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Determinants of Leather Export in Ethiopia: Application of Vector Error Correction Model

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ABSTRACT

Modelling and forecasting of leather export in Ethiopia have been attempted by using vector auto-regression (VAR) and vector error correction (VEC) models, respectively. The variables are value of leather export, export price of leather, consumer price index (endogenous variables) and nominal exchange rate (exogenous variables), respectively. The series are seasonally adjusted through standard tests built in X-12 ARIMA program in E-Views 6 statistical software. Post seasonal adjustment tests also assured that all series were non-seasonal. Unit root tests of the series reveal that all the series are non-stationary at zero level and stationary after first difference. The result of Johansen test indicates the existence of two co-integration relation between the variables. This implies the legitimacy of vector error correction model (VEC) model of order one to the data. The final result shows that a VEC model of lag one with two co-integration equations best fits the data. Export price of leather has a negative effect on value of leather exports. A one percent increase in a unit price of leather export will cause 5.82% decrease in value of leather export in the long run. In the short run Exchange Rate has a negative effect on exports of leather as expected.

1. Introduction

Ethiopia is a leader in its livestock resources in Africa and possesses one of the world's largest livestock populations with a 57,829,953 cattle population. This puts the Ethiopia first in Africa and sixth in the world. Therefore Ethiopia has huge potential for leather industry. The Ethiopia with 28,892,380 sheep population and 29,704,958 goat populations is third in Africa and tenth and 8th in

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the world' respectively. The hides and skin supplied to the tanneries are 1.4 million cow hides, 6.7 million goat skins and 13.2 million sheep skins, respectively. The abundance of livestock in Ethiopia represents a natural strength. Ethiopian Herald (CSA, 2015).

Several studies about leather export with related variables have been conducted using univariate time series analysis. Univariate time series analysis is important but it is inadequate for the analysis of interaction and co-movement of several time series simultaneously. In contrast, multivariate time analysis involves a vector of time series that will be modeled simultaneously. The main objective of this paper is to evaluate determinants of leather export from Ethiopia. We will also try to find out (i) What kind of relationships exists among value of leather exports, nominal exchange rate, export price and consumer price index in the Ethiopian context, respectively? (ii) Is there long run relationship among the variables that is value of leather exports, nominal exchange rate, export price and consumer price index, respectively ?

2. Data

2.1 Data Sources

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

2.2 Definitions and Variables of the Study

1. Export value of leather products such as leather garments, foot wear, gloves, bags and other leather articles have been expressed in million U.S. dollars.
2. Export prices: A unit export price is the price at which a commodity trade out of a country.
3. Nominal Exchange Rate: An exchange rate is how much it costs to exchange one currency for another. Exchange rates fluctuate constantly throughout the week as currencies are actively traded. This pushes the price up and down, similar to other assets such as gold or stocks.
4. The market price of a currency is different than the rate one will receive from his bank when one exchanges currency.
5. Consumer price index: The Consumer Price Index (CPI) is a measure that examines the weighted average of prices of a basket of consumer goods and services, such as transportation, food and medical care. It is calculated by taking price changes for each item in the predetermined basket of goods and

averaging them. Changes in the CPI are used to assess price changes associated with the cost of living; the formula used to calculate the Consumer Price Index for a single item is as follows:

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

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

3. Description of Models

3.1 The Stationary Vector Autoregressive (VAR) Model

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

$$\boldsymbol{y_t} = \boldsymbol{c} + \boldsymbol{\pi_1}\, \boldsymbol{y_{t-1}} + \boldsymbol{\pi_2}\, \boldsymbol{y_{t-2}} +, \dots, + \boldsymbol{\pi_p}\, \boldsymbol{y_{t-p}} + \boldsymbol{\varepsilon_t} \quad t = 1, 2 \dots \mathrm{T} \qquad (3.1)$$

where $\mathbf{y_t}$ is a vector of responses at a time t,**c** denotes an (n×1) vector of constants and $\boldsymbol{\pi_j}$ is an (*n*×*n*) matrix of auto regressive coefficients, *j*= 1,2… p *and* ε_t is an (*n*×1) white noise vector process (serially uncorrelated) with time invariant with zero mean and positive definite covariance matrix **Σ**:

$$\mathrm{E}\,(\boldsymbol{\varepsilon_t}) = 0 \text{ and } \mathrm{E}\,(\boldsymbol{\varepsilon_t}, \boldsymbol{\varepsilon_s}) = \begin{cases} \Sigma\,, & \text{if } t = s \\ 0\,, & if\ t \neq s \end{cases} \qquad (3.2)$$

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

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

$$\mathbf{\Pi(z)}\ \boldsymbol{y_t} = \mathrm{c} + \boldsymbol{\varepsilon_t} \qquad (3.3)$$

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

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

$$\det\,(\boldsymbol{I_n} - \boldsymbol{\pi_1 z} - \boldsymbol{\pi_2 z^2} -, \dots, \boldsymbol{\pi_p z^p}) = 0 \qquad (3.4)$$

All roots lies outside the unit circle or have modules greater than one.

If $\boldsymbol{y_t}$in equation [3.1] is covariance stationary then,

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

and the unconditional mean is given by

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

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

$$\boldsymbol{y_t} = \boldsymbol{\pi_1}\, \boldsymbol{y_{t-1}} + \boldsymbol{\pi_2}\, \boldsymbol{y_{t-2}} +, \dots, + \boldsymbol{\pi_p}\, \boldsymbol{y_{t-p}} + \Phi \boldsymbol{D_t} + \mathrm{G}\boldsymbol{X_t} + \boldsymbol{\varepsilon_t} \qquad (3.5)$$

Where $\boldsymbol{D_t}$ represent an (L×1) vector of deterministic components

$\boldsymbol{X_t}$ represents an $(m \times 1)$ matrix of exogenous variables, and **Φ** and $\boldsymbol{G}$ are parameter matrices.

3.2 Vector Error Correction (VEC) Model

If a set of variables are found to have one or more co-integrating vectors, the corresponding error correction representations must be included in the system to evade misspecification and omission of the important constraints. Thus, the VAR should be re-parameterized as a Vector Error Correction Model (VECM) form, (Hamilton, 1994). That is,

$$\Delta \boldsymbol{Y}_t = \boldsymbol{\Pi Y}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{Y}_{t-i} + \boldsymbol{B X}_t + \boldsymbol{\varepsilon}_t \qquad (3.6)$$

(3.6) is known as a *Vector Error Correction Model (VECM)*, where $\boldsymbol{I}_n$ is the identity matrix, and $\boldsymbol{\Gamma}_i = -\sum_{j=i+1}^{p} \boldsymbol{A}_j$.

Where: Δ: Operator differencing where $\Delta = y_t - y_{t-1}$

$\mathbf{y_{t-1}}$: endogenous vector variable with first lag

$\boldsymbol{\varepsilon_t}$: residual vector, Π: matrix of cointegration coefficients ($\boldsymbol{\Pi = \alpha\, \beta'}$; $\boldsymbol{\alpha}$ = vector adjustment matrix with order (n × r) ; $\boldsymbol{\beta'}$ = vector cointegration (long - run parameter) matrix (r × n) Γ_i : Matrix of order (n × n) of coefficients of ith endogenous variable.

Estimation of Parameters

In this paper X-12 ARIMA and E-View 6 software package are used to fit of VAR (p) and VEC models.

3.4 Determination of the Order of the VAR

To determine the lag length for the VAR (p) model we will use model selection criteria which have following form:

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

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

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

$$AIC = \ln\left|\hat{\sum}_p\right| + \frac{2}{T} p n^2 \qquad (3.7)$$

$$BIC = \ln\left|\hat{\sum}_p\right| + \frac{\ln(T)}{T} p n^2 \qquad (3.8)$$

$$HQ = \ln\left|\hat{\sum}_p\right| + \frac{2\ln\ln(T)}{T} p n^2 \qquad (3.9)$$

The best model should have the smallest information criteria among the candidates VAR (p) models.

3.5 Co-integration Analysis

3.5.1 Co integration

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

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

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

Methods for testing co-integration are

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

In this article we used Johansson (1991) procedure.

3.5.2 Testing for the Number of Co- integration Relations Using Johansen's Methodology

The starting point in Johansen's procedure (1988, 1991) in determining the number of cointegrating vectors is the VAR representation of Y_t which is expressed as follows.

$$\boldsymbol{Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \mathrm{B} A_1 x_t + \varepsilon_t} \quad (3.10)$$

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

$$\boldsymbol{\Delta Y_t = \pi Y_{t-1} + \textstyle\sum_{i=1}^{p-1} \Gamma_i \, \Delta Y_{t-i} + \mathrm{B}\, x_t + \varepsilon_t}, t = 1, 2 \ldots \mathrm{T} \quad (3.11)$$

$$\text{Where } \boldsymbol{\pi = \textstyle\sum_{i=1}^{p} A_i - I}, \boldsymbol{\Gamma_i = -\textstyle\sum_{j=j+1}^{p} A_j} \quad (3.12)$$

Johansen (1988) proposed two tests for estimating the number of co-integrating vectors: the trace statistic and maximum eigenvalue. The trace statistic investigates the null hypothesis of r co-integrating relations against the alternative of n co-integrating relations, where n is the number of variables in the system for r = 0 ,1,2 …n-1. Define $\hat{\lambda}_i$, i=1, 2…k to be a complex modulus of eigenvalues of $\hat{\pi}$ and let them be ordered such that $\hat{\lambda}_1 \geq \hat{\lambda}_2 , \geq \hat{\lambda}_3 \geq \ldots \hat{\lambda}_n$. The trace statistic is computed as:

$$\lambda_{trace}(r) = -\mathrm{T} \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right) \quad (3.13)$$

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

$\hat{\lambda}_{max}$(r ,r+1) = -T ln (1- $\hat{\lambda}_{r+1}$) (3.14)

Where $\hat{\lambda}_{r+1}$ is the $(r+1)^{th}$ ordered eigenvalue of π and T is the sample size. The critical value stabulated by Johansen and Juselius (1990) have been used for these tests.

3.6 Tests for Stationarity

3.6.1. The Unit Root Test

For unit root test we used the Augmented Dickey-Fuller test (ADF) and the Phillip-Perron (1980) (PP) test.

Consider an AR (1) process:

$$\boldsymbol{y_t = \rho y_{t-1} + x_t^{'}\delta + \varepsilon_t} \quad (3.15)$$

Where $\boldsymbol{x_t}$ optional exogenous regressors which may consist a constant and trend, ρ and δ are parameters to be estimated and $\boldsymbol{\varepsilon_t}$ is assumed to be white noise. If | ρ | ≥1, $\boldsymbol{y_t}$ is a non-stationary series and the variance of $\boldsymbol{y_t}$ increases with time and approaches infinity. On the other hand, if

| ρ |<1, $\boldsymbol{y_t}$ is a stationary series. Thus, the hypothesis of (trend) stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one.

The hypotheses are:

H_0: The series are not stationary ($\rho \geq 1$)

H_1: The series are stationary ($\rho<1$)

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

The standard Dickey-Fuller (1979, 1981) test is conducted in the following manner: From equation (3.15) we have:

$$\boldsymbol{y_t - y_{t-1} = (\rho - 1)y_{t-1} + x_t^{'}\delta + \varepsilon_t} \ .$$

Or $$\Delta \boldsymbol{y_t = \pi y_{t-1} + x_t^{'}\delta + \varepsilon_t} \quad (3.16)$$

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

H0: $\pi \geq 0$

H1: $\pi < 0$ (3.17)

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

$$t_\pi = \frac{\hat{\pi}}{se(\hat{\pi})} \quad (3.18)$$

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

The ADF test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR (p) process and adding lagged difference terms of the dependent variable **y** to the right-hand side of the test regression:

$$\Delta \boldsymbol{y_t = \pi y_{t-1} + x_t^{'} + B_1 \Delta y_{t-1} + B_2 \Delta y_{t-2} +, \ldots, B_P \Delta y_{t-P} + U_t} \quad (3.19)$$

This augmented specification is then used to test the unit root test using the t-ratio (3.18).

3.7 Vector Error Correction Model (VECM)

Thus, the VAR can be re parameterized as a Vector Error Correction Model (VECM) form (Hamilton, 1994; Reinsel, 1993). VAR (p) model is expressed as.

$$\boldsymbol{Y_t = \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \ldots + \pi_p Y_{t-p} + \varepsilon_t} \quad (3.20)$$

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

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

$$\Delta \boldsymbol{Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta Y_{t-i} + \varepsilon_t} \quad (3.21)$$

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

3.8 Model Checking

We followed the following steps for checking the adequacy of the model.

3.8.1 Test of Residual Autocorrelation

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

$$\mathbf{Q}=\mathbf{T}\widehat{\boldsymbol{C}}'\widehat{\textstyle\sum^{-1}}\widehat{\boldsymbol{C}} \quad (3.22)$$

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

3.8.1.1 Autocorrelation LM Test

This test was developed by Breusch and Godfrey in 1978. Assume a VAR model for the error $\boldsymbol{\varepsilon_t}$ given by

$$\boldsymbol{\varepsilon_t = D_1 U_{t-1}} + \cdots + \boldsymbol{D_h U_{t-h} + V_t} \quad (3.23)$$

The quantity **Vt** denotes a white nose error term. Thus, to test autocorrelation in $\boldsymbol{U_t}$we test

$$H_0 = \boldsymbol{D_1} = \cdots = \boldsymbol{D_h}$$

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

We use the Lagrange multiplier method to perform the test. The Breusch Godfrey test statistic, say $Q^*{}_{BG}$, is a standard LM test statistic for the null hypothesis Y= 0

$$Q^*{}_{BG} = T\,\hat{\gamma}'(\widehat{\textstyle\sum}^{\gamma\gamma}\hat{\gamma})^{-1}\hat{\gamma} \quad (3.24)$$

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

$$[\boldsymbol{T}^{-1}\sum_{t=1}^{T}\begin{pmatrix}\widehat{\boldsymbol{U}}_t \otimes \boldsymbol{I}_n \\ \hat{\boldsymbol{z}}_t \otimes \boldsymbol{I}_n \\ \hat{\boldsymbol{z}}_{1t}\end{pmatrix}\widehat{\boldsymbol{\Omega}}^{-1}(\widehat{\boldsymbol{U}}_t{}' \otimes \boldsymbol{I}_n : \hat{\boldsymbol{z}}_t{}' \otimes : \hat{\boldsymbol{z}}_{1t}{}')] \quad (3.25)$$

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

Here $\widehat{\boldsymbol{\Omega}} = \boldsymbol{T}^{-1}\sum_{t=1}^{T}\widehat{\boldsymbol{u}}\,\widehat{\boldsymbol{u}}'$ is the residual covariance matrix estimator from the restricted auxiliary model. Therefore, under the null hypothesis, it follows from (3.22) for h→∞

$$Q^*_{BG} \rightarrow \ in\ distribution\ x^2(\text{h}k^2) \quad (3.26)$$

3.8.1.2 Portmanteau Autocorrelation Test

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

$$\widehat{C_J} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_{t-J}} \quad (3.27)$$

$\widehat{\boldsymbol{\varepsilon}_t} = \Delta\boldsymbol{Y}_t - \boldsymbol{\pi}\boldsymbol{Y}_{t-1} - \sum_{i=1}^{p-1}\boldsymbol{\Gamma}_i\,\Delta\,\boldsymbol{Y}_{t-i} - \mathbf{B}\,\boldsymbol{x}_t$ Where $\widehat{\boldsymbol{\varepsilon}_t}$ is an estimated residual.

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

$H_0 = E(\widehat{\boldsymbol{\varepsilon}_t}\widehat{\boldsymbol{\varepsilon}_{t-\iota}}') = 0$ for i=1, 2….

The test statistic is based on the residual auto covariances is as given below.

$$\boldsymbol{Q_p} = T\sum_{j=1}^{h} tr(\widehat{C_J}'\widehat{\Omega_J}^{-1}\widehat{C_J}\widehat{\Omega_J}^{-1}) \quad (3.28)$$

Where $\widehat{C_J} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_{t-J}}$ (3.29)

$$\widehat{\boldsymbol{\Omega}} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_J}' \quad (3.30)$$

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. Where k is number of endogenous variables h is number of observations and p is number of lag. A related statistic with potentially superior small sample properties is the adjusted Portmanteau statistic:

$$\boldsymbol{Q_p}^* = T^2\sum_{j=1}^{h}\frac{1}{T-j}tr\left(\widehat{C_J}'\widehat{C_0}^{-1}\widehat{C_J}\widehat{C_0}^{-1}\right) \quad (3.31)$$

Its asymptotic properties are the same as those of $\boldsymbol{Q_p}$.

3.9 Normality of the Residuals

Normality tests whether the residuals of the regression are normally distributed or not. The null hypothesis is that the residuals are normally distributed. Several tests for normality are available but we used in our article Jarque and Bera (1980). The JB test statistic is:

$$\text{JB=T}\left(\frac{\widehat{b_1}}{6} + \frac{\hat{k}^2}{24}\right) \quad (3.32)$$

Where $\widehat{b_1}$ and $\hat{k}$ are the sample skewness and kurtosis coefficients, respectively. This test statistic is asymptotically distributed as $x^2(2)$ under the null hypothesis;

thus large values of this test statistic relative to the quantiles from the $x^2(2)$ distribution lead to rejection of the null hypothesis. Degree of freedom is number of endogenous variables minus one (k-1).

3.10 Impulse Response Functions

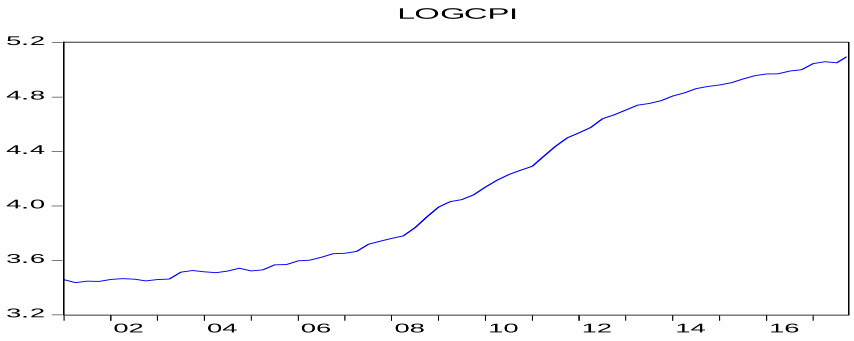
An impulse response function traces the response of a variable of interest to an exogenous shock. Often the response is portrayed graphically, with exogenous variables on the horizontal axis and response on the vertical axis. It traces the effect of a one standard deviation shock to one of the Innovations 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.

3.11 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.

4. Analysis and Results

E-Views 6 was used to estimate the relationship among the value of leather export (VLE), consumer price index (CPI), export price (EP) and nominal exchange rate (NER) in the case of Ethiopia. The time plot of each of the series is shown in Figure 4.1.



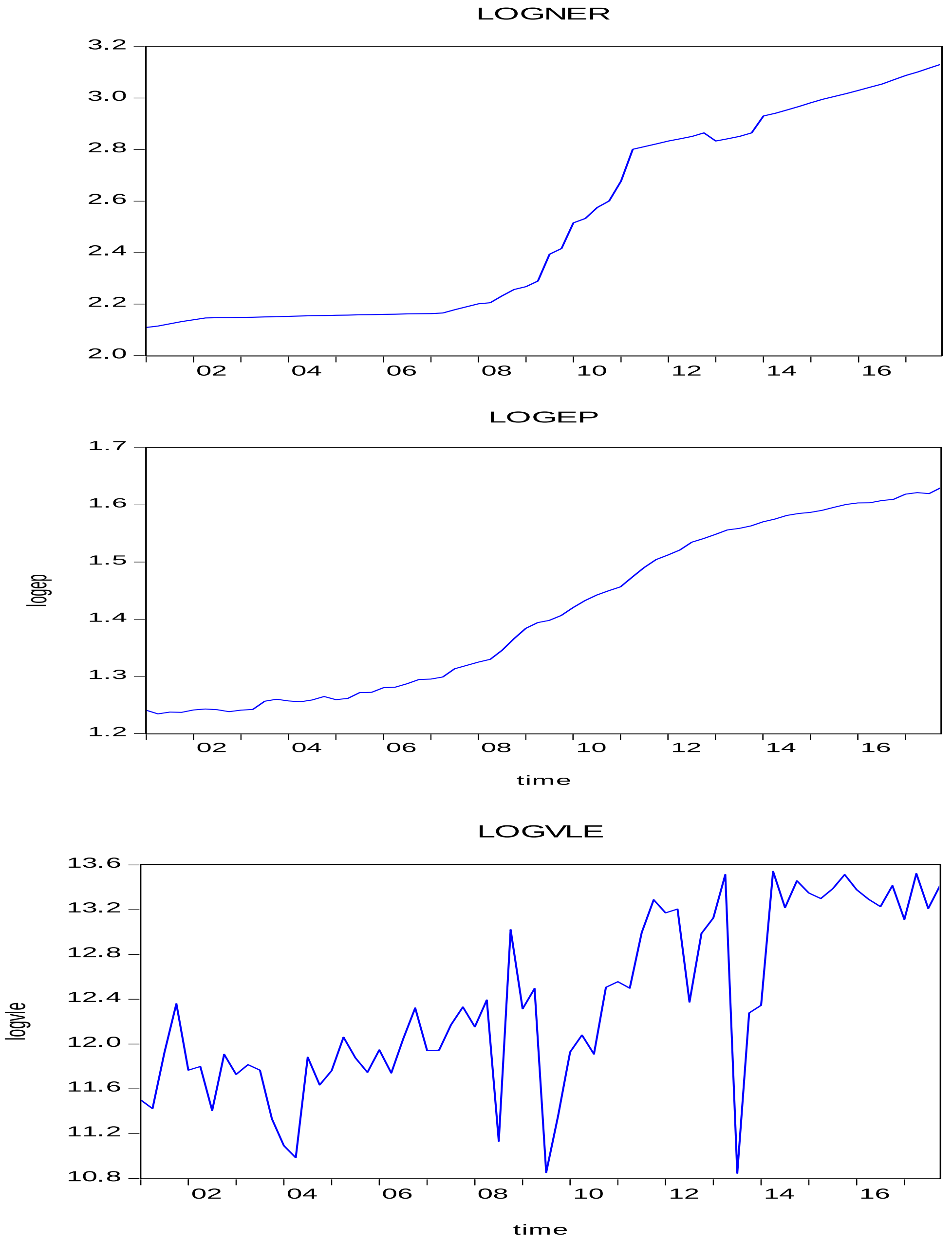


Figure 4.1

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

Table 4. 1: F Tests for Seasonality and Adjustment Quality Diagnostics of Original VLE.

Test for the presence of seasonality assuming stability				
	Sum of Squares	**Degrees of Freedom**	**Mean Square**	**F-Value**
Between quarters	91.6999	3	30.56665	5.413*
Residual	361.3901	64	5.64672	
Total	453.0901	67		
* No evidence of stable seasonality at the 0.1 per cent level.				
Nonparametric Test for the Presence of Seasonality Assuming Stability				
	Kruskal-Wallis Statistic	**Degrees of Freedom**	**Probability Level**	
	14.9807	3	0.183%	
Seasonality present at the one percent level				
Moving Seasonality Test				
	Sum of Squares	**Degrees of Freedom**	**Mean Square**	**F-Value**
Between years	121.1222	16	7.570135	2.546*
Error	142.7241	48	2.973419	
* Moving seasonality present at the one percent level.				
COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY IDENTIFIABLE SEASONALITY NOT PRESENT				
No evidence of residual seasonality in the entire series at the1 per cent level. F = 0.9 No evidence of residual seasonality in the last 3 years at the1 per cent level. F = 0.8 No evidence of residual seasonality in the last 3 years at the 5 per cent level. M1 = 3.000, M2 = 0.791, M3 = 0.037, M4 = 0.018, M5 = 0.929, M6 = 0.450, M7 = 0.163 Q = 0.31 ACCEPTED.				

Table 4.1 exhibits the full F-tests for seasonality of the original value of leather export (RVLE). The combined test for the presence of identifiable seasonality indicates that VLE has a seasonal pattern that can be identified by X-12 ARIMA. The M7 diagnostic (0.163<1), also strengths the identifiably. According to the

table the F-test assert that seasonality exist in quarterly original VLE series at 0.1 % level of significance. Before seasonal adjustment the seasonality never passed to years with in a confidence of 95% and also the residuals of the series are free from seasonality at 1% significance level. In addition to M7, all M-statistics are shown to be less than one and hence the Q-statistic (0.31) produced from them is also less than one. This condition assures that the seasonal adjustment performed on value of leather export is acceptable.

The M-statistic and Q-statistic for each series exceed one and hence both seasonal adjustments procedures made on both are not acceptable. Therefore no more seasonal adjustment is required for each variable.

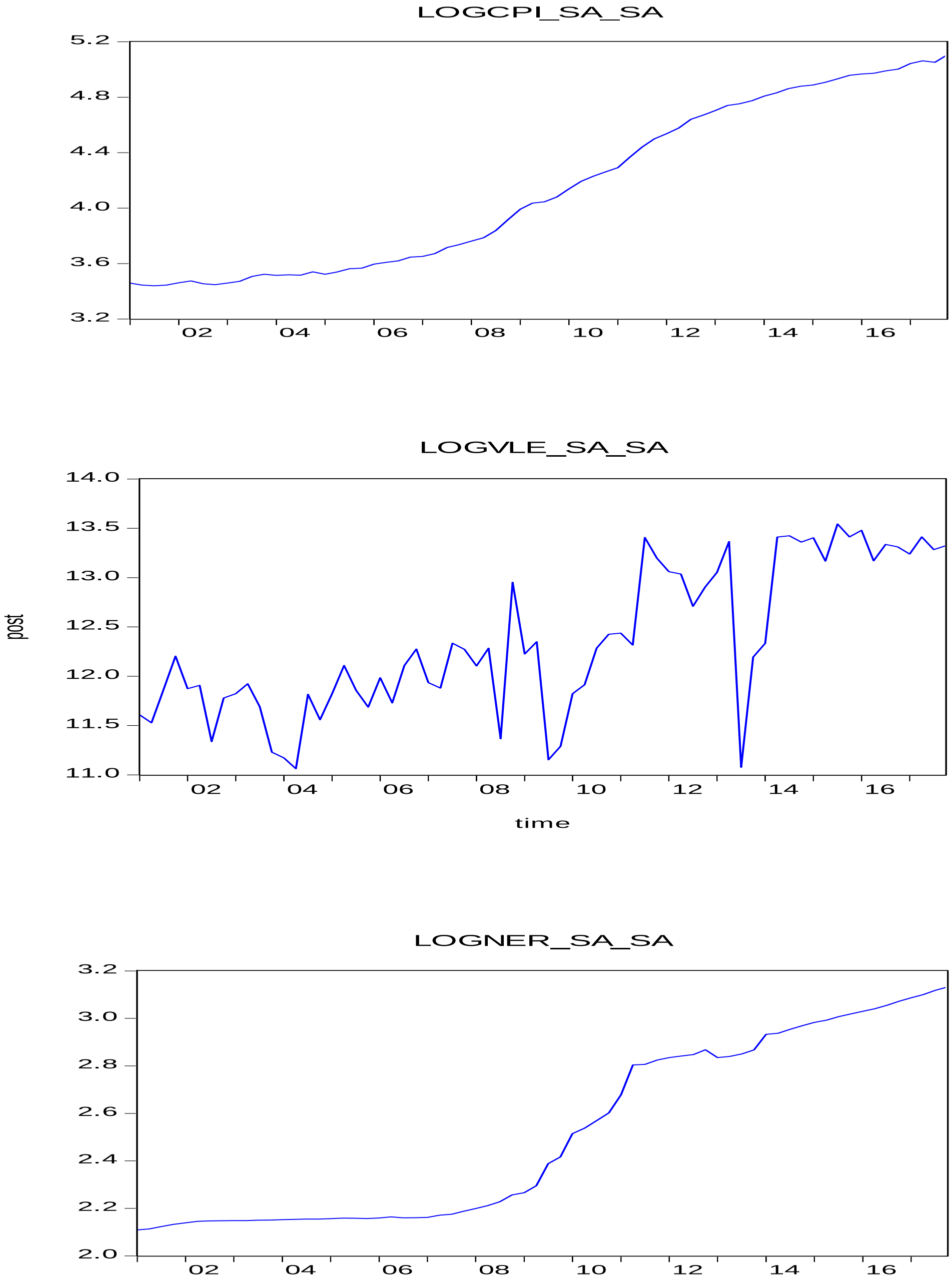
4.2.1 Seasonal Adjustments Features

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

Table 4. 2: F Tests for Seasonality of RVLE Series After Adjustment.

Test for the presence of seasonality assuming stability				
	Sum of Squares	**Degrees of Freedom**	**Mean Square**	**F-Value**
Between quarter	15.3499	3	5.11663	1.189
Residual	275.4764	64	4.30432	
Total	290.8263	67		
Nonparametric Test for the Presence of Seasonality Assuming Stability				
	Kruskal-Wallis Statistics	**Degrees of Freedom**	**Probability Level**	
	0.3474	3	95.089%	
No evidence of seasonality at the one percent level.				
COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY IDENTIFIABLE SEASONALITY NOT PRESENT				
Test for the presence of residual seasonality. No evidence of residual seasonality in the entire series at the 1 per cent level. F = 0.8 No evidence of residual seasonality in the last 3 years at the1 per cent level. F = 0.99 No evidence of residual seasonality in the last 3 years at the 5 per cent level. M7 = 2.411 Q = 1.95 REJECTED.				

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



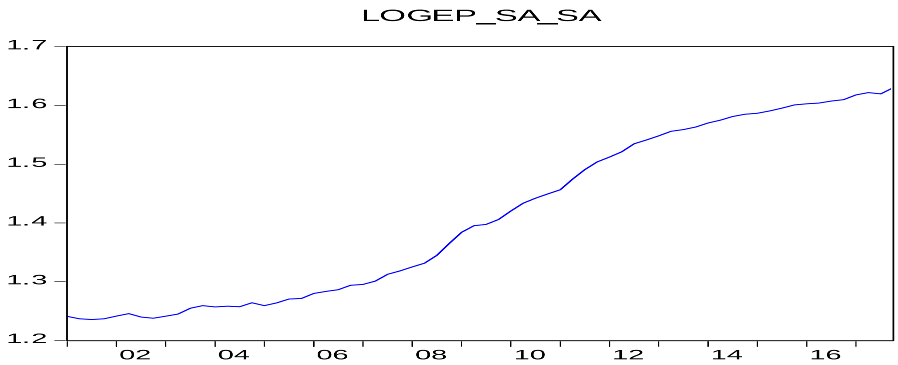


Figure : 4. 2

4.3. Unit Root Properties of Individual Series are Shown in Table 4.3.

Table 4.3: Stationarity Test in Level (Unit Root Test Results (at level)).

Serious	level with intercept				level with intercept and trend			
	Test statistics		P-value		Test statistics		p-value	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
LOGCPI	-0.91995	1.02150	0.7755	0.9964	-1.469445	-2.477	0.5424	0.3379
LOGNER	0.145870	0.50019	0.9669	0.9856	-2.084855	-1.836	0.5442	0.6761
LOGEP	-1.11220	0.64700	0.7060	0.9900	-1.476037	-2.322	0.5391	0.4163
LOGVLE	-1.98771	0.53159	0.2915	0.4187	-2.626239	-3.033	0.4441	0.2321
Critical value at 1 %	-3.533204				-4.103198			

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

Table 4. 4 : Stationarity Test at Difference (Unit Root Test Results (After First Difference)).

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

4.4. VAR Model Specification

Determination of Order of the VAR

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

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

$$\log y_t = c + \pi_1 \log y_{t-1} + \pi_2 \log y_{t-2} +, \ldots, + \pi_p \log y_{t-p} + \varepsilon_t$$

Where, $\log y_t = (y_{1t}, y_{2t}, y_{3t}, y_{4t})$ t = 1, 2, 3… 68

$$y_1 = log\ vle$$

$$y_2 = logner$$

$$y_3 = logcpi$$

$$y_4 = logep$$

VLE –value of leather export

NER-nominal exchange rate

CPI -consumer price index

EP-Export price of leather

Table 4. 5: VAR Lag Order Selection Results.

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

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

$$\log y_t = c + \pi_1 \log y_{t-1} + \varepsilon_t \quad (4.1)$$

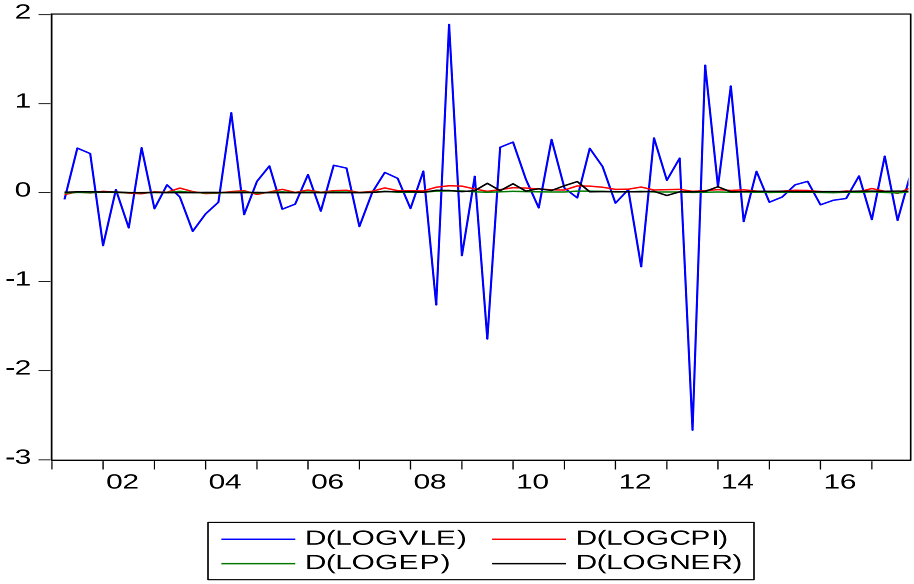
4.4.1 Lag Exclusion Test

To check whether the chosen lag is optimal, the Wald lag exclusion test is used. Given that VAR modeling requires uniform lag length for each variable, the result in Table 4.6 below shows that the first lag is significant for all variables at the one percent level of significance. Therefore, VAR (1) is found suitable for the data set and hence could be adopted.

Table 4.6 : Lag Exclusion Test.

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

Figure 4.3: **Plot of Time series plot of VLE, NER and CPI, EP, after first deference).**



4.5 Co-integration Analysis

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

Table 4. 7: Johansen Co-integration Test Results (By Assumption: Linear Deterministic Trend).

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

Normalized co-integrating coefficients (standard error in parentheses)

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

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

The results of Johansen co-integration test presented in above table 4.7, it can be observed that the trace or likelihood ratio statistic (65.81529, 34.60382) exceeds the respective critical value (29.79707, 15.49471) with p-value (0.0000, 0.0000). The maximum eigenvalue test also supports the same thing as trace test. This implies that the null hypothesis of no co-integration relation is rejected at the 5% significance level in favor of the alternative one which states that there exist two co-integration relations. Therefore, the rank of co-integration matrix is equal to two, meaning there are two co-integrating equations in the system. That means there exist long run association between value of leather export, consumer price index and export value leather.

Consequently, the co-integrating vector is given by

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

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

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

$$S_{t1} = log\ vle_t + 5.822219\ log\ ep_t \quad (4.2)$$

$$S_{t2} = log\ cpi_t - 3.688498\ log\ ep_t$$

The result S_t tells us that are stationary despite the fact that all the three series are non-stationary.

Since all of the variables are significant at the conventional significance levels, we can infer from this result that there exist long-run causal relationships among VLE, EP, and CPI. These long-run models are:

$$log\ vle_t = 20.5581 - 5.822219 logep_t \quad (4.3)$$

$$log\ cpi_t = -1.063825 + 3.688498\ log\ ep_t$$

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

4.6 Model Estimation

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

$$\Delta\ \boldsymbol{log\ Y_t = \mu + \sum_{i=1}^{p} \Gamma_i\ \Delta Y_{t-i} + \alpha\beta X_{t-1} + \varepsilon_t} \quad (4.4)$$

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

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

Table 4.8: Vector Error Correction Estimates.

Standard errors in ( ) & t-statistics in [ ]			
Cointegrating Eq:	**Coint Eq1**	**Coint Eq2**	
LOGVLE(-1)	1.000000	0.000000	
LOGCPI(-1)	0.000000	1.000000	
LOGEP(-1)	5.822219	-3.688498	
	(4.17992)	(0.16455)	
	[1.39290]	[-22.4160]	
C	-20.55811	1.063825	
Error Correction:	**D(LOGVLE)**	**D(LOGCPI)**	**D(LOGEP)**
CointEq1	-0.762099*	0.002513	0.000787
	(0.15657)	(0.00566)	(0.00144)
	[-4.86736]	[0.44429]	[0.54491]

CointEq2	6.208220*	-0.564528*	-0.132585*
	(3.71901)	(0.13434)	(0.03431)
	[1.66932]	[-4.20233]	[-3.86435]
D(LOGVLE(-1))	-0.124472	0.001641	0.000363
	(0.12054)	(0.00435)	(0.00111)
	[-1.03263]	[0.37690]	[0.32677]
D(LOGCPI(-1))	17.12201*	-1.150565	-0.267984
	(28.1994)	(1.01861)	(0.26015)
	[3.343331]	[-1.12954]	[-1.03010]
D(LOGEP(-1))	-38.95529	4.999045	1.177434
	(110.041)	(3.97486)	(1.01518)
	[-0.35401]	[1.25766]	[1.15983]
C	-4.124525*	-0.258757*	-0.054940*
	(1.91962)	(0.06934)	(0.01771)
	[-2.14861]	[-3.73171]	[-3.10230]
LOGNER	1.569882*	0.111973*	0.023986
	(0.77766)	(0.02809)	(0.00717)
	[2.01872]	[3.98616]	[0.60718]
R-squared	0.447651	0.452789	0.399121
Adj. R-squared	0.391480	0.397141	0.338015

The coefficient in the second part of Table 4.8 contains the coefficients of the error correction terms (ciontEq1andciontEq2) for the co-integration vector. These coefficients are called the adjustment coefficients and measure the short-run adjustments of the deviations of the endogenous variables from their longrun values. These first and second row coefficients identify the fraction of the long term gap that is closed by each endogenous variable in each period (quarter). In another saying, these figures provide information on the short run disequilibria percentage adjustment of each endogenous variable within one period of time (quarter in this case).

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

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

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

4.7 Model Checking

In order to ascertain whether the model provides an appropriate representation, a test for misspecification should be performed. Results are shown in Table 4.9 and 4.10.

4.7.1 Test of Residual Autocorrelation

Table 4.9: VEC Residual Portmanteau Tests for Autocorrelations.

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	Df
1	1.021282	NA*	1.036995	NA*	NA*
2	5.840361	0.7558	6.006669	0.7393	9
3	11.57188	0.8685	12.01112	0.8467	18
*The test is valid only for lags larger than the VAR lag order. df is degrees of freedom for (approximate) chi-square distribution.					

Table 4.10: VEC Residual Serial Correlation LM Tests.

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

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

4.7.2 Testing Normality

Multivariate version of the Jarque –Bera (1980) tests is used to test the normality of the residuals. It compares the 3rd and 4th moments (skewness and kurtosis) to those from a normal distribution. The test has null hypothesis indicating that the error term in the model has skewness and kurtosis corresponding to a normal distribution. The results in Table 4.11 show that the null hypothesis has to be rejected. It might be the case that there is the presence of outlier in the model. Furthermore, failed Jarque-Bera (1980) test is a common phenomenon, which will not crucially distort final results.

Table 4.11: Results from the Normality Tests.

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

4.8 Structural Analysis

4.8.1 Granger Causality Test

Granger (1981) causality test is considered a useful technique for determining whether one time series is good for forecasting the other. Table 4.12 presents results from the pair wise Granger-causality tests.

Table 4.12: Pairwise Granger Causality Test.

Pairwise Granger Causality Tests			
Sample: 2001Q1 2017Q4			
Null Hypothesis:	Obs	F-Statistic	Prob.
LOGCPI does not Granger Cause LOGVLE	67	25.9873	3.E-06
LOGVLE does not Granger Cause LOGCPI		0.00328	0.9545
LOGEP does not Granger Cause LOGVLE	67	25.0590	5.E-06
LOGVLE does not Granger Cause LOGEP		0.05439	0.8163
LOGNER does not Granger Cause LOGVLE	67	30.8430	6.E-07
LOGVLE does not Granger Cause LOGNER		1.03854	0.3120

LOGEP does not Granger Cause LOGCPI	67	43.2613	1.E-08
LOGCPI does not Granger Cause LOGEP		39.4074	3.E-08
LOGNER does not Granger Cause LOGCPI	67	0.57108	0.4526
LOGCPI does not Granger Cause LOGNER		5.82558	0.0187
LOGNER does not Granger Cause LOGEP	67	5.24909	0.0253
LOGEP does not Granger Cause LOGNER		10.5650	0.0018

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

4.8.2 Impulse-Response Functions

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

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

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

4.8.3 Forecast Error Variance Decomposition

Variance decompositions are used to understand the proportion of the fluctuation in a series explained by its own shocks versus shocks from other variables. The results of the decomposition of the endogenous variables of the model are presented in Figure 4.6A3 in Appendix. The results from the variance decomposition of VLE provide the percentage of the forecast error in each variable that could be attributed to innovations of the other variables for different time period. The Cholesky ordering employed is LOGVLE, LOGCPI and LOGEP.

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

In similar fashion, the variance decomposition analysis result of CPI in Figure 4.6 A3 in appendix shows that, at the first horizon (quarter) 92.75330 % of the variability in the CPI fluctuations is explained by its own innovations and the remaining 7.2467% is explained by VLE (7.2460707). Even up to tenth quarter, much of variability of CPI (74.21928) is explained by its shock the rest proportion is occupied by VLE (13.24698) and EP (12.53373). Similarly, the variance decomposition of EP shows that almost all variability is explained by their own fluctuations.

5. Conclusion

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

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

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

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

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

Jarque-Bera (1980) verified that residuals are normally distributed while Lagrange Multiplier (LM) and Portmanteau Q-statistic tests confirmed that residuals do not exhibit serial correlation.

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

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

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Appendix Figure 4.5 : (a-c)

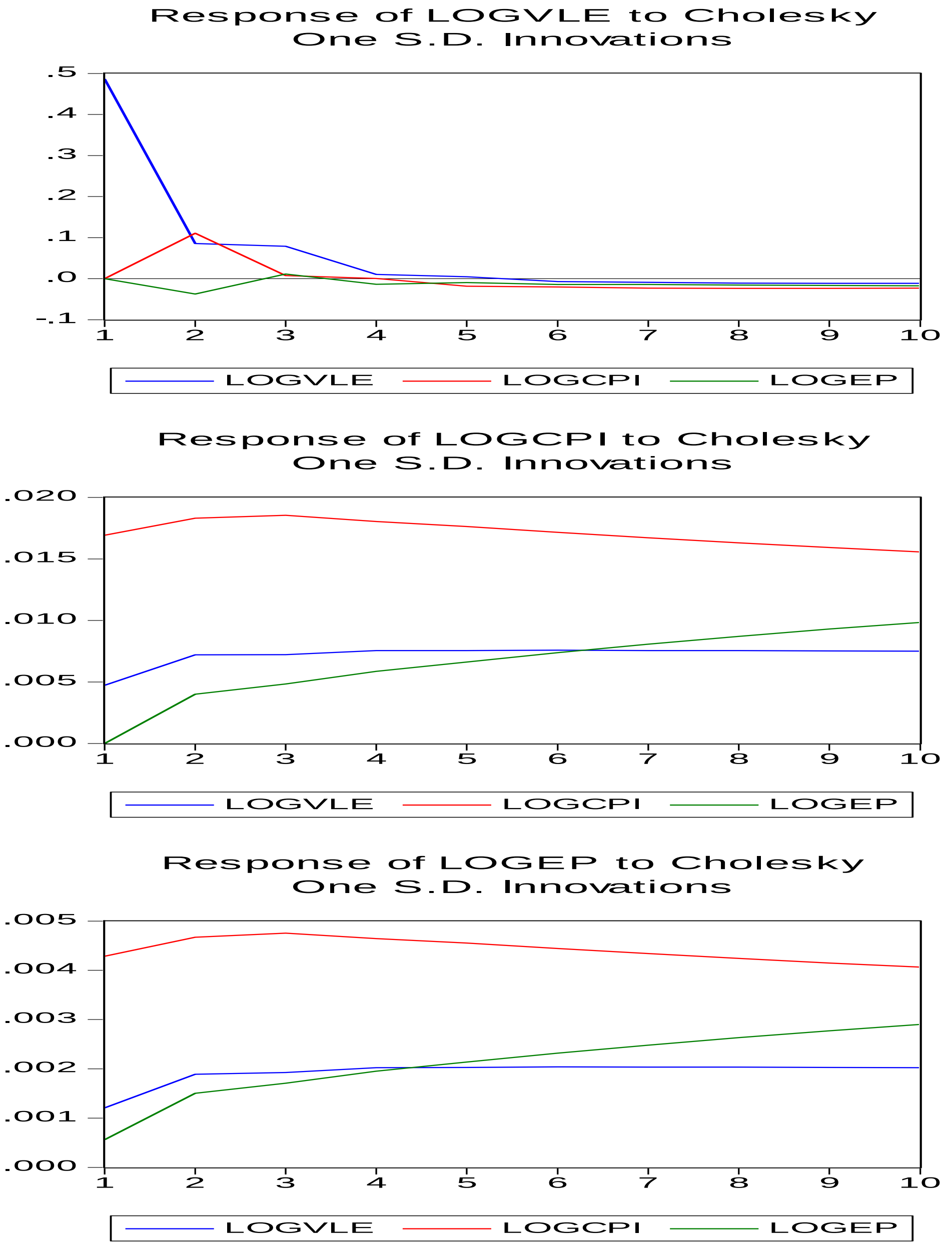

Figure 4. 1: A3 Variance Decomposition Results