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DETERMINANTS OF LEATHER EXPORT FROM ETHIOPIA: APPLICATION OF VECTOR ERROR CORRECTION MODEL

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ABSTRACT

Determinants of leather export from Ethiopia. Application of vector error correction model.

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Leather manufacturing is one of the oldest industry globally and particularly in Ethiopia which has remained and sprung forward as an economically important sector in terms of engaging citizens intensively and in export business. The study is aimed to use a multivariate time series model which explains the determinants of leather export from Ethiopia using vector auto-regression (VAR) and vector error correction (VEC) model. The data used are quarterly observations from September 2000 to august 2016. The variables are value of leather export, export price of leather, consumer price index (endogenous variables) And nominal exchange rate (exogenous variables).

The series are seasonally adjusted after they were known to be seasonal through standard tests built in X-12 ARIMA program in E-Views 6 statistical software. Post seasonal adjustment tests also assured that all series are non-seasonal. Unit root tests of the series under study reveal that all the series are non-stationary at level and stationary after first difference. The result of Johansen test indicates the existence of two co-integration relation between the variables and there is long-term dynamics between value of leather export, nominal exchange rate, export price and consumer price index. The three information criteria AIC, SIC and HQ recommended one lag length. Johnsen co-integration test indicated two long term equilibrium relationship occurred between variables. This immediately implied the legitimacy of vector error correction model (VEC) model of order one to be fitted than a pure VAR (1) model for time series data. The final result shows that a Vector Error Correction (VEC) model of lag one with two co-integration equations best fits the data. Export price of leather has a negative effect on value of leather exports. A one percent increase in a unit price of leather export will cause 5.82219 percent decrease in value of leather export in the long run. In the short run Exchange Rate has a negative effect on exports of leather as expected.

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Key words: *Co-integration, Consumer Price Index (CPI), Nominal Exchange rate (NER), Value of Leather Export (VLE), vector Auto-regression (VAR), Vector Error Correction model (VECM).*

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ACRONYMS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
CSA	Central Statistical Agency
HQ	Hannan-Quin Information Criteria
LM	Lagrange Multiplier
MAE	Mean Absolute Error
MPAE	Mean Percentage Absolute Error
MPE	Mean Percentage Error
MSE	Mean Square Error
MVTS	Multivariate Time Series Analysis
OLS	Ordinary Least Square
PP	Phillips and Perron test
PE	Percentage Error
RMSE	Root Mean Squared Error
SC	Schwarz Information Criterion
USD	United States Dollar
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
RVLE	Real Value of leather Export

CHAPTER ONE

INTRODUCTION

1.1 BACKGRUND OF THE STUDY

Foreign trade payments have a significance role in the development plans of many developing countries. For most of these countries, export represents an important share of the total development. Trades in the foreign sales are important in forecasting of overall growth of a country. For some developing countries, export trade is such an important factor that an estimate of the foreign exchange earnings represents a first step in the formulation of development plans. As the export of a given country continue to expand, new profit opportunities develop not only to provide inputs for export sector but also to take the advantage of external economic benefits (Hultman, 1967).

The analysis of the effect of export earnings in stability on the economic growth of developing countries has long interested economists for several reasons. First of all, from the beginning of the 1960s developing countries have experienced a steady and sustained growth in exports. The outcome of this process, initially encouraged by a growing demand for raw materials to be transformed in industrialized countries, is that today many developing countries find themselves with an exports structure which is highly restricted both in terms of products and in terms of outlets; this high level of exports concentration plus the turbulence and interdependence of world market is considered one of the reasons for the difficulty of promoting growth in a small economy dependent on the production of goods for exports (Aiello, 1999).

Developing countries often face scarcity of foreign exchange earnings to stimulate economic growth, international trade thus tends to be unstable, which is the only source of foreign exchange for these countries. Moreover, these countries mostly import technology and capital goods. Sub-Saharan countries have similar economic structures low per capital income, largely agrarian economies with very small industrial sectors, relatively low growth rates, and a strictly binding foreign exchange constraint, responses to instability in export earnings are likely to be similar among the nations of sub-Saharan countries (Brempong, 1991).

The African 'export problem' is not simply the general dependence on primary commodity exports, but also the heavy dependence of most countries on a narrow range of primary commodities. In the late 1990s, 39 African countries depended for more than half of their export earnings on just two primary commodities; hence collapse of world commodity prices in 1998 was equivalent to a real income loss of 2.6 percent of gross domestic product (GDP) in 1997-98 for Sub-Saharan Africa (SSA). Commodity prices have not shown any dramatic sign of recovery in recent years. For example, world coffee prices in 2002 were below a third of the level in 1997. Many developing countries are heavily dependent on primary commodities for their export earnings. At least half the countries in sub-Saharan Africa (SSA) and Latin America rely on three commodities for over 50% of their exports. There are some countries (mostly in SSA) whose reliance on one, two or three commodities is extreme. Reliance on exports of Renewable Natural Resources (RNR) commodities is also most pronounced in SSA. The aggregate export trend hides important differences when regional and sectorial developments are examined (Overseas Development Institute, 2010).

Leather manufacturing is one of the oldest industry globally and particularly in Ethiopia which has remained and sprung forward as an economically important sector in terms of engaging citizens intensively and in export business. The Ethiopian leather industry is relatively an older industry with more than 90 years of involvement in processing leather and producing leather products. The first two tanneries were established and vertically linked to two shoe factories: ASCO Tzannery and ASCO Shoe Factory (the present Addis Ababa Tannery and Tikur Abbay Shoe Factory) and Darmar Tannery and Shoe Factory (the present Awash Tannery and Anbessa Shoe Factory), pursuant to reports from LIDI (MOFED, 2015).

Ethiopia has sustained to be the leader in its livestock resources in Africa which proves the availability of a huge potential for the country's leather industry. The country possesses one of the world's largest livestock populations with a 57,829,953 cattle population that puts the country first in Africa and sixth in the world. The nation is also third in Africa and tenth in the world with 28,892,380 sheep population in addition to 29,704,958 goat population which makes the nation 3rd in Africa and 8th in the world. The hides and skin supplied to the tanneries have reached 1.4 million cow hides, 6.7 million goat skins and 13.2 million sheep skins. Accordingly, says Leather Industries Development Institute (LIDI) Corporate Communication Director Berhanu Serjabo, in relation to the leather sub-sector, the abundance of livestock in Ethiopia represents a natural strength, speaking to The Ethiopian Herald (CSA, 2015)

Sheep and goat skin represent the bulk of Ethiopian leather production. The country is known in the international leather market for its superior qualities of sheep skin, acknowledged as being the best in the world. The Ethiopian sheep skin are sought for high class and high value glove leather and the goat skin are equally acknowledged to be the finest for suede making for garments and footwear, according to Berhanu (CSA, 2015)

Being the first livestock producer in Africa, Ethiopia has a huge potential for the leather industry. While leather exports stood at USD 123 million in 2012, the government wants to grow the leather industry's annual exports to USD 500 million by the end of 2015.

Every year, the country produces about 2.7 million hides, 8.1 million sheepskins and 7.5 million goat skins. Moreover, with a population of 26 million, Ethiopia has the largest flock of hair sheep in the world. Hair sheep skin has a particularly fin and tight grain, making it highly valuable for female gloves of higher quality and luxury items.

Ethiopia's leather and leather product sector already produce a range of products from semi-processed leather in various forms to processed leathers including shoe uppers, leather garments, stitched upholstery, backpacks, purses, industrial gloves and finished leather. The government plans to fully utilize these resources through value addition and thereby create more jobs and boost exports. Ethiopian leather products are exported to markets in Europe (especially Italy and the UK), America, Canada, China, Japan and other Far Eastern countries and the Middle East. All exports are tested by the Quality and Standards Authority of Ethiopia (QSAE) (CSA, 2015)

Ethiopia offers a wide range of processed and semi-processed hides and skins to the world market. Some of the products, such as Ethiopian highland sheepskin, which has gained international reputation for making gloves, are well-known for their quality and natural characteristics. The high quality Ethiopian hides and skins exports include: Pickled sheep skin, wet blue sheep skin, crust sheep skin, wet blue goat skin, crust goat skin, crust cow hides, finished garment leather, finished glove leather, lining/upper leather, suede leather, full grain leather, corrected grain leather, embossed leather and patent leather (MOFED, 2015)

Ethiopian leather products have been exported to markets in Europe (especially Italy and the UK), America, Canada, China, Japan and other Far Eastern countries and the Middle East. Leather is also exported to other African countries including Nigeria and Uganda. Leather garments Ethiopian footwear factories produce men's casual shoes and children's shoe-uppers made from pure leather. The export of finished leather and leather products (such as leather garments, foot wear, gloves, bags and other leather articles) is also highly promising(MOFED,2015)

1.2 Statement of the Problem

Several studies about leather export and related variables are done utilizing univariate time series analysis. Univariate time series analysis is important but it is inadequate for the analysis of interaction and co-movement of several time series simultaneously. In contrast, multivariate time analysis involves a vector of time series that will be modeled simultaneously.

The following research questions will be addressed

1. What kind of relationships exists among value of leather exports, nominal exchange rate, Export price and consumer price index in the Ethiopian context?

2. Is there the long run relationship among the variables, value of leather exports nominal exchange rate, export price and consumer price index?

1.3 Objective of the Study

1.3.1 General objective

The main objective of this study is to evaluate determinants of leather export from Ethiopia.

1.3.2 Specific objectives

The specific objectives are:

- To assess impact of the major factors affecting leather exports from Ethiopia.
- Fit appropriate model to estimate short and long run relationships among the study variables.

1.4 Significance of the Study

There are few studies that have been designed to identify impact of major factors affecting leather exports in Ethiopia. This study were examining the impact of major determinants of leather exports identified using time series analysis. Researches are seldom identify determinates of on exports of leather from Ethiopia.

1.5 Limitation of the Study

Due to unavailability of data, some variables which are expected to affect value of leather export such as quarterly quality of leather, quarterly domestic price and quarterly gross domestic product are not analyzed in this study.

CHAPTER TWO

LITERATURE REVIEW

Review of the available studies on exports of agricultural commodities in general and leather in particular revealed that limited and scanty literature is available which delineate effect of major variables affecting leather exports in Ethiopia. There is however some relevant literature from other countries.

In Bangladesh, Sharif and Mainuddin (2003) narrated had been a continuous shift of leather, footwear and leather goods production from developed to developing countries mainly caused by price competitiveness. The developed countries imported low and medium end market leather footwear and leather goods from developing countries keeping their manufacturing limited to high fashioned costly products. Bangladesh had not yet been able to make a significant breakthrough in its leather sector through diversification and improvement of the quality of leather products.

Bangladesh needed to improve the quality of leather products for better market access and economic benefits from the international export market including the developed countries. Jordaan and Eita (2007)analyzed the determinants of South African exports of raw hides and skins (other than fur skins) and leather(H41) using annual data covering the period 1997 to 2004 for 32 main trading partners. The results showed that importer's GDP, South Africa's GDP, importer's population, South Africa's population, infrastructure of South Africa and importing country and some regional trade agreements were the main determinants of raw hides and skins (other than fur skins) and leather exports. The paper then investigated if there was unexploited trade potential. The investigation revealed that among others, South Korea, United Kingdom, USA, Zambia and Zimbabwe had unexploited export potential. It was important to focus efforts on the unexploited trade potential accelerated growth and alleviated poverty in South Africa.

In Pakistan, Siddiqui (2001) stated that the leather and leather products industry was mainly located at Karachi,Gujranwala, Multan, Peshawer, Lahore, Kasur and Sialkot. The major clusters of leather products were located at Korangi, Sialkot, Lahore and Kasur. There were 784 units, 461 leather garments manufacturing units, 348 gloves manufacturing units and over 524 footwear manufacturing units in the country. The leather sector was mainly an export oriented sector of our country. The major countries to which Pakistan was exported leather and leather products were

Italy, Portugal, Germany, France, USA, Dubai and Singapore etc. The leather sector during the last decade had shown remarkable progress in exports of value added products.

Bashar (2003) stated that high quality leather was mainly exported and was not available for high value-added leather products. Leather garments in Pakistan were made mostly from low quality and low grade leather. These garments faced tough competition from Chinese and Indian leather products. Because the cost of production was very high in Pakistan as compared to the China and India. The high cost of various kinds of raw material especially utilities and taxes made our products more costly in international markets. Pakistan could gained lost market share of leather industry by reducing the cost of production.

Massood (2009) narrated that Pakistan's leather exports showed a decline of 29 percent in the period of 2008-09 after a decade of constant growth. This sharp decrease in the exports of high value added and labor intensive leather products , because this sector was Pakistan's second largest foreign exchange earner after textiles and provided employment to 500,000 workers, was a matter of serious attention, demanding for immediate remedial steps to stem the tide.

Kalimullah (2010) stated that country's leather exports were likely to decrease by at least 30percent due to the killings of animals in vast numbers in the ongoing deluge in Khyber Pakhtunkhwa, Punjab, Sindh and Balochistan. President RCCI Kashif Shabbir talked to a group of businessmen and industrialists at his office, one billion dollar of leather industry had badly affected due to floods. Prices of leather products were likely to jump further due to the dearth of leather emerging fast after the killings of animals in the floods.

2.1 Ethiopian Leather Industry: The Overview

Bekele and Ayele (2008) described that in their study, it was clear that Ethiopia had a clear comparative advantage in raw skin and hides production. However, the comparative advantage was not yet turned into a competitive advantage in the global market. Globalization had brought value chain and competitiveness issues, where individual efficiencies are less important.

With an annual off-take rate of nearly 10% for cattle, 33%for sheep and 38% for goats, the country is endowed with enormous potential for cheap supply of skin and hide. There is a clear recognition of this potential by policy makers in Ethiopia as indicated by the Growth and Transformation Plan

(GTP) and several other national plans that preceded it. In the country GTP document, the leather and leather products industry is one of the priority industries that are expected to contribute considerably to export diversification and foreign exchange earnings through greater value addition and productivity improvement (FDRE, 2010).

According to MEDAC (1999), the livestock population of the country has risen to 34.1, 30.54, and 21.11 million head of cattle, sheep and goats, respectively, in the year 1998/99, up from the 1993/94 figures of 31.45, 27.5 and 19.76 million head of cattle, sheep and goats, respectively. The annual average growth rate was 1.2, 1.4 and 0.5 %, respectively (MEDAC, 1999).

Ethiopia has a long history of handcrafting and blacksmithing. The leather soaking and tanning industry emerged with the establishment of the ASCO tannery (the current Addis Ababa Tannery) in 1918 and Darmar/Awash (currently ELICO) tannery by Armenian traders in 1927. In the subsequent years, several local tanneries, such as Dire, Modjo and Kombolcha were set up. The emergency of the modern leather processing industry also dates back to the 1930s, a period associated with the establishments of two shoe factories, Tikure Abbay and Anbessa, by Armenian merchants. In the 1950s and the 1960s, for example, leather and leather goods production were small in volume and largely targeted the local market. In the 1974, all private tanneries were nationalized. The government subsequently established the National Leather and Shoe Corporation, which assumed the responsibility of managing eight tanneries and six shoe factories.

CHAPTER THREE
DATA AND METHODOLOGY

3.1 Data Sources

Secondary data were used to capture effect of different variables which have direct or indirect impacts on export supply of leather at country level. Data for export supply were collected for a period of quarterly 2000-2016. Data of real export value of leather products and data on other variables nominal exchange rate, export price of leather, and consumer price index taken from the national bank of Ethiopia.

3.2 Definitions and variables of the study

Export value of leather products such as leather garments, foot wear, gloves, bags and other leather articles expressed in million U.S. dollars.

Export prices: unit export prices is the price at which a commodity trade out of a country.

Nominal Exchange rate: An exchange rate is how much it costs to exchange one currency for another. Exchange rates fluctuate constantly throughout the week as currencies are actively traded. This pushes the price up and down, similar to other assets such as gold or stocks. The market price of a currency – how many U.S. dollars it takes to buy a Canadian dollar for example – is different than the rate you will receive from your bank when you exchange currency.

Consumer price index: The Consumer Price Index (CPI) is a measure that examines the weighted average of prices of a basket of consumer goods and services, such as transportation, food and medical care. It is calculated by taking price changes for each item in the predetermined basket of goods and averaging them. Changes in the CPI are used to assess price changes associated with the cost of living; the formula used to calculate the Consumer Price Index for a single item is as follows:

$$\text{CPI}=\frac{\text{Cost of Market Basket in Given Year}}{\text{Cost of Market Basket in Base Year}}\times 100$$

Value of leather export, consumer price index, and export price are an endogenous variables (which are determined in the system or market) and Nominal exchange rate is an exogenous variable (which is determined out of the system or out of market)

3.3 Methodology

Multivariate time series involves a vector of time series data that will be modeled simultaneously. Multivariate time series analysis is used to model and explain the interactions and co movements among a group of time series variables. The methodology adopted in this study follows the vector autoregressive (VAR) model and vector error correction model (VECM).

3.3.1 Vector Autoregressive (VAR) Models

The VAR model is one of the most successful, flexible and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. It often provides superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model.

In addition to data description and forecasting, the VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized. These causal impacts are usually summarized with impulse response functions and forecast error variance decompositions.

Co integration (Granger 1981) was designed for testing and estimating the long run and short run relationship among the variables. The estimation of long run relationship required the time series to be non-stationary in the level form. If the time series data are non-stationary then the common statistical tools are not suggested and regression becomes spurious in nature (Granger and Newbold, 1974). In co integration approach, first step is to test for stationary or non -stationary of data set. Second step is to test for long run relationship between variables.

3.3.1.1 Seasonality

Time series components

A time series can be decomposed in to four main unobserved components

Trend: indicates the long term tendency or pattern in time series.

Cyclical component: indicates the medium term fluctuation of a time series.

Seasonal component: represents intra year fluctuations more or less stable year after years with respect to timing, direction and magnitude.

Irregular components: indicates unpredictable effects, which are considered as random variables.

Seasonal Adjustments

Seasonal adjustments is the processes of estimating and removing the seasonal effects from the time series in order to better reveal certain non-seasonal features. A seasonality adjusted series is the combination of the underlying trend of the series and the irregular factors. Currently software seasonal adjustment techniques like an X12-ARIMA program are being popular and applicable. An X12-ARIMA program contains statistical tests for detecting seasonality. This program can be obtained in E-views 6.

3.3.2 Stationarity

Stationarity is an essential property to define a time series process. Stationarity may be strong (i.e. the whole distribution of the variable does not depend on time) or weak stationary.

3.3.2.1 strictly (strong) stationar*y*

A strictly stationary time series is one for which the probabilistic behavior of collection of values $\{x_{t1,}\ x_{t2,} \ldots, x_{tk}\}$ is identical to that of the time-shifted set $\{x_{t1+k,}\ x_{t2+k,} \ldots, x_{tk+k}\}$.

3.3.2.2 Weakly Stationary

Weakly stationary time series, $\boldsymbol{x_{t,}}$ is a finite variance process. Its mean function, $\mu_{t,}$, is constant and does not depend on time t i.e. $\mu_{t,} = \mu$ for all t. And the covariance function(s, t) depends on s and t only through their difference |t – s| which we call lags; for all s and t and is denoted by γ (h) where h = t - s. Most of the probability theory of time series is concerned with stationary time series, and for this reason, time series analysis often requires one to turn a non-stationary series into a stationary one so that one can use this theory (Brock well and Davis, 1996). To apply this theory we need to test for Stationarity, if not difference and test the differenced series.

3.3.2.3 Differencing

Differencing of a series can transform a non-stationary series to a stationary series. Hence, differencing turns out to be a useful 'filtering' procedure in the study of non-stationary time series.

The difference operatorΔ is defined by;

$\Delta y_t = y_t - y_{t-1}$

Note that

$$\Delta y_t = (1 - B) y_t$$

so that Δ can be expressed in terms of the back-ward shift operator B. In general, higher order differencing can be expressed as:

$$\Delta^n y_t = (1 - \mathrm{B})^n y_t$$

3.3.2.4 Integration (I (d))

A series that is stationary without any differencing is said to be integrated of order 0 (denoted by I (0)), and a series which is stationary after being differenced once is said to be integrated of order 1 (denoted by I (1)). A series which is I (1) is also said to have a unit-root. Differencing techniques are normally used to transform a time series from a non-stationary to stationary by subtracting each datum in a series from its predecessor. As such the set of observations that correspond to the initial time period (t) when the measurement was taken is described as the series in level. Differencing a series using differencing operations produces other sets of many observations such as the first-differenced values, the second-differenced values and so on. If a non-stationary time series has to be differenced d times to make it stationary, that time series is said to be integrated of order d and denoted as I (d) (Gujarati, 2004; Pole, 1994; Weigend, 1993).

3.4 Tests for Stationarity

3.4.1. The Unit Root Test

A series is stationary if its mean, variance and covariance all are independent of time or in other words remains constant over time. Conversely, a series is non stationary if it fails to satisfy any part of the above definition that means, its mean, variance or covariance change overtime.

Stationary tests are based for the most part on formal statistical tests and the difference between them lies in the strictness of the assumptions they use as well as in the form of the null and alternative hypotheses they adopt. The standard Dickey-Fuller test (DF) is based on identical and independent Errors and has as a null hypothesis that there is a unit root. On the other hand, the Phillips-Petron test is nonparametric and allows for some heterogeneity and serial correlation in the innovations. Several procedures have been developed to test for stationarity of time series. The most popular ones are Augmented Dickey- Fuller (ADF) test due to Dickey and Fuller (1979, 1981), and the Phillip-Perron (PP) test due to Phillips (1986) and Phillips and Perron (1988). The following discussion outlines the basic features of unit root tests (Hamilton, 1994). In this study, we will be use the most popular test called the Augmented Dickey-Fuller test (ADF) and the Phillip-Perron (PP) test.

Consider an AR (1) process:

$$\boldsymbol{y_t = \rho y_{t-1} + x_t{}' \delta + \varepsilon_t} \tag{3.0}$$

Where $x_t$optional exogenous regresses which may consist a constant and trend, ρ and δ are parameters to be estimated and ε_t is assumed to be white noise. If $|\rho| \geq 1$, y_t is a non-stationary series and the variance of y_t increases with time and approaches infinity. On the other hand, if $|\rho| < 1$, y_t is a stationary series. Thus, the hypothesis of (trend) stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one.

The hypotheses are:

H0: The series are not stationary ($\rho \geq 1$)

H1: The series are stationary ($\rho < 1$)

3.4.2 Augmented Dickey-Fuller (ADF) Unit-Root Test

Dickey-Fuller-test assume that the disturbances in the model(ε_t) are white noise they are not correlated an extension that accommodate some form of serial correlation among the disturbances is augmented dickey fuller test. The standard Dickey-Fuller test is conducted in the following manner: from equation we have:

$\boldsymbol{y_t - y_{t-1} = (\rho - 1)y_{t-1} + x_t{}'\delta + \varepsilon_t}$ .This can be rewritten as:

$$\Delta \boldsymbol{y_t = \pi y_{t-1} + x_t{}'\delta + \varepsilon_t} \quad (3.1)$$

Where $\pi = \rho - 1$.The null and alternative hypothesis may be written as:

H0: $\pi \geq 0$

H1: $\pi < 0$ (3.2)

The test statistic is the conventional t-ratio for π:

$$t_\pi = \frac{\hat{\pi}}{se(\hat{\pi})} \quad (3.3)$$

Where, $\hat{\pi}$ is the estimate of π and $se(\hat{\pi})$ is the standard error of $\hat{\pi}$.

Dickey and Fuller (1979) showed that, under the null hypothesis of a unit root, this statistic does not follow the conventional Student's t-distribution with degrees of number of observations minus one(n-1) , and they derived asymptotic results and simulated critical values for various tests and sample sizes. MacKinnon (1991, 1996) implemented a much larger set of simulations than those tabulated by Dickey and Fuller. In addition, MacKinnon estimated response surfaces for the simulation results, permitting the calculation of Dickey-Fuller critical values and p-values for arbitrary sample sizes. The simple Dickey-Fuller unit root test described above is valid only if the series is an AR (1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances ε_t is violated. The ADF test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR (p) process and adding lagged difference terms of the dependent variable Y to the right-hand side of the test regression:

$$\Delta \boldsymbol{y_t = \pi y_{t-1} + x_t{}' + B_1 \Delta y_{t-1} + B_2 \Delta y_{t-2} +, \ldots, B_P \Delta y_{t-P} + U_t} \quad (3.4)$$

This augmented specification is then used to test for unit root using the t-ratio [3.3]. An important result obtained by Fuller (1979) is that the asymptotic distribution of the t -ratio for t is independent of the number of lagged first differences included in the ADF regression. Moreover, while the assumption that Y follows an AR process may seem restrictive, Said and Dickey (1984) demonstrate that the ADF test is asymptotically valid in the presence of a moving average component, provided that sufficient lagged difference terms are included in the test regression.

3.5 The Stationary Vector Autoregressive Model

Let $y_{t,} = (y_{1t,} y_{2t,} \dots, y_{nt,})^T$ denotes an (n×1) vector of stationary time series variables. The basic p- lag vector autoregressive VAR (p) model has the form:

$$y_t = c + \pi_1\, y_{t-1} + \pi_2\, y_{t-2} +, \dots, +\pi_p\, y_{t-p} + \varepsilon_t \quad t = 1, 2\dots \mathrm{T} \tag{3.5}$$

where C denotes an (n×1) vector of constants and π_j is an (n×1) matrix of autoregressive coefficients, $j = 1, 2\dots\ p\ and\ \varepsilon_t$ is an (n×1) zero mean white noise vector process (serially uncorrelated) with time invariant and positive definite covariance matrix Σ:

$$\mathrm{E}\,(\varepsilon_t) = 0 \text{ and } \mathrm{E}\,(\varepsilon_t, \varepsilon_s) = \begin{cases} \Sigma\ , & \text{if } t = s \\ 0\ , & if\ t \neq s \end{cases} \tag{3.6}$$

Where, Σ is (n×n) positive definite matrix.

Using the lag operator notation, the VAR (p) is written as

$$\boldsymbol{\Pi}\ (\mathbf{z})\ \boldsymbol{y_t} = \mathbf{C} + \boldsymbol{\varepsilon_t} \tag{3.7}$$

Where $\boldsymbol{\Pi}\ (\mathbf{z}) = \boldsymbol{I_n} - \boldsymbol{\pi_1 z} - \boldsymbol{\pi_2}\ \boldsymbol{z^2} -, \dots, \boldsymbol{\pi_p z^p}$

The VAR (P) process is stationary (stable) if the roots of the determinant is equal zero. That is

$$\det\,(\boldsymbol{I_n} - \boldsymbol{\pi_1 z} - \boldsymbol{\pi_2}\ \boldsymbol{z^2} -, \dots, \boldsymbol{\pi_p z^p}) = 0 \tag{3.8}$$

All roots lies outside the unit circle or have modules greater than one. Assuming that the process has been initialized in the infinite past (p>∞), a stable VAR (p) process is stationary and ergodic with time invariant means, variances and covariance's. A process is said to be ergodic if the time average of a function along the trajectories is the same for all initial points or a system that evolves for a long time forgets its initial state.

If y_t in equation [3.1] is covariance stationary then,

$$\boldsymbol{y_t} = \boldsymbol{\Pi}(\mathbf{z})^{-1}\mathbf{c} + \boldsymbol{\Pi}(\mathbf{z})^{-1}\boldsymbol{\varepsilon_t}$$

And the unconditional mean is given by

$$E(\boldsymbol{y_t}) = \boldsymbol{\Pi}(\mathbf{z})^{-1}\mathbf{c}$$

The general form of the VAR (p) model with deterministic terms and exogenous variables is given by;

$$\boldsymbol{y_t} = \boldsymbol{\pi_1}\,\boldsymbol{y_{t-1}} + \boldsymbol{\pi_2}\,\boldsymbol{y_{t-2}} +, \dots, + \boldsymbol{\pi_p}\,\boldsymbol{y_{t-p}} + \Phi\boldsymbol{D_t} + \mathbf{G}\boldsymbol{X_t} + \boldsymbol{\varepsilon_t} \tag{3.9}$$

Where $\boldsymbol{D_t}$ represent an (L×1) vector of deterministic components $\boldsymbol{X_t}$ is an (m×1) vector of exogenous variables and Φ is an (n×L) and **G** is an (n×m) are parameter matrices.

3.5.1 Determination of the Order of the VAR

The lag length for the VAR (P) model may be determined using model selection criteria. The general approach is to fit VAR (P) models with orders P=0… p_{max} and choose the value of π which minimizes some model selection criteria. Model selection criteria for VAR (p) models have the form:

$$\text{IC (P)} = \ln\left|\hat{\sum}_p\right| + C_T * \Psi\,(n,p)$$

Where IC = Information Criteria, $\hat{\sum}_p = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon_t}\ \hat{\varepsilon}_t^{'}$ is the residual covariance matrix from a VAR (p) model, C_T is a sequence indexed by the sample size T, and Ψ (n,p) is a penalty function which penalizes large VAR (p) models.

The three most common information criteria to determine the order of VAR models are the Akaike (AIC), Schwarz – Bayesian (BIC) and Hannan – Quinn (HQ):

$$\text{AIC (P)} = \ln\left|\hat{\sum}_p\right| + \frac{2}{T}\,\mathrm{p}n^2 \tag{3.10}$$

$$\text{BIC (P)} = \ln\left|\hat{\sum}_p\right| + \frac{\ln(T)}{T}\,\mathrm{p}n^2 \tag{3.11}$$

$$\text{HQ (P)} = \ln\left|\hat{\sum}_p\right| + \frac{2\ln\ln(T)}{T}\,\mathrm{p}n^2 \tag{3.12}$$

The AIC criterion asymptotically overestimates the order with positive probability (not zero), whereas the BIC and HQ criteria estimate the order consistently under fairly general conditions if the true order P is less than or equal to p_{max} . For a model to be best it should have the smallest information criteria. Among the candidate VAR (P) models the one with minimum information criteria is preferred model.

3.6 Co-integration Analysis

3.6.1 Co integration

Testing for Co integration: Co integration technique identifies equilibrium long run as well as short run relationships between variables. If long run relationship exists between variables, then variables are co integrated. For implementation of co integration, two conditions must be fulfilled. First, at least two individual variables should be integrated of same order**.** Second, linear combination among variables should exist. Consider the co integration regression;

$$\boldsymbol{y_t}=\alpha+\beta \boldsymbol{x_t}+\boldsymbol{\mu_t}$$

If the series $\boldsymbol{y_t}$and $\boldsymbol{x_t}$are both I (1) and the error term $\boldsymbol{\mu_t}$ is I (0), then the series are co integrated of order I, (1, 0). In above equation, β measures the equilibrium relationship between the series $\boldsymbol{y_t}$and$\boldsymbol{x_t}$. $\boldsymbol{\mu_t}$ is the deviation from long run equilibrium path.

If the DF test fails to reject the null hypothesis of unit root in levels but reject the null hypothesis in first differences, then the series contain one unit root and is of integrated order one I (1). If the test fails to reject null hypothesis in levels and first differences but reject the null hypothesis in second differences, then the series contains two unit roots and is of integrated order to I (2) (Mencet *et al*., 2006).

The technique of co-integration involves three steps. The first step requires the determination of the order of integration of the variables of interest using ADF tests. In the second step, the co-integration regression using variables having the same order of integration is estimated. In the third step, residuals from the co-integration are subjected to test. The presence of co-integration is an evidence of a long-run equilibrium relationship between variables.

Methods for testing co-integration are

1. The Engle-Granger two-step method
2. The Johansen procedure and
3. Phillips-Ouliaris co- Integration Test

In practice, co integration is used for such series of integrated I (1) in typical econometric tests, but it is more generally applicable and can be used for variables integrated of higher order (to detect correlated accelerations or other second-difference effects). Multi co-integration extends the co-integration technique beyond two variables, and occasionally to variables integrated at different orders.

In this study the Johansson procedure will be used. Johansen's (1991) procedure considers maximum likelihood for a finite-order vector auto regressions (VARs) and is easily calculated for such systems. Johansson's procedure allows to deal with models with several endogenous variables. The procedure begins with unrestricted VAR involving potentially non stationary variables. A key aspect of the approach is isolating and identifying the co-integrating combinations among a set of k integrated variables and incorporating them into an empirical model. The purpose of the co-integration test is to determine whether a group of non-stationary series is co-integrated or not. Tests for co-integration assume that the co-integrating vector is constant during the period of study. In reality, it is possible that the long-run relationship between the underlying variables change (shifts in the co-integrating vector can occur).

The maximum likelihood theory of systems of potentially co integrated stochastic variables presupposes that the variables are integrated of order one or I (1) and that the data generating process is a Gaussian vector autoregressive model of finite order p, or VAR (p), possibly including some deterministic components. Let Y_t be a p-dimensional column vector of I (1) variables. Following Johansen (1995), the VAR (P) model can be re-written into VECM form as:

$$\Delta \boldsymbol{Y_t} = \boldsymbol{\pi Y_{t-1}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{p-1}} \boldsymbol{\Gamma_i} \, \Delta \, \boldsymbol{Y_{t-i}} + \boldsymbol{\varepsilon_t} \qquad \text{t =1, 2… T} \qquad (3.13)$$

Where $\mathbf{\Pi}$ the short-run parameter and$\boldsymbol{\Gamma_i}$, i= 1, 2… p-1 are p×p matrices of coefficients. The VECM representation of Equation (3.13) is convenient because the hypothesis of co-integration can be stated in terms of the long run impact matrix π. The dimension p×p is written as:

$$\boldsymbol{\pi}=\boldsymbol{\alpha}\boldsymbol{\beta}'$$

Where **α** and **β** are p×r matrices of full rank. The columns of **β** contain r co- integrating vectors and the columns of **α** are the r adjustment vectors. In these case πY_{t-1} is called the error correction term. Π has r Eigen values different from zero and hence there are r linear combinations that are stationary. These linear combinations are;

$\beta' Y_t$~~~~~~I (0)

If rank (π) =0 then there are no co- integrating vectors that is all rows (columns) are linearly dependent the system is non stationary in levels.in these case non stationary of I (1) variables is taken care of by differencing and we can analyze the system using VAR techniques.

If rank (π) =p that is full rank, then Y_t has no unit root (all of them are stationary in levels). In such case VAR methodology is applied to the system in levels.no about VEC model.

If rank (π) =r, where 0 <r <p, then this the case of co integration and we can write π as**;**

$\boldsymbol{\pi}=\boldsymbol{\alpha}\boldsymbol{\beta}'$ **α** and **β** are p×r matrix.

3.6.2 Testing for the number of co integration relations using Johansen's methodology

The starting point in Johansen's procedure (1988, 1991) in determining the number of co integrating vectors is the VAR representation of Y_t.It assumes a vector autoregressive model of order p and is expressed as follows:

$$\boldsymbol{Y_t = A_1\, Y_{t-1} + A_2\, Y_{t-2} + \ldots + A_p\, Y_{t-p} + \mathrm{B}A_1\, x_t + \varepsilon_t} \tag{3.14}$$

Where $\boldsymbol{Y_t}$ is a p-vector of non-stationary I (1) variables $\boldsymbol{x_t}$,is a d vector of deterministic variables and ε_t is a vector of innovations. We may be re-write this VAR is

$$\Delta\boldsymbol{Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i\, \Delta\, Y_{t-i} + \mathrm{B}\, x_t + \varepsilon_t} \quad t=1, 2\ldots T \tag{3.15}$$

$$\text{Where } \boldsymbol{\pi = \sum_{i=1}^{p} A_i - I} \qquad \boldsymbol{\Gamma_i = -\sum_{j=j+1}^{p} A_j} \tag{3.16}$$

Granger's representation theorem asserts that if the coefficient matrix $\mathbf{\Pi}$ has reduced rank r < p, then there exist p×r matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ each with rank r such that $\boldsymbol{\pi}= \boldsymbol{\alpha\beta}'$ where r is the number of co-integrating relations (the co-integrating rank) and each column of it is the co-integrating vector. The elements of †are known as the adjustment parameters in the VEC model. It can be shown that for a given ,r the maximum likelihood estimator of β defines the combination Y_{t-1} of that yields the r largest canonical correlations of $\Delta\boldsymbol{Y_t}$ with $\Delta\boldsymbol{Y_{t-1}}$ after correcting for lagged differences and deterministic variables when present. Johansen (1988) proposed two tests for estimating the number of co-integrating vectors: the trace statistic and maximum eigenvalue. The trace statistic investigates the null hypothesis of r co-integrating relations against the alternative of n co-integrating relations, where n is the number of variables in the system for r = 0 ,1,2 …n-1. Define $\hat{\lambda}_i$ i=1, 2…k to be a complex modulus of eigenvalues of $\hat{\pi}$ and let them be ordered such that $\hat{\lambda}_1 \geq \hat{\lambda}_{2\,,} \geq \hat{\lambda}_3 \geq \ldots \hat{\lambda}_n$. The trace statistic is computed as:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n} \ln\left(1-\hat{\lambda}_i\right) \tag{3.17}$$

The Maximum eigenvalue statistic tests the null hypothesis of ↿co-integrating relations against the alternative of r+1 co-integrating relations for r = 0, 1, 2 …n-1. This test statistic is computed as:

$$\hat{\lambda}_{max}(r, r+1) = -T \ln (1- \hat{\lambda}_{r+1}) \tag{3.18}$$

Where $\hat{\lambda}_{r+1}$ is the $(r+1)^{th}$ ordered eigenvalue of π and T is the sample size.

The critical values tabulated by Johansen and Juselius (1990) will be used for these tests. Neither of these tests statistics follows a chi square distribution in general. The asymptotic distributions of the test statistics (3.17) and (3.18) are not normal. Asymptotic critical values for the $\hat{\lambda}_{trce}$ and $\hat{\lambda}_{max}$ statistics have been calculated by Monte Carlo simulation and can be found also in Johansen and Juselius (1990) and are given also by most econometric software packages. Since the critical values used for the maximum eigenvalue and trace test statistics 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.

3.7 Vector Error Correction Modeling (VECM)

Studies in empirical macroeconomics almost always involve non stationary and trending variables. The finding that many time series may contain a unit root has spurred the development of the theory of non-stationary time series analysis. Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series' may be stationary. If such a stationary or I (0) linear combination exists, the non-stationary (with a unit root), time series are said to be co integrated. The linear combination which is stationary is called the co-integrating equation and may be interpreted as a long-run equilibrium relationship between the variables. A VEC model is a restricted VAR designed for use with no stationary series that are known to be co-integrated. The VEC has co-integration relations built into the specification, so that it restricts the long-run behavior of the endogenous variables to converge to their co-integrating relationships while allowing for short-run adjustment dynamics. The co-integration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments.

When the variables are co integrated, the corresponding error correction representations must be included in the system. By doing so, one can avoid misspecification and omission of the important constraints. Thus, the VAR can be re parameterized as a Vector Error Correction Model (VECM) form: (Hamelton, 1994; Reinsel, 1993). VAR (P) model is

$$\boldsymbol{Y_t = \pi_1\, Y_{t-1} + \pi_2\, Y_{t-2} + \ldots + \pi_p\, Y_{t-p} + \varepsilon_t} \tag{3.19}$$

Where $\boldsymbol{Y_t}$ is an n×1 vector of possibly non stationary I (1) variables and $\boldsymbol{\varepsilon_t}$ is an n×1 vector of innovations.

This VAR model can be re parametrized as a vector error correction model as (restricted VAR);

$$\Delta \boldsymbol{Y_t = \pi Y_{t-1}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{p-1}} \boldsymbol{\Gamma_i}\, \Delta\, \boldsymbol{Y_{t-i}} + \boldsymbol{\varepsilon_t} \tag{3.20}$$

Where, $\pi = \sum_{\boldsymbol{i=1}}^{\boldsymbol{p}} \boldsymbol{\pi_i} - \boldsymbol{I_n}$, $\boldsymbol{\Gamma_i} = -\sum_{\boldsymbol{j=j+1}}^{\boldsymbol{p}} \boldsymbol{\pi_j}$ i= 1, 2… p-1 and $\boldsymbol{I_n}$ is identity matrix

3.8 Model checking

A wide range of procedures is available for checking the adequacy of VAR and VECMs. They should be applied before a model is used for specific purpose to ensure that it represents the data adequately. They are several tests for checking adequacy of these models.

3.8.1 Test of residual autocorrelation

The two most popular tests for autocorrelation of residuals are: Breusch-Godfrey LM tests and portmanteau tests. They are both based on statistics of the form

$$Q=T\ \hat{C}'\widehat{\Sigma^{-1}}\hat{C} \tag{3.21}$$

Where $\widehat{\Sigma}$ is a suitable scaling matrix. In other words, they are based on the residual auto-covariance. The estimated of scaling matrix $\widehat{\Sigma}$ determines the type of test statistic and its asymptotic distribution under the null hypothesis of no residual AC. We will consider both types of tests in turn.

3.8.1.1Autocorrelation LM Test

This test was developed by Breusch and Godfrey in 1978. Assume a VAR model for the error ε_t given by

$$\varepsilon_t = D_1 U_{t-1} + \cdots + D_h U_{t-h} + V_t \tag{3.22}$$

The quantity V_t denotes a white nose error term. Thus, to test autocorrelation in U_t we test

$$H_0 = D_1 = \cdots = D_h$$

$$H_1 = D_j \neq 0\ for\ at\ least\ one\ j < h$$

We use the Lagrange multiplier method to perform the test. The Lagrange Multiplier (LM) test for p^{th}order serial correlation is computed first by estimating an auxiliary regression where the OLS residuals are regressed on the variables in the original model plus *p* lagged residuals. The test statistic is either T times R^2 from the auxiliary regression or an F test that the coefficients on the lagged residuals are 0. This method is very useful for finding optimal estimates under constraint conditions. Under H0, we only need to estimate the regular VAR model ($\varepsilon_t = V_t$).So the constrained case estimates are simple.

The Breusch-Godfrey test statistic, sayQ^*_{BG}, is a standard LM test statistic for the null hypothesis Y= 0

$$Q^*_{BG} = T\,\hat{\gamma}^{'}(\widehat{\sum}^{\gamma\gamma}\,\hat{\gamma}\,)^{-1}\hat{\gamma} \tag{3.23}$$

Where $\hat{\gamma}$the generalized least is square estimator of Y and $\widehat{\sum}^{\gamma\gamma}$ is the part of the inverse of this expression

$$[\,T^{-1}\sum_{t=1}^{T}\begin{pmatrix} \widehat{U}_t \otimes I_n \\ \hat{z}_t \otimes I_n \\ \hat{z}_{1t} \end{pmatrix}\hat{\Omega}^{-1}(\quad \widehat{U}_t^{'} \otimes I_n\!:\; \hat{z}_t^{'} \otimes\!:\hat{z}_{1t}^{'})] \tag{3.24}$$

Corresponding to γ and $\hat{z}_t = (1^{'}, y_t^{'}, \ldots ,\; y_{t-p+1}^{'})^{'}$.

Here $\hat{\Omega}$=$T^{-1}\sum_{t=1}^{T}\hat{u}\,\hat{u}^{'}$ is the residual covariance matrix estimator from the restricted auxiliary model. Therefore, under the null hypothesis it follows immediately from (3.23) the above that for h→∞

$$Q^*_{BG} \rightarrow \; in\ distribution\;\; x^2(\mathrm{h}k^2) \tag{3.25}$$

3.8.1.2 Portmanteau autocorrelation test

Suppose $Y_{t=}(Y_{1t}, \ldots Y_{kt})^{'}$ is k-dimensional vector of observable time series variables with r<k co-integration relations. The residual auto covariance is

$$\widehat{C_J} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_{t-J}} \tag{3.26}$$

$\widehat{\varepsilon_t} = \Delta Y_t - \pi Y_{t-1} - \sum_{i=1}^{p-1}\Gamma_i\,\Delta Y_{t-i} - \mathrm{B}\,x_t$ Where $\widehat{\varepsilon_t}$ is an estimated residual.

The Portmanteau test for residual autocorrelation checks the null hypothesis that all residual auto-covariance are zero, that is,

$H_0 = E\left(\widehat{\varepsilon_t}\,\widehat{\varepsilon_{t-\iota}}^{'}\right)$ =0 for i=1, 2….

It is tested against the alternative that at least one auto covariance and, hence, one autocorrelation is nonzero. The test statistic is based on the residual auto covariances and has the form:

$$Q_p = T\sum_{j=1}^{h} tr(\widehat{C_J}^{'}\,\widehat{\Omega_J}^{-1}\widehat{C_J}\widehat{\Omega_J}^{-1}) \quad (3.27)$$

Where $\widehat{C_J} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_{t-J}}$ (3.28)

$$\widehat{\Omega} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_J}^{'} \quad (3.29)$$

The approximate distribution of this test statistic is the chi-squared distribution with κ^2 (h-p) degrees of freedom in large samples if h is also large. Where k is number of endogenous variables h is number of observations and p is lag.

A related statistic with potentially superior small sample properties is the adjusted Portmanteau statistic:

$$Q_p{}^{*} = T^2\sum_{j=1}^{h}\frac{1}{T-j}tr\left(\widehat{C_J}^{'}\,\widehat{C_0}^{-1}\widehat{C_J}\widehat{C_0}^{-1}\right) \quad (3.30)$$

Its asymptotic properties are the same as those of Q_p.

3.8.2 Normality of the Residuals

Normality tests whether the residuals of the regression are normally distributed or not. The null hypothesis is that the residuals are normally distributed. Several tests for normality are available but the most commonly used test for normality of regression disturbances is due to Jarque and Bera (1980). The JB test statistic is:

$$JB=T\left(\frac{\widehat{b_1}}{6}+\frac{\hat{k}^2}{24}\right) \quad (3.31)$$

Where $\widehat{b_1}$ and $\hat{k}$ are the sample skewness and kurtosis coefficients, respectively.This test statistic is asymptotically distributed as $x^2(2)$under the null hypothesis; thus large values of this test statistic relative to the quantiles from the $x^2(2)$ distribution lead to rejection of the null hypothesis. Degrees of freedom is number of endogenous variables minus one (k-1).

3.9 Impulse Response Functions

An impulse response function traces the response of a variable of interest to an exogenous shock. Often the response is portrayed graphically, with horizon on the horizontal axis and response on the vertical axis. It traces the effect of a one standard deviation shock to one of the innovations on current and future values of the endogenous variables. A shock to the ith variable directly affects the i^{th} variable, and may also transmit to all of the endogenous variables through the dynamic structure of the VAR.

3.10 Forecast Error Variance Decompositions

Variance decomposition provides a different method of depicting the system dynamics. Impulse response functions trace the effects of a shock to an endogenous variable on the variable in the VAR. By contrast, variance decomposition decomposes variation in an endogenous variable in to the component shocks to the endogenous variables in the VAR. The variance decomposition gives information about the relative importance of each random innovation to the variables in the VAR. Usually, we plot the decomposition of each forecast variance as line graphs.

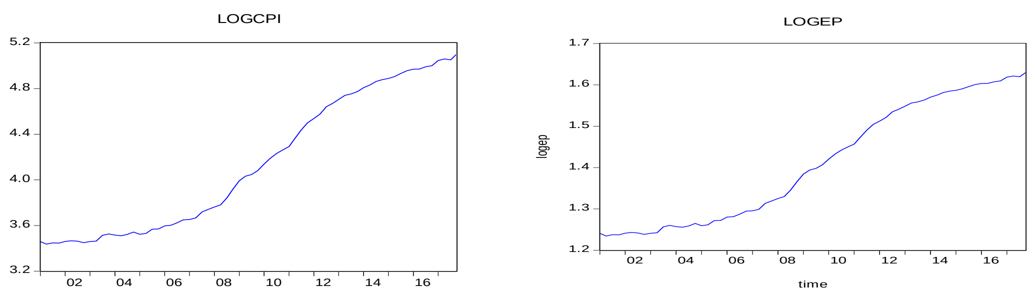
CHAPTER FOUR
ANALYSIS AND RESULTS

4.1 Descriptive Analysis and Time plot

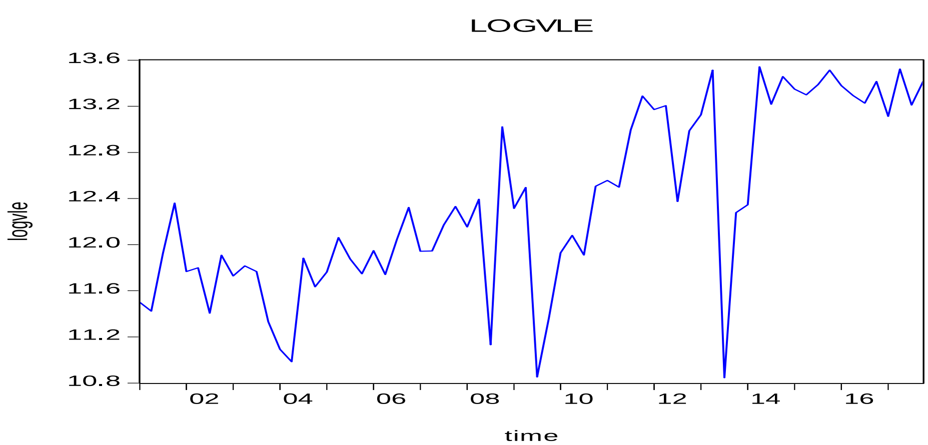
E-Views 6, the windows-based forecasting and econometric analysis package, was used to estimate the relationship among the value of leather export (VLE), consumer price index (CPI), export price (EP) and nominal exchange rate (NER) in the case of Ethiopia. The data in this study consist of quarterly value of leather export (in thousands of birr), quarterly consumer price index, and export price of leather (in birr) and nominal exchange rate (ETB/USD).The time period covered is from September 2000 to August 2016. The time plot of each of the series is shown in Figure 4.1. From the time plot we can observe that all show an increasing trend over the study period.

Figure 4. 1 Time plot of the log of original series

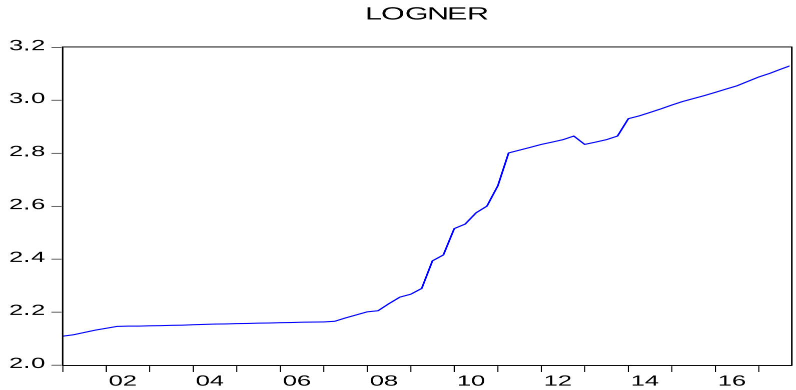
Y –axis: food consumer price index and X axis Time



Y –axis: value of leather export and X-axis Time



Y –axis: nominal exchange rate and X axis Time



From the above time plot we see that the series are looks trending which is the sign of their non Stationarity. That is we can observe that all the series show an increasing trend over the study period.

4.2 Seasonality test

From figure 4.1 it can be seen that there is a seasonality and general upward trend in the series. This implies that all the data are non-stationary. But it should be strongly noticed that only LOGVLE graph of inspections are not enough to conclude the series are seasonal and patterned. There are standard tests for both seasonality and stationarity which has been discussed in methodology and will be applied in analysis of the data as follow.

Before a series is seasonally adjusted, it should be shown that the series is seasonal. X-12ARIMA seasonal adjustment method will be employed to formally test the presence of seasonality for all series. When using X-12 ARIMA for seasonal adjustment, two diagnostics commonly used to determine seasonality are M7, diagnostic developed at Statistics Canada for X-11-ARIMA and the F-tests for seasonality of the series and residuals. Then the variable(s) in which seasonality is observed will be adjusted.

Table 4. 1: F tests for seasonality and adjustment Quality diagnostics of original VLE

Test for the presence of seasonality assuming stability.

	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	91.6999	3	30.56665	5.413*
Residual	361.3901	64	5.64672	
Total	453.0901	67		

* No evidence of stable seasonality at the 0.1 per cent level

Nonparametric Test for the Presence of Seasonality Assuming Stability

Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level
14.9807	3	0.183%

Seasonality present at the one percent level

Moving Seasonality Test

	Sum of Squares	Degrees of Freedom	Mean Square	F-value
Between Years	121.1222	16	7.570135	2.546*
Error	142.7241	48	2.973419	

* Moving seasonality present at the one percent level.

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY

IDENTIFIABLE SEASONALITY NOT PRESENT

No evidence of residual seasonality in the entire series at the1 per cent level. F = 0.9

No evidence of residual seasonality in the last 3 years at the1 per cent level. F = 0.8

No evidence of residual seasonality in the last 3 years at the 5 per cent level.

M1 = 3.000, M2 = 0.791, M3 = 0.037, M4 = 0.018, M5 = 0.929, M6 = 0.450, M7 = 0.163

Q = 0.31 ACCEPTED.

Table 4.1 presents the full F-tests for seasonality of the original value of leather export (RVLE). The combined test for the presence of identifiable seasonality indicates that VLE has a seasonal pattern that can be identified by X-12 ARIMA. The M7 diagnostic (0.163<1), also strengths the identifiably. From the table the F-test assert that seasonality exist in quarterly original VLE series at 0.1 % level of significance. Before seasonal adjustment the seasonality never passed to years with in a confidence of 95% and also the residuals of the series are free from seasonality at 1% significance level. In addition to M7, all M-statistics are shown to be less than one and hence the Q-statistic (0.31) produced from them is also less than one. This condition assures that the seasonal adjustment performed on value of leather export is acceptable.

The remaining pre adjustment tests for consumer price index, export price and nominal exchange rate can be seen in Table A1 (a-c) in appendix. As of those tables, similar tests are conducted for the remaining three series and based on the combined tests and M7-statistic (less than 1for each variable) seasonal effect of all variables can be identified by X-12 ARIMA. The results of F-tests indicate as seasonality do not existed in quarterly original series of CPI, EP and NER as well at 0.1% significance level. Seasonality is not inherited by the yearly data from quarterly ones. At 1% level of significance, the residuals also do not exhibit any seasonality for all these variables. The M-statistic and Q-statistic for each series exceed one and hence both seasonal adjustments procedures made on both are not acceptable. Therefore no more seasonal adjustment is required for each variable.

4.2.1 Seasonal Adjustments Features

A seasonal adjusted series should not have any estimable seasonal effects. A lack of residual seasonality is the most of fundamental requirement of good quality seasonal adjustment. This is to mean that no one should expect seasonality in either the seasonally adjusted series or irregular component.

From table 4.2 below, at 1% level of risk, the test for residual seasonality shows that there is no estimable seasonal effect left in the seasonally adjusted series of VLE and irregular component as it is also indicated by F-test at 0.1% and 1 %(for kruskal-Wallis test) significance level. The combined test for the presence of seasonality together with M7 diagnostic (a value of 3 which is greater than 1) is also assuring that no more seasonal adjustment will be necessary at 1% significance level.

Table 4. 2: F tests for seasonality of RVLE series after adjustment

Test for the presence of seasonality assuming stability.

	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	15.3499	3	5.11663	1.189
Residual	275.4764	64	4.30432	
Total	290.8263	67		

No evidence of stable seasonality at the 0.1 per cent level

Nonparametric Test for the Presence of Seasonality Assuming Stability

Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level
0.3474	3	95.089%

No evidence of seasonality at the one percent level.

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY
IDENTIFIABLE SEASONALITY NOT PRESENT

Test for the presence of residual seasonality.

No evidence of residual seasonality in the entire series at the 1 per cent level. F = 0.8

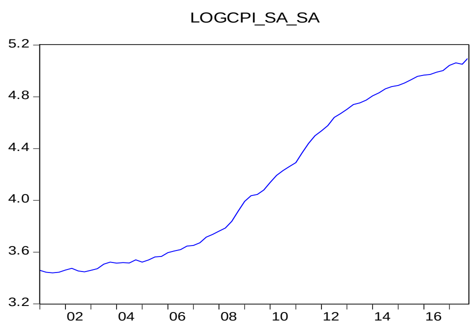
No evidence of residual seasonality in the last 3 years at the1 per cent level. F = 0.99

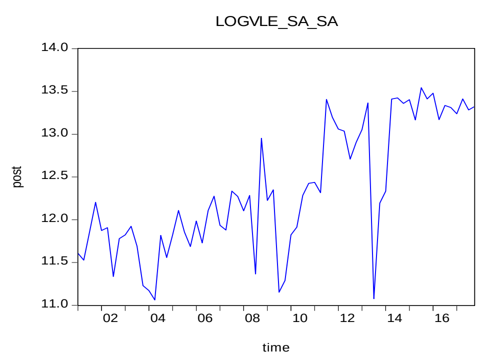
No evidence of residual seasonality in the last 3 years at the 5 per cent level.

M7 = 2.411 Q = 1.95 REJECTED.

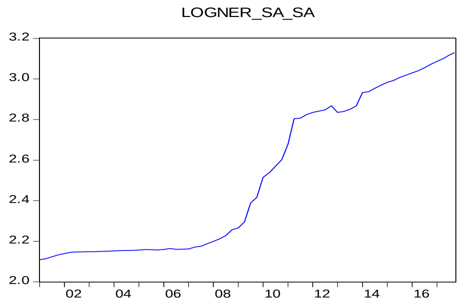
In addition to standard tests above, the time plots of each series seasonally adjusted series are shown below in figure 4.2.

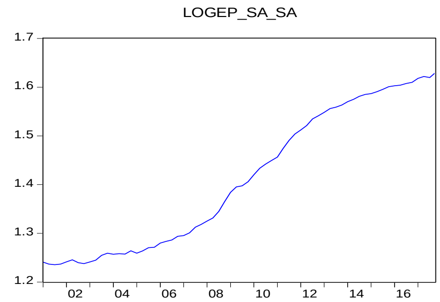
Figure 4. 2 seasonal adjustment time plot for all series





Y –axis: seasonally adjusted VLE and X axis Time   Y –axis: seasonally adjusted NER





4.3. Unit Root Properties of Individual Series

The time series under consideration should be checked for Stationarity before one can attempt to fit a suitable model. That is, variables have to be tested for the presence of unit root(s) and the order of integration of each series has to be determined. Figure 4.1 above suggests that the series of the endogenous variables display a non-stationary behavior. The Stationarity of each series can be tested using an Augmented Dickey-Fuller test and a Phillips and Perron test. The model with intercept but no trend is given as:

$$\Delta logY_t = \mu + \delta^* logY_{t-1} + \sum_{j=1\Phi}^{p} \Phi_j \, \Delta \, logY_{t-j} + u_t \qquad (4.1)$$

And the model with intercept and trend is given as:

$$\Delta logY_t = \mu + \beta t + \delta^* logY_{t-1} + \sum_{j=}^{p} \Phi_j \, \Delta \, logY_{t-j} + u_t \qquad (4.2)$$

The hypothesis to be tested is:

Ho: δ^*=0

H1: $\delta^* < 0$

The results of ADF and PP tests with intercept but no trend and with intercept and trend both at level and first difference for each series are presented in Tables 4.3 and 4.4, respectively. The critical values used for the tests are the McKinnon (1991) critical values. Test results presented in Table 4.3 indicate that the null hypothesis that the series in levels contain unit root could not be rejected for all of the four series. Since the null hypothesis cannot be rejected, in order to determine the order of integration of the non-stationary time series the same tests were applied to their first differences. The plots of the differenced series are presented in Figure A1 of Appendix.

Table 4. 3: Stationarity test in level (unit root test results (at level))

Serious	level with intercept				level with intercept and trend			
	Test statistics		P-value		Test statistics		p-value	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
LOGCPI	-0.91995	1.02150	0.7755	0.9964	-1.469445	-2.477	0.5424	0.3379
LOGNER	0.145870	0.50019	0.9669	0.9856	-2.084855	-1.836	0.5442	0.6761
LOGEP	-1.11220	0.64700	0.7060	0.9900	-1.476037	-2.322	0.5391	0.4163
LOGVLE	-1.98771	0.53159	0.2915	0.4187	-2.626239	-3.033	0.4441	0.2321
Critical value at1 %	-3.533204				-4.103198			

The results in Table 4.4 below indicate that the null hypothesis of unit root is rejected for the first differences of the three indices with intercept and trend using PP test. Similar results were also obtained from ADF test. This implies that the four time series are integrated of degree one (I (1)). Therefore, the ADF and PP test shows that all series are non-stationary in levels and stationary in the first differences.

Table 4. 4 : Stationarity test at difference (unit root test results (after first difference))

Serious	level with intercept				level with intercept and trend			
	Test statistics		P-value		Test statistics		p-value	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
D(LOGCPI)	-4.78901	-4.789	0.0002	0.0002	-4.97714	-4.977	0.0007	0.0007
D(LOGNER)	-3.92207	-5.936	0.0178	0.0000	-6.41773	-6.009	0.0057	0.0000
D(LOGEP)	-5.07378	-5.074	0.0001	0.0001	-5.103934	-5.109	0.0005	0.0004
D(LOGVLE)	-8.53826	-32.46	0.0000	0.0001	-8501610	-32.78	0.0001	0.0000
Critical value at1 %	-3.533204				-4.103198			

4.4. VAR Model Specification

Determination of Order of the VAR

Specifying the lag length has strong implications for subsequent modeling choices. For determining the appropriate lag length for the VAR model the Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quin (HQ) Information Criteria were used. The results are shown in Table 4.5.

The AIC, SC and HQ tests suggest that the appropriate lag length for the VAR model is one (1). We specify the VAR as a three variable system for a sample period from September 2000 to august 2016. The general form of the VAR model is

$$\mathrm{logy_t} = \mathrm{c} + \pi_1 \,\mathrm{logy_{t-1}} + \pi_2 \,\mathrm{logy_{t-2}} +, \dots, + \pi_p \,\mathrm{logy_{t-p}} + \varepsilon_t$$

Where, logy_t = (y_{1t}, y_{2t} , y_{3t}, y_{4t})   t=1, 2, 3… 68

$$y_1 = log\ vle$$

$$y_2 = logner$$

$$y_3 = logcpi$$

$$y_4 = logep$$

VLE –value of leather export

NER-nominal exchange rate

CPI -consumer price index

EP-Export price of leather

Table 4. 5: VAR lag order selection results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	260.3312	NA	7.09e-08	-7.947849	-7.745454	-7.868115
1	521.0977	480.7883*	2.72e-11*	-15.81555*	-15.30956*	-15.61622*
2	525.1665	7.120337	3.18e-11	-15.66145	-14.85187	-15.34252
3	532.2211	11.68434	3.40e-11	-15.60066	-14.48749	-15.16213
4	537.6824	8.533160	3.84e-11	-15.49007	-14.07331	-14.93194

From the above table we can observe that VAR (1) is the best since it has the minimum AIC, SC and HQ. Therefore, the VAR model to be estimated is:

$$\mathrm{logy_t} = \mathrm{c} + \pi_1 \,\mathrm{logy_{t-1}} + \varepsilon_t \qquad (4.3)$$

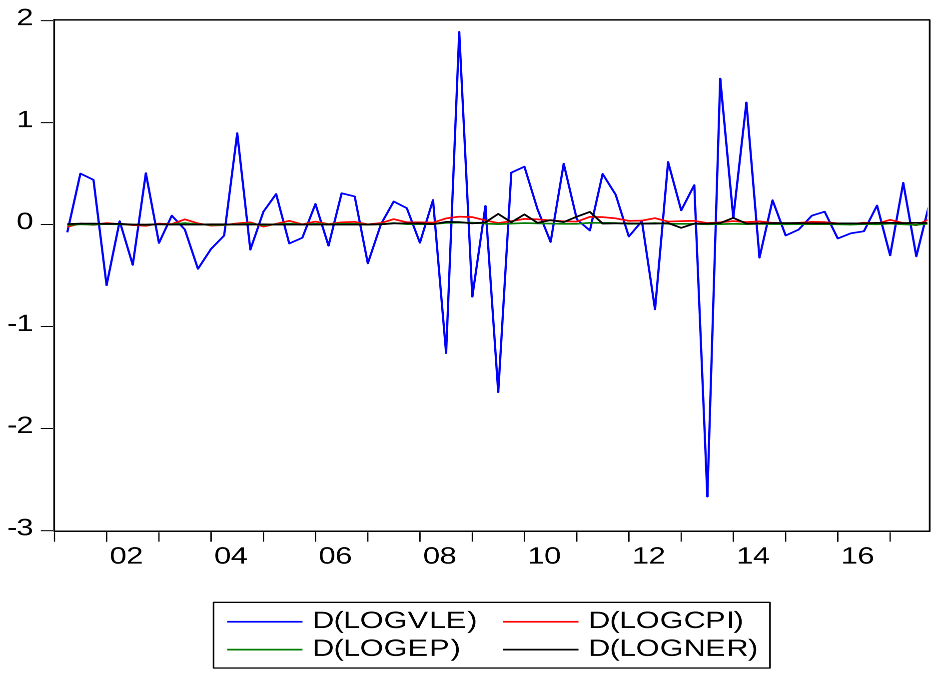
4.4.1 Lag exclusion test

To check whether the chosen lag is optimal, the Wald lag exclusion test is used. Given that VAR modeling requires uniform lag length for each variable, the result in Table below shows that the first lag is significant for all variables at the one percent level of significance. Therefore, VAR (1) is found suitable for the data set and hence could be adopted.

Table 4. 6 : lag exclusion test

	LOGVLE	LOGCPI	LOGEP	Joint
Lag 1	3.071481 [0.380735]	1615.662 [0.000000]	1825.639 [0.000000]	8887.770 [0.000000]
Df	3	3	3	9

Figure 4. 3 plot of Time series plot of VLE, NER and CPI, EP, after first deference)



4.5. Co-integration analysis

Since the variables are integrated of order one, we proceed to test for co-integration. Johansen (1995) co-integration test is applied at the predetermined lag 1. In these tests, Maximum Eigenvalue statistic is compared to special critical values. The maximum eigenvalue and trace tests proceed sequentially from the first hypothesis no co-integrating to an increasing number of co-integrating vectors.

Table 4. 7: Johansen Co-integration test results (By assumption: Linear deterministic trend)

Hypothesized number of Co-integrating equations	Eigenvalue	Trace test			Maximum eigenvalue test		
		statistic	Critical value 5%	Prob**	Statistic	Critical value 5%	Prob**
None *	0.376808	65.81529	29.79707	0.0000	31.21147	21.13162	0.0014
At most 1*	0.275904	34.60382	15.49471	0.0000	21.30686	14.26460	0.0033
At most 2	0.182471	3.29696	13.841466	0.0003	3.841466	3.841466	0.3030

Normalized co-integrating coefficients (standard error in parentheses)

LOGVLE	LOGCPI	LOGEP	LOGVLE	LOGCPI	LOGEP
1.000000	0.00000	5.822219	0.000000	1.00000	-3.688498
	(6.04691)	(4.17992)			(0.16455)
		[1.39290]			[-22.4160]

* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

From the results of Johansen co-integration test presented in table above, it can be observed that the trace or likelihood ratio statistic (65.81529, 34.60382) exceeds the respective critical value (29.79707, 15.49471) with p-value (0.0000, 0.0000). The maximum eigenvalue test also supports the same thing as trace test. This implies that the null hypothesis of no co-integration relation is rejected at the 5% significance level in favor of the alternative one which states that there exist two co-integration relation. Therefore, the rank of co-integration matrix is equal to two, meaning there are two co-integrating equations in the system. That means there exist long run association between value of leather export, consumer price index and export value leather.

Consequently, the co-integrating vector is given by

$$\beta=\begin{pmatrix} 1.0000 & 0.0000 & 5.822219 \\ 0.0000 & 1.0000 & -3.688498 \end{pmatrix}$$

The values correspond to the co-integrating coefficients of LOGVLE, LOGCPI, and LOGEP respectively.

As far as the main purpose of co-integrating analysis is to get a stationary series from two or more non stationary series, the resulting stationary is written as a linear combination of the non-stationary series under study. Accordingly, if this stationary series is designed by S_t, then using the results obtained from above table 4.7 S_t given by

$$S_{t1} = logvle_t + 5.822219 logep_t \quad (4.3)$$

$$S_{t2} = logcpi_t - 3.688498 logep_t$$

The result S_t tells us that is stationary despite the fact that all the three series are non-stationary. Since all of the variables are significant at the conventional significance levels, we can infer from this result that there exist long-run causal relationships among VLE, EP, and CPI. This long-run model are:

$$logvle_t = 20.5581 - 5.822219 logep_t \quad (4.4)$$

$$logcpi_t = -1.063825 + 3.688498 logep_t$$

The above equation indicates that export price of leather has a negative effect on value of leather exports as expected. A one percent increase in a unit price of leather export will cause 5.82219 percent decrease in value of leather export in the long run. Export price has a positive effect on consumer price index, a one percent increase in export price of leather will cause 3.688498 percent increase in exports of leather in the long run.

4.6 Model estimation

Having concluded that the variables in the VAR model appeared to be co-integrated, we proceed to estimate the short run behavior and the adjustment to the long run models, which is represented by VECM. The VEC model has the following structure:

$$\Delta \boldsymbol{logY_t} = \boldsymbol{\mu} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{p}} \boldsymbol{\Gamma_i}\, \Delta\, \boldsymbol{Y_{t-i}} + \boldsymbol{\alpha\beta X_{t-1}} + \boldsymbol{\varepsilon_t} \qquad \textbf{(4.3)}$$

Where, βX_t is the error term given by $\beta' Y_t$ and β is co-integrating vector. The responses of VLE, EP and CPI to short term output movements are captured by the Γ_i coefficient matrices.

The α coefficient vector reveals the speed of adjustment to the equilibrium which measures the deviation from the long-run relationship among the value of leather export. Coefficient estimates of the VEC model are presented in Table 4.8.

Table 4. 8 Vector Error correction Estimates

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

Cointegrating Eq:	CointEq1	CointEq2	
LOGVLE(-1)	1.000000	0.000000	
LOGCPI(-1)	0.000000	1.000000	
LOGEP(-1)	5.822219	-3.688498	
	(4.17992)	(0.16455)	
	[1.39290]	[-22.4160]	
C	-20.55811	1.063825	
Error Correction:	**D(LOGVLE)**	**D(LOGCPI)**	**D(LOGEP)**
CointEq1	-0.762099*	0.002513	0.000787
	(0.15657)	(0.00566)	(0.00144)
	[-4.86736]	[0.44429]	[0.54491]
CointEq2	6.208220*	-0.564528*	-0.132585*
	(3.71901)	(0.13434)	(0.03431)
	[1.66932]	[-4.20233]	[-3.86435]
D(LOGVLE(-1))	-0.124472	0.001641	0.000363
	(0.12054)	(0.00435)	(0.00111)
	[-1.03263]	[0.37690]	[0.32677]
D(LOGCPI(-1))	17.12201*	-1.150565	-0.267984
	(28.1994)	(1.01861)	(0.26015)
	[3.343331]	[-1.12954]	[-1.03010]
D(LOGEP(-1))	-38.95529	4.999045	1.177434
	(110.041)	(3.97486)	(1.01518)
	[-0.35401]	[1.25766]	[1.15983]
C	-4.124525*	-0.258757*	-0.054940*
	(1.91962)	(0.06934)	(0.01771)
	[-2.14861]	[-3.73171]	[-3.10230]
LOGNER	1.569882*	0.111973*	0.023986
	(0.77766)	(0.02809)	(0.00717)
	[2.01872]	[3.98616]	[0.60718]
R-squared	0.447651	0.452789	0.399121
Adj. R-squared	0.391480	0.397141	0.338015

The coefficients in the second part of Table 4.8 contains the coefficients of the error correction terms (ciontEq1and ciontEq2) for the co-integration vector. These coefficients are called the adjustment coefficients that measure the short-run adjustments of the deviations of the endogenous variables from their long run values. These first and second row coefficients identify the fraction of the long term gap that is closed by each endogenous variable in each period (quarter). In another saying, these figures provide information on the short run disequilibria percentage adjustment of each endogenous variable with in one period of time (quarter in these case).

From table 4.8 can be realized that each quarter, 76.2%, 56.4%, 13.2% of the long term gaps are closed by LOGVLE, LOGCPI and LOGEP respectively. The significant of VLE which is 76.2% of the short run disequilibria in value of leather export is adjusted within one quarter. In other words, 76.2% of the shock in the value of leather export is adjusted in the next quarter. CPI is significant, which is 56.4% of the short run disequilibria in value of consumer price index is adjusted within one quarter. In other words, 56.4% of the shock in the consumer price index is adjusted in the next quarter.

EP is significant, which is 13.2% of the short run disequilibria in value of export price of leather is adjusted within one quarter. In other words, 13.2% of the shock in the export price of leather is adjusted in the next quarter.

Exchange Rate has a positive elasticity on to value of leather export, for one dollar increase in the exchange rate the value of leather export is increased by 1.569882. Exchange rate has positive elasticity on to consumer price index, for a one unit increase in value of leather export the consumer price index increased by 0.111973. Consumer price index has positive elasticity on to value leather export, for a one percent increase in the consumer price index the value of leather export increased by 0.111973.

4.7 Model Checking

In order to ascertain whether the model provides an appropriate representation, a test for misspecification should be performed.

4.7.1. Test of residual autocorrelation

Table 4. 9 VEC Residual Portmanteau Tests for Autocorrelations

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	Df
1	1.021282	NA*	1.036995	NA*	NA*
2	5.840361	0.7558	6.006669	0.7393	9
3	11.57188	0.8685	12.01112	0.8467	18

*The test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution

Table 4. 10: VEC Residual Serial Correlation LM Tests

Lags	LM-stat	Prob
1	11.48233	0.2441
2	7.114915	0.6252
3	6.005796	0.7393

The above table presents the results of the portmanteau Q-statistic and Lagrange Multiplier (LM) test for VEC model residual serial correlation. These tests are used to test for the overall significance of the residual autocorrelations up to lag 3. Both results suggest that there is no obvious residual autocorrelation problem up to lag3 because all *p*-values are larger than the 0.05 level of significance.

4.7.2. Testing Normality

Multivariate version of the Jarque -Bera tests is used to test the normality of the residuals. It compares the 3rd and 4th moments (skewness and kurtosis) to those from a normal distribution. The test has null hypothesis indicating that the error term in the model has skewness and kurtosis corresponding to a normal distribution. The results in Table4.7 show that the null hypothesis has to be rejected. It might be the case that there is the presence of outlier in the model. Furthermore, failed Jarque-Bera test is a common phenomenon, which will not crucially distort final results.

Table 4. 11: Results from the Normality Tests

Component	Skew ness		Kurtosis	
	Value	Prob**	Value	Prob**
1	-1.45582	0.0000	7.316071	0.0000
2	0.532182	0.0776	2.673336	0.5880
3	-0.078282	0.7951	3.554540	0.3578
Joint		0.0000		0.0000

4.8 Structural Analysis

4.8.1 Granger Causality Test

Granger causality test is considered a useful technique for determining whether one time series is good for forecasting the other. Table 4.12 presents results from the pair wise Granger-causality tests

Table 4. 12 Pairwise Granger Causality Test

Pairwise Granger Causality Tests
Sample: 2001Q1 2017Q4

Null Hypothesis:	Obs	F-Statistic	Prob.
LOGCPI does not Granger Cause LOGVLE	67	25.9873	3.E-06
LOGVLE does not Granger Cause LOGCPI		0.00328	0.9545
LOGEP does not Granger Cause LOGVLE	67	25.0590	5.E-06
LOGVLE does not Granger Cause LOGEP		0.05439	0.8163
LOGNER does not Granger Cause LOGVLE	67	30.8430	6.E-07
LOGVLE does not Granger Cause LOGNER		1.03854	0.3120
LOGEP does not Granger Cause LOGCPI	67	43.2613	1.E-08
LOGCPI does not Granger Cause LOGEP		39.4074	3.E-08
LOGNER does not Granger Cause LOGCPI	67	0.57108	0.4526
LOGCPI does not Granger Cause LOGNER		5.82558	0.0187
LOGNER does not Granger Cause LOGEP	67	5.24909	0.0253
LOGEP does not Granger Cause LOGNER		10.5650	0.0018

Table 4.12 above presents result from the pairwise Granger causality tests at 5% significance level. The result shows that at 95% confidence level consumer price index, export value of leather, and nominal exchange rate Granger cause the value of leather export but the converse is not hold.

Nominal exchange rate does not Granger cause consumer price index and export price of leather granger cause consumer price index. Nominal exchange rate Granger cause export price of leather.

4.8.2. Impulse-Response Functions

Impulse responses trace out the responsiveness of the variables in the VAR to shocks to each of the variables. Therefore, for each variable a unit shock is applied to the error and the effects upon the VAR system over time are noted. Thus, if there are k variables in a system, a total of k^2 impulse responses could be generated. A standard Cholesky decomposition is used in order to identify the short run effects of shocks on the levels of the endogenous variables in the VAR (1).
A standard Choleski decomposition is used in order to identify the short run effects of shocks on the levels of the endogenous variables in the VECM.

Impulse responses are presented in Figures4.5A2 (a-c) in Appendix with the Cholesky ordering VLE, CPI, and EP. The x-axis gives the time horizon or the duration of the shock whilst the y-axis gives the direction and intensity of the impulse or the percent variation in the dependent variable away from its base line level.

Figure 4.5A2 (a) shows the responses of VLE, CPI and EP with respect to one standard deviation innovation in VLE. The result indicates VLE innovations has a positive impact on CPI. It exhibits declines trend initially and reaches 0.004549 and it stabilizes at around 3rd quarter time horizon. Moreover, the shocks of VLE have initially positive effect on EP and then become negative around 6rd quarter time horizon.

Impulse responses for CPI in Figure 4.5 A2 (b) show that the effect of a one standard deviation shock to EP is positive. It rises initially to 0.004839 and then stabilizes around 7th quarter time horizon. This figure also shows that VLE innovation has a positive effect on CPI and its effect is smooth. Impulse responses for EP in Figure 4.5 A2 (C) show that the effect of a one standard deviation shock to VLE is positive and CPI has appositive effect on EP.

4.8.3 Forecast Error Variance Decomposition

Variance decompositions offer a slightly different method for examining VAR system dynamics. The decomposition is used to understand the proportion of the fluctuation in a series explained by its own shocks versus shocks from other variables. In general we expect a variable to explain almost all its forecast error variance at short horizons and smaller proportions at longer horizons.

The results of the decomposition of the endogenous variables of the model are presented in Figure 4.6A3 in Appendix. The results from the variance decomposition of VLE provide the percentage of the forecast error in each variable that could be attributed to innovations of the other variables for different time period. The Cholesky ordering employed is LOGVLE, LOGCPI and LOGEP.

The variance decomposition analysis result of VLE in Figure 4.3 above shows that, at the first horizon, variation of VLE is explained only by its own shock. In the second quarter 94.70337 % of the variability in the VLE fluctuations is explained by its own innovations and the remaining 5.29663% is explained by CPI (4.757133) and EP (0.573863).Even up tenth quarter, much of variability of VLE (93.21419) is explained by its shock the rest proportion is occupied by CPI (5.668189) and EP (1.117617).it can be observed that, after ten quarter the variability of VLE is determined by CPI has shown increment to 5.66% and VLE shock revealed of total 6.8% decrement.

In similar fashion, the variance decomposition analysis result of CPI in Figure 4.6 in appendix shows that, at the first horizon (quarter) 92.75330 % of the variability in the CPI fluctuations is explained by its own innovations and the remaining 7.2467% is explained by VLE (7.2460707).Even up to tenth quarter, much of variability of CPI (74.21928) is explained by its shock the rest proportion is occupied by VLE (13.24698) and EP (12.53373). Similarly, the variance decomposition of EP shows that almost all variability are explained by their own fluctuations.

In study of determinants of leather exports from Pakistan, According to the findings, exchange rate showed a negative effect on exports of finished leather. The coefficient of this variable explains that for every one percent increase in exchange rate there might be 5.2 percent decrease in exports of finished leather in the long run. It is similar results on my findings. In Ethiopia no more literature to compare my objectives.

CHAPTER FIVE

CONCULSION AND RECOMMENDATION

5.1 CONCLUSION

Ethiopia has sustained to be the leader in its livestock resources in Africa which proves the availability of a huge potential for the country's leather industry. The country possesses one of the world's largest livestock populations around fifty seven million cattle population that puts the country first in Africa and sixth in the world.

The objective of this paper was to apply multivariate time series analysis of determinates of leather export from Ethiopia using quarterly data ranging from September 2000 to August 2016.

Initially all series were identified to be seasonal by using F-tests and M7 diagnostics for seasonality, thus all series are firstly adjusted for seasonality then differenced once to make them non seasonal and stationarity. Over the time period considered, all three series have an increasing pattern, that is, there is a sign of non-Stationarity in each of the series. Formally, the data were tested for Stationarity and all four series were found to be non-stationary using Augmented Dickey-Fuller and Phillips-Perron unit root tests. Appropriate differencing made the series stationary.

Using lag AIC, SC and HQ lag order selection criteria, the appropriate lag was found to be one and optimality test (lag exclusion test) of lag length is also approved the selected lag order. Error diagnosis of this model showed that the disturbance terms are white noise and normally distributed. This model expressed each variable under study as a function of its lag and the lag of other variables. Johansen co-integration test suggests that there is only one co-integrating vector at 95% confidence level and it has been clearly identified that vector error correction model, VEC (1) is the best fit the data. Which describes the long run relationship between VLE, NER and CPI. The appropriate number of lag identified was one.

From Vector Error Correction Model Export price of leather has a negative effect on value of leather exports, a one percent increase in a unit price of leather export will cause 5.82219 percent decrease in value of leather export in the long run. Export price has a positive effect on consumer price index, a one percent increase in export price of leather will cause 3.688498 percent increase in exports of leather in the long run.

In the short run the significant of VLE which is 76.2% of the short run disequilibria in value of leather export is adjusted within one quarter. In other words, 76.2% of the shock in the value of leather export is adjusted in the next quarter. CPI is significant, which is 56.4% of the short run disequilibria in value of consumer price index is adjusted within one quarter. In other words, 56.4% of the shock in the consumer price index is adjusted in the next quarter. EP is significant, which is 13.2% of the short run disequilibria in value of export price of leather is adjusted within one quarter. In other words, 13.2% of the shock in the export price of leather is adjusted in the next quarter.

Exchange Rate has a positive elasticity on to value of leather export, for one dollar increase in the exchange rate the value of leather export is increased by 1.569882. Exchange rate has positive elasticity on to consumer price index, for a one unit increase in value of leather export the nonfood consumer price index increased by 0.111973. Consumer price index has positive elasticity on to value leather export, for a one unit increase in the consumer price index the value of leather export increased by 0.111973.

Jarque-Bera verified that residuals are normally distributed while Lagrange Multiplier (LM) and Portmanteau Q-statistic tests confirmed that residuals do not exhibit serial correlation.

Impulse response function were also employed to study the dynamic relationship of the variables. The results of impulse response functions obtained by applying a standard Choleski decomposition indicate the result indicates VLE innovations has a positive impact on CPI. Impulse responses for CPI show that the effect of a one standard deviation shock to EP is positive. Impulse responses for EP show that the effect of a one standard deviation shock to VLE is positive and CPI has a positive effect on EP.

The variance decomposition analysis result of VLE shows that, at the first horizon, variation of VLE is explained only by its own shock. The variance decomposition of EP shows that almost all variability are explained by their own fluctuations.

5.2 RECOMMENDATION

Based on the findings of the current study we forward the following recommendations:

- The results of my study revealed that exchange rate of Ethiopian birr is not competent to U.S Dollars, therefore the government works to balance the currency of Ethiopian birr.
- Policy makers should consider the currency of the country to enhance leather export.
- The results of my study revealed that consumer price index is a positive effect on value of leather export, so the stakeholders of this sector promote the exports of leather from Ethiopia.
- Finally we recommended that further research should be identify determinates of leather export from Ethiopia to other countries.

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APPENDIX

Table 4. 13 A1 (a-c): F tests for seasonality and adjustment Quality diagnostics of original series

Table A1 (a): F tests for seasonality and adjustment Quality diagnostics of original CPI

Test for the presence of seasonality assuming stability.

	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	0.4119	3	0.13729	5 .061*
Residual	1.7361	64	0.02713	
Total	2.1480	67		

* No evidence of stable seasonality at the 0.1 per cent level

Nonparametric Test for the Presence of Seasonality Assuming Stability

Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level
12.5402	3	0.574%

Seasonality present at the one percent level.

Moving Seasonality Test

	Sum of Squares	Degrees of Freedom	Mean Square	F-value
Between Years	0.3603	16	0.022518	1.663
Error	0.6498	48	0.013538	

No evidence of moving seasonality at the five percent level.

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY
IDENTIFIABLE SEASONALITY PRESENT

Test for the presence of residual seasonality.
No evidence of residual seasonality in the entire series at the1 per cent level. F =0.09
No evidence of residual seasonality in the last 3 years at the 1 per cent level. F =0.79
No evidence of residual seasonality in the last 3 years at the 5 per cent level.
M1 = 0.329, M2 = 0.009, M3 = 0.000, M4 = 0.566, M5 = 0.200, M6 = 0.996, M7 = 0.999
Q=0.57

: F tests for seasonality of CPI series after adjustment

Test for the presence of seasonality assuming stability.

	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	0.1967	3	0.06556	0.071
Residual	58.8210	64	0.91908	
Total	59.0176	67		

No evidence of stable seasonality at the 0.1 per cent level

Nonparametric Test for the Presence of Seasonality Assuming Stability

Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level
0.8213	3	84.437%

No evidence of seasonality at the one percent level.

Moving Seasonality Test

	Sum of Squares	Degrees of Freedom	Mean Square	F-value
Between Years	15.7492	16	0.984323	2.894*
Error	16.3266	48	0.340137	

* Moving seasonality present at the one percent level.

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY

IDENTIFIABLE SEASONALITY NOT PRESENT

Test for the presence of residual seasonality.

No evidence of residual seasonality in the entire series at the1 per cent level. F = 0.04

No evidence of residual seasonality in the last 3 years at the1 per cent level. F = 1.71

No evidence of residual seasonality in the last 3 years at the 5 per cent level.

M7 = 3.000 Q=1.67

Table A1 (b): F tests for seasonality and adjustment Quality diagnostics of original NER

Test for the presence of seasonality assuming stability.

	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	0.2451	3	0.08169	0.774
Residual	6.7508	64	0.10548	
Total	6.9959	67		

No evidence of stable seasonality at the 0.1 per cent level.

Nonparametric Test for the Presence of Seasonality Assuming Stability

Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level
2.5126	3	47.303%

No evidence of seasonality at the one percent level.

Moving Seasonality Test

	Sum of Squares	Degrees of Freedom	Mean Square	F-value
Between Years	2.6610	16	0.166311	3.150*
Error	2.5345	48	0.052802	

* Moving seasonality present at the one percent level.

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY
IDENTIFIABLE SEASONALITY NOT PRESENT

Test for the presence of residual seasonality.

No evidence of residual seasonality in the entire series at the1 per cent level. F = 0.13
No evidence of residual seasonality in the last 3 years at the1 per cent level. F =1.89
No evidence of residual seasonality in the last 3 years at the 5 per cent level.
M1 = 1.036, M2 = 0.035, M3 = 0.000, M4 = 0.453, M5 = 0.200, M6 = 0.126, M7 = 3.000
Q =1.29

: F tests for seasonality of NER series after adjustment

Test for the presence of seasonality assuming stability.				
	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	0.1398	3	0.04660	0.478
Residual	6.2438	64	0.09756	
Total	6.3836	67		
No evidence of stable seasonality at the 0.1 per cent level				
Nonparametric Test for the Presence of Seasonality Assuming Stability				
	Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level	
	1.0981	3	77.754%	
No evidence of seasonality at the one percent level.				
Moving Seasonality Test				
	Sum of Squares	Degrees of Freedom	Mean Square	F-value
Between Years	1.8099	16	0.113119	1.661
Error	3.2681	48	0.068086	
No evidence of moving seasonality at the five percent level.				
COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY				
IDENTIFIABLE SEASONALITY NOT PRESENT				
Test for the presence of residual seasonality.				
No evidence of residual seasonality in the entire series at the 1 per cent level. F = 0.13				
No evidence of residual seasonality in the last 3 years at the 1 per cent level. F = 2.08				
No evidence of residual seasonality in the last 3 years at the 5 per cent level.				
M7 = 3.000, Q=1.50				

Table A1 (c): F tests for seasonality and adjustment Quality diagnostics of original EP

Test for the presence of seasonality assuming stability.				
	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	0.2494	3	0.08312	5.625*
Residual	0.9457	64	0.01478	
Total	1.1951	67		
* No evidence of stable seasonality at the 0.1 per cent level.				
Moving Seasonality Test				
	Sum of Squares	Degrees of Freedom	Mean Square	F-value
Between Years	0.2267	16	0.014171	1.936
Error	0.3514	48	0.007320	
Moving seasonality present at the five percent level				

Nonparametric Test for the Presence of Seasonality Assuming Stability		
Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level
12.9594	3	0.473%

Seasonality present at the one percent level.

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY

IDENTIFIABLE SEASONALITY NOT PRESENT

Test for the presence of residual seasonality.

No evidence of residual seasonality in the entire series at the1 per cent level. F = 0.09

No evidence of residual seasonality in the last 3 years at the1 per cent level. F = 0.82

No evidence of residual seasonality in the last 3 years at the 5 per cent level.

M7 = 1.067 Q= 1.57

F tests for seasonality of EP series after adjustment

Test for the presence of seasonality assuming stability.

	Sum of Squares	Degrees of Freedom	Mean Square	F-Value
Between quarters	0.0142	3	0.00472	0.400
Residual	0.7551	64	0.01180	
Total	0.7693	67		

No evidence of stable seasonality at the 0.1 per cent level.

Nonparametric Test for the Presence of Seasonality Assuming Stability

Kruskal-Wallis Statistic	Degrees of Freedom	Probability Level
0.2120	3	97.563%

No evidence of seasonality at the one percent level.

Moving Seasonality Test

	Sum of Squares	Degrees of Freedom	Mean Square	F-value
Between Years	0.0970	16	0.006063	1.056
Error	0.2755	48	0.005740	

No evidence of moving seasonality at the five percent level.

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY

IDENTIFIABLE SEASONALITY NOT PRESENT

Test for the presence of residual seasonality.

No evidence of residual seasonality in the entire series at the1 per cent level. F = 0.06

No evidence of residual seasonality in the last 3 years at the1 per cent level. F = 0.81

No evidence of residual seasonality in the last 3 years at the 5 per cent level.

M7 = 2.909 Q = 1.42

Table 4. 14A2: Least squares estimator of VLE, NER, EP and CPI

Estimation Method: Least Squares
Sample: 2001Q3 2017Q4
Included observations: 66
Total system (balanced) observations 198

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.762099	0.156574	-4.867357	0.0000
C(2)	6.208220	3.719013	1.669319	0.0968
C(3)	-0.124472	0.120540	-1.032625	0.3032
C(4)	17.12201	28.19942	0.607176	0.5445
C(5)	-38.95529	110.0410	-0.354007	0.0238
C(6)	-4.124525	1.919624	-2.148611	0.0330
C(7)	1.569882	0.777661	2.018723	0.0450
C(8)	0.002513	0.005656	0.444293	0.6574
C(9)	-0.564528	0.134337	-4.202335	0.0000
C(10)	0.001641	0.004354	0.376897	0.7067
C(11)	-1.150565	1.018609	-1.129545	0.2602
C(12)	4.999045	3.974863	1.257665	0.2102
C(13)	-0.258757	0.069340	-3.731712	0.0003
C(14)	0.111973	0.028090	3.986160	0.0001
C(15)	0.000787	0.001444	0.544908	0.5865
C(16)	-0.132585	0.034310	-3.864348	0.0002
C(17)	0.000363	0.001112	0.326774	0.7442
C(18)	-0.267984	0.260153	-1.030101	0.3044
C(19)	1.177434	1.015181	1.159826	0.2477
C(20)	-0.054940	0.017709	-3.102302	0.0022
C(21)	0.023986	0.007174	3.343310	0.4510
Determinant residual covariance		1.53E-11		

Equation: D(LOGVLE) = C(1)*(LOGVLE(-1) + 5.82221885*LOGEP(-1) - 20.5581146665) + C(2)*(LOGCPI(-1) - 3.68849818774*LOGEP(-1) + 1.06382512089) + C(3)*D(LOGVLE(-1)) + C(4)*D(LOGCPI(-1)) + C(5)*D(LOGEP(-1)) + C(6) + C(7)*LOGNER

Observations: 66

R-squared	0.447651	Mean dependent var	0.030212
Adjusted R-squared	0.391480	S.D. dependent var	0.623619
S.E. of regression	0.486471	Sum squared resid	13.96259
Durbin-Watson stat	1.903780		

Equation: D(LOGCPI) = C(8)*(LOGVLE(-1) + 5.82221885*LOGEP(-1) - 20.5581146665) + C(9)*(LOGCPI(-1) - 3.68849818774*LOGEP(-1) + 1.06382512089) + C(10)*D(LOGVLE(-1)) + C(11)*D(LOGCPI(-1)) + C(12)*D(LOGEP(-1)) + C(13) + C(14)*LOGNER

Observations: 66

R-squared	0.452789	Mean dependent var	0.025257
Adjusted R-squared	0.397141	S.D. dependent var	0.022632
S.E. of regression	0.017572	Sum squared resid	0.018218
Durbin-Watson stat	1.885166		

Equation: D(LOGEP) = C(15)*(LOGVLE(-1) + 5.82221885*LOGEP(-1) - 20.5581146665) + C(16)*(LOGCPI(-1) - 3.68849818774*LOGEP(-1) + 1.06382512089) + C(17)*D(LOGVLE(-1)) + C(18)*D(LOGCPI(-1)) + C(19)*D(LOGEP(-1)) + C(20) + C(21)*LOGNER

Observations: 66			
R-squared	0.399121	Mean dependent var	0.005992
Adjusted R-squared	0.338015	S.D. dependent var	0.005516
S.E. of regression	0.004488	Sum squared resid	0.001188
Durbin-Watson stat	1.887851		

Figure 4. 4 A1: The plots of the differenced series

Presented for LOGVLE, LOGNER, LOGEP and LOGCPI respectively.

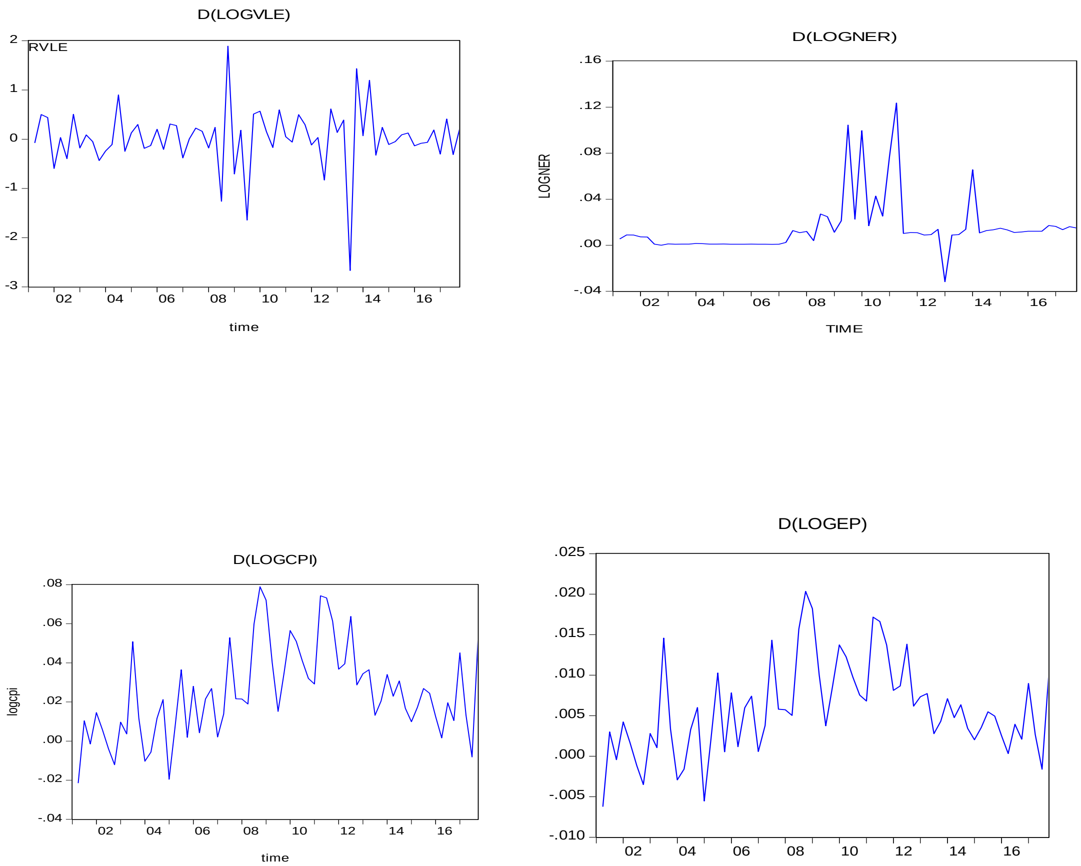


Figure 4. 5 A2 (a-c): Impulse-Response Functions to Cholesky one S.D. Innovations

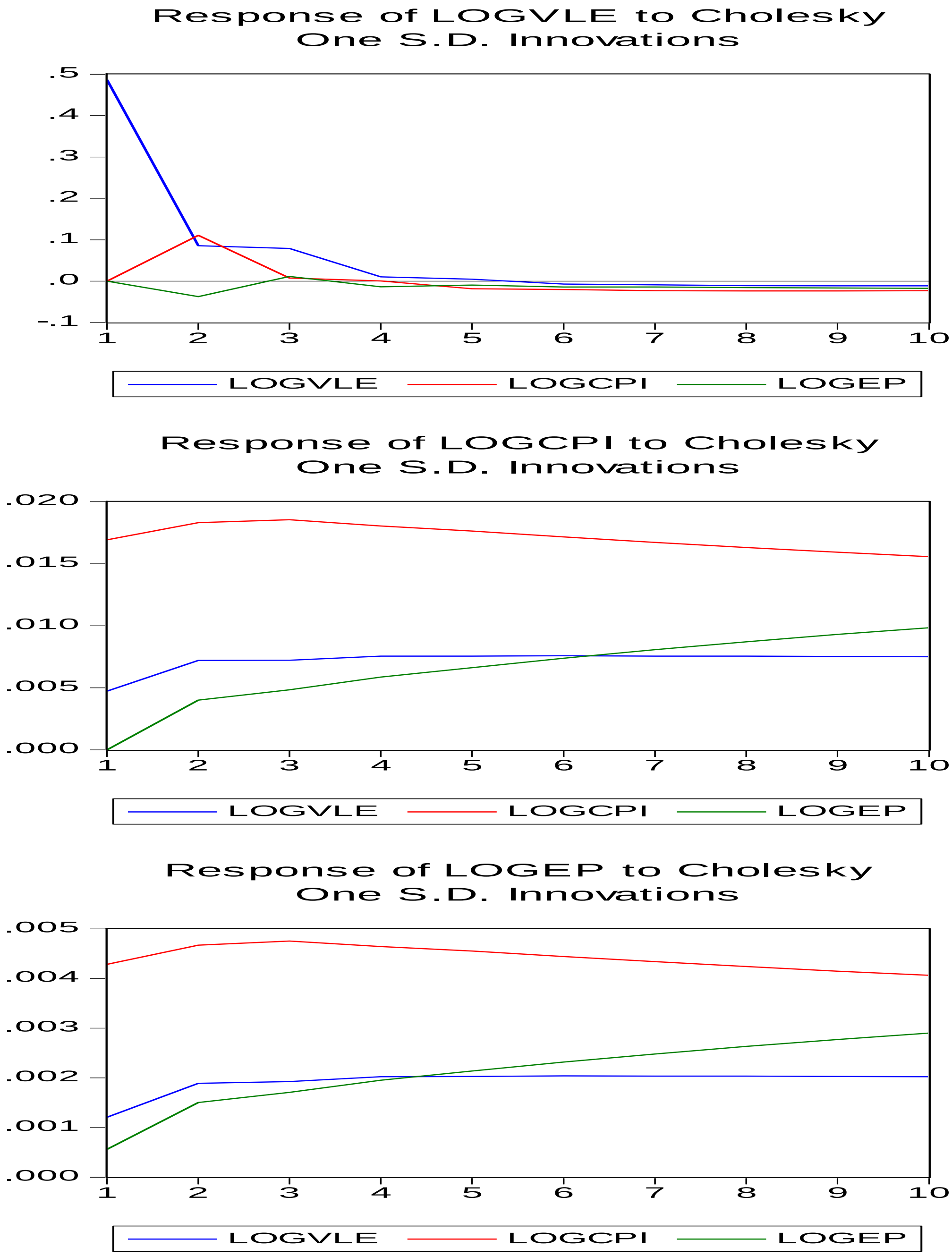


Table 4. 15A3 (a-c): Variance Decomposition Results

Variance Decomposition Results (Choleskey Ordering VLE, CPI, EP)

Table a: Variance Decomposition of VLE

Period	S.E.	LOGVLE	LOGCPI	LOGEP
1	0.486471	100.0000	0.000000	0.000000
2	0.507563	94.70337	4.757133	0.539500
3	0.513866	94.76402	4.662115	0.573863
4	0.514151	94.70023	4.657046	0.642728
5	0.514584	94.54895	4.776684	0.674369
6	0.515232	94.33027	4.922843	0.746890
7	0.516035	94.06642	5.111818	0.821766
8	0.516922	93.78804	5.300028	0.911928
9	0.517842	93.50215	5.487832	1.010018
10	0.518780	93.21419	5.668189	1.117617

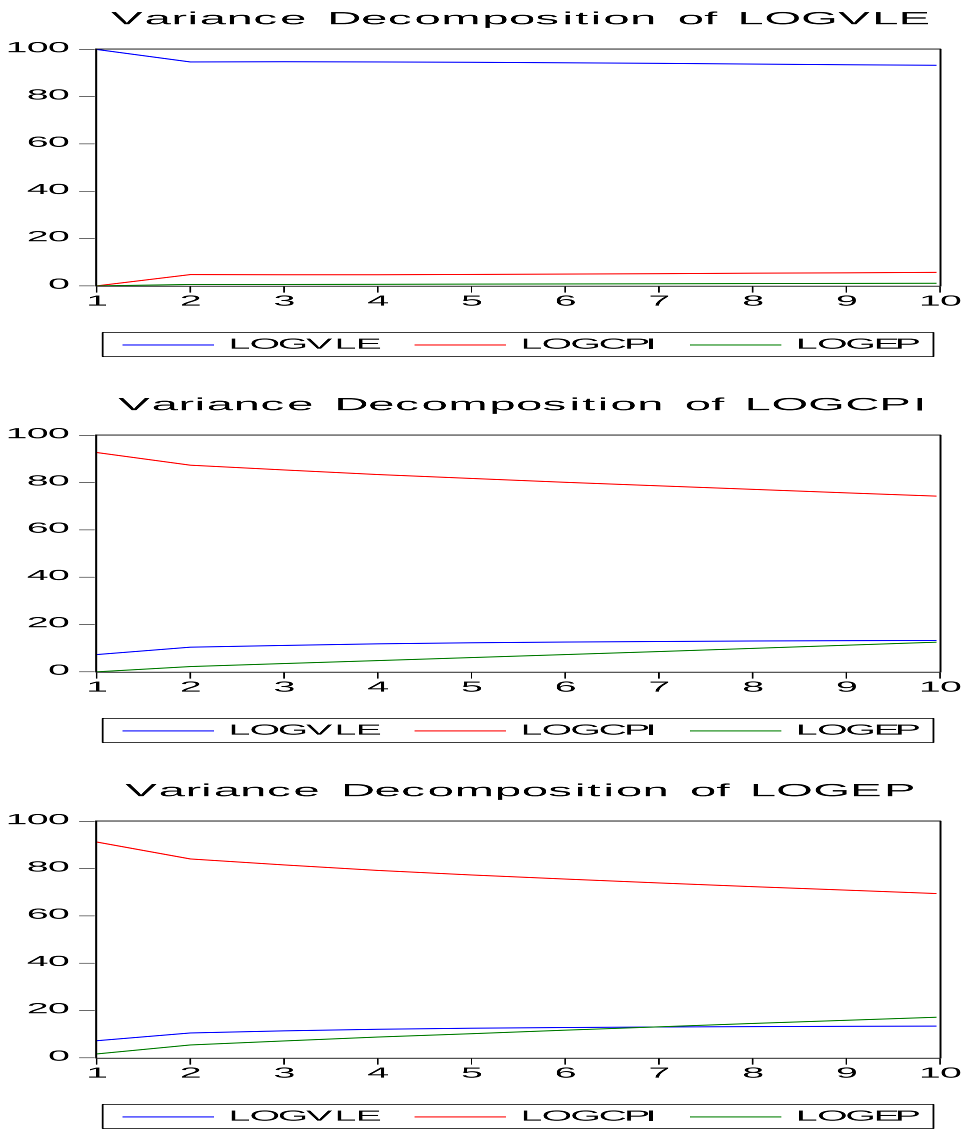
Table b: Variance Decomposition of CPI

Period	S.E.	LOGVLE	LOGCPI	LOGEP
1	0.017572	7.246703	92.75330	0.000000
2	0.026680	10.42396	87.33888	2.237168
3	0.033632	11.15967	85.36208	3.478250
4	0.039342	11.83515	83.40863	4.756224
5	0.044262	12.25246	81.75156	5.995989
6	0.048632	12.57400	80.15577	7.270228
7	0.052599	12.81159	78.62370	8.564712
8	0.056259	12.99545	77.12517	9.879387
9	0.059676	13.13719	75.65798	11.20483
10	0.062900	13.24698	74.21928	12.53373

Table c: Variance Decomposition of EP

Period	S.E.	LOGVLE	LOGCPI	LOGEP
1	0.004488	7.226446	91.20332	1.570236
2	0.006911	10.50559	84.10775	5.386666
3	0.008774	11.33845	81.52645	7.135103
4	0.010318	12.04243	79.21587	8.741703
5	0.011655	12.46537	77.32439	10.21025
6	0.012849	12.77584	75.56966	11.65451
7	0.013936	12.99503	73.93129	13.07368
8	0.014942	13.15668	72.36704	14.47628
9	0.015883	13.27501	70.86627	15.85872
10	0.016772	13.36152	69.42016	17.21832

Figure 4. 6 A3 Variance Decomposition Results



DECLARATION

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

Declared by:
Name: ________________________________

Signature: _____________________________

Date: _________________________________

Confirmed by Advisor:
Name: ________________________________

Signature: _____________________________

Date: _________________________________