ADDIS ABABA UNIVERSITY

GRADUATE STUDIES PROGRAME

COLLEGE OF COMPUTATIONAL AND NATURAL SCIENCES

DEPARTMENT OF STATISTICS



Modeling and Forecasting The Domestic Price Volatility of Coffee in Ethiopia

By: Belete Dejen

A Thesis Submitted to the Departement of Statistics in Parcial Fulfillment of the Requirements for the Degree of Masters of Science (Applied Statistics)

Advisor: Prof. MK. Sharma

Addis Ababa University

Addis Ababa, Ethiopia

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School of Graduate Studies

This is to certify that the thesis prepared by Belete Dejen, entitled: **Modeling and Forecasting the Volatility of Domestic Price of Coffee in Ethiopia** and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Statistics (Applied Statistics), complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

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Chair of Department or Graduate Program Coordinator

DECLARATION

I, hereby, 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.

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This thesis has been submitted for examinations with my approval as an advisor.

Advisor Name: Sharma (Prof.) Signature_____ Date _____

ACKNOWLEDGEMENTS

First of all, I would like to extend my unshared thanks to the almighty God and his mother saint Mary for being with me in all aspects during my life, granting me the opportunity to study at this university, persue my graduate study, for giving me the strength to pass all the obstacles and for his mercy.

My special gratitude and appreciation goes to my advisor Prof. Sharma for his advices, comments and guidance throughout the process of completion of this research study. No words can suffice to express my feelings of gratitude to teachers and friends, Dr. Emmanuel G/Yohannes, Atalay Nigussie, Mastewal Biazin, Mengesha Assefa, Getnet Melak, Getinet Asimare, Simachew Gashaw and Ermiyas Kefelegn who gave me moral support and assistance throughout my research work. At last, my deepest and heartfelt gratitude goes to my family that has been a source of pride and encouragements throughout my study.

Finally, I would like to extend my heartfelt thanks to Addis Ababa University Department of Statistics for giving me the opportunity to grasp a profound knowledge and financial support.

Contents

ACKNOWLEDGEMENTS iv
List of Tables ix
Abstruct xi
CHAPTER ONE 1
INTRODUCTION 1
1.1. Background of the study 1
1.2. Statement of the problem 3
1.3. Objectives of the study 4
1.3.1. General Objective 4
1.3.2. Specific Objective 4
1.4. Significance of the study 4
CHAPTER TWO 5
LITERATURE REVIEW 5
2.1. Background 5
2.2. Coffee Production, Consumption and Marketing in Ethiopia 5
2.3. Theoretical and Numerical Overview of Volatility 7
2.4. Characteristics of Financial Time Series 8
2.5. Theoretical Literature Review 9
2.6. Empirical Liturature Review 11
CHAPTER THREE 18
DATA AND METHODOLOGY 18
3.1. Sources of Data 18
3.2. Variables Consider in the Study 18
3.2.1. Dependent Variable 18
3.2.2. Independent Variables 18
3.3. Statistical Methodology 18
3.3.1. Stochastic Process 19
3.3.2. Stationarity 20
3.3.2.1. Weak Stationarity 20
3.3.2.2. Strong (Strict) Stationarity 20
3.3.3. Stationarity Test (Unit Root Test) 21

3.3.3.1. Augmented Dickey-fuller (ADF) Unit Root Test 22
3.3.3.2. Phillips and Perron (PP) Unit Root Tests 23
3.3.4. ARIMA Family Models 24
3.3.4.1. Autoregressive (AR) Process 24
3.3.4.2. Moving average (MA) processes 25
3.3.4.3. Autoregressive Moving average (ARMA) Process 26
3.3.4.4. Autoregressive Integrated Moving Average (ARIMA) Process 27
3.3.5. Building ARIMA Family Models 28
3.3.5.1. Model Identification and Order Selection 28
3.3.5.2. Parameter Estimation for ARIMA family models 30
3.3.5.3. Diagnostic Checking for ARIMA family models 30
3.3.5.4. Forecasting for ARIMA Family models 33
3.3.6. GARCH Family Models 35
3.3.6.1. Autoregressive Conditionally Hetroscedasticity (ARCH) Model 36
3.3.6.2. Generalized ARCH (GARCH) Models 38
3.3.6.3. Exponential GARCH (EGARCH) model 39
3.3.6.4. Threshold GARCH (TGARCH) Model 40
3.3.7. Building GARCH Family Models 41
3.3.7.1. Testing for ARCH effects 41
3.3.7.2. Model order selection 42
3.3.7.3. Model parameter Estimation 42
3.3.7.5. Forecasting GARCH family models 44
CHAPTER FOUR 45
RESULTS AND DISCUSSIONS 45
4.1. Descriptive statistics 45
4.2. Unit root test for non stationarity 47
4.3. Conditional Mean Equation 49
4.3.1. Model identification 49
4.3.2. Parameter Estimation 50
4.3.3. Diagnostic checking 51
4.3.4. Forecasting of ARMA(3,3) model 52
4.4. Test for ARCH Effects 54

4.5. Volatility Models 55
4.5.1. Model selection of GARCH Family Model 55
4.5.2. Parameter Estimation 56
4.5.3. Model Adequacy Checking 58
4.5.4. Forecasting price volatility 59
CHAPTER FIVE 60
CONCLUSION AND RECOMMENDATIONS 60
5.1. Conclusion 60
5.2. RECOMENDATION 61
REFERENCES 60
APPENDIX 68
Appendix A: Tables 68
Appendix B: Figures 76

List of Figures

Figure 4.1: The average monthly domestic price trend of coffee over the study periods..... 46

Figure 4.2: The absolute monthly domestic price return series of coffee over the study periods 47

Figure 4.3: Out-of-sample forecast for ARMA(3,3) model..... 53

Figure 4.4: In-sample forecast of monthly domestic price volatility of coffee 59

Figure B1: Time plot of monthly domestic price ofcoffee and its returns at level..... 76

Figure B2: Time plot of monthly export price of coffee at level..... 76

Figure B3: Time plot of monthly exchange rate price at level and first difference..... 77

Figure B4: Time plot of monthly fuel oil price at level and first difference 77

Figure B5: Time plot of monthly food inflation rate at level 78

Figure B6: Time plot of monthly nonfood inflation rate at level and first difference..... 78

Figure B7: Time plot of monthly saving interest rate at level and first difference..... 79

Figure B8: Time plot of monthly total government revenue at level and first difference..... 79

Figure B9: Normality test of ARMA(3,3) -EGARCH(3,0) model with normal distributional assumption for residuals 79

List of Tables

Table 3.1: Behavior of the ACF and PACF for ARMA models 28
Table 4.2: Summary statistics for monthly prices of the variables in the Ethiopian market 45
Table 4.3: Unit root result for the variables at level 47
Table 4.4: Unit root result for the variables after first difference 48
Table 4.5: Model summary for various orders of ARMA models 49
Table 4.6: Parameter estimation for ARMA(3,3) model 50
Table 4.7: Summary result of Breusch-Godfrey serial correlation LM test for fitted models 51
Table 4.8: Normality test of residuals from the mean equation 52
Table 4.9: In-sample forecast accuracy measures for ARMA(3,3) model 52
Table 4.10: ARCH effect test using LM test for squared residuals of the fitted model 54
Table 4.11: Forecasting accuracy statistics for residuals from the variance equation 55
Table 4.12: ML parameter estimation of EGARCH(3,0) model under normal distribution 56
Table 4.13: ARCH-LM test for standardized residuals of the fitted volatility model 58
Table A1: Unit root test result at level for the variable under consideration 68
Table A2: Unit root test at first difference for the variables under the study 68
Table A3: Summary result on mean equation specification and order selection criteria for the monthly return series of domestic price of coffee 69
Table A4: Mean equation specification for the log return series of the domestic price of coffee 69
Table A5: Breusch-Godfrey serial correlation LM test for residuals of ARMA(3,3) model 70
Table A6: Jarque-Bera normality test for residuals of ARMA(3,3) model 70
Table A7: GARCH model specification and order selection criteria for monthly domestic price returns of coffee 70
Table A8: EGARCH model specification and order selection criteria for monthly domestic price returns of coffee 72
Table A9: Remaining ARCH effect in residuals for EGARCH(3,0) model with normal distribution 74
Table A10: Ljung-Box test for the presence of serial correlation in the residuals of the mean equation 74
Table A11: Ljung-Box test for standardized residuals from volatility model for domestic price return of coffee 75

List of Acronyms

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AICc	Bias Correlated Akaike Information Criterion
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedastic
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
CSA	Central Statistical Agency
EGARCH	Exponential Generalized Autoregressive Conditionally Heteroscedastic
EPE	Ethiopian Petroleum Enterprise
FAO	Food and Agricultural Organization
GARCH	Generalized Autoregressive Conditionally Heteroscedastic
GARCH-M	Generalized Autoregressive Conditionally Heteroscedastic in Mean
GED	Generalized Error Distribution
JB	Jarque-Bera
LM	Lagrange Multiplier
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Maximum Likelihood
MSFE	Mean Square Forecast Error
NBE	National Bank of Ethiopia
OLS	Ordinary Least Square
PACF	Partial Autocorrelation Function
PP	Phillips-Perron
RMSE	Root Mean Square Error
SBIC	Schwarz Bayesian Information Criteria
TGARCH	Threshold Generalized Autoregressive Conditionally Heteroskedasticity

Abstruct

Coffee is the most popular globally traded soft drink in the world. Ethiopia is the birth place of Coffee Arabica and remains the largest producer and exporter of coffee in Africa. The aim of this study was to model and forecast the domestic price volatility of coffee in Ethiopia using an appropriate financial time series models. The data used are monthly observations of the domestic price of coffee, food price index, fuel oil price, exchange rate, interest rate etc. from January 2003 to December 2016.

The price return series of coffee has been show the characteristics of financial time series such as volatility clustering, leptokurtic distributions and leverage effects. Thus ARIMA family models for mean equation and GARCH family models for variance equation were employed to model the monthly domestic price volatility of coffee in Ethiopia. Among GARCH family models considered in this study, ARMA (3, 3)-EGARCH (3, 0) model with normal distributional assumption of residuals were found to be a better fit for domestic price volatility of coffee.

Export price of coffee, exchange rate, food inflation rate, nonfood inflation rate and total government revenue were found to have statistically significant effect on average monthly price volatility of coffee. The asymmetric term was found to be positive and statistically significant in EGARCH (3, 0) volatility model for coffee. This is an indication that unanticipated increase in domestic price had larger impact on domestic price volatility than unanticipated decrease in the domestic price of coffee.

Finally, various forecast accuracy measure statistics indicates that the estimated ARMA(3, 3) model is good enough to describe the domestic price of coffee. Moreover, the out-of-sample forecasts indicates that the domestic price of coffee has almost a constant trend. The in-sample forecast using the best-fit asymmetric model, that is EGARCH(3, 3) model indicates that the domestic price volatility of coffee remained at almost a constant level around the begining and ending of the study. But it increased steadily with increasing rate from December 2010 to January 2011, immidiatlly dropes sharply with increasing rate till March 2011.

***Key words**: Coffee, ARIMA, GARCH, Forecasting, Ethiopia*

CHAPTER ONE

INTRODUCTION

1.1. Background of the study

Coffee is the most popular soft drink in the world and billion cups are consumed every day. Its popularity and volume of consumption are growing every year, and coffee shops are the fastest growing part of the restaurant business. Coffee grows in many tropical and sub-tropical parts of the world. Latin America, Africa, Asia and Oceania account for 60, 30, 20 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 (Yohannes, 2010). It is common knowledge that there are two types of coffee, namely Arabica and Robusta. Arabica coffee represents by far (70-75%) the largest share of the overall production of coffee. Ethiopia produces Arabica coffee, whereas a new comer on this market, namely Vietnam, produces exclusively Robusta, and Brazil produces both types. Oromia and SNNP are the two main regions of coffee production in Ethiopia. Coffee production involves over a million farming households (with land plots of 0.5 ha in average) and about 25% of the population of the country.

Ethiopia is the birth place of Coffee Arabica. It is the primary center of origin and genetic diversity of the Arabic coffee plant, earlier known as jasminum arabicum laurifolia (Tora, 2009). 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 (Mekuria et al., 2004). There are currently hundreds of types of coffee under cultivation, each with varying aromas, tastes or colors, especially in the Southwestern part of the country. Ethiopian coffee ranks highly in intrinsic quality of the bean due to the diverse agro- ecological zones and immense genetic diversity aforementioned (Kufa, 2006).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).

Like other developing countries, the Ethiopian economy is based on agriculture, which contributes about 45% to GDP and more than 80% of exports, and employs 85% of the

population. Ethiopia heavily relies on agriculture for its foreign exchange earnings. The major agricultural export crop is coffee, providing approximately 35% of Ethiopia's foreign exchange earnings. Ethiopia produced around 5% of the world's production and 39% of the total production of coffee in Sub- Saharan Africa (International Coffee Organization, 2012). Ethiopia is the hometown of coffee and well- known for its production of high-quality coffee. Thus, it is the first coffee-producing African country and stands fifth in the world. Coffee is currently providing 31% of Ethiopia's foreign exchange earnings (CSA, 2012). In 1882, ICO enters into the Coffee Exchange of New York (later part of the Coffee, Sugar and Cocoa Exchange), coffee prices became more volatile (Noemie Eliana Maurice and Junior Davis (2011)).

Volatility is the relative rate at which the price of a security moves up and down. It shows how the prices fluctuate in a given period of time. The more the price moves up and down, the more volatility it is considered to have. Price volatility may be derived from country specific factors as well as from various influences emanating from the global market place. In keeping with any open economy devoting a substantial proportion of its resources to domestic production; prices received for such domestics are a crucial determinant of aggregate income and social welfare (Valadkhani, Layton, and Karunaratne, 2005). Price volatility is also influenced by exogenous impacts affecting supply and demand conditions. Examining the underlying causes of coffee price volatility has great role for managing price instability for producers, consumers, whole sellers and agricultural price policy reforms for the country as well.

Commodity prices have shown considerable volatility over the past decade. In recent years financial and commodity markets have been highly volatile. The price boom between 2002 and 2008 was the most pronounced in several decades in magnitude, duration and breadth. Moreover, the price decline following the onset of the recent global crisis in mid-2008 stands out both for its sharpness and for the number of commodities affected. Since mid-2009, and especially since the summer of 2010, global commodity prices have been rising again rapidly (excepting some temporary setbacks in the second quarter of 2011).

Coffee price volatility is essentially influenced by the conditions of coffee supply, demand and other macro-economic factors. The supply situation is determined by the production cycle in exporting countries and variations in stock levels. The price-elasticity of demand is equally weak since the final price of the consumer product does not reflect a significant part of the price of the

underlying raw materials. The volatility of coffee prices was similar to that of most agricultural products over the past 50 years. Now a day the price of coffee is among the most volatile of agricultural commodity prices.

Therefore, this study has been employed econometric methods to explore the patterns and determinates of domestic price volatility of coffee in Ethiopia by developing GARCH family models with Box-Jenkins ARIMA family models for conditional mean specification. The autoregressive conditional heteroscedasticity (ARCH) model developed by Engle (1982), and later generalized by Bollerslev (1986) (GARCH), are the most popular method used for analyzing volatility of financial time series data. Standard GARCH models assume that positive and negative shocks have a symmetric effect on the volatility, that is, good and bad news have the same effect on volatility. In practice this assumption is frequently violated, in particular by stock returns, in that volatility increases more after bad news than after good news. From an empirical point of view, volatility reacts asymmetrically to the sign of the shocks and, therefore, a number of parameterized extensions of the standard GARCH model have been suggested recently. Thus, in this paper we have been used exponential Generalized Autoregressive Conditional Hetroskedasticity (EGARCH) and the threshold GARCH (TGARCH) models for capturing the asymmetric phenomena.

1.2. Statement of the problem

Price volatility has an impact on the economy of developing countries like Ethiopia and is an important factor for decision to the policy makers. Coffee production and marketing in Ethiopia has an effect on its domestic price. These cause heavy and sudden fluctuation in domestic price of coffee and create serious problems in national income. Studying the price volatility in response to shocks due to different factors is of crucial importance for a developing economy like Ethiopia whose policy is oriented towards price stability. Several studies have been conducted on coffee in Ethiopia. But most of these studies were focused on the performance, production and export price, by ignoring domestic prices volatility. Therefore, this study attempts to identify the pattern of domestic price volatility of coffee by using an appropriate time series models. Hence, the study attempted to address the following problems:

- Is there domestic price volatility on coffee in Ethiopia?
- Is the problem a current issue in Ethiopia?
- What are the major factors that will determine the domestic price volatility of coffee?
- Are GARCH family models fits well to the data for domestic price volatility of coffee and its determinants?

1.3. Objectives of the study

1.3.1. General Objective

The general objective of this study is to model and forecast the domestic price volatility of coffee in Ethiopia by using an appropriate financial time series models.

1.3.2. Specific Objective

The specific objectives of this study are:

- To investigate and assess the key macroeconomic factors that have a significant effect on the domestic price volatility of coffee in the Ethiopian market.
- To make in sample forecast for domestic price volatility of coffee in Ethiopia.

1.4. Significance of the study

This study aims at identifying the presence and degree of domestic price volatility and its determinants of coffee in Ethiopia. Information about domestic price volatility and its determinants are necessary to country policy makers as well as the producers and consumers. Therefore this study is very important to cooperative societies, investors, researchers, governmental and nongovernmental organizations for policy formulation and planning in coffee marketing. Hence the outcome of this research will provide information to policy makers and domestic price of coffee sectors to take intervention actions towards key determinant factors that lead to the Ethiopian coffee export volatility. In addition to this, the result of this study may be used as a basis for further studies in this area.

CHAPTER TWO

LITERATURE REVIEW

2.1. Background

Coffee is one of the most important soft drink and globally traded agricultural commodity, with consumption occurring mostly in developed countries and production in developing ones. Coffee originated in Africa, in the Ethiopian region known as Kaffa. From Ethiopia, coffee was taken to Arabia and finally brought into Europe. Coffee houses started emerging in Europe in the mid-1600s first in Italy and later in England. Coffee reached America in 1607. In global markets, Ethiopia's Arabica coffee is valued for its unique taste. Ninety five percent of the country's coffee is cultivated by an estimated 4 million primarily smallholder, often poor, farming households. Yet despite its leading position in Africa and the positive changes made in the coffee trade in the last decade, the Ethiopian coffee sector is underperforming, according to recent research by IFPRI, the Ethiopian Development Research Institute (EDRI), and Bonn University's Institute for Food and Resource Economics. Ethiopian yields are slightly higher than those of Kenya and Rwanda, but lower than Uganda's and only one half to one third the size of major Latin American producers.

2.2. Coffee Production, Consumption and Marketing in Ethiopia

Coffee production is important to the Ethiopian economy with about 15 million people directly or indirectly deriving their livelihoods from coffee. Coffee is also a major Ethiopian export commodity generating about 25% of Ethiopia's total export earnings. Ethiopia is the largest producer of coffee in Sub-Saharan Africa and is the fifth largest coffee producer in the world next to Brazil, Vietnam, Colombia, and Indonesia, contributing about 7 to 10% of total world coffee production. Ethiopia is the birthplace of Arabica coffee and produces mostly Arabica coffee. Coffee has economical, environmental as well as social significance to the country.

In Ethiopia coffee production is increased by 0.3% over the past year. it is endowed with a good production environment for growing coffee with a combination of appropriate altitude, temperature, rainfall, soil type, and PH. Coffee grown at various altitudes ranging from 1200-

2750 meters above sea level, where there is sufficient rainfall with an amount between 1500-2500 mm and where there are optimum temperatures between15-25 degree Celsius. Different literature said that Ethiopia is the center of origin for Coffee Arabica. Coffee Arabica grows naturally in tropical forest areas of the country. The country possesses a diverse genetic base for this Arabica coffee with considerable heterogeneity. Ethiopia produces a range of distinctive Arabica coffees and has considerable potential to sell a large number of specialty coffees (Nure, 2008). Little of the lower-value Robusta coffee is produced in Ethiopia, being better suited for production in lower altitude equatorial climates. Coffee production in Ethiopia is almost exclusively situated in the two regions of Oromia and the Southern Nations, Nationalities, and People Regions (SNNPR) in the south and west of the country.

There are four different ways of producing coffee in Ethiopia. These are: forest coffee, semi-forest coffee, garden coffee, and plantation coffee.

Forest coffee is a wild coffee grown under the shade of natural forest trees, with no defined owner.

Semi-forest coffee farming is a system where a farmer living near by a forest coffee does some thinning and pruning on the forest coffee to finally claim ownership of the forest coffee. The thinning will allow adequate light to reach the coffee plant without exposing the plant to too much sunlight. The farmer who prunes and weeds the forest area claims to be the owner of the semi-forest coffee and can collect the annual yield of the plant.

Garden coffee is normally found close to a farmer's residence. Farmers use organic fertilizers to produce Garden coffee and inter-crop it with other crops.

Plantation coffee grows on commercial farms, which were built by the government or private investors for export purposes. This type of coffee plantation most commonly applies fertilizers and herbicides.

Coffee consumption over the past year has not changed significantly. Ethiopians are remain heavy coffee drinkers, ranked as one of the largest coffee drinking countries in Africa. Nearly half of Ethiopians coffee production is locally consumed. Coffee has both social and cultural value and is mainly consumed during social events such as family gatherings, religious celebrations, and at times of mourning (Abu Tefera et al., 2014). It 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 and Rural Development, 2000).

Throughout the Derg regime that started in 1975, the Ethiopian Coffee Market Corporation (ECMC) controlled about 80% of the internal and external marketing of coffee. During this era, domestic coffee prices were set by the Ministry of Coffee and Tea, while export minimum prices were set by the Central Bank (Petit, 2007). Farmers were obliged to supply certain quotas of coffee to the government (Gemech and Stuthers, 2007) and only licensed collectors (sebsabies), and suppliers (agrabies), were allowed to trade coffee at the auctions in Addis Ababa and Dire Dawa, where all coffee was priced. After the end of the Derg regime in 1991, the parastatal ECMC was closed down and export price controls, as well as farm gate price floors, were gradually removed. However, although license fees related to the trade of coffee were reduced, the supply chain through primary collectors, suppliers and auctions remained (Petit, 2007). In addition, although the deregulation of the coffee market led to an improvement in the transmission of price signals from the world market to the domestic market, farmers and traders (akrabies and sesabies) insufficient access to market information and credit, along with high transaction costs and uncompetitive markets, substantially limited the effect (Love, 2001; Worako et al., 2008).

2.3 . Theoretical and Numerical Overview of Volatility

The main characteristic of any financial asset is its return which is typically considered to be a random variable. The spread of outcomes of this variable, known as assets volatility, plays an important role in numerous financial applications. Its primary usage is to estimate the value of market risk. Volatility also provides a measure of the possible variation or movement in a particular economic variable. It indicates how much and how quickly a value changes over time, for example the price of a sugar. While this concept may seem obvious, a precise definition of volatility is elusive and measurement prone to subjectivity. In economic theory, volatility connects two principal concepts: variability and uncertainty; the former describing overall movement and the latter referring to movement that is unpredictable. Volatility is also a key parameter for pricing financial derivatives. All modern option pricing techniques rely on a

volatility parameter for price evaluation. Volatility is also used for risk management assessment and in general portfolio management. It is crucial for financial institutions not only to know the current value of the volatility of the managed assets, but also to be able to predict their future values. Volatility forecasting is especially important for institutions involved in options trading and portfolio management.

Volatility refers to the spread of all outcomes of an uncertain variable. In finance, we are interested in the outcomes of assets returns. Volatility is associated with the sample standard deviation of returns over some period of time. It is a quantified measure of market risk. Volatility is related to risk, but it is not exactly the same. Risk is the uncertainty of a negative outcome of some event (e.g. stock returns); volatility measures the spread of outcomes. This includes positive as well as negative outcomes. Price volatility in commodity markets has been studied extensively in the academic literature. Many researchers have examined commodity price volatility from different perspectives. One can characterize the key feature of the various financial market volatility series with some stylized facts. The first feature of volatility is that it is not directly observable. Therefore, one observes the price return series which are used as input to estimate the volatility of the underlying price. Though unobservable, volatility is characterized by some special features that are well documented and widely accepted. Firstly, there exist volatility clusters (Fama, 1965) which is the tendency for volatility in financial markets to appear in bunches. Large return is expected to follow large return. This implies that future volatility can be predicted by past and current volatility. According to (Worako et al., 2008), the domestic price of coffee in Ethiopia adjusts more rapidly to world price changes.

2.4 . Characteristics of Financial Time Series

Modeling financial time series is a complex problem. This complexity is not only due to the varieties of the series in use (stocks, exchange rates, interest rates, etc.), to the importance of the frequency of observation (second, minute, hour, day, etc) or to the availability of very large data sets. It is mainly due to the existence of statistical regularities (stylized facts) which are common to a large number of financial series and are difficult to reproduce artificially using stochastic models (Francq and Zakoian, 2010). Financial time series data sets have several characteristics which are crucial to note for the purposes of modeling and forecasting.

Non stationarity of price series: Samples paths of prices are generally close to a random walk without intercept. On the other hand, sample paths of returns are generally compatible with the second-order stationary assumption.

Fat tail: When the empirical distribution of returns is drawn, one can generally observe that it does not resemble a Gaussian distribution, which means market returns have distributions with fatter tails than the normal distribution. Classical tests typically lead to rejection of the normality assumption at any reasonable level. More precisely, the densities have fat tails (decreasing to zero more slowly than normal and are sharply peaked at zero), and they are called leptokurtic. A measure of the leptokurticity is the kurtosis coefficient, defined as the ratio of the sample fourth-order moment to the squared sample variance. Asymptotically equal to three for Gaussian iid observations, this coefficient is much greater than three for returns series. When the time interval over which the returns are computed increases, leptokurticity tends to vanish and the empirical distributions get closer to a Gaussian.

Volatility clustering: refers to the phenomenon that large changes tend to be followed by large changes of either sign, and small changes tend to be followed by small changes. A quantitative manifestation of this fact is that, while returns themselves are uncorrelated, absolute returns or their squares display a positive, significant and slowly decaying autocorrelation function.

Leverage effect: It was noted by Black (1976), and refers to an asymmetry of the impact of past positive and negative values on the current volatility. Negative returns (corresponding to price decreases) tend to increase volatility by a larger amount than positive returns (price increases) of the same magnitude.

2.5. Theoretical Literature Review

The Box-Jenkins approach of time series model such as Autoregressive (AR), Moving Average (MA) and ARMA models are often very useful in modeling general time series. However; they all have the assumption of homoskedasticity or constant variance for the errors. Under the homoskedastic assumption has the implication that uncertainty or volatility remains constant over time (Gebhard and Jurgen, 2007). Numerous studies have documented evidence showing that financial time series exhibit the phenomenon of volatility clustering, leptokurtosis and

asymmetry. Volatility clustering occurs when large commodity price changes are followed by large price change of either sign, and small price changes are followed by periods of small price changes. Leptokurtosis means that the distribution of price returns is not normal but exhibits fat-tails. Asymmetry, also known as leverage effects, means that a fall in return is followed by an increase in volatility greater than the volatility induced by an increase in returns. This implies that more prices wander far from the average trend in a crash than in a bubble because of higher perceived uncertainty (Mandelbrot, 1963; Fama, 1965; Black, 1976).

Linear models are unable to explain a number of important features common to much financial data, including leptokurtosis, volatility clustering and leverage effects. That is, because the assumption of homoscedasticity (or constant variance) is violated when using financial data, in such instances it is preferable to examine patterns that allow the variance to depend upon its history. Therefore, to model the non-constant volatility parameter, GARCH-type models were considered. First ARCH (q) proposed by Engle (1982) and its generalization GARCH (p, q) proposed by Bollerslev (1986) were developed. Extending the framework of Engle (1982), Bollerslev (1986) and Taylor (1986) generalized the ARCH (q) model to GARCH (p, q) in which they added the p lags of past conditional variance into the equation. GARCH allows the conditional variance of a price index to be dependent upon previous own lags. Literature has found evidence in support the capability of GARCH family models in volatility estimation (Akgiray, 1989, Pagan & Schwert, 1989) as well as volatility forecast (Brailsford and Faff, 1996) rather than other non-GARCH models. GARCH (p, q) model allows for both autoregressive and moving average components in the heteroskedasticity variance. Empirical findings suggest that GARCH model is more parsimonious than ARCH model.

Although GARCH model has been the most popular volatility model, it has three main problems. Firstly, non-negativity constraint may be violated by the estimated models. Secondly, GARCH model does not take into account the leverage effect and lastly it does not allow for feedback between the conditional variance and conditional mean (Brook, 2002). After the introduction of simple GARCH models, a huge number of extensions and alternative specifications such as EGARCH (Nelson, 1991), Threshold GARCH (Glosten, Jagannathan and Runkle, 1993), GARCH X and GARCH-M were attempted to better capture the characteristics of return series.

2.6. Empirical Liturature Review

Price volatility in commodity markets has been studied extensively in the academic literature. Many researchers have examined commodity price volatility from different perspectives. Commodity price in general and agricultural commodity prices in particular are volatile and renowned for their continuously volatile nature (Newbery, 1989). Coffee prices exhibited high inter year variations from season to season. These variations are a combined effect of the factors reecting domestic supply and the periodic trends of the global coffee demand and supply situation (ECX, 2012). Findings show that stock markets, particularly the SP500 exerts positive impact on the coffee market. The findings also suggests that the energy markets influence the coffee market positively, whereas the bond market volatility affects it negatively. In addition, the structural analysis of coffee price volatility shows that the conditional variance appears to be more volatile in response to positive shocks than to negative shocks, contrary to the equity market (Anastasios, 2010).

Exchange rate can affect commodity price through a number of channels, including international purchasing power. using co-integration test (Gilbert, 1989; Loening et al., 2009) found that domestic food price are significantly determined by the exchange rate in the long-run. According to (liefert and persuad, 2009), exchange rate movements can change countries domestic price and export price, thereby affecting incentives to produced, consumed and trade goods. According to the findings of (Frankel et al. 1986) using linear regression model, interest rate has a significant influence on the agricultural market in general by affecting the cost of holding inventory, affecting investment decision (land, machinery and input purchases) and also affecting the overall farms business risk. (Bond, 1984; Frankel, 2006) suggested that interest rate play an important role in determining total commodity supply and rising interest rate cause commodity price to fall. As noted by (Frank, 2006) using linear regression model, the level of real interest rate affects commodity price through a number of supply and demand channels. (Hammoudeh, 2008; yuan, 2008) using GARCH model also found that rising interest rates have a dulling effect on price volatility. In general, the domestic price adjusts more rapidly to world price changes today than it did prior to the reforms according to many studies. However, their is an indication that negative price changes transmit much faster than positive ones. According to (FAO; 2008), external factors like increase in international commodity prices and fuel oil price account for the

recent food price ination in Ethiopia and (Mitchell, 2008) there was a transmission of fuel oil price volatility to agricultural prices.(Swaray, 2007) found that fluctuations in business cycles and macroeconomic variables, including fuel oil prices have a significant impact on non-fuel primary commodities. (Junior, 2011) using EGARCH and Granger Causality models found that there is a long run causality between oil prices and coffee. (Grennes ; Lapp, 1986) studied the extent to which macroeconomic factors alter agricultural prices and they found that real aggregated agricultural prices have not been altered by the level of general ination. However, (Chambers, 1984) using monthly and quarterly data, found that agricultural prices were altered by the level of general ination. (Belay, 2011) using EGARCH model found that ination rate from non-food items had positive effect on price volatility of maize and teff crops.

Many studies have documented that high variability in world prices can transmit to domestic markets and worsen price instability. According to (Worako et al., 2008) , the domestic price of coffee in Ethiopia adjusts more rapidly to world price changes. Research done in Colombia by (Carlos et al., 1991) using co-integration and error correlation models indicates that domestic price of coffee continued to exhibit some degree of short term integration with world price and the price continues to diverge in the long run. The production of a particular agricultural commodity is dependent on growing seasons. The dependence of production of a specific commodity on growing seasons can cause seasonal variations or volatilities in supply and demand. The variation in supply and demand of the commodity causes seasonal fluctuations in prices (Richardson, 2004; Moledina et al., 2003).

Engle (1982) studied on ARCH and GARCH models, and revealed that these models were designed to deal with the assumption of heteroscedasticity found in real life financial data. ARCH and GARCH models have been applied to a wide range of time series analyses, but applications in finance have been particularly successful. Financial decisions are generally based upon the tradeoff between risk and return; the econometric analysis of risk is therefore an integral part of asset pricing, portfolio optimization, option pricing and risk management. The analysis of ARCH and GARCH models and their many extensions provide a statistical approach on which many theories of asset pricing and portfolio analysis can be tested. The goal of such models is to provide a volatility measure like a standard deviation that can be used in financial decisions concerning risk analysis, portfolio selection and derivative pricing. According to

Chatfield (2000), the idea behind a GARCH model is similar to that behind ARMA model in the sense that a higher order AR or MA model may often be approximated by a mixed ARMA model, with fewer parameters, using a rational polynomial approximation. Thus a GARCH model can be thought of as an approximation to a higher-order ARCH model. The GARCH(1,1) model has become the standard model for describing changing variance for no obvious reason other than relative simplicity.

Brooks (2008) studied stochastic volatility models and found that most time series models such as GARCH will have forecasts that tend towards the unconditional variance of the series as the prediction horizon increases. This is a good property for a volatility forecasting model to have, since it is well known that volatility series are mean-reverting. This implies that if they are at a lower level relative to their historic average, they will have a tendency to rise back towards the average. This feature is accounted for in GARCH volatility forecasting models. Claessen and Mittnik (2002) investigated a range of alternative strategies for predicting volatility in financial markets applying GARCH model to daily returns on the DAX index, the major German stock index. The work of these two scholars investigated the suitability of several forecasting techniques for the volatility of the returns of the German DAX index and examined whether or not the German DAX–index options market is informational efficient. By combining both sources of information, the in–sample fitting and out–of–sample forecasting results give strong support for the hypothesis that historic returns contain no information beyond the market's volatility expectation that is reflected in DAX–index option prices. In summary, they concluded that implied volatility is a biased but highly informative predictor for future volatility. Moreover, implied volatilities are informational efficient relative to other historic volatility information sources. Valadkhani, Layton and Karunaratne (2005), in their study of domestic price volatility in Australia, tried to show the extent to which Australia's domestic prices relate to world prices using quarterly time-series data spanning the period 1969 quarter 4-2002 quarter 3. Using a parsimonious GARCH (1,1), they showed that Australia's domestic prices are relatively more volatile in both the pre-1975 and post-1975 periods compared to that of other countries. Song et al. (1998) employed GARCH models to analyze the volatility on the two main official stock exchange markets, Shanghai and Shenzhen, in China using monthly data from May 1992 to February 1996. The result showed that GARCH-M (1,1) model was a better-fit model among the

GARCH Mean (M) models of stock return series of both Shanghai and Shenzhen markets. Moreover, the one month forecast suggests a similar pattern for the conditional variances of the two markets' return.

Amos (2009) studied the inflation rate in South Africa using data spanning from January 1994 to December 2008. In the study, the seasonal autoregressive integrated moving average (SARIMA) model and the generalized autoregressive conditional heteroscedasticity (GARCH) model were fitted to the data. A best fitting model for each family of models offering an optimal balance between goodness of fit and parsimony was selected. SARIMA(1,1,0)x(0,1,1) and GARCH(1,1) models were chosen to be the best fitting models for determining the two years forecasts of inflation rate of South Africa. According to the results, GARCH(1,1) was observed to be superior in producing future forecasts because of its ability to capture volatility in the data. Zheng et al. (2008) apply GARCH model to examine whether unexpected news affects food price volatility. They use monthly prices for 45 foodstuffs in the US. The results confirm that the amplifying effect of the news is present only in one third of the products. They argue that the increasing concentration of the distribution and retailing of food on large firms is absorbing the price volatility.

Hayo et al. (2012) assessed using GARCH model the impact of the US monetary policy on the price volatility of different commodities (agricultural, livestock, energy and metals). They arrive at the conclusion that expected target interest rate changes and communications do decrease volatility, whereas unexpected interest rate movements and innovative measures do increase it. Ghosh et al. (2010) used GARCH(1,1), the best fit model among GARCH, GARCH-dummy, EGARCH-M models and OLS estimation method, to examine the price volatility and supply response for rice, jowar, bajra, maize, groundnut and cotton in India. Using annual prices, they check whether trade liberalization indeed exacerbates volatility of agricultural products. The results show that the prices of major agricultural products become more unstable in India after the signing of the WTO agreement. Swaray (2007) in the same country used E-GARCH(2,1), the better fit model among an Exponential GARCH and a Threshold GARCH model, to assess the impact of the suspension of international commodity agreements on the asymmetry and persistency of volatility in monthly prices for cocoa, coffee, rubber, sugar and tin. The results demonstrate a rise in the asymmetry but a decrease in the persistence of the shocks.

Perniagaan et al. (2004) explored the varying volatility dynamics of inflation rate in Malaysia for the period from August 1980 to December 2004. The generalized autoregressive conditional heteroscedasticity (GARCH) models and the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) models were used to capture the stochastic variations and asymmetries in the series. An in-sample evaluation of the sub-periods volatility was done. Based on the results, both GARCH(1,1) model and EGARCH(1,1) produced good estimates of subperiods volatility. But due to the nature of the data of having highly irregular fluctuation, EGARCH model was selected to be the best. Yang et al. (2001) investigate the effects of the market-oriented US FAIR act in 1996 on agricultural price volatility using GARCH models for corn, oat, soybeans, wheat and cotton daily futures prices. The results show that agricultural liberalization policy causes: an increase in price volatility for the three major commodities (corn, soybean and wheat); a little change for oats; and a decrease for cotton. Apergis and Rezitis (2003) employ a multivariate GARCH model of relative food price index in Greece. Macroeconomic factors such as money supply, income per capita, real exchange rate, budget deficit/surplus during 1985–1999 are used in order to investigate the volatility spillover effects between food and macroeconomic fundamentals. The results from a GARCH-X(1,1) model showed that a significant and positive effect is imposed by those derivations on the volatility of relative food prices. Moreover, the inclusion of macroeconomic shocks gets them closer to permanency. Kontonikas (2004) analyzed the relationship between inflation and inflation uncertainty in the United Kingdom from 1973 to 2003 with monthly and quarterly data. Different types of GARCH Mean (M)-Level (L) models that allow for simultaneous feedback between the conditional mean and variance of inflation were used to test the relationship. They found that there was a positive relationship between past inflation and uncertainty about future inflation.

Assis et al. (2006) compared the forecasting performance of different time series methods for forecasting cocoa bean prices at Bagan Datoh cocoa bean in Malaysia. The monthly average of Bagan Datoh cocoa bean prices graded for the period of January 1992 to December 2006 was used. Four different types of univariate time series models were compared; namely the exponential smoothing, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroscedasticity (GARCH) and the mixed ARIMA/GARCH models. Root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and Theil`s inequality coefficient (U-statistics) were used as selection

criteria to determine the best forecasting model. The study revealed that the series was influenced by a positive linear trend factor while the regression test results showed the nonexistence of seasonal factors. Moreover, the autocorrelation function (ACF) and the Augmented Dickey-Fuller (ADF) test showed that the time series was not stationary in levels but became stationary after the first differentiating process was carried out. Based on the results of the expost forecasting (starting from January until December 2006) GARCH model outperformed the exponential smoothing, ARIMA, and mixed ARIMA/GARCH models for forecasting Bagan Datoh bean prices.

Chong et al. (2002) used seven years of daily observed Sterling exchange rate in Malaysia. The GARCH model including the family of GARCH Mean model were used to explain the commonly observed characteristics of the unconditional distribution of daily rate of returns series. The results indicated that the hypotheses of constant variance model could be rejected, at least within sample, since almost all the parameter estimates of the ARCH and GARCH models were significant at five percent level of significant. The Box-Ljung statistics (Q- statistics) and the Lagrange Multiplier test revealed that the use of the long memory GARCH model was preferable to the short memory and high order ARCH model. The results from various goodness of fit statistics were not consistent for Sterling exchange rates. It appeared that the BIC and AIC test proposed GARCH models to be the best for within sample modeling while the mean square forecast error (MSFE) suggested the GARCH mean model to be the best for modeling the variance of daily exchange rates.

Igogo (2010) did a study on the effect of real exchange rate volatility on trade flows in Tanzania for the period from 1968 to 2007. The study employed recent ARCH family models to measure volatility. Firstly, the GARCH(1,1) model was employed and found to violate the non-negativity condition. Consequently, the study employed EGARCH(1,1) model proposed by Nelson (1991) to resolve the problem. The adequacy of the EGARCH(1,1) model to measure the real exchange rate volatility was confirmed by testing for ARCH effect after running the model. Furthermore, the study reveals that it is the real exchange rate rather than its volatility that is found to have a significant effect on trade flows although the effect is larger on exports than on imports. Therefore, in the short-run imports are mainly affected by domestic income while exports are mainly affected by the real exchange rate.

Shiferaw (2012) employed ARCH/GARCH models to capture the log-return price volatility of price returns of crops in Ethiopia. He found that GARCH(1,1), GARCH(1,2) and GARCH(2,1) models were good fit for the log-returns price of cereal, pulse and oil crops, respectively. The sum of the coefficients of the ARCH and GARCH terms is close to one in each crop. These results indicate that the volatility shocks are permanent or persistent in each of the three agricultural crops. Regarding the forecasting capability, after obtaining the three satisfactory GARCH models, the forecast process was analyzed based on root mean square error (RMSE). The study concludes that the above GARCH models are suitable to forecast the long-return volatility of crops because the value of RMSE calculated using these models were small. Findings of this study could give good insight to forecast volatility of price of agricultural products in Ethiopia.

Sebsib (2009) studied the volatility of export prices of sesames in Ethiopia using data from January 1998 to June 2013. In the study, the autoregressive moving average (ARMA) and autoregressive conditional hetroscedasticity (GARCH) models were fitted to the data. A best fitting model for each family of model based on AIC and BIC criteria selection procedure was used. ARMA(0,1,1) is found as the most appropriate model for the conditional mean of export price of sesame. The study also found GARCH(2,1) for modeling volatility of sesame as a best fitting model. In addition, the result suggest that the export price volatility is persistent, indicating that past volatility is important in predicting (forecasting) future volatility. Atalay(2017) also studied the volatility of export price of coffee in Ethiopia using the data from January 2002 to January 2016. In this study, the autoregressive moving average (ARMA) and autoregressive conditional hetroscedasticity (GARCH) models were fitted to the data. A best fitting model from each family of model were selected based on AIC and BIC selection criteria. ARMA(1,1,1) is found as the most appropriate model for the conditional mean of export price of coffee. The study also found EGARCH(3,1) for modeling volatility of coffee as a best fitting model.

CHAPTER THREE

DATA AND METHODOLOGY

3.1. Sources of Data

To assess the average monthly domestic price volatility of coffee in Ethiopia the data were secondary data, which are obtained from central statistical agency (CSA) and national bank of Ethiopia (NBE). The domestic price of coffee were obtained from CSA but the remaining explanatory variables like export price of coffee, exchange rate, fuel oil, saving interest rate, food inflation rate, non-food inflation rate and total government revenue were obtained from National Bank of Ethiopia (NBE) over the period from January 2003 to December 2016 GC.

3.2. Variables Consider in the Study

3.2.1. Dependent Variable

The response variable in this study is the average monthly domestic price of coffee in Ethiopia.

3.2.2. Independent Variables

The independent variables that will assumed to cause the average monthly domestic price of coffee to be volatile are Exchange rate in dollar to birr (X_{1t}), Export price of coffee (X_{2t}), Fuel oil price (X_{3t}), Food inflation rate (X_{4t}), Nonfood inflation rate (X_{5t}), saving Interest rate (X_{6t}) and total government revenue (X_{7t}).

3.3. Statistical Methodology

Time series is broadly defined as series of measurements taken sequentially across a period of time. It can be classified in to two major parts: univariate and multivariate time series. Univariate time series are used to model a single time series data independently. On the other hand, multivariate time series used to model a vector of time series data that will be modeled simultaneously. Since the nature of the data is a single time series data the methodology adopted in this study follows univariate financial time series model.

The (Box-Jenkins, 1976) approach of time series model such as AR, MA and ARMA models are often useful in modeling general time series data. However; they all requires the assumption of

homoskedasticity or constant variance for the errors. This assumption has the implication that uncertainty or volatility remains constant over time (Gebhard and Jurgen, 2007). This may not be appropriate when dealing with some special characteristic in the financial and macroeconomic time series variables, since they exhibit a set of unique characteristics, like the return of financial assets displays volatility clustering(large change in return series followed by large changes and small changes followed by small changes), return series is fat tailed (the distribution of return series tends to be leptokurtic distribution) and the return series has leverage effect (Mandelbort, 1963). These characteristics of financial time series can't be explained by the general models of ARIMA. Hence it makes sense to consider a model that does not assume that the variance is constant, and which describes how the variance of the errors evolves. Consequently the ARCH model which was proposed by (Engle, 1982) and generalized by (Bollerslev, 1986; Taylor, 1986) have been proved to be sufficient in capturing properties of time varying return volatility.

Thus in this study there are two distinct equations or specifications, the first for the conditional mean and the second for the conditional variance. We first employ an autoregressive moving average (ARMA) model for the conditional mean in the return series as an initial regression. Then a test of the null hypothesis of there is no ARCH effect in the residual series is conducted. If the hypothesis tells the presence of ARCH effect then, autoregressive conditional heteroscedasticity (ARCH) and its generalization (GARCH) models represent the main methodologies that has been applied in modelling and forecasting the volatility of domestic price of coffee. Since the structure of the data is time series data regarding with the domestic price of coffee we used the statistical model preferable for this time series data. Specifically, we used univariate financial time series models such as ARIMA and GARCH family models. But before fitting time series models, the series should undergo stationary test.

3.3.1. Stochastic Process

A stochastic process is a series of time indexed random variables $Y(S,t)$, where S belongs to a sample space and t to an index set. For a fixed set t, $Y(S,t)$ is a random variable; for a given $S, Y(S,t)$ as a function of t is called a realization. The population that consists of all possible realizationxs is called the ensemble in stochastic process and time series analysis. Thus, a time series is a realization or sample function from a certain stochastic process (William, 2006). A

time series $\{Yt\}$ is a collection of observations on a variable indexed sequentially over several time points $t = 1, 2 \ldots T$. Time series observations Y1, Y2….Yt are inherently dependent. From a statistical modeling perspective, this means it is inappropriate to treat a time series data as a random sample of independent observations**.**

3.3.2. Stationarity

The foundation of time series analysis is Stationarity and it is an essential property to define a time series process. Stationarity may be weak or strong (strict).

3.3.2.1. Weak Stationarity

A stochastic process $\{Y_t\}$ is said to be weakly stationary or covariance stationary if both the mean of Y_t , the variance of Y_t and the covariance between Y_t and Y_{t+h} are time invariant, where h is an arbitrary integer. More specifically, the time series $\{Y_t\}$ is weakly (covariance) stationary if:

- $E\ (Y_t) = \mu$(Constant and finite mean)
- Var $(Y_t) = \ \delta^2 \ < \infty$ (Finite variance).
- For any *t Cov* $(Y_t\ , Y_{t+h}\ ) = \gamma_x(h)$ which depends only on h and not on t.

If one of these properties or characteristics violated the time series process $\{Y_t\}$ is non stationary.

3.3.2.2. Strong (Strict) Stationarity

A time series is said to be strictly stationary if its properties are not affected by a change in the time origin. That is, if the joint probability distribution associated with *n* observations $\{Y_1, Y_2 \ldots Y_n\}$ made at any set of times t_1, $t_2 \ldots t_n$ is exactly the same as the joint probability distribution of the observations $\{Y_{t+1}\ , Y_{t+2}\ \ldots Y_{t+k}\}$ made at times $t_{1+k}, t_{2+k} \ldots t_{n+k}$. Mathematically it can be expressed as:

$$F\ (Y_{t1} \leq \tau_1\ , Y_{t2} \leq \tau_2, \ldots Y_{tn} \leq \tau_n\ ) = F\ (Y_{t1+k} \leq \tau_1\ , Y_{t2+k} \leq \tau_2, Y_{tn+k} \leq \tau_n) \qquad [3.1]$$

Therefore weak (covariance) Stationarity does not mean that strong or strict Stationarity. In a common sense Stationarity mean weak Stationarity.

3.3.3. Stationarity Test (Unit Root Test)

Many econometric and financial time series exhibits non-stationary and different statistical issues arise when analyzing this process. A non-stationary process arises when one of the conditions for stationarity does not hold. When we deal with non-stationary series, the effect of a shock never dies away and it leads a regression with time series data that are very likely to result in spurious regression, that is, one regresses completely unrelated series and results high R^2 (indicating how good one term is at predicting another) and the standard tests are not valid (Granger and Newbold, 1986). In order to handle this result we can use different methods, like differencing. Most commonly a non-stationary process can be stationary by applying differencing for appropriate number of times.

In order to ensure the condition of Stationarity, a non-stationary series must to be integrated. A non-stationary time series is called integrated if it can be transformed into a stationary process by differencing once or a very few times. The order of integration is the minimum number of times the series needs to be differenced to yield a stationary series. If the series is differenced d times the process is called integrated of order d that is I (d). The first step for an appropriate analysis is to determine whether the time series is stationary or not. A test for Stationarity that has become widely popular over the past several years is the $unit\ root\ test$.

Consider a random walk (AR (1)) process with drift:

$$Y_t = \mu + \phi_1 Y_{t-1} + u_t \qquad [3.2]$$

Where $u_t's$ are a white noise proces. Unit root tests are based on testing the null hypothesis that:
$H_0 : \phi_1 = 1$ (the series is not stationary) against
$H_1 : \phi_1 < 1$ (the series is stationary)

They are called unit root tests because, under the null hypothesis, the characteristic polynomial has a root equal to unity. There are several unit root tests. But the most widely used ones are Augmented Dickey- Fuller (ADF) test due to Dickey and Fuller (1979), and the Phillip-Perron (PP) test due to Phillips and Perron (1988).

3.3.3.1. Augmented Dickey-fuller (ADF) Unit Root Test

The ADF test is used to tests whether a unit root is present in an autoregressive model or not. It is developed by the statisticians David Dickey and Wayne Fuller in 1979. In its simplest form it considers an autoregressive of order one process with drift given by:

$$Y_t = \mu + \phi_1 Y_{t-1} + u_t \quad [3.3]$$

Where Y_t is the variable of interest and u_t Are the error term which is assumed white noise.
If a unit root is present (if $\phi_1 = 1$), then the model would be non-stationary. We must have to use first difference to make it stationary, meaning that subtracting Y_{t-1} from both sides and the resulting regression model can be written as:

$$\nabla Y_t = \mu + (\phi_1 - 1)Y_{t-1} + u_t = \mu + \Pi Y_{t-1} + u_t \quad [3.4]$$

Where $\Pi = \phi_1 - 1$ and therefore, the null hypothesis of the above unit root test is equivalent to:
$H_o : \Pi = 0$ (The series is not stationary) against
$H_1 : \Pi < 0$ (The series is stationary)

The test statistic is given by:

$$t = \frac{\widehat{\Pi}}{se(\widehat{\Pi})} \quad [3.5]$$

Where $\widehat{\Pi}$ is the OLS estimator of Π and se ($\widehat{\Pi}$) is the standard error of $\widehat{\Pi}$.

Dickey and Fuller (1979) showed that, under the null hypothesis of a unit root the test statistic given by (3.5) 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 from 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 that the disturbances in the

model are white noise is violated and 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 to the right-hand side of the test regression:

$$\nabla Y_t = \Pi Y_{t-1} + \beta_1 \nabla Y_{t-1} + \cdots + \beta_p \nabla Y_{t-p} + u_t \quad [3.6]$$

This augmented specification is then used to test for unit root using the t-ratio. An important result obtained by Dickey-Fuller (1979) is that the asymptotic distribution of the statistic is independent of the number of lagged first differences included in the ADF regression. Moreover, while the assumption that u_t 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.

3.3.3.2. Phillips and Perron (PP) Unit Root Tests

The statistic proposed by Phillips and Perron (1988) arise from their considerations of the limiting distributions of the various Dickey-Fuller statistics when the assumption that is an iid process is relaxed. The test regression in the Phillips-Perron test is given by:

$$Y_t = \alpha + \beta t + \Pi Y_{t-1} + u_t \quad [3.7]$$

Where u_t is a stationary process (which may be heteroscedastic). The PP test correct for any serial correlation and heteroskedasticity in the errors of the test regression by directly modifying the Dickey-Fuller test statistic. The modified statistics, denoted by $Z_t \; and \; Z_\Pi$, are given by:

$$Z_t = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{1/2} t_{\Pi=0} - \frac{1}{2}\left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right)\left(\frac{T\, se(\hat{\Pi})}{\hat{\sigma}^2}\right) \quad [3.8]$$

$$Z_\Pi = T\,\Pi - \frac{1}{2}\left(T^2 \frac{se(\hat{\Pi})}{\hat{\sigma}^2}\right)\left(\hat{\lambda}^2 - \hat{\sigma}^2\right) \quad [3.9]$$

The terms $\hat{\lambda}^2 \; and \; \hat{\sigma}^2$ are the variance parameters that are given by:

$$\hat{\sigma}^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E(U_t{}^2) \quad [3.10]$$

$$\hat{\lambda}^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E(S_t{}^2) \qquad \text{Where } S_t{}^2 = \sum_{t=1}^{T} U_t \quad [3.11]$$

Under the null hypothesis that $H_0 : \Pi = 0$, the statistics $Z_t \; and \; Z_\Pi$ have the same asymptotic distributions as the ADF t-statistic. In the Dickey-Fuller specification, we can use the critical values given by Dickey and Fuller for the various statistic if u_t is identically and independently distributed. Alternatively, we should use Phillips-Perron's counter parts if u_t is not identically and independently distributed. 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, and the user does not have to specify a lag length for the test regression.

3.3.4. ARIMA Family Models

The ARIMA approach was first popularized by Box and Jenkins, and are often referred to as Box-Jenkins models. The ARIMA procedure analyzes and forecasts equally spaced univariate time series data, transfer function data, and intervention data using the Autoregressive Integrated Moving Average (ARIMA) or Autoregressive Moving Average (ARMA) model. An ARIMA model predicts a value in a response time series as a linear combination of its own past values, past errors (also called shocks or innovations), and current and past values of other time series. Given a time series of data Y_t, the ARMA model is a tool for understanding and, perhaps, predicting future values in this series. The most general class of time series models for forecasting models of time series that can be stationary by transformations such as differencing, logging, and or deflating is the family of Autoregressive Integrated Moving Average (ARIMA) models, usually associated with (Box Jenkins, 1976).

Assumptions of the ARMA Model:

- The expected values of the error term is zero.
- Homoscedasticity (constant variance) for the error term.
- No serial autocorrelation among each successive standardized residual in the model.

3.3.4.1. Autoregressive (AR) Process

Autoregressive models are based on the idea that the current value of a series, Y_t can be expressed as a function of the past values of itself plus some noise term or shocks (innovations). An autoregressive model of order p, abbreviated AR (p), have the form:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + u_t \quad [3.12]$$

It is equivalent to:

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + u_t \quad [3.13]$$

Where U_t is a white noise series with mean zero and finite variance: σ^2

Using the backward shift operator Z ($Z^P Y_{t=} Y_{t-p}$) equation 3.12 can also be written as:

$$\phi(Z) Y_t = u_t \quad [3.14]$$

Where $\phi(Z) = 1 - \phi_1 Z - \phi_2 Z^2 - \ldots - \phi_P Z^P$ is a polynomial in Z of order p.

It can be shown that equation (3.12) has a unique causal stationary solution provided that the roots of $\phi(Z) = 0$ lie outside the unit circle. If it is so, the stationary AR process can be expressed as an infinite order moving average process and it can be expressed as:

$$Y_t = \sum_{j=0}^{\infty} \varphi_i u_{t-i} \quad [3.15]$$

For some constants φ_j such that $\sum_{j=0}^{\infty} \varphi_j^2 < \infty$

Typically an AR process is stationary provided that the roots of $\phi(Z) = 0$ lie outside the unit circle or absolute value of Z greater than 1 or absolute value of ϕ less than 1 (Chatfield, 2000). An important property of an AR (p) process is that the partial ACF is zero at all lags greater than p (cuts off after lag p) and the ACF damps out. This means that the sample partial ACF can be used to determine the order of an AR process by assuming the order is unknown as is usually the case by looking for the lag value at which the sample partial ACF "cuts off" (approximately zero, or at least not significantly different from zero, for higher lags) (Chatfield, 2000).

3.3.4.2. Moving average (MA) processes

A stationary time series $\{Y_t\}$ is said to be a moving average process of order q (abbreviated by MA (q)) if it is a weighted linear sum of the last q random shocks and is defined as:

$$Y_t = u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \quad [3.16]$$

It is equivalent to:

$Y_t = \sum_{j=0}^{q} \theta_j \, u_{t-j}$ [3.17]

Where $\theta_1, \ \theta_2 \ldots \theta_q \neq 0$ are parameters and $\{u_t\}$ is assumed to be white noise.

Using the backward shift operator Z ($Z^q u_t = u_{t-q}$) equation 3.16 can be expressed as:

$Y_t = \theta \ (Z) \ u_t$ [3.18]

Where $\theta \ (Z) = 1 + \theta_1 Z + \ \theta_2 \ Z^2 + \cdots + \ \theta_q \ Z^q$ is a polynomial in Z of order q. If all the roots of $\theta \ (Z) = 0$ lie outside the unit circle, the MA process is invertible and has an autoregressive representation of generally an infinite order. That is: $u_t = \sum_{j=1}^{\infty} \phi_j Y_{t-j}$ with $\sum_{j=1}^{\infty} |\phi_j| < \infty$.

The order of such a model can be determined by using the autocorrelation function, ACF, which cuts off after q lags and partial ACF that decays exponentially fast. Unlike the autoregressive process, the moving average process is stationary for any values of the parameters, because shocks are stationary at level and a moving average process is expressed only as a function of past and present values of shocks or innovations (Chatfield, 2000).

3.3.4.3. Autoregressive Moving average (ARMA) Process

In some applications, the AR or MA models become cumbersome because one may need a higher-order model with many parameters to adequately describe the dynamic structure of the series. To overcome this difficulty, a parsimony model called the autoregressive moving-average (ARMA) models were introduced (Box, *et al* (1994)). Basically, an ARMA model is the combination of the ideas of AR and MA models into compact form so that the number of parameters used is kept small.

A mixed autoregressive moving average model with p autoregressive terms and q moving average terms (abbreviated by ARMA (p, q)) can be expressed as:

$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p \ Y_{t-p} + u_t + \ \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q}$ [3.19]

It is equivalent to:

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=0}^{q} \theta_j u_{t-j} \quad [3.20]$$

Using the back ward shift operator Z ($Z^P Y_{t=} Y_{t-p}$ and $Z^q u_t = u_{t-q}$) it can be written as:

$$\phi(Z) Y_t = \theta(Z) u_t \quad [3.21]$$

Where ϕ (Z) = 1- $\phi_1 Z - \phi_2 Z - \ldots - \phi_P Z$ and $\theta(Z) = 1 + \theta_1 Z + \theta_2 Z^2 + \cdots + \theta_q Z^q$ are a polynomial in Z of finite order *p* and *q*, respectively. Equation (12) has a unique causal stationary solution if the roots of ϕ (Z) = 0 lie outside the unit circle and the process is invertible if the roots of $\theta(Z)$ = 0 lie outside the unit circle.

The importance of ARMA process is that many real world time series may be approximated in a more parsimonious way by a mixed ARMA model rather than by an individual AR or MA process. The characteristics of an ARMA process is determined by both partial ACF and ACF. The ACF alone can distinguish between a pure autoregressive and a pure moving average process. However, an ARMA process will have a geometrically declining ACF, as will a pure AR process. So, the partial ACF is useful for distinguishing between an AR (*p*) process and an ARMA (*p, q*) process. The former will have a geometrically declining autocorrelation function, but a partial autocorrelation function which cuts off to zero after *p* lags, while the latter will have both autocorrelation and partial autocorrelation functions which decline geometrically.

3.3.4.4. Autoregressive Integrated Moving Average (ARIMA) Process

Sometimes, many time series are non-stationary and we cannot apply stationary AR, MA or ARMA processes directly. One possible way of handling this non-stationary series is to apply differencing so as to make them stationary. Differencing of a series can transform a non-stationary series to a stationary series. One advantage of differencing over de-trending to remove trend is that no parameters are estimated in the differencing operation, however one disadvantage is that differencing does not yield an estimate of the stationary process Y_t. If an estimate of Y_t is essential, then de-trending may be more appropriate over differencing. But if the aim is to make the data stationary, then differencing may be more appropriate than de-trending. Therefore the first difference operator ∇ is defined by: $\nabla Y_t = Y_t - Y_{t-1}$, using the back ward shift operator Z

it is equivalent to: $\nabla Y_t = (1 - Z)\ Y_t$. In general, higher order differencing can be expressed as: $\nabla^n Y_t = (1 - Z)^n\ Y_t$.

A series that is stationary without any differencing is said to be integrated of order zero (denoted by I (0)), and a series which is stationary after being differenced d times is said to be integrated of order d (denoted by I (d)) (Pole, 1994; Weigend, 1993). If the original data series is differenced d times before fitting an ARMA (p, q) process, then the model for the original indifference series is said to be an ARIMA (p d q) process. It is defined as:

$$\phi(Z)\ \nabla^d Y_t = \theta\ (Z)\ u_t \qquad [3.22]$$

Where $\nabla = 1 - Z$, d is the order of integration, $\phi\ (Z) = 1 - \phi_1 Z - \phi_2 Z^2 - \ ... - \phi_P Z^p$ and $\theta\ (Z) = 1 + \theta_1 Z + \ \theta_2\ Z^2 + \cdots + \ \theta_q\ Z^q$

3.3.5. Building ARIMA Family Models

3.3.5.1. Model Identification and Order Selection

The first step in ARIMA modeling is identification of the appropriate model. ARIMA procedures are mainly based on the analysis of plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF), which are essential diagnostic instruments to identify the dependence structure of the series. Hence by using plots of the autocorrelation and partial autocorrelation functions of the time series variable we can decide the tentative (if any) autoregressive or moving average components in the model. It can be summarized in Table 3.1:

Table 3.1: Behavior of the ACF and PACF for ARMA models

Process	ACF	PACF
AR(p)	Infinite: damps out	Finite: cuts off after lag p
MA(q)	Finite: cuts off after lag q	Infinite: damps out
ARMA(p, q)	Infinite: damps out	Infinite: damps out

A model selection criterion is used to consider the "best approximating model" from a set of competing models. In time series analysis there may be several adequate models that can fit a

given data set. Thus, various criteria for model selection have been introduced in the literature. When there are multiple adequate models, the selection criterion is normally based on the likelihood function and the number of free parameters from the fitted model or on forecast errors calculated from out-of sample forecast. The traditional model selection criteria such as the Akaike information criterion (AIC) proposed by Akaike (1974) and the Schwartz Bayesian information criterion (BIC) proposed by Schwartz (1978) were employed to identify the optimal lag specification for the model.

3.3.5.1.1. Akaike's Information Criterion (AIC)

Akaike (1973) suggested measuring the goodness of fit for ARMA (*p, q*) by balancing the error of the fit against the number of parameters in the model. It is defined by:

$$AIC = -2ln(L) + 2k \quad [3.23]$$

Where $L\ is$ the maximized value of the likelihood function and k is the number of (free) parameters in the model (i.e. $p + q + 1$). Given a set of candidate models, the preferred model is the one with the minimum AIC value. However, AIC may not result in the selection of a parsimonious model, that is, it may favor over-parameterized models. In order to remove this deficiency, Hurvich and Tsai (1989) introduced a corrected version, *AICc*, defined by:

$$AICc = -2ln(L) + \frac{2KT}{T-K} \quad [3.24]$$

Where T is the sample size and L and K are as described above.

3.3.5.1.2. Bayesian Information Criterion (BIC)

Bayesian information criterion (Schwarz, 1978) is another criterion for model selection among a set of competing models. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC). It is defined by:

$$BIC = -2ln(L) + kln(T) \quad [3.25\ ]$$

BIC is also called the Schwarz Bayesian Information Criterion (SBIC). Various simulation studies have tended to verify that BIC does well at getting the correct number of parameters in

large samples, whereas bias corrected AIC (AICc) tends to be superior in smaller samples where the relative number of parameters is large (McQuarrie and Tsai, 1998).

3.3.5.2. Parameter Estimation for ARIMA family models

Having identified an appropriate order for ARMA models the next step is to estimate the parameters of the autoregressive and moving average terms included in the model. We can estimate the unknown parameters by ordinary least squares (OLS) or by maximum likelihood (ML) methods. Both estimation procedures are based on the innovation series U_t. The least-squares methods minimize the sum of squares of the innovation terms, while the ML method maximizes the joint probability density function of the innovation terms.

3.3.5.3. Diagnostic Checking for ARIMA family models

Once a model has been identified and the parameters are estimated, it should be subjected to diagnostic checking before the model is used for specific purpose (e.g. forecasting) for possible mis specifications. If some key model assumptions seem to be violated, then a new model should be specified, fitted and checked again until the model is found that provides an adequate fit to the data. As with most statistical models, the goodness of fit of the univariate and multivariate time series model is based on residuals and more specifically on the standardized residuals. Hence checking of some key model assumptions include tests of serial correlation and normality of the residuals.

3.3.5.3.1. Test of serial correlation of residuals

Two types of tests of serial correlation of the residual series will apply in this work: Breusch-Godfrey LM and Ljung-Box tests.

Lagrange Multiplier (LM) Test

This test was developed by Breusch and Godfrey in 1978. This test is based on an AR representation of residuals and is used to test for serial correlation in the error terms. We first construct an auxiliary regression and estimate the sample residuals u_t . Suppose that the residuals u_t follow an autoregressive scheme given by:

$$u^2{}_t = \alpha_0 + \alpha_1 u^2{}_{t-1} + \alpha_2 u^2{}_{t-2} + \ldots + \alpha_m u^2{}_{t-m} + \varepsilon_t \qquad [3.26]$$

Where ε_t is a white noise process and α_i 's are parameters of the model.

The Lagrange Multiplier (LM) test for order serial correlation is computed first by estimating the sample residuals u_t (that is $\hat{u}_t$) by ordinary least squares (OLS) and regress the current residual $\hat{u}_t$ on the *p* lagged residuals. So, the fitted auxiliary regression model of residuals is given by:

$$\hat{u}^2{}_t = \alpha_0 + \alpha_1 \hat{u}^2{}_{t-1} + \alpha_2 \hat{u}^2{}_{t-2} + \ldots + \alpha_m \hat{u}^2{}_{t-m} \varepsilon_t \quad [3.27]$$

The significance of the parameters α_i would indicate the presence of serial correlation under the null hypothesis. Here the null hypothesis of absence of serial correlation up to lag *m* is:

$H_0: \alpha_1 = \alpha_2 = \ldots = \alpha_m = 0$ (there is no serial correlation among the residuals). If the usual R^2 statistic is computed for this model, the test statistic is:

$$LM = TR^2 \quad [3.28]$$

The distribution of a test statistic is: $TR^2 \sim \chi^2(m)$ Where $R^2 is$ the coefficient of determination from the auxiliary regression and T is the sample size.

Ljung-Box Test

The Ljung-Box (LB) test is one of the widely used lack-of-fit tests, that is, a test for the appropriateness of the fitted model. It was developed by Box and Pierce (1970) and modified by McLeod, et al. (1983). It is a statistical test which is used to test whether there is serial correlation in the residuals or not. Hence the null hypothesis of absence of serial correlation up to lag *m* is: $H_0: \rho_1 = \rho_2 = \cdots \rho_m$ (There is no serial correlation) againest the alternative hypothesis.

The test statistic is given by:

$$Q = T(T+2) \frac{\sum_{i=1}^{m} \hat{\rho}_i{}^2}{T-K} \quad [3.29]$$

Where $\hat{\rho}_i$ is $i^{th} - lag$ sample autocorrelation of the residuals of the fitted model and $T$is the number of observations. If the series is not based upon results of ARIMA estimation, then under the null hypothesis Q is asymptotically distributed as chi-square with $m - k = m - (p + q)$ degrees of freedom. But if the series represents the residuals from ARIMA estimation, the appropriate degrees of freedom should be adjusted to represent the number of autocorrelations less the number of AR and MA terms.

3.3.5.3.2. Testing Normality of the Residual

Normality tests are used to ascertain 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 of the residuals are available but the most commonly used test is Jarque-Bera test developed by Jarque and Bera (1981)

Jarque-Bera test of normality

One of the most commonly applied tests for normality is the Jarque-Bera (JB) test. This test uses the property of a normally distributed random variable that the entire distribution is characterized by the first two moments - the mean and the variance. The standardized third and fourth moments of a distribution are known as its skewness and kurtosis respectively. Skewness measures the extent to which a distribution is not symmetric about its mean value, and kurtosis measures the peakedness or flatness of the distribution of the series. Jarque and Bera (1981) formalize these ideas by testing whether the coefficients of skewness and excess kurtosis are jointly zero or not. If $\bar{Y}$ is the sample mean, $\hat{\mu}_3$ and $\hat{\mu}_4$ are estimates of the third and the fourth central moments, respectively and σ^2 is an estimate of the second central moment (variance). Thus the sample skewness (S) and kurtosis (K) coefficients are computed as:

$$\hat{s} = \frac{\hat{\mu}^3}{\hat{\sigma}^3} \frac{\frac{1}{T}\sum_{i=1}^{T}(y_i-\bar{y})^3}{(\frac{1}{T}\sum_{I=1}^{T}(y_i-\bar{y})^2)^{3/2}} \quad [3.30]$$

$$\hat{k} = \frac{\hat{\mu}^4}{\hat{\sigma}^4} \frac{\frac{1}{T}\sum_{i=1}^{T}(y_i-\bar{y})^4}{(\frac{1}{T}\sum_{I=1}^{T}(y_i-\bar{y})^2)^2} \quad [3.31]$$

The JB test statistic is defined as:

$$JB = T\{\frac{\hat{s}^2}{6} + \frac{(\hat{k}-3)^2}{24}\} \quad [3.32]$$

Under the null hypothesis this test statistic asymptotically follows a chi-square distribution with two degrees of freedom. Thus, large values of this test statistic relative to the quantiles from the chi-square distribution with two degrees of freedom lead to rejection of the null hypothesis (Brooks, 2002).

3.3.5.4. Forecasting for ARIMA Family models

The last step in ARIMA modeling is forecasting. One of the reasons for the popularity of the ARIMA modeling is its success in forecasting. As mentioned earlier the ARIMA(p, d, q) process is given by:

$$\phi(Z)\,\nabla^d Y_t = \theta\,(Z)\,u_t \qquad [3.33]$$

Where ∇=1 – Z, d is the order of integration, ϕ (Z) = $1 - \phi_1 Z - \phi_2 Z - \cdots - \phi_P Z$ is a stationary AR operator and $\theta\,(Z) = 1 + \theta_1 Z + \theta_2 Z^2 + \cdots + \theta_q Z^q$ is an invertible MA operator.

Suppose that at time t we have the observations $Y_t, Y_{t-1}, \ldots$ and wish to forecast the h-step ahead future value Y_{t+h} as a linear combination of the observations $Y_t, Y_{t-1} \ldots$ (denoted by $\hat{Y}_t\,(h)$ h ≥ 1). Let F_t be the information set at time t. The minimum mean square error forecast $\hat{Y}_t\,(h)$ of Y_{t+h} is given by its conditional expectation.

$$\hat{Y}_t\,(h) = E(\,Y_{t+h}|F_t), h \geq 1 \qquad [3.34]$$

For t is replaced by $t + h$, $h \geq 1$, we have:

$$Y_{t+h} = \phi_1 Y_{t+h-1} + \phi_2 Y_{t+h-2} + \cdots + \phi_{p+d} Y_{t+h-p-d} + u_{t+h} + \theta_1 u_{t+h-1} + \theta_2 u_{t+h-2} + \cdots + \theta_q u_{t+h-q}$$

Then, by taking the conditional expectation given the information set at time t, we get the minimum mean square error forecast value of Y_{t+h} :

$$\hat{Y}_t\,(h) = \phi_1\,\hat{Y}_t\,(h-1) + \phi_2 \hat{Y}_t\,(h-2) \ldots\ldots + \phi_{p+d}\hat{Y}_t\,(h-p-d) + \hat{u}_t\,(h) + \theta_1 \hat{u}_{t-1}\,(h-1) + \theta_2 \hat{u}_{t-2}\,(h-2) + \ldots\ \theta_q \hat{u}_{t-q}\,(h-q) \qquad [3.35]$$

Forecasting accuracy measures

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 and can be measured by Mean Square Error (MSE), Mean Absolute Error (MAE),

Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE). The Theilâs U test statistic can also be used as a measure of forecasting accuracy. Like MAPE statistic, high values of U suggest poor performance in the forecast. The scaling of U is that it will always lie between 0 and 1. If U = 0, for all forecasts there is a perfect fit and if U = 1 the predictive performance is not good.

If Y_{t+h} , h=1, 2. . . K is the actual observation for the period $(t + h)$ and $\hat{Y}_t\ (h)$ is the forecast of Y_{t+h} then the forecast error is defined as:

$$\hat{\varepsilon}_t\ (h) = Y_{t+h} - \hat{Y}_t \qquad [3.36]$$

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 (MS): $\frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_t\ (h)$ [3.37]

Mean Absolute Error (MAE): $\frac{1}{T}\sum_{t=1}^{T}|\hat{\varepsilon}_t\ (h)|$ [3.38]

Mean Squared Error (MSE): $\frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_t^{\,2}(h)$ [3.39]

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

$PE_t = \left(\frac{Y_{t+h}-\hat{Y}_t}{Y_{t+h}}\right) * 100$ [3.40]

Then the following two relative measures are frequently used to determine the forecasting ability of the model under consideration.

Mean Percentage Error (MPE) = $\frac{1}{T}\sum_{t=1}^{T}PE_t$ [3.41]

Mean Percentage Absolute Error (MPAE) = $\frac{1}{T}\sum_{t=1}^{T}|PE_t|$ [3.42]

Equation [3.38] can be used to compute the percentage error for any time period. These can be averaged as in equation [3.39] to give the mean percentage error. However, as with the ME, the MPE is likely to be small since positive and negative PEs tend to offset one another. Hence the MAPE is defined using absolute values of PE in equation [3.42].

Theil's U statistic is also used as a measure of forecasting accuracy. Like MAPE statistic, high values of Theil's U suggest poor performance in the forecast and it can be estimated as:

$$\frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_{t+h}-\hat{Y}_t)^2}(h)}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\hat{Y}_t(h)^2}+\sqrt{\frac{1}{T}\sum_{t=1}^{T}Y_{t+h}{}^2}} \qquad [3.43]$$

The scaling of U is such that it will always lie between 0 and 1. If U = 0, $(Y_{t+h} = \hat{Y}_t)$ for all forecasts and there is a perfect fit and if U = 1 the predictive performance is not good.

3.3.6. GARCH Family Models

The Box-Jenkins time series model such as Autoregressive (AR), Moving Average (MA) and ARMA and ARIMA are often very useful in modeling general time series data. However; they all require the assumption of homoscedasticity (or constant variance) for the error term in the model. So, this may not be appropriate when dealing with some special characteristics in the financial and economic time series and this leads to the introduction to GARCH (Generalized Autoregressive Conditional Heteroskedasticity) family models. As explained in detail in the literature families of these model includes ARCH (Autoregressive Conditional Heteroskedasticity), GARCH (Generalized Autoregressive Conditional Heteroskedasticity), TGARCH (Threshold Generalized Autoregressive Conditional Heteroskedasticity) and EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) models that has been used to fit financial time series data that have heteroskedastic error variance. Most problems in finance have motivated the study of volatility, or variability, of a time series. Unlike ARMA models which assume a constant variance, in GARCH family models the fact that large absolute returns tend to be followed by large absolute returns (whatever the sign of the price variations) is hardly compatible with the assumption of constant conditional variance. This phenomenon is called conditional heteroscedasticity that is the variance is time variant and hence they are used for the study of volatility.

Most financial studies are often concerned with the analysis of returns of assets, rather than the prices of assets.The main reason is that the return series are easier to handle than price series, since the former have more attractive statistical properties, such as:

- ❖ The return series usually shows no or little autocorrelation;
- ❖ Asset prices are generally non stationary but eturns are usually stationary ;
- ❖ Returns of an asset are a scale-free measure of the investment opportunity;
- ❖ Serial independence between the squared values of the series is often rejected;
- ❖ Volatility of the return series appears to be clustered;
- ❖ Normality tends to be rejected in favor of some thick-tailed distribution.

If y_t is the domestic price of coffee at time t, Instead of analyzing y_t, which often displays unit-root behavior and thus cannot be modeled as stationary, we often analyze log returns on y_t (Fryzlewicz, 2007). That is the return series r_t is defined to be:

$$r_t = log(\frac{y_t}{y_{t-1}}) = logy_t - logy_{t-1} \quad [3.44]$$

The basic idea behind volatility study is that the series $\{r_t\}$ is either serially uncorrelated or has lower order serial correlations, but is a dependent series. Typically for financial series, The log return series (r_t) displays many of the typical behaviors in financial series such as: Absence of autocorrelations, aggregational Gaussianity, volatility clustering, conditional heavy tails, leverage effect, volume/volatility correlation and asymmetry. Therefore to study this return $\{r_t\}$ we used volatility models or GARCH family models.

To put the volatility models in proper perspective, it is informative to consider the conditional mean and variance of ε_t given the information set available at time $t-1$, ψ_{t-1}. That is:

The conditional mean and variance respectivlly are:

$$E(\varepsilon_t|\psi_{t-1}) = \mu \text{ and } var\ (\varepsilon_t|\psi_{t-1}) = E[(\varepsilon_t - \mu_t)^2|\psi_{t-1}] = {\sigma_t}^2 \quad [3.45]$$

The mean equation for ε_t should be simple, and we assume that ε_t follows a simple time series model such as a stationary ARMA (p, q) model.

3.3.6.1. Autoregressive Conditionally Hetroscedasticity (ARCH) Model

One of the simplest volatility models is the Autoregressive Conditional Heteroscedasticity (ARCH) model suggested by Engle (1982). ARCH models are the first attempt to capture the

characteristics of financial time series without the assumption of constant variance. It is unlikely in financial time series that the variance of the error terms will be constant over time. Therefore, allowing for conditional heteroscedasticity in return series analysis is reasonable. The ARCH model resembles a regression model, the fact that the conditional variance is not directly observable (and hence is called a latent variable) introduces some subtlety in the use of ARCH models in data analysis and they are specifically designed to model and forecast conditional variances.

Let Y_t denote a stationary time series with conditional mean of ARMA family models. The error terms ε_t are split into a stochastic component η_t and a time dependent standard deviation σ_t characterizing a typical size of the term given by:

$$Y_t = \mu + \varepsilon_t\,, \qquad \varepsilon_t = \sigma_t \eta_t \tag{3.46}$$

To allow conditional heteroscedasticity,we assume that the variance of the residuals for the mean equation is $var\,(\varepsilon_t|\psi_{t-1}) = E[(\varepsilon_t - \mu_t)^2|\psi_{t-1}] = {\sigma_t}^2$, since $E\,(\varepsilon_t|\psi_{t-1}) = 0$, where ψ_{t-1} denotes the information set at time $(t-1)$. Here ${\sigma_t}^2$ denotes the variance conditional on the information set at time $(t-1)$ and is modeled as:

$$\sigma_t{}^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}{}^2 + \alpha_2 \varepsilon_{t-2}{}^2 \ldots + \alpha_q \tag{3.47}$$

It is equivalent to:

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}{}^2 \tag{3.48}$$

Where $\varepsilon_{t-1}{}^2\, \varepsilon_{t-2}{}^2 \ldots \varepsilon_{t-q}{}^2$ are the lagged values of the squared innovation terms in the conditional mean equation of the series Y_t and we impose non-negativity constraints $\alpha_0 > 0$ and $\alpha_i \geq 0, for\ i = 1, 2, \ldots, q$. The time varying volatility is captured by allowing volatility to depend on the lagged values of the squared innovation terms $\varepsilon_{t-i}{}^2$ and q is chosen such that the residuals of the variance equation are white noise and $\{\eta_t\}$ is a sequence of independently and identically distributed random variables each with zero mean and unit variance.

The conditional variance equation for ARCH (q) model with explanatory variables is given by:

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i} + \sum_{j=1}^{p} \beta_j x_{jt} \tag{3.49}$$

Where p and q are non-negative integers, α_0 shows long term volatility and α_i indicate the effect of past shocks irrespective of their sign, β_j are coefficients of the explanatory variables x_{jt}. Even though the ARCH model is simple, many parameters are required to estimate the volatility of price returns. So, the problem of parsimony led to a more general framework proposed by Bollerslev (1986) and Taylor (1986).

3.3.6.2. Generalized ARCH (GARCH) Models

Since the ARCH model requires many parameters to estimate the volatility of price returns. The problem of parsimony led to a more general framework proposed by Bollerslev (1986) and Taylor (1986) and developing a technique that allows the conditional variance to be an ARMA process. Specifically the symmetric GARCH (p, q) model is defined as:

$$\varepsilon_t = \sigma_t \eta_t \,, \quad \sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon^2{}_{t-i} + \sum_{j=1}^{p} \beta_j \, \sigma^2{}_{t-j} \qquad [3.50]$$

Where the restrictions $\alpha_0 > 0$, $\alpha_i \geq 0$ and $\beta_j \geq 0$ Ensure that the variance is always greater than zero and the restriction $(\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1)$ is a necessary and sufficient condition for the stability of the conditional variance equation (Cryer and Chan, 2008). $\{\eta_t\}$ is i.i.d. random variable that is independent of past realization ε_{t-i} , and the conditional and unconditional means of ε_t are equal to zero.

The parameter α_0 is generally interpreted as long-term volatility to which the system converges. On the other hand, the ARCH term $\sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}$ reflects the effect of lagged shocks on the volatility at time t. Moreover, the GARCH term $\sum_{j=1}^{p} \beta_j \, \sigma^2{}_{t-j}$ measures the effect of past-expected variance on the current volatility.

The conditional variance equation of a GARCH (p, q) model with explanatory variables:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 + \sum_{j=1}^{p} \beta_j x_{jt} \qquad [3.51]$$

Where α_0 shows long term volatility; $\alpha_1, \alpha_2, \ldots, \alpha_p$ indicate the effect of past shocks and $\beta_1, \beta_2, \ldots, \beta_q$ show the influence of past volatility on the current volatility.

The GARCH (p, q) model allows both autoregressive and moving average components in the heteroscedastic variance equation. The benefits of the GARCH model is that the GARCH model

is a more parsimonious model of the conditional variance than a high-order ARCH model that is much easier to identify and estimate. Moreover, to ensure that the conditional variance is finite and stationary ($\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$). GARCH models responds to good and bad news. They are quite useful in modeling volatility, but they lack in capturing "leverage effect" and information asymmetry. The rational and underlying logic of asymmetric or leverage effect is that the distribution of price return is highly asymmetric. Bad news (negative returns) is followed by larger increase in price volatility than good news (positive returns) of the same size. As possible solutions in handling financial data, Nelson (1991) proposed an exponential GARCH or EGARCH model.

3.3.6.3. Exponential GARCH (EGARCH) model

To overcome some weaknesses of the GARCH model in handling financial time series, Nelson (1991) proposes the exponential GARCH (EGARCH) model. EGARCH models are the earliest extension of the GARCH model that incorporates asymmetric effects in price returns based on a logarithmic expression of the conditional variability of variable under analysis to relax the positivity constraint of model coefficients. In particular, it allows for asymmetric effects between positive and negative returns.

The EGARCH (*p, q*) model can be written as:

$\varepsilon_t = \sigma_t \eta_t$

$$ln\ \sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\ |\eta_{t-i}| + \sum_{i=1}^{q} \tau_i\ \eta_{t-i} + \sum_{j=1}^{p} \beta_j\ ln\ \sigma^2{}_{t-j} \qquad [3.52]$$

An EGARCH (p, q) variance equation with explanatory variables is given by (Ling and McAleer 2000, Lee and Brorsen 1997):

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i\ |\eta_{t-i}| + \sum_{i=1}^{q} \tau_i\ \eta_{t-i} + \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2) + \sum_{j=1}^{p} \phi_j x_{jt} \qquad [3.53]$$

Where $\eta_{t-i} = \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$ and the parameters $\alpha_i, \tau_i\ and\ \beta_j$ can be estimated by using the maximum likelihood method. The parameter τ_i thus signifies the leverage effect of ε_{t-i}. Bad news can have a larger impact on volatility; again, we expect τ_i to be negative in real applications. In

macroeconomic analysis, financial markets and corporate finance, a negative shock usually implies bad news, leading to a more uncertain future.

In contrast to the GARCH models, the EGARCH models do not have any restrictions on the parameters in the model and always produces a positive conditional variance independently of the signs of the estimated parameters in the model. This is preferable when the restrictions in the GARCH model sometimes create problems when estimated parameters violate the constraints.

3.3.6.4. Threshold GARCH (TGARCH) Model

Another volatility model commonly used to handle leverage effects is the threshold generalized autorigresive conditional heteroscedasticity (TGARCH) model which was proposed by Glosten, Jagannathan, Runkle (1993) and Zakoian (1994).

The general specification of the conditional variance equation using the TGARCH (*p, q*) model is given as follows:

$$\varepsilon_t = \sigma_t \eta_{t,} \quad {\sigma_t}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, {\varepsilon^2}_{t-i} + \sum_{i=1}^{q} \lambda_i s_{t-i} {\varepsilon^2}_{t-i} \sum_{j=1}^{p} \beta_j \, {\sigma^2}_{t-j} \qquad [3.54]$$

Where s_{t-i} is a dummy variable (indicator function) given by:

$$s_{t-i} = \begin{cases} 1 \; if \; \varepsilon_{t-i} < 0 \,, \text{ bad news} \\ 0 \; if, \text{if } \varepsilon_{t-i} \geq 0, \text{ good news} \end{cases}$$

The conditional variance equation of the TGARCH (p, q) model in the presence of explanatory variables is given by:

$${\sigma_t}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, {\varepsilon^2}_{t-i} + \sum_{i=1}^{q} \lambda_i s_{t-i} {\varepsilon^2}_{t-i} \sum_{j=1}^{p} \beta_j \, {\sigma^2}_{t-j} + \sum_{j=1}^{p} \phi_j x_{jt} \qquad [3.55]$$

Where $\alpha_i, \lambda_i \; and \; \beta_j$ are parameters satisfying the conditions for non-negativity of ${\sigma_t}^2$, that is $\alpha_0 > 0, \alpha_i > 0$ and $\alpha_i + \lambda_i > 0$. Depending upon whether ε_{t-i} is above or below the threshold value, ${\varepsilon^2}_{t-i}$ has different effect on the conditional variance. In case of negative shocks, the impact of the shocks on ${\sigma^2}_t$ is $(\alpha_i + \lambda_i) \; {\varepsilon^2}_{t-i}$, but for positive shocks this quantity is $\lambda_i \, {\varepsilon^2}_{t-i}$. That is negative shocks have higher impact on the conditional variance than positive shocks. The model uses zero as its threshold to separate the impacts of past shocks.

3.3.7. Building GARCH Family Models

3.3.7.1. Testing for ARCH effects

The Box-Jankins(1976) approach is based on the assumption that the residuals are homoskedastic (remain constant over time) for ARIMA family models. But in financial time series data, (Asteriou Hall, 2007; Lee, 2008), thus, the presence of ARCH effect (whether or not volatility varies over time) has to be tested in the series through the square residuals which is known as ARCH effect (Tsay, 2005). Therefore, before estimating a full GARCH family models, it is usually a good practice to test for the presence of ARCH effect in the squared residuals. If there is no ARCH effects in the squared residuals, then the GARCH family models are unnecessary and miss-specified. To test this the Lagrange Multiplier (LM) test and the Ljung-Box test were applied for this study.

Lagrange Multiplier (LM) Test

In order to test the presence of ARCH effects in the residuals we can use the AR representation of squared residuals in the following way. First we construct an auxiliary regression:

$$u^2{}_t = \alpha_0 + \alpha_1 u^2{}_{t-1} + \alpha_2 u^2{}_{t-2} + \ldots + \alpha_m u^2{}_{t-m} + \varepsilon_t \qquad [3.56]$$

Where ε_t is a white noise process and α_i 's are parameters of the model. The Lagrange Multiplier (LM) test for order serial correlation is computed first by estimating the sample residuals u_t (that is $\hat{u}_t$) by ordinary least squares (OLS) and regress the current residual $\hat{u}_t$ on the *m* lagged residuals. So, the fitted auxiliary regression model of residuals is given by:

$$\hat{u}^2{}_t = \alpha_0 + \alpha_1 \hat{u}^2{}_{t-1} + \alpha_2 \hat{u}^2{}_{t-2} + \ldots + \alpha_m \hat{u}^2{}_{t-m}\, \varepsilon_t \qquad [3.57]$$

The significance of the parameters α_i would indicate the presence of serial correlation in the squared residuales under the null hypothesis. Here the null hypothesis of absence of serial correlation up to lag *m* is:

H_0 : $\alpha_1 = \alpha_2 = \ldots = \alpha_m = 0$ (there is no serial correlation). If the usual R^2 statistic is computed for this model, the test statistic is: $LM = TR^2$. The distribution of a test statistic is: $TR^2 \sim \chi^2(m)$, Where $R^2 is$ the coefficient of determination from the auxiliary regression and T is the sample size.

Ljung-Box (LB) Test

The Ljung-Box (LB) test is one of the widely used lack-of-fit tests, that is, a test for the appropriateness of the fitted model. It was developed by Box and Pierce (1970) and modified by McLeod, et al. (1983). It is used to test the presence of serial correlation in the residuals. Hence, the null hypothesis is: $H_0 : \rho_1 = \rho_2 = \cdots \rho_m$ (There is no serial correlation up to lag *m*) againest the alternative hypothesis. The test statistic is given by:

$$Q = T(T+2)\frac{\sum_{i=1}^{m} \hat{\rho}_i^{\,2}}{T-K} \qquad [3.58]$$

Where $\hat{\rho}_i$ is $i^{th} - lag$ sample autocorrelation of residuals of the fitted model and T is the number of observations for the study under consideration. If the series is not based upon results of ARIMA estimation, then under the null hypothesis Q is asymptotically distributed as chi-square with $m - k = m - (p + q)$ degrees of freedom.

3.3.7.2. Model order selection

A model selection criterion considers the "best approximating model" from a set of competing models. An important practical problem is the determination of the ARCH order q and the GARCH order p for a particular series. Since GARCH models can be treated as ARMA models for squared residuals, traditional model selection criteria such as the Akaike information criterion (AIC) proposed by Akaike (1974) and the Schwartz Bayesian information criterion (BIC) proposed by Schwartz (1978) were employed to identify the optimal lag specification for the model. Given the criterion values of two or more models, the one with minimum AIC or BIC is most representative of the true model and it may be interpreted as the best approximating model among those being considered (Dayton, 2003).

3.3.7.3. Model parameter Estimation

Under the presence of ARCH effects, OLS estimation is not efficient, since volatility models we used is non-linear in conditional variance through linear in mean. In addition, OLS involves minimizing the sum of squares of residuals which depends on the mean equation not on the conditional variance. Therefore, as many studies indicated the commonly used method to estimate the unknown parameters of the GARCH family models is the maximum likelihood

(ML) method with various distributional assumptions for the error terms. Financial time series data possess volatility clustering and leptokurtosis characteristics that leads to the use of different distributional assumptions such as: normal, student-t and the generalized error distribution (GED) to estimate the parameters. The appropriate error distribution for the residuals can be identified based on in-sample forecast error statistics and the final analysis may proceed based on the selected distribution for residuals in the mean equation.

Essentially, the maximum likelihood (ML) method works by finding the most likely values of the parameters given the actual data. More specifically, a log-likelihood function (L) is formed and the values of the parameters that maximize it are sought. Maximum likelihood estimation can be employed to find parameter values for both linear and non-linear models. Unfortunately, maximizing the log likelihood function for a model with time-varying variances is trickier than in the homoscedastic case. Analytical derivatives of the log likelihood function with respect to the parameters have been developed, but only in the context of the simplest of GARCH specifications. Moreover, maximization of the likelihood function of the model analytically in terms of its parameter is impossible because of non-linearity of GARCH family model, and thus, a numerical procedure is often used instead to maximize the log-likelihood function and this was done by statistical package versions either R software, Eviews or SAS. Essentially, all methods work by 'searching' over the parameter-space until the values of the parameters that maximize the log-likelihood function are found (Brook, 2008).

3.5.7.4. Model diagnostic checking

When a model has been fitted to a time series, it is advisable to check that the model really does provide an adequate description of the data. As with most statistical models the goodness of fit of the GARCH family models are based on residuals and more specifically on the standardized residuals. It is essential to check whether the model is correctly specified, that is, whether the model assumptions are supported by the data. If some key model assumptions seem to be violated, then a new model should be specified; fitted, and checked again until a model that provides an adequate fit to the data found. Therefore, to check the adequacy of the fitted model the following methods were used for this study:

a) The ACF and PACF of the standardized residuals: If the model is adequate the ACF and PACF of squared standardized residuals should be indicative of a white noise process.
b) Jarque-Bera test: It is used to check whether the standardized residuals identically and independently distributed standard normal, even if student-t and generalized exponential distribution (GED) are assumed (Tsay, 2010).
c) The Ljung-Box test: It is one of the most widely used lack-of-fit tests, that is, a test for the appropriateness of the fitted model. The Ljung-Box test uses the Q-statistic to test whethe the autocorrelations in the standardized residuals are not significantly different from zero for the first *m* lags and the Breusch–Godfrey Serial Correlation LM tests whether the standardized residuals exhibit remaining ARCH effects for GARCH specification. Thus, if the statistic *Q* at all lags and LM test are non-significant, it indicates the absence of autocorrelation in the standardized residuals and this is an evidence that the model selected fits the data well.

3.3.7.5. Forecasting GARCH family models

An important task of modeling conditional volatility is to generate forecasts for both the future value of a financial time series as well as its conditional volatility. Conditional variance forecasts from GARCH family models are obtained with similar approach to forecasts from ARMA models by iterating with the conditional expectations operator. In other words, when the estimation of the unknown parameters is done, estimates of the standard deviation series can be calculated recursively via the definition of the Conditional variance for the GARCH (p, q) family process which helps to examine the past behavior of average monthly domestic price volatilities of the series under consideration. Once a GARCH family model is fitted and satisfies all the diagnostic tests, then we can use it to forecast the volatility of the series. The accuracy of a forecasting model depends on how close the forecast values. If the model is doing a good job in forecasting the actual data so, the forecast error will be relatively small.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

The objective of this study was to model and forecast the volatility of domestic price of coffee in the Ethiopian market by using GARCH family models. To undertake these tasks, Eviews 8 software for symmetric and asymmetric GARCH analysis have been employed.

4.1. Descriptive statistics

The data used in this thesis were the average monthly domestic prices (in Birr per kilogram) of coffee for the period from January 2003 to December 2016 GC which have a sample of 167 selected markets in the country. The logarithmic return series $Y_t = log\ (Y_t/Y_{t-1})$ were computed from the monthly domestic price series of coffee to measure domestic price volatility. The Summary statistics are displayed in Table 4.2 below.

Table 4.2: Summary statistics for monthly prices of dependent and independent variables in the Ethiopian market over the study periods

Statistics	D.price of coffee	Return of D.price	Ex.coffee price	Exchange rate	Food Inflation	Fuel oil	N.food Inflation	Interest Rate	Total gov.t revenue
Mean	46.906	0.012	47.074	13.438	16.951	50576.76	12.068	4.144	79029.17
Median	39.655	-0.003	39.603	12.111	12.634	7491.146	10.658	4.250	55595.42
Maximum	99.520	0.668	154.929	21.720	61.064	756873.1	25.073	5.000	243671.6
Minimum	7.020	-0.773	10.683	8.569	-5.670	171.043	-0.381	3.000	13310.50
Std. Dev.	27.715	0.139	27.795	4.814	15.024	132291.1	7.250	0.884	65827.41
Skewness	0.195	0.062	0.526	0.313	1.250	3.278	0.177	-0.357	0.888
Kurtosis	1.653	12.127	2.666	1.395	4.054	13.446	1.951	1.373	2.591
Jarque-Bera	13.741	579.821	8.468	20.637	51.200	1058.314	8.537	21.980	23.111
Probability	0.001	0.000	0.014	0.000	0.000	0.000	0.014	0.000	0.000
Observations	167	167	167	167	167	167	167	167	167

As we can seen from table 4.2 above the average monthly domestic price of coffee and export price of coffee was 46.906 and 47.074 birr per kg with a standard deviation of 27.715 and 27.795 respectivly. Also the average monthly price of exchange rate and fuel oil was 13.438 birr and 50576.76 birr per metric ton with a standard deviation of 4.814 and 13229.1 respectivly. Additionally the average monthly price of food inflation rate, nonfood inflation rate, saving interest rate and total government revenue were 16.951, 12.068, 4.144 and 79029.17 with a

standard deviation of 15.024,7.250, 0.884 and 65827.41 respectively. Moreover, the minimum and maximum domestic price of coffee were 7.020 and 99.520 birr per Killogram respectively. The return series display a positive skewness of about 0.062 and the kurtosis coefficient of domestic price return for coffee were about 12.127, indicating that the return series are highly leptokurtic. This phenomenon has been widely known in the literature of return series. Likewise, the Jarque-Bera (JB) test also confirms that the null hypothesis of normality for the monthly return series should be rejected at 1% level of significance. The rejection of the hypothesis of normality of domestic price return series for coffee might be due to the existence of excess kurtosis.

The graphical description of the trend of average monthly domestic price of coffee and its returns are as shown in figure 4.1 below. From the figure it can be observed that average monthly domestic price of coffee shows increasing pattern followed by a period where price is decreased up to the end of the forecasting periods under consideration.

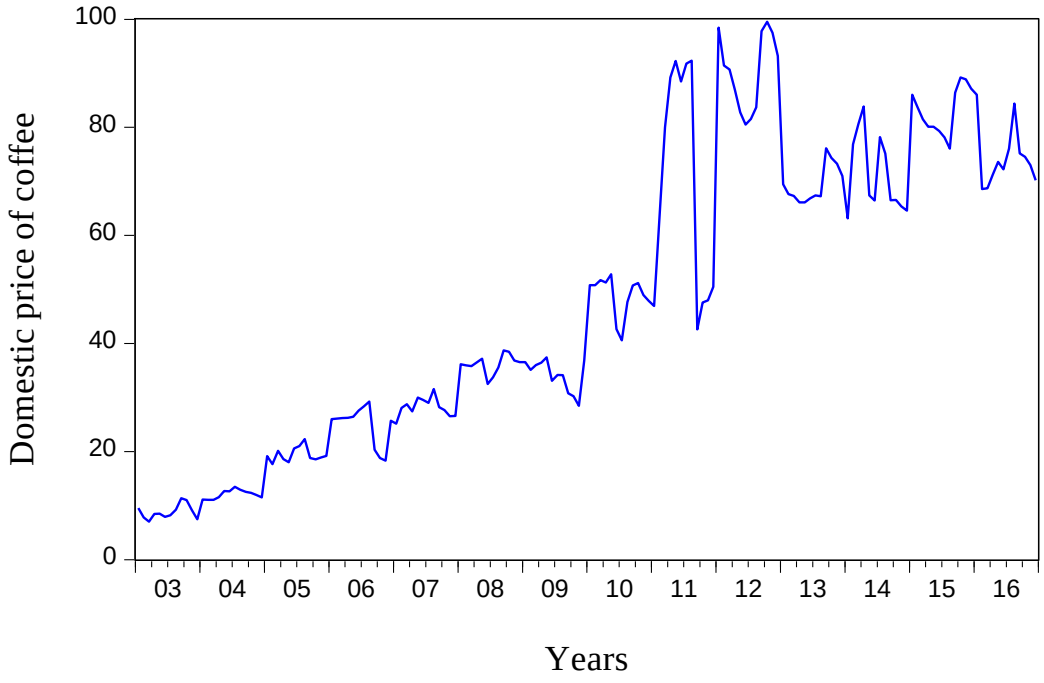

Figure 4.1: The average monthly domestic price trend of coffee over the study periods

The absolute return series were constructed for domestic price of coffee in order to examine the presence of volatility in the series. As can be seen from Figure 4.2, periods of high volatility is followed by periods of high volatility and periods of low volatility is followed by periods of low volatility for the series.

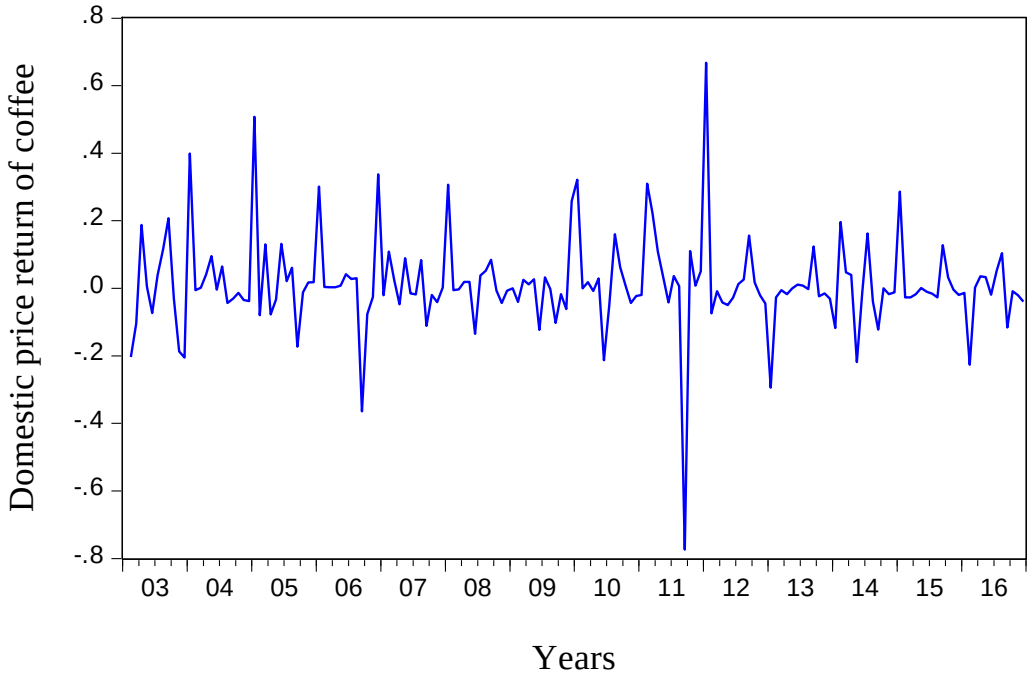

Figure 4.2: The absolute monthly domestic price return series of coffee over the study periods

4.2. Unit root test for non stationarity

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 for each series should be determined. The unit root tests first impose the null hypothesis that the series has a unit root problem, versus the alternative hypothesis that the series is stationary. In this study, Augmented Dickey-Fuller test (ADF) and Phillip Perron (PP) tests were used to check the stationarity of the monthly logarithm return series of domestic prices of coffee and explanatory variables.

Table 4.3: Unit root result for the variables at level

Variables	ADF Test		PP Test		Critical values		
	t -Statistic	P -value	t- Statistic	P -value	1%	5%	10%
D. price return of coffee	-9.432111	0.0000	-39.16592	0.0001	-3.46	-2.88	-2.58
Export price of coffee	-5.0407	0.0003	-7.3909	0.0000			
Exchange rate	-2.136100	0.5214	-2.9091	0.1623			

Fuel oil	-2.7537	0.2168	-4.8429	0.0006	
Food Inflation rate	-4.8936	0.0005	-2.8044	0.1978	
Nonfood Inflation rate	-0.0986	0.5421	-1.1166	0.9223	
Saving interest rate	-1.8784	0.6613	-1.9079	0.6460	
Total government revenue	1.1136	0.9999	3.1633	1.000	

Table 4.3 summarizes the unit root test results for the price return series of domestic price of coffee and explanatory variables under consideration. As we can see from the table, the null hypothesis of unit root would be rejected for domestic price return series of coffee, indicating that the price return series is stationary at level. From the explanatory variables export price of coffee and food inflation rate are stationary at level, since the null hypothesis of unit root is rejected at the 1% level of significance. But the other five explanatory variables are not stationary at level, since the null hypothesis of unit root is not rejected at 1% level of significance. So we have to take first differences of the series in order to make them stationary and determine the order of integration.

Table 4.4: Unit root result for the variables after first difference

Variables	ADF Test		PP Test		Critical values		
	t -Statistic	P -value	t- Statistic	P -value	1%	5%	10%
Exchange rate	-13.6012	0.0000	-12.5324	0.0000	-3.46	-2.88	-2.58
Fuel oil	-14.9344	0.0000	-19.6887	0.0000			
Nonfood Inflation rate	-4.2618	0.0046	-3.4603	0.0472			
Saving interest rate	-12.9237	0.0000	-12.9241	0.0000			
Total government revenue	-2.6540	0.0257	-2.6943	0.0240			

As we have seen from Table 4.4, the null hypothesis of unit root is rejected at 1% level of significance for these five explanatory variables by both ADF and PP tests. Thus, except export price of coffee and food inflation rate all explanatory variables are integrated of order one, I (1).

4.3. Conditional Mean Equation

In order to model the volatility of the return series, first we need to specify their conditional mean equation, since the return for current time will depend on returns in previous periods (autoregressive component) and the error terms in current and previous periods (moving average component). To model the conditional mean equation for the series the Box-Jenkins modeling approach has been used. The Box-Jenkins modeling approach of a stationary time series involves the following four steps: model identification, model estimation, diagnostic checking and forecasting. We have seen that the return of domestic price of coffee becomes a stationary time series at level. So, the model that we are looking at is ARMA(p,q). Hence we have to identify a good-fit model, estimate its parameters, apply diagnostic checking for the residuals and finally achive our objectives of in-sample and out-of-sample forecasting of the domestic price of coffee.

4.3.1. Model identification

In the specification of the mean equation, the sample ACF and PACF plots of the stationary series can be used to tentatively identify the order of autoregressive terms and/or moving average terms (Green, 1993). In most applications lower order ARMA models are often considered, so in this study, the fifteen combinations of AR (0-3) and MA (0-3) were considered. Table A3 (in Appendix A) presents AIC and BIC statistics for optimal order selection for each combination of the conditional mean models across different lag specifications. Models with no serial correlation in the residuals are presented in Table 4.5

Table 4.5: Model summary for various orders of ARMA models

Model	AIC	BIC	Serial correlation
ARMA(0,1)	-1.0854	-1.0481	No
ARMA(0,2)	-1.1015	-1.0455	Yes
ARMA(0,3)	-1.1256	-1.0509	Yes

ARMA(1,0)	-1.0937	-1.0562	No
ARMA(1,1)	-1.1476	-1.0914	No
ARMA(1,2)	-1.1509	-1.0759	No
ARMA(1,3)	-1.1468	-1.0531	No
ARMA(2,0)	-1.0884	-1.0320	No
ARMA(2,1)	-1.1583	-1.0830	No
ARMA(2,2)	-1.1842	-1.0901	No
ARMA(2,3)	-1.1834	-1.0709	No
ARMA(3,0)	-1.0900	-1.0144	No
ARMA(3,1)	-1.1588	-1.0643	No
ARMA(3,2)	-1.1893	-1.0759	No
ARMA(3,3)	-1.2484	-1.1161	No

As discussed in the methodology part, a model with small AIC and BIC is preferable. Based on these selection criterias, ARMA(3,3) model have the smallest AIC and BIC and is found to be the best fit model for the domestic price of coffee in Ethiopia.

4.3.2. Parameter Estimation

Once an appropriate order of ARMA model has been identified, the next step is estimating model parameters. The parameters can be estimated by ordinary least squares (OLS) or by maximum likelihood (ML) methods. Both estimation procedures are based on the innovation series ε_t. The least-square method minimize the sum of squares of the innovation terms, while the ML method maximizes the joint probability density function of the innovation terms $\varepsilon_1\ \varepsilon_2$ ... ε_T. Even it is possible to ese both estimation methods, but in this study least square estimation method was used to estimate the parameters of the model.

Table 4.6: Parameter estimation for ARMA(3,3) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.012852	0.004024	3.194122	0.0017
AR(1)	0.959534	0.105121	9.127885	0.0000
AR(2)	-1.043083	0.054818	-19.02827	0.0000
AR(3)	0.603459	0.100337	6.014325	0.0000

MA(1)	-1.122192	0.065197	-17.21242	0.0000
MA(2)	1.201165	0.028417	42.26894	0.0000
MA(3)	-0.898089	0.066328	-13.54017	0.0000

From Table 4.6, the estimated parameters of the moving average term and the constant term are statistically significant at 5% level of significant. So the equation of the fitted ARMA model is given by:

$$Y_t = 0.013 + 0.959Y_{t-1} - 1.043\,Y_{t-2} + 0.603\,Y_{t-3} - 1.122\,\varepsilon_{t-1} + 1.201\,\varepsilon_{t-2} - 0.898\,\varepsilon_{t-3} + \varepsilon_t$$

4.3.3. Diagnostic checking

Before we consider the fitted model as a better fit and interpret its findings, it is essential to check whether the model is correctly specified, that is, whether the model assumptions are supported by the data. If some key model assumptions seem to be violated, then a new model should be specified until it provides an adequate fit to the data.

4.3.3.1. Test of serial correlation in the residuals

The presence of serial correlation in the residuals was tested using the Lagrange Multiplier (LM) and Ljung-Box tests for ARMA(3,3) model. The null hypothesis asserts that there is no serial correlation in the residuals up to lag 22. The results of this examinations are summarized in Table 4.7.

Table 4.7: Summary result of Breusch-Godfrey serial correlation LM test for fitted models

F-statistic	1.185626	Probability	0.3050
Obs*R-squared	12.20643	Probability	0.2715

The Breusch–Godfrey serial correlation LM test results in Table 4.7 provide an evidence of absence of serial correlation in the residuals of the mean equation, since the null hypothesis is not rejected at 1% level of significance. The Ljung-Box test (Table A6 of Appendix A) also indicates that there is no significant serial correlation for lags up to 22 for the series. Hence, we can conclud that there is no significant serial correlation in the residuals of the mean equation.

4.3.3.2. Test of normality of the residuals

To investigate whether the residuals of the fitted model in the mean equation are normally distributed or not, the Jarque-Bera test has been applied. The results are reported in Table A7 (Appendix A).

Table 4.8: Normality test of residuals from the mean equation

Variable	Skweness	Kurtosis	Jarque-Bera Statistic	p-value
Price return series	-0.6022	5.662	20.154	0.2015

As we can see from Table 4.8 the Jarque-Bera statistic is insignificant and hence, there is no a significant evidence to reject the null hypothesis of normality. This indicates that the residuals of the fitted model are approximatlly normally distributed for the series under consideration.

4.3.4. Forecasting of ARMA(3,3) model

One of the fundamental applications of time series analysis or developing a time series model is forecasting. The previous discussion has shown that the ARMA(3,3) model is a good-fit model to describe the domestic price of coffee. In this section we examine the forecasting accuracy of the fitted model and then make in-sample and out-of-sample forecast.

Evaluation of in-sample forecast

The forecasting performance of a model can be examined by the standardized statistical tools such as root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil's inequality.

Table 4.9: In-sample forecast accuracy measures for ARMA(3,3) model

Acuracy measures	Values
Root Mean Squared Error	0.125602
Mean Absolute Error	0.083246
Mean Absolute Percentage Error	738.2790

Theil Inequality Coefficient	0.0637561
Bias Proportion	0.000222
Variance Proportion	0.417826
Covariance Proportion	0.581951

Here as we have seen from Table 4.9 most of the statistics are small. Moreover, the U statistic is 0.063, which is approximated to zero. Besides that the bias and the variance proportion are also close to zero. This indicate that the forecasting performance of the model is good.

Out-of-sample forecasting

The out-of-sample forecast is performed from January 2014 to December 2016 generating 24 observations. The out-of-sample forecast graph is displayed in Figure 4.3 below.

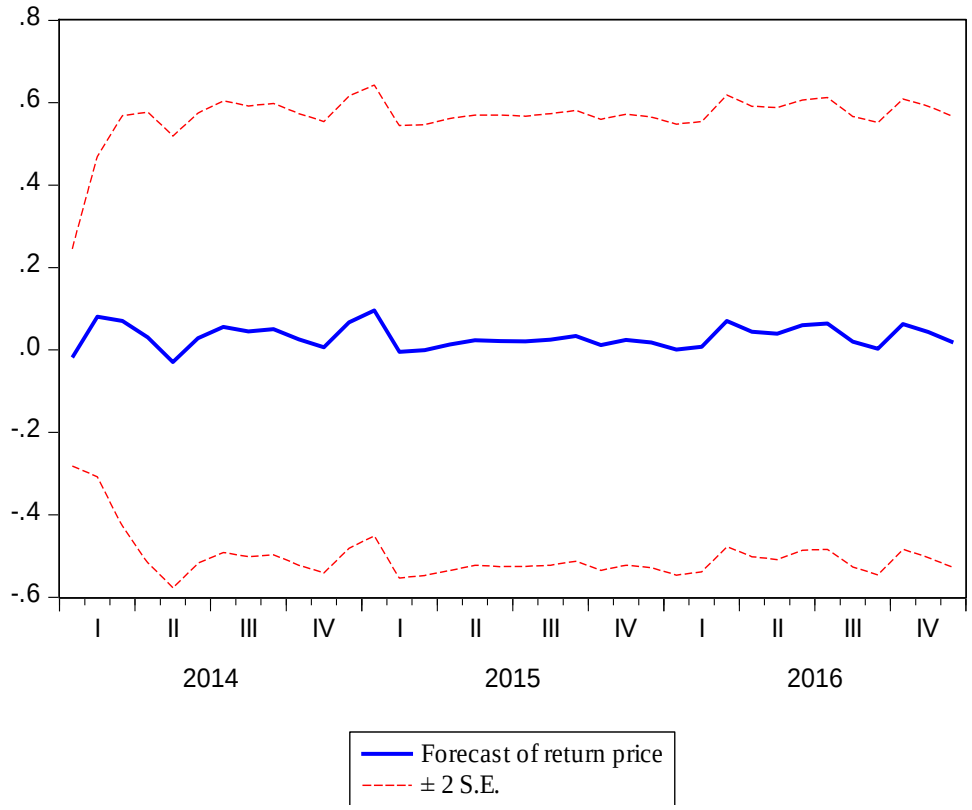

Figure 4.3: Out-of-sample forecast for ARMA(3,3) model

As we can seen from the figure above the forecasting trend of domestic price of coffee shows an increasing and decreasing pattern over the forecasting periods under consideration.

4.4. Test for ARCH Effects

To proceed with volatility modeling, ARCH effects (whether or not volatility varies over time) in the residuals from the selected ARMA model should be tested. The approaches for testing heteroscedasticity (ARCH effect) were the Lagrange Multiplier (LM) test proposed by Engle (1982) and Ljung-Box (1978) test for squared residuals.

Table 4.10: ARCH effect test using LM test for squared residuals of the fitted model

Heteroskedasticity Test: ARCH

F-statistic	2.629980	Probability	0.00365
Obs*R-squared	10.16909	Probability	0.00377

The results of Lagrange Multiplier (LM) test for ARCH effects in the squared residuals are presented in Table 4.10 above. As we can be seen from the table, the null hypothesis of no ARCH effect in the first four lags of residuals from the mean equations for monthly price return series is rejected. This implies that the conditional variance of monthly return series of domestic price of coffee is non-constant (hetroskedastic).

We can also apply the Ljung-Box test for the squared residuals of the fitted model to test the presence of ARCH effects. The null corresponds to insignificance of correlation coefficients in the squared residuals up to lag *q*. Table A12 (Appendix A) shows the results of ARCH effect using the Ljung-Box test up to lag 22 for the squared residuals of the mean equation. The Q-statistics confirmed the presence of significant correlation in the squared residuals.

Thus, both tests provide strong evidence for the presence of ARCH effects in the squared residuals. These results indicate that the respective return series under consideration have a non-constant variance (heteroscedasticity) and need to be modeled using GARCH family models.

4.5. Volatility Models

4.5.1. Model selection of GARCH Family Model

Once the ARCH effects are determined, then the optimal lag specifications for GARCH family models were determined prior to the construction of the final model to investigate the determinants of domestic price volatility. Even though there is consensus that GARCH(1,1) family model is the most convenient specification in the financial literature (Bollerslev et al., 1992 and Lee, 2009) to fit data with parsimonious model. But in this study we considered higher order models. As a result, the GARCH(1,1) family model is compared to various higher-order models from 1,2 and 3 or three months relationship of volatilities, since GARCH family model was used for short-term forecasting (Haydee, 2008) based on the value of AIC and BIC.

In our model selection procedure we first fit different GARCH family models of different orders of p and q. The summary of empirical results of GARCH and EGARCH model specifications and information criteria for order selection are displayed in Table A10 (Appendix A). As we can seen from the table GARCH(0,1) model under all distributional assumptions (under normal distribution, t-distribution and GED distribution), EGARCH(2,3) model under students t-distributional assumption for residuals and EGARCH(3,0) model under both normal and GED distributional assumptions for residuals were selected as candidate models for the domestic price volatility of coffee, since they possesses minimum AIC and/or BIC.

Moreover, to select an appropriate conditional volatility model, we consider the forecasting performance of the selected GARCH family models. The forecasting performance of the fitted GARCH family models are evaluated by RMSE, MAE, MAPE and Theil inequality coefficients . The model with the smallest statistics is considered to be better fit for modeling the conditional volatility of the domestic price of coffee in Ethiopia. The results are summarized in Table 4.11.

Table 4.11: Forecasting accuracy statistics for residuals from the variance equation

Model	Error distribution	Forecast accuracy measure				Assymetric effect
		RMSE	MAE	MAPE	Theil	
GARCH(0,1)	Normal	0.139	0.082	387.798	0.87	-
GARCH(0,1)	Student's t	0.138	0.079	209.696	0.83	-
GARCH(0,1)	GED	0.139	0.079	176.4142	0.96	-

EGARCH(3,0)	Normal	0.136	0.076	411.4207	0.83	Significant
EGARCH(2,3)	Student's	0.138	0.078	217.6615	0.88	Insignificant
EGARCH(3,0)	GED	0.137	0.077	297.5681	0.87	Significant

As we can seen from table 4.9 above GARCH (0,1) model with Student's t-distributional assumption for residuals from symmetric models possess the smallest forecast error measures in the majority of the statistics. But from asymmetric models EGARCH (3, 0) model with Normal distributional assumption for residuals possess the smallest forecast error measures in the majority of the statistics and the assymetric effect is significant . The significance of asymmetric term in the volatility model also suggests that the EGARCH model could be a favoring model than a symmetric GARCH model to fit data with asymmetric effects. Therefore the best fit model is selected from asymmetric models. Thus EGARCH(3,0) model with normal distributional assumption perform better to describe the volatility of domestic price return series of coffee.

4.5.2. Parameter Estimation

Once the GARCH(0,1) with Student's t-distributional assumption for residuals and EGARCH(3,0) model with Normal distributional assumption for residuals were selected as better fit models based on AIC and /or BIC and forecast accuracy measures, then the next step is estimation of parameters to perform analysis of the determinants of average monthly domestic price volatility of coffee. The parameters in the mean and variance equations are estimated using the maximum likelihood (ML) estimation method. The results are shown in Tables 4.12.

Table 4.12: ML parameter estimation of EGARCH(3,0) model under normal distribution

Parameters	Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation	Constant	0.011347	0.002178	5.210553	0.0000
	AR(1)	-0.019515	0.021581	-0.904266	0.3659
	AR(2)	-0.310849	0.008683	-35.79907	0.0000
	AR(3)	0.052359	0.027916	1.875616	0.0607
	MA(1)	-0.109835	0.027418	-4.005921	0.0001
	MA(2)	0.279913	0.003004	93.18124	0.0000
	MA(3)	-0.188574	0.026752	-7.048884	0.0000

	Constant	-2.310519	0.121047	-19.08774	0.0000
	ARCH(-1)	-0.441916	0.148480	-2.976272	0.0029
	ARCH(-2)	-0.988712	0.077416	-12.77138	0.0000
	ARCH(-3)	-1.351308	0.066508	-20.31813	0.0000
	Asymmetric(-1)	0.534899	0.111082	-4.815367	0.0000
Variance Equation					
	Export price	0.017290	0.003137	5.512633	0.0000
	Food inflarion	-0.020742	0.005368	-3.863874	0.0001
	Exchange rate	0.960499	0.150692	6.373930	0.0000
	Fuel oil price	1.70E-06	1.53E-06	1.115987	0.2644
	Nonfood inflation	0.178339	0.036306	4.912143	0.0000
	Total gov.t revenue	-0.000696	8.11E-05	-8.583913	0.0000
	Saving interest rate	-1.513298	1.009102	-1.499648	0.1337

The results from the variance equation above show that among the explanatory variables which are considered in this study the cofficients of price of fuel oil and saving interest rate are statistically insignificant at 1% level of significance. This shows that fuel oil price and saving interest rate has no significant impact on domestic price volatility of coffee. This result is consistent with Khin (2010). Alternatively the coefficients of export price of coffee, exchange rate (in birr against US dollar) and Nonfood inflation rate are positive and statisticaly significant at 1% level of significance. That is export price of coffee, exchange rate and nonfood inflation rate has a positive significant effect on the current monthly domestic price volatility of coffee. This indicates that an increase in export price of coffee, exchange rate and nonfood inflation rate leads to an increase in the monthly domestic price volatility of coffee.

The coefficients of food inflation rate and total government revenue are negetive and statisticaly significant at 1% level of significance, that is food inflation rate and total government revenue

have a negative influence on the monthly domestic price volatility of coffee. This implies that as food inflation rate and total government revenue increases the monthly domestic price volatility of coffee decreases (this results is inconsistent with the findings of Anteneh (2012).

The results also show that the coefficient of 1, 2 and 3 month lagged shocks (i.e ARCH(-1) ARCH(-2) and ARCH(-3) terms) were negative and statistically significant at the 1% level. This shows that the current monthly domestic price volatility of coffee was affected by its 1-month, 2-month and 3-month lagged shocks.

Additionally, the coefficient of the asymmetric term was positive and statistically significant at 1% level of significance. This indicating that bad news (unexpected increase in monthly domestic price of coffee) had larger impact on the domestic price volatility of coffee than good news (unexpected decrease in monthly domestic price of coffee).

4.5.3. Model Adequacy Checking

In order to check whether the fitted model is a good fit to the data or not, that is the presence of remaining ARCH effect in the residuals, ARCH LM test and Ljung-Box Q-tests were performed. The Ljung-Box test indicates that the autocorrelations in the standardized residuals are not significantly different from zero for the first 22 lags (Tables A11 in Appendix A). As can be seen from Table 4.13, the Breusch–Godfrey Serial Correlation LM test indicates that the standardized residuals of the fitted model did not exhibit any additional ARCH effect.

Table 4.13: ARCH-LM test for standardized residuals of the fitted volatility model

Heteroskedasticity Test: ARCH

F-statistic	0.002155	Probability	0.9630
Obs*R-squared	0.002182	Probability	0.9627

Additionally, the Jarque-Bera statistic is used to test the normality of the residuals in the fitted model. The results are presented in Figure A9 (Appendix B) shows that the Jarque-Bera test statistic were also insignificant and hence, there is no enough evidence to reject the null hypothesis of normality. This indicates that the residuals of the fitted model were approximately

normally distributed. So, the selected EGARCH(3,0) model with normal distributional assumption to investigate the the domestic price volatility of coffee were well justified.

4.5.4. Forecasting price volatility

One of the fundamental uses of developing GARCH family models is forecasting. the volatility of domestic prices using variance as volatility measures was forecasted using the in-sample observations under static forecasting. The results are displayed as we can seen from figure 4.4.

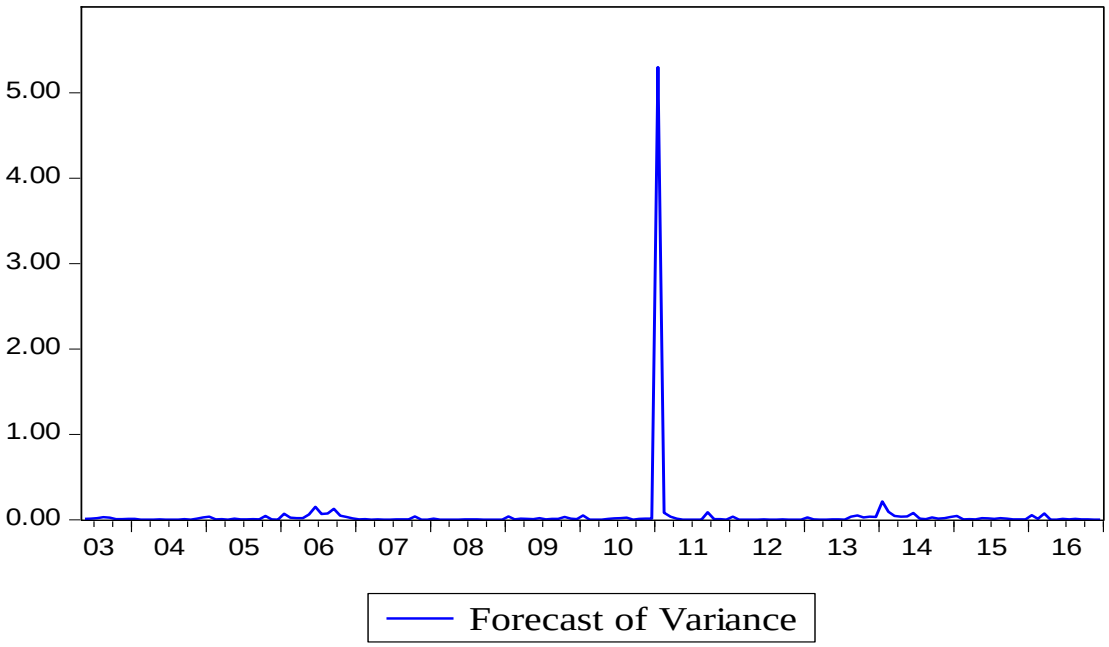

Figure 4.4: In-sample forecast of monthly domestic price volatility of coffee

As we can see from Figure 4.4, the domestic price volatility of coffee remained at almost a constant level from the begining of the study till December 2010, increased steadily with increasing rate from the years December 2010 to January 2011, immidiatlly dropes sharply with increasing rate till March 2011 and remained almost constant up to the end of the study. Moreover, high domestic price volatility was observed around the year January 2011.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study investigates modeling and forecasting average domestic price volatility of coffee in Ethiopia over the study periods from January 2003 to December 2016 GC. From the preliminary analysis over the time period considered, the domestic price of coffee series shows increasing pattern followed by a period where the price is decreasing at low rate. Additionally, the price return series of coffee shows the characteristics of financial time series such as clustering volatility and leptokurtic distributions. This provides an adequate ground for the use of GARCH family models with different error distributional assumptions.

Before we go to the specification of volatility models, we have to examine and specify the conditional mean equation using ARIMA family models. From the empirical results of AIC and/ or BIC value, after examining different competitive models, we came to the conclusion that ARMA (3, 3) model provides the best-fit model for the domestic price return series of coffee.

Moreover, the ARCH-LM and Ljung-Box tests support the presence of ARCH effects in the residuals of the conditional mean equations. Therefore, Generalized Autoregressive Conditionally Heteroscedasticity (GARCH) family models including both symmetric models such as GARCH (p, q) and asymmetric models such as EGARCH (p, q) models were considered in order to model the price volatility of coffee in the Ethiopian domestic market.

An asymmetric model was found to fit better than symmetric models, since the asymmetric term is significant. Hence, EGARCH (3, 0) model with normal distributional assumption for residuals was found to be better fit for the domestic price volatility of coffee. The forecast performances of the models were evaluated using the MAE, MAPE, RMSE and Theil inequality coefficients.

There was significant evidence that many of the candidate explanatory variables have an impact on average monthly domestic price return volatilities of coffee over the study period. Thus, export price of coffee, exchange rate, food inflation rate, nonfood inflation rate and total government revenue have statistically significant effect on average monthly domestic price

volatility of coffee. However, fuel oil price and saving interest rate have no significant effect on the study under consideration. There was also an evidence to conclude that the variance of domestic price return of coffee at current month was influenced by 1-month, 2-month and 3-month lagged shocks since the ARCH terms were found to be statistically significant.

Finally, forecasts have been made using ARMA (3, 3) and EGARCH (3, 0) models. The in-sample forecast accuracy measures using root mean square error, mean absolute error, mean absolute percentage error and Theil's U statistics indicates that the estimated ARMA(3,3) and EGARCH(3,0) models are good enough to describe the domestic price and volatility of coffee. Moreover, out-of-sample forecasts were made from January 2014 to January 2016. The result indicates that the return domestic price of coffee has an increasing and decreasing trend over the forecast periods. The in-sample forecast using the best-fit EGARCH (3, 0) also indicates that the variance almost remains constant from the beginning of the study till December 2010, increased steadily at increasing rate till January 2011, decrease steadily at increasing rate till March 2011 and followed by a period where volatility remained at almost a constant level up to the end of the study period. Moreover, high price volatility was observed at the beginning of the year 2011.

5.2. RECOMMENDATION

From the empirical findings of this study, a researcher recommends the following:

- The domestic price volatility of coffee was influenced by macroeconomic factors such as export price of coffee, exchange rate, food inflation rate, nonfood inflation rate and total government revenue. Therefore, the government and concerned bodies should give due attention to these macroeconomic factors during policy formulation.
- Further studies to employ multivariate models such as seasonal or dynamic conditional correlation multivariate model to analyze the time varying correlation of domestic price of coffee with other variables.
- Further analysis to include supply level and demand level specifically in each region, zone and werda to identify high production areas and observe regional and zonal spillover effects.
- Other researchers to include seasonal dummies as a determinant factor and observe seasonal effects on domestic price volatility of coffee.

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APPENDIX

Appendix A: Tables

Table 14: Unit root test result at level for the variable under consideration

Variables	ADF Test		PP Test		Critical values		
	t -Statistic	P -value	t- Statistic	P –value	1%	5%	10%
D. price return of coffee	-9.432111	0.0000	-39.16592	0.0001	-3.46	-2.88	-2.58
Export price of coffee	-5.0407	0.0003	-7.3909	0.0000			
Exchange rate	-2.136100	0.5214	-2.9091	0.1623			
Fuel oil	-2.7537	0.2168	-4.8429	0.0006			
Food Inflation rate	-4.8936	0.0005	-2.8044	0.1978			
Nonfood Inflation rate	-0.0986	0.5421	-1.1166	0.9223			
Saving interest rate	-1.8784	0.6613	-1.9079	0.6460			
Total government revenue	1.1136	0.9999	3.1633	1.000			

Table 15: Unit root test at first difference for the variables under the study

Variables	ADF Test		PP Test		Critical values		
	t -Statistic	P -value	t- Statistic	P –value	1%	5%	10%
Exchange rate	-13.6012	0.0000	-12.5324	0.0000			
Fuel oil	-14.9344	0.0000	-19.6887	0.0000			
Nonfood Inflation rate	-4.2618	0.0046	-3.4603	0.0472			
Saving interest rate	-12.9237	0.0000	-12.9241	0.0000			
Total government revenue	-2.6540	0.0257	-2.6943	0.0240			

Table 16: Summary result on mean equation specification and order selection criteria for monthly return series of domestic price of coffee

Model	AIC	BIC	Serial correlation
ARMA(0,1)	-1.0854	-1.0481	No
ARMA(0,2)	-1.1015	-1.0455	Yes
ARMA(0,3)	-1.1256	-1.0509	Yes
ARMA(1,0)	-1.0937	-1.0562	No
ARMA(1,1)	-1.1476	-1.0914	No
ARMA(1,2)	-1.1509	-1.0759	No
ARMA(1,3)	-1.1468	-1.0531	No
ARMA(2,0)	-1.0884	-1.0320	No
ARMA(2,1)	-1.1583	-1.0830	No
ARMA(2,2)	-1.1842	-1.0901	No
ARMA(2,3)	-1.1834	-1.0709	No
ARMA(3,0)	-1.0900	-1.0144	No
ARMA(3,1)	-1.1588	-1.0643	No
ARMA(3,2)	-1.1893	-1.0759	No
ARMA(3,3)	-1.2484	-1.1161	No

Table 17: Mean equation specification for the natural log return series for the domestic price of coffee

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012852	0.004024	3.194122	0.0017
AR(1)	0.959534	0.105121	9.127885	0.0000
AR(2)	-1.043083	0.054818	-19.02827	0.0000
AR(3)	0.603459	0.100337	6.014325	0.0000
MA(1)	-1.122192	0.065197	-17.21242	0.0000
MA(2)	1.201165	0.028417	42.26894	0.0000
MA(3)	-0.898089	0.066328	-13.54017	0.0000
R-squared	0.174826	Mean dependent var		0.012897

Adjusted R-squared	0.143290	S.D. dependent var	0.138692
S.E. of regression	0.128372	Akaike info criterion	-1.226029
Sum squared resid	2.587247	Schwarz criterion	-1.093718
Log likelihood	107.5344	Hannan-Quinn criter.	-1.172316
F-statistic	5.543805	Durbin-Watson stat	1.912098
Prob(F-statistic)	0.000031		
Inverted AR Roots	.70	.13-.92i	.13+.92i
Inverted MA Roots	.90	.11+.99i	.11-.99i

Table 18: Breusch-Godfrey serial correlation LM test for residuals of ARMA(3,3) model

F-statistic	1.185626	Prob. F(10,147)	0.3050
Obs*R-squared	12.20643	Prob. Chi-Square(10)	0.2715

Table 19: Jarque-Bera normality test for residuals of ARMA(3,3) model

Variable	Skweness	Kurtosis	Jarque-Bera Statistic	p-value
Price return series	-0.6022	5.662	20.154	0.2015

Table 20: GARCH model specification and order selection criteria for monthly domestic price returns of coffee

Model	Error distribution	Information criteria		Serial correlation
		AIC	SBIC	
GARCH(0,1)	Normal	-1.1788	0.8764	No
	T	-1.4175	-1.1151	No
	GED	-1.4142	-1.1118	No
GARCH(0,2)	Normal	-1.1697	-0.8484	No
	T	-1.4018	-1.0850	No
	GED	-1.3140	-1.9927	No
GARCH(0,3)	Normal	-1.1689	-0.8287	No

	T	-1.3582	-1.0180	No
	GED	-1.3758	-1.0356	No
GARCH(1,0)	Normal	-0.9851	-06827.	No
	T	-1.3529	-1.0505	No
	GED	-1.3236	-1.0212	No
GARCH(1,1)	Normal	-1.0401	-0.7187	No
	T	-1.1821	-0.8608	No
	GED	-1.1902	-0.8689	No
GARCH(1,2)	Normal	-1.0511	-0.7109	No
	T	-1.2109	-0.8707	No
	GED	-1.2606	-0.9204	No
GARCH(1,3)	Normal	-1.0724	-0.7132	No
	T	-1.1837	-0.8246	No
	GED	-1.2365	-0.8774	No
GARCH(2,0)	Normal	-1.0682	-0.7469	No
	T	-1.3058	-0.9845	No
	GED	-1.2868	-0.9655	No
GARCH(2,1)	Normal	-1.0301	-0.6899	No
	T	-1.1809	-0.8407	No
	GED	-1.2305	-0.8903	No
GARCH(2,2)	Normal	-1.0498	-0.6907	No
	T	-1.3928	-1.0337	No
	GED	-1.2270	-0.8679	No
GARCH(2,3)	Normal	-1.0441	-0.6660	No
	T	-1.2407	-0.8626	No

	GED	-1.2196	-0.8416	No
GARCH(3,0)	Normal	-1.0408	-0.7005	No
	T	-1.2803	-0.9400	No
	GED	-1.2731	-0.9328	No
GARCH(3,1)	Normal	-1.0850	-0.7259	No
	T	-1.2567	-0.8975	No
	GED	-1.2002	-0.8411	No
GARCH(3,2)	Normal	-1.0457	-0.6677	No
	T	-1.2419	-0.8639	No
	GED	-1.2119	-0.8338	No
GARCH(3,3)	Normal	-1.9911	-0.5942	No
	T	-1.2148	-0.8179	No
	GED	-1.2218	-0.8249	No

Table 21: EGARCH model specification and order selection criteria for monthly domestic price returns of coffee

Model	Error distribution	Information criteria		Serial correlation
		AIC	BIC	
EGARCH(0,1)	Normal	-1.5370	-1.2157	No
	T	-1.6534	-1.3321	No
	GED	-1.6900	-1.3687	No
EGARCH(0,2)	Normal	-1.5776	-1.2374	No
	T	-1.6474	-1.3072	No
	GED	-1.6801	-1.3399	No
EGARCH(0,3)	Normal	-1.5670	-1.2079	No

	T	-1.5993	-1.2401	No
	GED	-1.6785	-1.3193	No
EGARCH(1,0)	Normal	-1.5120	-1.1906	No
	T	-1.6828	-1.3614	No
	GED	-1.6642	-1.3429	No
EGARCH(1,1)	Normal	-1.5348	-1.1946	No
	T	-1.6371	-1.2968	No
	GED	-1.6871	-1.3468	No
EGARCH(1,2)	Normal	-1.5329	-1.1737	No
	T	-1.6165	-1.2574	No
	GED	-1.6572	-1.2981	No
EGARCH(1,3)	Normal	-1.6190	-1.2410	No
	T	-1.7007	-1.3227	No
	GED	-1.7077	-1.3297	No
EGARCH(2,0)	Normal	-1.4751	-1.1349	No
	T	-1.6023	-1.2620	No
	GED	-1.6162	-1.2760	No
EGARCH(2,1)	Normal	-1.6098	-1.2507	No
	T	-1.6952	-1.3361	No
	GED	-1.6952	-1.3360	No
EGARCH(2,2)	Normal	-1.5411	-1.1631	No
	T	-1.6424	-1.2644	No
	GED	-1.6363	-1.2583	No
EGARCH(2,3)	Normal	-1.6735	-1.2766	No
	T	-1.8270	-1.4301	No

	GED	-1.7705	-1.3736	No
EGARCH(3,0)	Normal	-1.7182	-1.3591	No
	T	-1.2537	-1.3946	No
	GED	-1.7597	-1.4006	No
EGARCH(3,1)	Normal	-1.5961	-1.2181	No
	T	-1.7646	-1.3886	No
	GED	-1.7579	-1.3799	No
EGARCH(3,2)	Normal	-1.6934	-1.2965	No
	T	-1.7119	-1.3150	No
	GED	-1.7393	-1.3424	No
EGARCH(3,3)	Normal	-1.6802	-1.2644	No
	T	-1.7705	-1.3546	No
	GED	-1.7523	-1.3364	No

Table 22: Remaining ARCH effect in residuals for EGARCH(3,0) model with normal distributional assumptions

Heteroskedasticity Test: ARCH

F-statistic	0.002155	Prob. F(1,161)	0.9630
Obs*R-squared	0.002182	Prob. Chi-Square(1)	0.9627

Table 23: Ljung-Box test for the presence of serial correlation in the residuals of the mean equation

Date: 01/06/80 Time: 18:56
Sample: 2003M01 2016M12
Included observations: 164
Q-statistic probabilities adjusted for 6 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.041	0.041	0.2862	
.|. |	.|. |	2	-0.024	-0.025	0.3797	
.|. |	.|. |	3	-0.010	-0.008	0.3963	

*|. |	*|. |	4	-0.158	-0.159	4.6589	
.|. |	.|. |	5	0.000	0.013	4.6589	
.|. |	.|. |	6	-0.052	-0.062	5.1196	
.|. |	.|. |	7	-0.015	-0.012	5.1597	0.023
.|. |	.|. |	8	0.066	0.040	5.9209	0.052
.|. |	.|. |	9	0.072	0.070	6.8209	0.078
.|. |	.|. |	10	0.069	0.051	7.6629	0.105
.|* |	.|* |	11	0.078	0.078	8.7370	0.120
.|. |	.|. |	12	0.044	0.060	9.0913	0.169
.|. |	.|. |	13	-0.034	-0.012	9.2978	0.232
.|. |	.|* |	14	0.050	0.082	9.7488	0.283
.|. |	.|. |	15	0.012	0.040	9.7771	0.369
.|* |	.|* |	16	0.106	0.136	11.844	0.296
.|* |	.|* |	17	0.093	0.091	13.458	0.264
.|. |	.|. |	18	-0.009	0.019	13.474	0.336
.|. |	.|. |	19	0.001	0.003	13.474	0.412
*|. |	*|. |	20	-0.165	-0.151	18.620	0.180
.|. |	.|. |	21	-0.011	0.008	18.645	0.230
.|. |	*|. |	22	-0.035	-0.067	18.885	0.275

Table 24: Ljung-Box test for standardized residuals from volatility model for domestic price return of coffee

Date: 01/27/80 Time: 10:15
Sample: 2003M01 2016M12
Included observations: 164
Q-statistic probabilities adjusted for 6 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.071	0.071	0.8523	
*|. |	*|. |	2	-0.079	-0.084	1.8990	
.|. |	.|. |	3	0.060	0.073	2.5020	
**|. |	**|. |	4	-0.258	-0.280	13.788	
*|. |	.|. |	5	-0.100	-0.043	15.513	
.|. |	.|. |	6	0.002	-0.045	15.514	
.|. |	.|. |	7	-0.018	0.012	15.573	0.000
.|* |	.|* |	8	0.147	0.093	19.334	0.000
.|. |	.|. |	9	0.031	-0.029	19.508	0.000
.|. |	.|. |	10	-0.014	-0.002	19.544	0.011
.|. |	.|. |	11	0.055	0.033	20.084	0.021
.|. |	.|. |	12	-0.042	0.009	20.404	0.022
.|. |	.|. |	13	-0.043	-0.012	20.740	0.054
.|. |	.|. |	14	0.061	0.060	21.424	0.076
.|. |	.|. |	15	-0.037	-0.031	21.677	0.120
.|* |	.|* |	16	0.098	0.118	23.450	0.089
.|* |	.|. |	17	0.087	0.042	24.843	0.100
.|. |	.|* |	18	0.028	0.082	24.991	0.115
.|. |	.|. |	19	-0.011	-0.046	25.015	0.233
*|. |	*|. |	20	-0.182	-0.147	31.269	0.045
.|. |	.|. |	21	-0.012	0.063	31.297	0.068
.|. |	.|. |	22	-0.036	-0.063	31.547	0.121

*Probabilities may not be valid for this equation specification.

Appendix B: Figures

Figure 5: Time plot of monthly domestic price ofcoffee and its returns at level

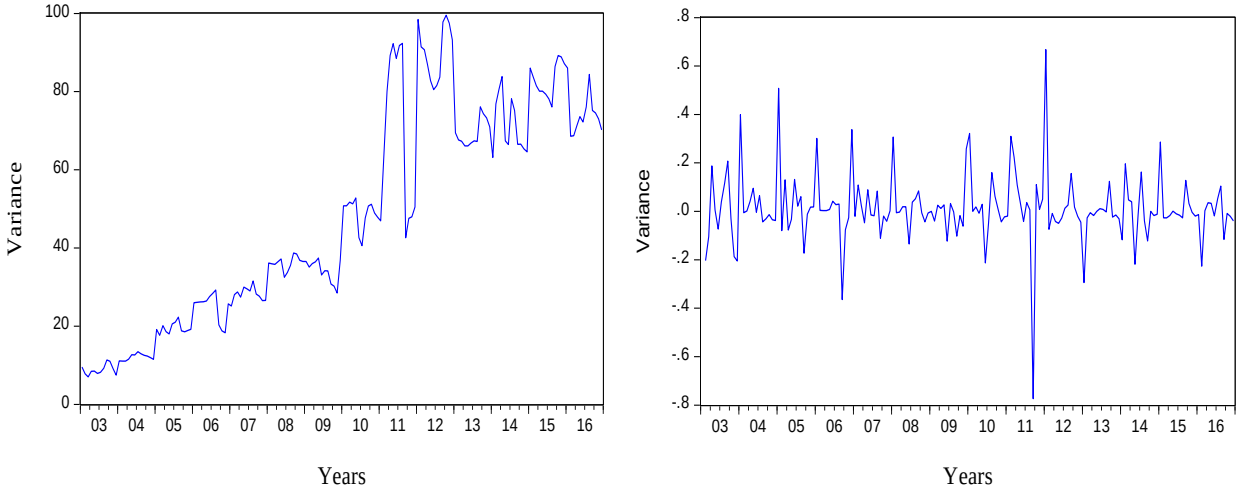


Figure 6: Time plot of monthly export price of coffee at level

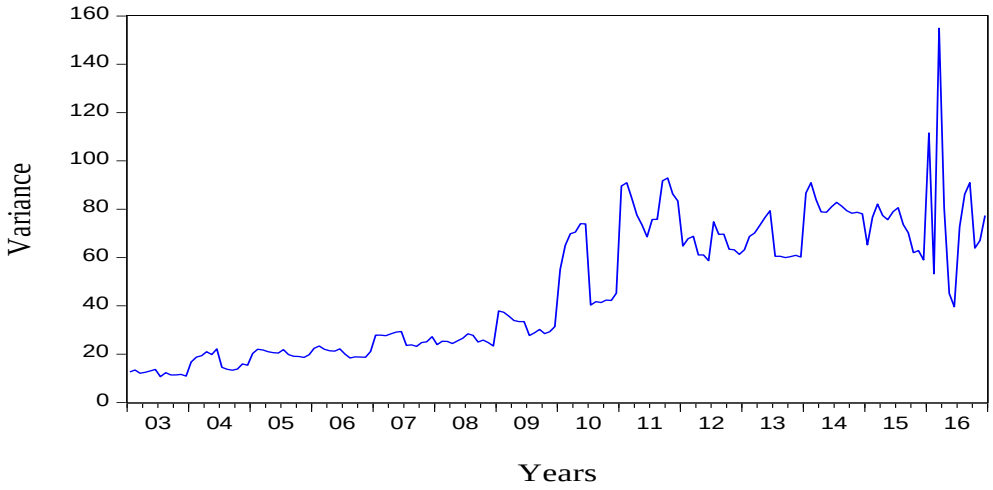


Figure 7: Time plot of monthly exchange rate price at level and first difference

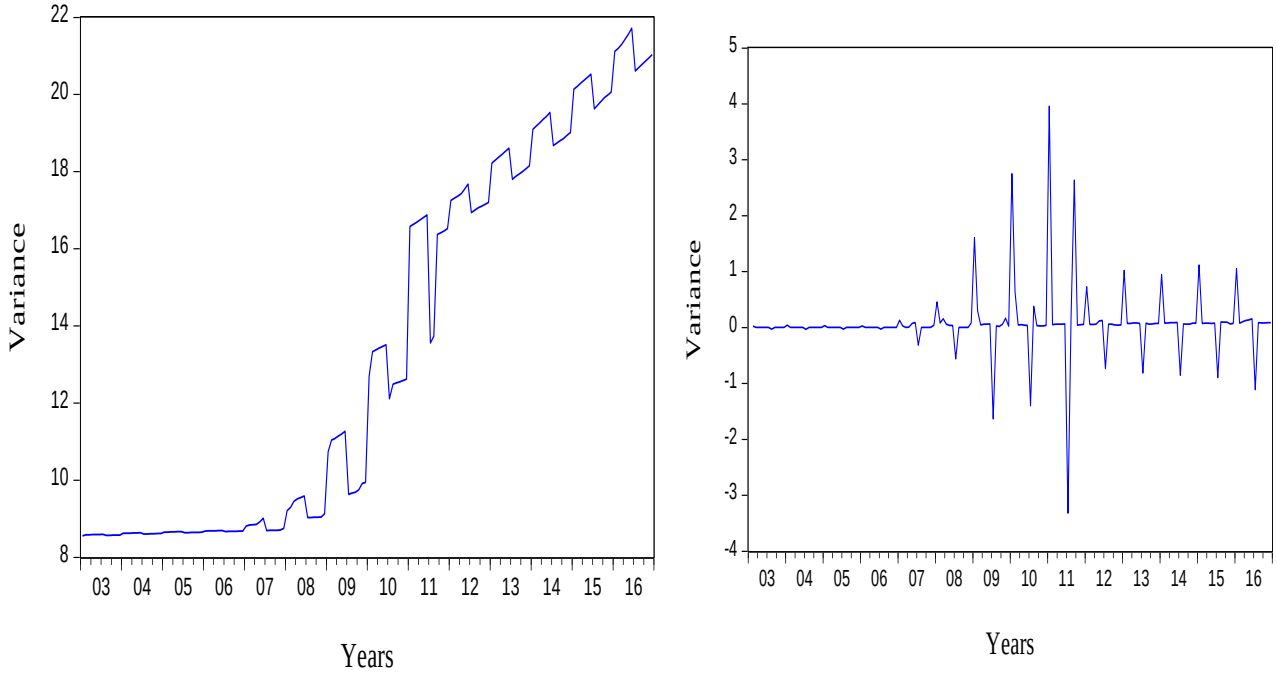
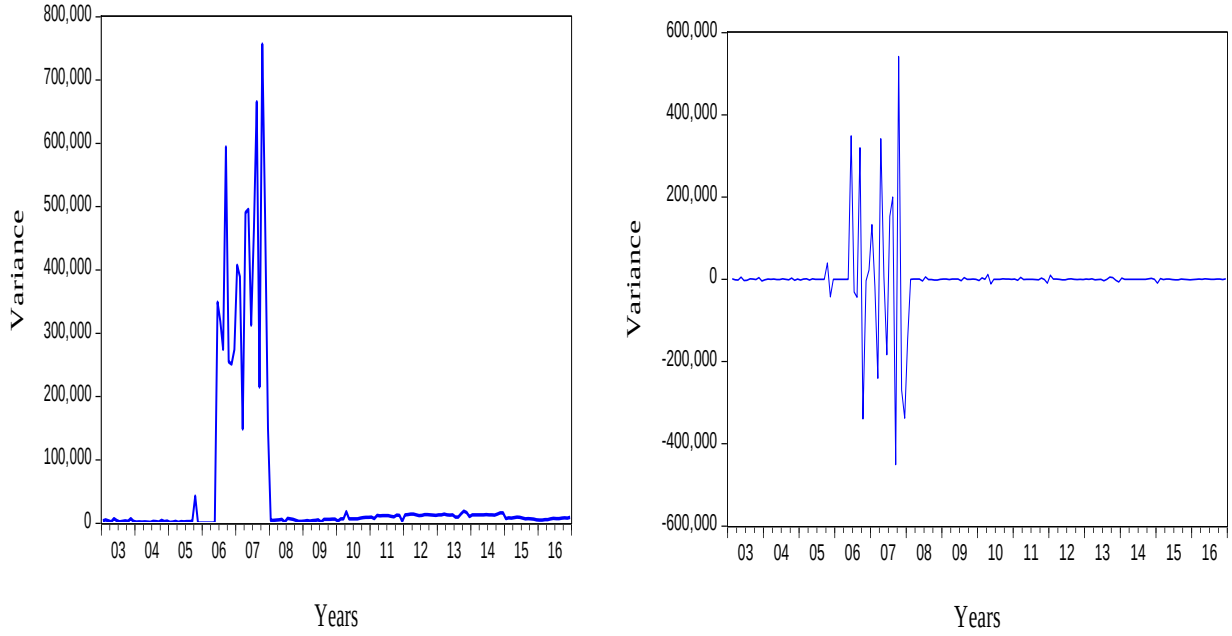


Figure 8: Time plot of monthly fuel oil price at level and first difference



ғigure 9: Time plot of monthly food inflation rate at level

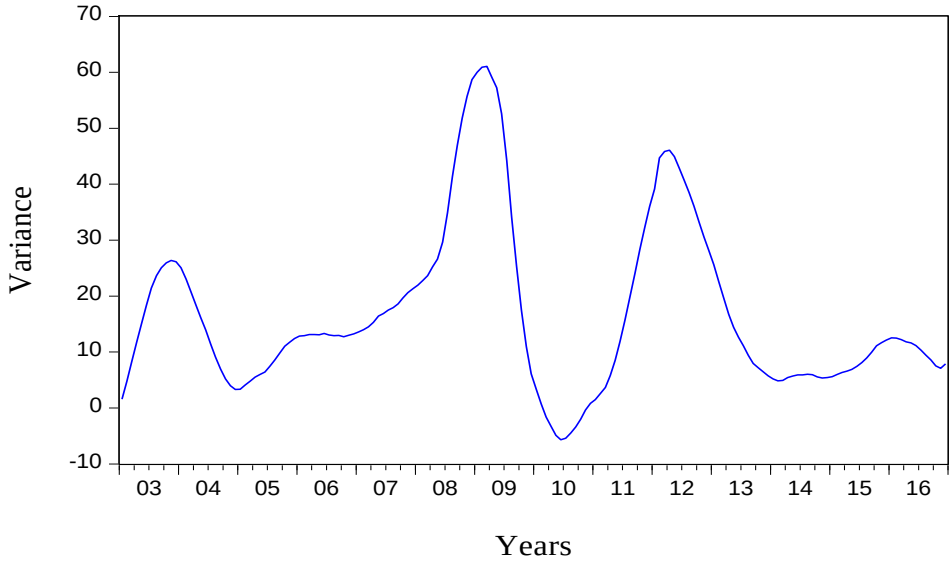
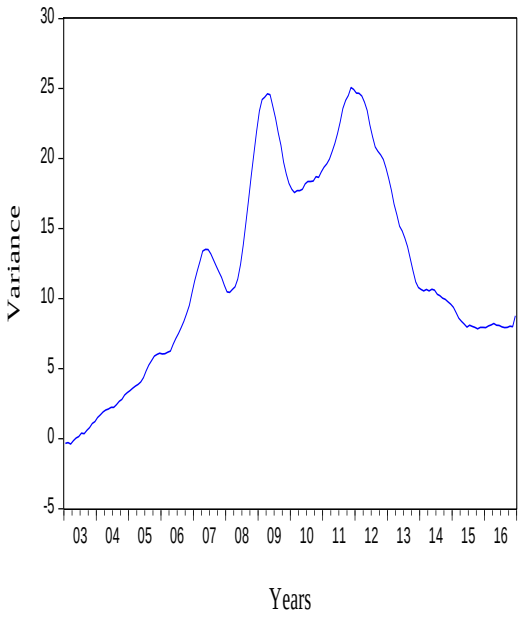


Figure 10: Time plot of monthly nonfood inflation rate at level and first difference



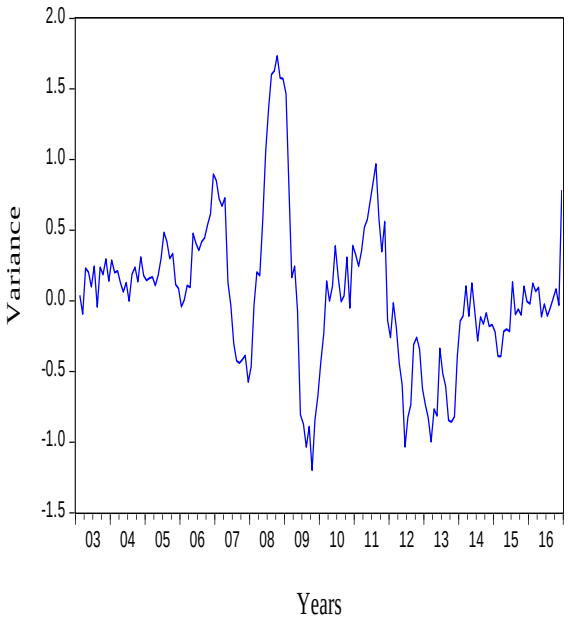


Figure 11: Time plot of monthly saving interest rate at level and first difference

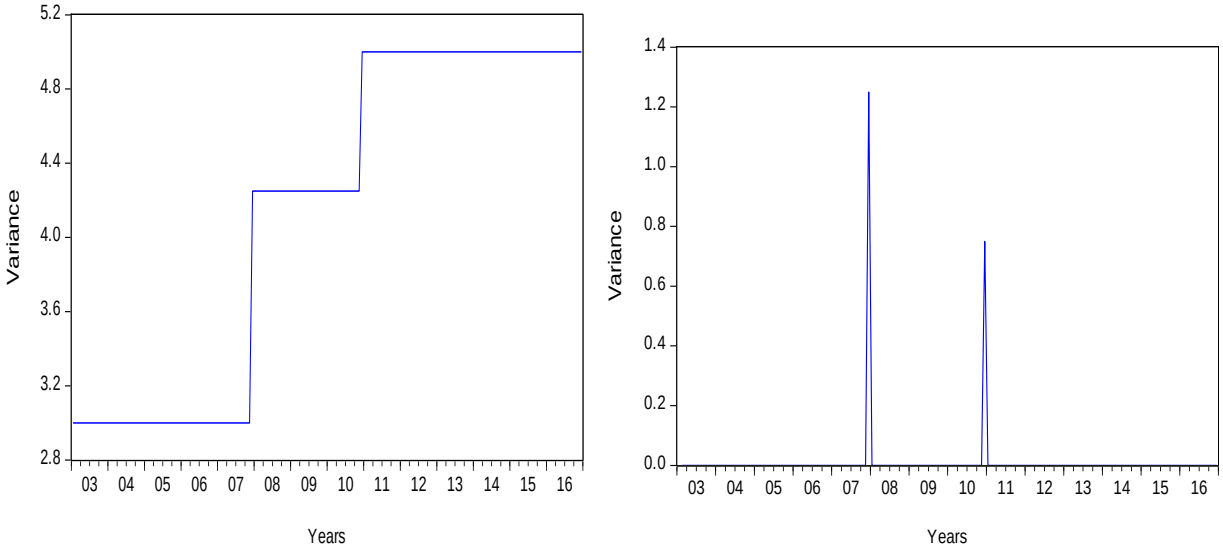


Figure 12: Time plot of monthly total government revenue at level and first difference

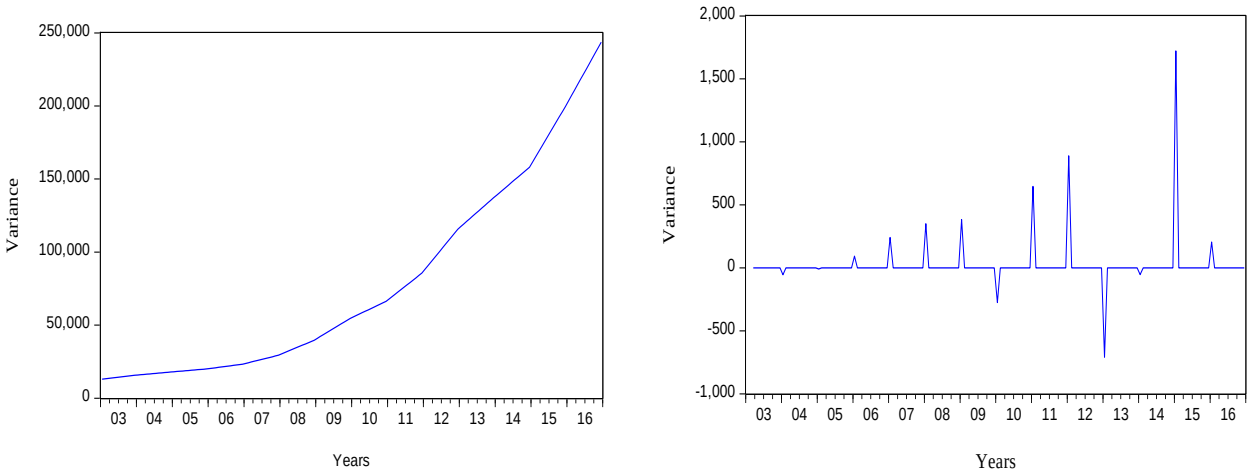
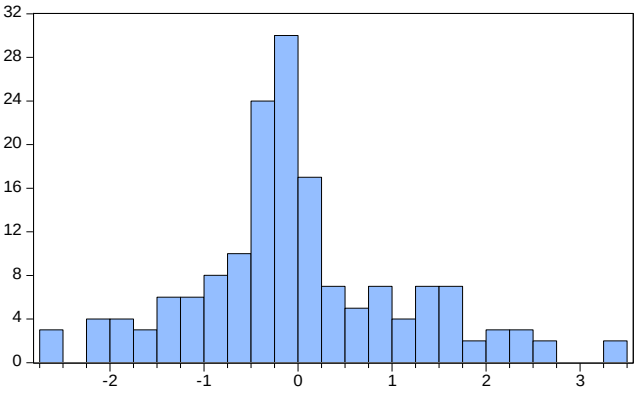


Figure 13: Normality test of ARMA(3,3) -EGARCH(3,0) model with normal distributional assumption for residuals



Series: Standardized Residuals	
Sample 2003M05 2016M12	
Observations 164	
Mean	0.000668
Median	-0.118152
Maximum	3.425212
Minimum	-2.660365
Std. Dev.	1.130496
Skewness	0.383001
Kurtosis	3.456562
Jarque-Bera	5.433914
Probability	0.066076