of multivariate cointegration indicates the presence of stationary long run relationship between exports, imports and GDP. The estimated VECM suggested economic growth is driven by exports. Test result also confirms that economic growth causes export growth for manufacturing export. The empirical finding indicates that an important determinant of the fast growing Malaysian economy is import of foreign technology. And Duasa (2007) examined the short- and long-run relationships between trade balance and its determinants for Malaysia. The determinants are real exchange rates, money supply, and income. Using an autoregressive distributed lag (ARDL) approach to cointegration, the variables are found to be cointegrated.

Agbola (2004) analyzed the long-run relationships between Ghana's trade balance and real domestic income, foreign income, real money supply, interest rates and exchange rate using annual data for the period 1970-2002. The Johansen MLE multivariate co-integration procedure reveals that Ghana's trade balance and key determinants are co-integrated, and thus share a long-run equilibrium relationship. The Stock-Watson dynamic OLS model (DOLS), which is superior to a number of alternative estimators, found empirical evidence of significant long run relationship between Ghana's trade balance and real domestic income, foreign income, foreign interest rates and exchange rates. The empirical result suggests that devaluation does not improve the trade balance of Ghana in the long run.

Gómez (2006) used multivariate cointegration tests for non-stationary data and vector error correction models to examine the determinants of trade balance for Argentina over the year 1965 to 2005. His result shows the existence of long-run relationships among trade balance, real exchange rate and foreign and domestic incomes for Argentina during different real exchange rate management policies. Gomes and Paz (2005) and Tsen (2006) demonstrate the existence of a long-run relationship among balance of trade, real exchange rate, foreign and domestic income for Brazil and for Malaysia during 1965-2002, respectively.

Waliullah, Kakar and Khan (2006) by using autoregressive distributed lag (ARDL) approach have found that the domestic income level as measured by GDP is an important determinant of trade balance in Pakistan. Every 1% increase in real income yields an average 1.5% improvement in the trade balance under Schwartz Bayesian Criterion (SBC) selection criterion result and a 1.30% improvement under the Akaike Information Criterion (AIC) selection criterion result. Similarly, the sign of money supply variable is consistent with the monetary approach to trade balance. And the impact of the exchange rate on the trade balance is positive and statistically significant. The devaluation or depreciation of domestic currency by 1% on average improves the trade balance by 0.56% and 0.44% in the long run as suggested by the SBC and AIC selection criteria, respectively. It indicates that the sum of elasticities of exports and imports exceeds unity in the long run and that devaluation/depreciation improves the trade balance in Pakistan.

Ling and Wai-Mun (2007) try to identify the relationship between the real exchange rate and trade balance in Malaysia from year 1955 up to 2006. This study uses unit root test, cointegration techniques, Engle-Granger test, Vector Error Correction Model (VECM) and impulse response analyses. They found that long run relationship exists between trade balance and exchange rate. Other important variables that determine trade balance such as domestic income shows a long run positive relationship with trade balance, and foreign income shows a long run negative relationship. The real exchange rate is an important variable to trade balance, and devaluation will improve trade balance in the long run in Malaysia.

Mohammed (2010) studied the long run as well as the short run determinant of trade deficit with reference to Pakistan by using johansen cointegration approach and error correction model (ECM). The findings of this study suggested that foreign income, foreign direct investment, domestic house hold consumption and real effective exchange rate significantly affect the trade deficit. To highlight the short run dynamics, vector error correction model (VECM) was used. The result of VECM pointed out that there is disequilibrium in the short run which will be adjusted with in one year. The results also show that foreign income, real effective exchange rate and export have positive impact on balance of trade. Himarious (1989) and Bahmani-Oskooe (1985) found a strong association between balance trade and real effective exchange rate in Pakistan.

The above literatures show that balance of trade mainly depends up on the gross domestic product, exchange rate, interest rate, foreign income, money supply and debt of a country. Error correction model and Johansen cointegration approach are commonly used to analyze the relationship between balance of trade of a country with these macroeconomic variables. In view of this and availability of data; debt, real effective exchange rate, foreign income and real gross domestic product are selected and examined to see their short-run and long-run relation with balance of trade through error correction model and Johansen cointegration approach in the context of Ethiopia.

3. DATA AND METHODOLOGY

3.1. Sources of Data

This study uses secondary data on real gross domestic product, debt, balance of trade, foreign income, real effective exchange rate index and price deflator in Ethiopia for the period 1974/75 to 2009/10 from National Bank of Ethiopia (NBE), Ministry of Finance and Economic Development (MoFED), Central Statistical Agency (CSA) and World Bank CD 2000.

3.2. Variables of the Study

The variables of interest in this study are balance of trade as dependent variable, and foreign income, real effective exchange rate index, debt, real gross domestic product (RGDP) as independent variables. All the above variables are in real terms meaning their values are variable are obtained through dividing the nominal value by implicit price deflator at the base year 1999/2000.

Implicit price deflator is a price index calculated as the ratio of nominal gross domestic product to real gross domestic product. Also commonly referred to as the GDP price deflator, the implicit price deflator is used as an indicator of the economy's average price level.

$$\text{GDP deflator} = \frac{\text{Nominal GDP}}{\text{Real GDP}} \times 100$$

In economics, nominal value refers to a value expressed in money terms (that is, in units of a currency) in a given year or series of years. By contrast, real value adjusts nominal value to remove effects of price changes over time.

3.2.1. Description of Variables

Table 3.1 Description of variables

Type of variable	Variable designation	Definition	Unit of measurement
Dependent variable	BT	Balance of trade	In million Birr
Independent variables	RGDP	Real gross domestic product	In million Birr
	DT	Debt	In million Birr
	REERI	Real effective exchange rate index	No unit
	FINC	Foreign income	In million Birr

3.2.2. Definition of Variables

Balance of trade (BT): **-** The difference in value between a country's total exports and imports over a specific period of time.

Real gross domestic product (RGDP): **-** It is gross domestic product in constant price. In other words, it is a nation's total output of goods and services, adjusted for price changes.

Debt (DT): - A sum of money that is owed or due to be paid because of an expressed agreement; a specified sum of money that is obligated to pay and that another party has the legal right to collect or receive.

Real effective exchange rate index (REERI):- It measures weighted average of nominal effective exchange rates against the currencies of principal trading partners, adjusted for relative movements in price or cost indicators against those selected trading partners.

Foreign income (FINC)**: -** Is the weighted sum of GDP of the major trading partners. The weight is calculated by NBE according to the trade that the countries made with Ethiopia.

3.3. Stationarity and Unit-Root Problem

A given series is said to be stationary if its mean and variance are constant over time and the value of the covariance between any two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed.

Generally the concept of stationarity can be summarized by the following conditions. A time series $\{y_t\}$ is said to be stationary if:

$$E[y_t] = E[y_{t-s}] = \mu$$

$$E[y_t - \mu]^2 = E[y_{t-s} - \mu]^2 = \sigma_y{}^2 \text{ and}$$

$$E[y_t - \mu][y_{t-s} - \mu] = E\left[y_{t-j} - \mu\right]\left[y_{t-j-s} - \mu\right] = \gamma(s)$$

where $\mu, \sigma_y{}^2, \gamma(s)$ are all constant (free from t).

Stationarity may be weak or strong stationary (i.e. the whole distribution of the variable does not depend on time). Time series said to be weak stationary if, $E(Y_t)$ is constant and independent of time, Var(Y_t) is a finite, positive constant and independent of time and Cov (Y_t, Y_k) is a finite function of $t - k$ but not of t or k.

The assumption of stationarity is somewhat unrealistic for most macroeconomic variables. A non-stationary process arises when at least one of the conditions for stationarity does not hold.

Let us consider an autoregressive of order 1, AR (1) process:

$$Y_t = \emptyset Y_{t-1} + \varepsilon_t \qquad [1]$$

where ε_t denotes a serially uncorrelated white noise error term with a mean of zero and a constant variance.

Equation [1] can be expressed as follows

$$Y_t = \emptyset^T Y_{t-(T+1)} + \varepsilon_t + \emptyset\varepsilon_{t-1} + \emptyset^2\varepsilon_{t-2} + \emptyset^3\varepsilon_{t-3} + \emptyset^4\varepsilon_{t-4} + \cdots + \emptyset^T\varepsilon_{t-T} \qquad [2]$$

Non-stationarity can originate from various sources but the most important one is the presence of so-called “unit roots”, which means when $\emptyset = 1$ in equation [1] or $\emptyset^T$ remain equal to one as T goes to infinity in equation [2]. Equation [1] and [2] becomes random walk without drift model. So, the shocks never die away. If $|\emptyset|<1$, $\emptyset^T$ goes to zero as T goes to infinity. So the shocks die away. This is stationary case. If $\emptyset > 1$, $\emptyset^T$ goes to infinity as T goes to infinity and the effect of a shock become large over time.

If a variable is stationary in level, i.e. without running any differencing, then the variable is said to be integrated of order zero, denoted by $I(0)$. Similarly, if it becomes stationary by differencing once, then the variable is side to be integrated of order 1, written as I(1). Unit-root test helps to detect whether a variable is stationary or not. It also provides the order of integration at which the variable can be stationary.

3.3.1. Unit Root Test

A test of stationarity (or non-stationarity) that has become widely popular over the past several years is the unit root test**.** For a number of reasons, it is important to know whether or not an economic time series has a unit root. A Nelson and Plosser (1982) pointed out, non stationarity often has important economic implications. It is therefore very important to be able to detect the presence of unit roots in time series, normally by the use of what are called unit root tests. For these tests, the null hypothesis is that the time series has a unit root and the alternative is that it is I(0).The widely used unit-root tests are Augmented Dickey Fuller test (ADF) and Phillips Perron (PP).

3.3.1.1. The Dickey Fuller (DF) Test

The simplest form of the DF (Dickey fuller, 1979) test amounts to estimating

$$y_t = ay_{t-1} + u_t. \quad [3]$$

One could use a t- test to test the hypothesis $a = 1$ against $a < 1$. Alternatively, one can rearrange the model as follows:

$$y_t - y_{t-1} = \nabla y_t = (a-1)y_{t-1} + u_t$$

or, in short ,

$$\nabla y_t = \rho y_{t-1} + u_t \quad [4]$$

where $u_t \sim IID(0, \sigma^2)\ with\ \rho = a - 1$

The test hypotheses are $H_0: \rho = 0$ against $H_1: \rho > 0$. However, using regression equation like equation [4] is valid when the overall mean of the series is zero. When the underline data generating process is not known, it is better to allow a constant or/ and a time trend and then to test for a unit root. In that case, the model needed to be tested for the null hypothesis of stochastic trend (non stationary) against the alternative of stationary up to deterministic trend. In practice, the model may involve a constant or a trend. Dickey and Fuller (1979) actually considered the three models:

1. $\nabla y_t = \rho y_{t-1} + u_t$,
2. $\nabla y_t = \mu + \rho y_{t-1} + u_t$ and
3. $\nabla y_t = \mu + ct + \rho y_{t-1} + u_t$.

For each model, one will need to use different critical values. The reason is that, under non stationarity the t-like statistic computed does not follow a standard t-distribution, but rather a DF distribution.

3.3.1.2. The Augmented Dickey Fuller (ADF) Test

The ADF test is comparable with the simple DF test, but it is augmented by adding lagged values of the first difference of the dependent variable as additional regressors which are required to account for possible occurrence of autocorrelation. Consider the AR (p) model:

$$y_t = \mu + \emptyset_1 y_{t-1} + \cdots \ldots \ldots \ldots \ldots \ldots \emptyset_p y_{t-p} + a_t \qquad [5]$$

We can write equation [5] as:

$$\nabla y_t = \mu + \rho y_{t-1} + \sum_{i=2}^{p} \psi_i \Delta y_{t-p} + a_t \qquad [6]$$

where: $\rho = -(1 - \sum_{i=2}^{p} \emptyset_i)$ and $\psi_i = \sum_{j=i}^{p} \emptyset_j$

The test statistics is $t_{DF} = \frac{\hat{\rho}}{s.e\hat{\rho}}$ where $\hat{\rho}$ is the OLS estimate of $\rho = (\emptyset - 1)$, t_{DF} has to be compared against the 95% critical value of the appropriate DF distribution, which depends on the inclusion of the linear trend and the lag structure. Then we use the t-statistic on the ρ coefficient to test whether we need to difference the data to make it stationary or we need to put a time trend in the regression model to correct for the variables deterministic trend. The null hypothesis for the test is given as $H_o: \rho = 0$, there exists a unit root problem.

3.3.1.3. The Phillips and Perron (PP) Test

An important assumption of the DF test is that the error terms u_t are independently and identically distributed. The ADF test adjusts the DF test to take care of possible serial correlation in the error terms by adding the lagged difference terms of the dependent variable. Phillips and Perron use nonparametric statistical methods to take care of the serial correlation in the error terms without adding lagged difference terms.

The test statistic for the PP tests is

$$\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_o}{f_o}\right)^{1/2} - \frac{T(f_o - \gamma_o)(se(\hat{\alpha}))}{2f_o^{1/2}s}$$

where $\hat{\alpha}$ is the estimate, $\hat{t}_\alpha$ is the t -ratio of α, $se(\hat{\alpha})$ is coefficient standard error and s is the standard error of the test statistic. In addition, γ_o is a consistent estimate of the error variance and it is calculated as $(T-k)s^2/T$, where k is the number of regressors and f_o is an estimator of the residual spectrum at frequency zero.

3.4. Introduction to Time Series and ARIMA Model

A time series is a sequence of dependent observations ordered in time. Mostly these observations are collected at equally spaced, discrete time intervals. When there is only one variable up on which observation are made then we call this a single time series or more specifically a univariate time series. A basic assumption in any time series analysis/modelling is that some aspects of the past pattern will continue to remain in the future. Also under this set up, often the time series process is assumed to be based on past values of the main variable but not on explanatory variables which may affect the system. There are two main reasons for resorting to such time series models. First, the system may not be understood, and even if it is understood it may be extremely difficult to measure the cause and the effect relationship. Second, the main concern may be only to predict what will happen and not to know why it happens. Most of the time, collection of information on causal factors (explanatory variables) affecting the study variable(s) may be cumbersome/ impossible and hence availability of long series data on explanatory variables is a problem. In such situations, the time series models are a boon for forecasters.

3.4.1. AR Process

The auto correlation function of pure AR (p) processes should decay gradually at increasing lag length. If the ACF exhibits slow decay and the PACF cuts off sharply after lag p, we would identify the series as AR (p). Hence, for the pure AR (p) process, the theoretical ACF and PACF are as follow:

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

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

The ACF at lag i, denoted by ρ_i is defined as

$$\rho_i = \frac{cov\{Y_t, Y_{t-i}\}}{v\{Y_t\}} = \frac{\gamma_i}{\gamma_0}$$

where γ_i is the covariance at lag i and γ_0 is the variance. Since both covariance and variance are measured in the same units, ρ_i is a unitless, or pure number and lies between [-1, 1]. In time series data the main source of correlation between Y_t and Y_{t-i} originates from the correlations they have with intervening lags; that is, $Y_{t-1}, Y_{t-2}, \dots, Y_{t-i+1}$. The partial correlation measures the correlation between observations that are i time periods apart after controlling for correlations at intermediate lags; that is, it removes the influence of these intervening variables. In other words, partial autocorrelation is the correlation between Y_t and Y_{t-i} after removing the effect of intermediate Y's.

The PACF at lag *i* is the regression coefficient on Y_{t-i} when Y_t is regressed on a constant, $Y_{t-1,\dots\dots\dots,}Y_{t-k}$. This is a partial correlation since it measures the correlation of Y values that are *i* periods apart after removing the correlation from the intervening lags. If the pattern of autocorrelation is one that can be captured by an autoregression of order less than *i*, then the partial autocorrelation at lag *i* will be close to zero.

The partial autocorrelation at lag *i* is computed by

$$\emptyset_i = \begin{cases} \tau_1 \; for \; i = 1 \\ \frac{\tau_i - \sum_{j=1}^{i-1} \emptyset_{i-1}, j_{i-j}^{\tau}}{1 - \sum_{j=1}^{i-1} \emptyset_{i-1}, j_{i-j}^{\tau}} \text{ for i>1} \end{cases}$$

where $\tau_k$is the estimated autocorrelation at lag *i*, and where,

$$\emptyset_{i,j} = \emptyset_{i-1,j} - \emptyset_i \emptyset_{i-1,i-j}$$

3.4.2. MA Process

The behaviour of the correlogram and partial correlogram of the pure MA (q) is the inverse of pure AR (p) processes. The auto correlogram of pure MA (q) process should die out after q lags. The partial auto correlogram of pure MA process, on other hand, only decays slowly over time (similar to auto correlogram of pure AR process). Hence, for a pure MA (q) process, the theoretical ACF and PACF are as follows:

ACF (*i*) = 0 for all *i* > q

PACF (*i*) ≠ 0 for all *i*

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

3.4.3. ARMA Process

Autoregressive moving average (ARMA) modelling is a specific subset of univariate modelling in which a time series is expressed in terms of past values of it self (the autoregressive component) plus current and lagged values of a ‘white noise’ error term (the moving average component). In general, an ARMA model is characterized by the notation ARMA (p, q) where, p and q are orders of autoregressive and moving average respectively.

The equation of an ARMA (p, q) process is given by:

$$y_t = \mu + \emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \qquad [7]$$

Or

$$\Phi_p(B)Y_t = \mu + \Theta_q(B)\varepsilon_t \qquad [8]$$

where $\Phi_p(B) = 1 - \emptyset_1 B - \cdots \ldots - \emptyset_p B^p$ and $\Theta_q(B) = 1 - \theta_1 B - \cdots \ldots - \theta_q B^q$

and B is the backward shift operator

3.4.4. ARIMA Process

Autoregressive Integrated Moving Average (ARIMA) model was introduced by Box and Jenkins (hence also known as Box-Jenkins model) in 1960s for forecasting a variable. Autoregressive Integrated Moving-Average (ARIMA) models consist of unit-root non-stationary time series which can be made stationary by the order of integration ‘d’. The general form of ARIMA (p, d, q) is written as follows:

$$\nabla^d \Phi_{\mathrm{p}}(B)Y_t = \mu + \Theta_q(B)\varepsilon_t \qquad [9]$$

where ∇ =1-B, d is the order of integration.

3.4.5. Model Identification

Once the series process is made stationary, the next step is to find the appropriate ARIMA form to model the stationary series (i.e. to identify appropriate values of the model; that is p, d, and q.). There are two main approaches to identification of ARIMA models in the literature. Theses are penalty function criteria and traditional Box-Jenkins procedure, in which traditional Box-Jenkins an iterative process of model identification, model estimation and model evaluation is followed. The box-Jenkins procedure is a quasi-formal approach with model identification relying on subjective assessment of plots of correlogram and partial auto correlogram of the series.

The Box-Jenkins methodology is not only about model identification but is, in fact, an iterative approach incorporating model estimation and diagnostic checking in addition to model identification. Theoretically the Box-Jenkins model identification is relatively easy if one has a pure AR and pure MA process. However, in the case of mixed ARMA models (especially of higher order) it can be difficult to interpret sample ACFs and PACFs, and Box-Jenkins identification become a highly subjective exercise depending on the skill and experience of the analyst.

3.4.5.1. Criteria for Model Selection

Because economic theory does not provide any guidance to the appropriate choice of model, some additional criteria can be used to choose from alternative models that are acceptable from a statistical point of view. As a more general model will always provide a better fit (within the sample) than a restricted version of it, all such criteria provide a trade-off between goodness-of-fit and the number of parameters used to obtain that fit.

$$AIC = log\hat{\sigma}^2 + 2\left[\frac{P + q + 1}{T}\right]$$

where p is number of autoregressive term, q is number of moving average term and $\hat{\sigma}^2$ is the estimated variance of ε_t. An alternative is Schwarz's Bayesian Information Criterion (*SC, BIC* or *SBC*), proposed by Schwarz (1978), which is given by

$$BIC = log\hat{\sigma}^2 + \left[\frac{P + q + 1}{T}\right]logT$$

Both criteria are likelihood-based and represent a different trade-off between 'fit', as measured by the log likelihood value, and 'parsimony', as measured by the number of free parameters, $p + q + 1$ (assuming that a constant is included in the model). Usually, the model with the smallest *AIC* or *BIC* value is preferred, although one can choose to deviate from this if the differences in criterion values are small for a subset of the models.

While the two criteria differ in their trade-off between fit and parsimony, the *BIC* criterion can be preferred because it has the property that it will almost surely select the true model, if $T \rightarrow \infty$, provided that the true model is in the class of *ARMA*(*p,q*) models for relatively small values of *p* and *q*. The *AIC* criterion tends to result asymptotically in over parameterized model.

3.4.5.2. R-squared, adjusted R-squared and standard error

The R-squared (R^2) statistic measures the success of the regression in predicting the values of the dependent variable within the sample. In standard settings, may be interpreted as the fraction of the variance of the dependent variable explained by the independent variables. Adjuster R^2 penalizes the R^2 for the addition of regressors which do not contribute to the explanatory power of the model. And standard Error of the Regression (S.E. of regression) is a summary measure based on the estimated variance of the residuals.

3.4.6. Model Estimation

Having identified the appropriate p, d and q values, and the next stage is to estimate the parameters of the autoregressive and moving average terms included in the model. Sometimes this calculation can be done by simple least squares but sometimes we will have to resort to nonlinear (in parameter) estimation methods.

3.4.7. Model Diagnostics

This step will be the formal assessment of each of the time series models. This will involve a rigorous assessment of the diagnostic tests for each of the competing models. As different models may perform reasonably similarly, a number of alternative formulations may have to be retained at this stage to be further assessed at the forecasting stage.

There are a number of diagnostic tools available for ensuring a satisfactory model is arrived at. Plotting the residuals of the estimated model is a useful diagnostic check. This should indicate any outliers that may affect parameter estimates and also point towards any possible autocorrelation or heteroskedasticity problems. If the model is correctly specified the residuals should be 'white noise'. Therefore, a plot of the autocorrelogram should immediately die out from one lag on. Any significant autocorrelations may indicate that the model is misspecified and may point to the solution.

3.4.7.1. Autocorrelation Test

Before an estimated model is used for statistical inference (*e.g.* hypotheses tests, forecasting, etc), the residuals must be examined for the presence of serial correlation. The Ljung-Box Q-statistic is often used as a test of whether the residual series is white noise. The Q-statistic, to test the null hypothesis of no autocorrelation up to lag k, is computed as:

$$Q_{LB} = T(T+2)\sum_{i=1}^{k}\left(\frac{r_I^2}{T-i}\right)$$

where r_i is the i-th lag autocorrelation and T is the number of observations. Under the null hypothesis, Q_{LB} is asymptotically distributed as chi-square with degrees of freedom equal to (k-m*)*, where m denotes the number of parameters in the model.

3.4.7.2. Heteroskedasticity

This displays the autocorrelations and partial autocorrelations of the squared residuals up to any specified number of lags and computes the Ljung-Box *Q*-statistics for the corresponding lags. The correlogram of the squared residuals can be used to check autoregressive conditional heteroskedasticity (ARCH) in the residuals. If there is no ARCH in the residuals, the autocorrelations and partial autocorrelations should be zero at all lags and the *Q*-statistics should not be significant.

3.4.7.3. Normality

This displays the frequency distribution of your series in a histogram. The histogram divides the series range (the distance between the maximum and minimum values) into a number of equal length intervals or bins and displays a count of the number of observations that fall into each bin. Complements of standard descriptive statistics are displayed along with the histogram. All of the statistics are calculated using the observations in the current sample.

Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$\text{Jarque} - \text{Bera} = \frac{N-K}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

where S is the skewness, K is the kurtosis, and K represents the number of estimated coefficients used to create the series. Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as χ^2 with 2 degrees of freedom. The reported Probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis—a small probability value leads to the rejection of the null hypothesis of a normal distribution

3.4.8. Forecasting Time Series Model

In applied macro economics and financial econometrics, often the main reason for estimating an econometric model is so that the estimated model can be used to compute forecasts of the series. While any type of econometric model can be used to compute forecasts (e.g. multivariate regression model, Autoregressive distributed lag model, etc) it is the univariate time series models such as AR and ARMA models that have proved to be the most popular. The forecasting theory for univariate time series model has long been established (Box and Jenkins, 1970) and univariate Box-Jenkins methods have continued to be popular with econometricians.

3.4.9. Forecast Evaluation and Forecast Accuracy Criteria

The accuracy of a forecasting method is determined by analyzing forecast error experiences. The forecasting performance of the estimators is judged on the basis of the differences between predictions and realizations. The smaller the difference between the predictions and the actual values of the dependent variable, the better is the forecasting performance of the estimator. The within-sample forecasting performance of the system should be assessed using standard statistical tools such as Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error and Theil's inequality Coefficient. The first two forecast error statistics depend on the scale of the dependant variables, and the remaining two statistics are scale invariant (i.e. unit free). In most instances unit free measures are preferable (Challen and Hagger, 1983). As a result Theil's Inequality coefficient (TIC) and Mean Absolute Percentage Error (MAPE) are preferable. If the forecast is good, the Mean Absolute Percentage Error and Theil's Inequality coefficient should be as small as possible. Theil's Inequality coefficient (TIC) suggested by Theil (1996) is a measure of the fit of a forecast. It ranges between zero and one. When it is equal to zero it indicates that a forecast has a perfect fit. TIC=1 indicates a forecast just as accurate as one of '' no change''($\Delta Y_t = 0$).Theil's Inequality Coefficient can be decomposed into bias, variance, and covariance proportions each showing a different source of forecast error.

- The bias proportion indicates how far the mean of the forecast is from the mean of actual series.
- The variance proportion indicates how far the variation of the forecast is from the variation of the actual series.
- The covariance proportion measures the remaining unsystematic forecasting error.

If the forecast is "good", the bias and variance proportion should be as small as possible so most of the bias should be concentrated on the covariance proportion.

3.4.9.1. Mean Squared Errors (MSE)

The mean squared error is an accuracy measure computed by squaring the individual error for each item in a data set and then finding the average or mean value of the sum of those squares.

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2$$

where MSE is mean squared error, n is time periods and e^2 is forecast error

3.4.9.2. Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error is the mean or average of the sum of all of the percentage errors for a given data set taken without regard to sign so as to avoid the problem of positive and negative values cancelling one another.

$$\mathrm{PE}_t = \left(\frac{Y_t - F_t}{Y_t}\right) * 100$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n} |\mathrm{PE}_t|$$

where PE is percentage error, Y_t is actual observation for time period t, F_t is forecast for the same period, MAPE is mean absolute percentage error and n is time periods

3.4.9.3. Theil's U-statistic

The U-statistic developed by Theil (1966) is an accuracy measure that emphasizes the importance of large errors (as in MSE) as well as providing a relative basis for comparison with naïve forecasting methods. Theil's equation is written as shown below:

$$U = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{F_{t+1} - Y_{t+1}}{Y_t}\right)^2}{\sum_{i=0}^{n}\left(\frac{Y_{t+1} - Y_t}{Y_t}\right)^2}}$$

where U is Theil's U-statistic, F_t is forecast value and Y_t is actual value

Theil's U-statistic can be interpreted as dividing the RMSE (Root Mean Square Error, or square root of the MSE) of the proposed forecasting method by the RMSE of a no-change (naïve, U=1) model. If U is equal to 1, it means that the proposed model is as good as the naïve model.

3.4.9.4. Root Mean Square Error

The RMSE is one of the most widely used measures of forecast accuracy.

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

where RMSE is mean squared error, n is time periods, F_t is the forecasted value and Y_t is the actual value.

3.5. Cointegration Test

Estimation of non-stationary time series data and analysis of short run dynamics is often done by first eliminating the trend in the variables, usually through the process of differencing till stationarity is achieved.

This procedure, however, throws away potential valuable information about long run relationships which economic theories have a lot to say about (Maddle, 1992). These problems of loosing long run information can easily be amended if it is possible to find a cointegration vector through a cointegration analysis.

The concept of cointegration mimics the existence of long run equilibrium to which an economic system converges over time, whereas the absence of cointegration leads to the problem of spurious regression (Harris, 1995: Harris and Sollis, 2003). Two broad approaches for cointegration have been developed. These are Engle and Granger (1987) method and the Johansen approach, due to Johansen (1998), based on vector autoregressive model (VAR) (Green, 2003).

3.5.1. The Johansen Approach

The Engle and Granger approach is based on assessing whether single equation estimates of the equilibrium errors appears to be stationary. In the Engle-granger approach to cointegration, two time series, say $Y_t \, and \, X_t$, are non stationary in level but stationary in the first difference (that is $Y_t \sim I(1) and\ X_t \sim I(1)$), and there exists a linear combination between these two series that is stationary. It follows that these two series are cointegrated implying they have reasonable long run relationships.

The Johansen procedure not only determines the number of cointegrating vectors but also provides estimates of these vectors. The Johansen approach is superior due to the following reasons. It does not require a prior distinction between endogenous and exogenous variables; it can deal with I(0) and I(1) variables avoiding much of the pre-testing problem and it can capture a wide range of data generating processes. In addition, it identifies multiple cointegrating vectors (if any) unlike Engle-Granger representation which assumes only one cointegrating vector. There are two types of tests for Johansen cointegration approach called trace test and the maximum eigenvalue test. The test statistics for the trace test and maximum eigenvalue test are shown in the following equations [10] and [11] respectively.

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln (1 - \hat{\lambda}_i) \qquad [10]$$

$$J_{max} = -T ln\left(1 - \hat{\lambda}_{i+r}\right) \qquad [11]$$

where T is the sample size, n is number of endogenous variables and $\hat{\lambda}_i$ is the largest eigenvalue. The trace test tests the null hypothesis of *r* cointegrating vectors against the alternative hypothesis of *n* cointegrating vectors. The maximum eigenvalue test, on the other hand, tests the null hypothesis of *r* cointegrating vectors against the alternative hypothesis of *r* +1 cointegrating vectors where r =1,2,.....n. Neither of these test statistics follows a chi square distribution in general; asymptotic critical values can be found in Johansen and Juselius (1990). Since the critical values used for the maximum eigenvalue and trace tests are based on a pure unit-root assumption, they will no longer be correct when the variables in the system are near-unit-root processes. Thus, the real question is how sensitive Johansen's procedures are to deviations from the pure-unit root assumption.

Although Johansen's methodology is typically used in a setting where all variables in the system are I(1), having stationary variables in the system is theoretically not an issue and Johansen (1995) states that there is little need to pre-test the variables in the system to establish their order of integration. If a single variable is I(0) instead of I(1), this will reveal itself through a cointegrating vector whose space is spanned by the only stationary variable in the model.

3.6. Error Correction Model (ECM)

Error Correction Models (ECMs) are a category of multiple time series models that directly estimate the speed at which a dependent variable returns to equilibrium after a change in an independent variable. ECMs are useful for estimating both short term and long term effects of one time series on another.

The cointegrating regression so far considers only the long-run property of the model, and does not deal with the short-run dynamics explicitly. Clearly a good time series modeling should describe both short-run dynamics and the long-run equilibrium simultaneously. For this purpose, the error correction model (ECM) is developed. Although ECM has been popularized after Engle and Granger

(1987), it has a long tradition in time series econometrics dating back to Sargan (1964).

To start, let us consider two time series $y_t \, and \, x_t$ and define the error correction term by

$$\xi_t = y_t - \beta x_t,$$

where β is a cointegrating coefficient and ξ_t is the error correction term which measures the speed at which prior deviations from equilibrium are corrected and it is stationary at level. Then an ECM is simply defined as follows:

$$\Delta y_t = \alpha \xi_{t-1} + \gamma \Delta x_t + u_t \qquad [12]$$

where u_t is iid. The ECM equation (12) simply says that Δy_t can be explained by the lagged ξ_{t-1} and Δx_t. ξ_{t-1} can be thought of as an equilibrium error (or disequilibrium term) occurred in the previous period.

Notice that β is called the long-run parameter, and α and γ are called short-run parameters. Thus the ECM has both long-run and short-run properties built in it. The former property is embedded in the error correction term ξ_{t-1} and the short-run behavior is partially but crucially captured by the error correction coefficient, α. All the variables in the ECM are stationary, and therefore, the ECM has no spurious regression problem. Error correction models can be used to estimate the following quantities of interest for all x variables.

- Short term effects of x on y
- Long term effects of x on y
- The speed at which y returns to equilibrium after a deviation has occurred.

3.7. Software

All the analysis will be carried out in Eveiws 6.

4. DATA ANALYSIS AND INTERPRETATION

4.1. Descriptive Statistics

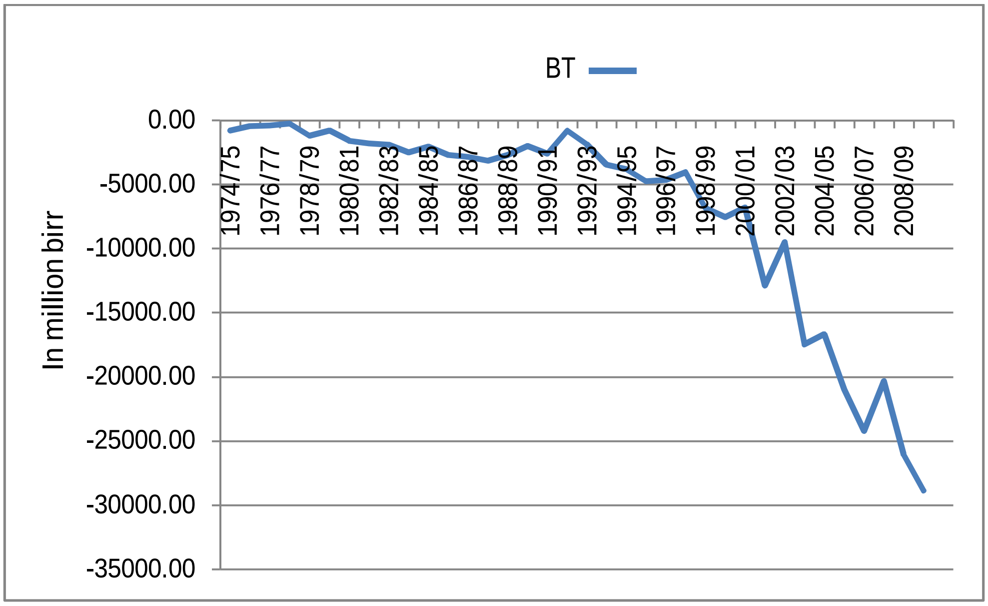
Summary statistics of balance of trade and selected macro-economic variables are presented in table 4.1. All figures are at constant price where the base year is 1999/2000. From the result for instance, the mean value of balance of trade, debt and real gross domestic product over the years are -6981.978, 24313.47 and 62192.58 million birr, respectively. And the maximum and minimum value of balance of trade is -253.2130 and -28862.90 respectively.

Table- 4.1. Descriptive statistics for macroeconomic variables

	BT (in billion)	DT (in billion)	RGDP (in billion)	FINC (in billion)	REERI
Mean	-6.98	24.31	62.19	13060.04	207.5
Median	-3.00	24.21	49.71	13024.81	220.6
Maximum	-0.25	65.82	152.40	19067.49	407.2
Minimum	-28.86	0.35	36.48	7627.59	63.6
S.d.	3.84	2.19	4.51	1.76	2.10

As we see from figure 4.1 below, the value of balance of trade has increased negatively in most of the years. From the 1974/75 up to 1990/91, balance of trade exhibits relatively small drop annually but after 1990/91 onwards it shows a sharp drop.

Figure-4.1. Balance of trade in Ethiopia from 1974/75 to 2009/10



4.2. ARIMA Model for Balance of Trade in Ethiopia

As we have seen in the methodology part, ARIMA modelling consist identification, estimation and diagnostic checking. To assess non-stationarity, result of ADF for BT is given in table 4.2.

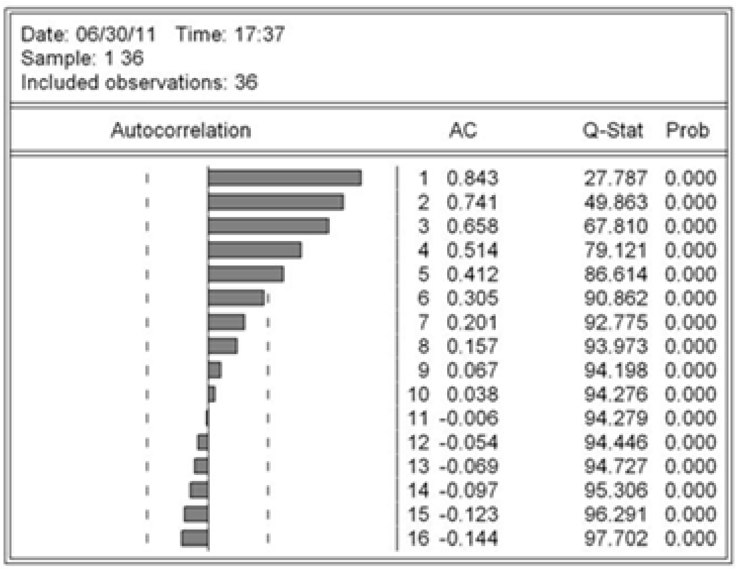
Table-4.2. ADF test for BT at level

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.365703	0.9999
Test critical values:	1% level	-4.262735	
	5% level	-3.552973	
	10% level	-3.209642	

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

The test statistic (1.365703) is greater than the critical value (-3.552973) with p value (0.9999). This implies that we fail to reject the null hypothesis that is there is a unit root problem at 5% level of significance. In addition to ADF test, the correlogram autocorrelation (Figure 4.2) shows that the autocorrelation function does not tail of quickly. This proves the presence of unit root in the series of balance of trade.

Figure-4.2. Correlogram for BT at level


Date: 06/30/11 Time: 17:37
Sample: 1 36
Included observations: 36

Autocorrelation		AC	Q-Stat	Prob
	1	0.843	27.787	0.000
	2	0.741	49.863	0.000
	3	0.658	67.810	0.000
	4	0.514	79.121	0.000
	5	0.412	86.614	0.000
	6	0.305	90.862	0.000
	7	0.201	92.775	0.000
	8	0.157	93.973	0.000
	9	0.067	94.198	0.000
	10	0.038	94.276	0.000
	11	-0.006	94.279	0.000
	12	-0.054	94.446	0.000
	13	-0.069	94.727	0.000
	14	-0.097	95.306	0.000
	15	-0.123	96.291	0.000
	16	-0.144	97.702	0.000

Due to the presence of unit root problem, we have to consider the first difference of the balance of trade data to make it stationary.

Table-4.3. ADF test for BT at first difference

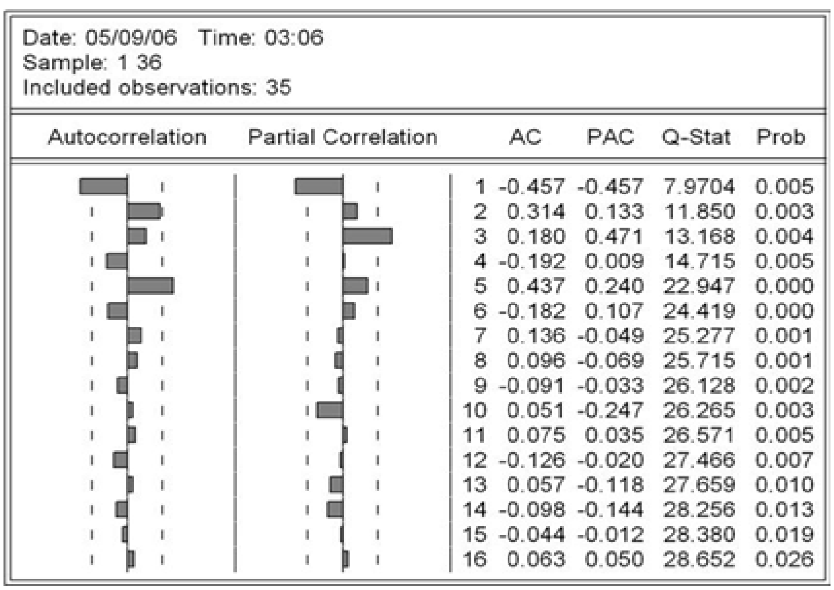
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-5.782298	0.0002

From Table 4.3 we can conclude that the BT time series data becomes stationary after the first difference.

4.2.1. Model Identification and Estimation

Because of highly subjective nature of the Box-Jenkins methodology, time series analysts have sought alternative objective methods for identifying ARIMA models. The penalty function statistics such Akakie's Information Criterion (AIC) and Schwarz's Bayesian criterion (SBC) are often used in the identification of ARIMA models. Usually the smallest AIC or BIC value is preferred.

Figure-4.3. Correlogram for BT at first difference



Date: 05/09/06 Time: 03:06
Sample: 1 36
Included observations: 35

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.457	-0.457	7.9704	0.005
		2	0.314	0.133	11.850	0.003
		3	0.180	0.471	13.168	0.004
		4	-0.192	0.009	14.715	0.005
		5	0.437	0.240	22.947	0.000
		6	-0.182	0.107	24.419	0.000
		7	0.136	-0.049	25.277	0.001
		8	0.096	-0.069	25.715	0.001
		9	-0.091	-0.033	26.128	0.002
		10	0.051	-0.247	26.265	0.003
		11	0.075	0.035	26.571	0.005
		12	-0.126	-0.020	27.466	0.007
		13	0.057	-0.118	27.659	0.010
		14	-0.098	-0.144	28.256	0.013
		15	-0.044	-0.012	28.380	0.019
		16	0.063	0.050	28.652	0.026

The above correlogram shows that the autocorrelation function has spike at lag one and five and the partial correlation function has spike at lag one and three.

These patterns suggest ARIMA models such as ARIMA(1,1,0), ARIMA(3,1,0), ARIMA(0,1,1), ARIMA(0,1,5), ARIMA(1,1,1), ARIMA(1,1,5), ARIMA(3,1,1) and ARIMA(3,1,5).

The corresponding fitted models are:

- ARIMA(1,1,0)

$$\Delta y_t = -805.9650 - 0.466801\Delta y_{t-1} + \varepsilon_t$$

- ARIMA(3,1,0)

$$\Delta y_t = -1221.923 - 0.554338\Delta y_{t-1} + 0.359390\Delta y_{t-2} + 0.704504\Delta y_{t-3} + \varepsilon_t$$

- ARIMA(0,1,1)

$$\Delta y_t = -790.4054 + 0.296570\varepsilon_{t-1} + \varepsilon_t$$

- ARIMA (0,1,5)

$$\Delta y_t = -833.3703 + 0.662138\varepsilon_{t-1} - 0.687997\varepsilon_{t-2} - 0.186660\varepsilon_{t-3} + 0.392785\varepsilon_{t-4} - 0.482239\varepsilon_{t-5} + \varepsilon_t$$

- ARIMA(1,1,1)

$$\Delta y_t = -807.7062 - 0.515609\Delta y_{t-1} - 0.061999\varepsilon_{t-1} + \varepsilon_t$$

➢ ARIMA(1,1,5)

$$\Delta y_t = -921.5980 - 0.514722\Delta y_{t-1} - 0.100956\varepsilon_{t-1} - 0.240550\varepsilon_{t-2} - 0.050440\varepsilon_{t-3} + 0.045240\varepsilon_{t-4} - 0.633717\varepsilon_{t-5} + \varepsilon_t$$

➢ ARIMA(3,1,1)

$$\Delta y_t = -1311.085 - 0.459472\Delta y_{t-1} + 0.393736 y_{t-2} + 0.695329 y_{t-3} + 0.159380\varepsilon_{t-1} + \varepsilon_t$$

➢ ARMA(3,1,5)

$$\Delta y_t = -3738.192 - 0.616414\Delta y_{t-1} + 0.396082\Delta y_{t-2} + 1.119790\Delta y_{t-3} - 0.062985\varepsilon_{t-1} + 0.136449\varepsilon_{t-2} + 0.803314\varepsilon_{t-3} - 0.104644\varepsilon_{t-4} + 0.218057\varepsilon_{t-5} + \varepsilon_t$$

4.2.2. Model Diagnostic

The third step will be the formal assessment of each of the time series models. This involves a rigorous assessment of diagnostic tests for each of the competing models. As different models may perform reasonably similar, a number of alternative formulations may have to be retained at this stage with further assessment to be done at the forecasting stage. There are a number of diagnostic tools available for ensuring a satisfactory model is arrived at. Plotting the residuals of the estimated models is a useful diagnostic check. This should indicate any outliers that may affect parameter estimates and also point towards any possible autocorrelation problem. If a model is correctly specified, the residuals should be white noise. Therefore, the plot of autocorrelogram should immediately die out from one lag on. That is, if the residuals are truly random, the autocorrelations and partial autocorrelations calculated using the residuals should be statistically equal to zero at all lags. If they are not, this is an indication that the fitted model is not good.

4.2.3. Assessing the Fitted Model

The following table shows that the selected ARIMA model with corresponding penalty function statistics.

Table-4.4. Model summery for selected ARIMA models

Selected models	Penalty function statistics					
	R^2	Adj R^2	SSE	AIC	SC	Serial correlation
ARIMA(1,1,0)	0.2148	0.1902	2185.03	18.27	18.36	Yes
ARIMA(3,1,0)	0.5068	0.4539	1842.25	17.99	18.18	No
ARIMA(0,1,1)	0.1382	0.1121	2261.43	18.34	18.43	Yes
ARIMA(0,1,5)	0.4968	0.4099	1843.48	18.03	18.29	No
ARIMA(1,1,1)	0.2165	0.166	2217.48	18.33	18.46	Yes
ARIMA(1,1,5)	0.4943	0.3819	1909.01	18.13	18.44	NO
ARIMA(3,1,1)	0.5087	0.436	1872.28	18.05	18.27	No
ARIMA(3,1,5)	0.6653	0.5489	1674.384	17.91	18.05	Yes

As discussed in the methodology part, a model with small AIC and BIC is preferable. Based on these selection criteria, ARIMA (3,1,5) seems the best.

However, the residual were found to be serially correlated. Based on the value of R^2 and adjusted R^2 (in addition to AIC and SC), the model ARIMA (3,1,0) is selected for further assessment. The results are shown below.

4.2.4. Candidate Model

ARIMA (3,1,0) model

The estimated ARIMA(3,1,0) model together with the diagnostic test results are shown in table 4.5 below.

Table-4.5. Estimated model for ARIMA(3,1,0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\emptyset_0$	-1221.923	768.5460	-1.589915	0.1231
$\emptyset_1$	-0.554338	0.165740	-3.344625	0.0024
$\emptyset_2$	0.359399	0.184834	1.944437	0.0620
$\emptyset_3$	0.704504	0.179617	3.922256	0.0005

R-squared	0.506761	Mean dependent var	-894.0527
Adjusted R-squared	0.453914	S.D. dependent var	2492.977
S.E. of regression	1842.251	Akaike info criterion	17.99183
Sum squared resid	95028895	Schwarz criterion	18.17505
Log likelihood	-283.8693	Hannan-Quinn criter.	18.05256
F-statistic	9.589207	Durbin-Watson stat	1.842203
Prob(F-statistic)	0.000161		

We can write the ARIMA (3,1,0) model as follows:

$$\nabla y_t = -1221.923 - 0.554338\nabla y_{t-1} + 0.359390\nabla y_{t-2} + 0.704504\nabla y_{t-3} + \varepsilon_t$$

We can write the above estimated model in level form as follows:

$$y_t - y_{t-1} = -1221.923 - 0.554338(y_{t-1} - y_{t-2}) + 0.359390(y_{t-2} - y_{t-3}) + 0.704504(y_{t-3} - y_{t-4}) + \varepsilon_t$$

After some mathematical manipulations the estimated model becomes:

$$y_t = -1221.923 + 0.445662y_{t-1} + 0.913737y_{t-2} + 0.345105y_{t-3} - 0.704504y_{t-4} + \varepsilon_t$$

The Jarque-Bera statistic and Q-statistics of the correlogram of residuals squared are not significance. These values indicate that, the candidate model full fills the assumption of normality and no heteroskedasticity in the residual (appendix 4.4 and 4.5).

4.2.5. Evaluation of in-sample forecast

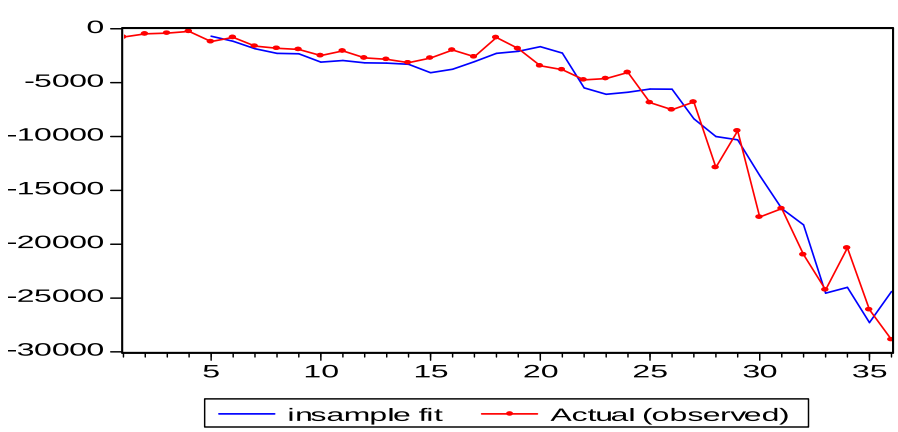
The forecasting performance of a model can be examined by the standardized statistical tools such as root mean square error, mean absolute error, mean absolute percentage error and Theil's inequality. But as discussed in the methodology part, mean absolute percentage error and Theil's inequality are unit-less and preferable. Due to this, we consider the values of mean absolute percentage error (MAPE) and Theil's inequality (TI).

Table-4.6. Summary table for ARIMA(3,1,0) model

Statistical tools	ARIMA(3,1,0)
RMSE	1723.268
MAE	1304.767
MAPE	29.91570
TIC	0.077181
Bias proportion	0.000000
Variance proportion	0.062371
Covariance proportion	0.937629

The mean absolute percentage error and Theil's inequality for ARIMA (3,1,0) model are 29.91570 and 0.077181, respectively. The value of Theil's inequality is close to one. This value indicates that the forecasting performance of the model is good. The other model fit criteria also point towards the ARIMA (3,1,1) model has good forecasting performance (meaning that Figure 4.4 shows that the line of actual and forecasted is overlap each other). Thus, we consider this model for out-of-sample forecast. A graph of the actual and the ARIMA (3,1,0) in-sample fit values of trade balance is shown in Figure 4.4 below.

Figure-4.4. Actual versus forecasted graph for balance of trade



4.2.6. Forecasting

We have the estimated ARIMA (3,1,0) model from the estimation part. Then we can forecast the value of balance of trade in Ethiopia based on the fitted model from year 2011/12 up to 2015/16. The forecasted results are given in the Table 4.8 and it indicates that the deficit in balance of trade is expected to keep on rising.

Table-4.7. Forecasted value of ARMA model from 2010/11 to 2015/16

Year	Forecasted real BT (in billion birr)
2010/11	-35.40
2011/12	-36.62
2012/13	-37.83
2013/14	-39.06
2014/15	-40.27
2015/16	-41.50

4.3. Cointegration Test

To determine the long run relationship between balance of trade and selected macroeconomic variables in this study, the Johansen multivariate cointegration test is used. It involves the following steps. First, we determine the order of integration for each of the variables under consideration and then estimate cointegrating regression with a vector autoregression model. Finally, if the time series are cointegrated, we construct the error correction model (ECM).

4.3.1. Testing for Presence of Unit-Root

Prior to conducting a parametric analysis and make any meaningful inferences about the relationship of the variables, the time series characteristics of the data have to be estimated. That is, variables have to be tested for the presence of unit root(s) thereby the order of integration of each series is determined. To determine the maximum order of integration of the series, standard unit root tests are employed. The results of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test with trend and intercept; both at level and first difference for each series is presented in the following table.

Table-4.8. ADF test for macroeconomic variables at level

variables	Test statistics		p-value		Remark
	ADF	PP	ADF	PP	
BT	1.365703	0.166859	0.9999	0.9968	Non stationary
DT	-0.64024	-1.190437	0.9699	0.8971	Non stationary
FINC	-2.566978	-2.560235	0.2966	0.2995	Non stationary
REERI	-2.005095	-2.153864	0.5784	0.4992	Non stationary
RGDP	4.012526	8.447047	1.0000	1.0000	Non stationary

As we see clearly from the table 4.9 the test failed to reject the null hypothesis of a unit root for each variable. That is, the respective ADF and PP statistics are less than the critical value at both 5 % and 10 % significance levels. But after differencing the series once, the series under question become stationary. The next table shows the result of the ADF and PP test result after differencing the series.

Table-4.9 ADF and PP test for macroeconomic variables at 1st difference

variable	Test statistics		p-value		Remark
	ADF	PP	ADF	PP	
BT	-5.782298	-11.84171	0.0002	0.0000	Stationary
DT	-4.222260	-4.199128	0.0108	0.0114	Stationary
FINC	-4.057421	-3.752533	0.0163	0.0325	Stationary
REERI	-4.843436	-4.761528	0.0023	0.0028	Stationary
RGDP	-3.551144	-3.403263	0.0497	0.0677	Stationary

Thus, the results of both ADF and PP tests show that all the given variables become stationary at first differences at the 5 % level of significance (at the 10 % level of significance for PP test of RGDP).

4.3.2. The Johansen Cointegration Approach

Because all of the variables appear to be integrated of order one and their first differences appear to be stationary, they all are candidates to be included in a long-run relationship. The next procedure is to test for cointegration. The idea behind cointegration analysis is that, although macroeconomic variables may tend to trend up and down over time, groups of variables may drift together.

To determine the number of cointegrating relationships, the Johansen approach to cointegration is applied. The two tests for the number of roots are the trace test and the maximum eigenvalue statistics. Here, these two test statistics are computed to determine the number of cointegrating vectors in the model. The results of cointegration test are presented in the following table.

Table-4.10. Johansen's trace cointegration test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.678795	78.95256	69.81889	0.0078
At most 1	0.484354	41.47522	47.85613	0.1740
At most 2	0.316027	19.61819	29.79707	0.4491
At most 3	0.123574	7.083587	15.49471	0.5679
At most 4	0.079419	2.730771	3.841466	0.0984

From table 4.11, we observe that the trace statistic (78.95256) exceeds the respective critical value (69.81889) with p-value (0.0078). That is, the trace test result indicates only one cointegrating equation at 1 % level of significance. This implies that the null of no-cointegration relations is rejected at the 1% significance level in favour of the alternative one cointegration relation.

Table-4.11. Johansen maximum eigenvalue cointegration test

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Prob.**
None *	0.678795	37.47734	0.0178
At most 1	0.484354	21.85703	0.2278
At most 2	0.316027	12.53460	0.4959
At most 3	0.123574	4.352816	0.8204
At most 4	0.079419	2.730771	0.0984

On the other hand, as shown in table 4.12, the max-eigenvalue statistic (37.47734) exceeds the critical value (33.87687) with p-value (0.0178). Thus, the max-eigenvalue test suggests only one cointegrating relationship since the null of no cointegrating equation is rejected at the 5 percent significance level. Rejection of the null implies that variables do not drift apart and share at least a common stochastic trend in the long run.

Both test results indicate that one cointegrating equation is sufficient. The next output in table 4.13 gives the normalized cointegrating coefficients for one cointegrating equation. The numbers in the parenthesis under the estimated coefficient are the asymptotic standard errors. Some of the normalized coefficients will be shown without standard errors. That will be the case for coefficients that are normalized to 1.0 and for coefficients that are not identified.

Table-4.12. Normalized cointegration coefficient

1 Cointegrating Equation(s):	Log likelihood	-1519.879		
Normalized cointegrating coefficients (standard error in parentheses)				
BT	DEBT	REERI	RGDP	FINC
1.000000	0.081967	11.65709	0.368749	-0.001028
	(0.02353)	(3.08601)	(0.03324)	(0.00024)

The main rationale of cointegrating analysis is to get a stationary series from two or more non stationary series. The resulting stationary series is written as a linear combination of the non stationary series. In our case, we found that there is only one stationary cointegrated series from the non stationary series. This stationary series, denoted by ECT, is simply a linear combination of the study variables. Then using the result in table 4.13 we can write this ECT as follows:

$$ECT = BT + 0.081967DEBT + 11.65709REERI + 0.368749RGDP - 0.001028FINC$$

The result shows that, in the long run, ECT is stationary despite the fact that all the five series are non stationary. One can infer from this result that there exists a long run relationship between balance of trade and the selected macro economic variables, that is, balance of trade has negative long run relationship with debt, real effective exchange rate index and real gross domestic product and positive long run relationship with foreign income. This negative long run relation proves that Ethiopia is an import compressed economy. And the positive long run relationship shows that the rise in foreign income of trade partners increases their import capacity of Ethiopia's goods.

The previous ECT equation shows that the variables tend to move together in the long run. Short run deviations, however, could occur due to shocks to any of the variables. The Johansen representation showed that if cointegration exists between non stationary variables, then an error correction representation exists for the variables. Therefore, to analyze the short run dynamics, the next step is to specify and estimate an appropriate Error Correction Model (ECM).

Before the construction of an error correction model, we have to check the stationarity of the error correction term (ECT). This error correction term should be stationary at level or I(0). The following table shows the test of unit root for the error correction term. The result shows that we to reject the null hypothesis that is there is a unit root problem at the 5% level of significance.

Table-4.13. ADF test for ECT at level

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-4.372358	0.0075

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

After we check the stationarity of the error correction term, we can construct an error correction model as follows:

$$\nabla BT_t = c_1 + c_2 \nabla DEBT_t + c_3 \nabla FINC_t + c_4 \nabla REERI_t + c_5 \nabla RGDP_t + c_6 ECT_{t-1} + \varepsilon_t$$

Table-4.14 Estimated error correction model

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	5030.535	2128.764	2.363124	0.0253
C(2)	0.038049	0.056731	0.670701	0.5079
C(3)	0.001459	0.002456	0.593836	0.5574
C(4)	-2.664253	9.257829	-0.287784	0.7756
C(5)	-0.400454	0.098591	-4.061785	0.0004
C(6)	-0.777911	0.229524	-3.389235	0.0021
R-squared	0.442189	Mean dependent var		-743.8757
Adjusted R-squared	0.342580	S.D. dependent var		2410.667
S.E. of regression	1954.603	Akaike info criterion		18.15255
Sum squared resid	1.07E+08	Schwarz criterion		18.42190
Log likelihood	-302.5933	Hannan-Quinn criter.		18.24441
F-statistic	4.439247	Durbin-Watson stat		2.003274
Prob(F-statistic)	0.004205			

The above estimated error correction model is tested for normality, serial correlation and heteroscedasticity of the residuals. The diagnostic tests indicate that the residuals are serially uncorrelated, homoscedastic and normal (appendix 4.1, 4.2 and 4.3). Then we can say the following based on the fitted error correction model:

- The coefficient of first ordered difference of real gross domestic product (-0.400454) is statistically significant at the 1 % level. This indicates that RGDP has a negative short run impact on the change in balance of trade.

- Debt, foreign income and real effective exchange rate index do no have short run effect on balance of trade since the coefficients of their first order difference are statistically insignificant at 5 % level of significance.

- The coefficient of the error correction term equals -0.777911. This indicates that about 77.8 % of shock (short-run disequilibria) will be adjusted within the same year.

5. CONCLUSION

The objective of this study was to analyze the long run as well as the short relationship between balance of trade and selected macro economic variables such as real gross domestic product, real effective exchange rate index, debt and foreign income in Ethiopia by using Johansen cointegration approach and error correction model as well as to forecast the balance of trade using ARIMA models.

Under Johansen cointegration approach only one cointegrated equation is obtained. That indicates the presence of long run relationship between balance of trade and real gross domestic product, real effective exchange rate index, debt and foreign income. The error correction model (ECM) shows both the short run and long run relationship among the selected macroeconomic variables. Balance of trade has negative short run relationship with real gross domestic product. But the variables debt, foreign income and real effective exchange rate index are insignificant meaning that they do not have short run relation with balance of trade in Ethiopia. The coefficient of the error correction term indicates that 77.8 % of shock (short-run disequilibria) will be adjusted within the same year. This result is in agreement with movements in the balance of trade in Ethiopia. As can be seen from Figure 4.1, the balance of trade has shown some improvements in the years 2002/03 and 2006/07. However, these improvements were short-lived (temporary) in the sense that the balance of trade keeps on increasing negatively in subsequent years.

Based on this fitted ARIMA (3,1,0) model the balance of trade is forecasted from the year 2011/12 up to 2015/16. The forecasted result shows that the deficit in the balance of trade in Ethiopia is expected to increase from 2011/12 up to 2015/16.

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Appendices

1. Estimated ARIMA models

1.1.Estimated model for ARIMA(1,1,0)

Dependent Variable: D(BT)

Method: Least Squares

Sample (adjusted): 3 36

Included observations: 34 after adjustments

Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-805.9650	255.5611	-3.153708	0.0035
AR(1)	-0.466801	0.157784	-2.958483	0.0058

R-squared	0.214774	Mean dependent var	-834.9484
Adjusted R-squared	0.190236	S.D. dependent var	2428.164
S.E. of regression	2185.029	Akaike info criterion	18.27367
Sum squared resid	1.53E+08	Schwarz criterion	18.36345
Log likelihood	-308.6524	Hannan-Quinn criter.	18.30429
F-statistic	8.752625	Durbin-Watson stat	1.794481
Prob(F-statistic)	0.005774		

Inverted AR Roots	-.47

1.2.Estimated model for ARIMA(0,1,1)

Dependent Variable: D(BT)

Method: Least Squares

Sample (adjusted): 2 36

Included observations: 35 after adjustments

Convergence achieved after 16 iterations

MA Backcast: 1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-790.4054	273.2443	-2.892669	0.0067
MA(1)	-0.296570	0.175083	-1.693879	0.0997

R-squared	0.138234	Mean dependent var	-802.3021
Adjusted R-squared	0.112119	S.D. dependent var	2399.973
S.E. of regression	2261.433	Akaike info criterion	18.34083
Sum squared resid	1.69E+08	Schwarz criterion	18.42971
Log likelihood	-318.9645	Hannan-Quinn criter.	18.37151
F-statistic	5.293437	Durbin-Watson stat	2.192336
Prob(F-statistic)	0.027863		

Inverted MA Roots	.30

1.3.Estimated model for ARIMA(0,1,5)

Dependent Variable: D(BT)

Method: Least Squares

Sample (adjusted): 2 36

Included observations: 35 after adjustments

Convergence achieved after 22 iterations

MA Backcast: -3 1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-833.3703	399.1692	-2.087762	0.0457
MA(1)	-0.662138	0.183629	-3.605849	0.0012
MA(2)	0.687997	0.212646	3.235407	0.0030
MA(3)	0.186660	0.251612	0.741855	0.4641
MA(4)	-0.392785	0.213795	-1.837200	0.0764
MA(5)	0.482239	0.180554	2.670893	0.0123

R-squared	0.496749	Mean dependent var	-802.3021
Adjusted R-squared	0.409982	S.D. dependent var	2399.973
S.E. of regression	1843.483	Akaike info criterion	18.03151
Sum squared resid	98554441	Schwarz criterion	18.29814
Log likelihood	-309.5514	Hannan-Quinn criter.	18.12355
F-statistic	5.725068	Durbin-Watson stat	1.753657
Prob(F-statistic)	0.000859		

Inverted MA Roots	.62-.53i	.62+.53i	.10-.95i	.10+.95i
	-.79			

1.4.Estimated model for ARIMA (1,1,1)

Dependent Variable: D(BT)

Method: Least Squares

Sample (adjusted): 3 36

Included observations: 34 after adjustments

Convergence achieved after 13 iterations

MA Backcast: 2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-807.7062	267.2236	-3.022586	0.0050
AR(1)	-0.515609	0.358039	-1.440093	0.1599
MA(1)	0.061999	0.441354	0.140475	0.8892

R-squared	0.216546	Mean dependent var	-834.9484
Adjusted R-squared	0.166001	S.D. dependent var	2428.164
S.E. of regression	2217.486	Akaike info criterion	18.33023
Sum squared resid	1.52E+08	Schwarz criterion	18.46491
Log likelihood	-308.6140	Hannan-Quinn criter.	18.37616
F-statistic	4.284192	Durbin-Watson stat	1.832998
Prob(F-statistic)	0.022762		

Inverted AR Roots	-.52
Inverted MA Roots	-.06

1.5.Estimated model for ARIMA (1,1,5)

Dependent Variable: D(BT)

Method: Least Squares

Sample (adjusted): 3 36

Included observations: 34 after adjustments

Convergence achieved after 52 iterations

MA Backcast: -2 2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-921.5980	420.9848	-2.189148	0.0374
AR(1)	-0.514722	0.297227	-1.731750	0.0947
MA(1)	0.100956	0.267882	0.376867	0.7092
MA(2)	0.240550	0.182511	1.318003	0.1986
MA(3)	0.050440	0.213084	0.236716	0.8147
MA(4)	-0.045240	0.214862	-0.210556	0.8348
MA(5)	0.633717	0.168187	3.767926	0.0008

R-squared	0.494279	Mean dependent var	-834.9484
Adjusted R-squared	0.381897	S.D. dependent var	2428.164
S.E. of regression	1909.011	Akaike info criterion	18.12780
Sum squared resid	98396728	Schwarz criterion	18.44205
Log likelihood	-301.1726	Hannan-Quinn criter.	18.23497
F-statistic	4.398193	Durbin-Watson stat	1.789059
Prob(F-statistic)	0.003179		

Inverted AR Roots	-.51			
Inverted MA Roots	.67-.56i	.67+.56i	-.27+.92i	-.27-.92i
	-.90			

1.6.Estimated model for ARIMA(3,1,5)

Dependent Variable: D(BT)

Method: Least Squares

Sample (adjusted): 5 36

Included observations: 32 after adjustments

Convergence achieved after 25 iterations

MA Backcast: 0 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3738.192	9241.236	-0.404512	0.6896
AR(1)	-0.616414	0.126391	-4.877023	0.0001
AR(2)	0.396082	0.163260	2.426071	0.0235
AR(3)	1.119790	0.129792	8.627556	0.0000
MA(1)	0.062985	0.270972	0.232442	0.8183
MA(2)	-0.136449	0.273610	-0.498700	0.6227
MA(3)	-0.803314	0.153972	-5.217265	0.0000
MA(4)	0.104644	0.231316	0.452385	0.6552
MA(5)	-0.218057	0.230636	-0.945458	0.3543

R-squared	0.665313	Mean dependent var	-894.0527
Adjusted R-squared	0.548900	S.D. dependent var	2492.977
S.E. of regression	1674.384	Akaike info criterion	17.91654
Sum squared resid	64481888	Schwarz criterion	18.32877
Log likelihood	-277.6646	Hannan-Quinn criter.	18.05318
F-statistic	5.715105	Durbin-Watson stat	1.953438
Prob(F-statistic)	0.000463		

Inverted AR Roots	.97	-.79+.72i	-.79-.72i	
	Estimated AR process is nonstationary			
Inverted MA Roots	1.00	.10+.48i	.10-.48i	-.63+.73i
	-.63-.73i			

2. Residual test for selected ARIMA models

2.1. Residual Q-statistics for Estimated ARIMA(1,1,0) model

Correlogram of Residuals

Date: 05/03/06 Time: 13:03
Sample: 3 36
Included observations: 34
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.036	0.036	0.0490	
		2	0.299	0.298	3.4627	0.063
		3	0.374	0.391	8.9841	0.011
		4	0.036	-0.039	9.0368	0.029
		5	0.438	0.278	17.120	0.002
		6	0.044	-0.074	17.206	0.004
		7	0.123	-0.068	17.889	0.007
		8	0.183	-0.064	19.464	0.007
		9	-0.091	-0.134	19.871	0.011
		10	0.075	-0.148	20.161	0.017
		11	0.063	0.105	20.373	0.026
		12	-0.131	-0.094	21.331	0.030
		13	-0.044	-0.134	21.445	0.044
		14	-0.156	-0.108	22.926	0.043
		15	-0.096	0.024	23.516	0.052
		16	-0.037	0.043	23.607	0.072

2.2. Serial correlation LM test for the estimated ARIMA(3,1,0) model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.154779	Prob. F(2,26)	0.8574
Obs*R-squared	0.376512	Prob. Chi-Square(2)	0.8284

2.3. Serial correlation LM test for the estimated ARIMA(0,1,1) model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	4.005658	Prob. F(2,31)	0.0284
Obs*R-squared	7.186111	Prob. Chi-Square(2)	0.0275

2.4. Serial correlation LM test for the estimated ARIMA(0,1,5) model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.309436	Prob. F(2,27)	0.7364
Obs*R-squared	0.782500	Prob. Chi-Square(2)	0.6762

2.5.Serial correlation LM test for the estimated ARIMA(1,1,5) model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.611580	Prob. F(2,25)	0.5504
Obs*R-squared	1.585340	Prob. Chi-Square(2)	0.4526

2.6. Serial correlation LM test for the estimated ARIMA(3,1,5) model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	3.150723	Prob. F(2,21)	0.0636
Obs*R-squared	7.227437	Prob. Chi-Square(2)	0.0270

2.7. Serial correlation LM test for the estimated ARIMA(3,1,1) model

Breusch-Godfrey Serial Correlation LM Test:

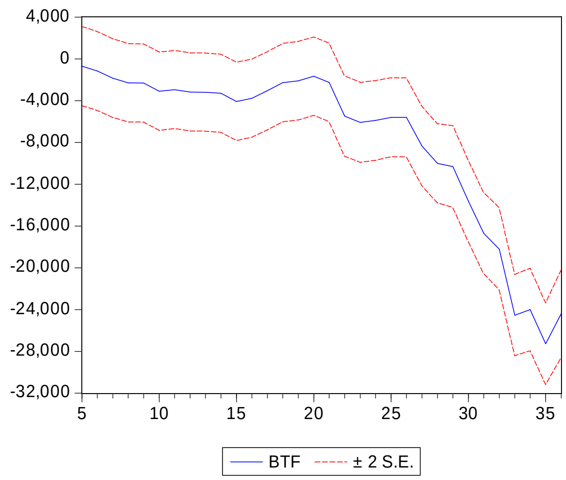
F-statistic	1.349457	Prob. F(2,25)	0.2776
Obs*R-squared	3.117896	Prob. Chi-Square(2)	0.2104

2.8.Serial correlation LM test for the estimated ARIMA(1,1,1) model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	6.964498	Prob. F(2,29)	0.0034
Obs*R-squared	11.03181	Prob. Chi-Square(2)	0.0040

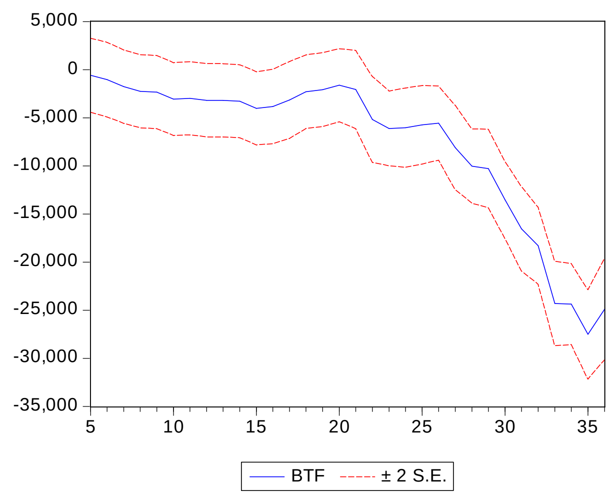
2.9.Forecasted graph for the estimated ARIMA(3,1,0) model



Forecast: BTF
Actual: BT
Forecast sample: 1 36
Adjusted sample: 5 36
Included observations: 32

Root Mean Squared Error	1723.268
Mean Absolute Error	1304.767
Mean Abs. Percent Error	29.91570
Theil Inequality Coefficient	0.077181
Bias Proportion	0.000000
Variance Proportion	0.062371
Covariance Proportion	0.937629

2.10. Forecasted graph for the estimated ARIMA(3,1,1) model



Forecast: BTF
Actual: BT
Forecast sample: 1 36
Adjusted sample: 5 36
Included observations: 32

Root Mean Squared Error	1719.801
Mean Absolute Error	1294.844
Mean Abs. Percent Error	29.66524
Theil Inequality Coefficient	0.076863
Bias Proportion	0.000004
Variance Proportion	0.043875
Covariance Proportion	0.956122

3. Unit root test for the selected macroeconomic variables

3.1. ADF test for debt at level

Null Hypothesis: DEBT has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.640241	0.9699
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

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

3.2. ADF test for debt at first difference

Null Hypothesis: D(DEBT) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.222260	0.0108
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.3.ADF test for REERI at level

Null Hypothesis: REERI has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.005095	0.5784
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

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

3.4.ADF test for REERI at first difference

Null Hypothesis: D(REERI) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.843436	0.0023
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.5.ADF test for RGDP at level

Null Hypothesis: RGDP has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 2 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		4.012526	1.0000
Test critical values:	1% level	-4.262735	
	5% level	-3.552973	
	10% level	-3.209642	

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

3.6.ADF test for RGDP at first difference

Null Hypothesis: D(RGDP) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.551144	0.0497
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.7. ADF test for FINC at level

Null Hypothesis: FINC has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 1 (Automatic based on SIC, MAXLAG=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.566978	0.2966
Test critical values:	1% level	-4.262735	
	5% level	-3.552973	
	10% level	-3.209642	

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

3.8. ADF test for FINC at first difference

Null Hypothesis: D(FINC) has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic based on SIC, MAXLAG=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.057421	0.0163
Test critical values:	1% level	-4.262735	
	5% level	-3.552973	
	10% level	-3.209642	

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

3.9.PP test for BT at level

Null Hypothesis: BT has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 4 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		0.166859	0.9968
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

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

3.10. PP test for BT at first difference

Null Hypothesis: D(BT) has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 3 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-11.84171	0.0000
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.11. PP test for debt at level

Null Hypothesis: DEBT has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 2 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.190437	0.8971
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

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

3.12. PP test for debt at first difference

Null Hypothesis: D(DEBT) has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 1 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.199128	0.0114
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.13. PP test for import at level

Null Hypothesis: IM has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 2 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		0.391526	0.9984
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

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

3.14. PP test for REERI at level

Null Hypothesis: REERI has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 2 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.153864	0.4992
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

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

3.15. PP test for REERI at first difference

Null Hypothesis: D(REERI) has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 7 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.761528	0.0028
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.16. PP test for RGDP at level

Null Hypothesis: RGDP has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 13 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		8.447047	1.0000
Test critical values:	1% level	-4.243644	
	5% level	-3.544284	
	10% level	-3.204699	

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

3.17. PP test for RGDP at first difference

Null Hypothesis: D(RGDP) has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 2 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.403263	0.0677
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.18. PP test for FINC at level

Null Hypothesis: FINC has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 4 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.560235	0.2995
Test critical values:	1% level	-4.252879	
	5% level	-3.548490	
	10% level	-3.207094	

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

3.19. PP test for FINC at first difference

Null Hypothesis: D(FINC) has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 5 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.752533	0.0325
Test critical values:	1% level	-4.262735	
	5% level	-3.552973	
	10% level	-3.209642	

4. Diagnostic checking for error correction and ARIMA(3,1,0) models

4.1. serial correlation LM test for ECM

Breusch-Godfrey Serial Correlation LM Test:

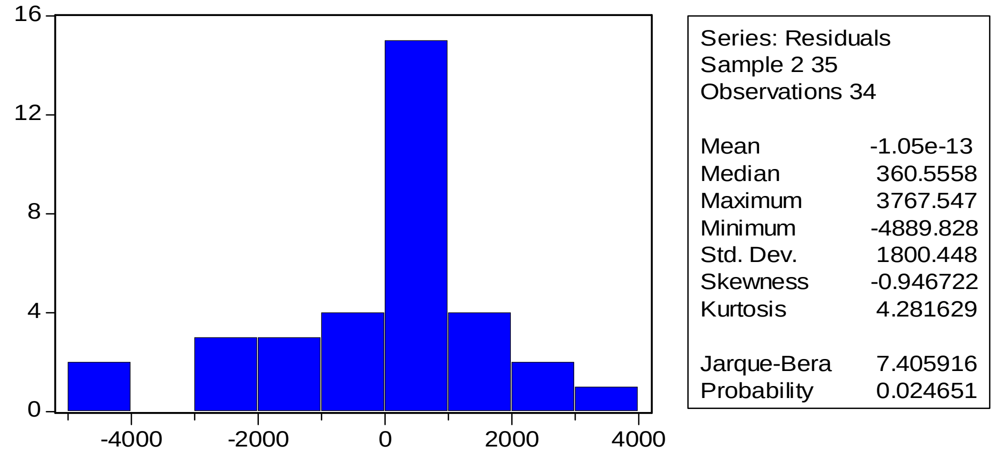
F-statistic	2.400819	Prob. F(2,26)	0.1105
Obs*R-squared	5.300227	Prob. Chi-Square(2)	0.0706

4.2. Heteroskedasticity test for ECM

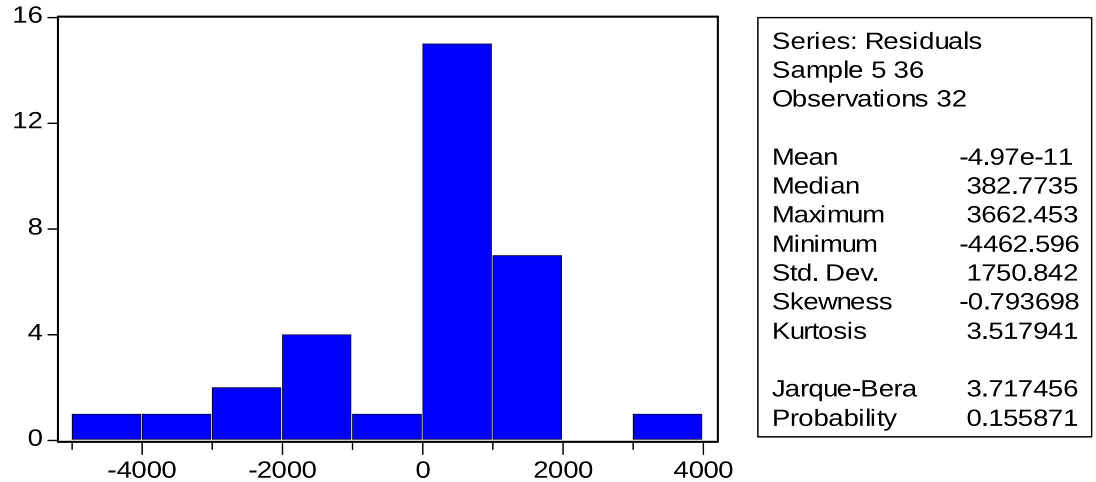
Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.183747	Prob. F(9,24)	0.3489
Obs*R-squared	10.45275	Prob. Chi-Square(9)	0.3151
Scaled explained SS	11.63183	Prob. Chi-Square(9)	0.2349

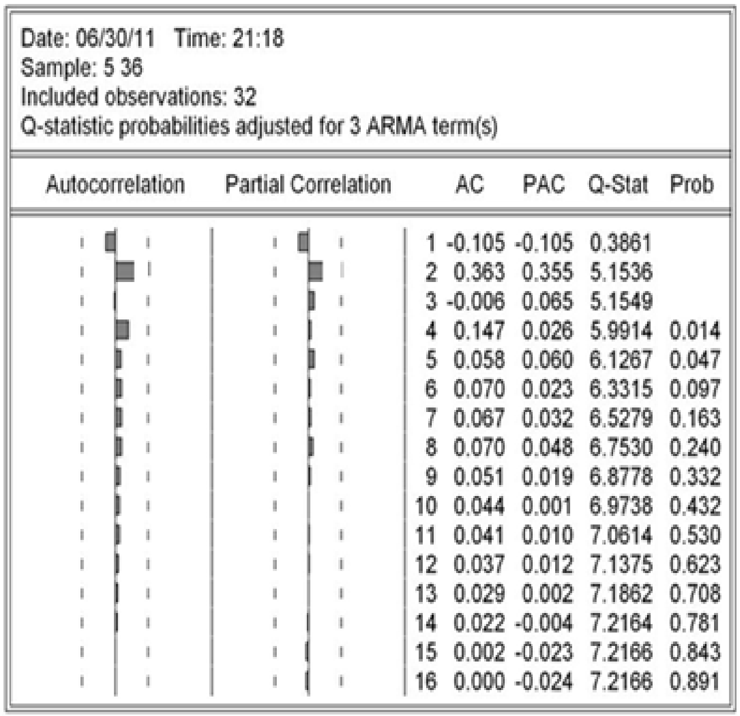
4.3. Normality for ECT



4.4. Normality test for ARIMA(3,1,0)



4.5. Heteroskedasticity for ARIMA(3,1,0)



Date: 06/30/11 Time: 21:18
Sample: 5 36
Included observations: 32
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.105	-0.105	0.3861	
		2	0.363	0.355	5.1536	
		3	-0.006	0.065	5.1549	
		4	0.147	0.026	5.9914	0.014
		5	0.058	0.060	6.1267	0.047
		6	0.070	0.023	6.3315	0.097
		7	0.067	0.032	6.5279	0.163
		8	0.070	0.048	6.7530	0.240
		9	0.051	0.019	6.8778	0.332
		10	0.044	0.001	6.9738	0.432
		11	0.041	0.010	7.0614	0.530
		12	0.037	0.012	7.1375	0.623
		13	0.029	0.002	7.1862	0.708
		14	0.022	-0.004	7.2164	0.781
		15	0.002	-0.023	7.2166	0.843
		16	0.000	-0.024	7.2166	0.891

Dedication

This thesis is dedicated to my family with due respect, love and indebtedness with all the best wishes; as attribute for what they have done for me throughout my life. My family, I know the prices you paid. You will be in my heart always! **I love you**!