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MULTIVARIATE TIME SERIES ANALISIS OF EXPORT OF ETHIOPIAN LIVESTOCK PRODUCTS

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ABSTRACT

Ethiopia has one of the largest livestock populations in Africa. The study is aimed to fit a multivariate time series model which explains the cointegration of Ethiopian livestock products export using vector auto regression (VAR) and vector error correction (VEC) model. Secondary data on exports of livestock products export first quarter of 2002 to the third quarter of 2017, which is obtained from national bank of Ethiopia, is used. Unit root tests of the series under study revealed that all the series are non-stationary at level and stationary after first difference; all the series are not affected by periodicity. The result of Johansen test indicates the existence of one cointegration relation between the volume of live animals, meat and leather export and there is long-term dynamics between these exports of Ethiopian livestock products. From the error correction model result, about 18.1 percent of disequilibrium in the volume of live animals export is corrected each quarter. Exchange rate has negative and significant elasticity on the volume of leather export. Furthermore, the volume of meat export is not affected by exchange rate. The empirical finding of this study recommend concerned bodies to give due attention to exchange rate in policy formulation.

ACRONYMS

ACF	**A**uto**c**orrelation **F**unction
ADF	**A**ugmented **D**ickey **F**uller
AGP	**A**gricultural **G**rowth **P**rogram
ANRS	**A**far **N**ational **R**egional **S**tate
ARDL	**A**uto**R**egressive **Di**stributed **L**ag
ARMA	**A**uto**R**egressive **M**oving **A**verage
CSA	**C**entral **S**tatistical **A**gency
ESAP	**E**thiopian **S**ociety of **A**nimal **P**roduction
FAO	**F**ood and **A**griculture **O**rganization
FDRE	**F**ederal **D**emocratic **R**epublic of **E**thiopia
GDP	**G**ross **D**omestic **P**roduct
IFAD	**I**nternational **F**und for **A**gricultural **D**evelopment
ILRI	**I**nternational **L**ivestock **R**esearch **I**nstitute
IRF	**I**mpulse **R**esponse **F**unction
IUCN	**I**nternational **U**nion for **C**onservation of **N**ature
LM	**L**agrange **M**ultiplier
MAE	**M**ean **A**bsolute **E**rror
MOA	**M**inistry **O**f **A**griculture
MPAE	**M**ean **P**ercentage **A**bsolute **E**rror

MSE	**M**ean **S**quare **E**rror
MVTS	**M**ulti**V**ariate **T**ime **S**eries
NBE	**N**ational **B**ank of **E**thiopia
ONRS	**O**romia **N**ational **R**egional **S**tate
PP	**P**hillips-**P**erron
SVAR	**S**tructural **V**ector **A**uto**R**egressive
VAR	**V**ector **A**uto**R**egressive
VECM	**V**ector **E**rror **C**orrection **M**odel

CHAPTER ONE

INTRODUCTION

1.1. Background

Ethiopia has one of the largest livestock populations in Africa. The recent estimate of livestock population of Ethiopia shows that there are about 57.8 million heads of cattle, 28.9 million sheep, 29.7 million goats and 47.1 million poultry , plus an assortment of horses, donkeys, camels (CSA, 2015, MOA, 2015).

In Ethiopia, livestock is the basis of the livelihood of both smallholder producers and pastoralists.The whole of our agriculture is based on livestock, either to use for farming related activities or as a livelihood (Bailey *et al.* 1999).Almost the entire rural population was involved in some way with animal husbandry, whose role included the provision of draft power, food, cash, transportation, fuel, and, especially in pastoral areas, social prestige. In the highlands, oxen provided draft power in crop production.

Livestock is economically an important sector; it provides draught power, income for farming communities, means of savings and investment and is an important source of foreign exchange earnings to the nation. The economic contribution of the livestock sub-sector in Ethiopia is also about 11 % of the total Gross Domestic Product (GDP) and 24 % of the agricultural GDP. (Ethiopia, NBE 2016).

Ethiopia's commercial red meat (beef, mutton and goat) industry has made remarkable progress to date and shows considerable growth potential for the future. The government of Ethiopia encourages investments in meat processing, especially focusing on exporting value-added products abroad. A couple of U.S. companies have already invested in the red meat sector and others have expressed interest. A large chunk of this commercially-produced red meat, most of which is currently mutton and goat meat is largely going for export to the Middle East in order to generate foreign exchange. Beef exports are also growing, with additional market opportunities on the horizon. (Hurissa, Belachew 2005)

It can be argued that Ethiopia would benefit more from exporting meat than from exporting live animals, because there are several problems in exporting live animals. First, there is a limited marketing infrastructure, including feeding and watering facilities. Second, live animal exports have also been observed to enhance the chances of disease transmission. Furthermore, the live animal export trade from Ethiopia is observed to be very seasonal. Assegid (2000).

Ethiopia also exports leather to Germany, Italy, United Kingdom, China, Mainland, and Japan. In 1980 leather and leather products accounted 11 percent of the total exports but in 2008/09 the share of leather and leather products has declined to 5 percent. and in 2016/17 Export earnings from leather & leather products decreased by 1.1 percent due to 1.6 percent fall in export volume despite 0.5 percent rise in international price. Consequently, the share of leather & leather products in total export revenue stood at 3.9 percent. NBE (2016)

Recently, Ethiopia exports approximately 200,000 live animals annually. This is significantly higher than the annual official exports of cattle (12,934 head), sheep (13,554 head) and goats (1,247 head) between 1998 and 2003 (Asefaw and Mohammad 2007). Cattle, goat, sheep and camels are exported animals from Ethiopia to different countries. Djibouti, Egypt, Somalia, Sudan, Saudi Arabia, Yemen and United Arab Emirate are the major importers of the Ethiopian live animals.

Ethiopia has great potential for increased livestock production, both for local use and for export. However, expansion was constrained by inadequate nutrition, disease, lack of support services such as extension services, insufficient data with which to plan improved services, and inadequate information on how to improve animal breeding, marketing, and processing. The high concentration of animals in the highlands, together with the fact that cattle are often kept for status, reduces the economic potential of Ethiopian livestock. Due to lack of livestock market structure, performance, prices are poor and inadequate for designing policies and marketing system, the sector has remained stagnant. (Tegegne *et al*. 1999).

1.2. Statement of the problem

Cointegration analysis for analyzing and modeling non-stationary economic time series Variables, proposed by Engle and Granger (1987), has become a dominant paradigm in empirical economic research. Several studies about livestock products export and related variables are done using univariate time series analysis. However, to the best of our knowledge, little information (study) is available in multivariate time series (MVTS) analysis about livestock products. 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, MVTS analysis involves a vector of time series that will be modeled simultaneously. MVTS deals with the interaction, co-movement and bi-directional causality of several time series. This study examined the different statistical techniques like VAR and VECM for analyzing multivariate time series using quarterly livestock products export data.

The following research questions are addressed:

- ✓ What kind of relationships exist among the volume of live animals, meat and leather export in the Ethiopian context?
- ✓ Which multivariate time series model best describes the relationship among the study variables and can be used for forecasting purpose?
- ✓ Is the volume of livestock products export affected by exchange rate? If so, what kind of effect does it have?

1.3. Objectives of the study

General objective

- ❖ The general objective of this study is to fit a multivariate time series model which explains the relationship among the export of Ethiopian livestock products.

Specific objective

- To examine the general trend of the volume of export of Ethiopian livestock products
- To examine the effect of exchange rate on the export of livestock products.
- To forecast the export of livestock product

1.4. Significance of the study

The results of this study is a good stepping-ground for other studies on livestock marketing and livestock products export. In brief, this research is useful to cooperative societies, researchers, and governmental and nongovernmental organizations for policy formulation, planning and development of livestock marketing for both pastoralists and livestock product producers and exporters in Ethiopia, which help to achieve the development goals of the country with this regard.

1.5. Organization of the study

This work is organized into the following chapters. Chapter one is introduction of the thesis. This chapter briefly addresses the thesis objectives and significance and gives brief background of the study. Following chapter two, which reviews the literature with emphasis on the statistical tools relevant to modeling the livestock products export, Chapter three explains the methodology applied in building VAR and VEC models and estimating their parameters. Chapter four presents the results of analysis. Finally, chapter five presents conclusions of the study.

CHAPTER TWO

LITERATURE REVIEW

2.1. Ethiopian livestock market

Marketing involves all activities involved in the production and flow of goods and services from point of production to hands of consumers. Marketing includes all activities of exchange conducted by producers and middlemen in commerce for the purpose of satisfying consumer demand. All business activities facilitating the exchange of goods and service are included in marketing (Lemma *et al.*, 2005).

Livestock production in Africa accounts for about 30% of the gross value of agricultural production, with 92% of that coming from the production of beef cattle, dairy cattle, goats, sheep and chickens (IFAD, 2009; IUCN, 2010). Livestock production is increasing throughout Africa, driven by growth of human population, living standards (increases in the demand for livestock products as incomes rise) and urbanization (IUCN, 2010; Philip *et al.*, 2007). The livestock population in Ethiopia that reaches more than 80 million heads is the largest in Africa and the 10th in the world. It constitutes a large component of the Ethiopian agricultural sector and is well integrated with the farming systems found in the highlands and provides the sole means of subsistence for the nomadic pastoralists in the lowlands (FDRE, 2001). And it is also the continent's top livestock producer and exporter. Although domestic demand for animal products in Ethiopia is increasing driven by the urban middle and upper-classes export potential is the key force encouraging expansion and intensification of livestock production.

In Ethiopia, many producers only sell their livestock when they need the money or when a drought hits. As a result, most farmers do not consider the livestock trade as a profitable endeavor and ignore husbandry practices that could increase their livestock's market value, such as providing adequate and proper nourishment during the years of growth and development, preventing scarring, and do not consider the timing of sale designed to maximize sales price. Farmers that live in rural area sell livestock and livestock products to cover household cash expenses and to purchase crop inputs to their families. Live animals are marketed through traditional marketing routes developed over the years which were based on visual assumption on body condition of animals (Azage *et al.*, 2010).

According to Belete A (2006) the existing livestock and their products marketing system are generally under developed. The low level of facilities is not conducive to efficient marketing. Transportation is on-hoof, which leads to considerable weight loss of animals as well as physical injuries and health. Trucking is very limited and used only during holidays and festivals to move finished cattle and small stock to city centers and exportable animals to ports. Poor infrastructure development hampers the flow of trade stock from pastoral areas to consumption sites.

In 2008, livestock accounted for approximately US$150 million in formal export earnings, making up 10 percent of formal exports (DeHaan, 2002). Roughly half of this value comes from live animal and meat exports, the remainder being from hides and skins. Formal live animal exports are predominantly cattle about 70 percent, meat exports are almost entirely from sheep and goats, and hides and skins are primarily from cattle. Trends over the last 10-20 years show meat and live animals becoming increasingly important to livestock exports relative to hides and skins beyond formal sector trade, there is significant informal cross border trade in live animals, which substantially increases livestock's export importance (CSA, 2005/06).

Estimates of informal trade volume vary widely between 250,000 and 500,000 head of cattle per year , but appear to dwarf formal exports 84,000 head in 2008 (Fadiga and Amare, 2010). A study by Fadiga and Amare estimates the value of informal livestock exports at US$150-300 million per year. The Middle East has been, and remains, the traditional destination for Ethiopia's export of live animals and meat. This applies equally to formal trade, as to informal trade, and many exported cattle transit Djibouti. About two-thirds of illegal exports move from Eastern Ethiopia to Somalia, and other destinations include northeast Kenya and Sudan. Akinleye *et al*. (2005)

Nationwide export of livestock and livestock products assist in earning foreign exchange and import substitution. Without considering the illegal exports which accounts with large flow of income from about 150,000 cattle and 300,000 small ruminant exports per annum, live animal and hides and skin export earns the country with large amount of foreign exchange.

Field studies in different parts of the highland of Ethiopia show that livestock account for 37–87% of total farm cash income of farmers, indicating the importance of livestock in rural livelihood (Gryseels 1988).There is little evidence of strategic production of livestock for marketing except some sales targeted to traditional Ethiopian festivals. The primary reason for selling livestock is to generate income to meet unforeseen expenses. Sales of live animals are taken as a last resort and large ruminants are generally sold when they are old, culled, or barren. In the highlands, large numbers of cattle are kept to supply draft power for crop production whereas prestige and social security are the predominant factors in the lowland pastoral areas.

Even including the cross-border trade, the vast bulk of Ethiopia's livestock output is consumed domestically. Household expenditure on livestock products was estimated in 2008-09 at 19 billion EB. Generous estimates of the total value of livestock sector exports places their value at slightly more than 4 billion EB in that year. Domestic consumption outweighs exports by a factor of nearly five to one.

As the agricultural extension package programs have been largely focusing on crop production, low participation of farmers in the livestock sub-sector packages shows a serious problem of policy biases against the livestock production and the income generate from this subsector. This undermines the potential economic gain that would have been obtained from the sector.

In satisfying the requirement of human needs accordingly in terms of quality food of animal origin and supply of raw material for the manufacture of goods needed in the day to day activity, animal products play an important role as suppliers of inputs to processing and manufacturing industry. Meat is processed to improve its handling capacity for proper utilization and in the equity supply of the product to the different locations. Other products such as honey, wax, skin and hides, wool, etc. are used for the production of different materials of human benefit other than food items.

2.2. Empirical Literature Review

The current rapid growth in demand for meat products in the world represents a potential opportunity for livestock-rich countries like Ethiopia. Things have improved since then, and the total livestock exports have gradually increased, as has the livestock population. There has been a growing consensus that, with increasing economic growth and urbanization, the demand for livestock will continue to grow and that animal Livestock Production and Marketing products will rapidly become major sources of protein (Delgado *et al.*, 1999)

Cho, Sheldon and McCorrison (2002) on their study, using monthly data disaggregated by markets of destination and sectors, found that there is strong negative impact of exchange rate uncertainty on livestock trade compared to other sectors for a simple bilateral trade flows across countries.

The study by De Grawue and Bellefoid (1986), Steinherr (1989) demonstrate that the trade volume is more affected by the long run changes in exchange rate than do short run exchange rate fluctuations. This confirms the result obtained by Cho, Sheldon and McCorrison (2002).

A major problem with the leather sector is the by-product status of hides and skins. Cattle, goats and sheep are mainly used for meat (Aklilu, Yacob 2002). Thus, the product, i.e. hides and skins, becomes available when meat is needed, not when it is appropriate for leather processing. This shows the direct dependence of leather sector on meat.

CHAPTER THREE

DATA AND METHODOLOGY

3.1. Data

The study used secondary data, which is obtained from the National Bank of Ethiopia over the period from 2002 first quarter to 2017 third quarter. The data have information about the quarterly volume of live animals, meat and leather export of Ethiopia; and the quarterly exchange rate.

The endogenous (response) variables in the study are the quarterly volume of Ethiopian live animals, meat and leather export. The exogenous (explanatory) variable considered is exchange rate (Birr against the US dollar).In this paper all the variables are abbreviated as

- LLA : the quarterly volume of Ethiopian live animals export
- LLR : the quarterly volume of Ethiopian leather export
- LME : the quarterly volume of Ethiopian meat export
- LER : the quarterly exchange rate

And all the variables (LLA, LLR, LME and LER) are in the logarithmic form.

3.2. Methodology

Time series is broadly defined as series of measurements taken sequentially across time. It can be divided into two major parts: univariate and multivariate time series. Univariate time series uses only the past history of the time series being forecast plus current and past random error terms. ARIMA modeling is a specific subset of univariate modeling in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of a 'white noise' error term (the moving average component). On the other hand, 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 methodologies adopted in this study are the vector autoregressive (VAR) model and vector error correction model (VECM).

3.2.1. 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 elaborates 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.

3.2.1.1 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.

Covariance (Weak) Stationarity

A stochastic process $\{Y_t\}$ is covariance stationary if:

- ✓ $E(Y_t)$ is constant
- ✓ $Var(Y_t)$ is constant and
- ✓ For any t, $i \geq 1$, $Cov(Y_t, Y_{t+i})$ depends only on i and not on t.

Strong (Strictly) Stationarity

A strictly stationary time series is one for which the probabilistic behavior of every collection of values $\{Y_{t1}, Y_{t2}, \ldots, Y_{tk}\}$ is identical to that of the time shifted set $\{Y_{t1+i}, Y_{t2+i}, \ldots, Y_{tk+i}\}$ That is,

$P\{ Y_{t1} \le C_1, \ldots, Y_{tk} \le C_k\} = P\{ Y_{t1+i} \le C_1, \ldots, Y_{tk+i} \le C_k\}$, $i=0, \pm1, \pm2, \ldots$

If a time series is strictly stationary, then all of the multivariate distribution functions for subsets of variables must agree with their counter parts in the shifted set for all values of the shift parameter i.

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 operator Δ 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: $\mathbf{\Delta^n Y_t = (1-B)^n Y_t}$

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 20 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; Weigend, 1993).

The Stationary Vector Autoregressive Model

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

$$Y_t = C + \mathbf{\Pi}_1 Y_{t-1} + \mathbf{\Pi}_2 Y_{t-2} + \ldots + \mathbf{\Pi}_p Y_{t-p} + \varepsilon_t,\ t = 1, 2, \ldots, T \ldots\ldots\ldots\ldots\ldots (3.1)$$

Where C denotes an (n× 1) vector of constants and Π_j an (n × n) matrix of autoregressive coefficients, j = 1, 2, . . . , p and ε_t is an (n × 1) unobservable zero mean white noise vector process (serially uncorrelated) with time invariant covariance matrix Σ:

$$E(\varepsilon_t) = 0 \text{ and } E(\varepsilon_t \varepsilon'_s) = \begin{cases} \Sigma & t = s \\ 0 & t \neq s \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

with Σ an (n × n) symmetric positive definite matrix.

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

$$\mathbf{\Pi}(L) Y_t = C + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

Where $\mathbf{\Pi}(L) = I_n - \mathbf{\Pi}_1 L - \ldots - \mathbf{\Pi}_p L^p$

The VAR (p) is stable if the roots of

$$\text{Det}\,(I_n - \mathbf{\Pi}_1 L - \ldots - \mathbf{\Pi}_p L^p) = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

lie outside the complex unit circle (has modulus greater than one). Assuming that the process has been initialized in the infinite past, a stable VAR (p) process is stationary with time invariant means, variances and autocovariances.

If Y_t in [3.1] is covariance stationary, then the unconditional mean is given by

$$\upsilon = (I_n - \mathbf{\Pi}_1 - \ldots - \mathbf{\Pi}_p)^{-1} c$$

The mean-adjusted form of the VAR (p) is then

$$Y_t - \upsilon = \mathbf{\Pi}_1 (Y_{t-1} - \upsilon) + \mathbf{\Pi}_2 (Y_{t-2} - \upsilon) + \ldots + \mathbf{\Pi}_p (Y_{t-p} - \upsilon) + \epsilon_t \ldots\ldots\ldots\ldots (3.5)$$

The basic VAR (p) model may be too restrictive to represent sufficiently the main characteristics of the data. In particular, other deterministic terms such as a linear time trend or seasonal dummy variables may be required to represent the data properly. Additionally, exogenous variables may be required as well. The general form of the VAR (p) model with deterministic terms and exogenous variables is given by

$$Y_t = \mathbf{\Pi}_1 Y_{t-1} + \mathbf{\Pi}_2 Y_{t-2} + \ldots + \mathbf{\Pi}_p Y_{t-p} + \Phi\, D_t + GX_t + \epsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3.6)$$

Where: D_t represents an $(I \times 1)$ vector of deterministic components, X_t represents an $(n \times 1)$ vector of exogenous variables and Φ and G are parameter matrices.

Testing Stationarity: Unit-Root test

The assumption of stationarity is somewhat an unrealistic situation in most macroeconomic variables. Trivially, a non-stationary process arises when one of the conditions for stationarity does not hold. We deal for non-stationarity because with non-stationary series the effect of a shock never dies away and it leads to spurious regressions; that is one can regress completely unrelated series and find high R^2(indicating how good one term is at predicting another) and the standard tests are not valid. The first step for an appropriate analysis is to determine whether the data series is stationary or not. Time series data generally tend to be non-stationary. Due to the non-stationarity, regressions with time series data are very likely to result in spurious results. The problem stemming from spurious regression has been described by Granger and New bold (1974). In order to ensure the condition of stationarity, a series must to be integrated of order of zero (I (0)).

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), 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). Consider an AR (1) process:

$Y_t = \rho Y_{t-1} + X'_t \delta + \epsilon_t$ …………………………………………….. (3.7)

Where $\mathbf{X_t}$ are optional exogenous regressors which may consist of constant or a constant and trend, $\boldsymbol{\rho}$ and $\boldsymbol{\delta}$ are parameters to be estimated and $\boldsymbol{\epsilon_t}$ is assumed to be white noise.

If | **ρ|≥1**, Y is a non-stationary series and the variance of Y increases with time and approaches infinity. On the other hand, if | **ρ|<1**, Y 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 (**ρ≥1**)

H1: The series are stationary (**ρ** <1)

3.2.1.1.1. Augmented Dickey-Fuller (ADF) Unit-Root Test

The standard Dickey-Fuller test is conducted in the following manner: from equation (3.7) we have:

$Y_t - Y_{t-1} = (\rho-1)Y_{t-1} + X'_t \delta + \epsilon_t$ This can be rewritten as:

$\Delta Y_t = \alpha Y_{t-1} + X'_t \delta + \epsilon_t$ ……………………………(3.8)

Where $\alpha = \boldsymbol{\rho}-1$. The null and alternative hypothesis may be written as:

$H_0: \alpha \geq 0$

$H_1: \alpha < 0$……………………………………………….. (3.9)

The test statistic is the conventional t – ratio for α

$t_\alpha = \tilde{\alpha} / (se(\tilde{\alpha}))$.. (3.10)

Where $\tilde{\alpha}$ is the estimate of α and se ($\tilde{\alpha}$) is the standard error of $\tilde{\alpha}$.

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, 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:

$$\Delta Y_t = \alpha Y_{t-1} + X'_t \delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \ldots + \beta_p \Delta Y_{t-p} + \upsilon_t \text{............} \quad (3.11)$$

This augmented specification is then used to test for unit root using the t-ratio [3.10]. An important result obtained by Fuller (1979) is that the asymptotic distribution of the t -ratio for $\boldsymbol{\alpha}$ 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.

3.2.1.1.2. Phillips-Perron (PP) Unit-Root Test

Phillips and Perron (1988) developed a number of unit-root tests that have become popular in the analysis of financial time series. The Phillips-Perron (PP) unit-root tests differ from the ADF tests mainly in how they deal with serial correlation and heteroskedasticity in the errors. In particular, where the ADF tests use a parametric auto regression to approximate the ARMA structure of the errors in the test regression, the PP tests ignore any serial correlation in the test regression. The test regression for the PP tests is

$$\Delta Y_t = \alpha_0 + \alpha_2 t + \Pi Y_{t-1} + \epsilon_t \text{...} \ (3.12)$$

Where ϵ_t is I(0) and may be heteroskedastic. The PP tests correct for any serial correlation and heteroskedasticity in the errors ϵ_t of the test regression by directly modifying the Dicky-Fuller test statistics $t_{\pi = 0}$ and $t_{\pi = \hat{\pi}}$

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

These modified statistics, denoted by Z_t and Z_π, are given by:

$$Z_t = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{1/2} t_{\pi=0} - \frac{1}{2}\left(\frac{\hat{\lambda}^2-\hat{\sigma}^2}{\hat{\lambda}^2}\right) * \left(\frac{T\ SE(\hat{\pi}\ )}{\hat{\sigma}^2}\right)$$

$$Z_\pi = T_{\hat{\pi}} - \frac{1}{2}\left(\frac{T^2\ SE(\hat{\pi}\ )}{\hat{\sigma}^2}\right)(\hat{\lambda}^2 - \hat{\sigma}^2)$$

The terms $\hat{\lambda}^2$ and $\hat{\sigma}^2$ are consistent estimates of the variance parameters:

Under the null hypothesis that H_o: $\pi = 0$, and the alternative is H_1: $\pi \neq 0$ the PP Z_t and Z_π statistics have the same asymptotic distributions as the ADF t-statistic and normalized bias statistics. One advantage of the PP tests over the ADF tests is that the PP tests are robust to general forms of heteroskedasticity in the error term ε_t. Another advantage is that the user does not have to specify a lag length for the test regression.

3.2.1.2. Estimation 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 $P = 0,\dots,P_{max}$ and choose the value of p which minimizes some model selection criteria. Model selection criteria for VAR (p) models have the form:

$$IC(p) = \ln|\textstyle\sum_p| + C_T.\varphi(n.p) \quad \text{..} \quad (3.13)$$

Where

IC = Information Criteria, $\sum_p = T^{-1} \sum \varepsilon_t\, \varepsilon_t'$ is the residual covariance matrix from a VAR (p) model, C_T is a sequence indexed by the sample size T, and $\varphi(n.p)$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):

$AIC\ (p) = \ln|\sum_p| + \frac{2}{T} pn^2$.. (3.14)

$BIC\ (p) = \ln|\sum_p| + \frac{lnT}{T} pn^2$... (3.15)

$HQ\ (p) = \ln|\sum_p| + \frac{2lnT}{T} pn^2$.. (3.16)

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.

3.2.2. Co-integration Analysis

Co integration

If two or more series are integrated together (i.e. in the time series sense) but some linear combination of them has a lower order of integration, then the series are said to be Co-integrated. A common example is where the individual series are first-order integrated (I (1)) but some (cointegrating) vector of coefficients exists to form a stationary linear combination of them. 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 and PP 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. The three main 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 was applied. Johansen’s (1991) procedure considers maximum likelihood for finite-order vector auto regressions (VARs) and is easily calculated for such systems. Johansson’s procedure allows dealing 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 reason for this might be technological progress, economic crises, changes in people's preferences and behavior, policy or regime alteration and organizational or institutional developments. This is especially likely to be the case if the sample period is long.

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:

$$\Delta Y_t = \Pi\, Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-j} + \epsilon_t,\ \ t = 1, 2, \ldots, T \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.17)$$

Where Π and the short-run parameter Γ_i, i=1, 2,…, p-1 are p × p matrices of coefficients. The VECM representation of Equation (3.17) 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:

$$\Pi = \alpha\, \beta' \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.18)$$

Where α and β are p × r matrices of full rank. β contains the co integration relations in vector form and α is the matrix of loadings. If r = 0, then $\pi = 0$, and there exists no linear combination of the elements of Y_t that is stationary.

At the other extreme, if rank (π) = p,Y_t is a stationary process. In the intermediate case, when 0 < r < p, there exist r stationary linear combinations of the elements of Y_t, along with p-r stochastic trends.

3.2.2.1. Testing for cointegration 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:

$$Y_t = A_1Y_{t-1} + A_2Y_{t-2} + \dots + A_pY_{t-p} + BX_t + \epsilon_t \quad \text{......................... (3.19)}$$

where Y_t is a p-vector of non-stationary I(1) variables, X_t is a d vector of deterministic variables and $\boldsymbol{\epsilon_t}$ is a vector of innovations.

We may re-write this VAR as:

$$\Delta Y_t = \Pi\ Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \beta\ X_t + \epsilon_t \quad \text{................................. (3.20)}$$

where

$$\Pi = \sum_{i=1}^{p} A_{i-1}, \Gamma_i = -\sum_{j=i+1}^{p} A_j \quad \text{.. (3.21)}$$

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank r < p, then there exist p × r matrices α and β each with rank r such that $\pi = \alpha\ \beta'$, where r is the number of co-integrating relations (the co-integrating rank) and each column of it is the cointegrating vector. The elements of α 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 of Y_{t-1} that yields the r largest canonical correlations of ΔY_t with 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 λ_i , i = 1, 2, …, k to be a complex modulus of 32 eigenvalues of π and let them be ordered such that $\lambda_{1,}$ λ_2,…, λ_n. The trace statistic is computed as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \log[1 - \lambda_i] \quad (3.22)$$

The Maximum eigenvalue statistic tests the null hypothesis of r 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:

$$\lambda_{max}(r,r+1) = -T \log(1- \lambda_{r+1}) \quad (3.23)$$

Where λ_{r+1} is the $(r+1)^{th}$ ordered eigenvalue of Π, and T is the sample size. The critical value tabulated by Johansen and Juselius (1990) is used for these tests. Neither of these tests statistics follows a chi square distribution in general. The asymptotic distributions of the test statistics (3.22) and (3.23) are not normal. Asymptotic critical values for the λ_{trace} and λ_{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.

3.2.3. Vector Error Correction Modeling (VECM)

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 in [3.23] can be re parameterized as a Vector Error Correction Model (VECM) form: (Hamelton, 1994; Reinsel, 1993).

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \beta X_t + \epsilon_t \quad \text{..............................} \quad (3.24)$$

Where

$\Pi = -I_n + \sum_{i=1}^{p-1} A_i$, $\Gamma_i = -\sum_{j=i+1}^{p} A_j$ and I_n is the identity matrix.

The above specification of VECM contains information on both the short and the long-run adjustment to changes in Y_t via estimating Γ and π, respectively. Matrix π can be decomposed as $\pi = \alpha \beta'$, where α is $p \times r$ matrix of speed of adjustments, and β is an $p \times r$ matrix of parameters which determines the co-integrating relationships matrix of long-run coefficients such that $\beta' Y_{t-k}$ represent the multiple co-integration relationships. The columns of β are interpreted as long-run equilibrium relationships between variables. The matrix α determines the speed of adjustment towards this equilibrium. Values of α close to zero imply slow convergence and r , $0 \leq r \leq n$ is the rank of the matrix π and represents the number of co-integrating vectors in the system which can be determined using the Johansen Maximum Likelihood method.

3.2.4. 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.

3.2.4.1. Test of Residual Autocorrelation

Two types of tests for residual AC are popular in applied work, Breusch-Godfrey LM tests and portmanteau tests. They are both based on statistics of the form

$$Q = TC' \sum^{-1} C \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.25)$$

Where Σ is a suitable scaling matrix. In other words, they are based on the residual auto covariance. The estimated of scaling matrix Σ 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.

Portmanteau autocorrelation test

Suppose $Y_t = (Y_{1t}, Y_{2t}, \ldots, Y_{kt})'$ is k-dimensional vector of observable time series variables with r, r < k co-integration relations. From equation (3.27) the residual auto covariance is

$$C_j = \frac{1}{T}\sum\sum_{t=1}^{T} \epsilon_t \, \epsilon_{t-j} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.26)$$

Where $\epsilon_t = \Delta Y_t - \Pi Y_{t-1} - \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-j} - \beta X_t$ where ϵ_t is an estimated residual.

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

$$H_o : E(\epsilon_t \epsilon_{t-j}) = 0 \quad (i = 1, 2, \ldots) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.27)$$

Where the $\boldsymbol{\epsilon_t}$'s are the estimated residuals. 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 covariance and has the form:

$$Q_p = T\sum_{j=1}^{h} tr(C_j'\Omega - 1C_j\Omega - 1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.28)$$

Where

$\mathbf{C_j = \frac{1}{T} \sum \epsilon_t \epsilon_{t-j}}$ ………………………………………… (3.29)

$\mathbf{\Omega = \frac{1}{T} \sum \epsilon_t \epsilon_t'}$ ……………………………………………. (3.30)

The approximate distribution of this test statistic is the chi-squared distribution with k^2 (h-p) degrees of freedom in large samples if h is also large.

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 $(C'_j C_0^{-1} C_j C_0^{-1})$................................... (3.31)

Its asymptotic properties are the same as those of Q_p.

Autocorrelation LM Test

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

$\epsilon_t = D_1 U_{t-1} + \ldots + D_h U_{t-h} + \upsilon_t$.. (3.32)

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

H0: $D_1 = \ldots = D_h = 0$ against

H1: $D_j \neq 0$ 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 H_0, we only need to estimate the regular VAR model ($\epsilon_t = \upsilon_t$). So the constrained case estimates are simple.

The Breusch-Godfrey test statistic, say Q^*_{BG}, is a standard LM test statistic for the null hypothesis $\gamma = 0$:

$$Q^*_{BG} = T\,\gamma' \left(\sum \gamma\gamma \right)^{-1} \gamma \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (3.33)$$

Where γ is the generalized least square estimator of Y

Here $\Omega = T^{-1} \sum U_t U't$ and, hence, Ω is the residual covariance matrix estimator from the restricted auxiliary model. Therefore, under the null hypothesis it follows immediately from the above that for $h < \infty$

$$Q^*_{BG} \xrightarrow{d} \chi^2 (hk^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (3.34)$$

3.2.4.2. Normality of the *R*esiduals

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:

$$JB = T\,[\, b_1/6 + K^2/24] \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (3.35)$$

Where b_1 and k are the sample skewness and kurtosis coefficients, respectively.

This test statistic is asymptotically distributed as $\chi^2(2)$ under the null hypothesis; thus large values of this test statistic relative to the quantiles from the $\chi^2(2)$ distribution lead to rejection of the null hypothesis.

3.2.4. Forecasting

Forecasting is one of the main objectives of multivariate time series analysis. Forecasting from a VAR model is similar to forecasting from a univariate AR model and the following gives a brief description. Consider first the problem of forecasting future values of Y_t when the parameters Π of the VAR (p) process are assumed to be known and there are no deterministic terms or exogenous variables. The best linear predictor in terms of minimum means squared error (MSE) of Y_{t-1} or 1-step forecast based on information available at time T is:

$$Y_{T+1/r} = C + \Pi_1 Y_r + \Pi_2 Y_{r-1} + \ldots + \Pi_p Y_{r-p+1} \text{.................................} \quad (3.36)$$

For $T \geq p$, forecasts for longer horizons h (h-step forecasts) can be obtained using the chain-rule of forecasting as:

$$Y_{T+h/r} = C + \Pi_1 Y_{r+h-1/r} + \Pi_2 Y_{r+h-p/r} + \ldots + \Pi_p Y_{r+h-p/r} \text{.................} \quad (3.37)$$

where $Y_{r+h/T} = Y_{r+j}$, for $j \leq 0$.

The h-step forecast errors may be expressed as:

$$Y_{T-h} - Y_{T+h/T} = \sum \Psi_s \epsilon_{T+h-s} \text{..} \quad (3.38)$$

Where the matrices Ψ_s are determined by recursive substitution:

$$\Psi_s = \sum \Psi_{s-j} \Pi_j \text{ ....} \quad (3.39)$$

With $\Psi_0 = I_n$ and $\Pi_j = 0_{n \times n}$ for $j > p$. The forecasts are unbiased since all of the forecast errors have expectation zero, and the MSE matrix for $Y_{t+h/T}$ is

$$\Sigma (h) = MSE (\Sigma \Psi_s \epsilon_{T+h-s})$$

$$= \Sigma \Psi_s \Sigma \Psi'_s \text{ ....} \quad (3.40)$$

Now consider forecasting Y_{T+h} when the parameters of the VAR (p) process are estimated using multivariate least squares. The best linear predictor of Y_{T+h} is now:

$$Y_{T+h/T} = \Pi_1 Y_{T+h-1/T} + \ldots + \Pi_1 Y_{T+h-p/T} \text{..................................} \quad (3.41)$$

where Π_j are the estimated parameter matrices. The h-step forecast error is given by:

$$Y_{T+h/T} = \Pi_1 Y_{T+h-1/T} + \ldots + \Pi_p Y_{T+h-p/T} \text{ ....} \quad (3.42)$$

and the term Y_{T+h} - $Y_{T+h/T}$ captures the part of the forecast error due to estimating the parameters of the VAR. The MSE matrix of the h-step forecast is then:

$$\Sigma (h) = \Sigma (h) + MSE (\Sigma \Psi_s \epsilon_{T+h-s}) \text{...} (3.43)$$

In practice, the second term MSE ($\Sigma \Psi_s \boldsymbol{\epsilon}_{\mathbf{T}+h-s}$) is often ignored and $\Sigma(h)$ is computed using [3.43] as:

$$\Sigma (h) = \Sigma \Psi_s \Psi_s' \text{..} \quad (3.44)$$

With $\Psi_s = \Sigma \Psi_{s-j} \Pi_j$

Lütkepohl (1991) gives an approximation to MSE ($\Sigma \Psi_s \epsilon_{T+h-s}$) which may be interpreted as a finite sample correction to [3.44].

3.2.4.1. Measures of Forecasting Accuracy

In most forecasting situations, accuracy is treated as the overriding criterion for selecting a forecasting method. In many instances, the word "accuracy" refers to the goodness of fit, which intern refers to how well the forecasting model is able to reproduce the data that are already known. To the consumer of forecasts, it is the accuracy of the future forecast that is most important.

If Y_{jt}, j=1, 2, . . . k is the actual observation for the period t and F_{jt} is the forecast of Y_{jt}, then the residual is defined as:

$\varepsilon_{jt} = Y_{jt} - F_{jt}$ ………………………………………………….. (3.45)

Where F_{jt} is the estimated forecast for Y_{jt}.

Usually F_{jt} is calculated using data $Y_{j1}, Y_{j2,\dots}\ Y_{jt-1}$. It is a one-step forecast because it is forecasting one period ahead of the last observation used in the calculation. Therefore, we describe $\hat{\varepsilon}_{jt}$ as a one-step forecast error. It is the difference between the observation Y_{jt} and forecast made using all observations up to but not including Y_{jt}.

If there are observations and forecasts for T time periods, then there will be T error terms, and the following standard statistical measures can be defined:

Mean Error(ME) = $1/T \ \Sigma \ \hat{\varepsilon}_{jt}$…………………………………………………. (3.46)

Mean Absolute Error (MAE)= $1/T \ \Sigma \ |\hat{\varepsilon}_{jt}|$………………………………. (3.47)

Mean Squared Error (MSE) = $1/T \ \Sigma \ \hat{\varepsilon}^2_{jt}$.. (3.48)

To make comparisons we need to work with relative or percentage error measures. First let us define a relative or percentage error as

$PE_t = \{(Y_{jt} - F_{jt}) / Y_{jt}\} \times 100$……... (3.49)

Then the following two relative measures are frequently used:

Mean Percentage Error(MPE) = 1/T Σ PE_t.................................... (3.50)

Mean percentage Absolute Error(MPAE) =1/T Σ|PE_t| .... (3.51)

Equation [3.49] can be used to compute the percentage error for any time period. These can be averaged as in equation [3.50] to give the mean percentage error. However, as with the ME, the MPE is likely to be small since positive and negative PEs tends to offset one another. Hence the MAPE is defined using absolute values of PE in equation [3.51].

Alternatively, Theil's U- statistic can be used as a measure of forecasting accuracy. Like MAPE statistic, high values suggest poor performance in the forecast.

The scaling of U is such that it will always lie between 0 and 1. If U =0, $Y_{jt} = F_{jt}$ for all forecasts and there is a perfect fit; if U = 1 the predictive performance is not good.

3.2.5. Structural Vector Autoregressive (SVAR) Analysis

The general VAR (p) model has many parameters and they may be difficult to interpret due to complex interactions and feedback between the variables in the model. As a result, the dynamic properties of a VAR (p) are often summarized using various types of structural analysis. The three main types of structural analysis are discussed below.

3.2.5.1. Granger causality tests

One of the main uses of VAR models is forecasting. The structure of the VAR model provides information about the forecasting ability of a variable or a group of variables. The Granger causality test helps us to measure whether one variable can be used to forecast the other. For instance, if the volume of live animals export (LLA) is found to be helpful for predicting the volume of leather export (LLR), then LLA is said to Granger-cause LLR. The following intuitive notion of a variable's forecasting ability is due to Granger (1969). If a variable (or group of variables) Y_1 is found to be helpful for predicting another variable (or group of variables) Y_2 then Y_1 is said to Granger-cause Y_2. Formally, Y_1 fails to Granger-cause Y_2 if for all s > 0, the MSE of a forecast of $Y_{2,t+s}$

based on ($Y_{2,t}$, $Y_{2,t-1}$, . . .) is the same as the MSE of a forecast of $Y_{2,t+s}$ based on (($Y_{2,t}$, $Y_{2,t-1}$, . . .) and ($Y_{1,t}$, $Y_{1,t-1}$, . . .) Clearly, the notion of Granger causality does not imply true causality. It only implies forecasting ability. If Y_1 causes Y_2 and Y_2 also causes Y_1, the process (Y_{1t}, Y_{2t}) is called a feedback system.

For example, in a bivariate VAR (p) model for $Y_1 = (Y_{1t}, Y_{2t})'$ fails to Granger-causeY_1 if all of the p VAR coefficient matrices $\pi_1, \pi_2, \ldots, \pi_p$ are lower triangular.

So that all of the coefficients on lagged values of Y_2 is zero in the equation for Y_1. Similarly, Y_1 fails to Granger-cause Y_2 if all of the coefficients on lagged values of Y_1 are zero in the equation for Y_2.

The p linear coefficient restrictions implied by Granger non-causality may be tested using the Wald statistic which is asymptotically distributed as $\chi 2$ with p (= number of lags in the VAR) degree of freedom. A large value of Wald statistic is evidence against the null hypothesis of non-causality. Notice that if Y_2 fails to Granger-cause Y_1 and Y_1 fails to Granger-cause Y_2, then the VAR coefficient matrices $\pi_1, \pi_2, \ldots, \pi_p$ are diagonal. Testing for Granger non causality in general n variable VAR (p) models follows the same logic used for bivariate models.

3.2.5.2. 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 i^{th} variable directly affects the i^{th} variable, and may also transmit to all of the endogenous variables through the dynamic structure of the VAR.

Any covariance stationary VAR (p) process has a Wald representation of the form:

$$Y_t = \upsilon + \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \ldots \quad (3.53)$$

Where the (n × n) moving average matrices ψ_s are determined recursively. It is tempting to interpret the (i, j^th^) element of a matrix, ψ^s_{ij}, of the vector Y_s as the dynamic multiplier or impulse response:

However, this interpretation is only possible if var (ε_t) = Σ is a diagonal matrix so that the elements of ε_t are uncorrelated. One way to make the errors uncorrelated is to follow Sims (1980) and estimate the triangular structural VAR (p) model

$$Y_{1t} = c_1 + \gamma'_{11}Y_{t-1} + \ldots + \gamma'_{1p}Y_{t-p} + \eta_{1t}$$
$$Y_{2t} = c_2 + \beta_{21}Y_{1t} + \gamma'_{21}Y_{t-1} + \ldots + \gamma'_{2p}Y_{t-p} + \eta_{2t}$$
$$Y_{3t} = c_3 + \beta_{31}Y_{1t} + \beta_{32}Y_{2t} + \gamma'_{31}Y_{t-1} + \ldots + \gamma'_{3p}Y_{t-p} + \eta_3$$
$$\vdots$$
$$Y_{nt} = c_3 + \beta_{n1}Y_{1t} + \ldots + \beta_{n,n}Y_{n-1,t} + \gamma'_{n1}Y_{t-1} + \ldots + \gamma'_{np}Y_{t-p} + \eta_{nt} \quad \text{.......} \quad (3.55)$$

In matrix form, the triangular structural VAR (p) model is

$$\beta Y_t = C + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots + \Gamma_p Y_{t-p} + \eta_t \quad \text{....................................} \quad (3.56)$$

where

B is a lower triangular matrix with 1's along the diagonal and c is vector of constants. The algebra of least squares will ensure that the estimated covariance matrix of the error vector η_t is diagonal. The uncorrelated/orthogonal errors η_t are referred to as structural errors. The triangular structural model [3.60] imposes the recursive causal ordering

$$Y_1 \rightarrow Y_2 \rightarrow \ldots \rightarrow Y_n \quad \text{...} \quad (3.58)$$

The ordering means that the contemporaneous values of the variables to the left of the arrow → affect the contemporaneous values of the variables to the right of the arrow but not vice versa. These contemporaneous effects are captured by the coefficients β_{ij} in [3.55]. For example, the ordering $Y_1 \rightarrow Y_2 \rightarrow Y_3$ imposes the restrictions: Y_{1t} affects Y_{2t} and Y_{3t} but Y_{2t} and Y_{3t} do not affect Y_{1t}; Y_{2t} affects Y_{3t} but Y_{3t} does not affect Y_{2t}.

For a VAR (p) with n variables there are n! Possible recursive causal orderings. Which ordering to use in practice depends on the context and whether prior theory can be used to justify a particular ordering. Results from alternative orderings can always be compared to determine the sensitivity of results to the imposed ordering.

Once a recursive ordering has been established, the Wald representation of Y_t based on the orthogonal errors η_t is given by

$Y_t = \upsilon + \Theta_0 \eta_t + \Theta_1 \eta_{t-1} + \Theta_2 \eta_{t-2} + \ldots$ .... (3.59)

Where $\Theta_0 = B^{-1}$ is a lower triangular matrix.

A plot of Θ^s_{ij} , the $(i,j)^{th}$ element of Θ_s , against S is called the orthogonal impulse response function (IRF) of Y_i with respect to η_{jt} With n variables there are n^2 possible impulse response functions.

In practice, the orthogonal IRF [3.59] based on the triangular VAR (p) [3.54] may be computed directly from the parameters of the non-triangular VAR (p) [3.1] as follows. First, decompose the residual covariance matrix $\hat{\Sigma}$ as

$\hat{\Sigma} = ADA'$.. (3.61)

Where A is an invertible lower triangular matrix with 1's along the diagonal and D is a diagonal matrix with positive diagonal elements. Next, define the structural errors as

$$\eta_t = A^{-1} \varepsilon_t$$

These structural errors are orthogonal by construction since:

$$Var(\eta_t) = A^{-1} \Sigma A^{-1\prime} = A^{-1} ADA'A^{-1\prime} = D$$

Finally, re-express the Wald representation [3.59] as:

$$Y_t = \upsilon + AA^{-1} \varepsilon_t + \psi_1 AA^{-1} \varepsilon_{t-1} + \psi_2 AA^{-1} \varepsilon_{t-2} + \ldots$$

$$= \upsilon + \Theta_0 \eta_t + \Theta_1 \eta_{t-1} + \Theta_2 \eta_{t-2} + \ldots$$

Where $\Theta_j = \Psi_j A$ .Notice that the structural B matrix in [3.56] is equal to A^{-1}.

3.2.5.3. 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. The variance decomposition is displayed as separate line graphs with the y-axis height measuring the relative importance of each innovation.

The forecast error variance decomposition (FEVD) answers the question: what portion of the variance of the forecast error in predicting $Y_{i,T+h}$, is due to the structural shock η_j ? Using the orthogonal shocks η_t the h-step ahead forecast error vector, with known VAR coefficients, may be expressed as:

$$Y_{T-h} - Y_{T+h/T} = \sum_{s=0}^{h-1}. \Theta_s \, \eta_{T+h-s}$$

For a particular variable $Y_{i,T+h}$, this forecast error has the form:

$$Y_{i,T+h} - Yi_{,T+h/T} = \sum_{s=0}^{h-1}. \Theta_{i1} \, \eta_{1,T+h-s} + \ldots + \sum_{s=0}^{h-1}. \Theta_{in} \, \eta_{n,T+h-s}$$

Since the structural errors are orthogonal, the variance of the h-step forecast error is:

$$Var(Y_{i,T+h} - Y_{i,T+h/T}) = \delta^2 \, \eta_1 \sum_{s=0}^{h-1}. (\Theta_{i1})^2 + \ldots + \delta^2 \, \eta_n \sum_{s=0}^{h-1}. (\Theta_{in})^2$$

Where

$\delta^2 \eta_j = var(\eta_{jt})$. The portion of $Var(Y_{i,,T+h} - Y_{i,T+h/T})$ due to shock η_j is then:

$$FEVD_{i,j}(h) = \frac{\delta 2 \, \eta j \sum_{s=0}^{h-1}. (\Theta ij)2}{\delta 2 \, \eta j \sum_{s=0}^{h-1}. (\Theta i1)2 + \ldots + \delta 2 \, \eta n \sum_{s=0}^{h-1}. (\Theta in)2}, i,j = 1,2,\ldots n \quad \ldots\ldots\ldots(3.62)$$

In a VAR with n variables there will be n^2 $FEVD_{i,j}(h)$ values. It must be kept in mind that the FEVD in [3.62] depends on the recursive causal ordering used to identify the structural shocks η_t and is not unique. Different causal orderings will produce different FEVD values.

The general step for the analysis of cointegration is given in the conceptual diagram below.

3.2.6. Conceptual frame work

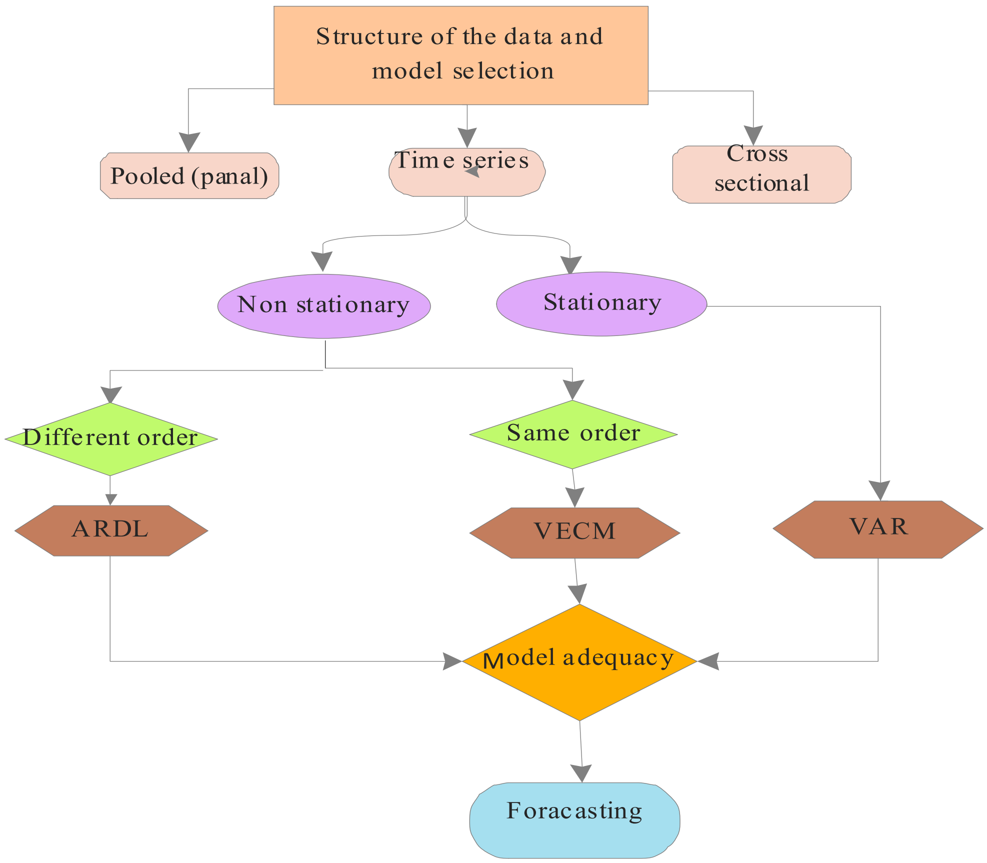


Figure 3.1. Conceptual diagram for co integration analysis

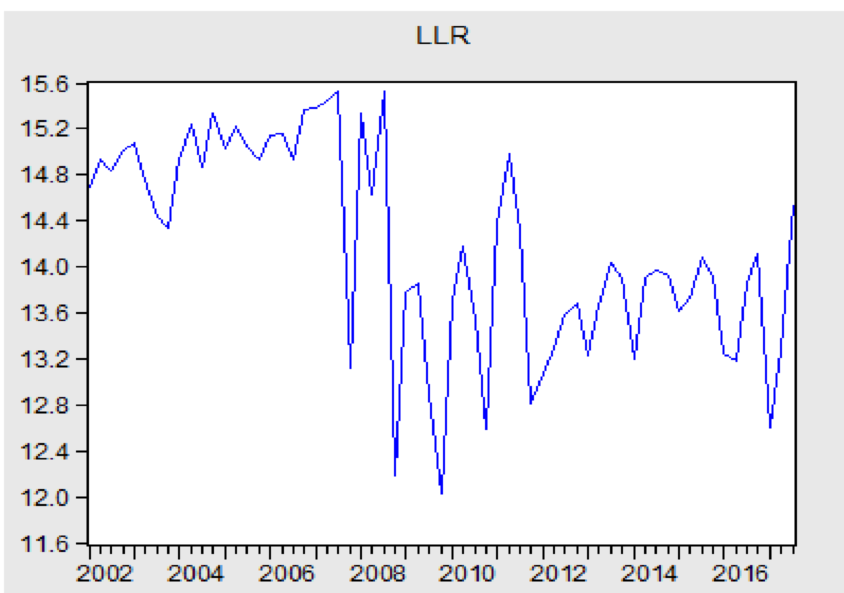
CHAPTER FOUR

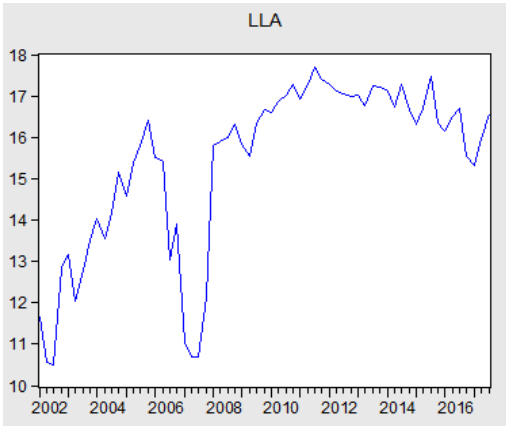
RESULTS AND DISCUSSIONS

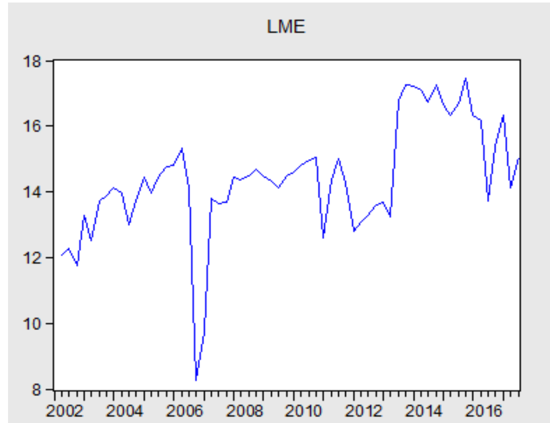
4.1. Descriptive Statistics and Time plot

To estimate the relationship among the volume of live animal export, leather export and meat export of Ethiopia we used Eviews 10. The data in this study consist log of quarterly volume(net weight) of live animal export(LLA), leather export(LLR) and meat export(LME) in kilograms; and quarterly exchange rate(birr against us dollar).The time period covered is from the first quarter of 2002 to third quarter of 2017. The time plot of each of the series is shown in Figure 4.1 below. From the time plot we can observe that all the series except the volume of leather export show an increasing trend over the study period. The volume of live animals and meat export highly declined in 2007.

Figure 4.1 Time plot of the series







4.2. Stationarity test of series

4.2.1 Seasonality test

There are two reasons that might cause our data to be affected by seasonality; first the quarterly nature of the data itself and second our consumption of meat is highly seasonal on holidays which in turn affects the export of livestock products. Therefore before directly test for the Stationarity of the series we have to check for the periodicity of the data: so that we can test the unit root using the appropriate method. In doing this M7 and the F-tests for seasonality of the series are commonly used to determine the seasonality. Then the variable(s) in which seasonality is observed will be adjusted. The result of seasonality test for the three series are presented in Tables 4.1below

Table 4.1. Seasonality test results

variables	F-value	M 7	Kruskal - Wallis statistics (P – value)
LLA	1.942	1.955	5.776 (12.304 %)
LLR	4.590	1.224	7.601 (5.502 %)
LME	0.565	3.000	1.753 (62.51o %)

The seasonality test above shows that, at 1% level of significance there is no evidence of stable seasonality for all variables. That means all the series are not affected by seasonality. It is also indicated by 1 %(for Kruskal-wallis test)) and its probability values. Furthermore the M7 diagnostics (all greater than one) is also assuring that no seasonal adjustment is necessary at 1% level of significance.

Alternatively more than one significant coefficients in all of the series from Table A1 (appendices) indicate that there is no periodicity effect in the series; i.e. all the series are not affected by seasonality. Now we can use ADF and PP tests to check for Stationarity.

4.2.2. Unit root test

Before we attempt to fit a suitable model we have to test for the presence of unit root(s) and the order of integration of each series has to be determined. From the above time plot we have seen 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 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 4.2 and 4.3, respectively. The critical values used for the tests are the MacKinnon (1996) critical values. Test results presented in Table 4.1 indicate that the null hypothesis that the series in levels contain unit root could not be rejected for all of the three series.

Table 4. 2. Unit root test results (At level)

Series	Level with intercept				Level with intercept and trend			
	Test statistics		P - value		Test statistics		P – value	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
LLA	-2.228	-2.250	0.198	0.591	-2.519	-2.606	0.317	0.278
LLR	-1.264	-1.282	0.640	0.637	-1.635	-1.177	0.766	0.892
LME	-1.653	1.512	0.449	0.525	-2.845	-3.726	0.188	0.228
Critical value(1%)	-3.5402				-4.1130			

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

The result in Table 4.3 below shows that the null hypothesis of unit root is rejected for the first difference of the series with intercept and trend using ADF test. Similar result was also obtained from the PP test. This implies that the time series are integrated of degree one (I (1)). Therefore, the ADF and PP test shows that all series are non-stationary in level and stationary in the first differences.

Table 4. 3. Unit root test results (after first difference)

Series	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(LLA)	-7.657	-7.657	0.000	0.000	-7.698	-7.679	0.000	0.000
D(LLR)	-19.517	-19.511	0.000	0.000	-10.867	-19.615	0.000	0.000
D(LME)	-8.757	-12.594	0.000	0.000	-8.704	-12.478	0.000	0.000
Critical value(1%)	-3.5420				-4.1156			

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

4.3. VAR model specification

4.3.1. Estimation of order of VAR

For subsequent modeling choices specifying the lag length have strong implications. The Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quin (HQ) Information Criteria were used to determine the appropriate lag length for the VAR. The results are shown in Table 4.4 below. The VAR lag order selection result suggests three different lag lengths for the three methods. Of these three methods the Schwarz Information Criterion (SC) is consistent than others, so this paper used it as a best selection criteria; That is, the best fitting model is the one that minimize SC. and then SC test suggests that the appropriate lag length for the VAR model is one (1). Accordingly, the thesis adopt VAR (1) model for prediction and forecasting purposes.

Table 4.4. VAR lag order selection results

Lag	AIC	SC	HQ
0	8.511446	8.722721	8.593919
1	7.589817	8.118004*	7.796000
2	7.357062	8.202162	7.686955*
3	7.447725	8.609737	7.901327
4	7.190811*	8.669736	7.768123

* indicates lag order selected by the criterion

4.3.2.1. Lag exclusion test

To check the optimality of the chosen lag, the Wald lag exclusion test is used. Given that VAR modeling requires uniform lag length for each variable, the result in Table 4.5 shows that the first lag is significant for all variables at the five percent level of significance. Therefore, VAR (1) is found suitable for the data set and hence could be adopted.

Table 4.5. VAR lag exclusion Wald test

	LLA	LLR	LME	Joint
Lag 1	113.2980 [0.000000]	9.89497 [0.019890]	15.85797 [0.001213]	125.0405 [0.000000]
df	3	3	3	9

The results of the estimated VAR model are presented in Table 4.6. The coefficients with "*" are statistically significant at the 5% level of significance.

Table 4.6. Vector autoregression estimates

Standard errors in ( ) , t-statistics in [ ] & p-value in {}

	LLA	LLR	LME
LLA(-1)	0.704077 *	-0.017754	0.035190
	(0.08483)	(0.07108)	(0.10257)
	[8.30022]	[-0.24977]	[0.34309]
	{0.0000}	{0.8031}	{0.7319}
LLR(-1)	-0.329685 *	0.162461	-0.096766
	(0.16331)	(0.13685)	(0.19747)
	[-2.01873]	[1.18717]	[-0.49003]
	{0.0451}	{0.2368}	{0.6247}
LME(-1)	0.213836 *	-0.066473	0.439452 *
	(0.10606)	(0.08887)	(0.12824)
	[2.01616]	[-0.74795]	[3.42671]
	{0.0453}	{0.4555}	{0.0008}
C	6.188944	15.83389 *	6.840305
	(3.21149)	(2.69106)	(3.88316)
	[1.92713]	[5.88389]	[1.76153]
	{0.0556}	{0.0000}	{0.0799}
LER	0.016085	-1.053676 *	0.800327
	(0.48027)	(0.40244)	(0.58072)
	[0.03349]	[-2.61819]	[1.37816]
	{0.9733}	{0.0096}	{0.1700}

Table 4.6. Shows that the volume of live animal export is significantly explained by its own past and by past volume of leather and meat export. This implies that for a percent increases in one time lagged volume of leather and meat export the volume of live animal is decreased by 0.33 and increased by 0.214 percent respectively. The volume of meat export is only explained by its own past. This indicates that the volume of live animal and leather export has almost no significant relation with the volume of meat export. It is inconsistent with that of Aklilu and Yacob(2002) who found the direct dependence of leather sector on live animals. Exchange rate has a negative and significant elasticity on the volume of leather export. This confirms the result by Sheldon and Mc corrosion(2002). A one percent increase in the exchange rate leads to decrease the volume of leather export by 1.05 percent.

4.3.3. Cointegration analysis

Since the variables are integrated of the same order, we proceed to co integration test. Johansen (1991) co integration test is applied at the predetermined lag 1 model. The value of trace statistic and maximum Eigen value statistic are compared to special critical values. The maximum Eigen value and trace tests proceed sequentially from the first hypothesis of no co integration to an increasing number of co integrating vectors.

The results of co integrating tests for LLA, LME and LLR are reported in Table 4.7.Both tests (trace and maximum Eigen value) indicate that there is one co integrating vector in the system.

Table 4.7. Johansen Co-integration test results (assumption: linear deterministic trend)

Number of co integrating vector	Eigen value	Trace test			Maximum eigenvalue test		
		statistic	0.05 critical value	Prob.**	statistic	0.05 critical value	Prob.**
None *	0.3202	35.912	29.797	0.009	23.160	21.131	0.026
At most 1	0.1593	12.752	15.494	0.124	10.416	14.264	0.186
At most 2	0.0381	2.3368	3.8414	0.126	2.3368	3.8414	0.126

Normalized co integrating coefficients (standard error in ( ) and t-statistic in [ ])

LLA	LLR	LME
1.00000	0.209379	-2.406884
	(0.46220)	(0.24081)
	[0.465301]	[-9.99479]

The main purpose of co integration analysis is to get a stationary series from two or more non-stationary series. The resulting stationary series is written as a linear combination of the non-stationary series under study. From the Johansen co integration test, it was determined that the rank of co integration matrix to be equal to one. That means, there is one stationary co integrated series from the three non-stationary series. Consequently the co integrating vector is given by

$$\beta = (1, 0.209379, - 2.406884)$$

If we denote this stationary series by Z_t then using the results obtained from Table 4.7 and Table 4.8 (constant) we have the following.

Z_t = LLA + 0.21 LLR – 2.41 LME + 16.18

The result tells us that Z_t is stationary despite the fact that all the three series are non-stationary. We can infer from this result that there exist long-run causal relationships among LLA, LLR and LME. This long-run model is:

LLA = 2.41 LME – 0.21 LLR – 16.18

The long run equation above shows that the volume of live animals has a positive long run relationship with the volume of meat export. The value -0.209 suggests that a one percent increase in the volume of leather export induces, on average, a decrease of about 0.21 percent in the volume of live animals. On the other hand, for a one percent increase in the volume of meat, the volume of live animals is increased by 2.41 percent.

4.4. 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:

$$\Delta Y_t = \mu + \alpha\beta Y_{t-1} + \sum_{i=1}^{p}. \Gamma_i \Delta Y_{t-i} + GX_t + \varepsilon_t$$

Where β is the cointegrating vector. The responses of LLA, LLR and LME to short-term output movements are captured by the Γi coefficient matrices. The α coefficient vector reveals the speed of adjustment to the equilibrium, which measures the deviation from the long-run relationship between the volumes of livestock products export. X_t is vector of exogenous variables and G is a parameter matric.

Coefficient estimates and their probability value of the VEC model are presented in Table 4.8 below and Table A2(appendices) respectively.

Table 4.8. Vector error correction estimates

Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
LLA(-1)	1.000000		
LLR(-1)	0.209379 (0.46220) [0.45301]		
LME(-1)	-2.406884 (0.24081) [-9.99479]		
C	16.17810		
Error Correction:	**D(LLA)**	**D(LLR)**	**D(LME)**
CointEq1	-0.180565* (0.05472) [-3.30009]	0.051872 (0.05516) [0.94033]	0.329464* (0.06471) [5.09176]
D(LLA(-1))	0.042865 (0.12023) [0.35652]	0.088441 (0.12122) [0.72962]	0.130441 (0.14218) [0.91741]
D(LLR(-1))	-0.141597 (0.12706) [-1.11438]	-0.398191* (0.12810) [-3.10833]	-0.122493 (0.15026) [-0.81519]
D(LME(-1))	-0.315409* (0.11859) [-2.65972]	0.076878 (0.11956) [0.64301]	0.378188* (0.14024) [2.69673]
C	1.349359 (0.76783) [1.75736]	-0.545890 (0.77412) [-0.70517]	-1.080689 (0.90803) [-1.19015]
LER	-0.475567 (0.29044) [-1.63739]	0.199249 (0.29282) [0.68045]	0.426994 (0.34347) [1.24317]

*denotes significance of the coefficients' at the 0.05 level

The coefficients in the second part of Table 4.8 are called the adjustment coefficients that measure the short-run adjustments of the deviations of the endogenous variables from their long run values. Using the error correction term as another independent variable in the unrestricted VAR model we can estimate the following Vector Error Correction Model.

$$\Delta LLA_t = -0.18*(LLA+0.21* LLR - 2.41 *LME+16.18) +0.04*\Delta LLA_{t-1} -0.14*\Delta LLR_{t-1} - 0.32*\Delta LLE_{t-1} -0.48*LER+1.35$$

$$\Delta LLR_t = 0.05*(LLA+0.21* LLR - 2.41 *LME+16.18) +0.09*\Delta LLA_{t-1} -0.40*\Delta LLR_{t-1}+ 0.08*\Delta LLE_{t-1}+ 0.20*LER -0.54$$

$$\Delta LME_t = 0.33*(LLA+0.21* LLR - 2.41 *LME+16.18) +0.13*\Delta LLA_{t-1} -0.12*\Delta LLR_{t-1}+ 0.38*\Delta LLE_{t-1} + 0.43*LER - 1.08$$

Where: 'Δ' stands for first difference (D), the value in the bracket is the error correction term and the coefficients of error correction term are called adjustment coefficients.

Therefore, the above vector error correction models show that the volume of live animals export is significantly affected by lagged value of the volume of meat export in the short run. On the other hand, the volume of leather export doesn't have significant effect on the volume of live animals export. Furthermore, the vector error correction models shows that18.1% of the short run disequilibrium in the volume of live animals export is adjusted within one quarter, while the remaining shocks are adjusted in the subsequent quarters. Similarly, 32.9% of the short run disequilibrium in the volume of meat export is adjusted within the next one quarter. On the other hand, the volume of leather and meat export is significantly affected by their lagged values in the short run.

4.5. Structural analysis

4.5.1 Granger causality test

Granger causality test is considered as a useful technique for determining whether one time series is good for forecasting the other. Table 4.9 presents results from the pair wise Granger-causality tests.

Table 4.9. Pairwise granger causality test

Null Hypothesis:	F-Statistic	Prob.
LLR does not Granger Cause LLA	5.88042	0.0184
LLA does not Granger Cause LLR	7.14285	0.0097
LME does not Granger Cause LLA	4.47634	0.0386
LLA does not Granger Cause LME	3.28038	0.0752
LME does not Granger Cause LLR	5.98894	0.0174
LLR does not Granger Cause LME	4.00379	0.0510

The result from Table 4.9 shows that the volume of leather and meat export granger causes the volume of live animals. This indicates that, the change on the volume of leather and meat export lead to the change on the volume of live animals export. That is, the volumes of leather and meat export provide important information to forecast future value of the volume of live animals export. On the hand the volume of live animals doesn’t granger-cause on the volume of meat export. This is an indication that the change on the volume of live animals doesn’t lead to the change on the volume of meat export. Similarly the change on the volume of meat export is not affected by the change on the volume of leather export.

4.5.2. Impulse- response function

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 n variables in a system, a total of n^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). The x-axis in Figure 4.2 below and in Figures A2 in the Appendix 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. The combined graphs of these IRF functions are given in Figure 4.2 and Figures A2 of Appendix with the Cholesky ordering LLA, LLR and LME.

Figure 4.2. Impulse Response Function of LLA

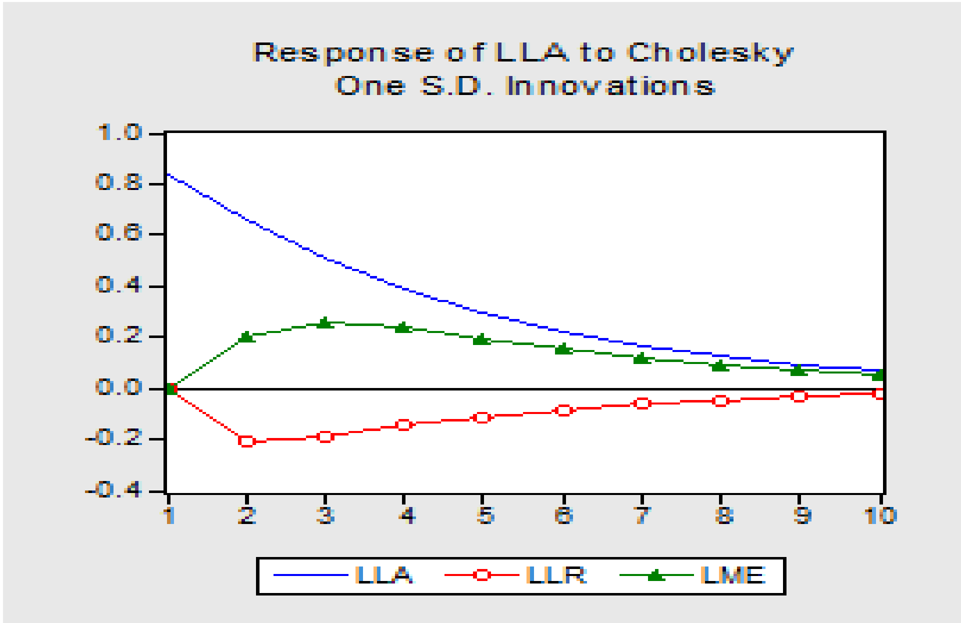


Figure 4.2 above shows the response of LLA, LLR and LME to a one standard deviation in LLA. The result indicates the volume of live animal export innovations initially have a positive effect on the volume of meat export and then have negative effect after the fourth quarter of time horizon. It exhibits rising trend initially and reaches 0.2 and it stabilizes at around third quarter. It has also initially negative effect on the volume of leather export and then has a positive effect after third quarter time horizon.

Similarly, Figure A2 of Appendix shows that a one standard deviation shock applied to the volume of meat has negative impact on the volume of leather export initially and the volume of leather export is almost not affected by one SD change. Furthermore the volume of leather export innovations has almost no effect on the volume of live animal and meat exports.

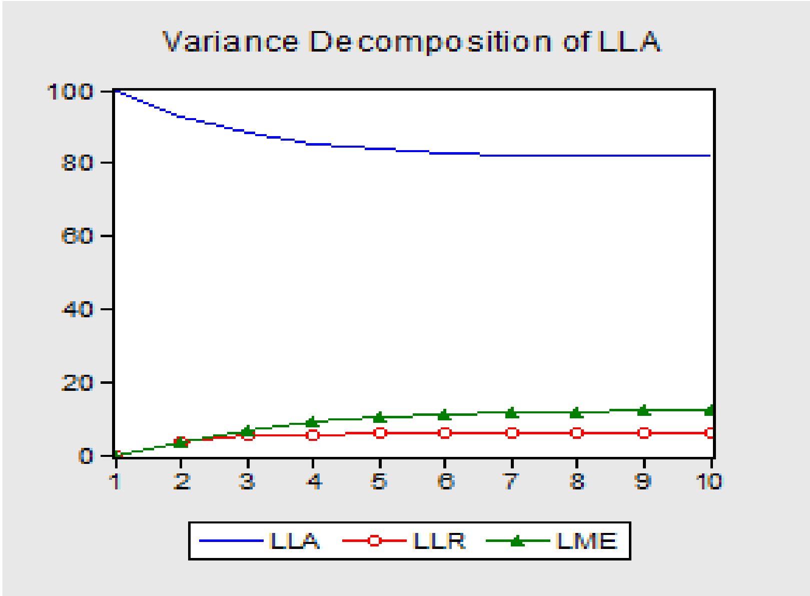
4.5.3. Forecast Error Variance Decomposition

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 Table 4.10 and Figure 4.3 below and Table A1 and Figure A3 of the Appendix. The results from the variance decomposition of LLA 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 LLA, LLR and LME.

Table 4.10. Variance decomposition of LLA

Variance Decomposition of LLA:				
Period	S.E.	LLA	LLR	LME
1	0.835363	100.0000	0.000000	0.000000
2	1.105118	92.88874	3.624653	3.486603
3	1.259070	88.09384	5.049786	6.856373
4	1.347530	85.30358	5.599132	9.097284
5	1.397888	83.72305	5.835364	10.44158
6	1.426325	82.83517	5.947145	11.21769
7	1.442299	82.33809	6.003622	11.65829
8	1.451243	82.06030	6.033349	11.90636
9	1.456240	81.90521	6.049381	12.04541
10	1.459029	81.81868	6.058150	12.12317

Figure 1.3. Variance decomposition of LLA



The variance decomposition analysis results of LLA in Figure 4.3 and Table 4.10 above show that, at the first horizon, the variation of live animals export is explained by its own shock only. In the second quarter, shock to the volume of live animals export accounts for 93% variation of the fluctuation in live animals export(own shock) and the remaining 7 percent is explained by the volume of meat export. After third quarter shock to the volume of leather export also contribute in the variation of live animals export; then after shock to the volume live animals, leather and meat export account for 82%, 6% and 12% of the variability in the volume of live animals export respectively.

Similarly, in Figures A3 and TableA2 of the Appendix, the variance decomposition of LME shows that 90% of the variability in the volume of meat export fluctuation is explained by its own innovations: and the rest 9% from shock to the volume of live animals export and 1% from LLR. Furthermore, from the variance decomposition of LLR we conclude that shock to the volume of leather export accounts for 98% variation of the fluctuation in the volume of leather export and the rest 2% is explained by the volume of live animals and meat export(1% from each).

4.6 Results from Diagnostic Tests

Table 4.11. Results from the Diagnostic Tests

Test	Statistics	p- value
Normality Jarque- Bera statistics	1.9348	0.164
Serial correlation Breusch- Godfrey serial correlation LM test	7.3757	0.598
ARCH test Autoregressive conditional heteroscedasticity	1.5726	0.121
Hetroscedasticity White hetroscedasticiy test	1.4915	0.141
Stability Chow forecast test	1.1128	0.369
Specification error Ramsey RESET test	0.1045	0.917

The diagnostics table above shows that there is no significant evidence to reject the null hypothesis of normality; which indicates that the residuals of the regression are normally distributed. The Breusch–Godfrey Serial Correlation LM test indicates that the residuals of the estimated correction model do not suffer from autocorrelation. The Autoregressive Conditional Heteroskedasticity (ARCH) test indicates there is no significant evidence of ARCH. Using White-Heteroskedasticity test, it was found that there is no significant evidence for the existence of heteroskedasticity. The insignificant result of the chow forecast test indicates that the parameters of the model are stable across various sub samples of the data in the study. The Ramsey RESET (Regression Specification Test) did not reject the null of correct specification indicating that the model was correctly specified. Generally the results indicate that the model is well specified.

4 .7. Forecasting

One of the fundamental applications of time series analysis or developing a time series model is forecasting. The previous discussion confirms that VAR (1) model is a good model to describe the series. In this section we examine the forecasting accuracy of the fitted model and then make a forecast.

4.7.1. Evaluation of forecast accuracy

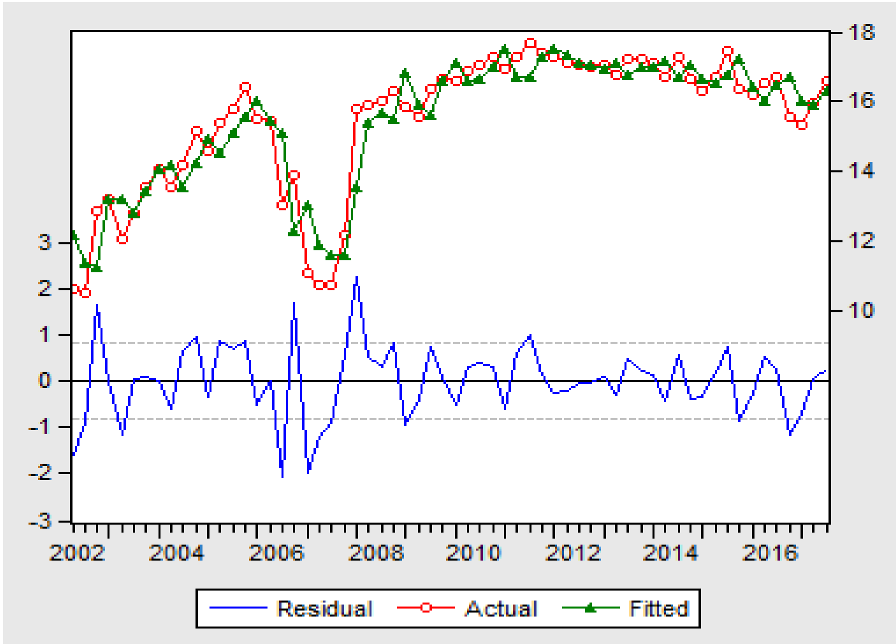
The mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and Theil U statistics were used to assess the forecasting performance. The RMSE and MAE statistics are scale-dependent measures but allow a comparison between the actual and forecast values. The Theil-U statistics is independent of the scale of the variables and is constructed to lie between zero and one, zero indicating a perfect fit. Table 4.11 reports the forecasting accuracy statistics of the estimated model.

Table 4.12. Forecasting Accuracy statistic

Accuracy measure	Variables		
	LLA	LLR	LME
Root mean square error	1.258	0.996	0.673
Mean absolute error	0.977	0.526	0.505
Mean absolute percentage error	7.079	4.329	3.661
Theil inequality coefficient	0.041	0.035	0.024

For the VAR (1) model the MAPE in forecasting LLA, LLR and LME are 7.079, 4.329 and 3.661 respectively. These computed values show that High percentage error for the first equation (LLA as dependent variable) is committed to forecast the study variable. The Theil-U statistic is relatively close to zero, indicating that the difference between the actual values and the predicted values are very small. That is the predictive power of the models are healthier and suitable for n-step ahead forcast.The graph of the predicted values together with the actual observations for LLA is given in Figure 4.4 below and the remaining plots for the other variables are presented in Figures A4 (i-iii) of Appendix .

Figure 4.4. Graph of Actual, Fitted and Residual plot of LLA



4.7.2. Out of sample forecasting analysis

Table 4.13. Forecasted series from the VAR (1) model

year	Quarter	LLA	LLR	LME
2015	I	16.82727	13.44110	15.41072
	II	17.09412	13.34435	15.49281
	III	17.32257	13.30795	15.54433
	IV	17.50464	13.27586	15.58761
2016	I	17.65207	13.24604	15.62652
	II	17.77343	13.22081	15.66016
	III	17.87577	13.19308	15.69481
	IV	17.96575	13.16655	15.72874
2017	I	18.03600	13.18066	15.72561
	II	18.08499	13.16091	15.74322
	III	18.13198	13.13935	15.76708

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

In this empirical work, an attempt is made to apply multivariate time series analysis to model the volume of Ethiopian export of livestock products using quarterly data from 2002 to 2017. Formally, the data were tested for seasonality and all the series were not affected by periodicity and hence no seasonal adjustment was necessary. Augmented Dickey-Fuller and Phillips-Perron unit root tests show that all three series were found to be non-stationary at level and became stationary after first difference.

Different vector autoregressive models were tested using AIC, SC and HQ information criteria to fit the series. Among all candidate VAR models, VAR (1) was found to be the best to describe the data using SC. Error diagnosis of this model showed that the disturbance terms are white noise and normally distributed. The VAR (1) model analysis result shows the volume of live animals is significantly explained by its own past and by lagged value of leather and meat export. Furthermore a percent increase in the exchange rate leads to decrease the volume of leather export by 1.05 percent.

Co integration test shows that there is one co integrating vector in the system. This implies that there exists a long run association between the volumes of Ethiopian live animals, leather and meat export. From the error correction result, the co integrating coefficient tells us that 18.1% and 32.9% of the short run disequilibrium in the volume of live animals and meat export is adjusted each quarter, respectively. Furthermore the volume of leather and meat export is significantly affected by their lagged values in the short run.

Forecasting accuracy statistics show that the predictive power of the model was healthier and suitable for out of sample forecast. And the results from structural analysis shows that the change in the volume of meat and leather export leads to a change on the volume of live animals export.

5.2. Recommendation

From the empirical findings, this study draws the following conclusions

- The volume of leather export was influenced by exchange rate. Therefore, concerned bodies should give due attention to this factor in policy formulation.
- It is also recommended to include more exogenous factors like fuel oil price.

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APPENDICES

Figure A1 Time plots of the Differenced Series

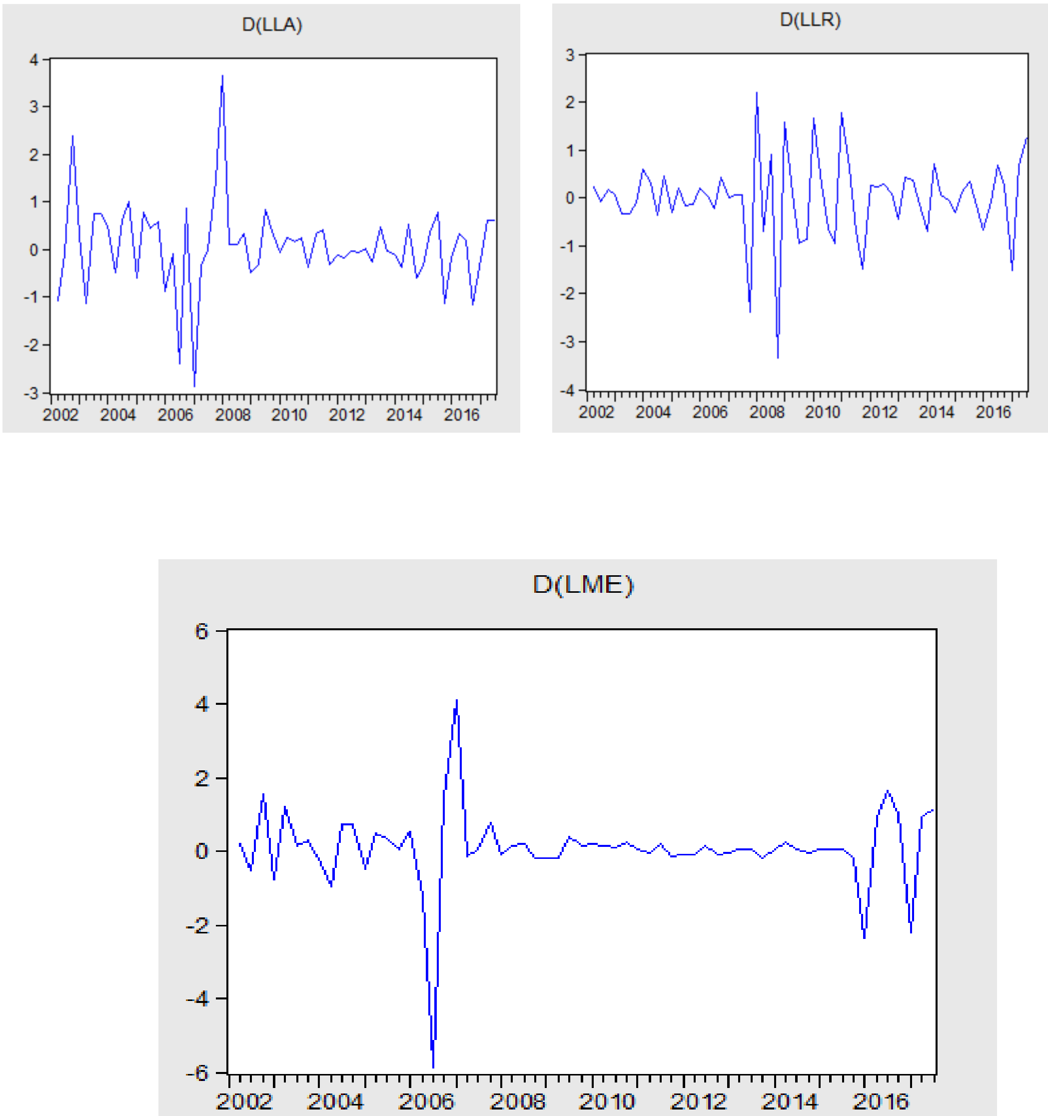


Figure A2 Impulse Response Functions for LLA, LME and LLR

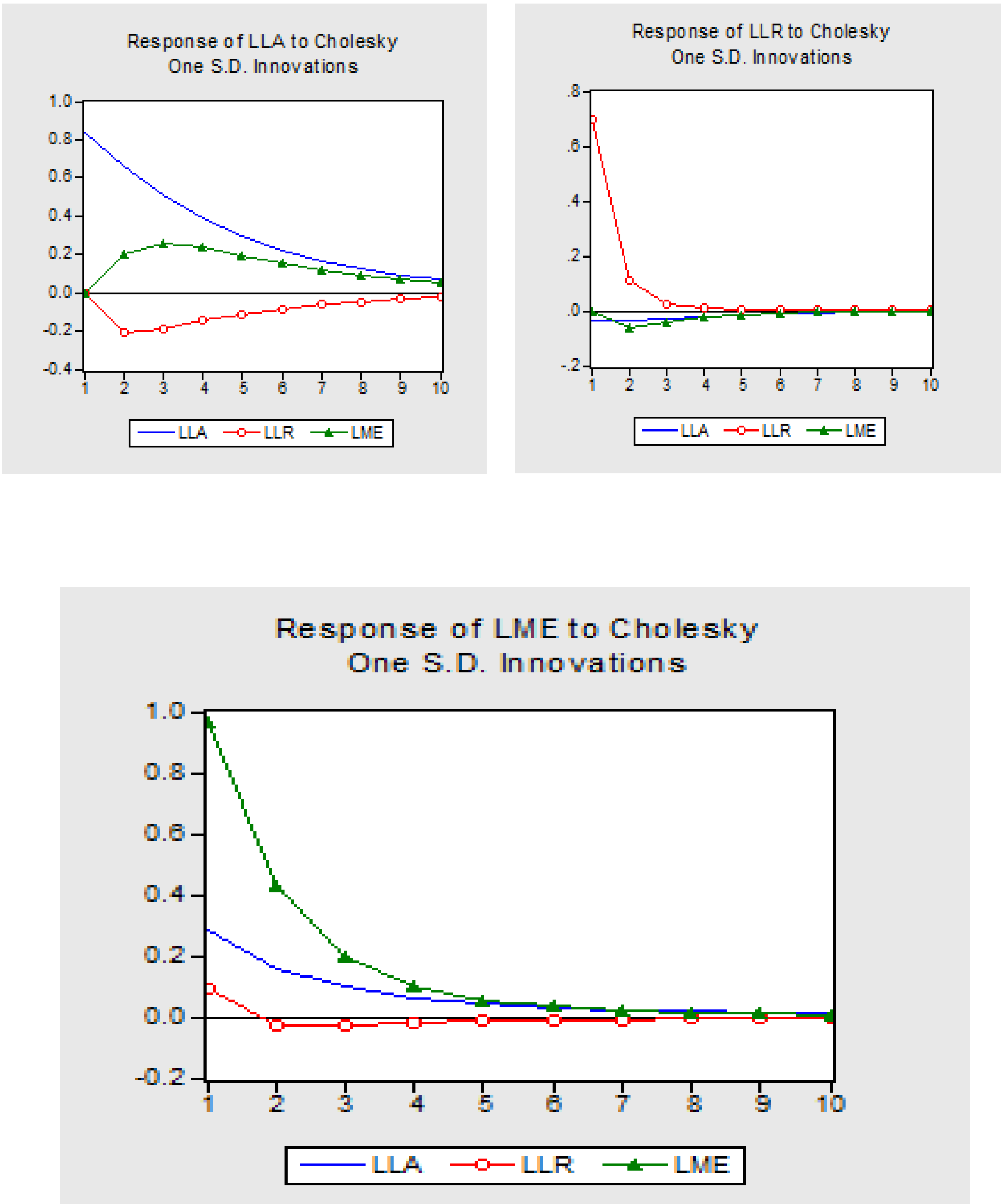


Figure A3 Variance decomposition for LLA, LME and LLR

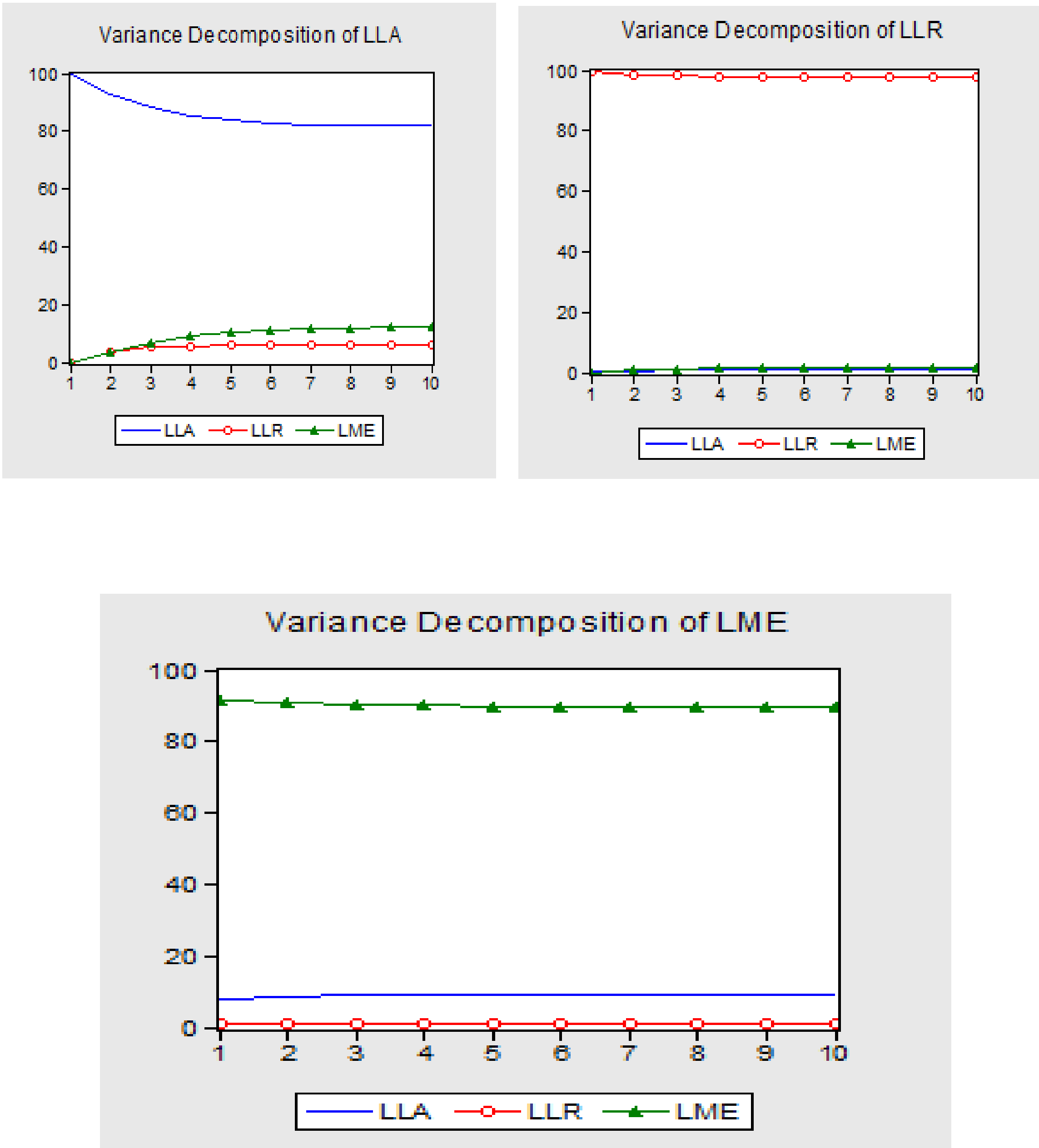
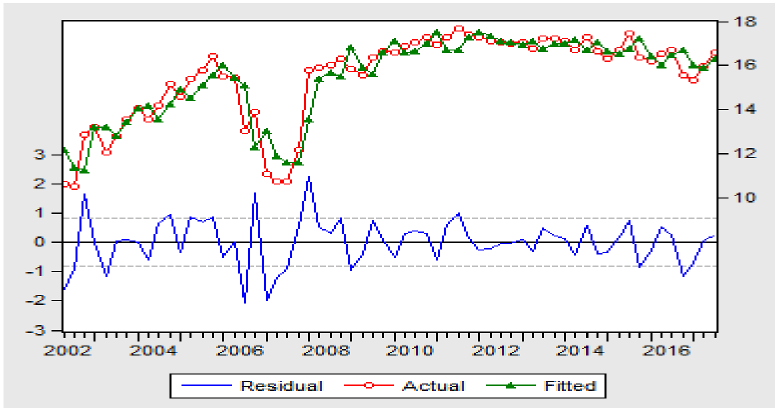
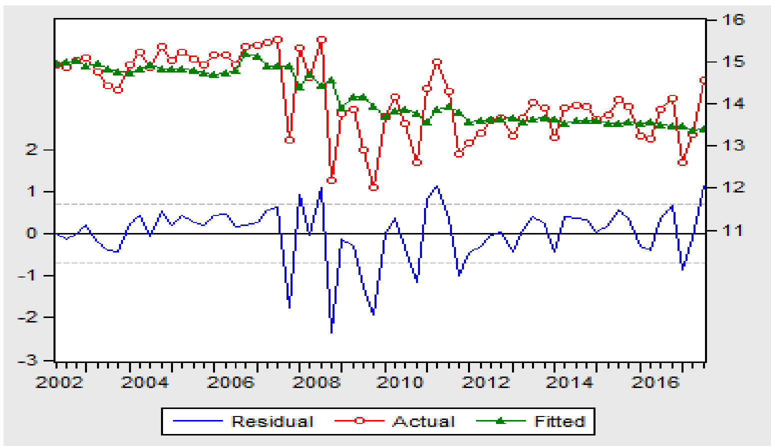


Figure A4

i) Graph of Actual, Fitted and Residual plot of LLA



ii) **Graph of Actual, Fitted and Residual plot of LLR**



iii) Graph of Actual, Fitted and Residual plot of LME

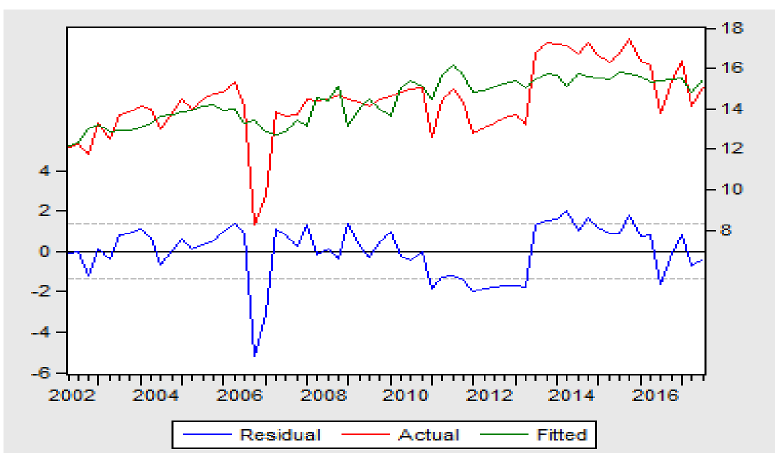


Table A1 Seasonality test

i) Dependent Variable: **LLA**

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.085612	0.175202	-0.488646	0.6271
LLA(-1)	0.914906	0.132604	6.899523	0.0000
LLA(-2)	0.014563	0.175349	0.083049	0.9341
LLA(-3)	2.169547	1.001133	2.167092	0.0347
LLA(-4)	0.020322	0.124436	0.163310	0.8709

ii) Dependent Variable: **LLR**

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.089412	1.701536	1.227957	0.2248
LLR(-1)	0.261960	0.114980	2.278306	0.0267
LLR(-2)	0.005260	0.120835	0.043528	0.9654
LLR(-3)	0.011511	0.123778	0.092994	0.9263
LLR(-4)	0.569796	0.118274	4.817606	0.0000

iii) Dependent Variable: **LME**

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.175782	1.918929	2.697224	0.0093
LME(-1)	0.800001	0.135883	5.887433	0.0000
LME(-2)	-0.455587	0.165782	-2.748100	0.0081
LME(-3)	0.340091	0.170594	1.993565	0.0513
LME(-4)	-0.039744	0.136196	-0.291818	0.7715

Table A2 OLS estimates of VAR (order by variables)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.704076	0.084826	8.300220	0.0000
C(2)	-0.329685	0.163313	-2.018728	0.0451
C(3)	0.213836	0.106061	2.016160	0.0453
C(4)	6.188942	3.211489	1.927125	0.0556
C(5)	0.016085	0.480274	0.033492	0.9733
C(6)	-0.017754	0.071080	-0.249773	0.8031
C(7)	0.162461	0.136848	1.187166	0.2368
C(8)	-0.066473	0.088873	-0.747949	0.4555
C(9)	15.83389	2.691058	5.883892	0.0000
C(10)	-1.053676	0.402444	-2.618192	0.0096
C(11)	0.035190	0.102567	0.343093	0.7319
C(12)	-0.096766	0.197470	-0.490030	0.6247
C(13)	0.439452	0.128243	3.426710	0.0008
C(14)	6.840305	3.883161	1.761530	0.0799
C(15)	0.800327	0.580722	1.378159	0.1700

Table A3 OLS estimates of VECM (order by variables)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.180564	0.054715	-3.300087	0.0012
C(2)	0.042865	0.120231	0.356523	0.7219
C(3)	-0.141597	0.127064	-1.114376	0.2667
C(4)	-0.315409	0.118587	-2.659725	0.0086
C(5)	1.349359	0.767834	1.757356	0.0807
C(6)	-0.475567	0.290442	-1.637391	0.1035
C(7)	0.051872	0.055163	0.940331	0.3484
C(8)	0.088441	0.121216	0.729615	0.4667
C(9)	-0.398191	0.128105	-3.108329	0.0022
C(10)	0.076878	0.119559	0.643015	0.5211
C(11)	-0.545890	0.774124	-0.705170	0.4817
C(12)	0.199249	0.292821	0.680446	0.4972
C(13)	0.329464	0.064705	5.091763	0.0000
C(14)	0.130441	0.142184	0.917411	0.3603
C(15)	-0.122493	0.150264	-0.815187	0.4161
C(16)	0.378188	0.140240	2.696728	0.0077
C(17)	-1.080688	0.908031	-1.190144	0.2357
C(18)	0.426993	0.343473	1.243165	0.2156

Table A4 Variance decomposition results

i) For LLA

Variance Decomposition of LLA:

Period	S.E.	LLA	LLR	LME
1	0.835363	100.0000	0.000000	0.000000
2	1.105118	92.88874	3.624653	3.486603
3	1.259070	88.09384	5.049786	6.856373
4	1.347530	85.30358	5.599132	9.097284
5	1.397888	83.72305	5.835364	10.44158
6	1.426325	82.83517	5.947145	11.21769
7	1.442299	82.33809	6.003622	11.65829
8	1.451243	82.06030	6.033349	11.90636
9	1.456240	81.90521	6.049381	12.04541
10	1.459029	81.81868	6.058150	12.12317

ii) For LLR

Variance Decomposition of LLR:

Period	S.E.	LLA	LLR	LME
1	0.699990	0.272134	99.72787	0.000000
2	0.712171	0.571935	98.61677	0.811293
3	0.714367	0.728991	98.11450	1.156507
4	0.715135	0.806718	97.91981	1.273472
5	0.715457	0.846483	97.83755	1.315965
6	0.715609	0.867501	97.79913	1.333372
7	0.715685	0.878855	97.77984	1.341300
8	0.715725	0.885069	97.76973	1.345200
9	0.715747	0.888496	97.76429	1.347217
10	0.715759	0.890395	97.76131	1.348293

iii) For LME

Variance Decomposition of LME:

Period	S.E.	LLA	LLR	LME
1	1.010076	7.862281	0.862919	91.27480
2	1.107051	8.566500	0.775271	90.65823
3	1.129434	8.956561	0.812586	90.23085
4	1.135900	9.163308	0.840172	89.99652
5	1.138172	9.272231	0.855669	89.87210
6	1.139113	9.330276	0.864120	89.80560
7	1.139551	9.361650	0.868743	89.76961
8	1.139771	9.378801	0.871287	89.74991
9	1.139887	9.388248	0.872695	89.73906
10	1.139949	9.393477	0.873475	89.73305

Cholesky Ordering: LLA LLR LME