ADDIS ABABA UNIVERSITY

GRADUATE STUDIES PROGRAMME

COLLEGE OF COMPUTATIONAL & NATURAL SCIENCES

DEPARTMENT OF STATISTICS

VECTOR AUTOREGRESSIVE AND COINTEGRATION ANALYSIS OF COFFEE EXPORT: the case of Ethiopia

Gebretsadik Gebru

A Thesis submitted to

The Department of Statistics

Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science

Addis Ababa University

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School of Graduate Studies

This is to certify that the thesis prepared by Gebretsadik Gebru, entitled: *vector autoregressive and co-integration analysis of the price-volume relationship of coffee export: the case of Ethiopia* and submitted in partial fulfillment of the requirements for the Degree of Master of Science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Chair of Department or Graduate Program Coordinator

ABSTRACT

Vector autoregressive and cointegration analysis of the price-volume relationship of coffee export: the case of Ethiopia.

Gebretsadik Gebru,

Addis Ababa, 2012

Ethiopia is known as the birth place of Coffee Arabica and it has been and remains the leading cash crop and export commodity of Ethiopia. It accounts on average for about 5% of gross domestic product (GDP), 10% of total agricultural production and 60% of total export earnings for the past three to four decades; and 50% of the total produced is consumed locally. The study is aimed to develop a multivariate time series model which explains the price-volume relationship of coffee export in Ethiopia using vector autoregression (VAR) and vector error correction (VEC) model. The data used are monthly observations from September 2006 to July 2011 of the volume of coffee export, free-on-board price, producer price and world price.

Unit root tests of the series under study reveal that all the series are non-stationary at level and stationary after first difference. The result of Johansen test indicates the existence of one cointegration relation between the variables and there is long-term dynamics between volume of coffee export, free-on-board price, producer price and world price. Granger causality test indicates that there is no transmission of price signals from the world market to the local market. VAR (1) model analysis show that free-on-board price is significantly explained by its own past and by lagged value of producer price. Furthermore, the result indicates that the volume of Ethiopian coffee export is not affected by price.

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ACRONYMS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
CSA	Central Statistical Agency
ECM	Error Correction Model
ECMC	Ethiopian Coffee Marketing Corporation
FEVD	Forecast Error Variance Decomposition
FOB	Free-On-Board Price
GDP	Gross Demostic Production
GMM	Generalized Method of Moments
HQ	Hannan-Quin Information Criteria
ICO	International Coffee Organization
IMF	International Monitoring Fund
IRF	Impulse Response Function
JB	Jarque Bera Statistic
LM	Lagrange Multiplier
MAE	Mean Absolute Error
MPAE	Mean Percentage Absolute Error
MPE	Mean Percentage Error
MSE	Mean Square Error
MVTS	Multivariate Time Series Analysis
OLS	Ordinary Least Square
PP	Phillips and Perron test

PE	Percentage Error
RMSE	Root Mean Squared Error
SC	Schwarz Information Criterion
SAP	Structural Adjustment Program
SVAR	Structural Vector Autoregressive
USD	United States Dollar
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
VOL	Volume of Coffee Export
WOP	World Price

1. Introduction

1.1 Background

Coffee grows in many tropical and sub tropical parts of the world. Latin America, Africa, Asia and Oceania account for 60, 30, and 10 percent of the total world coffee production, respectively. About 18 countries around the world derive 25 or more percent of their export earnings either from coffee, tea, or cocoa (Mwandha, 1985; Yohannes, 2010). Ethiopia is known as the birth place of Coffee Arabica. Coffee has been and remains the leading cash crop and export commodity of Ethiopia. It has accounted on average for about 5% of gross domestic product (GDP), 10% of total agricultural production and 60% of total export earnings for the past three to four decades (Mekonen, 2009; Zerihun, 2008).

Among the many legends that have developed concerning the origin of coffee, one of the most popular accounts is that of Kaldi, an Abyssinian goatherd. One day he observed his goats behaving in abnormally exuberant manner, skipping, rearing on their hind legs and bleating loudly. He noticed they were eating the bright red berries that grew on the green bushes nearby. And so the global love affair with coffee began in what is now known as Ethiopia. Whether the fable is true or not is, to a large extent now immaterial as experts are in agreement that the deoxyribonucleic acid (DNA) of coffee can be traced back to Ethiopia (Demeke, 2007).

Settled agriculture began in Ethiopia some 2000 years ago. Since time immemorial, coffee Arabica has been grown in the wild forests of the south-western massive highlands of the Kaffa and Buno districts of the country. Ethiopia is the primary center of origin and genetic diversity of the Arabic coffee plant, earlier known as jasminum arabicum laurifolia (Tora, 2009). The word

”coffee” comes from the name of a region of Ethiopia where coffee was first discovered, namely ‘Kaffa’. The name ‘Kaffa’ is inherited from the hieroglyphic nouns ‘KA’ and ‘AFA’. ‘KA’ is the name of God and ‘AFA’ the name of earth and all plants that grow on earth. So the meaning of Koffee (coffee) from its birth place bells on as the land or plant of God. Botanically, coffee belongs to the family Rubiaceae in the genus coffee. Although the genus coffee includes four major subsections (Chevalier, 1947), 66% of the world production mostly comes from coffee Arabica and 34% from coffee canophora, pierreex and Froehner (robusatype) respectively (Mekuria, 2004).

Coffee is one of the highest valued commodities in international trade, with annual export revenues worth around $10 billion on average and annual retail sales of approximately $50 billion. It is a highly labor-intensive industry employing an estimated 100 million people in over 60 developing countries, where it is often a vital source of export revenues and income to producers, many of whom are smallholders. The dependence on coffee is greatest in Africa, where there are some 25 coffee exporting countries. There are two major varieties of coffee, namely coffee Arabica and robusta coffee. Ethiopia produces only Arabica coffee, which is believed to have originated in the rain forests of south western Ethiopia.

More genetically diverse strains of coffee Arabica exist in Ethiopia than anywhere else in the world, which has lead botanists and scientists to agree that Ethiopia is the center for origin, diversification and dissemination of the coffee plant (Bayetta, 2001). Over a million coffee farming households and about 25% of the total population of the country are dependent on production, processing, distribution, and export of coffee. Coffee is the major agricultural export crop, providing currently 35% of Ethiopia’s foreign exchange earnings, down from 65% a decade ago because of the slump in coffee prices since the mid 1990s. The low level productivity of coffee in Ethiopia had been largely attributed to the lack of cultivars suited to different agro-ecologies, traditional cultural practices, agedness of coffee trees, and pest/disease problems. In an attempt to address these complex problems, the national coffee research center has developed local land race development program (Ministry of Agriculture & Rural Development, 2000).

Coffee is the most widely consumed stimulant beverage in Ethiopia and about 50% of the total produce is consumed locally. The annual per capital consumption of coffee in Ethiopia is about 2.4 kilograms. This is comparable to the consumption level of the leading coffee consuming countries. One can bravely say that coffee in Ethiopia is not produced only for export purposes, but also as highly prized and much favored traditional beverages (Ministry of Agriculture & Rural Development, 2000). In Oromo culture, for instance, coffee has a deep rooted culture, where one can observe diverse uses of coffee. Coffee beans are roasted and mixed with butter, and consumed as food on long journeys and on different culture festivities and is called 'Buna Qalaa'. Coffee leaves are also consumed as tea, beside the normal coffee brew. Similarly, coffee leaf is cooked with different hot spices and consumed as soup, called chemo in many ethnic groups in southern Ethiopia.

Given the importance of coffee for environment, economy and culture of the nation, there is a need for research and development to fully exploit the potential that exists in the country. For this, partnership between research organizations and end users like private companies is also of paramount importance (Ethiopian Coffee Forest Forum and Robera P.L.C., 2007).

Worldwide production of coffee grew erratically from 2003 to 2007/2008 to approximately 118 million bags of coffee, while worldwide import demand for coffee has grown at a steady 2.3%

over that same time period to roughly 99 million bags. Unfortunately, throughout the 2008/2009 growing season, exporters began to hold onto supplies of beans due to expectations of currency depreciation as well as the global decline in coffee prices. The effect of this was swift and dramatic resulting in what appeared to be a collapse in the Ethiopian coffee export market through the end of the 2008 season. Producers believed that the government would try to build foreign currency reserves, thus depreciate the Birr. Ethiopia is struggling to raise hard currency reserves due to high demand for energy imports, lack of port access and few exportable commodities besides coffee. Additionally, over the same time period declines in global coffee prices incentivized local producers to hold their supplies to drive up prices and wait until currency devaluation made it favorable to sell into international markets. The sum of these beliefs caused vast delays in the shipment of product (Zakaria, 2000).

As data from the Ethiopian commodity exchange development indicate, Ethiopian producers recently received the equivalent of USD 0.48/kg, while their production costs may have been as high as USD 50.57/kg thereby discouraging production. Moreover, prices paid to producers by state trading authorities and service cooperatives were low in comparison to prevailing world market prices. Ethiopian coffee export prices and producers' prices have been closely correlated. Thus, an increase in export earnings can motivate farmers to expand marketed production. Under the conditions where both producers and exporters obtain economic profit from exports, Ethiopia could also increase export earnings by re-allocating coffee production among different markets (Zakaria, 2000).

This study is concerned with modeling multivariate time series data using VAR and co-integration analysis, which consists of simultaneous observations on four related variables of interest. Our main variables of study are volume, FOB price, producer price, and world price of export of coffee Arabica in Ethiopia. We analyze data and develop a multivariate time series (MVTS) model which can adequately describe the innate relationship among the four study variables.

1.2 Statement of the problem

Several studies about coffee export and related variables are done utilizing univariate time series analysis. Univariate time series analysis is important but it is inadequate for the analysis of interaction and co-movement of several time series simultaneously. In contrast, 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 will examine the different statistical techniques for analyzing multivariate time series data which consist of monthly volume of export of coffee, FOB price of coffee export, producer price, and world price of coffee. In the Ethiopian coffee export sector it is clear that studying the relationship among the above variables is very important to improve the quality and quantity of coffee export. The following research questions will be addressed:

1. What kind of relationships exists among volume, FOB price, producer price and world price of export of coffee in the Ethiopian context?
2. Which multivariate time series analysis model best describes the relationship among the study variables and can be used for forecasting purpose?
3. Is volume and FOB price of export of coffee affected by producer price and world price? If so, what kind of effect do they have?

1.3 Objective of the study

1.3.1 General objective

The general objective of this study is to develop a multivariate time series model which explains the relationship among volume and FOB price of export of coffee, producer price and world price in Ethiopia.

1.3.2 Specific objectives

- To show the various statistical techniques of analyzing multivariate time series data.
- To examine the relationships among volume and FOB price of export of coffee, producer price and world price in Ethiopia using co-integration and vector error correction techniques.
- To forecast the volume and price of coffee using the appropriate fitting model.

1.4 Significance of the Study

There are few studies that have been designed to identify empirically the relative impact of external and domestic factors contributing to volume of coffee export in Ethiopia. The results of this paper could help understand factors that govern the volume of coffee export in Ethiopia. Moreover, this study could be a good stepping-ground for other studies on agricultural marketing and marketing cooperatives. In brief, this research would be useful to cooperative societies, researchers, and governmental and nongovernmental organizations for policy formulation, planning and development of agricultural marketing for both coffee exporters and producers in Ethiopia, which helps to achieve the development goals of the country.

1.5 Limitation of the Study

Due to unavailability of data, some variables which are expected to affect the volume of coffee export such as monthly auction price and monthly gross domestic product are not analyzed in this study.

1.6 Organization of the study

The study is organized into five chapters. Following the introductory chapter one, chapter two gives a review of the literature on price-volume relationship of coffee export. Chapter three discusses the methodology and sources of data used in the study. Chapter four deals with model estimation and interpretation of results. Finally, chapter five presents conclusions of the study.

2. Literature Review

2.1 Ethiopian Coffee Market

In Ethiopia, the coffee industry affects the livelihoods of approximately one quarter of the population, providing jobs for farmers, local traders, processors, transporters, bankers and exporters. The various taxes on the crop are also important sources of government revenue (CTA, 1999; CTA, 2002). Ethiopia is the largest coffee producer and exporter in Africa, followed by the Ivory Coast and Uganda. It has been contributing more than 4% of world coffee production and exports since 2000 (ICO, 2006). About one million small-scale farmers produce over 95% of Ethiopia's coffee on very small plots of land. Farmers in major coffee-producing areas are heavily dependent on coffee income as the main source of their livelihoods. In slack seasons when farmers lack cash income, coffee trees serve as collateral to obtain credit from informal moneylenders. In addition, a large proportion of coffee farmers are food deficit and depend on purchased food grains for family consumption (Zerihun, 2008).

Despite its economic and social importance for the Ethiopian economy, the performance of the coffee sub-sector has remained unsatisfactory. No significant change in mode of production and processing has taken place for several decades. Amongst other things, imperfection in the policy market and the low base of market infrastructure were cited as major causes of weak performance (IFPRI, 2003). During the military regime (1974 - 1991) the Ethiopian Coffee Marketing Corporation (ECMC), a state monopoly, operated using fixed price arrangements and handled about 80% of the entire coffee trade. Private traders had a limited role in both domestic and export marketing. Similarly, coffee farmers also had very limited power when it came to securing their proper share of the market price.

According to various researchers who studied the performance of this subsector prior to 1992 (Gebremariam, 1989; Mulat, 1979; ULG & Food Study Group, 1987), coffee growers in

Ethiopia have historically received a very small share of the export price, receiving between 30 and 45% of the FOB price, while competitors from Brazil, Colombia, Kenya and India were receiving above 80% of the FOB price (ICO/CFC, 2000).

Since 1992 the Ethiopian government, pressured by the World Bank and the IMF's Structural Adjustment Program (SAP), has introduced various policy measures aimed at encouraging private traders to participate in a liberalized coffee market at all levels. These include the devaluation of the Ethiopian birr from 2.07 to 5.1 birr/$ in October 1992, foreign exchange auctioning, simplification of entry barriers (Pro. No., 70/1993), consolidation of all taxes and duties levied on coffee exports into a single tax family (Pro. No. 99/1998), abolition of the quota system at auction, allowing private traders to trade washed coffees and allowing suppliers and exporters to sell coffee domestically at market-determined prices (IMF, 2008a; IMF, 2008b).

These coffee market reform measures aimed at opening the domestic and export coffee markets were envisaged to present coffee producers with 'right prices' as a means of stimulating productivity and growth (i.e. bringing producer prices closer to international levels and reducing disincentives emanating from policy and non-policy imperfections at the production and marketing levels). It was hypothesized that it would improve transmission of world and auction market price signals to domestic growers, which in turn was expected to improve the supply and quality of coffee.

The deregulation of the marketing system opened up opportunities for the private sector to participate in all tiers of the marketing chain. As a result, the primary coffee marketing chain is characterized by a large number of buyers and sellers with relatively better levels of competition compared to the pre-reform period. In 2005/06 about 1,080 active wholesalers and over 89 active exporters were participating in coffee marketing (Ben, 2004; AMPD, 2006). This increase in private participation raised the coffee supply to the auction market from 60,000 tons in 1991 to 221,000 tons in 2005/06. However, as some anecdotal information on the post-reform coffee marketing system in Ethiopia shows, this has resulted in the concentration of power at the export market, mounting illegal trade across borders, unhealthy competition in the primary and auction markets, and high transaction costs (AMPD, 2006; Petit, 2007).

2.2 Empirical Literature Review

Brazil and Colombia have been the top world coffee producers for most of the twentieth century. This situation has changed recently with the extremely fast growth of coffee production in Vietnam. In 1999/2000, Colombia was replaced by Vietnam as the world's second largest producer. In 2010, Vietnam produced 17.5 million 60kg bags of coffee nearly double that of Colombia at 8.8 million 60 kg bags. Coffee producers in Africa, for their part accounted for about 12% of global supply and approximately 11% of global exports of the product for the 2009/10 production season. Africa's exports in recent times have been comparable to those of Indonesian's, which is the fourth largest world producer of the commodity.

Kang and Kennedy (2009) studied the effect of coffee price, production volume, real gross domestic product (GDP), and exchange rate on export volume using annual data from 1977 to 2007 in five countries (i.e. Brazil, Colombia, Vietnam, Indonesia, and Cote d'Ivore). They employed both the method of robust ordinary least square (OLS) and generalized method of moments (GMM) to analyze the data. They found a negative relationship between export volume and export price. That is, exporting countries tend to increase their exporting volumes even if export prices decrease. This causes decreased profit in exporting countries and a “coffee crisis” for producers. Empirical results suggest that the world coffee market is characterized by "coffee paradox" (Increase of export volume contributes to decrease of export coffee price. However, decrease of export coffee price causes increase of retail coffee price in importing countries) due to different changes between retail and export prices of coffee, and that it is the existence of market power in importing countries that is the main contributor to the condition of price asymmetry.

Arnold (2011) analyzed the impact of policy reform in Colombia, Ghana and Ivory Coast. A key question is whether producers of coffee beans received a higher share of the international price after reforms, as was the desired policy outcome. Using the error correction model (ECM) and co-integration analysis, he examined price transmission from the world coffee market to local market. He found that the reforms induced stronger relationships among domestic and international prices in Colombia, but not in Ghana or the Ivory Coast. The institutional arrangements coordinating the domestic coffee system and contract enforcement may help explain the differences.

Ekaterina (2005) evaluated the impact of coffee sector reforms during late 1980s and early 1990s on coffee growers in main coffee producing countries. The data for this study were monthly world market prices and prices paid to producers in approximately 20 coffee exporting countries collected by the International Coffee Organization (ICO). In nine out of 14 countries investigated the grower prices were integrated with the world market prices in the long- run. Earlier evidence suggests that the reforms increased the share of producer prices in the world price of coffee. This hypothesis is tested in the study with the help of co-integration analysis, and the results show that in most countries the long-term producer price share has indeed increased substantially after the liberalization. Moreover, the results suggest that the reforms induced a closer co-integrating relationship between grower prices and world market prices. Finally, estimation of an error-correction model reveals that short-run transmission of price signals from the world market to domestic producers has improved, such that domestic prices adjust faster today to world price fluctuations than they did prior to the reforms. However, there is some evidence of asymmetries in the way positive and negative world price changes are transmitted to domestic markets.

Kuhlin et al. (2009) studied the market power of traders/exporters on the coffee auctions in Kenya and Tanzania by estimating the Lerner Index of monopsony power as well as looking at pass-through from the terminal market to the local auctions. The Lerner Index is estimated by using a structural model for the producer side of the coffee supply chain and error correction models (ECM) are estimated to determine how fast and complete traders/exporters pass-through cost changes to local traders. According to their findings, both the market power of traders/exporters on the coffee auctions and the Lerner Index for both Kenya and Tanzania indicate that the markets are very close to being perfectly competitive. Further, when estimating ECMs they found that changes in the terminal market price and in the foreign exchange market are transmitted extremely fast to the local auctions. Hence, they find no reason to believe that the large multinational companies use their market power to squeeze local traders in Kenya and Tanzania.

Lindsey (2010) studied a Granger causality analysis to explore a potential causal relationship between the increase in Vietnamese coffee production and the decline in world coffee price. The analysis includes both forward and reverse causality. General micro economics predicts the existence of forward causality, where an increase in supply leads to a reduction in price. Reverse causality posits that the decrease in world coffee price causes an increase in Vietnamese coffee production. Although this is an illogical pattern since a decrease in price does not typically encourage production due to the decrease in potential profits, Vietnam's unique coffee export pattern provides motivation to test causality in both directions. Each type of causality forward and reverse has a specific regression model and thus requires a separate hypothesis test. Following the methods of Dodaro (1993), a Granger causality analysis between Vietnamese coffee exports and ICO composite price produced neither forward nor reverse causality between these two variables. That is, the results suggest that there is not enough evidence to conclude that the increase in Vietnamese coffee production caused the decrease in world coffee price (for forward causality) and also there is not enough evidence to conclude that the growth of ICO composite price caused the growth of Vietnamese coffee production (for reverse causality). This analysis originally predicted an insignificant test statistic in the reverse causality analysis due to the fact that the causal pattern is illogical according to any current economic theories.

Mengistu (2010) analyzed the price transmission system on the level of the producer, the auction market and the foreign (international) market in the Ethiopian coffee market in the short as well as in the long run. The study covers the periods from December 1991 to April 2009. Using the VECM, the study was an attempt to examine the three most important elements in price transmission analysis. These are causality, speed of adjustment and asymmetric response. The finding indicates that there is a long run co-integration between these three markets. The long run analysis further shows that if there is a 10% change in auction market, the long run impact on the producer price is 9.56%. This implies that these two markets move closely together in the long run. On the other hand, a 10% change in foreign price has only 6.5% and 5.7% impact on the auction and producer market, respectively, in the long run. The result on the VECM indicates that the producer market and the foreign market are poorly dependent and have very weak relationships to one another as compared to auction to the foreign market.

Worako et al. (2008) studied the producer, auction and FOB prices of coffee. Each price series is based on monthly price from October 1992 to September 2006. Their finding indicated that there is a stronger long-run relationship among grower, wholesaler and exporter prices. The estimation of the error correction model (ECM) shows that the short-run transmission of price signals from world to domestic markets has improved, but has remained weak in both auction-to-world and producer-to-auction markets. This might be explained by the weak institutional arrangement coordinating the domestic coffee system and contract enforcement. In general, the domestic price adjusts more rapidly to world price changes today than it did prior to the reforms. However, there is an indication that negative price changes transmit much faster than positive ones.

Zerihun et al. (2008) studied the interrelationships among producer, auction and world prices based on monthly nominal time series national price data which include producer price, auction price and world price ranging from October 1992 to September 2006 in Ethiopia. Using the VAR and VECM they found that there is a unidirectional transmission of shocks from the world price to the auction price and then to the producer price; asymmetries in price transmissions and adjustments in the auction market; weak interrelationship between producer and world prices causing producer price to be less responsive to changes in the world price. In general, their results imply that coffee growers will benefit little from positive changes in the world price compared with participants in the auction markets. This is also true given the presence of information asymmetry in the coffee value chain characterized by increasing level of market concentration.

Tadese et al. (2008) studied the price of the producer, auction and Free-On-Board price (FOB) that extend from October 1992 to September 2006, and the price data includes four major Ethiopian coffee types by original growing region (Sidama, Harar, Wollega and Jimma). Using ECM they found that there is a strong long-run relationships among growers, wholesaler and exporter prices. The estimation of the ECM shows the transmission of price shocks from the world price to the auction price and then to the producer price. This asymmetry in price transmission could be the results of the higher demand that coffee commands in the domestic market.

3. DATA AND METHODOLOGY

3.1 Data

The data for the study consists of four variables. The data obtained were collected on monthly basis from September 2006 to July 2011. A brief description of each is presented below.

i. Volume (net weight) of Export of Coffee (VOL): is the sum of net weight of all coffee Arabic that is exported monthly to the destination countries. The source of the data is the Ethiopian Revenue and Customs Authority (ERCA) planning, monitoring and evaluation section.

ii. FOB Price of Coffee Export (FO*B):* FOB price here refers to the price of total volume (net weight) of monthly export of coffee which includes price of coffee, cost of transportation to port, plus cost of loading onto ship. The unit of measurement is USD per kilogram and the source of data is the ERCA planning, monitoring and evaluation section.

iii. Producer Price (PP): this is the price at which the producers (owners) sold coffee to the exporters. The unit of measurement is USD per kilogram and the source of data is the Central Statistical Agency (CSA).

iv. World Coffee Price (WOP): This is the monthly price of coffee over the world and its unit of measurement is USD per kilogram. The source of data is the International Coffee Organization (ICO) website.

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 methodology adopted in this study follows 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 elaborate theory-based simultaneous equations models. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model.

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

3.2.2 Stationarity

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

3.2.2.1 Covariance (Weak) Stationarity

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

1. $\mathrm{E}(Y_t)$ is constant
2. $\mathrm{Var}(\mathrm{Y_t})$ is constant and
3. For any t, $h \geq 1$, $Cov(Y_t, Y_{t+h})$ depends only on h and not on t.

3.2.2.2 Strong (Strictly) Stationarity

A strictly stationary time series is one for which the probabilistic behavior of every collection of values $\{y_{t_1}, y_{t_2}, \cdots, y_{t_k}\}$ is identical to that of the time shifted set $\{y_{t_{1+h}}, y_{t_{2+h}}, \cdots, y_{t_{k+h}}\}$.

That is,

$$P\{y_{t_1} \leq c_1, \cdots, y_{t_k} \leq c_k\} = P\{y_{t_{1+h}} \leq c_1, \cdots, y_{t_{k+h}} \leq c_k\},$$

$h = 0, \mp 1, \mp 2, \cdots$.

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

3.2.2.3 Differencing

Differencing of a series can transform a non-stationary series to a stationary series. Hence, differencing turns out to be a useful ‘filtering’ procedure in the study of non-stationary time series. The difference operator ∇ is defined by:

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

Note that

$$\nabla y_t = (1 - B)y_t,$$

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

$$\nabla^n y_t = (1 - B)^n y_t$$

3.2.2.4 Integration (I (d))

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

3.2.3 The Stationary Vector Autoregressive Model

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

$$Y_t = c + \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \ldots + \pi_p Y_{t-p} + \varepsilon_t \text{ , } t = 1, 2, \ldots \text{ T} \quad \text{.......................(3.1)}$$

where c denotes an $(n \times 1)$ vector of constants and π_j an $(n \times n)$ matrix of autoregressive coefficients, j = 1, 2,..., p and ε_t is an $(n \times 1)$ unobservable zero mean white noise vector process (serially uncorrelated) with time invariant covariance matrix Σ:

$$\mathrm{E}(\varepsilon_t) = 0 \text{ and } \mathrm{E}(\varepsilon_t \varepsilon_s') = \begin{cases} \Sigma & \mathrm{t = s} \\ 0 & t \neq s \end{cases} \quad \text{...(3.2)}$$

with Σ an $(n \times n)$ symmetric positive definite matrix.

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

$$\pi(L) Y_t = c + \varepsilon_t \quad \text{...(3.3)}$$

where $\pi(L) = I_n - \pi_1 L - \ldots - \pi_p L^p$.

The $VAR\ (p)$ is stable if the roots of

$$\det\left(I_n - \pi_1 z - \ldots - \pi_p z^p\right) = 0 \text{ ....(3.4)}$$

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

$$u = (I_n - \pi_1 - \ldots - \pi_p)^{-1} c$$

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

$$\mathrm{Y_t - u = \pi_1(Y_{t-1} - u) + \pi_2(Y_{t-2} - u) + \ldots + \pi_p\left(Y_{t-p} - u\right) + \varepsilon_t} \text{ ......(3.5)}$$

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

$$Y_t = \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \ldots + \pi_p Y_{t-p} + \Phi D_t + G X_t + \varepsilon_t \text{ ....(3.6)}$$

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.

3.2.4 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 Newbold (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, 1981), and the Phillip-Perron (PP) test due to Phillips (1986) and Phillips and Perron (1988). The following discussion outlines the basic features of unit root tests (Hamilton, 1994).

Consider an AR (1) process:

$$Y_t = \rho Y_{t-1} + X_t'\delta + \varepsilon_t \quad \text{...(3.7)}$$

where X_t are optional exogenous regressors which may consist of constant or a constant and trend, ρ and δ are parameters to be estimated and ε_t is assumed to be white noise.

If $|\rho|\geq 1$, Y is a non-stationary series and the variance of Y increases with time and approaches infinity. On the other hand, if $|\rho|<1$, 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:

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

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

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

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

$Y_t - Y_{t-1} = (\rho - 1)Y_{t-1} + X_t'\delta + \varepsilon_t$. This can be rewritten as:

$$\Delta Y_t = \alpha Y_{t-1} + X_t'\delta + \varepsilon_t \quad \text{.........}(3.8)$$

where $\alpha = \rho - 1.$ 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:

$$t_\alpha = \hat{\alpha}/_{(se(\hat{\alpha}))} \quad \text{...(3.10)}$$

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

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:

$$\Delta Y_t = \alpha Y_{t-1} + X_t' + B_1 \Delta Y_{t-1} + B_2 \Delta Y_{t-2} + \ldots + B_p \Delta Y_{t-p} + U_t \quad \text{.....(3.11)}$$

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 α 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.

3.2.4.2 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 autoregression 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

$$\nabla Y_t = a_0 + a_2 t + \pi Y_{t-1} + \varepsilon_t. \quad \text{..........}(3.12)$$

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

$$t_{\pi=\hat{\pi}} = {}^{\hat{\pi}}/_{(se(\hat{\pi}))}$$

where $\hat{\pi}$ 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:

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

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

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

$$\sigma^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} \mathrm{E}(\varepsilon_t^2)$$

$$\lambda^2 = \lim_{T\to\infty} \sum_{t=1}^{T} \mathrm{E}(T^{-1} S_T^2)$$

where $S_T = \sum_{t=1}^{T} \varepsilon_t$. The sample variance of the least square residual $\hat{\varepsilon}_t$ is a consistent estimate of σ^2, and the Newey-West long-run variance estimate of ε_t using $\hat{\varepsilon}_t$ is a consistent estimate of λ^2.

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.

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

$$IC(p) = ln\left|\hat{\Sigma}_p\right| + C_T \, . \, \varphi(n.p) \quad \text{.......}(3.13)$$

where

IC = Information Criteria, $\hat{\Sigma}_p = T^{-1} \sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t'$ is the residual covariance matrix from a

VAR (p) model, C_T is a sequence indexed by the sample size T, and $\varphi(n.p)$ 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):

$$AIC(p) = ln\left|\hat{\Sigma}_p\right| + \frac{2}{T}\, pn^2 \quad \text{.......}(3.14)$$

$$BIC(p) = ln\left|\hat{\Sigma}_p\right| + \frac{\ln T}{T}\, pn^2 \quad \text{.......}(3.15)$$

$$HQ(p) = ln\left|\hat{\Sigma}_p\right| + \frac{2 \ln \ln T}{T}\, pn^2 \quad \text{.......}(3.16)$$

The AIC criterion asymptotically overestimates the order with positive probability (not zero), where as 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.

3.2.6 Co-integration Analysis

3.2.6.1 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 (co-integrating) 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 Cointegration 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 a finite-order vector auto regressions (VARs) and is easily calculated for such systems. Johansson's procedure allows to deal with models with several endogenous variables. The procedure begins with unrestricted VAR involving potentially non stationary variables. A key aspect of the approach is isolating and identifying the co-integrating combinations among a set of k integrated variables and incorporating them into an empirical model.

The purpose of the co-integration test is to determine whether a group of non-stationary series is co-integrated or not. Tests for co-integration assume that the co-integrating vector is constant during the period of study. In reality, it is possible that the long-run relationship between the underlying variables change (shifts in the co-integrating vector can occur). The 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:

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

where Π and the short-run parameter Γ_i, i= 1, 2, …, p-1 are $p \times p$ 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:

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

where α and β are $p \times r$ matrices of full rank. β contains the cointegration 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.

Testing for co integration 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:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + BX_t + \varepsilon_t \quad \text{.............................(3.19)}$$

where Y_t is a p-vector of non-stationary I(1) variables, X_t is a d vector of deterministic variables and ε_t is a vector of innovations.

We may re-write this VAR as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_\mathrm{i} \, \Delta Y_{t-i} + BX_t + \varepsilon_t \quad \text{... (3.20)}$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I, \; \Gamma_\mathrm{i} = -\sum_{j=i+1}^{p} A_j \quad \text{...(3.21)}$$

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank r < p, then there exist $p \times r$ 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 co-integrating 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 $\hat{\lambda}_i$, i = 1, 2, ..., k to be a complex modulus of eigenvalues of $\widehat{\Pi}$ and let them be ordered such that $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_n$. The trace statistic is computed as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \log\left[1 - \hat{\lambda}_i\right] \quad \ldots\ldots(3.22)$$

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, $\ldots n - 1$. This test statistic is computed as:

$$\hat{\lambda}_{max}(r, r+1) = -T \log\left(1 - \hat{\lambda}_{r+1}\right) \quad \ldots\ldots(3.23)$$

where $\hat{\lambda}_{r+1}$ is the $(r+1)^{th}$ ordered eigenvalue of Π, and T is the sample size. The critical values tabulated by Johansen and Juselius (1990) will be used for these tests. Neither of these tests statistics follows a chi square distribution in general. The asymptotic distributions of the test statistics (3.22) and (3.23) are not normal. Asymptotic critical values for the $\hat{\lambda}_{trace}$ and $\hat{\lambda}_{max}$ statistics have been calculated by Monte Carlo simulation and can be found also in Johansen and Juselius (1990) and are given also by most econometric software packages. Since the critical values used for the maximum eigenvalue and trace test statistics are based on a pure unit-root assumption, they will no longer be correct when the variables in the system are near- unit-root processes.

3.2.7 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).

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_{\mathrm{i}} \, \Delta Y_{t-i} + BX_t + \varepsilon_t \quad \text{...(3.24)}$$

where

$\Pi = -I_n + \sum_{i=1}^{p} A_i,\ \Gamma_{\mathrm{i}} = -\sum_{j=i+1}^{p} A_j$ 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.

3.2.8 Model Checking

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

3.2.8.1 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

$$Q = T\hat{c}'\hat{\Sigma}^{-1}\hat{c} \quad \text{……} \quad (3.25)$$

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

Portmanteau autocorrelation test

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

$$\hat{C}_j = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_{t-j} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.26$$

where $\hat{\varepsilon}_t = \Delta y_t - \pi Y_{t-1} - \sum_{i=1}^{p-1} \Gamma_{\mathrm{i}} \Delta Y_{t-i} - BX_t$ where $\hat{\varepsilon}_t$ is an estimated residual.

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

$$H_0 : \mathrm{E}(\varepsilon_t \varepsilon_{t-i}') = 0 \text{ (i = 1, 2,...)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.27)$$

where the $\hat{\varepsilon}_t$'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's and has the form:

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

where

$$\hat{C}_j = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_{t-j} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.29)$$

$$\widehat{\Omega} = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t{}' \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.30)$$

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:

$$Q_p{}^* = T^2 \sum_{j=1}^{h} \frac{1}{T-j} tr(\hat{C}_j' \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}) \quad \text{...(3.31)}$$

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

$$\varepsilon_t = D_1 u_{t-1} + \ldots + D_h u_{t-h} + v_t \quad \text{...(3.32)}$$

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

H_0: $D_1 = \cdots = D_h = 0$ against

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

We use the Lagrange multiplier method to perform the test. The Lagrange Multiplier (LM) test for p^{th} order serial correlation is computed first by estimating an auxiliary regression where the OLS residuals are regressed on the variables in the original model plus *p* lagged residuals. The test statistic is either T times R^2 from the auxiliary regression or an F test that the coefficients on the lagged residuals are 0. This method is very useful for finding optimal estimates under constraint conditions. Under H_0, we only need to estimate the regular VAR model ($\varepsilon_t = v_t$). So the constrained case estimates are simple.

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

$$Q^*_{BG} = T\hat{\Upsilon}' \left(\hat{\Sigma}^{\Upsilon\Upsilon}\right)^{-1}\hat{\Upsilon} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.33)$$

where $\hat{\Upsilon}$ is the generalized least square estimator of Υ and $\hat{\Sigma}^{\Upsilon\Upsilon}$ is the part of

$$\left(\mathrm{T}^{-1}\sum_{t=1}^{T}\begin{bmatrix}\hat{U}_t \otimes I_k \\ \hat{\mathrm{z}}_{\mathrm{t}} \otimes I_k \\ \hat{\mathrm{z}}_{1\mathrm{t}}\end{bmatrix}\hat{\Omega}^{-1}\left[\hat{U}'_t \otimes I_k : \hat{\mathrm{z}}'_{\mathrm{t}} \otimes I_k : \hat{\mathrm{z}}'_{1\mathrm{t}}\right]\right)^{-1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.34)$$

corresponding to Υ.

here $\hat{\Omega} = \mathrm{T}^{-1}\sum_{\mathrm{t}=1}^{\mathrm{T}} \hat{\mathrm{u}}_{\mathrm{t}}\hat{\mathrm{u}}'_{\mathrm{t}}$ and, hence, $\hat{\Omega}$ Type equation here. is the residual covariance matrix estimator from the restricted auxiliary model. Therefore, under the null hypothesis it follows immediately from the above that for $h \rightarrow \infty$

$$Q^*_{BG} \xrightarrow{d} \chi^2(hk^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.35)$$

3.2.8.2 Normality of the Residuals

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

$$JB = T\left[\frac{\hat{b}_1}{6} + \frac{\hat{k}^2}{24}\right] \quad \ldots\ldots (3.36)$$

where $\hat{b}_1$ and $\hat{k}$ 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.

3.2.9 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:

$$Y_{T+1\backslash T} = C + \Pi_1 Y_T + \Pi_2 Y_{T-1} + \cdots + \Pi_p Y_{T-p+1} \quad \ldots\ldots (3.37)$$

for $T \geq p$.

Forecasts for longer horizons h (h-step forecasts) can be obtained using the chain-rule of forecasting as:

$$Y_{T+h\backslash T} = C + \Pi_1 Y_{T+h-1/T} + \ ... \ + \Pi_p Y_{T+h-p\backslash T} \qquad (3.38)$$

where $Y_{T+j\backslash T} = Y_{T+j}$, for $j \leq 0$.

The h-step forecast errors may be expressed as:

$$Y_{T+h} - Y_{T+h\backslash T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s} \qquad (3.39)$$

where the matrices Ψ_s are determined by recursive substitution:

$$\Psi_s = \sum_{j=1}^{p-1} \Psi_{s-j} \Pi_j \qquad (3.39)$$

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

$$\Sigma(h) = MSE\left(\sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s}\right)$$

$$= \sum_{s=0}^{h-1} \Psi_s \Sigma \Psi_s' \qquad (3.40)$$

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:

$$\hat{Y}_{T+h/T} = \hat{\Pi}_1 \hat{Y}_{T+h-1/T} + \dots + \hat{\Pi}_p \hat{Y}_{T+h-p/T} \quad \text{...(3.41)}$$

where $\hat{\Pi}_j$ are the estimated parameter matrices. The h-step forecast error is given by:

$$Y_{T-h} - \hat{Y}_{T+h/T} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{T-h-s} + (Y_{T-h} - \hat{Y}_{T+h/T}) \quad \text{......................(3.42)}$$

and the term $Y_{T+h} - \hat{Y}_{T+h/T}$ 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:

$$\hat{\Sigma}(h) = \Sigma(h) + MSE\left(\sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s}\right) \quad \text{...(3.43)}$$

In practice, the second term $MSE\left(\sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s}\right)$ is often ignored and $\hat{\Sigma}(h)$ is computed using [3.43] as:

$$\hat{\Sigma}(h) = \sum_{s=0}^{h-1} \hat{\Psi}_s \hat{\Sigma} \hat{\Psi}_s' \quad \text{...(3.44)}$$

with $\hat{\Psi}_s = \sum_{j=1}^{s} \hat{\Psi}_{s-j} \hat{\Pi}_j$.

Lütkepohl (1991) gives an approximation to $MSE\left(\sum_{s=0}^{h-1} \Psi_s \varepsilon_{T+h-s}\right)$ which may be interpreted as a finite sample correction to [3.44].

3.2.10. 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:

$$\hat{\varepsilon}_{jt} = Y_{jt} - F_{jt} \quad \text{......(3.45)}$$

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

Usually F_{jt} is calculated using data $Y_{j1}, Y_{j2}, \ldots Y_{jt-1}$. It is a one step forecast because it is forecasting one period ahead of the last observation used in the calculation. Therefore, we describe $\hat{\varepsilon}_t$ 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:

$$Mean\ Error\ (ME) = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_{jt} \quad \text{......(3.46)}$$

$$Mean\ Absolute\ Error\ (MAE) = \frac{1}{T}\sum_{t=1}^{T} \left|\hat{\varepsilon}_{jt}\right| \quad \text{......(3.47)}$$

$$Mean\ Squared\ Error\ (MSE) = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_{jt}^{2} \quad \text{......(3.48)}$$

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

$$PE_t = \left(\frac{Y_{jt} - F_{jt}}{Y_{jt}}\right) \times 100 \quad \text{..........} (3.49)$$

Then the following two relative measures are frequently used:

$$Mean\ Percentage\ Error\ (MPE) = \frac{1}{T} \sum_{t=1}^{T} PE_t \quad \text{..........} (3.50)$$

$$Mean\ Percentage\ Absolute\ Error\ (MPAE) = \frac{1}{T} \sum_{t=1}^{T} |PE_t| \quad \text{..........} (3.51)$$

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. Theil's U can be estimated as:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_{jt} - F_{jt})^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n} {F_{jt}}^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n} {Y_{jt}}^2}} \quad \text{..........} (3.52)$$

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.

3.2.11 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.

3.2.11.1. 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 volume of coffee is found to be helpful for predicting the FOB price of the coffee export, then volume of export of coffee is said to Granger-cause FOB price of export of coffee. 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 $y_1 = (y_{1t}, y_{2t})'$, y_2 fails to Granger-cause y_1 if all of the p VAR coefficient matrices $\pi_1, \pi_2, \ldots \pi_p$ are lower triangular.

That is, the VAR (p) model has the form

$$\begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & 0 \\ \pi_{21}^1 & \pi_{22}^1 \end{pmatrix} \begin{pmatrix} Y_{1t-1} \\ Y_{2t-1} \end{pmatrix} + \ldots + \begin{pmatrix} \pi_{11}^p & 0 \\ \pi_{21}^p & \pi_{22}^p \end{pmatrix} \begin{pmatrix} Y_{1t-p} \\ Y_{2t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

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 χ^2 with p (= number of lags in the VAR) degree of freedom. A large value of wald statistic is an 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-causey_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.

3.2.11.2. 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:

$$Y_t = u + \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \ \dots \qquad \text{...(3.53)}$$

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_{ij}^{s}, of the vector Y_s as the dynamic multiplier or impulse response:

$$\frac{\partial y_{i,t+s}}{\partial \mathcal{E}_{j,t}} = \frac{\partial y_{i,t}}{\partial \mathcal{E}_{j,t-s}} = \psi_{ij}^{s} \text{ , i, j = 1, 2, ..., n} \qquad \text{...(3.54)}$$

However, this interpretation is only possible if $var(\varepsilon_t) = \Sigma$ 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

$$\left.\begin{array}{l} y_{1t} = c_1 + \gamma'_{11}Y_{t-1} + \ldots + \gamma'_{1p}Y_{t-p} + \eta_{1t} \\ y_{2t} = c_2 + \beta_{21}y_{1t} + \gamma'_{21}Y_{t-1} + \ldots + \gamma'_{2p}Y_{t-p} + \eta_{2t} \\ y_{3t} = c_t + \beta_{31}y_{1t} + \beta_{32}y_{2t} + \gamma'_{3p}Y_{t-1} + \ldots + \gamma'_{3p}Y_{t-p} + \eta_{3t} \\ \vdots \\ y_{nt} = c_1 + \beta_{n1}y_{1t} + \ldots + \beta_{n,n-1}y_{n-1,t} + \gamma'_{nt}Y_{t-1} + \ldots + \gamma'_{np}Y_{t-p} + \eta_{nt} \end{array}\right\} \ldots.(3.55)$$

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

$$\mathrm{B}Y_t = c + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots + \Gamma_p Y_{t-p} + \eta_t \quad \ldots\ldots(3.56)$$

where

$$B = \begin{pmatrix} 1 & 0 & \ldots & 0 \\ -\beta_{21} & 1 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -\beta_{n1} & -\beta_{n2} & \ldots & 1 \end{pmatrix} \quad \ldots\ldots(3.57)$$

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

$$y_1 \rightarrow y_2 \rightarrow \ldots \rightarrow y_n \quad \ldots\ldots(3.58)$$

The ordering means that the contemporaneous values of the variables to the left of the arrow

$\longrightarrow$ 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_1; 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

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

where $\Theta_0 = \mathrm{B}^{-1}$ is a lower triangular matrix. The impulse responses to the orthogonal shocks η_{jt} are

$$\frac{\partial y_{i,t+s}}{\partial \eta_{j,t}} = \frac{\partial y_{i,t}}{\partial \eta_{j,t-s}} = \theta_{ij}^{s}\text{ , i,j = 1,2, . . . n; s>0} \quad \text{...(3.60)}$$

where θ_{ij}^{s} is the $(i,j)^{th}$ element of Θ_s. A plot of θ_{ij}^{s} against s is called the orthogonal impulse response function (IRF) of y_i with respect to η_j. 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

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

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:

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

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

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

3.2.11.3. 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:

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

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

$$var\left(y_{i,T+h} - y_{i,T+\frac{h}{T}}\right) = \delta_{\eta 1}^{2} \sum_{s=0}^{h-1} (\theta_{i1}^{s})^2 + \ldots + \delta_{\eta n}^{2} \sum_{s=0}^{h-1} (\theta_{in}^{s})^2$$

where $\delta_{\eta j}^{2} = var(\eta_{jt})$. The portion of $var\left(y_{i,T+h} - y_{i,T+\frac{h}{T}}\right)$ due to shock η_j is then:

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

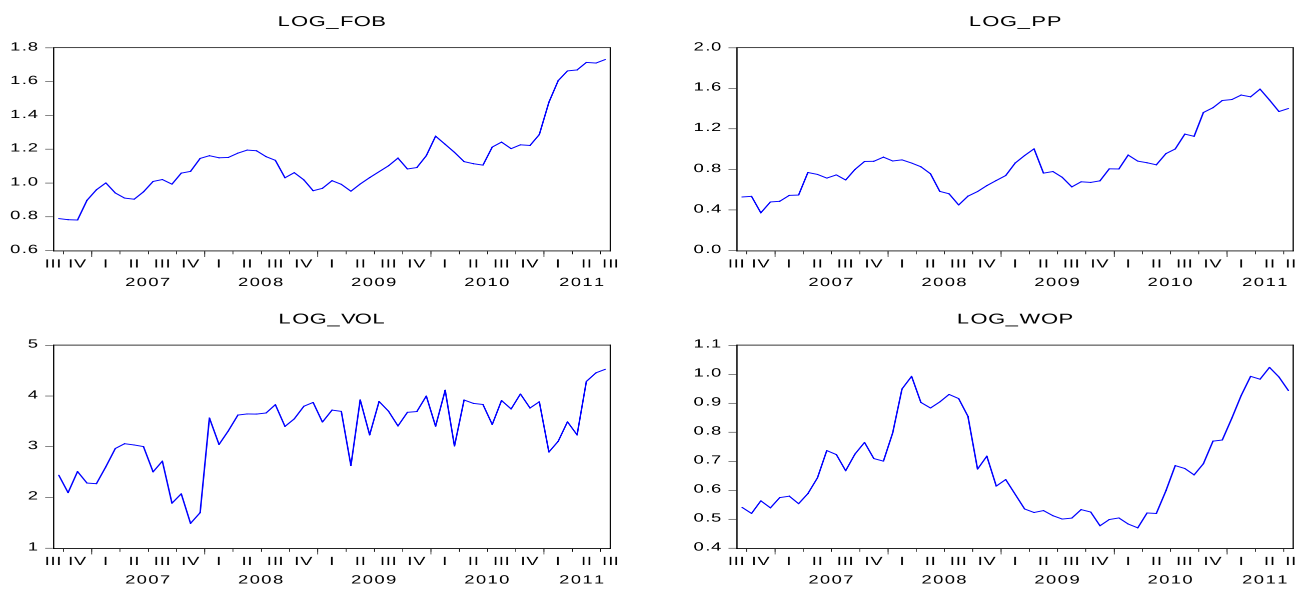
In a VAR with n variables there will be n^2 $FEVD_{i,j}(h)$ values. It must be kept in mind that the FEVD in [3.62] depends on the recursive causal ordering used to identify the structural shocks η_t and is not unique. Different causal orderings will produce different FEVD values.

4. ANALYSIS, RESULTS AND DISCUSSIONS

4.1 Descriptive Analysis and Time plot

EViews 7, the windows-based forecasting and econometric analysis package, was used to estimate the relationship among the volume of coffee export (VOL), free-on-board price (FOB), producer price (PP) and world price (WOP) in the case of Ethiopia. The data in this study consist of monthly volume (net weight) of coffee export (in million of kilograms), monthly free-on-board price (in USD per kilogram), monthly producer price (in USD per kilogram) and monthly world price of coffee (in USD per kilogram). The time period covered is from September 2006 to July 2011. 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 world price show an increasing trend over the study period. World price of coffee has declined in 2008-2009 and rose up then after.

Figure 4.1 Time plot of the original series



4.2. Unit Root Properties of Individual Series

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

$$\nabla \mathrm{log} y_t = \mu + \delta^* log y_{t-1} + \sum_{j=1}^{p} \phi_j \Delta \mathrm{log} y_{t-j} + u_t \text{ ....} 4.1$$

and the model with intercept and trend is given as:

$$\nabla \mathrm{log} y_t = \mu + \beta t + \delta^* log y_{t-1} + \sum_{j=1}^{p} \phi_j \Delta \mathrm{log} y_{t-j} + u_t \text{ ....} 4.2$$

The hypothesis to be tested is:

Ho: $\delta^* = 0$

H1: $\delta^* < 0$

The results of ADF and PP tests with intercept but no trend and with intercept and trend both at level and first difference for each series are presented in Tables 4.1 and 4.2, respectively. The critical values used for the tests are the McKinnon (1991) 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 four series.

Since the null hypothesis cannot be rejected, in order to determine the order of integration of the non stationary time series the same tests were applied to their first differences. The plots of the differenced series are presented in Figure A1 of Appendix B.

Table 4.1 Unit root test results (At level)

Series	**Level with Intercept**				**Level with Intercept and trend**			
	Test Statistic		**Prob.***		**Test Statistic**		**Prob.***	
	ADF	**PP**	**ADF**	**PP**	**ADF**	**PP**	**ADF**	**PP**
Log_FOB	-0.474	0.016	0.888	0.956	-1.548	-1.004	0.801	0.935
Log_PP	-0.665	-0.866	0.847	0.792	-2.355	-1.926	0.399	0.628
Log_VOL	-1.910	-2.887	0.326	0.053	-2.845	-3.726	0.188	0.228
Log_WOP	-0.947	-1.147	0.766	0.691	-1.035	-1.177	0.906	0.892
Critical value (1%)	-3.548				-4.121			

*MacKinnon (1996) one-sided p-values

The results in Table 4.2 below indicate that the null hypothesis of unit root is rejected for the first differences of the four 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 4.2: Unit root test results (after first difference)

Series	Level with Intercept				Level with Intercept and trend			
	Test Statistic		Prob.*		Test Statistic		Prob.*	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
D(Log_FOB)	-5.347	-5.207	0.000	0.000	-5.359	-5.217	0.000	0.001
D (Log_PP)	-4.013	-7.487	0.003	0.000	-3.919	-7.454	0.017	0.000
D(Log-VOL)	-12.594	-12.594	0.000	0.000	-12.478	-12.478	0.000	0.000
D(Log_WOP)	-6.126	-6.088	0.000	0.000	-6.066	-6.024	0.000	0.000
Critical value (1%)	-3.548				-4.121			

*MacKinnon (1996) one-sided p-value

4.3. VAR Model Specification

4.3.1. Estimating for 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 4.3.

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 four variable system for a sample period from September 2006 to July 2011. The general form of the VAR model is

$$logY_t = c + \pi_1 logY_{t-1} + \pi_2 logY_{t-2} + \ldots + \pi_p logY_{t-p} + \varepsilon_t \quad 4.3$$

where $logY_t = (Y_{1t},\ Y_{2t}, Y_{3t}, Y_{4t})$ where Y_1 = Log_FOB, Y_2 = Log_PP, Y_3 = Log_VOL and Y_4 = Log_WOP, t = 1, 2, … , 59.

Table 4.3: VAR lag order selection results

lag	AIC	SC	HQ
1	-6.611245	-5.874584	-6.327144
2	-6.432789	-5.106799	-5.921407
3	-6.383314	-4.467996	-5.644651

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

$$logY_t = c + \Pi_1 logY_{t-1} + \varepsilon_t \quad \text{...} \; 4.4$$

4.3.2 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 4.4 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 4.4: VAR Lag Exclusion Wald Tests

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	LOG_FOB	LOG_PP	LOG_VOL	LOG_WOP	Joint
Lag 1	1105.695 [0.000000]	656.2622 [0.000000]	66.78052 [1.08e-13]	541.9360 [0.000000]	2409.610 [0.000000]
df	4	4	4	4	16

The results of the estimated VAR model are presented in Table 4.5. The coefficients with "*" are statistically significant at the 5% level of significance.

Table 4.5: Vector Autoregression Estimates

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

	LOG_FOB	LOG_PP	LOG_VOL	LOG_WOP
LOG_FOB(-1)	0.870927*	0.020933	0.914548	-0.015494
	(0.06650)	(0.12017)	(1.29351)	(0.07082)
	[13.0968]	[0.17419]	[0.70703]	[-0.21876]
LOG_PP(-1)	0.129998*	0.980535*	-0.390259	0.076484
	(0.03712)	(0.06708)	(0.35670)	(0.03953)
	[3.50210]	[14.6173]	[-1.09409]	[1.93483]
LOG_VOL(-1)	-0.011674	0.012165	0.549766*	-0.016330
	(0.01097)	(0.01983)	(0.10542)	(0.01168)
	[-1.06403]	[0.61359]	[5.21478]	[-1.39762]
LOG_WOP(-1)	0.006877	-0.101081	-0.558686	0.905044*
	(0.05170)	(0.09343)	(0.49678)	(0.05506)
	[0.13303]	[-1.08194]	[-1.12461]	[16.4376]
C	0.083495	0.037356	0.368589	0.068686
	(0.04369)	(0.07896)	(0.41987)	(0.04653)
	[1.91091]	[0.47310]	[0.87787]	[1.47602]
R-squared	0.954259	0.925274	0.557524	0.910915
Adj. R-squared	0.950807	0.919635	0.524130	0.904191
Sum sq. resids	0.128774	0.420540	11.89079	0.146064
S.E. equation	0.049292	0.089077	0.473661	0.052497
F-statistic	276.4236	164.0656	16.69513	135.4840
Log likelihood	94.89564	60.57466	-36.34274	91.24205
Akaike AIC	-3.099850	-1.916368	1.425612	-2.973864
Schwarz SC	-2.922225	-1.738743	1.603236	-2.796239
Mean dependent	1.144778	0.877612	3.330044	0.692019
S.D. dependent	0.222240	0.314218	0.686630	0.169602
Determinant resid covariance (dof adj.)		1.11E-08		
Determinant resid covariance		7.75E-09		
Log likelihood		212.3919		
Akaike information criterion		-6.634203		
Schwarz criterion		-5.923705		

From the Table 4.5 we can see that free-on-board price is significantly explained by its own past and by producer price lagged by one period. This implies that a one dollar increase in a onetime lagged producer price leads to an increase of free-on-board price by an amount of USD 0.13. Volume of coffee export is significantly explained by its own past only. This indicates that Ethiopian coffee export has almost no significance relationship with producer price, free-on-board price and world price. World price and producer price are also significantly explained by their own past. This result is similar with Zerihun and Tadesse (2008) and Mengistu (2010) who found producer market and foreign marketto be poorly dependent. However, it is inconsistent with that of Kang and Kennedy (2009) who found a negative relationship between export volume and price.

4.3.3 Co integration analysis

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

The results of cointegration tests for Log_FOB, Log_PP, Log_VOL and Log_WOP are reported in Table 4.6. The trace statistic indicates that there is one cointegrating vector in the system at the 95 percent confidence level (estimated LR statistic, 50.69 > 47.86 at 95 percent critical value).

Table 4.6: Johansen Cointegration test results (assumption: linear deterministic trend)

Number of Cointegrating vector	Eigenvalue	Trace Test			Maximum Eigenvalue Test		
		Statistic	0.05 Critical Value	Prob.**	Statistic	0.05 Critical Value	Prob.**
None *	0.374670	50.69621	47.85613	0.0264	26.29067	27.58434	0.0725
At most 1	0.284347	24.40554	29.79707	0.1838	18.73533	21.13162	0.1048
At most 2	0.094000	5.670211	15.49471	0.7341	5.528069	14.26460	0.6742
At most 3	0.002535	0.142141	3.841466	0.7062	0.142141	3.841466	0.7062

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

FOB	PP	VOL	WOP
1.000000	-0.917434*	-0.013367*	-0.189454*
	(0.14929)	(0.00566)	(0.07642)
	[-6.14537]	[-2.36183]	[-2.47911]

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

The main purpose of cointegration 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. In our case, we found out that there is one stationary cointegrated series from the four non-stationary series. If we denote this stationary series by Z then using the results obtained from Table 4.6 we have the following.

$$Z_t = logFOB_t - \underset{(0.000)}{0.91743} logPP_t - \underset{(0.023)}{0.01337} logVOL_t - \underset{(0.017)}{0.18945} \log WOP_t - 0.654292$$

The result tells us that Z is stationary despite the fact that all the four 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 FOB, PP, VOL and WOP. This long-run model is:

$$logFOB_t = 0.654292 + \underset{(6.14537)}{0.91743} logPP_t + \underset{(2.36183)}{0.01337} logVOL_t + \underset{(2.47911)}{0.18945} \log WOP_t$$

From the long run equation above the value 0.92 indicates that a one dollar increase in producer price induces, on average, an increase of about \$ 0.92 in free-on-board price in the long-run. Similarly, a one dollar increase in world price leads to increase by about \$ 0.19 in the free-on-board price. On the other hand, a one kilogram increase in volume of coffee export induces on average an increase of about \$ 0.01 in free-on-board price in the long-run. This result is similar with Zerihun et al. (2008) in that there is a long-run relationship among grower, wholesaler and exporter price.

4.4. 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:

$$\Delta logY_t = \mu + \sum_{i=1}^{p} \Gamma_i \Delta \log Y_{t-i} + \alpha Z_{t-1} + \varepsilon_t \text{ .... } 4.5$$

where Z is the error correction term.

The responses of Log_FOB, Log_PP, Log_VOL and Log_WOP 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 price-volume relationship of coffee export. Coefficient estimates of the VEC model are presented in Table 4.8 below.

Table 4.7: Vector Error Correction Estimates

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

Cointegrating Eq:	CointEq1
LOG_FOB(-1)	1.000000
LOG_PP(-1)	-0.917434 (0.14929) [-6.14537]
LOG_VOL(-1)	-0.013367 (0.00566) [-2.36183]
LOG_WOP(-1)	-0.189454 (0.07642) [-2.47911]
C	-0.654292

Error Correction:	D(LOG_FOB)	D(LOG_PP)	D(LOG_VOL)	D(LOG_WOP)
CointEq1	-0.147401* (0.04205) [-3.50566]	-0.12819* (0.06309) [2.03186]	0.201158 (0.43728) [0.46003]	-0.126959* (0.04733) [-2.68258]
D(LOG_FOB(-1))	0.337402* (0.11963) [2.82038]	0.042776 (0.23641) [0.18094]	0.742911 (1.24410) [0.59715]	0.159835 (0.13465) [1.18704]
D(LOG_PP(-1))	-0.127559 (0.08182) [-1.55907]	0.005829 (0.16169) [0.03605]	-0.315149 (0.85088) [-0.37038]	-0.056057 (0.09209) [-0.60870]
D(LOG_VOL(-1))	-0.010053 (0.01207) [-0.83282]	-0.001074 (0.02386) [-0.04502]	-0.501495* (0.12554) [-3.99467]	0.011959 (0.01359) [0.88017]
D(LOG_WOP(-1))	0.082207 (0.11843) [0.69417]	-0.025611 (0.23404) [-0.10943]	0.027347 (1.23161) [0.02220]	0.064196 (0.13330) [0.48160]
C	0.014560 (0.00669) [2.17643]	0.014632 (0.01322) [1.10679]	0.052970 (0.06957) [0.76137]	0.004765 (0.00753) [0.63280]
R-squared	0.316351	0.107827	0.247042	0.190348
Adj. R-squared	0.249326	0.096856	0.173223	0.110970
Sum sq. resids	0.112447	0.439157	12.16182	0.142465
F-statistic	4.7199 (0.001)	2.2110 (0.067)	3.3465 (0.011)	2.39799 (0.049)
Log likelihood	96.62764	57.80009	-36.85413	89.88423
Akaike AIC	-3.179917	-1.817547	1.503654	-2.943306
Schwarz SC	-2.964859	-1.602489	1.718712	-2.728248

The coefficients in the second part of Table 4.7 are called the adjustment coefficients that measure the short-run adjustments of the deviations of the endogenous variables from their long-run values. Therefore, from this table we can see that free-on-board price is significantly affected by its lagged value in the short-run. On the other hand, the insignificant coefficient of world price implies there is no price transmission from world price to free-on-board price. Furthermore, 14.74% of the short run disequilibria in FOB is adjusted within one month. Similarly, 12.82% of the short run disequilibria in producer price is adjusted within one month. On the other hand, volume of coffee export is significantly affected by its lagged value in the short run. World price is affected by neither of FOB, PP and VOL in the short run and 12.69% of its short run disequilibria is adjusted within one month. This finding is inconsistent with Arnold (2011) who found that there is price transmission from world price to producer price in Colombia and consistent with the results he obtained in Ghana and Ivory Coast.

4.5 Structural Analysis

4.5.1 Granger Causality Test

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

Table 4.8 Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Probability
LOG_PP does not Granger Cause LOG_FOB	58	10.6358	0.0001
LOG_FOB does not Granger Cause LOG_PP		0.69051	0.5059
LOG_VOL does not Granger Cause LOG_FOB	58	0.80224	0.4538
LOG_FOB does not Granger Cause LOG_VOL		7.72569	0.0512
LOG_WOP does not Granger Cause LOG_FOB	58	0.30806	0.7362
LOG_FOB does not Granger Cause LOG_WOP		1.96555	0.1503
LOG_VOL does not Granger Cause LOG_PP	58	1.87303	0.1639
LOG_PP does not Granger Cause LOG_VOL		2.52507	0.0898
LOG_WOP does not Granger Cause LOG_PP	58	1.21794	0.3041
LOG_PP does not Granger Cause LOG_WOP		3.12716	0.0522
LOG_WOP does not Granger Cause LOG_VOL	58	1.90973	0.1584
LOG_VOL does not Granger Cause LOG_WOP		0.41071	0.6653

The result shows that producer price granger causes free-on-board price. This indicates that, the change in producer price leads to change in the free-on-board price. That is, producer price provides important information to forecast future value of the free-on-board price. All the other pairs do not Granger-cause each other. For example, world price does not Granger-cause free-on-board price and producer price. This is an indication that there is no transmission of price signals from the world market to the local market. This result is consistent with Zerihun et al. (2008) who found weak interrelationship between producer price and world price causing producer price to be less responsive to change in the world market.

4.5.2. Impulse-Response Functions

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

The x-axis in figure 4.2 below and in Figures 2 (A-D) in Appendix B 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. In our case there are 16 potential impulse response functions. The combined graphs of these IRF functions are given in Fig.4.2 and Figures 2 (A-D) of Appendix B with the Cholesky ordering Log_FOB, Log_PP, Log_VOL and Log_WOP.

Figure 4.2: Impulse Response Function of Log_FOB

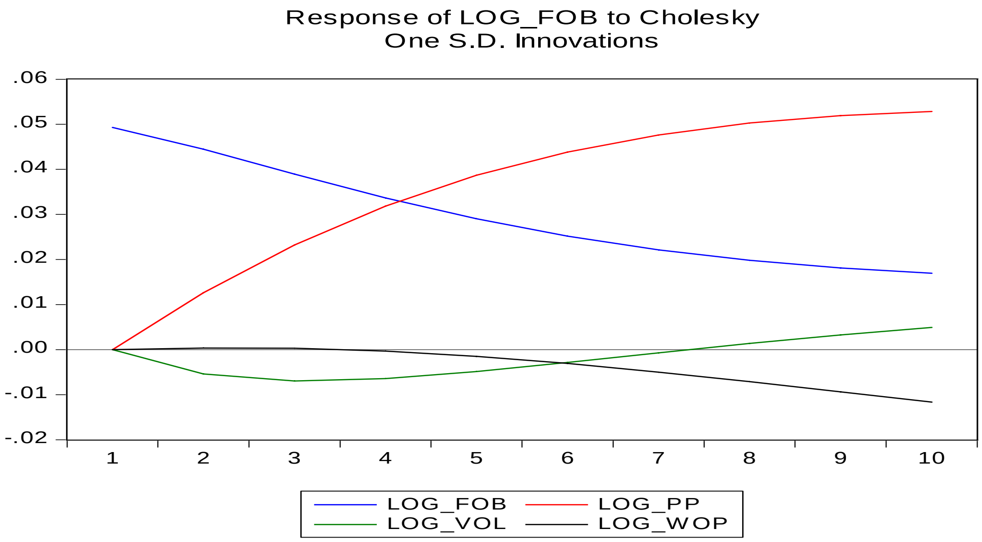


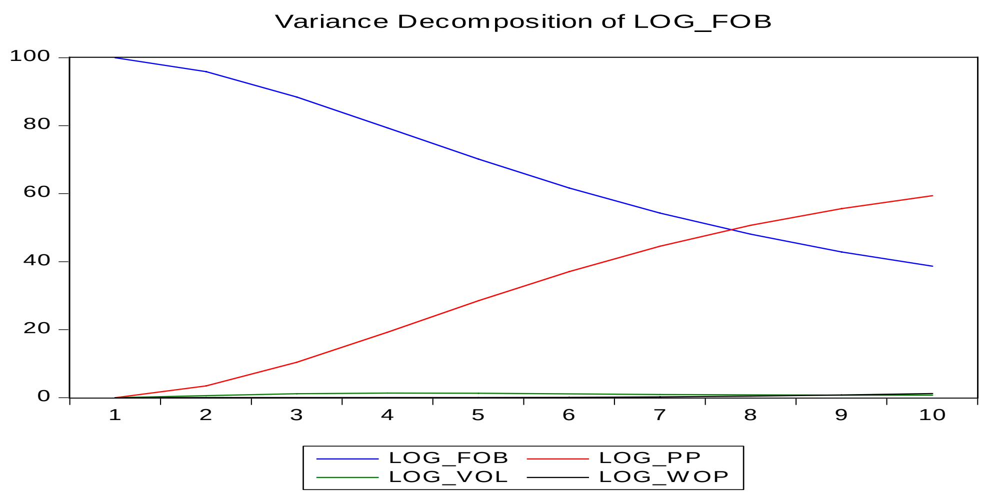
Figure 4.2 above shows the responses of Log_FOB, Log_PP, Log_VOL and Log_WOP to a one standard deviation innovation in Log_FOB. The result indicates free-on-board price innovations have a positive impact on producer price. This implies producer price positively affects free-on-board price. It exhibits a rising trend initially and reaches 0.07 and it stabilizes at around 10 month time horizon. Furthermore, VOL and WOP are almost not affected by one SD change.

Similarly, Figure 2 of Appendix B shows that a one standard deviation shock applied to producer price has a positive impact on free-on-board price. Impulse responses for volume of coffee export have initially a negative effect on free-on-board price and then have positive effect after around 2 month time horizon. It has also initially negative effect on producer price and then has a positive effect after 6 month time horizon. Furthermore, it has a negative effect on world price. Finally, world price innovation has a negative effect on free-on-board price and volume of coffee export, and has a positive effect on producer price.

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 Figure 4.3 below and Figure 3 (A-D) of Appendix B. The results from the variance decomposition of FOB 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 Log_FOB, Log_PP, Log_VOL and Log_WOP.

Figure 4.3: Variance decomposition for Log_FOB



The variance decomposition analysis result of FOB in Figure 4.3 above shows that, at the first horizon, variation of FOB is explained only by its own shock. In the second month 94.42 % of the variability in the FOB fluctuations is explained by its own innovations and the remaining 5% is explained by PP. The proportion decreases dramatically and PP shocks increase as the contribution of FOB shock decreases. They crossed each other at around 6 month time horizon which has equal contribution almost 50% each and after that, when PP increase, FOB price will decrease. The impact of VOL and WOP shocks are almost not significant in determining FOB.

Similarly, in Figures 3: B-D of Appendix B, the variance decomposition of PP, VOL and WOP shows that almost all variability are explained by their own fluctuations. That is, VOL and WOP have almost insignificant impact in explaining PP. FOB and PP have almost insignificant impact on volume of coffee export in Ethiopia.

4.6 Results from Diagnostic Tests

Table 4.9: Results from the Diagnostic Tests

Test	F-statistic	Probability
1. Normality		
Jarque-Bera Statistic	2.373	0.305
2. Serial correlation		
Breusch-Godfrey serial correlation LM test	2.377	0.129
3. Autoregressive conditional heteroscedasticity		
ARCH LM test	0.05	0.975
4. Heteroscedasticity		
White heteroscedasticity test	1.998	0.0575
5. Stability		
Chow forecast test	1.938	0.126
6. Specification error		
Ramsey RESET test	0.647	0.425

Table 4.9 shows that the Jarque-Bera statistic is not significant and hence, there is no significant evidence to reject the null hypothesis of normality. This indicates 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 Ramsey RESET (Regression Specification Test) did not reject the null of correct specification indicating that the model was correctly specified. Generally the model was tested for serial correlation, autoregressive conditional heteroscedasticity, specification error and stability. 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 for August 2011 to July 2012.

4.7.1. Evaluation of forecast accuracy

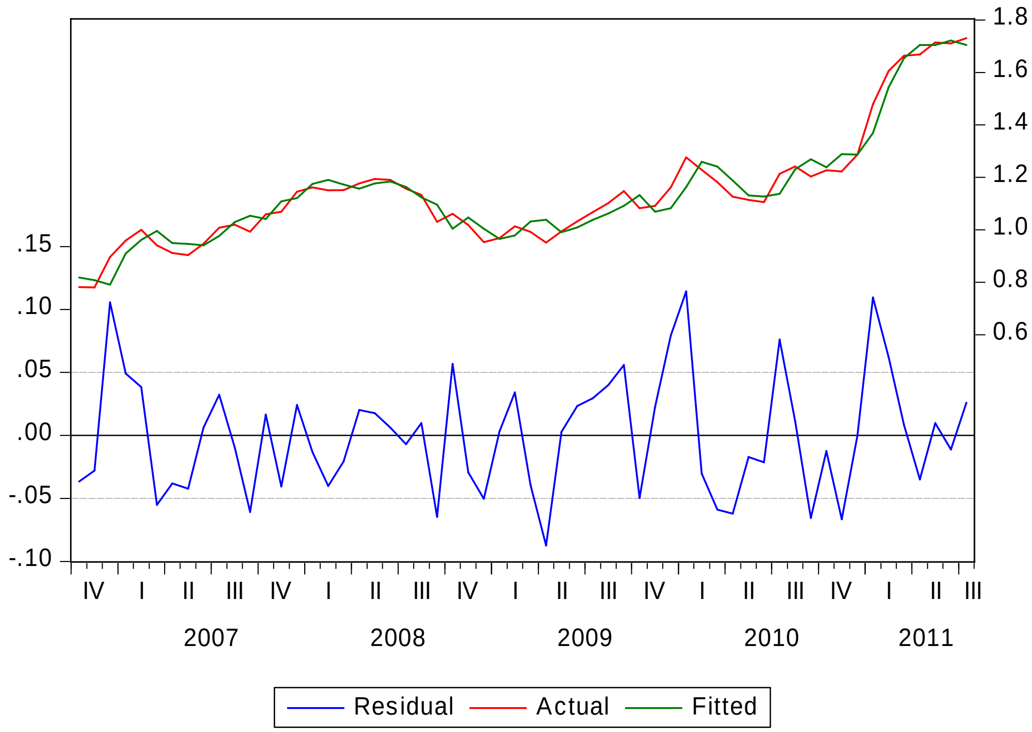
The mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and Theil U statistics were used to assess the forecasting performance. The RMSE and MAE statistics are scale-dependent measures but allow a comparison between the actual and forecast values. The Theil-U statistics is independent of the scale of the variables and is constructed to lie between zero and one, zero indicating a perfect fit. Table 4.10 reports the forecasting accuracy statistics of the estimated model.

Table 4.10: Forecasting Accuracy statistic

Accuracy measure	Variables			
	Log_FOB	Log_PP	Log_VOL	Log_WOP
Root Mean Squared Error	0.070	0.174	1.479	0.099
Mean Absolute Error	0.058	0.149	0.362	0.078
Mean Absolute percent error	3.031	3.256	3.651	2.216
Theil Inequality Coefficient	0.011	0.019	0.023	0.013

For the VAR (1) model, the MAPE in forecasting Log_FOB, Log_PP, Log_VOL and Log_WOP are 3.03, 3.26, 3.65 and 2.22, respectively. These computed values show that the average percentage error for each of the equations used to forecast the study variables is less than 4%. The Theil-U statistic is relatively close to zero, indicating that the difference between the actual values and the predicted values are very small. The graph of the predicted values together with the actual observations for Log_FOB is given in Figure 4.4 below and the remaining plots for the other variables are presented in Figures 4: B-D of Appendix B.

Figure 4.4: Graph of Actual, Fitted and Residual plot of log of free-on-board price



4.7.2. Out of sample forecasting analysis

Out of sample forecasted values for the series under study, using the vector autoregressive model, are presented in Table 4.11 below.

Table 4.11: Forecasts from the VAR (1) models

months	Log_FOB	Log_PP	Log_VOL	Log_WOP
Aug-11	5.482	4.629	66.874	2.577
Sep-11	5.66	4.754	78.275	2.644
Oct-11	5.771	4.8876	83.304	2.683
Nov-11	5.895	4.999	92.0698	2.697
Dec-11	6.028	5.119	93.012	2.752
Jan-12	6.108	5.237	94.817	2.809
Feb-12	6.272	5.352	95.982	2.866
Mar-12	6.420	5.465	98.523	2.923
Apr-12	6.569	5.577	99.396	3.07
May-12	6.718	5.676	101.707	3.115
Jun-12	6.893	5.776	102.688	3.154
Jul-12	7.032	5.878	103.536	3.195

The results indicate that the free-on-board price and producer price have high increasing trend. However, the volume of coffee export and world price exhibit slow increment rates.

5. CONCLUSION

The objective of this paper was to apply multivariate time series analysis to price-volume relationship of coffee export in Ethiopia using monthly data ranging from September 2006 to July 2011. Over the time period considered, all four series have an increasing pattern, that is, there is a sign of non-stationarity in each of the series. Formally, the data were tested for stationarity and all four series were found to be non-stationary using Augmented Dickey-Fuller and Phillips-Perron unit root tests. Appropriate differencing made the series stationary.

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. Error diagnosis of this model showed that the disturbance terms are white noise and normally distributed. This model expressed each variable under study as a function of its lag and the lag of other variables. The Granger causality test tells us that producer price Granger causes free-on-board price. That is, producer price provides important information to forecast future value of the free-on-board price. Furthermore, producer price does not Granger cause world price and vice versa.

The VAR (1) model analysis result shows that free-on-board price is significantly explained by its own past and by lagged value of producer price. This implies that a one dollar increase in producer price leads to an increase of free-on-board price by an amount of $ 0.92. Similarly, volume of coffee export, producer price and world price are significantly explained by their own past values.

The cointegration analysis results show that the trace statistic indicates that there is one cointegrating vector in the system at the 95 percent confidence level. We can infer from this result that there exist long-run causal relationships among free-on-board price, producer price, volume of coffee export and world price. From the VEC model we can observe that free-on-board price is significantly affected by its lagged value in the short-run. Furthermore, 14.74% and 12.825% of the short run disequilibria in free-on-board and producer price is adjusted within one month, respectively. Similarly, volume of coffee export is significantly affected by its lagged value in the short run. World price is affected by neither of free-on-board price, producer price and volume of coffee export in the short run and 12.69% of its short run disequilibria is adjusted within one month.

IRF and FEVD analysis based on VAR (1) model were also performed. The IRF analysis result shows that the response of a variable for a one standard deviation (SD) of its innovations change increases from time to time except for volume of coffee export. Free-on-board price has a positive response for a one SD change in producer price.

Variance decomposition analysis, conducted in order to supplement the outcomes of impulse response analysis, indicated similar results. It was observed that free-on-board price is explained by its own innovations and by producer price shocks. The variability of producer price, volume of coffee export and world price are largely explained by their own innovations.

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APPENDICES

List of figures

Figure A1 Time plots of the Differenced Series

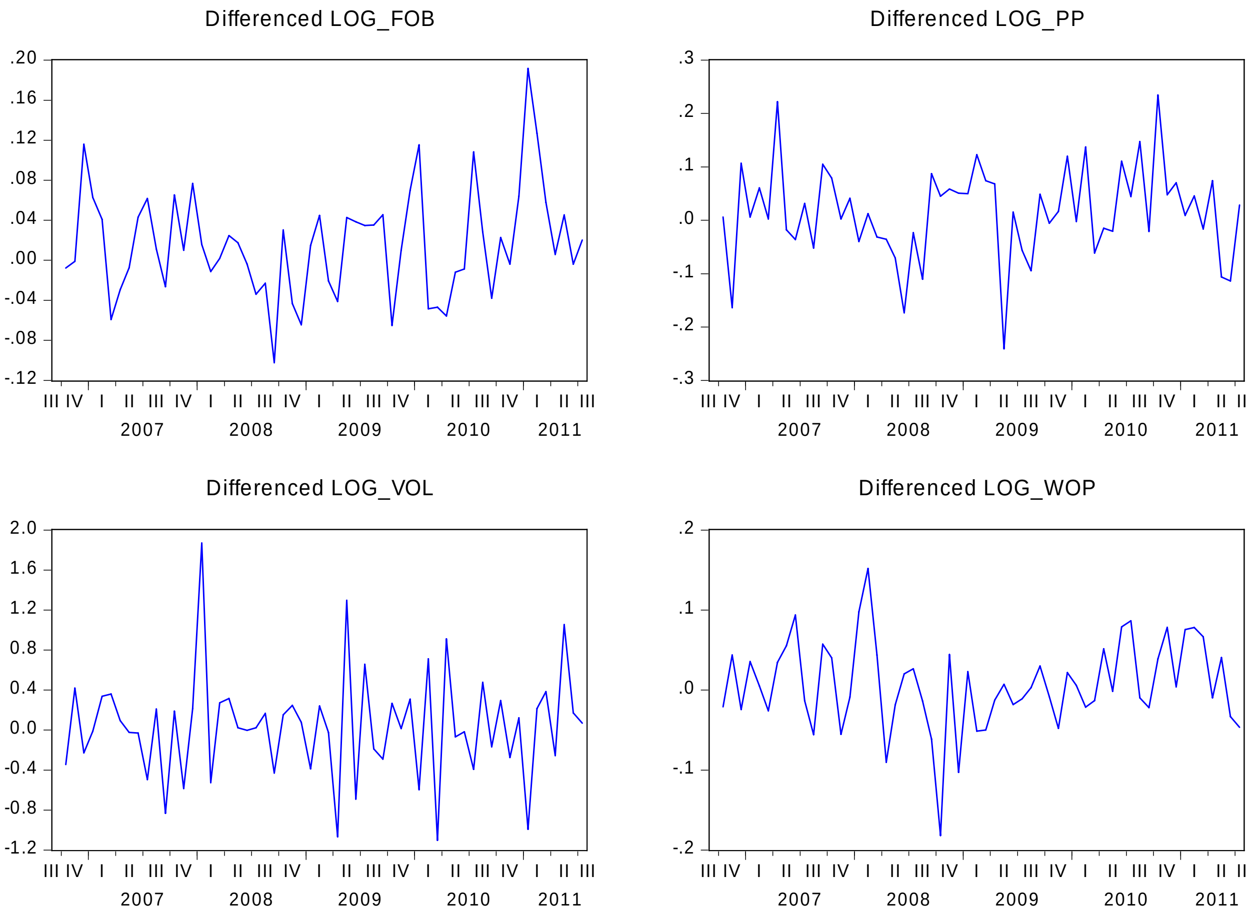


Figure A2: Impulse Response Functions for Log_FOB, Log_PP, Log_VOL and Log_WOP

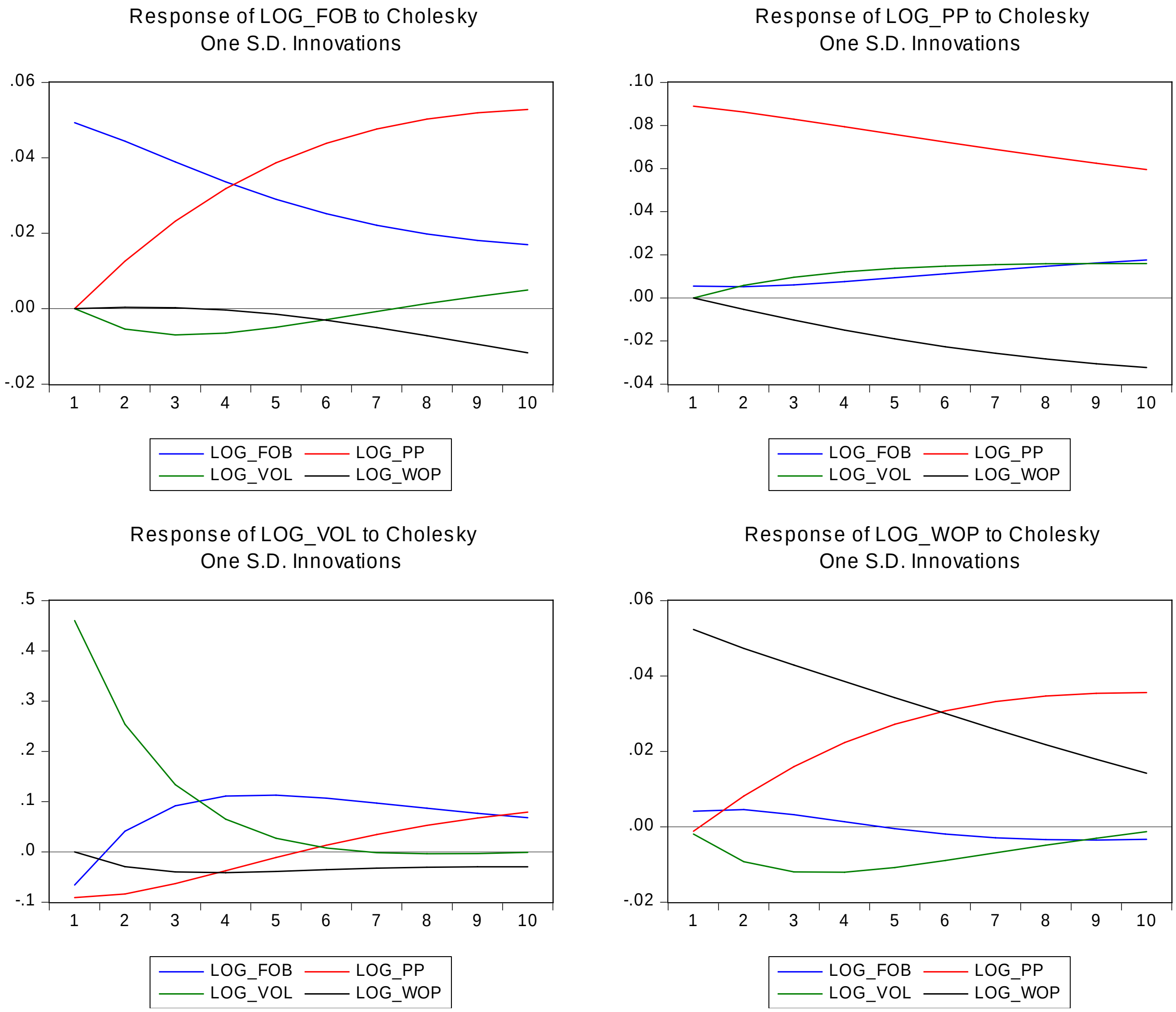


Figure A3: Variance decomposition for Log_FOB, Log_PP, Log_VOL and Log_WOP

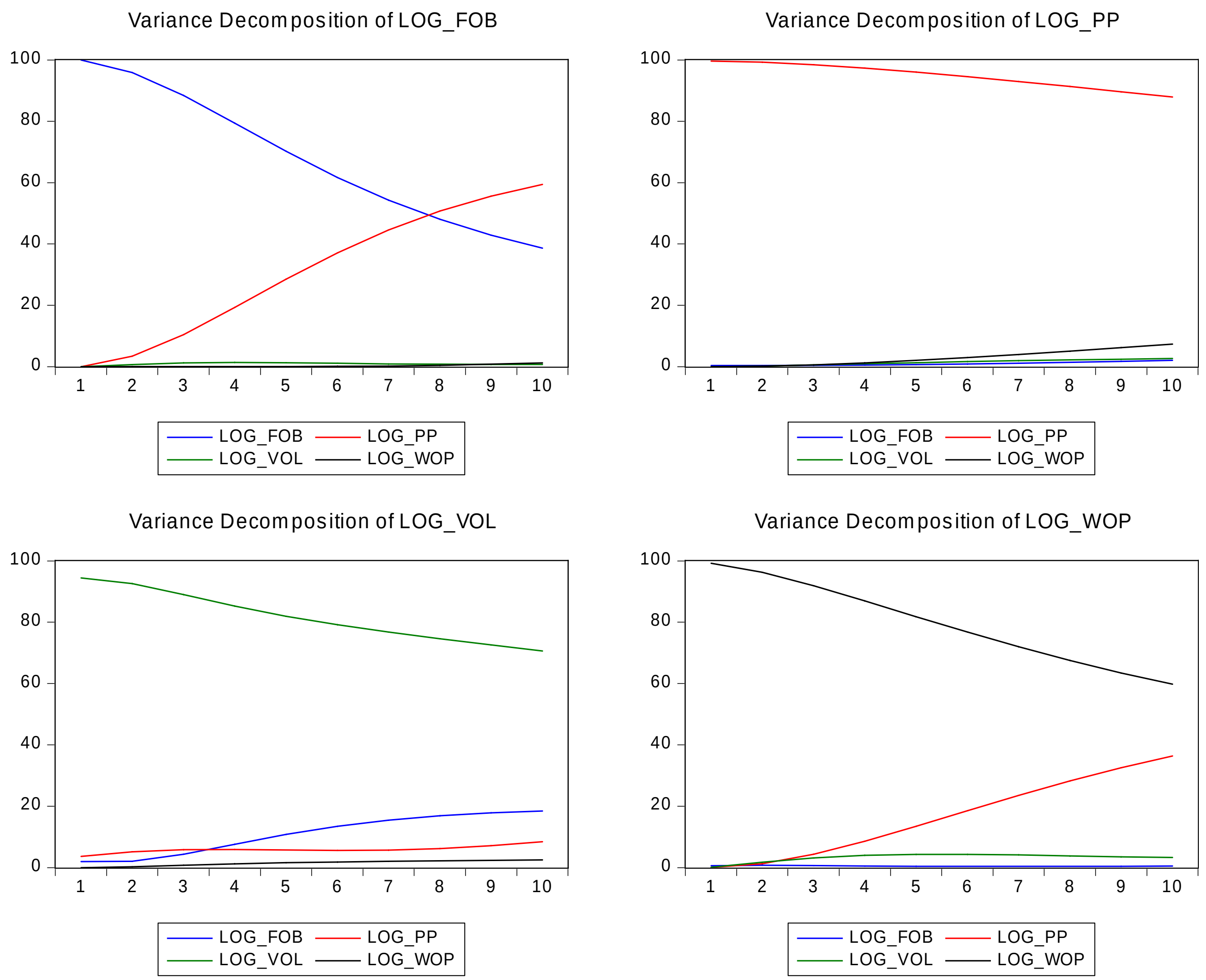


Figure 4A: Graph of Actual, Fitted and Residual plot of log free-on-board price

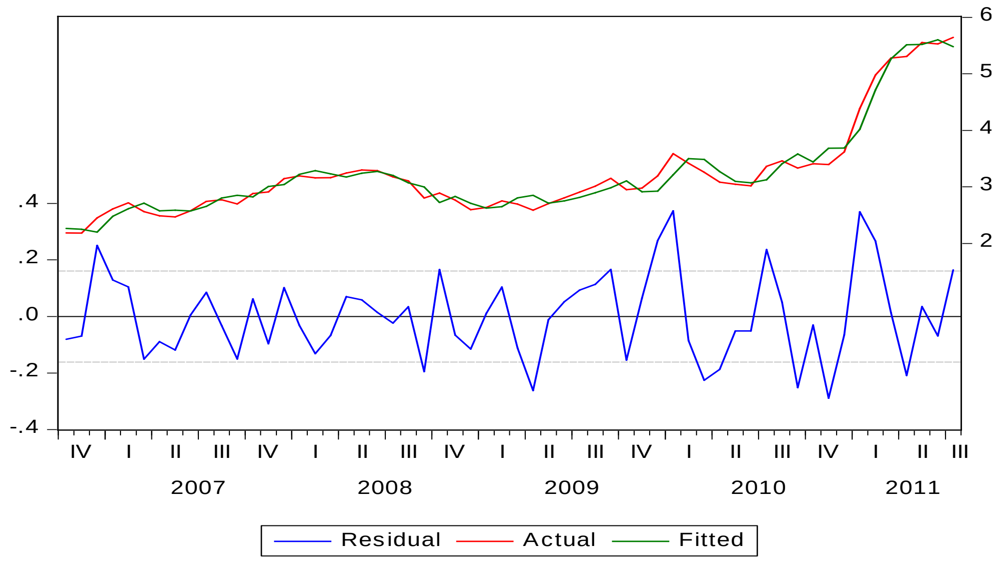


Figure 4 B: Graph of Actual, Fitted and Residual plot of log of producer price

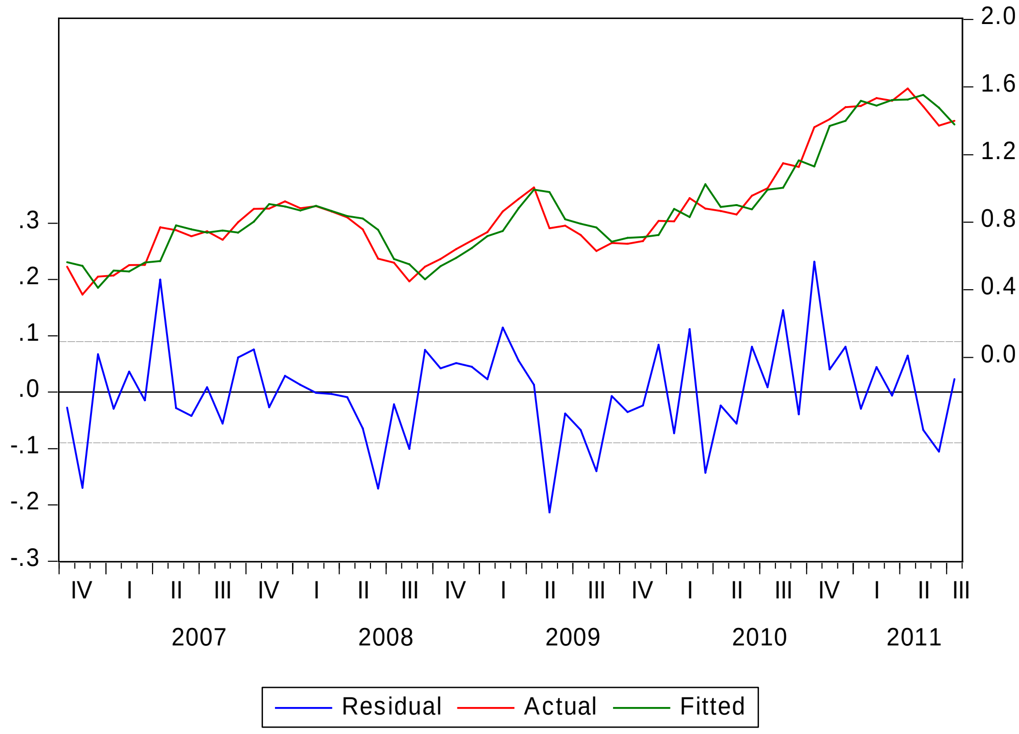


Figure 4C: Graph of Actual, Fitted and Residual plot of log of volume of coffee export

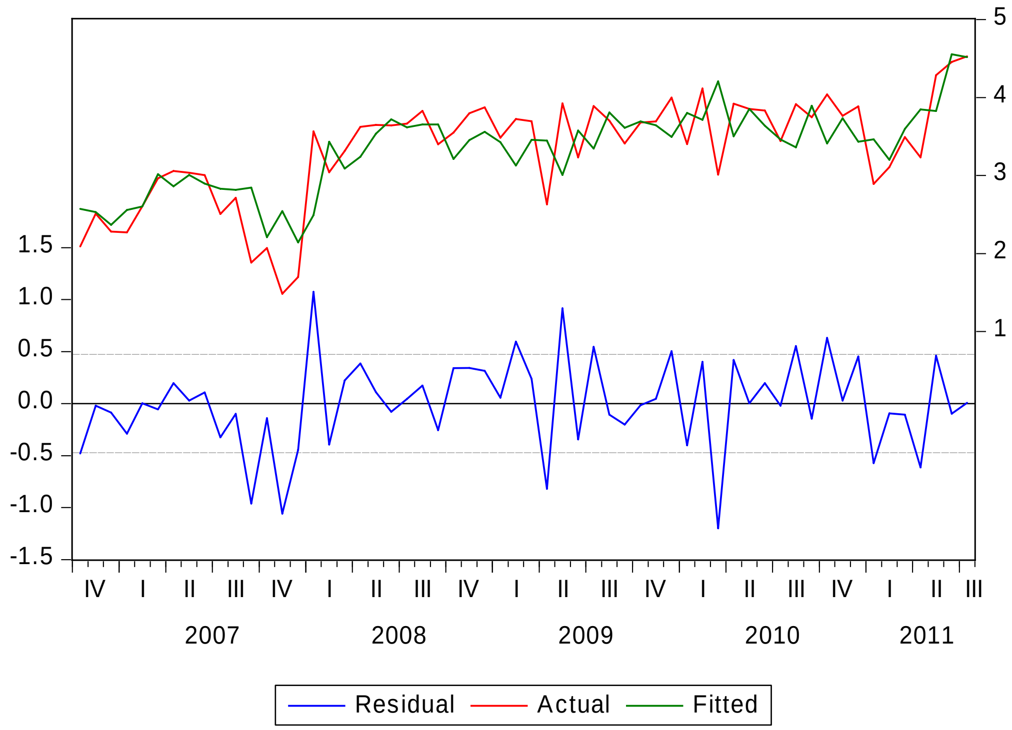
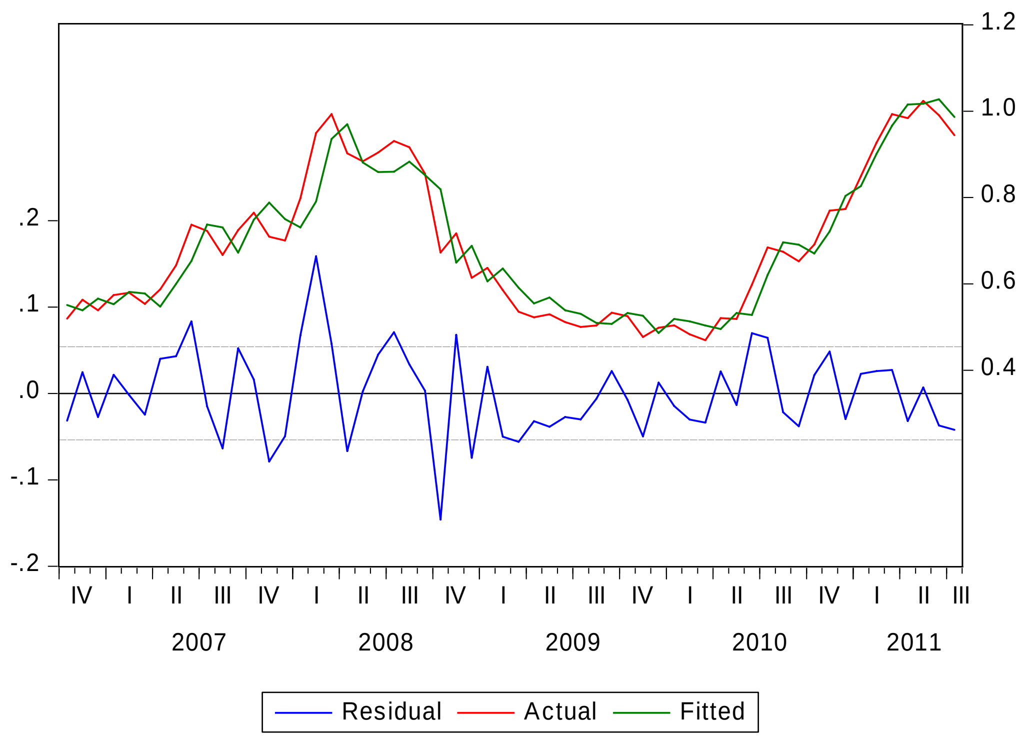


Figure 4D: Graph of Actual, Fitted and Residual plot log of world price of coffee export



DECLARATION

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

Declared by:

Name: ________________________________

Signature: _____________________________

Date: _________________________________

Confirmed by Advisor:

Name: ________________________________

Signature: _____________________________

Date: _________________________________