TIME SERIES MODELLING OF OIL PRICE FLUCTUATIONS: APPLICATIONS TO LIBYA AND NIGERIA

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CANDIDATE DECLARATION

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ABSTRACT

This study aims to analyse the behaviour of crude oil prices and to determine the dynamic relationships between domestic crude oil prices and fundamental macroeconomic variables in Libya and Nigeria. The analysis in this study involves two stages. The first stage is to analyse and model oil price returns of the Libyan, Nigerian and OPEC markets. Unlike previous studies, this study examines the existence of a structural break in crude oil prices data. The empirical analysis uses the AR-GARCH, AR-EGARCH, AR-GJR-GARCH, AR-APARCH, AR-CGARCH and AR-ACGARCH models for modelling the conditional mean and conditional variance of the oil prices returns under three error distributions, namely the normal distribution, student-t distribution and generalized error distribution. The results show that the three return series exhibit no structural break in the mean and variance equations but we find evidence of volatility clustering and leverage effect response to good and bad news in the asymmetric models in the three markets. We also assess the out-of-sample forecasts of the class of GARCH models by using four loss functions. The results indicate that the AR-CGARCH-GED model is the best model for forecasting oil returns in Libya, whilst the best models for Nigeria and OPEC are the AR-GARCH-GED and AR-EGARCH-t models, respectively. The second stage is to examine the dynamic relationship between oil prices and GDP, exchange rate and inflation using annual data for the 1970-2017 periods in Libya and Nigeria. Both short-run and long-run relationships between these variables are explored by applying cointegration tests, the vector autoregressive model (VAR), and vector error correction (VECM) model, Granger causality tests, impulse response functions and forecast variance decompositions. The results show that there is a cointegrating relationship between domestic oil prices and macroeconomic variables in both Libya and Nigeria. Furthermore, the results show that there is a unidirectional Granger-causality relationship running from Libyan oil prices to Libya's GDP. Moreover, the results show a unidirectional causality running from Nigerian oil prices to GDP and exchange rate in Nigeria. The findings of the impulse response functions suggest significant impacts of domestic oil prices shocks on the macroeconomic variables in Libya and Nigeria in the short and long term. The results of the variance decompositions analysis indicate that the changes in Libyan oil prices can impact Libyan GDP. While, Nigerian oil price shocks could affect most of macroeconomic variables in Nigeria. The main policy implications from these findings are that policymakers should

monitor and predict future oil prices and take these expectations into account when adopting a particular monetary policy.

DEDICATION

This thesis is dedicated to:

The soul of my father Hussein Awidan, who passed away on 14th of January 2018, Allah's mercy on his soul. Ameen!

My mother with all my love.

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CHAPTER 1: Introduction and Background

1.0 Introduction

Oil is one of the most important strategic commodities and sources of energy around the world (Basher and Sadorsky, 2006; Yaziz et al., 2011; Yan, 2012; Chen and Xu, 2019). Oil is considered a key product especially to the oil producing nations and plays a crucial role in affecting the global economy, financial markets and macroeconomic factors such as gross domestic product (GDP), stagnation, inflation, interest rates, exchange rates, and others. Thus, fluctuations of crude oil prices have major effects on the life in this world at the level of individuals, groups, institutions, governments and nations (Hamilton, 2009; Vo, 2009; Wei et al., 2010; Wang and Wu, 2012; Zhang et al., 2015). In the past few years, the prices of oil have shown significant variation, they have increased and decreased dramatically in different periods, which greatly affecting daily life in an undeniable way, from all modes of transport, including trains, cars and flights to other consumer products, also affects some macroeconomic variables of the concerned economies (Hamilton, 1996, 2010; Pinduck, 1999; Kilian, 2008; Ahmed and Shabri, 2014; Zhao et al., 2017).

The price of oil is considered to be a vital indicator of the economic development of different global economies (Yan, 2012; Ahmed and Shabri, 2014; Zhang et al., 2019), particularly, the oil producing nations. Thus, understanding and modelling the dynamic behaviour of crude oil prices, their fluctuations and investigating the link between prices of crude oil and macroeconomic variables across different oil producing countries in order to achieve a very accurate forecast to the complications of the crude oil prices are becoming issues of interest, especially among the relevant stakeholders such as marketers, buyers, investors, policy makers/ regulators, government agencies, energy economists and indeed the price/market analysts in order to planning their activities effectively (Arouri et al., 2012; Charles and Darne, 2014).

The remainder of the chapter is structured as follows. Section 1.1 states the background to the research. Section 1.2 briefly describes the Organization of Petroleum Exporting Countries. Section 1.3 outlines scope and limitations of the study area. Section 1.4 presents the research problem. Section 1.5 discuses research aims, objectives and questions. Section 1.6 highlights the contributions to knowledge. Section 1.7 outlines the structure of the thesis and finally, section 1.8 concludes this chapter.

1.1 Background to the Research

In general, right from the oil crisis situation, which began in 1973, prices of both energy and crude oil have often fluctuated more than other commodities prices (Dehn, 2001; Cashin and McDermott, 2002; Regnier, 2007; Arouri et al., 2012). Hamilton (2009) examines various factors influencing crude oil prices by determining factors responsible for changes in its global demand and supply condition in oil markets; these factors include future markets, role of speculation, price elasticity, income elasticity and role of OPEC. There are also many other non-marketing related factors such as speculations, political challenges, military conflicts, climate changes and natural disasters (Cheong, 2009). Social unrest disrupts market activities and therefore may impact investment for various reasons than the uncertainties associated with high expected government turnover. Indeed, political turmoil, collective violence, civil wars, and material threats to workers can have direct effects on productivity and thus on the rate of return of investment. Alesina and Perotti (1996) study the relationship beetwen income distribution and investment, by focusing on sociopolitical instability as the channel which links these two variables. They found that income inequality and investment are inversely related. According to Asteriou and Siriopoulos (2003), there are some arguments saying that the political instability negatively affects economic growth by affecting investments, savings, corporate decisions and economic development in general. Moreover, from a global viewpoint, political instability in the Middle East in particular leads to fluctuations in prices of crude oil, as the the Middle East region represents the lion's share of oil supplies worldwide, this is because the Middle East encompasses some of the world's largest crude oil producers, including Saudi Arabia, the United Arab Emirates, and Iran (Stanislaw and Tergin, 1993). Therefore, political instability and any security threats to this region would have major impacts on global prices of crude oil, given the influence on supply and demand.

Cheng et al. (2019) summarise some other factors that affect crude oil prices, including previous crude oil prices, strategic reserves, extraction costs, crude oil inventories, exchange rates and the interrelationship between different oil markets. These factors, combined are seen to have exposed the prices of oil to the high level of fluctuation, witnessed over the last few decades (Aloui et al., 2012). Unfortunately, the level of fluctuations that have majorly to plunging the global economy to recessions experienced in recent years. With these challenges, it is therefore imperative to underpin the dynamic behavior of oil price, especially for the benefits of the traders, investors, and relevant stakeholders across the world oil industry (Obadi et al., 2013).

In recent years, a large body of studies has been devoted to understanding the behavior of oil price worldwide (Ferderer, 1996; Hamilton, 1996, 2010; Sadorsky, 2006; Pindyck, 1999; Sadorsky, 1999, 2003; Yang et al., 2002; Regnier, 2007; Cheong, 2009; Wei et al., 2010; Ahmed and Shabri, 2014; Omojolaibi, 2014; Nademi and Nademi, 2018). These numerous studies indicate the high importance of this commodity in the global economy due to its fluctuations on the one hand and the significant impact of these fluctuations on macroeconomic indicators on the other hand (Kang et al., 2011).

Fluctuations (also referred to as variability or volatility) in oil prices mean huge gains or losses for investors in oil markets and uncertainties in revenue flow and economic management by financial policy makers, especially in oil producing and oil-exporting nations. They influence portfolio allocations, risk management's decisions and oil-related investments' decisions by the investors. Thus, government and investors pay close attention to the extent of fluctuations in oil prices in order to make informed policy and investment decisions (Hamilton, 1983; Yang et al., 2002; Sadorsky, 2006; Wei et al., 2010; Salisu and Fasanya, 2012; Salisu, 2014). Pindyck (2003) argues that understanding oil price fluctuations is critical issue because persistent changes in the price of oil could expose industrial producers and consumers to serious risk, affecting investments in oil stocks, production facilities and transportation. Salisu (2014) states that the most substantial concern is how to model the prices of oil when facing large fluctuations.

Modelling and forecasting the prices of crude oil are gaining increased attention globally because oil prices influence other main sectors of the economy, including the stock market, and many operations in the petroleum industry, for instance, upstream production and downstream sales (Wei et al., 2010; Ahmed and Shabri, 2014; Nademi and Nademi, 2018). Hamilton (2009) notes that analyzing and forecasting the price of oil tend to be difficult task due to the random nature of oil price and because it tends to vary substantially over time. Therefore, this task is still one of the biggest challenges faced by statisticians and econometricians (Zhao et al., 2017; Cheng et al., 2019). Oil price forecasts are critical inputs to macroeconomic forecasts, especially because of the impact of oil prices on production and inflation, and hence on monetary policy. Furthermore, accurately forecasting oil price changes are crucial for financial decisions involving portfolio risk management and oil investments, particularly with regard to issues of evaluation of oil-related products and instruments of energy derivatives (De Albuquerquemello et al., 2018; Cheng et al., 2019). In the sense that an investor with efficient forecast of oil prices could use them to better manage its portfolio (Kroner et al., 1995).

1.1.1 Oil Price Fluctuations and Its Impacts on Economic Performance

According to Thankgod and Maxwell (2013), for many decades oil price change has remained an issue of public interest such that different efforts have been made towards explaining how oil prices behave in relation to the macroeconomic impacts of its volatility. This is because slight fluctuations in the prices of crude oil can lead to either positive or negative impacts on most macroeconomic indicators, including gross domestic product (GDP), inflation, investment returns and exchange rates (Cheong, 2009).

Sadorsky (1999) indicates that the shocks of oil price fluctuations have asymmetric impacts on the economy, and sometimes movements in the price of oil influence economic activities, but the fluctuations in economic activities have little effects on the price of oil, so that changes of oil price have significant macroeconomic effects. Oil price changes create uncertainty, and thus an unstable economy over the last decade for both energy-exporting countries and energy-importing countries. Rising crude oil prices lead to an increase in inflation and a consequent recession, as prices of crude oil are negatively associated with economic activities (Ferderer, 1996; Yang et al., 2002; Jimenez-Rodriguez and Sanchez, 2005; Narayan and Narayan, 2007; Mohammadi and Su, 2010).

According to Lardic and Mignon (2008) and Abeysinghe (2001), changes in prices of crude oil influence real economic activites in several methods. One of these effects is the classic supply side effect. The rise in the prices of oil leads to an increase in the production cost, which in turn leads to a decline in the growth of production. The rise in the prices of oil negatively affects the trade of oil importing countries. Another impact is about the demand for money. As the prices of oil increases, the magnitude of the money demanded also increases. If the government does not react strongly to this increase, the country's inflation rate may increase, investments may decline, and the gross domestic product may eventually drop. Additionally, in the short term, the prices of oil may impact production structure and thus have a negative influence on unemployment indicator. In the long term, however, the increase in the prices of oil will lead to structural movements in energy sectors.

Researchers through early empirical analysis of different economies have pointed out that fluctuations in prices of oil have major effects on economic activity (Hamilton, 1983; Mork, 1989; Bernanke et al., 1997; Bernanke, 2004). Moreover, movements in prices of oil have effects for the national economy and, particularly, exchange rate changes. Ogundipe and Ogundipe (2013) outline that there conservable evidence to indicate the vital role of fluctuations of oil price in determining the exchange rate pattern. According to Krugman (1983), the value of the exchange rate rises in response to high prices of oil and falls in response to the decrease in prices of oil in the oil-exporting countries, while the opposite is predictable in the oil-importing countries case. According to Englama et al (2010), the volatility in the exchange makes investments and international trade more difficult because it raises the risk and uncertainty in foreign transactions.

In fact, while there are many studies covering these perspectives of oil price dynamics, there is relatively little work done in emerging markets such as Libya, Nigeria and Sub-Saharan African countries, as against the developed nations. For instance, Iwayemi and Fowowe (2011) observe that many studies have been concerned on the influence of crude oil prices on the macroeconomic variables for developed economies; but those relating to the developing, oil-exporting countries are relatively small in number. Meanwhile, some of the recent studies on the oil price-macroeconomy with respect to Africa countries include Ebaidalla (2014) for Sudan, Omojolaibi (2014) for Nigeria, and Bouchaour and Zeaud (2012) for Algeria.

Blanchard and Gali (2007) argue that the impacts of variations in prices of crude oil on the economy vary across different countries. For oil-importing economies it is expected that increases in prices of oil will impact economic development negatively, but positively for oil-exporting economies. Zhang et al. (2008) state that the increase in oil prices often leads to an increase in inflation, damaging the economies of oil-importing countries and the decline in oil prices could lead to economic stagnation and political instability in oil-exporting countries where economic development can be delayed. Moreover, it is generally accepted that the increase in the price of oil leads to the reduction of economic growth, stock market activities and the performance of non-oil industries in almost all oil-importing countries, while there are some positive impacts in increasing the price of oil for exporting countries (Arouri et al., 2012).

Omojolaibi (2014) points out that in most oil-exporting countries such as Libya and Nigeria, the funds needed for government spending come from oil revenues. So the financial and monetary policies in these countries depend on the price of oil. In these economies, fluctuations in oil prices lead to variation in oil revenues, which in turn lead to instability in the economy. In this case the alleged resource curse occurs. When the price of oil rises, the government has more money to spend. Therefore, incompetent public spending and financial expansion lead to waste. This destructive strategy over time makes the economy more vulnerable to volatile oil prices, especially in the existence of imperfections in the capital market (Anashasy et al., 2005). In contrast, when an oil price descends, it may lead to some financial imbalances and the most disappointing thing is that such a decline is difficult to predict. Considering this background, fluctuations of oil prices play a key role in macroeconomic activity in oil-exporting countries; so, studying this role and investigating the influences of oil price changes on the main macroeconomic indicators are of great importance, where only a few studies have focused on oil-exporting countries (Berument et al., 2010).

1.2 The Organization of Petroleum Exporting Countries

The Organization of Petroleum Exporting Countries (OPEC) is a global organization of 14 countries that rely heavily on oil exports to achieve their income. It was founded in Baghdad in 1960 included by first five members Saudi Arabia, Iran, Iraq, Kuwait and Venezuela, and headquartered since 1965 in Vienna. The OPEC members are working to increase revenues from the sale of oil in the world market. As of September 2018, OPEC members accounted for an estimated 44% of world oil production and 81.5% of the world's oil reserves (OPEC, 2019), giving OPEC a significant impact on world oil prices. The current members of an organization are the following: Algeria, Angola, Austria, Cameroon, Congo, Ecuador, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, Syria, United Arab Emirates, and Venezuela. Qatar and Indonesia are former members.

OPEC is an oil-based organization, although its main objective is to create a more stable oil market for both producers and consumers. This is carried out by trying to avoid fluctuations of oil price in the market by controlling a large share of the total supply of crude oil (Dunsby et al., 2008). The OPEC Reference Basket of crude oil has been considered as a major benchmark for prices of oil since 2000. It is measured as a weighted average price for oil blends from the OPEC member countries: Algeria, Angola, Ecuador, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates, and Venezuela (OPEC, 2019). According to Nademi and Nademi (2018), crude oil revenue in oil exporting countries such as OPEC members is determined by the prices of crude oil which have a crucial role on the financing of government budget.

1.2.1 State of Libya

Libya is a developing country located in North Africa bordered by the Mediterranean Sea to the north, Chad and Niger to the south, Egypt to the east, Sudan to the southeast, Algeria and Tunisia to the west. The Libyan economy relies almost entirely on hydrocarbon production, with natural gas and crude oil accounting for about 96% of total government revenues and 60% of GDP (Libya *OPEC*, 2018*)* According to the Energy Information Administration (EIA) (2013), in 2012; it provided almost 98% of all export revenue. In 2012, at least 79% of all government revenue received resolved from crude oil exports or almost $ 4 billion per month.

Libya has the biggest oil reserves in Africa. Libyan crude oil is "a sweet" crude, which means that it contains a small percentage of impurities and this feature is highly desirable. Libya's total recoverable reserves are estimated at about 46 billion barrels of oil, about 3.4% of the world's total reserves and the world's ninth biggest reserves. In recent years, oil production peaked in October 2012 at 1.5 million barrels per day (Etelawi et al., 2017). According to Etelawi et al., (2017) the production of oil fell sharply with the Libyan revolution and continued conflict in the country in 2013. However, oil remains the main source of future growth in the economy. Mills (2008) points out that Libya is an important member of OPEC; however, Libya's potential as an oil exporter is hampered by political turmoil and sanctions.

1.2.2. State of Nigeria

Nigeria is a Federal Republic in the West Africa that is bordered respectively on the West, North, East and South by Benin, Chad and Niger, the Cameroon, and Atlantic Ocean. Its south coast lies on the Gulf of Guinea in the Atlantic Ocean. It is comprised of 36 states and the Federal Capital Territory, Abuja. Nigeria is one of the democratic secular countries in Africa (Cashin et al., 2014). Nigeria depends primarily on petroleum products in particular since gaining independence in 1960. Oil is the key source of energy in Nigeria and the world generally, where; the Nigerian oil industry plays a main role in the economic life of the country. Nigeria is considered as the twelfth largest producer of petroleum all around the globe, one of the eighth largest exporters, and has the tenth largest reserves. Nigeria became a member of the OPEC in the year 1971. The petroleum industry is considered the largest industry in Nigeria and key generator of GDP with oil revenues having reached \$340 billion in exports since the seventies and a maximum capacity of crude oil production reached about 2.5 million barrels per day (Akpanta and Okorie, 2014). Since discovering oil in commercial amounts, Nigeria was to a large extent a single-product economy. The value of total export revenues in Nigeria in 2010 stood at \$70,579 million, while revenues from oil exports of the total export earnings was \$61,804 million, accounting for about 87.6% (Ogundipe et al., 2014). In addition, the absolute reliance on revenue from oil exports accentuates the shocks to Nigeria's economy due to fluctuations in oil prices.

1.3 Scope and Limitations of the Study Area

The thesis will be focused only on the study and modeling of the dynamic behavior for the domestic oil prices time series of only two countries: Libya and Nigeria. Libya and Nigeria have been selected for several reasons. Firstly, the two African countries are developing countries and are considered to be two of the largest oil producing countries in the world and also possess the largest oil reserves. Secondly, Libya and Nigeria economies depend largely on the export and production of crude oil and they are important and active members of the OPEC. Finally, Libya and Nigeria economies are similar in their dependence on the export revenues of crude oil, as well as the existence of some similar historical and geographical of these two countries. In addition, OPEC prices have also been analysed for comparison purposes to provide a useful benchmark.

1.4 The Research Problem

Due to the fact that crude oil is an important energy source and exceedingly used in all vital sectors of the Libyan and Nigerian economies with no effective and cost-beneficial alternative, and given that its price dynamics have been comparatively volatile in recent years, we would like to examine whether the traditional hypothesis, as pioneered by Hamilton (1983), that fluctuations in crude oil prices may adversely influence the macroeconomic performance of the two countries selected for study. Moreover, a few published studies have been concerned with modeling and forecasting oil price fluctuations and exploring the relationships among the prices of oil and selected macroeconomic variables in developing countries such as Libya and Nigeria. In reviewing previous empirical literatures, it can be seen that there is lack of studies on developing countries compared to developed economies. Therefore, this study seeks to address the gaps in this field with updated evidence for Libya and Nigeria through modeling and forecasting domestic oil prices and studying the dynamic relationships among oil prices, GDP, exchange rate and inflation as the indicators of economic activity in these two countries. The selection of these economic indicators is fundamentally driven by similar studies, in particular Hamilton (1983), Burbidge and Harrison (1984) and Cologni and Manera (2008) are used as a standard, which have been conducted in developing countries and in line with economic theories. Additionally, the oil price, GDP, inflation rate and exchange rate have a main role in the measurement of the monetary policy stance and they are the crucial macroeconomic indicators that reflect the functioning of an economy. Consequently, it is interesting to study the relationships among oil prices, GDP, exchange rate and inflation due to their significant contribution to the development of the Libyan and Nigerian economies.

1.5 Research Aims, Objectives and Questions

Libya and Nigeria are mono-product economies, where the major export commodity is crude oil. Therefore, fluctuations in prices of oil can have significant effects on government revenue and the Libyan and Nigerian economies which depend heavily on oil sectors. Thus, this will negatively impact the economy growth. This research aims to use appropriate time series models to explore the comparative oil price dynamics in the two countries and analyse the dynamics between domestic oil prices and basic macroeconomic indicators such as gross domestic product, exchange rates and inflation for the Libyan and Nigerian economies.

1.5.1 The Research Objectives

1. To determine whether there exist structural breaks in the oil prices for Libyan, Nigerian and OPEC markets.

2. To identify the best conditional mean and conditional variance models to perform statistical time-series analysis and forecasting of crude oil prices returns for the Libyan, Nigerian and OPEC oil markets under different error distributions.

3. To study whether domestic oil prices fluctuations would affect GDP, exchange rates and inflation in the short run and in the long run in Libya and Nigeria.

4. To identify a suitable econometric-time series model that allows us to determine the dynamic relationships between oil price, GDP, exchange rate and inflation in the previously mentioned countries.

5. To detect the possible existence of causality relationships between oil price, GDP, exchange rate and inflation in Libya and Nigeria.

1.5.2 The Research Questions (RQs)

This section discusses a wide range of research questions tailored along with the research objectives of the study. It is not intended that the questions replace the objectives in subsequent chapters of the thesis. Both objectives and questions are complementary. The specific research questions are as follows:

RQ1: Do structural breaks exist in the oil price time series data?

RQ2: Which time series models are more suitable for describing and forecasting crude oil price returns in Libya, Nigeria and OPEC markets?

RQ3: Are there any relationships between domestic oil price and GDP, exchange rates and inflation in Libya and Nigeria in the short run and long run?

RQ4: What form of time series modelling is suitable for exploring the relationship between oil prices and selected macroeconomic indicators for Libya and Nigeria?

RQ5: Are there any long run causality relationships and short run causality effects running between, oil price, GDP, exchange rate and inflation in Libya and Nigeria?

1.6 Contributions to Knowledge

The fundamental objectives of this study are to investigate the dynamic behaviour of oil price fluctuations and related macroeconomic modelling, linked to selected macroeconomic indicators in the short and long-run for two African OPEC member countries, Libya and Nigeria. The literature on crude oil price analysis indicates a lack of comprehensive studies on this subject in Libya and Nigeria. This research attempts to bridge these gaps in the present literature by providing empirical investigation of the numerous aspects of oil markets in Libya and Nigeria. Therefore, this research extends the existing literature as this study contribution to the assessment of fluctuations in the prices of crude oil and their effects on some important macroeconomic variables in two African OPEC member countries using each country's domestic crude oil price. In contrast to previous studies, which have used global prices of crude oil, such as the West Texas Intermediate (WTI) or the Brent price, this study uses each country's actual oil prices, namely: Libya (Ess Sider), and Nigeria (Bonny Light). In fact, this is very significant because each type of crude oil has different prices.

The performance of different time series models for investigating the dynamic behaviour of oil prices fluctuations will be critically reviewed and compared. Suitable models for Libya and Nigeria will then be identified. The findings from this study will provide Libyan and Nigerian financial policy makers, governments and decision makers with an updated understanding some aspects of the fluctuations behavior and possible influences of oil prices on macroeconomic performance of the Libyan and Nigerian economies.

This study and its results are especially important for the Libyan situation because Libya is currently undergoing political and economic transition points. The results also will be pedagogically relevant in refreshing the teaching of time series econometric modelling in Libyan and Nigerian universities in a way that makes connection with the economy and economic management policies. It is also expected that any methodological novelties will be emulated by others, especially those countries which face similar economic difficulties as Libya and Nigeria.

1.7 The Structure of the Thesis

The rest of the thesis is organized as follows. Chapter 2 presents the literature review pertaining to modelling and forecasting oil prices and examines the relationships among oil price and the main macroeconomic indicators such as GDP, exchange rate and inflation. The literature review is divided into three main sections, an overview of time series analysis and empirical literature on modeling and forecasting crude oil prices, the literature review and the empirical studies on the investigation of the dynamic relationships between prices of oil and some macroeconomic variables in short-run and long-run. The final part summarises existing gaps in the literature and highlights the expected contribution of this study to bridging some of these gaps.

Chapter 3 discusses the methodology of univariate time series analysis with a number of statistical techniques that are applied throughout the thesis for the oil prices data, including the presentation of some stylized facts on returns, augmented Dickey-Fuller and Phillip

Perron unit root tests, numerous univariate time series such as the autoregressive (AR) model, the moving average (MA) model, the autoregressive moving average (ARMA) model, the autoregressive conditional heteroscedastic (ARCH) model and the generalized autoregressive conditional heteroscedastic (GARCH) model. Furthermore, this chapter explains how to select the best model in-sample and in the forecasting stage.

Chapter 4 presents in details the empirical findings obtained by analyzing and modelling of oil price returns for Libyan, Nigerian and OPEC markets using monthly prices covering the period from January 1997 to April, 2018. This chapter displays the descriptive statistics of oil prices, the outcomes of the augmented Dickey-Fuller, and Phillip Peron tests and unit root tests with breakpoint. In addition, the chapter deals with modelling the conditional mean and conditional variance of returns data and the evaluation of out-of-sample forecasting accuracies for used models. The main objectives this chapter seeks to address are objectives 1 and 2.

Chapter 5 presents the methodology of multivariate time series analysis and several statistical techniques. This chapter explains in details the vector autoregressive (VAR) model and its advantages and disadvantages, the concept of cointegration and the vector error correction (VECM) model. Furthermore, this chapter provides a detailed explanation of three types of structural analysis under the VAR model and the VEC model in case the variables are cointegrated to analyse particular aspects of relationships between variables of interest. The three major types of structural analysis are called Granger causality tests, impulse response functions, and forecast error variance decompositions.

Chapter 6 presents the results obtained by applying multivariate time series analysis methodology in order to explore the dynamic relationships among domestic oil prices and selected macroeconomic indicators in Libya and Nigeria. Moreover, this chapter deals with the results of unit root tests for each variable separately and determine the best lag length in the VAR model. In addition, it presents the results of Johansen's cointegration test to examine and identify the long-term relationships, the results of causality relationship and structural analysis. The main objectives this chapter seeks to address are objectives 3, 4 and 5.

Chapter 7 discusses the findings of the study which have been obtained by using various statistical tests indicated in the chapters of methodology, in order to accomplish the study objectives and for answering the study questions.

Finally, chapter 8 concludes and summarises the results obtained from the study, by highlighting the main results by research objectives, the policy recommendations and suggestions for future work, hoping that interested people in this area will benefit from the implications of the results of this research.

1.8 Summary

In this chapter, the key aims, objectives, questions, and expected contributions to knowledge have been outlined. It was noted that this is the first time a comprehensive investigation of this nature is conducted across remits which link detailed time series modelling of oil price dynamics in Libya and Nigeria to the key macroeconomic variables, with a focus on theoretical and practical relevance of the results to future studies and Libya’s and Nigeria’s economic management.

CHAPTER 2: Literature Review

2.0 Introduction

Due to the great importance of crude oil, its price and the effect on the global economy it is not surprising that considerable effort has been given to developing methods and techniques for modelling and forecasting the prices of oil, their fluctuations levels and investigating the dynamic relationships between oil prices and some macroeconomic indicators. Therefore, this chapter contains of three main sections: the first section focuses on techniques that are found in the literature in modelling the prices of crude oil and view previous studies that concerned with modeling and forecasting crude oil prices which can be adapted to the Libyan, Nigeria and OPEC cases. The second section considers literature and empirical studies that investigate the dynamic relationships among oil prices and some macroeconomic indicators in the short-run and long-run based on time series modelling techniques. The final section summarises existing gaps in the literature and highlights the expected contribution of this study to bridging some of these gaps.

2.1 Literature Review on Oil Prices Analysis, Modeling and Forecasting Methods

There are numerous methods and techniques that are well established that enable the modelling and forecasting of crude oil prices. (Frey et al., 2009) conducted a survey of methods used; in general, they found three main categories (1) time series models, (2) structural economic models, and (3) artificial intelligence models. This was further found by (Behmiri and Manso, 2013; Drachal, 2016). The first of these will form the main focus of the discussion, time series methods are well developed and understood compared to the other two methods.

Structural economic modeling approach (or fundamental models) uses a response variable (price of oil for example) as a function of a selection of explanatory variable or fundamental variables and implemented through the use of a linear regression to and make predictions and usually based on econometric theory (Frey et al., 2009). Pinduck (1999) states that the structural economic models are more appropriate in providing fairly reasonable explanations of the underlying causes of oil price movements in supply and demand, but they were not always useful in oil price forecasts because it remains difficult to forecast the explanatory variables in these models. On the other hand, Behmiri and Pires Manso (2013) argue that due to the difficulties and complexities of structural models there is a small number of studies that performed structural analyzes in order to model and forecast oil prices.

Similarly artificial intelligence methods whilst being an exciting new development are still in their infancy. There also tend to be "black box" methods giving no physical interpretation of the parameters in the artificial intelligence functions. This is the disadvantage of artificial intelligence (AI) models compared to other models. Recently, nonlinear models including Artificial Neural Networks (ANNs) and Support Vector Machines (SVM) models have attracted remarkable attention in the field of prediction of the time series (Adhikari and Agrawal, 2013). According to Zhang (2003), one of the most significant features when applied to time series prediction problems is the ability of these AI methods in nonlinear modeling without any assumption of statistical distribution of the values of the time series. These techniques were also applied to the crude oil modelling and forecasting, for example, (Kaboudan, 2001; Mirmirani and Li, 2004; Wang et al., 2005; Moshiri and Foroutan, 2006; Yu et al., 2007; Yu et al., 2008; Tehrani and Khodayar, 2011) applied ANNs models and SVM are explored by (Xie et al., 2006; Ahmed and Shabri, 2014). However, Behmiri and Manso (2013) argue that although the number of modeling techniques and methods has increased in the literature, there is still no general consensus on which techniques are more reliable and effective. Therefore, in this thesis, a time series modelling approach is utilized to undertake crude oil prices modelling for the two countries Libya and Nigeria.

2.1.1 Linear Time Series Models

A time series model is a mathematical function that links the value of the time series with its previous values, their errors term and time, to describe the dynamic structure of a time series. Therefore, this model is referred to as a stochastic process (Bowerman, 1993). Moreover, time series models use historical data on the phenomena (oil prices for example) to investigate the statistical characteristics of the data such as autocorrelation, non-stationarity and seasonality. Time series models mainly assume that the time series is a stationary process. More importantly, the error terms have a Gaussian distribution or white noise (Brockwell, 2002). These models can be divided into two key categories, univariate and multivariate. Univariate models refer to a time series model that consists with single time series data, such as prices of crude oil. While in the multivariate models the dependent variable is also explained by other independent variables. Time series models may be categorized as either linear or nonlinear models depending on whether the current value of the time series data is a linear or nonlinear function in its past observations (Tsay, 2005). According to Behmiri and Manso (2013), time series models are often used when, a) the data show a systematic behaviour such as autocorrelation, b) the number of possible independent variables is large and their interactions suggest a complex structural model, and c) predicting the dependent variable requires predicting independent variables that may be more effective than predicting the dependent variable itself. Also, they said that all these situations seem to apply in the case of oil prices.

Classic linear time series models are proposed by Box and Jenkins (1976), including Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA). These models assume that future values of a variable have a linear relationship with current and past values as well as with the error terms. Although AR, MA and ARMA models can be used under the stationary assumption (Box and Jenkins, 1976), the data exhibit non-stationary behaviour in many economic practical applications (Banerjee et al., 1993). However, the ARIMA model is considered the most popular model in this set and applied widely in forecasting application over the previous three decades (Zhang, 2003) mainly because they can be applied to non-stationary series. Moreover, Chatfield (1996) recommends that a good ARIMA model requires that the size of series be moderately long and not less than 50 observations. ARIMA and ARMA models are applied in various studies for modelling and forecasting the prices of crude oil, for instance; (Kumar, 1991; Lalonde et al., 2003; Chinn et al., 2005; Moshiri and Foroutan, 2006; Xie et al., 2006; Hamilton, 2009; Yazizet et al., 2011; Xiong et al., 2013; Cao et al., 2015; Zou et al., 2015; Tularam and Saeed, 2016).

The empirical analysis of Kumar (1991) and Moshiri and Foroutan (2006) are based on the crude oil of New York Mercantile Exchange's (NYMEX) futures contracts. Kumar (1991) applied the ARMA(1,2) model as the best model for the period from June 1985 to October 1990. On the other hand, in the study of Moshiri and Foroutan, (2006), over twenty years started from April 4, 1983 to January 13, 2003 the ARMA(1,3) model is selected as the best linear model. Lalonde et al. (2003), Chinn et al. (2005), Xie et al. (2006), Hamilton (2009), Yaziz et al. (2011), Xiong et al. (2013), Cao et al. (2015), Zou et al. (2015) and Tularam and Saeed (2016) analyse the crude oil prices behaviour of the West Texas Intermediate (WTI). Lalonde et al. (2003) use the AR(1) model and the sample period is from 1974Q2 to 2001Q4. Chinn et al. (2005) investigate the link among spot and futures prices for different energy commodities including WTI for oil price data. However, the outcomes show that the crude oil price data is stationary while the other energy commodities prices require differencing to be stationary. The ARMA(1,1) model is estimated for oil price data and ARIMA (1,1,1) is applied for other prices.

Xie et al. (2006) use the ARIMA(1,1,0) model for forecasting monthly WTI crude oil prices covering the period from January 1970 to December 2003 containing 408 observations. The experimental result of this study shows that the linear ARIMA model can capture the linear structural of the time series but are insufficient to describe the dynamics of nonlinearity. In contrast, the empirical results of the study by Hamilton (2009) investigate the statistical characteristics of oil piece behaviour. The results show that correlations in the historical oil data can be modelled as a random walk process without drift.

Yaziz et al. (2011) apply the ARIMA(1,2,1) model for forecasting daily crude oil prices of WTI over the period from January,2 1986 to September, 30 2009. Xiong et al. (2013) employ the random walk model for the weekly spot price from the WTI crude oil. Cao et al. (2015) use the ARIMA(1,1,1) process to forecast the price of WTI crude oil., Zou et al. (2015) apply the ARMA model to forecast return movements of the daily prices in both WTI and Brent crude oil markets, covering the interval from 2 January 2002 to 3 August 2015. However, Tularam and Saeed (2016) compare the performance accuracy of three types of univariate models including the exponential smoothing (ES), Holt-Winters (HW) and ARIMA models for WTI crude oil prices from October 2015 and March 2016. They find that ARIMA (2,1,2) is the best-fitting model in oil market.

In general, the results of these studies indicated that ARIMA models are sufficient and can give reasonable and acceptable forecast results for the prices of oil in the short term (Yaziz et al., 2011; Behmiri and Manso, 2013; Xiong et al., 2013; Cao et al., 2015). Furthermore, ARIMA models are usually inadequate to capture the nonlinear behavior of the time series (Brockwell, 2002; Xie et al., 2006). According to Behmiri and Manso (2013), oil price and its fluctuations exhibit significant nonlinearity, which indicates that a small shock to the economy could has large and unpredictable impacts for oil price and its fluctuations Moreover, the ARIMA model cannot capture the heteroscedastic outcomes (changing variance or time-varying volatility), of a time series analysis, characteristically examined when there exists volatility in the data series, or in the shape of high kurtosis (Yaziz et al., 2011; Ahmed and Shabri, 2014).

Perrelli (2001) mentioned that the nonlinear time series models are adequate for forecasting conditional variance (volatility) of the time series as proxy for risk. However, these linear time series models that operateg under the assumption of constant variance (homoscedastic models) and that have been used for modelling the conditional mean of a time series but they have some weaknesses because they unable to capture and explain a number of important characteristics common to financial time series data, such as the leptokurtosis, heteroscedastic, volatility clustering and leverage effects (all these features will be explained in detail in chapter 3). Therefore, the models which include these features provide more accurate modelling (Meade and Cooper, 2007).

2.1.2 Nonlinear Time Series Models

Numerous nonlinear time series models have been suggested in literature and these nonlinear models are used in modeling and forecasting volatility oil price changes including, the autoregressive conditional heteroscedastic (ARCH) model of Engle (1982), the generalized ARCH (GARCH) model of Bollerslev (1986) which explain a conditional variance that changes over time. This type of models have been widely used for modelling volatility in time series data and particularly in modelling oil price volatility (Ramirez et al., 2012).The ARCH and GARCH models are constructed to allow for past volatility in the current volatility equation. Further, these models can be extended and modified in a variety of ways yielding a vast array of further models for which ARCH and GARCH are the parents. These modified models include asymmetric GARCH family models such as Exponential GARCH (EGARCH) proposed by Nelson (1991), Threshold GARCH (TGARCH) proposed by Zakoian (1994) and Power GARCH (PGARCH) proposed by Ding et al. (1993).

In order to model and forecast the conditional variance of crude oil price, the GARCH model is widely used due to its good performance in capturing the time-varying feature of the data (Mohammadi and Su, 2010; Wang and Wu, 2012; Zhang et al., 2019). In addition, asymmetric GARCH models such as EGARCH and GJR-GARCH have been shown to have good out-of-sample performance when forecasting oil price volatility (Mohammadi and Su 2010; Hou and Suardi 2012). However, various studies focused on modelling and forecasting oil price including a comparison of model performance and forecasting accuracy between ARIMA and GARCH models, for example (Moshiri and Foroutan, 2006; Yazizet et al., 2011; Ahmed and Shabri, 2014; Yao and Zhang, 2017). Moshiri and Foroutan (2006) compare the forecasting performance of out-of-sample for daily futures crude oil prices of NYMEX markets over twenty years started from April 4, 1983 to January 13, 2003. Based on three forecasting error measures include the Mean Square Error (MSE), the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), the results suggest that the AR(1)-GARCH(2,1) model outperforms the ARMA(1,3) model.

Yazizet et al. (2011), Ahmed and Shabri (2014) and Yao and Zhang (2017) use daily crude oil prices of WTI for evaluatoin the performance of ARIMA and GARCH models. Yazizet et al. (2011) evaluate the forecasting performance for GARCH(1,1) and ARIMA(1,2,1) models for out-of-sample period. The comparison in forecasting stage based on error measurements nominated GARCH (1,1) as the best model with small forecast error value and the GARCH(1, 1) is superior to model the prices of oil due to its ability to capture the conditional variance by modeling the volatility. In contrast, the study of Ahmed and Shabri (2014) indicate that the ARIMA model outperforms GARCH model based on two measures of forecast accuracy, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). While the results of the study for Yao and Zhang (2017) gave mixed results. The values of RMSE suggest an AR(1)-GARCH(1,1) model as the best model compared to the ARIMA(1,1,0) model whereas the MAE values propose the ARIMA(1,1,0) model as the best one.

A wide range of studies has focused on using GARCH model and their modifications (such as EGARCH, TGARCH etc.) for evaluation the comparative performances of models for dealing with modelling oil prices volatility, for example, (Pindyck, 1999; Adrangi et al., 2001; Sadorsky, 2006; Narayan and Narayan, 2007; Cheong, 2009; Marzo and Zagaglia, 2010; Kang et al., 2009; Mohammadi and Su, 2010; Wei et al., 2010; Kang and Yoon, 2013; Salisu and Fasanya, 2012; Salisu, 2014; Lux et al., 2016; Herrera et al., 2018). Moreover, the empirical results on the performance of these models in modeling crude oil prices volatility were mixed.

Pindyck (1999) studies the stochastic behaviour of crude oil, coal and natural gas prices covering the period from 1887 to 1996. The study shows that the volatility of oil price was more than those of the other energy commodities. In addition, the large changes in the prices of oil lead to increased uncertainty about the future prices which leads to delays in business investments. According to Sadorsky (2006), there are a wide range of studies emerge to model and forecast the volatility in stock markets as well as foreign exchange markets. In contrast, although the oil has a great importance there is relatively little work for modeling and prediction of petroleum price volatility.

Adrangi et al. (2001) and Sadorsky (2006) employ daily prices of WTI on crude oil for future markets with GARCH models and their variants. Adrangi et al. (2001) use GARCH(1,1), EGARCH(1,1) and AGARCH(1,1) for daily futures prices including crude oil, unleaded gasoline and heating oil. This study finds that the GARCH(1,1) models perform well for each contract, and the EGARCH(1,1) model seemed to satisfactorily fit the crude oil and unleaded gasoline prices series. In contrast, Sadorsky (2006) estimates and compares various univariate and multivariate time series models including historical mean moving average, exponential smoothing, random walk, linear regression model, GARCH(1,1), TGARCH(1,1), vector autoregression (VAR) and bivariate GARCH (BIGARCH) models to forecast the volatility of energy commodity prices. Sadorsky analyzes data for daily future crude oil prices, heating oil, unleaded gasoline and natural gas. The comparison results of out-of-sample forecasting suggest that the GARCH(1,1) model is the best for the volatility of crude oil and unleaded gasoline, while the best model for other prices was the TGARCH(1,1) model.

The study of Narayan and Narayan (2007) appears to be the first study effort for modelling the conditional variance of daily crude oil prices using different subsamples. They use EGARCH model with normal distribution of errors. The study finds that across full sample and different sub-samples there is an evidence of asymmetry effects. Additionally, oil price behaviour tends to vary over short periods of time.

Cheong (2009) and Marzo and Zagaglia (2010) compare various volatility models based on different error distributions for oil prices data. Cheong (2009) focus on two crude oil markets, WTI and Brent to investigate the behaviour of oil price volatility using the GARCH, APARCH, Fractionally Integrated GARCH (FIGARCH) and FIAPARCH models with normal and student-*t* of errors. The results of model selection indicate that the FIAPARCH-*t* and the GARCH-student-*t* are most appropriate models for Brent. For model selection of WTI there is not model is superior to others, but in general the ARCH-student-*t* models have small AIC and SIC values. Forecasting evaluation of out sample suggests that the FIGARCH-type models are the best to fit both the WTI and Brent data. Marzo and Zagaglia (2010) evaluate the forecasting performance of GARCH, EGARCH and GJR model based on normal, student-*t* and the generalized error distribution (GED) for daily futures prices of crude oil. The results of out-of-sample forecasting suggest that the GARCH-GED provides the best forecasts for short horizons.

Kang et al. (2009) focus on forecasting the conditional variance of three crude oil returns WTI, Brent and Dubai using daily of spot price coveringr the interval from January 1992 to December 2006. They use various volatility models including the GARCH(1,1), IGARCH(1,1), FIGARCH(1,1) and CGARCH(1,1) models. Data of the last year are used to evaluate out-of-sample forecasting, the results show that the CGARCH model for crude oil of WTI and FIGARCH model for the Brent and Dubai crude oil are best than GARCH and IGARCH models. They conclude that the FIGARCH and CGARCH models give the better performance in out-of-sample forecasts.

Mohammadi and Su (2010) examine the forecasting ability of four ARIMA-GARCH models include GARCH, APARCH, EGARCH and FIGARCH covering the period from January 1997 to October 2009 by employing weekly spot prices of oil for eleven international markets. This study assumes that the innovations distribution followed a skewed student-t distribution. The finding of out-of-sample forecasting performance are slightly mixed, however in most cases, the EGARCH model appears to outperform the FIGARCH model, this evidence is contrast to Kang et al. (2009). This study broadly suggests that the APARCH forecasts perform better than those of GARCH, FIGARCH and EGARCH. Thus, MA(1)-APARCH and the MA(1)-EGARCH models are superior than others.

Wei et al. (2010) and Kang and Yoon (2013) expand the study of Kang et al. (2009) respectively. Wei et al. (2010) apply a number of GARCH-class models to examine the properties of conditional variance for two oil markets, WTI and Brent covering the span from January 1992 to December 2009. They employ daily price data with GARCH, GJR, IGARCH, FIGARCH, EGARCH, APARCH, HYGARCH and FIAPARCH. In estimation results the HYGARCH, FIAPARCH and FIGARCH fit the returns better than others model for Brent market. Overall, the results show that there is no model that can outperform the other models of either the WTI or the Brent market. In forecasting, the last three years are employed to evaluate the out-of-sample forecasting, thus, results suggest that the nonlinear GARCH-class models, APARCH, EGARCH, FIGARCH, GJR, HYGARCH and FIAPARCH are superior to capture asymmetric volatility and/or long-memory property, and they display better forecasting accuracy than the standard GARCH model over longer time horizons. These results are different from the findings of Kang et al. (2009) which found the FIGARCH model to be the superior to the GARCH and IGARCH models.

Kang and Yoon (2013) investigate the dynamics of the same financial assets studied by Adrangi et al. (2001) and Sadorsky (2006). They employ daily data of oil for WTI market, heating oil and unleaded gasoline with ARIMA-GARCH, ARFIMA-IGARCH, ARFIMA-FIGARCH and ARFIMA-GARCH models. While the ARFIMA–FIGARCH model better captures the feature of long-memory of returns and conditional variance, the out-of-sample forecasts show that none of the models is outperforming the other for all three types of petroleum futures contracts.

Salisu and Fasanya (2012) and Salisu (2014) analyes the price of oil through three sub samples which are before, during and after the global financial crisis using AR(1)-GARCH (1,1), AR(1)-GARCH-M(1,1), AR(1)-TGARCH (1,1) and AR(1)-EGARCH (1,1) with skewed student-*t* distribution. Salisu and Fasanya (2012) use daily oil price returns for WTI and compare the performance of the four GARCH models. Findings of the study show that the price of oil was the most volatile during the global crisis compared to other periods. This study chose the AR(1)-EGARC(1,1) model for the full sample, during and after the global crisis while the AR(1)- GARC(1,1) is the best for the subsample before the global financial crisis. In general these results find that the models EGARCH(1,1) and TGARCH(1,1) are better than the symmetric models. Salisu (2014) expands the study of Salisu and Fasanya (2012) to add the Brent market to WTI. The study suggests the AR(1)-TGARCH(1,1) model for the full sample, before and after the global financial crisis while the AR(1)-EARCH(1,1) is the best for the subsample during the global financial crisis for Brent market.

Lux et al. (2016) extend the study of Wei et al. (2010) by applying the GARCH-class models and the Markov switching multifractal (MSM) models for modelling and forecasting oil price volatility using daily prices of WTI market covering two different sample periods. The evaluation results of the forecasting performance of MSM models, AR(1) process with GARCH, EGARCH, IGARCH, GJR-GARCH, APARCH, Markov switching GARCH (MS-GARCH), FIGARCH, HYGARCH , FIAPARCH and RiskMetrics model indicate that none of volatility models can outperform all other models in the short and long horizons across several forecasting error functions. Also the forecasting performance of the volatility models varies from one sample period to another. However, the nonlinear or/and long memory volatility models are more suitable for forecasting oil price volatility. These findings are confirmed the results of Wei et al. (2010). Moreover, for the some standard forecasting error functions such as MSE or MAE, the two multifractal models mostly cannot be outperformed.

Herrera et al. (2018) investigate the predictive abilities of the GARCH, asymmetric GARCH, FIGARCH, RiskMetrics and MS-GARCH models with the normal, Student-*t*, and GED distributions daily spot price for the WTI crude oil. The findings of this study can be summarised as follows : (i) the models with a Student-*t* distribution is generally are favored in the parametric models over those with a normal due to the extremely high kurtosis in oil return; (ii) GARCH(1,1) and RiskMetrics models have good forecasting accuracies for short forecasts horizons, while the EGARCH(1,1) model produces good forecasts at medium horizons; and (iii) the MS-GARCH model at long horizons shows a superior predictive ability.

It is clear from the previous empirical studies review that the use of GARCH family models to capture crude oil price fluctuations has remained prominent in the literature, but there is still lack of consensus in selection of the most appropriate model for modeling these fluctuations.

2.1.3 Type of Oil Price Data and Oil Price Benchmark

According to Cheong (2009), the two key benchmarks in the international markets of crude oil are the West Texas Intermediate (WTI) in North America (USA) and Brent (North Sea) in Europe benchmarks due to their low sulfur and geographical location. The majority of the studies use WTI crude oil prices, for example, (Adrangi et al., 2001; Sadorsky, 2006; Xie et al., 2006; Narayan and Narayan, 2007; Yazizet et al, 2011; Ahmed and Shabri, 2014; Yao and Zhang, 2017). Cheong (2009), Wei et al. (2010) and Salisu (2014) use WTI and Brent crude oil prices. Kang et al. (2009) use almost all types of data – Brent, Dubai- and WTI prices. In the literature, several studies for modelling and forecasting crude oil prices have focused on crude oil futures price volatility (e.g., Adrangi et al., 2001; Sadorsky, 2006; Marzo and Zagaglia, 2010; Kang and Yoon, 2013), while some studies focused on crude oil spot price (e.g., Xie et al., 2006; Narayan and Narayan, 2007; Cheong, 2009; Wei et al., 2010; Salisu, 2014; Lux et al., 2016; Herrera et al., 2018).

The most of studies have used daily data of crude oil prices, in particular, for volatility modelling which are more appropriate for traditional volatility modelling of prices, for example, (Adrangi et al., 2001; Sadorsky, 2006; Narayan and Narayan, 2007; Cheong, 2009; Kang et al., 2009; Marzo and Zagaglia, 2010; Wei et al., 2010; Salisu and Fasanya, 2012; Salisu, 2014; Lux et al., 2016; Herrera et al., 2018). Mohammadi and Su (2010) and Xiong et al. (2013) use weekly prices. Chinn et al. (2005), Wang et al. (2005) and Xie et al. (2006) use monthly prices for their studies. Moreover, the range of the data may have effects on the statistical features of the variable. As a result, the selection of data frequency can lead to significant impacts in the performance of the forecasting model. However, daily, monthly, quarterly or yearly data are sometimes used depending on the specific research objectives. For example, in terms of the granularity of the data, daily data are primarily used for volatility modelling because low frequencies tend to smooth volatility (Frey et al., 2009).

2.2 Empirical Evidence on Studying the Dynamic Relationship among Oil Price Fluctuations and Macroeconomy

Investigating the linkage among crude oil prices and several macroeconomic indicators has started since 1970s. A large number of literatures have grown to examine the relationships among influence of oil price and macroeconomy. Nevertheless, most of the attention in these studies focused on developed oil-importing countries, especially the United States and some European countries. These studies use various methods of analysis and have yielded different outcomes, sometimes sharply different, sometimes modestly.

The early studies on shocks of oil price focused on the US economy. They have assumed a linear relationship among oil shocks and GDP growth (Hamilton, 1983; Burbidge and Harrison, 1984; Mork, 1989; Hooker, 1996; Sadorsky, 1999). The first study to investigate the link among oil shocks and the macroeconomy was by Hamilton (1983). This study provides some evidence for a strong negative relationship among change in oil prices and real gross national product (GNP) growth in U.S., by employing annual data through the span from 1948 to 1980. The empirical work based on the vector autoregressive (VAR) model introduced by Sims (1980) with six variables, include real GNP; the implicit deflator for non-farm business income; unemployment; hourly compensation per worker; the money supply and import prices. The results indicate that the oil prices are negatively related to US output growth between 1948 and 1980. In addition, changes in the prices of oil Granger-caused changes in GNP and unemployment in the US economy. Based on Hamilton’s work, Burbidge and Harrison (1984) examine the impacts of oil price changes on a number of macroeconomic indicators for five industrial countries, which are the U.S., Japan, Germany, the United Kingdom, and Canada, using the VAR model and impulse response function with seven variables and employing monthly data over the period from 1961 to 1982. The results indicated that the shocks of oil price have a major negative influence on industrial production. Mork (1989) extends the results which are presented by Hamilton (1983). The empirical work confirms Hamilton's (1983) outcomes by finding that a strong negative relationship with higher oil prices and the growth of GNP for the U.S. Hooker (1996) argue that it has been found strong evidence that the prices of oil no longer Granger cause many macroeconomic variables in U.S during the period after 1973. This study explores the link between oil price, unemployment and GDP growth using VAR model over the period from 1973 to 1994. The findings show that there is substantial evidence that prices of crude oil do not Granger-cause a range of U.S. macroeconomic indicators.

Sadorsky (1999) use a VAR framework on oil prices, interest rates, stock prices, and US industrial production as a measure of output using monthly data covering the interval 1947-1996 to study the influence of oil price shocks and economic activity. The outcomes show that variations in oil prices influence economic activity but, variations in economic activity have little influence on oil prices. This is evidence of unidirectional in causality also; the volatility of oil price shocks has asymmetric effects on the economy. In particular, the shocks of oil price have a positive impact on interest rates.

However, the long-run relationship among the prices of oil and some macroeconomic indicators have investigated in several studies using the cointegration technique such as the Johansen-Juselius (JJ) cointegration and the Vector Error Correction (VECM) Model, for example (Amano and Van Norden, 1998; Sadorsky, 2000; Chang and Wong, 2003; Ito, 2008; Bekhet and Yusop, 2009; Ran et al., 2010; Masih et al., 2011; Bouchaour and Zeaud, 2012; Altay et al., 2013; Bass, 2019).

Amano and Van Norden (1998) study the relationships among the real domestic prices of oil and exchange rates for Japan, Germany and the United States. Applying Johansen-Juselius cointegration test, they found an evidence of a long-run relationship between exchange rates and prices of oil which indicate that the oil prices capture the permanent innovations in the real exchange rate of all the three countries. Using cointegration tests, VECM and causality analysis, Sadorsky (2000) investigates the links between futures prices for heating oil, crude oil, exchange rate and unleaded gasoline. The results show a long-run relationship among these four variables, and results from the VECM indicate that movements in exchange rates precede changes in the futures prices of crude oil in the short-run. Moreover, the findings of

Granger causal relationships for both the long- and short-run suggest exchange rates transmit shocks to futures prices of energy.

Recently, the short- run and long-run relationships among prices of crude oil and several macroeconomic indicators have also been explored in a number of various economies in the world including oil-exporting developing countries. Papapetrou (2001) investigates the relationships between oil prices, real economic activity, interest rates, real stock prices and employment for Greece economy using VAR model. The data are monthly and covering the period from 1989 to 1999. The findings show that the changes in prices of oil affect employment and real economic activity. In addition, the prices of oil are significant to interpret the movements of stock price. Oil price shocks have a positive influence on interest rates. This outcome can be expected as increases in the prices of oil create inflationary impacts in the economy which consequently bring an upward pressure on interest rates.

Chang and Wong (2003) examine the long run relationships among oil price changes to the macroeconomy of Singapore using VECM and Johansen cointegration methodology for the quarterly sample period 1978 Q1 and 2000 Q3. Findings from impulse response functions and variance decomposition show that the shock of oil price provides a negative impact on macroeconomic activities in Singapore. Ito (2008) and Bass (2019) investigate the link among oil prices and selected macroeconmy indicators in Russia using a VEC framework. Ito (2008) use Ural oil price, real GDP, interest rate and inflation in the VEC system over the period from 1997:Q1 to 2007:Q4. The results based on generalized impulse response functions suggest that the result shows that an increase in prices of oil contributes to real GDP growth, whereas that to inflation. Bass (2019) use Brent oil price, exchange rate and consumption inflation in VEC framework for the period 2010-2017. The Johansen test is used based on VECM and the test indicates that show the evidence that Brent oil prices, exchange rate and CPI in Russia are cointegrated and they have similar trends of movement in the long term. The results in the short run exhibit that there is an important relationship among changes in Brent oil prices, CPI and exchange rate, thus, a rise in oil prices leads to a rise in inflation rate.

Bekhet and Yusop (2009) and Mantai and Alom (2016) investigate the impacts of oil price on the economic activity of Malaysia using Johansen and Juselius test and VEC model in order to determine the cointegrating relationships among the variables. Bekhet and Yusop (2009) use annual data from 1980 to 2005 of oil prices, energy consumption and macroeconomic performance for Malaysia. Thus, the result of cointegration implies that all variables are cointegrated and follow a common long run path. This study shows that the changes in prices of oil do not have any important influence to Malaysia's real GDP either in the short run or long run. In contrast, Mantai and Alom (2016) use annual data from 1981 to 2013 of crude oil prices, inflation (CPI) and exchange rate (EXR) on the economic activity (GDP) of Malaysia. The results of this study indicate the long-run relationship among the indicators. Alternatively, the results show a positive impact of crude oil price on the GDP in the short run and the tests do not identify any major effects of exchange rate and inflation on the GDP. Nonetheless, the causality tests have shown unidirectional causality from crude oil price to GDP and not from exchange rate and inflation to GDP.

Farzanegan and Markwardt (2009) study the impacts of oil price shocks on the Iranian economy using VAR model with quarterly data covering the period from 1975 to 2006. In this study six macroeconomic variables: real exchange rate, real industrial GDP, real imports, inflation and real public consumption expenditures. The results indicate that the shocks of oil prices have a significant effect on inflation and real effective exchange rate. The relationship between changes of oil prices and industrial output growth is a strong positive relationship. Lorde et al. (2009) use VAR model with annual data from 1966 to 2005 to analyse the macroeconomic effects of oil prices in Trinidad and Tobago. The variables in this study are oil price, government revenue, GDP, gross investment, net exports, government consumption and the price level. The results show that the price of oil is a ket determinant of economic activity of the Trinidad and Tobago. The Granger causality test pointed to a causal relationship from oil price to output.

Gausden (2010) examines the relationship among of oil prices and UK macroeconomic performance using VAR approach. The study uses quarterly data covering a period which from 1972 to 2005 of the real effective exchange rate, real GDP, the real oil price, the real consumer wage, the quarterly rate of consumer price inflation and the rate of interest. The results show that changes in oil prices have no direct effect upon macroeconomic activity, but shocks to the real price of oil exert a negative impact on the growth of real GDP. Ran et al. (2010) use a vector error correction model (VECM) to examine the relationship among oil price shocks and the macroeconomy in Hong Kong. The sample data are quarterly and cover the range of observations 1984 to 2004. The selected macroeconomic indicators are real

GDP, unemployment and interest rate. The Granger causality tests applied and the findings indicate that the price of oil does not Granger-cause the main macroeconomic variables.

Masih et al. (2011) study the impacts of the oil price fluctuations and, interest rate, economic activity and real stock returns using the VAR and VECM analysing monthly data for the period of May 1988–January 2005 in South Korea This study uses cointegration test in order to examine the long run relationships among oil price movement and economic activity of South Korea and also it uses impulse response functions and variance decomposition techniques. The results indicated that, there is a long run relationship among variables. Additionally, the Asian Financial Crisis of 1997 did not affect the stability of the data. Alternatively, the changes of oil price have a major influence on stock market. Also, there are two negative effect s because of oil price changes on the profitability of the firm which separates direct and indirect effect. Direct negative impact is because of increase the production cost of the firms and there is a negative indirect impact because investors made a forecast about the decrease in profit margins of firms and made decisions that have impacts on the stock market indexes.

Bouchaour and Zeaud (2012) examine the effects of oil price changes on Algerian Macroeconomics covering the annual data from 1980 to 2011. A VECM, variance decomposition and impulse response function with seven variables including real oil price, real GDP, money supply, unemployment, real effective exchange rate and inflation rate are employed. The results suggest that the prices of oil have no significant influence on the most variables during the short term, but they have a positive impact on inflation and negative influence on real effective exchange rate.

Altay et al. (2013) study the dynamic relationships among oil prices, employment and real output growth in Turkey using quarterly data covering the period 2000:1-2012:4. The empirical analysis of this study based on VECM methodology. Findings of the cointegration tests displayed a long-term relationship between the indicators. Moreover, the short-run causality results show an evidence of bi-directional causality relationship among oil prices and output, where unidirectional causality among oil prices and output to employment is established. On the other hand, the long-run causality test shows that the prices of oil and real output do not cause employment, real output and employment do not cause prices of crude oil, and the prices of oil and employment cause output.

Asteriou and Villamizar (2013) examine the causal relationship among the prices of oil and macroeconomy for a large number of both exporting and oil importing countries. The sample data were collected for 50 countries and covers the period from 1967 to 2011. They employed vector autoregressive (VAR) model for such variables as unemployment, gross domestic product (GDP), interest rates and consumer price index. Based on VAR model the pairwise Granger causality tests are estimated in order to understand the relationship among oil prices and the macroeconomic indicators for each country. The results did not find causality from prices of oil price to consumer price index for any of the OPEC members or other oil exporting country. The link between prices of oil and GDP through the pairwise test suggests that only three countries showed causality relationship running from oil price to GDP. Those were the cases of Ecuador, Iran, and Korea. Due to the small number of countries where causality was found, the study can conclude that prices of crude oil do not have an important influence on the level of growth over the short run regardless whether the country is oil importing or oil exporting.

Sibanda et al. (2015) use Johansen cointegration test and VECM framework to study the impacts of crude oil prices and exchange rates on inflation in South Africa. In this study the date are monthly and covering the period July 2002 to March 2013. The result of cointegration test implies that there is a long run relationship among the variables. The study also perform the impulse response function and variance decomposition, thus, the findings of this study suggest that both prices of crude oil s and the exchange rates have a positive impact on inflation in South Africa.

Anjanaraju and Marathe (2017) investigate the influence of crude oil prices fluctuations in China, India and USA on the inflation. They use cointegration test to study the long-run relationship among two or more variables, vector autoregression (VAR), vector error correction model (VECM) and Granger causality techniques to data form 1996–2015. The result of cointegration test shows that there is no long-run integration between USA, China, India inflation and crude oil, thus, the study then use VAR model to study the short term relationship among the variables. The outcomes suggest that the crude oil prices are significant in India and USA but it is not affecting the China’s economy. The results of Granger causality tests between USA, India, China crude oil prices and inflation show that there is unidirectional causality in India. China shows there is a positive impact among the crude oil prices and inflation and USA has no causality but has a positive effect among crude oil prices and inflation.

Alzyoud et al. (2018) analyse the impacts of crude oil prices on exchange rate and stock market returns in Canada using monthly data covering the span from 1986 to 2015. The study measures the long run relationships among the variables by employing Johansen cointegration method and VECM methodology. The outcomes show that there is no cointegration among prices of crude oil prices, stock market returns and exchange rate. Regression analysis shows that prices of crude oil, exchange rate have a positive and important impact on the Canadian stock market returns.

2.2.1 Empirical Evidence on Oil Price to the Libyan Economy

In a related study of the Libyan economy, there is not much literature on the study of the impact of fluctuations in prices of oil on the macroeconomic variables of the Libyan economy, but there is a paper provided by Aimer (2016) which explores the impacts of oil price shocks on economic development in Libya. This study uses annual data covering the span from 1968 to 2016 for four Libyan indicators, including oil price and variables of four economic sectors named agriculture, construction, manufacturing and transportation sector. The VEC methodology is applied to investigate the short-run and long-run relationship among variables as well as Johansen cointegration tests, Granger causality methods and impulse response function. The findings of this study show that the fluctuations of oil price have small opposite effect on agriculture and increasing the prices of crude oil leads to increasing manufacturing industry variable. The cointegrating relationship among variables existed. Unidirectional causality is found between the prices of oil and the variables of the manufacturing sectors.

2.2.2 Empirical Evidence on Oil Price to the Nigerian Economy

In a related studies of the Nigerian economy, there have been some studies that have examined the relationships among changes in oil prices and macroeconomic variables, for instance, (Olomola and Adejumo, 2006; Aliyu, 2009; Thangod and Maxwell, 2013; Ogundipe et al., 2014; Okoli et al., 2018). Olomola and Adejumo (2006) use the VAR model to analyse the influence of oil price shocks on the real gross domestic output (real GDP), the money supply, the real exchange rate and inflation in Nigeria. This study uses quarterly data covering the period from 1970 to 2003. The cointegration tests are performed in this study following the approach of Johansen and Juselius (1990), thus the findings of these tests indicates that the cointegrating relationships exist among the variables. The result of the variance decomposition suggests that to oil price shocks do significantly influences the real exchange rate. On the other hand, the shocks of oil price do not significantly affect output and inflation rate in Nigeria.

Aliyu (2009) investigates the effects of oil price shocks and real exchange rate changes on real GDP in Nigeria using a VEC model. The study use quarterly data from 1986Q1 to 2007Q4 and applies Johansen cointegration technique and Granger pairwise causality test to study short-run and long-run relationships among variables. The outcomes of cointegration tests show the presence of a long run relationship among the three indicators in the Nigerian. Nevertheless, the empirical outcomes of causality tests display that there is a unidirectional relationship from prices of oil to real GDP and bidirectional causality from real exchange rate to real GDP. Moreover, findings suggest that oil price shocks and appreciation in the level of exchange rate exert positive effect on real GDP in Nigeria. Thangod and Maxwell (2013) study the relationships on the effect of oil prices on macroeconomic activity in Nigeria using annual data covering the interval from 1970 to 2009. The study uses data of domestic crude oil price, inflation rate, real effective exchange rate, real GDP, interest rate and government expenditure with lag-augmented VAR (LA-VAR) models and impulse response function. They apply the method of Johansen and Juselius (1990) to find out the number of cointegrating relationships among variables. The results show that all the variables included in the model have a long-run relationship. Moreover, investigating the causal relationship among oil price and macroeconomic variables based on the lag-augmented VAR (LA-VAR) model which is applicable to the Granger-causality test in the VAR model. Findings indicate that there is a unidirectional causality relationships exist between oil prices to both exchange rate and the interest rate. Nonetheless, an important relationship among prices of oil and real GDP was not found.

Ogundipe et al. (2014) explain the impact of the price of oil on exchange rate volatility for Nigeria. They use annual data over the period 1970 to 2011 using both the Johansen cointegration and vector error correction (VECM) model for investigating the long run relationship between the variables among the variables. The results show that the long-run changes in the price of oil cause more than proportionate changes in the volatility of exchange rates in Nigeria; which implies that exchange rate is susceptible to changes in the prices of oil in Nigeria. Additionally, there is a negative relationship among exchange rate and crude oil price.

Okoli et al. (2018) use the vector autoregressive (VAR) mode to examine the dynamic relationships between oil price and real GDP, inflation rate, nominal exchange rate, functional notation, interest rate, import and government expenditure using quarterly data from the period of 1980 to 2014. The analysis is based on the VAR methodology, pairwise Granger causality tests, the impulse response and the variance decomposition. The results of this study show that changes in oil prices have direct impact on real GDP, exchange rate, import, inflation, government expenditure and interest rate.

Overall, the empirical studies show that there is no consistency in the findings regarding the existence of links among fluctuations of oil prices and macroeconomic indicators. However, the most of empirical studies on studying the dynamic relationship among oil price, GDP, inflation, exchange rate and other macroeconomic variables show that there are a negative effect of oil price and the macroeconomic variables (Hamilton, 1983; Mork, 1989; Gausden, 2010). In contrast, there is a reverse result which is the prices of oil seem to provide the positive relationship to the macroeconomic variables for example, Sadorsky (1999) and Papapetrou (2001) concluded that there are negative relationships among oil price shocks on interest rates for USA and Greece economy respectively. Some studies have demonstrated that there was a long run relationship based on cointegration tests and vector error correction (VECM) model (Amano and Van Norden, 1998; Chang and Wong 2003; Ito, 2008; Bekhet and Yusop, 2009; Bouchaour and Zeaud, 2012; Altay et al., 2013; Bass, 2019). Some causality studies found that there is a unidirectional influence of oil price on some macroeconomic indicators, while the variables do not cause changes in oil prices. Generally, causality studies produced mixed results across different countries.

2.3 Summary of Gaps in Knowledge Relevant to the Libyan and Nigerian Contexts

Due to the limited literature on statistical and economic analysis in Libya and Nigeria, there are many gaps exist. In particular, no attempt has been made for modelling and forecasting domestic crude oil price in the Libyan, Nigerian and OPEC markets. Thus, the time series models presented in the previous literature will offer an important step in filling out this analytical gap in these markets, and will provide a starting point for future development and understanding on different aspects of oil price modelling in these countries.

Given the vast literature on studying the dynamic relationships among prices of oil and macroeconomic variables across developing countries and developed countries, the gap remains in covering this relationship in developing countries such as Libya and Nigeria. For the case of Libya there is no published study the influence of oil prices changes on GDP, exchange rate and inflation. Thus, this thesis seeks to address the gaps in this field by updating the available evidence for Libya and Nigeria and providing new evidence to the literature review.

Our study fills these gaps in the literature by modelling the prices of crude oil in Libya and Nigeria. Our work extends the previous studies in four several ways. First, the previous studies have used global prices of crude oil, such as the WTI or the Brent prices; this study uses each country's domestic crude oil prices for Libyan, Nigerian and OPEC markets. Second, we identify structural breaks that occur in our data using different structural break tests. Third, based on the studies of Cheong (2009) and Marzo and Zagaglia (2010), we use a number of univariate ARMA-GARCH family models with three error distribution include normal, Student-*t* and GED to describe several facts about volatility in domestic crude oil price returns for the two countries because Klar et al. (2012), pointed out that the incorrect specification of the distribution of the error terms may result in a significant loss of efficiency associating estimators, then we compare the forecasting performances of these different ARMA-GARCH models. Finally, in studying the dynamic relationships between prices of crude oil and macroeconomic variables, this study focuses on the effects of oil price changes on GDP, exchange rates and inflation rate of Libya and Nigeria. This thesis applies multiple time series models such as the vector autoregressive (VAR) model and the vector error correction (VECM) model which are used in the previous studies.

2.4 Summary

This chapter introduced three central aspects of research. The first aspect reviewed the methods and techniques in the literature, which are related with the aim of modeling and forecasting oil prices in order to take a clear look at them and locate the current research within the limits of these techniques. The second aspect discussed the empirical research in the study of the short-run and long-term relationships among oil prices, GDP, exchange rate and inflation, as well as other macroeconomic variables conducted in some different countries and in the two countries under study. Finally, the chapter finished by explaining the importance of the current study with previous literature.

CHAPTER 3: Methodology of Univariate Time Series Analysis

3.0 Introduction

This chapter is divided into a number of sections that explains the methodology of univariate time series analysis which used in this thesis, because it is the most appropriate technique for what the study seeks to achieve. In addition, this chapter describes a number of statistical techniques which support what the study tries to achieve in terms of answering research questions 1 and 2. The methodology, beginning with presentation some stylized facts and statistical properties on returns. Detecting stationarity is an important issue in time series analysis. Several stationary tests are explained such as the augmented Dickey-Fuller test and the Phillips-Perron test. Structural break is a major problem in time series; therefore, several tests are described, including breakpoint unit root tests, sequential Bai-Perron test and Chow's breakpoint test. The theoretical aspects that underpin the methodology are based on numerous univariate time series models because this research uses only one variable for each country. These models are the autoregressive (AR) model, the moving average (MA) model, the autoregressive moving average (ARMA) model, the autoregressive conditional heteroscedastic (ARCH) model, the generalized autoregressive conditional heteroscedastic (GARCH) model, the exponential GARCH model, the GJR-GARCH model, the asymmetric power ARCH (APARCH) model and the component GARCH model. The choice of the order of a model using autocorrelation function is explained in detail. Choosing the best model is based on information criteria that include Akaike information criterion (AIC), Schwarz information criterion and Hannan-Quinn information criterion (HQIC). Estimating the parameters of the model, after that checking and diagnostic the fitted model using different techniques should be carried out. Finally the evaluation of forecasting performance by root mean square error, mean absolute error, mean absolute percentage error and Thiel's inequality coefficient are dealt.

3.1 Some Stylized Facts and Statistical Properties on Returns

In most financial time series studies prices are not analysed directly, instead returns are used. This is a well understood and developed practice. For example, Campbell, Lo, and MacKinlay (1997) present two major reasons to use returns data. Firstly, for average investors, return of an asset is a complete and scale-free summary of the investment opportunity. Secondly, price values are more autocorrelated and the variance is changed over time also the return series data is easier to handle than prices data because return series have more attractive statistical characteristics. These statistical properties will be explained in the next section. However, in most financial studies the common type of price change used is logarithmic returns. The difference of the natural logarithm of oil prices data $\{P_t\}$, t = 1, 2, …, N , where N is the total number of observation, is called a return series and is defined as

$$r_t = log\,(\frac{P_t}{P_{t-1}}) = log(P_t) - log(P_{t-1}), \qquad (3.1)$$

where $\{r_t\}$ is a return series and $P_t,\ P_{t-1}$ are the prices at time t and $t-1$. In addition, the variance of a return series is indicated as volatility. Indeed, in the literature there are different ways to define the expressions "volatility", for example volatility is used to define the variance of price returns and sometimes it is referred to as the conditional variance or the conditional standard deviation of return. Also, the basic idea with volatility study is that the returns series are serially uncorrelated, but not independent (Tsay, 2005). Financial time series, for example oil prices returns, present some general statistical characteristics which are known as stylized empirical facts. According to Cont (2001; 2007), some of these stylized facts of returns can be described as follows:

- **Absence of autocorrelations:** Asset returns usually do not present autocorrelation. The linear autocorrelations of returns are often insignificant, except for very small time scales (≈ 20 minutes).

- **Positive excess kurtosis and Non-normal distribution:** These features are commonly observed on the returns distribution. Probability distributions of many returns have a positive excess kurtosis. Since excess kurtosis of the normal distribution is zero, the distributions of returns with positive excess kurtosis are called to be leptokurtic. In addition, probability distributions of returns sometimes exhibit skewness.

- **Heavy-tailedness:** This characteristic exhibits on the returns distribution (Leptokurtic) when they have large values of kurtosis and it is said to have heavy tails which tend to contain more extreme values compared to the normal distribution.

- **Volatility Clustering:** This phenomenon in returns shows that the volatility of a time series is time-varying, such that small movements tend to be followed by small movement, of either sign, and large movements tend to be followed by large movements (Mandelbrot, 1963).

- **Leverage effect:** The negative correlation among both the past returns and future volatility. In other words, volatility tends to react differently to both a high price increase and a high price decrease.

However, these stylized facts are statistical properties that appear to be present in many financial returns. Moreover, some of these stylized facts are mainly explored through the visual inspection, descriptive and exploratory data analysis stages. Additionally, there is a number of various models have been used to explain various stylized facts about financial returns. Therefore, the best model must be able to capture these properties.

3.2. Investigation of Stationarity

According to Maddala and Kim (1998), statistical and econometric literature has been concerned with the concept of stationary or unit roots which plays a key role in time series data analysis. Stationarity means that the mean and variance of a time series remain constant over time. In such a case, the behavior of a series in the future will be similar to the past and reliable forecasts can easily be obtained based on the previous data of the series.

In the analysis of oil prices, Maslyuk and Smyth (2008) answered this question "why does stationarity of crude oil prices matter?" and they said that the changes of stochastic characteristics of oil prices have significant effects for prediction and decision makers in investment firms. Because if the prices of oil are non-stationary or units root exist then the future prices cannot be forecasted using historical prices. Moreover, they would like to understand the behavior of oil prices structurally because they are movements in supply and demand factors that make price to be volatile. If the time series data is non-stationary, it then requires transformation into stationary series by using different mathematical transformations and differencing operator for the original data. Therefore, the power transformation approach was suggested by Box and Cox (1964) using different mathematical transformations for the original data, such as natural logarithm transformations (log) or square root which use for positive data. Although the selection of the adequate transformation is significant, Guerrero (1993) argued that the use of power transformation functions does not improve the forecasting performance. However, the natural logarithm transformations is common in financial time series applications and has been considered for instance for volatility (variance) analysis (Proietti and Lutkepohl, 2013). Lutkepohl and Xu (2012) tried to find out the usefulness of choosing the log in forecasting and economic analysis. The results of his study indicate that heterogeneous time series that have unstable variance become more homogeneous after taking logs transformation and is helpful for forecasting.

Box and Jenkins (1976) suggest using differencing operator (Δ^d) in order to convert non-stationary time series to stationary series. Then the use of visual inspection of the sample autocorrelation functions for determining the parameter d. In addition, they indicated that in practice the integrated order is often 0, 1, or at most 2, with $d = 0$ related to stationary pattern. However, the idea that the parameter d is equal to the number of unit roots led to replace the visual inspection of the autocorrelations function with formal statistical tests of the unit root null hypothesis. These statistical unit root tests will be discussed in the next subsection. Moreover, non-stationarity can be confirmed by using different formal methods which are called unit root tests. Unit root tests are good tools to determining the order of differencing. The most famous tests which are widely used in applications are the augmented Dickey Fuller (ADF) test, and the Philips-Perron test (PP). Here is a brief overview of these tests which have been applied in this thesis.

3.2.1 The Augmented Dickey Fuller (ADF) Test

The most common statistical nonstationary test is the standard Dickey-Fuller (DF) test (1979). It is based on an underlying time series following a first order autoregressive model. Practically, the residuals in the DF test naturally show evidence for the presence of autocorrelation; in order to solve this problem, Dickey and Fuller developed the augmented Dickey Fuller test. The ADF test (1981) is an extension of the Dickey–Fuller (DF) test, which is used to test some forms of the structural effects (or autocorrelations) for larger and more complex sets of time series models. The Augmented Dickey-Fuller (ADF) test assuming that the series P_t follows an AR(p) process with p lagged order. To test whether there is a unit root uses the same rationale as for the DF test, that is a test is performed on the null hypothesis H_0: $\beta = 1$, versus the alternative hypothesis H_1: $\beta < 1$ (meaning that the process is stationary), applying the equation

$$P_t = c_t + \beta P_{t-1} + \sum_{i=1}^{p-1} \varphi_i \, \Delta P_{t-i} + \varepsilon_t, \tag{3.2}$$

where c_t is a deterministic function can be zero, constant, constant and linear trend and $\Delta P_t = P_t - P_{t-1}$ the differencing operator of the variable of interest (P_t), ε_t is the error term with mean zero and variance σ_ε^2, and $\varphi_1, \dots, \varphi_{p-1}$ are the parameters of AR model.

If H_0: $\beta = 1$ it means a unit root exists in which case the model is non-stationary, whilst if H_1: $\beta < 1$ the process is stationary. TheADF t-ratio statistics can be calculated as following

$$ADF - test = \frac{\hat{\beta} - 1}{std\ (\hat{\beta})}, \tag{3.3}$$

where $\hat{\beta}$ is the least squares estimated value of β and $std\ (\hat{\beta})$ is the standard error estimates of $\hat{\beta}$. However, the asymptotic distribution of the *ADF* is nonstandard. More specifically, the test statistics does not follow the usual t-distribution or the normal distribution, but it has a specific distribution a non-standard 'Dickey-Fuller' distribution (Dickey and Fuller, 1979). The Dickey-Fuller table used to provide the critical values; therefore, the null hypothesis is rejected if the computed test statistic is less than the critical value. Generally the ADF test form employs for three versions of the unit root models for the data generating process of P_t, a model without intercept and trend, a model with an intercept and a model with an intercept and deterministic time trend. However, the procedure of the test is the same regardless of the selected model, but each of these models has it owns critical value which are different according to the numerous specification of a deterministic trend in each model.

Moreover, it is substantial to decide which model to use before continuing with testing, because the addition of irrelevant terms in the equation will increase the critical values of ADF test and make rejection of the null hypothesis more difficult. Harris and Sollis (2003) propose inspecting the figures of the series, if the series shows some tendency to an upward or downward trend over time suggesting that it may suitable to add a linear trend into the model. An intercept term should be added if the plot of the series does not start from zero. A model with both an intercept and a linear trend terms is probably the best because the other two cases are just special specification of this model. However, "One never knows the deterministic trends with great precision before analysis begins. Economic theory does not give any guidance. "Proper handling "of deterministic trend is an impossible task" (Maddala and Kim, 1998, p. 73). The main practical issue in applying the ADF test is the specification of the optimal number of lagged terms which be added to the test equation to remove autocorrelation in the residuals. While the statistical distribution of the ADF statistic does not depend on the approximate lag length, it can be sensitive to the lag order in finite samples (Cheung and Lai, 1995). Nevertheless, Schwert (1989) proposes selecting the maximum lag $p_{max} = 12(T/100)^{\frac{1}{4}}$, where T is the sample size and delete insignificant lags. Because if p is too low, the test will be affected by autocorrelation and if p is too large will reduce the power of the test (Arltová and Fedorová, 2016). Moreover, there are numerous techniques to select the optimal length of lags. Such techniques include different information criteria (which will be discussed later) for possible models and make sure there is no autocorrelation. However the most statistical software provides both manual and automatic lag length choice options. In this thesis the automatic lag length selection was chosen based on the information criteria.

3.2.2 The Philips-Perron (PP) Test

In fact, the Dickey-Fuller tests are based on the assumption that the term of errors is independent and has a constant variance. Phillips and Perron (1988) suggest a non-parametric method for testing the unit root of a time series which is generated by the process with serial correlation and heteroscedasticity. Therefore, the PP test corrects for any autocorrelation and heteroscedasticity in the errors term and it just adjustments of the ADF-*t* statistics that take into account the less restrictive nature of the error terms. The PP test involves fitting the following regression which may include a constant or a trend term.

$$P_t = \varphi_0 + \varphi_1 P_{t-1} + \varepsilon_t \qquad (3.4)$$

where φ_0 and φ_1 are parameters, and ε_t is a stationary process which probably may be heteroscedastic. However, the expressions of the PP test is extremely complex to derive and the statistic of PP test is given by

$$\tilde{t}_{\varphi_1} = t_{\varphi_1}(\frac{\gamma_0}{f_0})^{\frac{1}{2}} - \frac{T\ (f_0 - \gamma_0)(se(\widehat{\varphi_1}))}{2\ f_0^{\frac{1}{2}}\ S} \qquad (3.5)$$

where $\widehat{\varphi_1}$ is the estimate, and t_{φ_1} the t-ratio of the coefficient φ_1, γ_0 is a consistent estimate of the error variance in (3.4), f_0 is an estimator of the residual spectrum at frequency zero, T is the number of observations, $se(\widehat{\varphi_1})$ is coefficient standard error, and *S* is the standard error of the test regression. The PP test is applied for the null hypothesis of unit root versus alternative hypothesis of stationarity through rejection of the null hypothesis when the *p*-value is less than the critical value obtained. The key advantages of the PP test over the ADF tests are that, firstly the PP test is performing serial correlation and heteroskedasticity in the error process. Secondly, the user does not require specifying a lag length in the test regression. In contrast, the ADF tests perform better than the PP tests in small samples (Davidson and MacKinnon, 1993). The asymptotic distribution of the PP *t*-statistic is the same as the ADF *t*-statistic. As with the ADF test, the PP test can be carried out by including an intercept, an intercept and linear trend, or neither in the test regression.

3.3 Detecting Structural Breaks

Time series data can often have structural breaks, due to changes in policy or sudden events to the economy like the abrupt policy changes, great depression and oil price shocks. Therefore, structural break is a major problem in time series and affects all inferential procedures in the analysis of time series data. Additionally, structural change can lead to huge forecasting error and unreliability of a model (Salisu and Fasanyya, 2013). A simple example of such structural change is a time series whose mean changes at a single breakpoint or a change in the structure of a parameter occurring in a time series (Maddala and Kim, 1998).

The potential significance of a structural change in the applications and interpretation of unit root tests was first emphasized by Perron (1989), Rappoport and Reichlin (1989). However, Perron (1989) indicated that a structural break in the series data could affect the findings of unit root tests and proposed allowing for known structural breaks in the Augmented Dickey-Fuller (ADF) tests. To assess whether there is evidence of this structural change, a statistical test is needed as these tests help to determine when and if there is a significant change in our data. We not only need to know that breaks exist, but also the location of the breaks. Therefore, numerous tests for breakpoints have been suggested to test whether a structural break exists or not and to identify the location of a break. In the next subsection, some tests for detecting structural breaks used in this thesis will be presented. The used tests are the breakpoint unit root test, the Bai-Perron test and the Chow test and below a brief discussion about them.

3.3.1 Breakpoint Unit Root Test

Perron (1989) argues that the structural changes are common in time series data and are closely related with unit roots property. He points out that if there is the presence of a break in the deterministic trend in the time series, and then the traditional unit root tests will lead to be biased toward a false unit root null. However, here a brief discussion of the theoretical aspects underlining the methodology of testing which follows the fundamental structure outlined in Perron (1989), Vogelsang and Perron (1998). Perron (1989) has introduced a modified augmented DF test which allow for levels and trends that vary across a single break date. Thus, the break date is defined the break as the first date for the new regime. Before proceeding, we should define a few variables which allow us to characterize the breaks. Therefore, the following variables are describe in terms of a particular break date T_b and referred as break variable.

- An intercept break variable that takes the value 0 for all dates before to the break, and 1 after that and denotes

$$DU_t(T_b) = \begin{cases} 1 \ \text{ if } t \geq T_b \\ 0, \ \text{otherwise} \end{cases} \tag{3.6}$$

- A trend break variable that takes the value 0 for all dates before to the break, and is a break date re-based trend for all subsequent dates and denotes as following

$$DT_t(T_b) = \begin{cases} t - T + 1 & \text{if } \ t \geq T_b \\ 0, & \text{otherwise} \end{cases} \tag{3.7}$$

- A one-time break dummy variable thar takes the value of 1 only on the break date and 0 otherwise and denoted as

$$D_t(T_b) = \begin{cases} 1 \ \text{ if } t = T_b \\ 0, \ \text{otherwise} \end{cases} \tag{3.8}$$

- **The model**

Following Perron (1989), we consider four fundamental models for both non-trending data and trending data with a one-time break. Therefore, we have a model (0) which allows for a one-time change in level for non-trending data. On the other hand, for trending data, we have three models, (1) Model A, which allows for a one-time change in the level (intercept) of the series; (2) Model B allows for a change in both level and trend, and (3) model C which allows for a change in trend. Moreover, Perron (1989), proposed two different forms of the four models which vary in their treatment of the break dynamics. These forms are called innovational outlier (IO) and additive outlier (AO) models. IO model supposes that the change occurs gradually, whilst AO model supposes the breaks occur immediately. In these tests, the null hypothesis is that the data has a unit root, possibly with a structural change(s) versus the alternative hypothesis that the date is stationary with break.

- **Innovational Outlier (IO) Tests**

In the IO model, a general Dickey-Fuller test equation is written as following

$$r_t = \varphi_0 + \beta t + \theta DU_t(T_b) + \gamma DT_t(T_b) + \omega D_t(T_b) + \varphi_1 r_{t-1} + \sum_{i=1}^{k} c_i \, \Delta \, r_{t-i} + \varepsilon_t \qquad (3.9)$$

where θ, γ and ω are the break parameters, k is the number of lag length and ε_t is the error term. Following Perron (1989), Perron and Vogelsang (1992a, 1992b), and Vogelsang and Perron (1998), we consider four numerous specifications for the Dickey-Fuller equation which based on various assumptions for the break dynamics and trend:

- **Model 0:** For non-trending series with intercept break:

$$r_t = \varphi_0 + \theta DU_t(T_b) + \omega D_t(T_b) + \varphi_1 r_{t-1} + \sum_{i=1}^{k} c_i \Delta \, r_{t-i} + \varepsilon_t \qquad (3.10)$$

- **Model 1:** For trending series with intercept break

$$r_t = \varphi_0 + \beta t + \theta DU_t(T_b) + \omega D_t(T_b) + \varphi_1 r_{t-1} + \sum_{i=1}^{k} c_i \Delta \, r_{t-i} + \varepsilon_t \qquad (3.11)$$

- **Model 2:** For trending series with intercept and trend break:

$$r_t = \varphi_0 + \beta t + \theta DU_t(T_b) + \gamma DT_t(T_b) + \omega D_t(T_b) + \varphi_1 r_{t-1} + \sum_{i=1}^{k} c_i \Delta \, r_{t-i} + \varepsilon_t \qquad (3.12)$$

- **Model 3:** For trending series with trend break:

$$r_t = \varphi_0 + \beta t + \gamma DT_t(T_b) + \varphi_1 r_{t-1} + \sum_{i=1}^{k} c_i \Delta \, r_{t-i} + \varepsilon_t \qquad (3.13)$$

- **Additive Outlier (AO) Tests**

Based on the AO model for testing a unit root, a two-step procedure should be performed. In the first stage, the series are detrended using OLS regressions for a model with appropriate intercept, trend, and breaking variables. Testing for the significance of $DU_t(T_b)$ or $DT_t(T_b)$. The four different specifications for the Dickey-Fuller equation which based on various assumptions for the break dynamics and trend are:

- **Model 0:** For non-trending series with intercept break:

$$r_t = \varphi_0 + \theta DU_t(T_b) + r_t^* \qquad (3.14)$$

- **Model 1:** For trending series with intercept break:

$$r_t = \varphi_0 + \beta t + \theta DU_t(T_b) + r_t^* \quad (3.15)$$

- **Model 2:** For trending series with intercept and trend break:

$$r_t = \varphi_0 + \beta t + \theta DU_t(T_b) + \gamma DT_t(T_b) + r_t^* \quad (3.16)$$

- **Model 3:** For trending series with trend break

$$r_t = \varphi_0 + \beta t + \gamma DT_t(T_b) + r_t^* \quad (3.17)$$

In the second stage under the AO model, let r_t^* be the residuals obtained from the detrending equation. The produced Dickey-Fuller unit root test equation is given by,

$r_t^* = \sum_{i=0}^{k} \omega_i D_{t-i}(T_b) + \varphi_1 r_{t-1}^* + \sum_{i=1}^{k} c_i \Delta r_{t-i}^* + \varepsilon_t$, for models 0, 1 and 2.

$r_t^* = \varphi_1 r_{t-1}^* + \sum_{i=1}^{k} c_i \Delta r_{t-i}^* + \varepsilon_t$, for model 3. Then the Dickey-Fuller t-statistic used to compare $\hat{\varphi}_1$to 1 for testing the null hypothesis of a unit root. To choose the number of lag in the Dickey-Fuller equations, we follow the approach of Hall (1994) and Ng and Perron (1995), where the number of lag is chosen to minimize the information criteria among models (information criteria will be discussed later).

3.3.2 Bai-Perron Multiple Structural Break Point Test

More recently, Bai and Perron (1998, 2003) develop tests for detecting one or more unknown structural changes in the sample. Their method involves sequential application of breakpoint tests. The model and test statistics of the Bai-Perron method are briefly discussed below. Consider the following multiple linear regression with T periods and *m* potential breaks (producing *m* + 1 regimes), for the observations T_j, T_j+1,..., $T_{j+1} - 1$ in regime *j* we have the regression model

$$y_t = \grave{X}_t B + \grave{Z}_t \delta_j + \varepsilon_t \quad (3.18)$$

For the regimes $j = 0, \ldots, m$, the regressors are divided into two groups X and Z, and we use the convention in defining the break date to be the first date of the subsequent regime by $T_0 = 1$ and $T_{m+1} = T + 1$. In this model, y_t is the observed dependent variable at period *t*, X_t is a matrix $(p \times 1)$ of the variables are those whose coefficients do not change across regimes and Z_t is a matrix $(q \times 1)$ of the matrix of the variable gave parameters which are allowed to vary between regimes, B and δ_j are the corresponding vectors of parameters; ε_t is the error term. The break points $(T_1, \ldots, T_m)$ are treated as unknown. The estimation procedure is that based on the least-squares method by Bai and Perron (1998), to obtain the estimators of unknown regression parameters together with the break points. Bai-Perron test is performed for testing of the alternative of l+1 breaks versus the null hypothesis of l breaks. A main feature of the Bai and Perron test is that it permits to test for multiple breaks at unknown dates. The asymptotic distribution of this test statistic is non-standard and derived in Bai and Perron (1998) and asymptotic critical value ise tabulated in Bai and Perron (1998, 2003).

3.3.3 Chow's Breakpoint Test

According to Maddala and Kim (1998), the initial test for structural break in the literature is proposed by Chow (1960) which is for stationary data and a single known break. The idea of Chow's breakpoint test is to divide the data into two subsamples, estimating the same equation for each subsample separately, to test if there are significant differences in the estimated equations, significant differences indicate structural changes in the data. However, in order to employ the Chow's breakpoint test the following steps are followed:

Step 1 Divide the data into subsamples and then estimating up to three models, for each of the full data and for both subsamples.

Step 2 Obtain the sum of squared residuals (SSR) for the three models and then comparing the *SSR* from the separate models with that of the whole sample.

Step 3 Calculate the following *F* statistic to examine whether there is a structural change between the period prior and after the chosen break:

$$F = \frac{(SSR-(SSR_1+SSR_2)/k}{(SSR_1+SSR_2)/(T-2k)}, \tag{3.19}$$

where SSR is the restricted sum of squared residuals of the whole sample, SSR_1 and SSR_2 are the sum of squared residuals from subsample 1 and subsample 2 respectively, T is the total number of observations, and k is the number of coefficients in the model equation.

Step 4 Comparing the calculated *F* statistic obtained above with the critical $F(k, T-2k)$ for the required significance level. If the calculated *F* statistic is greater than the critical value from the *F*-distribution, then we reject the null hypothesis that the coefficients are stable for the entire data set, and conclude that there is evidence of structural changes at specified break date. A limitation of the Chow's breakpoint test is that a break date must be chosen a priori. The breakpoint is the time at which the structural change occurs under the alternative hypothesis.

There are two ways have been proposed for chosen the break date. One way is by using exogenous information such as a priori known event based on some known characteristic of the time series data or via graphical. An alternative way is to choose the break date arbitrarily. However, there are problems with both ways. In the first way the true breakpoint can be missed so the Chow test may be uninformative. In the second way, the test can be misleading because the break points correlated with the data and the test might suggest a break even though no structural change exist (Hansen, 2001).

3.4 Univariate Time Series Models

3.4.1 The Autoregressive Model of Order p or AR(p)

A stationary Autoregressive Model (AR) of order p is a model which defines the current value r_t as a linear function of its past p values and an error term and defined by the following mathematical equation:

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \ldots. + \varphi_p r_{t-p} + \varepsilon_t\ ,\ t = 1, \ldots, T \qquad (3.20)$$

where $\varepsilon_t \sim (0, \sigma^2)$ and $r_t, r_{t-1}, \ldots., r_{t-p}$ are the values of the interest variable at time $t, \ldots, t - p,\ p$ is a non-negative integral order of the AR model, φ_0 is a constant , $\varphi_1, \ldots., \varphi_p$ are the coefficients of AR(p) model and ε_t is the error term with mean zero and variance σ_ε^2 (white noise time series). A simple stationary autoregressive model of the first order (1) is denoted by AR(1) and written as

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t, \qquad (3.21)$$

where φ_0 and φ_1 are the coefficients of AR(1) model that must be estimated subject to the assumptions

1. $E(\varepsilon_t) = 0$
2. $E(\varepsilon_t \varepsilon_s) = \begin{cases} \sigma_\varepsilon^2, \; if\ t = s \\ 0 \;, \; if\ t \neq s \end{cases}$
3. $E[(r_{t-1} - \mu)\varepsilon_t] = 0,$ where μ is the mean of r_t.

However, the mean and the variance of an AR(1) process in Equation (3.21) can be obtained respectively as follows

$$\mu = E(r_t) = E(\varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t) \tag{3.22}$$

By weak stationary of the AR(1) model, the expected value of either $r_t\ or\ r_{t-1}$, equals μ (due to stationarity); while the expected value of the error term, ε_t equals zero, such that

$$E(r_t) = E(\varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t) = \varphi_0 + \varphi_1 E(r_t)$$

$$\mu = \varphi_0 + \varphi_1 \mu \quad \rightarrow \mu = \frac{\varphi_0}{1-\varphi_1} \tag{3.23}$$

The mean exists if the parameter $\varphi_1 \neq 1$ and it is equal zero when, $\varphi_0 = 0$. If we use $\varphi_0 = (1 - \varphi_1)\,\mu$, the AR(1) model in Equation (3.21) can be written as

$$r_t = (1 - \varphi_1)\,\mu + \varphi_1 r_{t-1} + \varepsilon_t \rightarrow (r_t - \mu) = \varphi_1 (r_{t-1} - \mu) + \varepsilon_t \tag{3.24}$$

By squaring both sides and then taking the expected value we obtain

$$V(r_t) = E(r_t - \mu)^2 = E(\varphi_1 (r_{t-1} - \mu) + \varepsilon_t)^2 = E[(\varphi_1 (r_{t-1} - \mu))^2 + 2\varphi_1 (r_{t-1} - \mu)\varepsilon_t + \varepsilon_t^2]$$

$$= \varphi_1^2 E(r_{t-1} - \mu)^2 + 2\varphi_1 E[(r_{t-1} - \mu)\varepsilon_t] + E(\varepsilon_t^2)$$

$$V(r_t) = \varphi_1^2 V(r_{t-1}) + \sigma_\varepsilon^2 \tag{3.25}$$

Under these assumption $[\varepsilon_t (r_{t-1} - \mu)] = 0$, $E(\varepsilon_t^2) = \sigma_\varepsilon^2$ and for weakly stationary $V(r_t) = V(r_{t-1})$ then

$$V(X_t) = \frac{\sigma_\varepsilon^2}{1-\varphi_1^2} \rightarrow \varphi_1^2 \neq 1 \tag{3.26}$$

The variance must be nonnegative and finite, so an AR(1) model to be weakly stationary process must achieve this condition $|\varphi_1| < 1$. Thus we can easily generalization the results obtained from AR(1) model to AR(p) models. However, the AR(p) model in Equation (3.20) can be written as this form

$$r_t - \mu = \varphi_1(r_{t-1} - \mu) + \varphi_2(r_{t-2} - \mu) + \cdots + \varphi_p(r_{t-p} - \mu) + \varepsilon_t,$$

where the constant $\varphi_0 = \mu\,(1 - \varphi_1 - \cdots - \varphi_p)$. In addition, we can written the AR(p) model by applying backshift operator (B) in this form

$$r_t - \varphi_1 r_{t-1} - \varphi_2 r_{t-2} - \cdots - \varphi_p r_{t-p} = \varepsilon_t$$

$$(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p) r_t = \varepsilon_t$$

$$\varphi_p(B) r_t = \varepsilon_t, \tag{3.27}$$

where $\varphi_p(B) = \left(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p\right)$ denotes the autoregressive operator, which is a polynomial of degree p. Then the overall expression of an autoregressive process of order$p$, AR(p) could be taken as a solution to (3.27), given as

$$r_t = \frac{1}{\varphi_p(B)} \varepsilon_t = \varphi_p{}^{-1}(B) \varepsilon_t \tag{3.28}$$

The mean of the stationary AR(p) model is$E(r_t) = \frac{\varphi_0}{1-\varphi_1-\cdots-\varphi_p}$. The polynomial equation of the AR(p) model is referred as the characteristic equation and it can be written as

$$1 - \varphi_1 r - \varphi_2 r^2 - \cdots - \varphi_p r^p = 0,$$

Here, the AR(p) process is stationary if and only if all the roots of the polynomial equation lie outside the unit circle.

3.4.2 The Moving Average Model of Order *q* or MA(*q*)

A stationary moving average time series model of order q defines the current values r_t as a linear function of its past random errors and can be defined by the following mathematical equation:

$$r_t = \theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots . - \theta_q \varepsilon_{t-q} \tag{3.29}$$

Where θ_0 is a constant, q is the order of the MA model, $\varepsilon_t, \dots, \varepsilon_{t-q}$ are errors terms with mean zero and variance σ_ε^2 and $\theta_1, \dots., \theta_q$ are parameters of MA(q).The equivalent formula for the MA(q) obtained by applying backshift operator (B) can be written in following form

$$r_t = \theta_0 + (1 - \theta_1 B - \cdots . - \theta_q B^q)\, \varepsilon_t = \theta_0 + \theta_q(B) \varepsilon_t, \qquad \text{where } q > 0,$$

and $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p)$ denotes the moving-average operator. Also MA models are always weakly stationary because their mean and the variance are time invariant or constant. The moving average model of order one, MA(1) is

$$r_t = \theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1}, \tag{3.30}$$

with expected value and variance respectively given by

$$\mu = E(r_t) = E(\theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1}) = \theta_0,$$

$$\sigma^2 = V(r_t) = V(\theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1}) = (1 + \theta_1^2)\sigma_\varepsilon^2$$

So for the general MA(q)

$$\mu = E(r_t) = E\left(\theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots . - \theta_q \varepsilon_{t-q}\right) = \theta_0, \text{ and}$$

$$\sigma^2 = V(r_t) = V\left(\theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots . - \theta_q \varepsilon_{t-q}\right) = \left(1 + \theta_1^2 + \theta_2^2 + \cdots + \theta_q^2\right)\sigma_\varepsilon^2$$

In general, the MA (q) models are always stationary and are said to be an invertible process if the roots of the polynomial operator for a moving-average are above one.

3.4.3 The Autoregressive Moving Average Model or ARMA(*p*,*q*)

ARMA(p,q) model is a model that comprises of both the autoregressive of order p, AR(p) and the moving average of order q MA(q) models. And it is a general class of models for investigating the dynamic structure and forecasting future values of a series. Thus, it is explored widely in different fields of financial/economic studies. The ARMA(p,q) model can be defined by the following mathematical equation:

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \ldots + \varphi_p r_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}, \tag{3.31}$$

where p and q are non-negative integers representing the orders of the AR and MA components of the model, respectively; $\varepsilon_t, \ldots, \varepsilon_{t-q}$ is a set of error terms with mean zero and variances σ_ε^2, as well as being uncorrelated across time. That is, $E(\varepsilon_t) = 0, E(\varepsilon_t^2) = \sigma^2$, $E(\varepsilon_t \varepsilon_s) = 0 \; for \; t \neq s$, φ_0 is a constant term and $\varphi_1, \ldots., \varphi_p$, $\theta_1, \ldots., \theta_q$ are the parameters of the ARMA(p,q) model. Further, ARMA (p,q) model can be expressed as:

$$\varphi_p(B) r_t = \varphi_0 + \theta_q(B)\varepsilon_t, \tag{3.32}$$

where is φ_0 a constant, $\varphi_p(B)r_t$ and $\theta_q(B)$ denote the autoregressive and moving-average operators, respectively. For modelling many different types of time series by applying AR, MA and ARMA models, it is supposed that the time series data are stationary. However, in many practical applications, the data exhibit non-stationary behaviour. There are specific mathematical transformations and difference operators which can be employed to convert non-stationary time series to stationary series.

3.5 Selecting and Determining the Order (p and q) of A Model

The autocorrelation (ACF) plot and the partial autocorrelation (PACF) plot of the stationary series are very useful tools used for determining the order p and q of the appropriate ARMA models, when they are compared to the theoretical pattern of these plots when the order is identified. The PACF can help us in determining the order of an AR(p) model because the PACF becomes zero at lag $p+1$ and greater. Whilst the feature of a MA(q) model is that its ACF becomes zero from lag q onwards. This feature enables us to identify a MA(q) model. The ACF and PACF decaying towards zero for an ARMA model. The Table 3.1 below presents the non-seasonal theoretical behavior of Box-Jenkins models.

Table 3-1: Non-seasonal Theoretical Behavior of Box-Jenkins Models.

	AR(p)	MA(q)	ARMA(p,q)
ACF	Dies down	Cuts of after lag q	Dies down
PACF	Cuts of after lag p	Dies down	Dies down

(Source: Box, Jenkins and Reinsel, 2008, *p*. 87)

3.6 Selection of a Time Series Model Based on Information Criteria

The approach widely used to analyse various models is the information criteria function; these models may be ranked according to their values of a selection information criteria, and then used to choose the optimal model with the minimum information criterion. There are different information criteria and all of them are likelihood-based. The information criteria used in this thesis are presented as follows.

3.6.1 Akaike Information Criterion (AIC)

Akaike information criterion (AIC) introduced by Akaike (1973), is a measure of goodness-of-fit of an estimated model. AIC is the most commonly employed criterion for choosing appropriate model in the studies. The is given by

$$AIC = -2l/T + 2k/T, \tag{3.33}$$

where k stands for the number of estimated coefficients in the model, l represents maximized value of the likelihood function for the estimated model which is computed as:

$l = \frac{T}{2}\ (1 + \log(2\pi) + \log(\hat{\varepsilon}'\hat{\varepsilon}/T)$, when T is the sample size. The suitable model that best fit to the data is that with the minimum AIC. Hannan (1982), McQuarrie and Tsai (1998) and Burnham and Anderson (2002) pointed out that the AIC tends to choose a complex model rather than the true model. That is, it has a tendency to over fit models.

3.6.2 Schwarz Information Criterion (SIC)

Schwarz information criterion (SIC), developed by Schwarz (1978). The SIC information criterion is given by

$$SIC = -2l/T + (klog\ T)/T, \tag{3.34}$$

wher l is the maximized value of the likelihood function for the estimated model, k represents number of observations in the model and T is the sample size. The model with the least SIC value is the most favorable from among estimated models. Koehler and Murrhree (1988) and Burnham and Anderson (2002, 2004) pointed out that the SIC is a better criterion for selecting the "true model" in applications when it compared with AIC. In addition, the SIC tends to be less prone to overfitting than AIC.

3.6.3 Hannan-Quinn Information Criterion (HQIC)

Hannan and Quinn (1979) developed an information criterion for strong consistency, in the context of order selection for autoregressive models. This information criterion is estimated from the following equation

$$HQIC = -2(l/T) + 2k\log(\log(T))/T, \tag{3.35}$$

where l, k and T are as defined under AIC and SIC. The model with the least HQIC value is the best model. According to Asghra and Abid (2007), choosing the appropriate lag length of an autoregressive models is one of the most complicated steps in ARMA modeling. They have compared a number of criteria for choice of the best lag length of the autoregressive process. These criteria includes AIC, SIC, HQ, Final Prediction Error (FPE) and corrected version of AIC (AICC). The comparison between these criteria to choose the lag length is made under the three different cases which are under structural break, normal errors and under non-normal errors. The study is based on a Monte Carlo simulation that included three phase. Firstly, the data are generated from an AR process. Secondly, the lag lengths have been selected, finally the comparison of performance of the lag length selection criteria is carried out. The results show that as long as the size of sample is concerned, the performance of all these criteria improves as the sample size increases. SIC is the best performance for large samples size (120 or greater) and there are no criteria that are not useful for choosing the correct true lag length in presence of structural breaks in the system.

It should be noted here that the results of Asghra and Abid's study are approximately comparable to a study achieved by Liew (2004) which is compared five selection criteria include AIC, SIC, FPE, HQ and BIC. According to the findings of this study the performance of AIC and FPE are better than others for small sample size (60 or less). While for large sample (60 or above) greater than 60, HQIC has the best performance.

3.7 Estimating the Parameters of a Model

The most common estimation methods used to estimated coefficients of the best fitting models is either ordinary least squares estimation (OLSE) or maximum likelihood estimation (MLE), depending on the model. However, in order to obtain the ordinary least square (OLS) estimates of the coefficients using function minimization procedures, so that the sum of squared residuals is minimized (Agung, 2011). The Maximum likelihood estimation (MLE) is the most popular parameters estimation technique in statistical modelling. The method is meant to determine coefficients that maximize the likelihood function of a variable. The likelihood function of data set clarifies the probability of obtaining that particular data set given that the probability density is known.

According to Box and Jenkins (2008), in the most cases, the estimates which are obtained using MLE method are closely approximated to the OLS estimates. In addition, many simulation studies have been compared the performance of least squares, and maximum likelihood estimators for ARMA models. However, simulation evidences suggest that the least squares estimators work as satisfactory approximations to the maximum likelihood estimators for large sample sizes. Therefore, the MLE method is preferred for small or moderate sample sizes. It should be noted here that the parameters of the ARMA models which have used for modelling the conditional mean in this thesis are automatically estimated using the least squares method using EViews.

The stage after selecting the model and estimating its parameters, diagnoses the adequacy of this model. More specifically, a good process to verify the adequacy of the model is by examining and analyzing the residual (error term) which is obtained from the model. That is, if the residuals are white noise, we accept the model; otherwise we reject and return to the first stage and remodel until the appropriate model is found. A number of diagnostic checking measures are available to ensure that the selected model is statistically adequate and to check the assumption of the errors term. Hence, the plots of the standardized residuals and its correlograms from the model must point to the fact that the residuals (errors term) are a white noise stationary process, and should have mean zero, no serial correlation, and are *i.i.d*. Also, the plots of its ACF and PACF are used to visualize the model assumptions. Therefore, these measures are illustrated as follows.

3.8 The Ljung-Box-Test

To explore the serial correlation in the residuals of the selected model, typically, the null hypothesis is that the errors terms have no autocorrelation, against the alternative hypothesis where there is at least one nonzero autocorrelation. The most common test statistics which will be used to test for serial correlation is the Ljung- Box test, based on the sample autocorrelation functions.

Ljung and Box (1978) suggest the Portmanteau statistic for testing the null hypothesis $H_0\colon \rho_1 = \cdots = \rho_m = 0$, against the alternative hypothesis $H_0\colon \rho_k \neq 0$, for some $k \in \{1, \dots, m\}$ and this statistic can be calculated as

$$Q(m) = T(T+2)\sum_{k=1}^{m} \frac{\hat{\rho}_k^2}{T-k}, \tag{3.36}$$

where T stands for the sample size, $\hat{\rho}_k$ is the estimated autocorrelation at lag k and m represents the number of lags. The Box-Ljung statistic has been preferred to test of model adequacy, because it appears to has an asymptotic distribution very much closer to the asymptotic is a chi-square (χ^2) with m degrees of freedom. Thus, null hypothesis H_0 will reject if $Q(m) > x_\alpha^2$, or H_0 shall be rejected if the p-value is less than the estimated significant level α.

3.9 Testing for Normally

For testing the normality of errors term with zero mean, there are a number of statistical methods are used and discussed in the literature, this thesis consider just three: (i) histogram; (ii) the Quantile-normal plot (QQ-plot); and (iii) Jarque–Bera test. A brief definition of them is as follows.

3.9.1 Histogram

A histogram is a simple graphical diagnostics tool that is used to present the empirical probability distribution of the time series data in form of bar graph. For testing normality we compare the histogram of the data set to a normal probability curve. Therefore, the data of the time series are normally distributed when the shape of the histogram is bell-shaped and resemble to the normal distribution (Gujarati, 2003).

3.9.2 The Quantile Normal Plot (QQ-Plot)

The QQ-plot is a graphical method to determine if two data sets are coming from populations with a common distribution, and if the properties such as location, scale and skewness are equal or different in the two distributions. More specifically, the QQ-plots are used to determine whether the data of a time series follow a specified probability distribution; *e.g.* whether the variable has a normal distribution (Cleveland, 1994; Chambers et al., 1983; Wilk and Gnanadesikan, 1968). Therefore, if the two distributions are identically distributed, the QQ-plot should be an approximately straight line. In contrast, if the QQ-plot does not lie on a straight line, the two distributions vary along some dimension.

3.9.3 Jarque–Bera (JB) Test

Jarque and Bera (1987) proposed a statistic to test whether a given distribution is normal or not. Jarque-Bera test is one of the tests of normality more commonly applied. In particular, this test combines both coefficient of skewness and the coefficient of excess kurtosis and the test statistic as follows:

$$JB = \frac{\hat{S}^2(r)}{6/T} + \frac{(\hat{K}(r)-3)^2}{24/T}, \tag{3.37}$$

where T is the size of sample and both $\hat{S}^2(r)$, $\hat{K}(r)$ are skewness and kurtosis calculated from sample data and $\hat{K}(r) - 3$ is referred as the excess kurtosis. More specifically, if $\{r_1, \dots, r_T\}$ is a variable with T observations. The sample skewness and the sample kurtosis are defined respectively as following

$\hat{S}(r) = \frac{1}{(T-1)\hat{\sigma}_r^3} \sum_{t=1}^{T} (r_t - \bar{r})^3$, and $K(r) = \frac{1}{(T-1)\hat{\sigma}_r^4} \sum_{t=1}^{T} (r_t - \bar{r})^4$,

where $\bar{r}$ is a sample mean and $\hat{\sigma}_r^2$ is a sample variance. Under the assumption of normality both $\hat{S}(r)$ and $\hat{K}(r)$ have asymptotically a normal distribution with zero mean and variances 6/ T and 24/ T respectively. Therefore, the *JB* statistic has asymptotically a Chi-square distribution with 2 degrees of freedom. We will reject null hypothesis ($H_{0:}$ the data are normally distributed) if $JB > x^2_{2,1-\alpha}$ and α % indicates the significance level.

Moreover, the normal distribution is symmetric around its mean, mesokurtic and its kurtosis equals to three, while a skewed distribution will not be because it has one tail is longer than the other. Furthermore, a leptokurtic distribution has fatter tails, the value of kurtosis is a large positive number and is more peaked than a normal distribution, while a platykurtic distribution is less peaked, with the excess kurtosis value is negative and thinner tails (Brooks, 2008; Tsay, 2005). Bollerslev (1987) and Nelson (1991) have early noted a property of the excess kurtosis in financial time series data, and therefore, normal distribution does not properly describe data. It is also known that stock market returns show negative values of skewness (Glosten et al., 1993). According to Brooks (2008), in practice, numerous financial and economic time series data characterise with a leptokurtic distribution.

3.10 Testing for ARCH Effects

In statistics the concept of homoskedasticity means that a set or vector of random variables have the same variance (the variance is constant), also called homogeneity of variance. Otherwise, if some of these variables have different variance from others, then this feature is called heteroskedasticty (the variance is not constant). In financial literature time-variation in volatility is known as heteroskedasticty (Brooks, 2008). For testing for conditional heteroskedasticity, the squared of the residuals, ε_t^2 will be used and referred to as the autoregressive conditional heteroskedastic (ARCH) effects. Tests are used in this thesis for this issue are the first test is Ljung-Box statistics $Q(m)$ statistic test (McLeod and Li, 1983) for testing the null hypothesis which is the first m lags of ACF of the series (ε_t^2) are zero and study the ACFs and PACFs of the squared residual series for evidence of significant autocorrelation. The second test is the Lagrange multiplier test (LM) which is proposed by Engle (1982). This test used for testing the null hypothesis which is there are no ARCH effects or in other words $H_0: \alpha_1 = \cdots = \alpha_m = 0$ and the alternative hypothesis are given by the regression $H_1: \varepsilon_t^2 = \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_m \varepsilon_{t-m}^2 + z_t$, where z_t is a white noise error term.

The LM statistic denoted as TR^2 where T is the sample size and R^2 is computed from the regression above and it is equivalent to the usual F statistic for the regression on the squared of residuals which follows a chi-square distribution with m degrees of freedom. The null hypothesis will reject if $F > \chi_m^2(\alpha)$ or the p-value of F less than α. Therefore, if the ARCH effects is statistically significant the analysis will proceed by modelling conditional variance (volatility).

3.11 Conditional Volatility Modelling

This section highlights the most important models that are used in this thesis for modelling the conditional variance of oil prices. The models for modelling and forecasting the volatility usually are referred to as conditional heteroskedastic models include the autoregressive conditional heteroskedastic (ARCH) model of Engle (1982), the generalized ARCH (GARCH) model of Bollerslev (1986), the exponential GARCH (EGARCH) model of Nelson (1991) and others. These models are widely applied in modelling the volatility in financial applications to describe the evolution of σ_t^2 (Tsay, 2005).

The autoregressive conditional heteroskedastic models have conditional mean and conditional variance components, (both are random variables), respectively, of a return series $\{r_t\}$ given F_{t-1}, where F_{t-1} indicates the information set available up to time $t-1$, specified by the equations:

$$E\ (r_t|F_{t-1}) = \mu_t \quad , \quad var(r_t|F_{t-1}) = E\ [\ (r_t - \mu_t)^2 \mid F_{t-1}] = \sigma_t^2 \tag{3.38}$$

where $E(\,.\,|.\,)$ denotes the conditional expectation and F_{t-1} usually consists of all linear functions of the past values. Now assume that r_t followed a simple stationary ARMA time series model, with some explanatory variables for example. Then we can write this model as

$$r_t = E\ (r_t|F_{t-1}) + \varepsilon_t = \mu_t + \varepsilon_t$$

$$\mu_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i\, r_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3.39}$$

where k, p and q are non-negative integers, μ_t is referred to as the mean equation of r_t and ε_t is residuals of a time series. Combining Eq. (3.38) and Eq. (3.39) we have

$$\sigma_t^2 = Var(r_t|F_{t-1}) = Var(\varepsilon_t|F_{t-1}) \tag{3.40}$$

Here, the conditional heterogeneity models are concerned with the evolution of σ_t^2. The pattern under which σ_t^2 evolves varies from one volatility model to another

Consequently, to allow for time-varying σ_t^2 and then ε_t can be presented as $\varepsilon_t = \sigma_t z_t$, where z_t is the error terms (white noise) with mean zero and variance 1. Moreover, the unconditional variance of ε_t is

$$\sigma^2 \equiv E\ (\varepsilon_t^2) = E\ [\ E\ (\varepsilon_t^2|F_{t-1})\ ] = E(\sigma_t^2) \tag{3.41}$$

This is usually supposed to be constant, that means $E(\sigma_t^2)$ is constant. In the financial context, ε_t is indicated to as the innovation or shock of return at time t and σ_t^2 is referred as the variance (volatility) equation of r_t.

3.11.1 The Autoregressive Conditional Heteroscedastic ARCH (p) Model

Engle (1982) was the first to introduce the conditional heteroskedasticity concept and changed the classical assumption of constant variance in time series models. He suggested that the ARCH model can allow the volatility to change over time as a function past squared of errors leaving the unconditional variance stable. Simply, the idea of the ARCH model is that the shock or the errors ε_t is serially uncorrelated, but dependent and the dependence of ε_t can be described by a function of its squared and lagged values. The mathematical formula for this model is as follows

$$r_t = \mu_t + \varepsilon_t \quad , \; \varepsilon_t = \sigma_t z_t \; , \; z_t \sim N(0,1),$$

$$\sigma_t^2 = \omega + \textstyle\sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2, \tag{3.42}$$

where $\omega > 0$, $\alpha_i \geq 0\,, i = 1, \dots, p$, and $p > 0$ is the order of ARCH model, z_t is a white noise with mean zero and variance 1. The ARCH coefficients α_i must satisfy stationary condition to ensure that the unconditional variation exists. If $\sum_{i=1}^{p} \alpha_i < 1$ the GARCH model is weakly stationary with constant unconditional variables:

$$\sigma^2 = \frac{\omega}{1 - \sum_{i=1}^{p} \alpha_i}$$

The ARCH model of order 1 can be written as following

$$\varepsilon_t = \sigma_t z_t \, , \; \sigma_t^2 = \omega + \alpha_1 \, \varepsilon_{t-1}^2$$

Here, the unconditional mean of the shocks ε_t is $E(\varepsilon_t) = E[E(\varepsilon_t | F_{t-1})] = E[\sigma_t E(z_t)] = 0$ and the unconditional variance of the shocks ε_t can be calculated as

$$Var(\varepsilon_t) = E(\varepsilon_t^2) = E[E(\varepsilon_t^2 | F_{t-1})] = E(\sigma_t^2)$$

$$= E(\omega + \alpha_1 \, \varepsilon_{t-1}^2) = \omega + \alpha_1 \, E(\varepsilon_{t-1}^2).$$

Under the stationary assumption of ε_t with $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = Var(\varepsilon_{t-1}) = E(\varepsilon_{t-1}^2)$. However, we have $Var(\varepsilon_t) = \omega + \alpha_1 \, Var(\varepsilon_t)$ and $Var(\varepsilon_t) = \frac{\omega}{1 - \alpha_1}$, for the variance of ε_t to be positive, α_1 must be $0 \leq \alpha_1 < 1$.

3.11.2 The Generalized Autoregressive Conditional Heteroscedastic GARCH(*p*,*q*) Model

After Engle introduced the ARCH process, it has been used widely on financial and economic time series data. However, many disadvantages of the model were found. For example, the ARCH model supposes that both positive and negative shocks have the same impacts on the conditional variance. Also because it depends on the past shocks squared, the lag length, and a large number of coefficients it is not easy to control the existence of negative variance. Thus, in order to solve this problem, Bollerslev (1986) suggested the generalized ARCH, the so called GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, by allowing the current volatility to depend on the first q past volatility as well as the p past squared innovations. This model can be written as

$$r_t = \mu_t + \varepsilon_t \quad , \; \varepsilon_t = \sigma_t z_t \;\; , \; z_t \sim N(0,1),$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2, \tag{3.43}$$

where $\omega > 0 \;, \alpha_i \geq 0, i = 1, \dots, p \; and \; \beta_j \geq 0, i = 1, \dots, q,$ are sufficient conditions to ensure that the conditional variance $\sigma_j^2 > 0$. Also z_t is a white noise with mean zero and variance 1. The parameter$s$ α_i represents the ARCH effect and β_j represents the GARCH effect. However, it is obvious that a GARCH process can be displayed as an ARMA model in form in squared residuals. In addition, to achieve the stationarity requirement in GARCH models the summation of $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j$ must be less than one. This summation reflects the persistence of innovations (shocks) to the volatility, meaning that the impact of a volatility shock disappears over time at an exponential rate.

Clearly when q = 0 the GARCH model will become the ARCH model. Hence, as its name suggests, GARCH is the generalisation of the ARCH mode. Therefore, the GARCH model of order one can be written as following, $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$. However, the GARCH(1,1) model is weakly stationary if $\alpha_1 + \beta_1 < 1$, in this case the unconditional variance can be as following $Var(\varepsilon_t) = \frac{\omega}{1-\alpha_1-\beta_1}$. On the other hand, the unconditional variance is infinite if $\alpha_1 + \beta_1 = 1$. Therefore, the GARCH model with $\alpha_1 + \beta_1 = 1$ is named integrated GARCH or IGARCH model.

However, the GARCH model can reduce the number of parameters required because it gives parsimonious models that are easy to estimate. More specifically, the GARCH model is equivalent to infinite order ARCH process with parameters that decline geometrically. For this reason, it is necessary to estimate GARCH(1,1) specifications as alternatives to high-order ARCH processes because with the GARCH(1, 1) we have less coefficients to estimate and therefore lose fewer degrees of freedom (Asteriou and Hall, 2011). In addition, the low-order GARCH(1,1) model has been shown to successfully capture thick tails of data as well as volatility clustering. In general, the GARCH(*p*,*q*) models are considered the most robust of the volatility models family (Bollerslev et al., 1992; Angelidis et al., 2004). According to Nelson (1991), the GARCH models have some limitations; first, the GARCH models cannot handle the negative correlation among current values and future values. Second, the GARCH process may over restrict the dynamics of volatility by coefficient restrictions. Further, these models can be extended and modified in a variety of ways yielding a vast array of further models for which ARCH and GARCH are the parents. Here, some of these models will be briefly explored and their suitability for modelling oil price volatility will be considered.

3.11.3 The Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model

Even if the GARCH process successfully captures the thick tails returns, and the volatility clustering, it is a poor model if one wishes to capture the leverage effect. Therefore, the GARCH model which allows for asymmetric effects among both positive and negative shocks of the returns of price is called the Exponential GARCH (EGARCH), which was suggested by Nelson (1991). The EGARCH(*p*,*q*) process uses the logarithm of conditional volatility thus:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{p} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2), \qquad (3.44)$$

where ω , α_i , β_j and γ_i are model coefficients. The γ_i coefficient indicates the leverage effect of ε_{t-i}. One characteristic to be mentioned is that negative shocks of the conditional variance tend to have a larger effect and therefore γ_i is often assumed to be negative.

If $\gamma_i = 0$, the impact to conditional variance is symmetry (Tsay, 2005). Here, there are no restrictions on the coefficients of EGARCH process because the transformation of the logarithmic ensures that the forecasts of the variance are non-negative. This model satisfies a sufficient condition for stationarity when $|\beta_j| < 1$.

3.11.4 The GJR-GARCH Model

This process suggested by Glosten, Jagannnathan and Runkle (1993) offers an alternative method to allow for asymmetric effects of negative and positive shocks to conditional variance. The specification of the GJR-GARCH (*p*,*q*) model can be written as following

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}(\alpha_i + \gamma_i I_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^2 \tag{3.45}$$

where $I_{t-i} = \begin{cases} 0, & \varepsilon_{t-i} \geq 0 \\ 1, & \varepsilon_{t-i} < 0 \end{cases}$ is an indicator function to differentiate among positive and negative shocks. The conditional variance is positive if $\omega > 0$, $\alpha_i, \gamma_i, \beta_j \geq 0$. The model is stationary if $\alpha + \beta + \frac{\gamma}{2} < 1$. Thus, there is an evidence of asymmetric effect if the asymmetry coefficient $\gamma_i > (<)\, 0$ which implies that negative (positive) shocks increase the volatility more than positive (negative) shocks of the same magnitude. Therefore, the negative sign of the coefficient on asymmetry in the case of EGARCH has an equivalent interpretation for the positive sign of the asymmetry coefficient in the GJR-GARCH process. If $\gamma_i = 0$, no asymmetric effect and the GJR-GARCH model reduces to the GARCH model.

3.11.5 The Asymmetric Power ARCH (APARCH) Model

The asymmetric power ARCH (APARCH) model was introduced by Ding, Granger and Engle (1993) to allow for leverage effects and it can be defined as follows:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p}\alpha_i(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^\delta + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^\delta, \tag{3.46}$$

where $\omega > 0$, $\alpha_i \geq 0$ and $\beta_j \geq 0$. $\delta > 0$ is the coefficient of the power term, the leverage coefficient is $|\gamma_i| \leq 1 \;\; for\; i = 1,2,\ldots\ldots,r$. In the APARCH model, if $\gamma_i \neq 0$ this captures asymmetric effects. The APARCH model reduces to the GARCH process when $\delta = 2$ and $\gamma_i = 0$ for all i. The APARCH process reduces to the GJR-GARCH model if $\delta = 2$.

3.11.6 Component Generalised Autoregressive Conditional Heteroscedasticity (CGARCH) Model

The CGARCH model was introduced by Engle and Lee (1999). This process is also known as the two components GARCH model, in which the aggregate volatility of the series is decomposed into two components to describe the long-run and the short-run movements. The first part is known as transitory volatility component that captures the short term effect of an innovation, while the second part is known as the permanent volatility component that specifies the long-term innovation. The CGARCH model of order one can be defined as follows:

$$\sigma_t^2 = q_t + S_t \tag{3.47}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \theta(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$$

$$S_t = \alpha\,(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$$

where q_t is the long-run (permanent) component, described as volatility trend, and S_t is the short term (transitory) component, i.e. the difference among the conditional variance and its trend. The conditions for the non-negativity of the CGARCH model are $\alpha+\beta < \rho < 1$, $\omega > 0, \alpha > 0$ and $0 < \theta < \beta$ is the forecast error. Moreover, Engle and Lee (1993) also combine the CGARCH model with the GJR-GARCH model to allow shocks to affect the volatility component asymmetrically. The asymmetric CGARCH (ACGARCH) model can be written as

$$\sigma_t^2 = q_t + S_t \tag{3.48}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \theta(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$$

$$S_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})D_{t-1} + \beta(\sigma_{t-1}^2 - q_{t-1})$$

Similarly to the CGARCH model, q_t is the long-run (permanent) component and S_t is the short-run (transitory) component, D_{t-1} is an indicator function, and $D_{t-1} = 1$ if $\varepsilon_{t-1} < 0, D_{t-1} = 0$ otherwise and $\gamma$is the coefficient indicates the leverage effect of ε_{t-1}. If $\gamma > 0$ this is indicating that there is leverage effect in the conditional variance.

3.11.7 The Error Distribution for GARCH Models

In relation to the probability distribution of the error (z_t), when Engle (1982) proposed the ARCH model, the assumption about the distribution of the error was normal distribution. While Bollerslev (1987) proposed the Student's t distribution with $v > 0$ degrees of freedom and Nelson (1991) suggested using the generalized error distribution (GED) .Therefore, in the presence off at tails, a characteristic often found in financial time series returns and oil price returns, both Students't and the GED are appropriate to capture this feature.

If z_t is assumed to be the standard normal distribution, then the probability density function (pdf) can be written as following

$$f(z_t) = \frac{1}{\sqrt{2\pi}} e^{\frac{-z_t^2}{2}}, \ for -\infty < z_t < \infty \tag{3.49}$$

If z_t is assumed to be the Student's t distribution with v degrees of freedom, then the probability density function (pdf) can be written as following

$$f(z_t; v) = \frac{\Gamma(\frac{v+1}{2})}{\sqrt{(v\pi)}\Gamma(\frac{v}{2})} (1 + \frac{z_t^2}{v})^{\frac{-(v+1)}{2}}, \ for -\infty < z_t < \infty \ and \ v > 0 \tag{3.50}$$

where $\Gamma(v) = \int_0^\infty e^{-x} x^{v-1} dx$ is the Gamma function. The probability density function of the Student's t distribution is symmetric around zero and for $v \to \infty$, the t-distribution converges to the standard normal distribution.

If z_t is assumed to be the generalized error distribution, then the probability density function (pdf) can be written as following

$$f(z_t; v) = \frac{v e^{-\frac{1}{2}\left|\frac{z_t}{\gamma}\right|^v}}{\gamma 2^{(1+\frac{1}{v})}\Gamma(\frac{1}{v})}, \ \text{with} \ \gamma \equiv [\frac{2^{\frac{-2}{v}}\Gamma(\frac{1}{v})}{\Gamma(\frac{3}{v})}]^{\frac{1}{2}}, \tag{3.51}$$

where $\Gamma(.)$ is the Gamma function, v is the shape (tail-thickenss) coefficient and $0 < v < \infty$. For $v = 2$, the distribution of z_t is standard normal distribution and when < 2 , z_t has heavy tails than the normal distribution while for $v > 2$, the probability density function of z_t has thinner tails than the normal distribution.Consequently, it is important to study the contribution of error distribution during the modelling of oil price volatility because applying the appropriate distribution of error in the volatility model enhances the efficiency of the process. However, the adequate volatility model is the one that sufficiently models heteroscadasticity in the error term and also captures the stylized facts of the return series such as fat tails and volatility clustering (Meade and Cooper, 2007).

3.12 Forecasting and Measuring the Performance of Forecasting Models

The final stage in time series analysis is forecasting, which is considered the main aim for building a model of the time series to make future predictions for a given series data. After fitting AR-GARCH models to actual data, then these models are used to forecast the future values. In particular, there are two kinds of forecasting; the first one is in-sample which is the expected value of the random variable give the estimates of the parameters, and the second kind is out- of-sample forecasting, which estimates the future values of a random variable that are not observed by the sample. According to Marzo and Zagaglia (2010), a good in-sample fit model provides no indication for the forecasting performance of a model out-of-sample. Therefore, Swanson et al. (2006) argue that we are expected to select a best model based on its forecasting performance rather than in sample fit. Therefore, this study evaluates the out-of-sample forecasting accuracies of the used models.

To compare the forecast accuracy and performance of the fitted models, there are different criteria some of very popular measures are adopted in this study and these are: root mean square error, mean absolute error, mean absolute percentage error and Theil inequality coefficient. The model with the lowest forecasting error measure is the best.

3.12.1 Root Mean Square Error

The root mean square error (RMSE) also known as the root mean square deviation (RMSD) is a common used measure of the difference among values forecasted predicted by a model and the values actually observed from the data that is being modelled. This measure depends on the scale of the dependent variable and used to compare forecasting ability for the same time series data across various models whose errors are measured in the same units. The RMSD is always non-negative, and a lower value of RMSD is better than a higher one and it is sensitive to outliers (Pontiuset el al., 2008; Willmott and Matsuura, 2006). The RMSE is defined as the square root of the mean squared error and given by

$$RMS = \sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}(\hat{r}_t - r_t)^2} \quad (3.52)$$

3.12.2 Mean Absolute Error

The mean absolute error (MAE) is another useful error statistic commonly used in forecasting evaluations. The MAE defines as the average of the absolute value of the residuals. The MAE depends on the scale of the dependent variable and it is very similar to the MSE but is less sensitive to large errors. Model with the smaller MAE is the better forecasting ability than others. The MAE is given by

$$MAE = \frac{1}{h}\sum_{t=T+1}^{T+h}|\hat{r}_t - r_t| \quad (3.53)$$

3.12.3 Mean Absolute Percentage Error

According to Sanders (1997) and Tayman and Swanson (1999), The mean absolute percentage error (MAPE) is the most common statistic to measure forecast errors and used in forecasting evaluations for both practitioners and academicians and it is the most used summary measure. The main advantage of the MAPE compared to the MSE such as that the finding can be interpreted as a percentage error (Makridakis, 1993). Moreover, several authors has described that the MAPE has some disadvantages. According to Armstrong and Collopy (1992), the key disadvantages of the MAPE statistic are that firstly, it is relevant only for ratio-scaled data. Secondly, the percentage error is division by zero when measured value is equal to zero. The MAPE equation is given by

$$MAPE = \frac{1}{h}\sum_{t=T+1}^{T+h}\left|\frac{(\hat{r}_t - r_t)}{\hat{r}_t}\right| * 100 \quad (3.54)$$

3.12.4 Thiel's Inequality Coefficient

Theil's coefficient of inequality is a measure of forecast accuracy less frequently cited in the literature (Theil, 1966; Morana, 2001), this statistic, also known as Thiel's U. The Theil-U metric can be given by:

$$U = \frac{\sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}(\hat{r}_t - r_t)^2}}{\sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}\hat{r}_t{}^2}\sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}r_t{}^2}} \quad (3.55)$$

Willmott and Matsuura (2005) indicate that MAE is the most appropriate measure for comparing accuracy across time series models. in contrast, Chai and Draxler (2014) state that the RMSE and MAE have been used as a standard statistical metric to measure model performance in different applications, but there is no consensus on the most best measure for model errors.

3.13 Summary

This chapter has provided the basic methodology of univariate time series analysis, starting with explaining some stylized facts on returns. Then the stationarity of the time series should be detected using the stationarity tests, the augmented Dickey-Fuller test and the Phillips-Perron test to check if the data are stationary in order to decide which the univariate time series model the research will use. For investigating a structural break in time series data, breakpoint unit root tests are presented under innovational outlier (IO) and additive outlier (AO) models. Moreover, Bai-Perron test and Chow's breakpoint tests are explained respectively to apply in the detection of structural changes in the mean and variance functions of time series data. The theoretical framework of the methodology is based on the univariate time series models such is the autoregressive (AR) process, the moving average (MA) process, the autoregressive moving average (ARMA) process, The autoregressive conditional heteroskedastic (ARCH) process, The generalized autoregressive conditional heteroskedastic (GARCH) process, The exponential GARCH process, the GJR-GARCH process, The asymmetric power ARCH (APARCH) process and The component GARCH process. Selected the best model for the time series is based on information Criteria that include Akaike information criterion (AIC), Schwarz information criterion and Hannan-Quinn information criterion (HQIC). Estimating the parameters of a model, also, checking and diagnostic the fitted model using different techniques. Finally, the chapter has shown the measurement of the predictive performance through root mean square error, mean absolute error, mean absolute percentage error and Thiel's inequality coefficient are dealt.

CHAPTER 4: Empirical Results of Modelling and Forecasting Crude Oil Price Returns for the Libyan, Nigerian and OPEC Markets

4.0 Introduction

This chapter identifies the details of the empirical findings obtained through analyzing time series data and applying the methodology of univariate time series analysis. The analysis seeks to address the Objectives 1 and 2 of the study. The first objective is to determine whether there exist structural breaks in the oil prices for the Libyan, Nigerian and OPEC markets. The second objective is identify the best conditional mean and variance models to perform statistical time-series analysis and forecasting of crude oil prices returns for the Libyan, Nigerian and OPEC oil markets under different error distributions. All the results are obtained using the statistical program EViews.

The starting stage for our analysis is characterization of the crude oil prices and their returns according to their graphical representation and descriptive statistics. Detecting stationarity using the correlogram, augmented Dickey-Fuller and Phillips-Perron unit root tests. To investigate structural changes in the oil prices, unit root tests with breakpoints to allow for structural breaks in the trend process are applied. Moreover, ARMA models are used for modelling the conditional mean of returns data. Then, investigating the existence of a structural changes in both mean and variance equations using Bai-Perron and Chow breakpoint tests. If the results of the heteroskedasticity test indicating that the ARCH effect presented in our data, then the conditional variance can be modeled using GARCH family models with different error distributions. Finally, the evaluation of out-of-sample forecasting accuracies for different ARMA-GARCH-class models that used based on four error functions is carried out.

4.1 Data Description and Sources

To analyse and model the returns of crude oil prices for the Libyan (LOP), Nigerian (NOP) and OPEC (OPEC) markets, the monthly spot prices (in US dollars per barrel) have been used in this chapter. Here, the OPEC Reference Basket for crude oil price is defined as a weighted average of prices for petroleum blends produced by OPEC members that include Libya and Nigeria. The OPEC oil prices are considered as a key benchmark for prices of crude oil. The data covers the period from January 2003 to April, 2018 for a total of 184 observations for the Libyan market and the period from January 1997 to April, 2018 for a total of 256 observations for the Nigerian and OPEC markets. It should be noted here that the available prices of Libyan market are available from 2003 and no older prices are available. The full samples have been divided into two parts as follows, the first part is data set in sample periods that are used for estimation purposes to identify the model, estimation of parameters and best model selection, while the out-of-sample part used for evaluation the performance of forecasting. However, the out-of-sample part covering the last 12 months for the three time series under study. The prices of crude oil for the three markets were obtained from the Monthly Oil Market Reports which is publicly available online from the official website of OPEC at https://www.opec.org/opec_web/en/21.htm

4.1.1 Justification of Monthly Data Selection

Due to the unavailability of daily data for domestic crude oil prices in both Libya and Nigeria, the study used the monthly domestic crude oil prices for the countries under study. Therefore, we are following several studies such as Chinn et al., 2005; Wang et al., 2005; Xie et al., 2006 that have used monthly prices of crude oil.

4.2 Graphical Representations of Variables

Figures 4-1 to 4-3 below illustrate the plots of the historical evolution of oil prices for Libya, Nigeria and OPEC in USD/Barrel for the full sample.

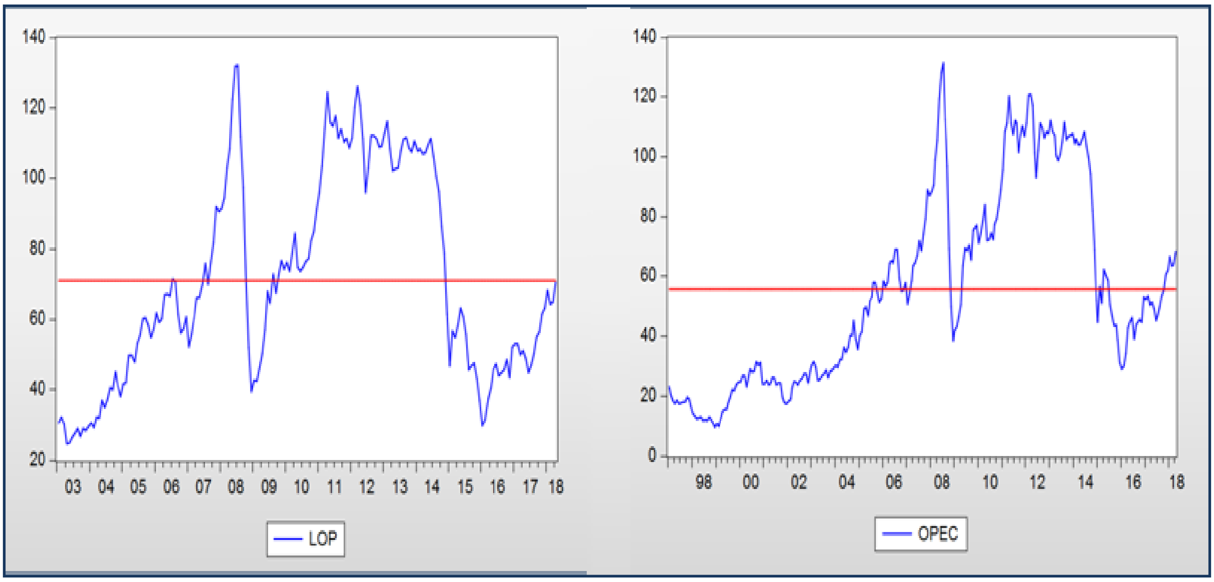


Figure 4-1: Time Series Plots of Monthly Libyan and OPEC Crude Oil Prices.

Figure 4-1 displays the historical behaviour of Libyan and OPEC crude oil prices. The Libyan crude oil prices covered the period from January 2003 to April 2018, while the OPEC prices covered the period from January 1997 to April 2018. However, from the visual inspection of oil prices data we can say that the OPEC prices decreased in 1997-1998 and reached to a low value of $9.96 in December 1998, due to the increase in oil production from Iraq, this also coincided with the Asian financial crises and these two issues led to the decline in demand. In September 2000 the prices of OPEC increased dramatically to $31.48. Generally, from 1999 till mid 2008, the price of Libyan oil and OPEC rose significantly. It was explained by the rising crude oil demand in countries such as China and India (Mouawad, 2007). In the mid of the financial crisis of 2007–2008, the prices of Libyan and OPEC crude oil underwent a significant increase and record peak in July 2008 to $132.14 and $131.22 in Libya and OPEC respectively. At the end of 2008 and the first quarter of 2009, oil prices declined abruptly to reach approximately $46 in both markets. Then, the prices of Libyan and OPEC crude oil quickly increased again in the end of 2009 until 2010 and again reached high levels above $100 in the years from 2011 to mid 2014. After that crude oil prices decreased significantly from the end of 2014 till the end of 2016, but at the beginning of 2017 until the beginning of 2018 the prices increased significantly and reaching almost $70.43 in Libya and $68.43 in OPEC from the end of 2017 till the beginning of 2018.

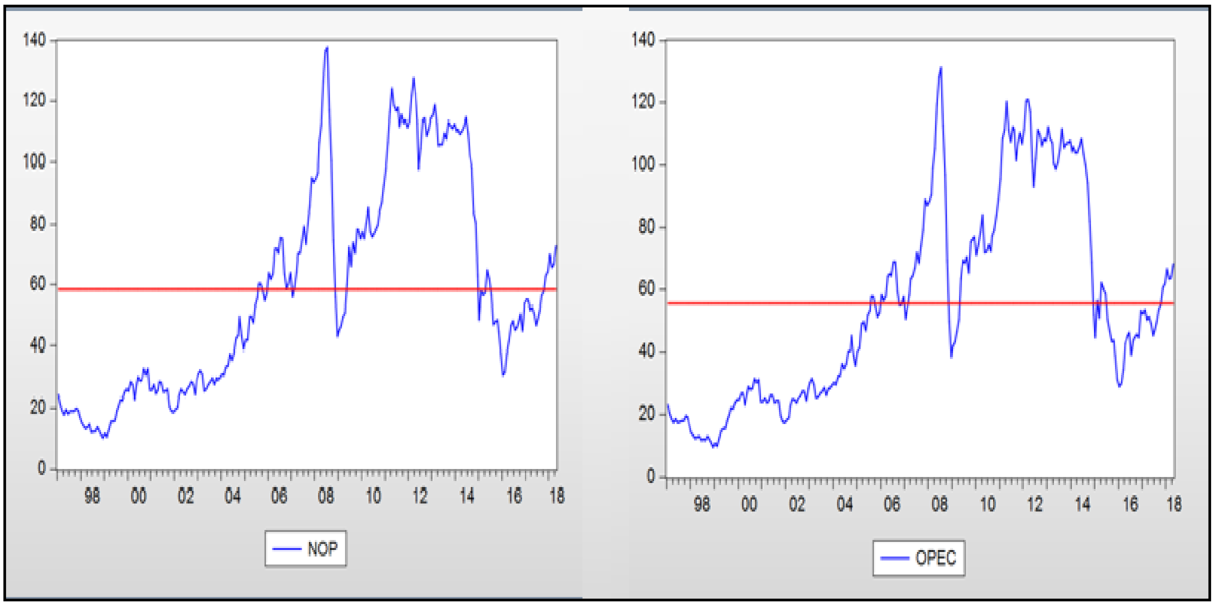


Figure 4-2: Time Series Plots of Monthly Nigerian and OPEC Crude Oil Prices.

Figure 4-2 shows the evolution of spot prices of Nigerian crude oil and OPEC which are covering the same period from January 1997 to April 2018. However, the prices of Nigerian and OPEC oil markets have an almost similar historical development. The prices are declined in 1997-1998 and they were ranging between $24-9 interestingly, both crude oil prices move in tandem until 2010 with a slight difference in the value of prices. In 2007-2008 Nigerian oil prices within a year increased from $56 to $137 also the OPEC prices increased from $50 to $131, but then dropped sharply till $43 and $38 in December 2008. At recent years prices of both Nigerian crude oil and OPEC were extremely volatile ranging between $30-113.

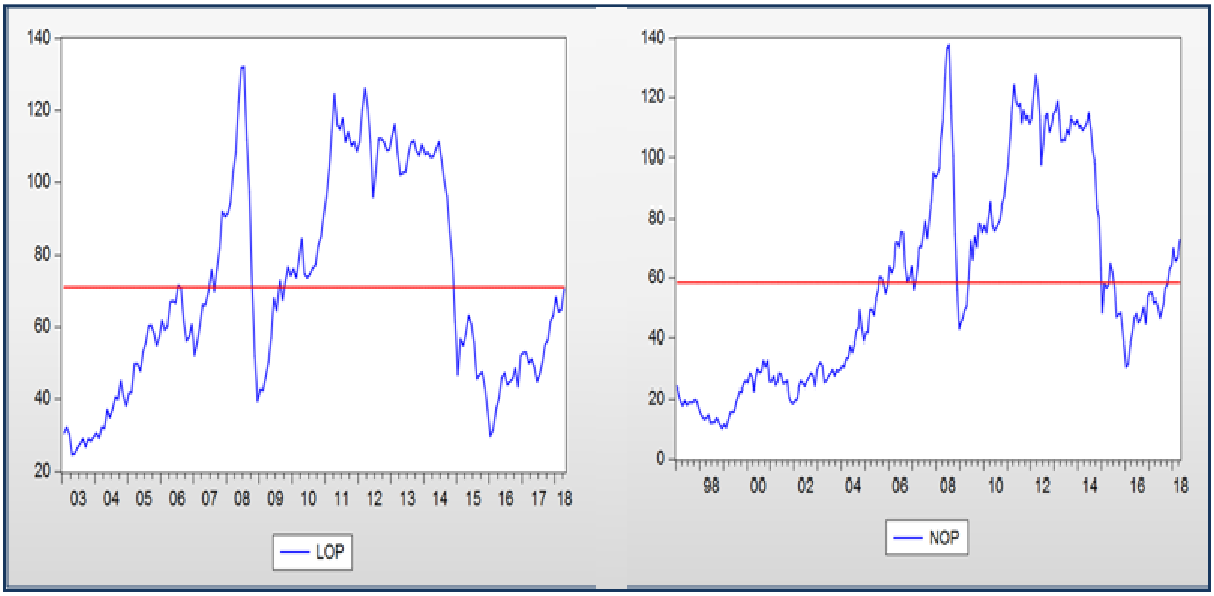


Figure 4-3: Time Series Plots of Monthly Libyan and Nigerian Crude Oil Prices.

Figure 4-3 illustrates the historical changes of Libyan and Nigerian crude oil prices. The prices of Libyan crude oil covered the period from January 2003 to April 2018, whilst the prices of Nigerian oil covered the period from January 1997 to April 2018. However, from the figure 4-3 we can say that the Nigerian oil prices declined in 1997-1998 and reached to a low level of $9 in December 1998. In September 2000, Nigerian oil prices increased dramatically to $32. In general, from 1999 till mid 2008, the prices of Libyan and Nigerian markets rose significantly. In the mid of the financial crisis of 2007–2008, the prices of Libyan and Nigerian crude oil underwent a significant increase and record peak in July 2008 to $132.14 and $137.64 in Libya and Nigeria respectively. At the end of 2008 and the first quarter of 2009, prices declined suddenly to reach almost $40 in both countries. Then, the prices quickly increased again in the end of 2009 until 2010 and again reached high levels above $100 in the years from 2011 to mid 2014. After that oil prices decreased significantly from the end of 2014 till the end of 2016, but at the beginning of 2017 until the beginning of 2018 the prices increased and reached almost $70.43 in Libya and $72.75 in Nigeria from the end of 2017 till the beginning of 2018.

However, according to Wei et al. (2010) and Kang et al. (2013) the prices of spot crude oil are heavily influenced by economic and geopolitical events that may cause price fluctuations in some periods. Consequently, here is a summary of some of these events which have a clear impact on oil prices for the samples of the study;

a) The marked decline in 1997-1998 due to the slowdown in Asian economic growth (Asian financial crisis).
b) The Organization of the Petroleum Exporting Countries (OPEC) reduced crude production by 4.2 million barrels per day between 2000 and 2001, leading to higher crude oil prices.
c) The uncertainty related with the September 11, 2001, and subsequent US military action in Iraq, beginning in March 2003, led to a reversal of oil prices.
d) During 2007-2009 the global financial crisis extremely influenced the world economy.
e) The Libyan revolution and the resulting closure of the Libyan oil fields and the cessation of production contribute in some way to the rise in oil prices between 2012 and 2015.

In fact, the graphs above give a clear picture that LOP, NOP and OPEC are close and that the difference between prices was slight also the historical evolution of these time series is very similar. Consequently, LOP, NOP and OPEC data show increasing and decreasing fluctuations at different periods. The visual inspection of the series reveals the following features; firstly, the presence of trends in the series is apparent suggesting non-constant means over time also there is a possibility of stochastic trends to be present in the oil price series. Secondly, we can observe changes in the variation of the price series around its central values, which means that the series could be non-stationary in their statistical properties. Thirdly, seasonal variations are not visible in all these time series. These features in all prices series are consistent with the results of the regression analysis using EViews. Here, simple regression with a time trend and seasonal factors was estimated. The results of the simple regression showed that the trend time coefficient was statistically significant. While the coefficients of seasonal factors were statistically insignificant, this means that all prices series have trend, but do not display seasonal patterns.

In this study, the first logarithmic price differences are taken in order to change the original price time series (op) to stationary series (price returns) in both mean and variance. Therefore, we have now price returns which is following $r_t = \Delta ln(op) = ln(p_t) - ln(p_{t-1})$

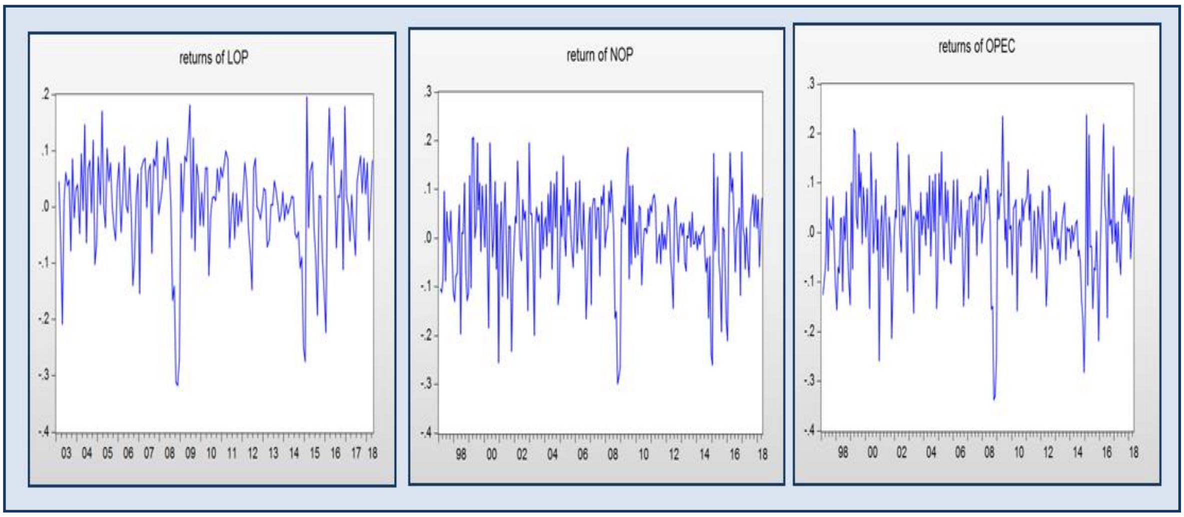


Figure 4-4: A Combined Graph for Monthly Returns of LOP, NOP and OPEC.

A combined figure 4-4 shows the plots of LOP, NOP and OPEC after taking the first difference of the logarithmic prices suggest that the return series seem to be stationary over time. In addition, returns series appear to have no obvious patterns such as trend or seasonality in the data which are consistent with the results of the regression analysis using EViews. Here, the simple regression with the time trend and seasonal factors indicating that the coefficients of both the time trend and seasonal factors are statistically insignificant. These results suggesting that all returns series do not exhibit trend and seasonal pattern.

All returns series are fluctuating to very around their mean levels, which are close to zero; also the variability period around 2008 appears to be much higher than any other period. This could be attributed to the fact that the global financial crisis extremely influenced the world. In general, volatility clustering phenomenon can also showed in the plots. This means that periods of large movements are followed by large movements and small movements are followed by small movements (Mandelbrot, 1963).

4.3 Descriptive Statistics

In this section, descriptive statistics are calculated for both the prices and return series and discussed. Table 4-1 provides the descriptive statistics for the monthly LOP, NOP, OPEC and their returns over the full sample.

Table 4-1: Descriptive Statistics of LOP, NOP, OPEC and Their Returns.

Statistics	Oil price market					
	LOP		NOP		OPEC	
	p_t	r_t	p_t	r_t	p_t	r_t
Mean	71.0036	0.0045	58.5010	0.0043	55.5821	0.0042
Std. Dev.	29.0968	0.0892	34.3393	0.0924	32.6733	0.0923
Skewness	0.3200	-1.0285	0.4815	-0.6493	0.5100	-0.6160
Kurtosis	1.8613	4.8439	2.0163	3.8221	2.0431	4.3308
Jarque-Bera	13.0802***	58.1954***	20.2151***	25.1017***	20.8654***	34.9494***
p-value	0.0014	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	184	183	256	255	256	255

*** Indicates rejection at 1% significance level.

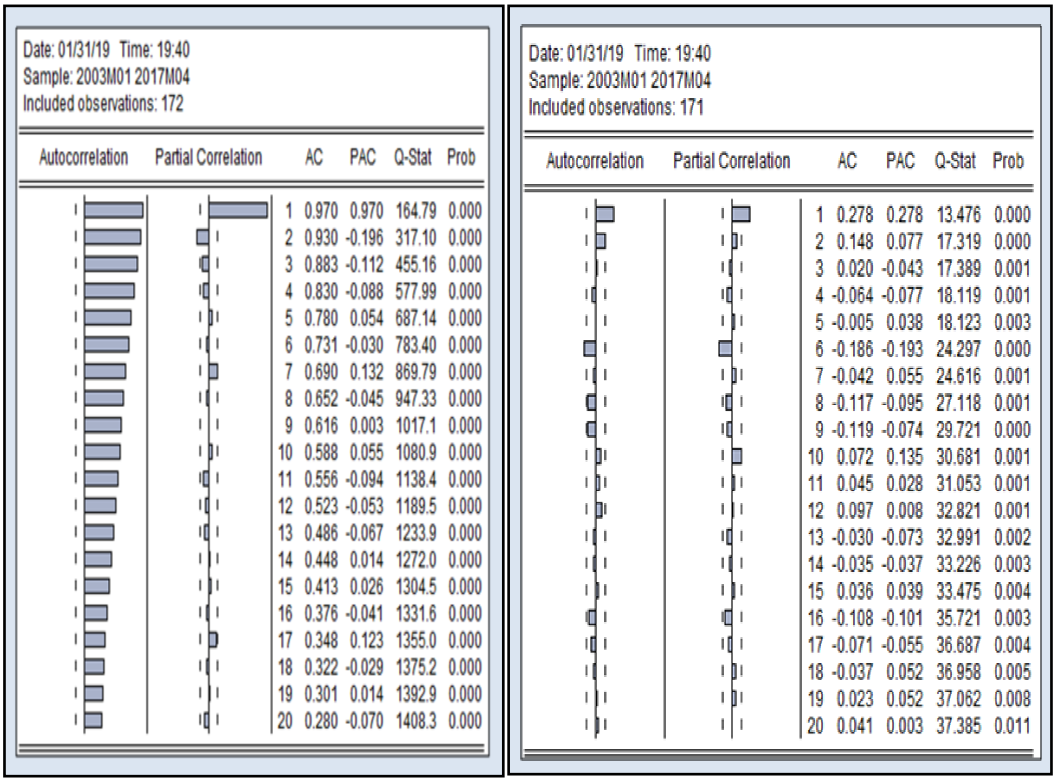
From Table 4-1 we can say, the LOP, NOP and OPEC returns exhibit similar statistical characteristics. The sample means of the three returns series are all positive and very close to zero. In comparison to the standard deviation the sample means are quite small for the three returns.

Regarding the empirical distribution of prices in the Libyan, Nigerian and OPEC markets reveal evidence of positive skewness implying that the right tail is particularly extreme. In relation to kurtosis, the distributions of crude oil prices with negative excess kurtosis are platyokurtic for the three markets indicating short ails than normal. Similarly, the Jarque-Bera statistics show evidence of non-normality for all the three markets. The values of the skewness are negative suggesting that there is non-symmetry of the empirical distributions of the three returns. All returns series are leptokurtic, since all the estimated values of kurtosis exceed 3 which is the kurtosis value for normal distribution. More specifically, the unconditional distributions of all returns series are peaked with fat tails.

The thee returns series have rejected the null hypothesis of normality of the Bera-Jarque test at the 1% significance level, therefore, the alternative non-normal distributions such Student-*t* and the generalized error distribution (GE) maybe are appropriate in this situation (see for example, Wilhelmsson, 2006).

4.4 Detecting Stationarity

The behavior of ACFs and PACFs in the correlogram up to 20th order (see graphs 4-5 and A1 to A2 in appendix A) of oil prices in logarithmic level and their returns series suggests that all the prices series decay extremely slowly. This means that all the prices series are non-stationary. Moreover, the *p*-values which are associated with the Ljung-Box statistic are close to zero indicating that the null hypothesis (i.e., that there is no serial autocorrelation in the data) is rejected and all prices series have a strong serial dependence and are considered non-stationary. While the behavior of sample ACFs and the sample PACFs plots of returns series die down fairly quickly after lag 2 while the PACFs die down fairly quickly after lag 1 and this pattern suggests that three returns under study are stationary.



Date: 01/31/19 Time: 19:40
Sample: 2003M01 2017M04
Included observations: 172

	AC	PAC	Q-Stat	Prob
1	0.970	0.970	164.79	0.000
2	0.930	-0.196	317.10	0.000
3	0.883	-0.112	455.16	0.000
4	0.830	-0.088	577.99	0.000
5	0.780	0.054	687.14	0.000
6	0.731	-0.030	783.40	0.000
7	0.690	0.132	869.79	0.000
8	0.652	-0.045	947.33	0.000
9	0.616	0.003	1017.1	0.000
10	0.588	0.055	1080.9	0.000
11	0.556	-0.094	1138.4	0.000
12	0.523	-0.053	1189.5	0.000
13	0.486	-0.067	1233.9	0.000
14	0.448	0.014	1272.0	0.000
15	0.413	0.026	1304.5	0.000
16	0.376	-0.041	1331.6	0.000
17	0.348	0.123	1355.0	0.000
18	0.322	-0.029	1375.2	0.000
19	0.301	0.014	1392.9	0.000
20	0.280	-0.070	1408.3	0.000

Date: 01/31/19 Time: 19:40
Sample: 2003M01 2017M04
Included observations: 171

	AC	PAC	Q-Stat	Prob
1	0.278	0.278	13.476	0.000
2	0.148	0.077	17.319	0.000
3	0.020	-0.043	17.389	0.001
4	-0.064	-0.077	18.119	0.001
5	-0.005	0.038	18.123	0.003
6	-0.186	-0.193	24.297	0.000
7	-0.042	0.055	24.616	0.001
8	-0.117	-0.095	27.118	0.001
9	-0.119	-0.074	29.721	0.000
10	0.072	0.135	30.681	0.001
11	0.045	0.028	31.053	0.001
12	0.097	0.008	32.821	0.001
13	-0.030	-0.073	32.991	0.002
14	-0.035	-0.037	33.226	0.003
15	0.036	0.039	33.475	0.004
16	-0.108	-0.101	35.721	0.003
17	-0.071	-0.055	36.687	0.004
18	-0.037	0.052	36.958	0.005
19	0.023	0.052	37.062	0.008
20	0.041	0.003	37.385	0.011

Figure 4-5: plots of Correlogram of ACFs and PACFs for Monthly prices of LOP in logarithm level and its Returns in Sample.

4.4.1 Standard Unit Root Tests

However, to confirm the stationary in these series, some unit root tests have been applied for both oil prices in logarithm level and their returns for the three crude oil markets. Table 4-2 below provides the results of unit-root tests using both ADF and PP statistics tests for testing the null hypothesis that the series data has a unit root. These unit root tests including intercept and trend, non-intercept and trend, intercept only and the optimal lag length are chosen using the SIC with maximum lag 13.

Table 4-2: Results of Unit Root Tests Without Breakpoints In-Sample for LOP, NOP and OPEC and Their Returns Series.

Variable	Augmented Dickey Fuller Test								
	ADF (None)			ADF (intercept)			ADF (intercept and liner trend)		
	t-Stat	Test critical value 5% level	*Prob.	t-Stat	Test critical value 5% level	*Prob.	t-Stat	Test critical value 5% level	*Prob.
LLOP	0.0657	-1.9427	0.702	-2.0886	-2.8784	0.249	-1.8130	-3.4365	0.694
$r_t$of LOP	-9.77***	-1.9427	0.000	-9.744***	-2.8784	0.000	-9.80***	-3.4365	0.000
LNOP	0.2485	-1.9421	0.758	-1.5524	-2.8733	0.505	-1.6265	-3.4285	0.779
r_t of NOP	-12.9***	-1.9421	0.000	-12.93***	-2.8733	0.000	-12.9***	-3.4285	0.000
LOPEC	0.2167	-1.9421	0.748	-1.6577	-2.8733	0.452	-1.8407	-3.4285	0.683
r_t of OPEC	-12.0***	-1.9421	0.000	-12.02***	-2.8733	0.000	-12.1***	-3.4285	0.000
Variable	Philips-Peron Test								
	PP (None)			PP(intercept)			PP(intercept and liner trend))		
	t-Stat	Test critical value 5% level	*Prob.	t-Stat	Test critical value 5% level	*Prob.	t-Stat	Test critical value 5% level	*Prob.
LLOP	0.1205	-1.9426	0.719	-2.0508	-2.8783	0.265	-1.7103	-3.4363	0.743
$r_t$of LOP	-9.85***	-1.9427	0.000	-9.827***	-2.8784	0.000	-9.8***	-3.4365	0.000
LNOP	0.1982	-1.9421	0.743	-1.4561	-2.8732	0.554	-1.6338	-3.4284	0.777
r_t of NOP	-12.9***	-1.9421	0.000	-12.92***	-2.8733	0.000	-12.9***	-3.4285	0.000
LOPEC	0.1770	-1.9421	0.737	-1.4954	-2.8732	0.534	-1.7743	-3.4284	0.714
r_t of OPEC	-11.9***	-1.9421	0.000	-11.99***	-2.8733	0.000	-11.9***	-3.4285	0.000

Null Hypothesis: data has a unit root and *MacKinnon (1996) one-sided p-values.** indicates rejection at the 1% significant level.

In order to determine whether there exists a unit root in the oil prices and their returns series we compare the calculated *t*-statistics and the critical values in Table 4-2. Therefore, the results of unit root tests of LOP, NOP and OPEC in level show that the ADF and PP test statistics are smaller in absolute terms than the critical value at the 5% suggesting that the null hypothesis is accepted and the three series of prices have unit roots or are non-stationary I(1). On the other hand, the results of unit root tests of LOP, NOP and OPEC returns show that the ADF and PP test statistics are higher in absolute terms than the critical value at the 5%, indicating that the three return series are stationary and the null hypothesis I(1) are rejected. All returns series are therefore stationary I(0) and may be modeled directly without future transformation.

Here we can summarize the following: the results obtained from the examination of the correlogram of ACFs and PACFs and the study of autocorrelation and partial autocorrelation coefficients between oil prices data and their lagged values agree with the results of the unit root tests for all the individual oil price data which are I(1), while after taking the first logarithmic price differences all the series became stationary or I(0). Additionally, the order of integration I(1) is the same for LOP, NOP and OPEC markets.

4.4.2 Unit Root Tests with a Breakpoint

To examine the stationarity of logarithmic oil prices and their returns we also perform the unit root test with breakpoints for two break specifications, innovational outlier and additive outlier based on different assumptions for the trend and break specifications which include non-trending data with intercept break and trending data with intercept break, intercept and trend break and with trend break. the optimal lag length are chosen automatic based on SICs with maximum lag 13 and the break date is unknown and estimated from the data and selected by minimizing the Dickey-Fuller t-statistic. The results of unit root tests with a breakpoint for the Libyan, Nigerian and OPEC oil prices and their returns are reported in Tables 4-3 to 4-5.

Based on the results of simple regression analysis obtained from EViews which indicating that all the prices series in logarithm level are trending data because coefficients of both intercept and time trend are statistically significant. Therefore, all the prices in logarithm level treat as trending data when applying unit root tests with breakpoints. In contrast, all returns series treat as non-trending because the result of simple regression suggesting that only the coefficient of intercept is statistically significant.

Table 4-3: Results of Unit Root Tests with Breakpoints In-Sample for LOP and Their Returns Series.

			Variable							
			LLOP			Returns of LOP			Test critical values	
Break type	Trend specification	Break specification	Break date	ADF t-Stat	*Prob	Break date	ADF t-Stat	*Prob	1%	5%
Innovation outlier	Intercept	Intercept	04/2004	-2.6204	0.862	10/2008	-10.3779	<0.01	-4.9491	-4.4436
	Trend and Intercept	Intercept	09/2014	-3.9419	0.408	-	-	-	-5.3476	-4.8598
		Trend and Intercept	11/2010	-3.5014	0.812	-	-	-	-5.7191	-5.1757
		Trend	03/2012	-3.4584	0.429	-	-	-	-5.0674	-4.5248
Additive outlier	Intercept	Intercept	11/2014	-2.9427	0.717	10/2008	-10.4397	<0.01	-4.9491	-4.4436
	Trend and Intercept	Intercept	8/2014	-3.9652	0.394	-	-	-	-5.3476	-4.8598
		Trend and Intercept	11/2014	-3.5942	0.769	-	-	-	-5.7191	-5.1757
		Trend	08/2012	-3.3936	0.358	-	-	-	-5.0674	-4.5248

Null Hypothesis: data has a unit root and lag length selected automatic based on Schwarz information criterion with max=13 and *Vogelsang (1993) asymptotic one-side p-values.

Table 4-3 describes the test that was performed for the Libyan oil prices market and its returns. The first, second and third columns report the break type and the trend and break specification. The other columns display the selected break date, the Augmented Dickey-Fuller *t*-statistic for the unit root test, along with Vogelsang's asymptotic *p*-values and test critical values for the 1% and 5% significance levels.

In this test, for oil prices under the assumption of innovation outlier and additive outliers breaks, for non-trending data with intercept break the selected break dates in these cases are 4/2004 and 11/2014 respectively. The augmented Dickey-Fuller *t*-statistics for the unit root tests are -2.6204 and -2.9427 with the corresponding *p*-value of 0.862 and 0.717 indicate we cannot reject the null hypothesis that the logarithmic Libyan prices has a unit root. On the other hand, under the assumption of innovation outlier and additive outliers breaks, for trending data with intercept, trend and intercept and trend break the selected break dates in this cases are different. The corresponding *p*-value of the augmented Dickey-Fuller *t*-statistics for the unit root tests indicates we cannot reject the null hypothesis that the logarithmic Libyan price has a unit root at the significance levels.

For the returns data of Libyan oil prices which is considered non-trending data we focused only on results under the assumption of innovation outlier and additive outliers breaks, for non-trending data with intercept break. In these cases, the selected break date is the same which is 10/2008. The augmented Dickey-Fuller *t*-statistics for the unit root tests are -10.37 and -10.43 with the corresponding *p*-value of less than 0.01, leading us to reject the null hypothesis of a unit root at the 1% significant level.

Table 4-4: Results of Unit Root Tests with Breakpoints In-Sample for NOP and Their Returns Series.

			Variable							
			LNOP			**Returns of NOP**			**Test critical values**	
Break type	Trend specification	Break specification	Break date	ADF t-Stat	*Pro	Break date	ADF t-Stat	*Pro	1%	5%
Innovation outlier	Intercept	Intercept	02/1999	-3.0175	0.676	10/2008	-13.4254	<0.01	-4.9491	-4.4436
	Trend and Intercept	Intercept	07/2014	-4.3047	0.206	-	-	-	-5.3476	-4.8598
		Trend and Intercept	11/2010	-4.0483	0.489	-	-	-	-5.7191	-5.1757
		Trend	02/2012	-4.0425	0.158	-	-	-	-5.0674	-4.5248
Additive outlier	Intercept	Intercept	02/1998	-2.9438	0.716	10/2008	-13.4789	<0.01	-4.9491	-4.4436
	Trend and Intercept	Intercept	05/2014	-4.2327	0.241	-	-	-	-5.3476	-4.8598
		Trend and Intercept	05/2012	-3.9878	0.529	-	-	-	-5.7191	-5.1757
		Trend	07/2012	-3.9219	0.141	-	-	-	-5.0674	-4.5248

Null Hypothesis: data has a unit root and lag length selected automatic based on Schwarz information criterion with max=13 and *Vogelsang (1993) asymptotic one-side p-values.

Table 4-4 reports the results of unit root test with a breakpoint for the Nigerian oil prices market and its returns. Under the assumption of innovation outlier and additive outliers breaks, for non-trending data with intercept break the selected break dates in these cases are 2/1999 and 2/1998 respectively. The Augmented Dickey-Fuller *t*-statistics for the unit root tests are - 4.30 and -2.94 with the corresponding *p*-values of 0.676 and 0.716 indicate that we cannot reject the null hypothesis that the logarithmic Nigerian price has a unit root.

Moreover, under the assumption of innovation outlier and additive outliers breaks, for trending data with intercept, trend and intercept and trend break the selected break dates in this cases are different. The corresponding *p*-values of the augmented Dickey-Fuller *t*-

statistics for the unit root tests indicate we cannot reject the null hypothesis that the logarithmic Nigerian price has a unit root at the significance levels. For the returns series of Nigerian oil prices which is considered non-trending data we focused only on results under the assumption of innovation outlier and additive outliers breaks, for non-trending data with intercept break. In these cases, the selected break date is the same which is 10/2008. The augmented Dickey-Fuller *t*-statistics for the unit root tests are -13.42 and -13.47 with the corresponding *p*-value of less than 0.01, leading us to reject the null hypothesis of a unit root at the 1% significance level.

Table 4-5: Results of Unit Root Tests with Breakpoints In-Sample for OPEC and Their Returns Series.

			Variable							
			LOPEC			**Returns of LOPEC**			**Test critical values**	
Break type	Trend specification	Break specification	Break date	ADF t-Stat	*Pro	Break date	ADF t-Stat	*Pro	1%	5%
Innovation outlier	Intercept	Intercept	2/1999	-3.0054	0.682	10/2008	-12.6024	<0.01	-4.9491	-4.4436
	Trend and Intercept	Intercept	08/2014	-4.6143	0.98	-	-	-	-5.3476	-4.8598
		Trend and Intercept	08/2010	-4.2932	0.341	-	-	-	-5.7191	-5.1757
		Trend	02/2012	-4.2813	0.095	-	-	-	-5.0674	-4.5248
Additive outlier	Intercept	Intercept	08/2003	-2.9954	0.689	10/2008	-12.6517	<0.01	-4.9491	-4.4436
	Trend and Intercept	Intercept	07/2014	-4.6356	0.092	-	-	-	-5.3476	-4.8598
		Trend and Intercept	07/2010	-4.0709	0.353	-	-	-	-5.7191	-5.1757
		Trend	07/2012	-4.1806	0.081	-	-	-	-5.0674	-4.5248

Null Hypothesis: data has a unit root and lag length selected automatic based on Schwarz information criterion with max=13 and
*Vogelsang (1993) asymptotic one-side p-values.

Table 4-5 displays the results of unit root test with a breakpoint for OPEC market and its returns. Under the assumption of innovation outlier and additive outliers breaks, for non-trending data with intercept break the selected break dates in these cases are 2/1999 and 8/2003 respectively. The augmented Dickey-Fuller *t*-statistics for the unit root tests are -3.00 and -2.99 with the corresponding *p*-value of 0.682 indicates we cannot reject the hypothesis that the logarithmic OPEC prices have a unit root. Moreover, under the assumption of innovation outlier and additive outlier breaks, for trending data with intercept, trend and intercept the selected break dates in this cases are different. The corresponding *p*-values of the augmented Dickey-Fuller *t*-statistics for the unit root tests indicate that we cannot reject the null hypothesis that the logarithmic of OPEC has a unit root. While we reject the null hypothesis of a unit root at the 10 % significance level for trending data with trend break under assumption of innovation outlier specification and when including an intercept and trend breaks for additive outlier assumption.

For the returns series of OPEC oil prices which is considered non-trending data we focused only on results under the assumption of innovation outlier and additive outliers breaks, for non-trending data with intercept break. In these cases, the selected break date is the same which is 10/2008. The augmented Dickey-Fuller *t*-statistics for the unit root tests is around -12.6 with the corresponding *p*-value of less than 0.01, leading us to reject the null hypothesis of a unit root at the 1% significance level.

In fact, the results obtained from unit root tests and the modified Dickey-Fuller tests with breakpoints under various specifications for the break to test the null hypothesis of the presence of a unit root for our time series (in log-levels and their returns) suggesting that the log-levels of oil prices under study reported unit root, in contrast the tests rejected the null hypothesis of the unit root when we examined the returns and all the returns are stationary. The only exception is NOP which is also stationary in log-level at the 10 % significance level when including intercept and trend breaks.

4.5 Modeling the Mean Equations of Returns Series

This section outlines modelling of oil price returns in the Libyan, Nigerian and OPEC markets after taking account of stationarity and structural break in trend. Knowing that the prices of crude oil in the logarithm level have non-stationarity property, in this step, we fit a statistics model to the returns. Thus, in this study, the most famous and flexible model, i.e., ARMA was applied to identify the mean equations of returns series.

- **Selection of ARMA Model Based on the Information Criteria**

In this subsection, various ARMA models with different specifications where $p \leq 2$ and $q \leq 2$ are estimated using least squares method, in order to select a suitable ARMA model to fit each of our returns series as the mean equation. The choices of these orders of AR and MA terms are depending on the visual inspection of ACFs and PACFs plots in figure 4-5 (see figures A1 to A2 in appendix A) for the three returns series. However, the ACFs plots appear significant spikes at lags 1 and 2 and tails cuts off after lag 1 for returns of NOP while it cuts off after lag 2 for returns of LOP and OPEC, which is indicating that the MA terms are probably with q =1 or 2. On the other hand the PACFs plots have a spike at lag 1 and it cuts off after lag 1 for the three returns series which are indicatting that the possible AR terms with p=1. Therfore, the mixed ARMA models may be appropriate to describe the linear relationship of these series.

Table 4-6 shows the results of comparison between ARMA models for the three returns series. Therefore, the best ARMA model is selected based on the three information criteria AIC, SIC and HQIC. The selected ARMA model with minimum value of information criteria is ARMA(1,0) - i.e. an AR(1) for all returns of prices under study. Although the AIC suggests ARMA(0,2) for LOP. Depending on the minimum value of SIC the smaller ARMA(1,0) - i.e. an AR(1) has been chosen as the appropriate model for Libyan, Nigerian and OPEC oil price markets.

Table 4-6: Information Criteria Comparison for ARMA Models of Returns Series.

ARMA *p/q*	**Returns of LOP**			**Returns of NOP**			**Returns of OPEC**		
	Information criteria								
	AIC	**SIC**	**HQIC**	**AIC**	**SIC**	**HQIC**	**AIC**	**SIC**	**HQIC**
(0,0)	-1.9529	-1.9346	-1.9455	-1.8918	-1.8774	-1.8860	-1.8936	-1.8792	-1.8878
(1,0)	-2.0172	-1.9803	-2.0022	-1.9187	-1.8899	-1.9071	-1.9549	-1.9261	-1.9433
(0,1)	-2.0073	-1.9705	-1.9924	-1.9158	-1.8871	-1.9042	-1.9393	-1.9106	-1.9278
(1,1)	-2.0089	-1.9535	-1.9864	-1.9137	-1.8705	-1.8963	-1.9512	-1.9079	-1.9338
(2,0)	-2.0093	-1.9538	-1.9868	-1.9110	-1.8676	-1.8935	-1.9500	-1.9067	-1.9326
(0,2)	-2.0192	-1.9640	-1.9968	-1.9086	-1.8654	-1.8912	-1.9541	-1.9109	-1.9367
(1,2)	-2.0075	-1.9337	-1.9776	-1.9066	-1.8489	-1.8833	-1.9463	-1.8887	-1.9231
(2,1)	-2.0028	-1.9287	-1.9727	-1.9039	-1.8460	-1.8806	-1.9633	-1.9055	-1.9400
(2,2)	-2.0146	-1.9220	-1.9770	-1.8956	-1.8233	-1.8665	-1.9385	-1.8662	-1.9094

4.5.1 Estimation of AR(1) Model Parameters for Mean Equations

The least squares method is used to estimate parameters of ARMA models. Table 4-7 shows the coefficients estimated of AR(1) models for returns of LOP, NOP and OPEC and the values of t-statistics, which are used to test the following hypotheses

$$H_0: \varphi_i = 0 \; against \;\; H_1: \varphi_i \neq 0,$$

where φ_i is any a particular coefficient in the ARMA model. In addition, the table contains the *p*-values in square brackets which are used directly to test the hypothesis. The null hypothesis will be rejected when the *p*-value is less than the significant levels 0.01 or 0.05.

Table 4-7: Estimation Results for ARMA(1,0) Models Using Returns Series.

Model Parameter	Returns of LOP	Returns of NOP	Returns of OPEC
Const (φ_0)	0.0027 [0.775]	0.0038 [0.599]	0.004 [0.608]
AR(1) (ϕ_1)	0.2783*** [0.000]	0.1818*** [0.004]	0.2519*** [0.000]
Diagnostic tests			
Q(20)	25.447 [0.146]	19.633 [0.417]	21.748 [0.297]
$Q^2(20)$	60.268***[0.000]	40.023***[0.003]	34.692**[0.015]
JB	6.3726**[0.041]	8.4516**[0.015]	7.8834**[0.019]
ARCH(1)			
F-statistic	36.0297***[0.000]	16.4234***[0.000]	11.0868***[0.001]
nR^2	29.9908***[0.000]	15.4960***[0.000]	10.6839***[0.001]
ARCH(5)			
F-statistic	11.6435***[0.000]	3.5690***[0.004]	3.4493***[0.005]
nR^2	44.2225***[0.000]	16.9956***[0.004]	16.4652***[0.005]
ARCH(10)			
F-statistic	5.5599***[0.000]	3.1567***[0.001]	2.6994***[0.004]
nR^2	43.4799***[0.000]	28.9962***[0.001]	25.2528***[0.005]

Notes: the number in square brackets are p-values of the statistics and Q(20) and $Q^2(20)$ are is the Ljung-Box statistic of order 20 computed on the residuals and squared residuals. *** and ** indicate rejection at the 1% and 5% significant level respectively.

From Table 4-7 the results of parameters estimation indicate that all the parameter of AR(1) model for LOP, NOP and OPEC are statistically significant at the 1% significant level, while the constant or intercept φ_0 is not significantly different from zero in AR(1) model for all returns series.

4.5.2 Diagnostic Checking for the Residuals of Mean Equations

In this stage, after selecting the best ARMA models for the oil price returns and estimating their parameters, different diagnostic tests are used to examine their adequacy. First, the best Box-Jenkins models must satisfy the stationary condition which is that the absolute values of all the characteristic roots of the model are less than 1. Secondly, we should test for autocorrelation, normality and heteroskedasticity of the errors terms. The results of these tests are summarised in Table 4-7 above. The results of the diagnostic tests in the Table 4-7 can be summarised and explained in the following points below

- **Stability of the ARMA models**

  The estimated AR(1) models for LOP, NOP and OPEC are stable and all the characteristic roots of the model are less than 1 and lie inside the unit circle. Based on this it can be said that all selected AR(1) models satisfy the stability condition.

- **Testing for Uncorrelated Errors**

  From the coreelogram for the ACFs and PACFs of the residuls of all AR(1) for LOP returns series up to 20^{th} in figure 4-6 (see a figure A3 in appendix A for NOP and OPEC). It is clear that all the spikes are within two standard errors limts and the *p*-values of Ljung-Box Q(20)-statistics are greater than the significant level 1%, meaning that all the autocorrelation coefficients are insignificant. That is, the residual series can be assumed to be white noise. On the other hand, the correlogram for the ACFs and PACFs of the squared residuls of all AR(1) for LOP (see a figure 4-7), NOP and OPEC (see a figure A4 in appendix A) returns series up to 20^{th} order presents significant spikes at different lags and and the *p*-values of Ljung-Box Q(20)-statistics are less than the significant level 1% which mean strong evidence that the squared of residuals are not independent which confirm the precense of ARCH effect (conditional heteroskedasticity) in the residuals.

Date: 02/01/19 Time: 13:35
Sample: 2003M03 2017M04
Included observations: 170
Q-statistic probabilities adjusted for 1 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	-0.019	-0.019	0.0620	
2	0.089	0.089	1.4475	0.229
3	-0.004	-0.001	1.4506	0.484
4	-0.082	-0.090	2.6245	0.453
5	0.070	0.069	3.5003	0.478
6	-0.205	-0.191	10.962	0.052
7	0.046	0.031	11.335	0.079
8	-0.092	-0.067	12.858	0.076
9	-0.124	-0.130	15.670	0.047
10	0.106	0.092	17.708	0.039
11	0.000	0.051	17.708	0.060
12	0.112	0.042	20.024	0.045
13	-0.057	-0.054	20.636	0.056
14	-0.042	-0.062	20.959	0.074
15	0.081	0.048	22.212	0.074
16	-0.114	-0.069	24.668	0.055
17	-0.042	-0.095	25.007	0.070
18	-0.032	0.013	25.200	0.090
19	0.027	0.056	25.343	0.116
20	0.023	0.003	25.447	0.146

Figure 4-6: A Graph of the Correlogram for Examining the ACF, PACF and the Ljung-Box Test on the Residuals of AR(1) for Returns of LOP Market.

Date: 02/01/19 Time: 13:49
Sample: 2003M03 2017M04
Included observations: 170
Q-statistic probabilities adjusted for 1 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	0.421	0.421	30.649	
2	0.315	0.167	47.897	0.000
3	0.034	-0.184	48.098	0.000
4	-0.031	-0.051	48.264	0.000
5	0.035	0.144	48.481	0.000
6	0.014	-0.017	48.514	0.000
7	0.060	0.003	49.155	0.000
8	0.030	0.009	49.318	0.000
9	0.020	0.001	49.389	0.000
10	0.047	0.048	49.794	0.000
11	0.101	0.099	51.675	0.000
12	0.031	-0.087	51.848	0.000
13	0.061	0.031	52.546	0.000
14	-0.048	-0.056	52.980	0.000
15	-0.042	-0.025	53.318	0.000
16	-0.068	-0.026	54.206	0.000
17	-0.093	-0.058	55.851	0.000
18	-0.085	-0.053	57.230	0.000
19	-0.043	0.056	57.587	0.000
20	-0.117	-0.135	60.268	0.000

Figure 4-7: A Graph of the Correlogram for Examining the ACF, PACF and the Ljung-Box Test on the Residuals Squared of AR (1) for Returns of LOP Market.

- **Testing for Normality of the Errors**

For normality test the Jarque–Bera test is used to test the null hypothesis that the residuals are distributed normal. The *p*-values of Jarque–Bera statistics in Table 4-7 indicate that all the selected AR(1) models for the three returns series are not normal and suggest the rejection of the null hypothesis at the 5% significant level. In contrast, the null hypothesis for normality do not reject at the 1 % which suggest that all the residuals seem to be distributed normal for LOP, NOP and OPEC returns series. Moreover, figure 4-8 (see figures A5 and A6 in appendix A) illustrates the histogram and QQ-plot of the residuals for AR(1) of LOP returns series. The histogram plots and descriptive statistics of the three residuals indicate that all the residuals have the approximately zero mean and small standard deviation. The values of skewness and kurtosis suggest that all the residuals have a negative skewed distribution with fat tails. While, the points of all residuals in the QQ-plots are almost closely follow a linear pattern and these residuals probably are consistent with normal distributions.

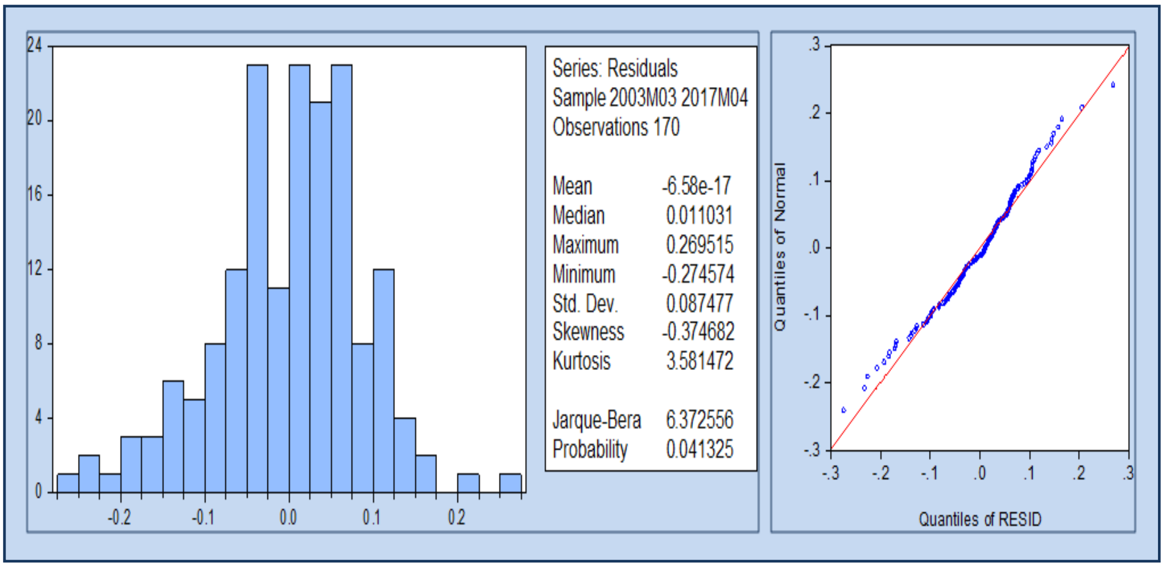


Figure 4-8: Histogram, Normality Test and QQ-Plot of AR(1) Residuals for LOP Returns.

- **Heteroskedasticity Test**

  To statistically test for ARCH effect, the Lagranger multiplier (LM) test for the null hypothesis of no conditional heteroskedasticity in the residuals from the AR(1) models of returns series is applied and results with *F*-statistic and nR^2 up to 10 lags and the *p*-values in Table 4-7 are clearly indicate that the conditional heteroskedasticity exists in squared residuals. The null hypotheses of heteroskedasticity are rejected at the 1% and 5% significance levels and this suggests that conditional variances of the error terms are not constant.

4.5.3 Breakpoint Tests for Mean and Variance Equations

In this subsection, two tests for structural breaks Bai-Perron and Chow breakpoint tests have been carried out in both the mean and variance equations of our oil prices returns and the results are presented in Table 4-8.

In multiple Bai-Perron test, we performed Sequential testing of l+1 breaks vs. l using the methods outlined by Bai (1997) and Bai and Perron (1998) for serial correlation that changes across breaks through the use of HAC covariance estimation and allowing up to 5 breaks in the model. Using the Bai and Perron (2003) critical values at significance levels of 0.01 and 0.05 in order to explore whether there exist more than one break in the mean and variance equations of returns series. It should be noted here that, the structural break date of Chow test had been identified by using unit root tests with breakpoints in Tables 4-3 to 4-5. Therefore, the chosen date for all returns series is the same which is October 2008. This date could be linked to the economic event of the global financial crisis that occurred during 2007-2009.

Table 4-8: Multiple (Bai-Perron) and Single (Chow) Breakpoint Tests in both the Mean and Variance Equations of Oil Prices Returns.

Returns	Mean equation					Variance equation				
	Bai-Perron tests		Chow test			Bai-Perron tests		Chow test		
	F-Stat	Scalded F-Stat	Break date	F-Stat	Prob.	F-Stat	ScaledF-Stat	Break date	F-Stat	Prob.
$r_t$of LOP	2.6867	5.3734	10/2008	2.5622	0.0802	0.3035	3.0353	10/2008	0.7700	0.3815
$r_t$of NOP	2.7565	5.5129	10/2008	2.7872	0.0642	3.3008	3.3008	10/2008	0.1398	0.7088
$r_t$of OPEC	1.1282	2.2563	10/2008	2.1892	0.1143	3.0338	2.0338	10/2008	1.4714	0.2263

Significant at the **5%and ***1% levels.
Bai-perron (Econmetric jornal, 2003) critical values for mean and varance equation are respectively 11.47, 15.37, 8.58 and 12.29.

The results of Bai-Perron test with *F*-statistic and the scaled *F*-statistic in Table 4-8 indicate that the three returns series exhibit no structural break in mean equation at the 1% and 5% significance levels. In this case, we cannot reject the null hypothesis l=0 versus the alternative hypothesis l+1 = 1 break and no structural break was detected in the all returns series. On the other hand, the results of Chow breakpoint tests in mean equations for the three returns series exhibit no structural break in mean equation. More specifically, the corresponding *p*-values of the F-statistics for the Chow test indicate we cannot reject the null hypothesis that no breaks at specified breakpoints of return series at 1% and 5% significance levels.. To test for breakpoint in the variance equation of each return series, the squared residuals of the estimated mean equation model (i.e. AR(1) models), where regressed on constant, and both Bai-Perron and Chow tests are then performed.

Moreover, the results of breakpoint tests in variance equation for the three returns series also exhibit no structural break in variance equation. More specifically, the results of Bai-Perron test with F-statistic and the scaled F-statistic indicate that the three returns series exhibit no structural break in variance equation at the 1% and 5% significance levels and we cannot reject the null hypothesis l=0 versus alternative hypothesis l+1 = 1 break and no structural break was detected in the all returns series. In addition, the corresponding *p*-values of the F-statistics for the Chow test indicate we cannot reject the null hypothesis that no breaks at specified breakpoints of the variance equation at 1% and 5% significance levels. The results of the structural changes tests indicate that for modelling oil price returns of the three oil markets under study we can proceeded with fitting AR(1) model without any structural breaks in the important date October 2008 which could be linked to the economic event of the global financial crisis that occurred during 2007-2009 in equation of the mean or variance.

4.6 Residual Analysis and ARCH/GARCH Family Models Building

The results of the heteroskedasticity tests in the residuals of the selected mean equation (i.e. AR(1) models for all returns series data) showed a significant presence of ARCH effect in the residual series. Thus the conditional heteroskedasticity (volatility) should be modeled using GARCH models. Therefore, different hybrid models of AR-GARCH family with three error distributions, namely normal distribution, student-t distribution and generalized error distribution (GED) are created in order to find which model can better describe and forecast the Libyan, Nigerian and OPEC oil prices returns series.

- **Determining the Order of A Conditional Variance Equation**

For modeling the conditional variance equation, the first order of GARCH model has been selected for the following reasons:

- Models with small orders such as GARCH(1,1) are sufficient to deal with non-constant variance (Franses and Van Dijk (1996) and Gokcan (2000)).
- Brooks (2008) pointed out that the first order of volatility models is sufficient to capture the volatility clustering phenomena which is present from the series data.

In the next stage, the maximum likelihood method is carried out to estimate coefficients of these models, the number of degrees of freedom of student-*t* distribution and the shape parameters of GED for the three returns under study. Tables 4-9 to 4-17 below show results of parameter estimation for six hybrids of AR-GARCH family models include GARCH, EGARCH, GJR, PARCH, CGARCH and ACGARCH with normal, student-t and GE distributions for each returns series data. The lower parts of these tables present the results of the diagnostic tests on standardized residuals and squared standardized residuals.

4.6.1 Estimation Results for Volatility Models of Libyan Oil Price Returns

Tables 4-9 to 4-11 present the results of the estimation of AR-GARCH family models to model Libyan oil price returns we can see that the estimated AR(1) coefficient, (ϕ_1), and the constant term in the conditional mean are statistically insignificant at the 1% level in most models with all the three error distributions. Except the AR(1) coefficient of AR-APGARCH model is statistically significant at the 5% significance level under the normal distribution and at the 1% level under Student-t and GED distributions.

The constant (ω) in the variance equation for all GARCH-class models is positive under the three distributions. The only exception is for the EGARCH process with the three error distributions where the constant is negative because the EGARCH process does not have any restrictions on its coefficients. Moreover, the estimated coefficient of constant for the GARCH, APARCH, CGARCH and ACGARCH models are not significant at any acceptable level. While this constant is statistically significant at the 1% significance level for the GJR model and statistically significant at the 5% significance level for the EGARCH process for all distributions.

In GARCH(1,1) model under the three error distributions the estimates of α are around 0.42 and the estimates of β are around 0.46. These estimates are statistically different from zero at the 1% level for all error distributions. Except that the parameter β is significant at the 5% significance level under the assumption of student-t and GE distributions. Furthermore, GARCH models satisfy the stability condition and $\alpha+\beta < 1 \sim (0.87)$ under all distributions. The estimated conditional variance persistence, $\alpha + \beta$ is high, which indicates that the volatility tomorrow is highly dependent on the volatility today. The estimated number of the degree of freedom of the conditional *t*-distribution in the GARCH model is insignificant at the 1%, 5% and 10% levels while the estimation of the shape parameter of GED is highly insignificant at the 1% significance level which implies that the returns of Libyan oil prices are conditionally non-normally distributed.

The estimates of α and β for the EGARCH(1,1) model are statistically significant for all error distributions. The estimate of the coefficient β must be $|\beta_1| < 1$ to ensure stationary of EGARCH. Therefore the β coefficient in the EGARCH(1,1) with normal, student-t and GE distributions highly statistically significant and less than 1. The persistence in EGARCH model is calculated as $\hat{\beta}$ which ranges from low of 0.71 under student *t*-distribution to the high of 0.77 normal distribution. It is interesting to note that the conditional variance persistence significantly reduced when heavy-tailed conditional distributions are considered and play an important role in the reduction of volatility persistence. The asymmetric parameter δ of shocks in the EGARCH(1,1) model is negative which proves that the leverage effect in the Libyan returns exists. More specially, the negative shocks have a greater impact on volatility rather than the positive shocks of the same magnitude under different distribution assumptions. However, this is statistically insignificant at the 1% level which suggests that asymmetry effect of shocks on Libyan market is not considerable. Moreover, the estimated number of the degree of freedom of the conditional *t*-distribution in the EGARCH model is insignificant at the 1% level, while estimating of the shape parameter of GED is highly significant at the 1% level.

The asymmetric leverage coefficient (γ) of the GJR-GARCH model is positive, such that bad news (negative shocks) increase the conditional variance more than the good news (positive shocks) and this coefficient is significant at the 5% level under the three error distributions and the leverage effect exists. In contrast, we can see that under the three assumption of the error term, the estimated coefficients of α, and β as well as the estimated number of the degree of freedom of the conditional *t*-distribution in the GJR model are highly insignificant at the 1%, 5% and 10% levels. Moreover, the shape parameter of GED is highly significant at the 1% level.

The estimated coefficients of α, and β in the APARCH model include are significantly different from 0 at the 1% level under the conditional *t*-distribution and GED. While under the assumption of normal distribution only the coefficient β is significant at the 1% level. The asymmetry coefficient γ is positive means negative residuals will reduce the volatility on the returns. Moreover, the asymmetry coefficient is insignificant at the 1% and 5% levels. This indicates that the Libyan market does not exhibit a leverage effect. The estimated of power parameter under the assumption of the three error distributions and the estimated number of the degree of freedom of the conditional *t*-distribution are insignificant. While the shape parameter of GED which is highly significant at the 1% level.

The short-run coefficients estimates of α and β in both CGARCH and ACGARCH specifications satisfy the stability condition and $\alpha+\beta < 1$ under all error distributions. Also $\alpha+\beta$ ranges from the low of 0.5275 for ACGARCH to the high of 0.8517 for AR-CGARCH indicating that the degree of persistence may vary across different error distribution assumptions. We observe that the (ρ) parameter of the long-run component is positive and statistically significant at the 10% level for both CGARCH and ACGARCH indicating that permanent component in the conditional variance is very strong. In addition, the magnitudes of $\alpha+\beta$ are lesser compared with ρ values suggesting that the long-run volatility component is more persistent than the short-run. Moreover for the stationarity assumption the coefficient (ρ) must be less than one, for CGARCH model under all the error distribution the coefficient is less than one. While in the ACGARCH model this assumption satisfies under student-*t* distribution only and the value of ρ under normal and GED equal unity indicating potential instability. However, the asymmetric coefficient estimates γ for ACGARCH model is positive and become statistically significant at the 5% level under the three error distributions suggesting significant leverage effect and Libyan market is more sensitive to negative news instead of good news. The estimated number of the degree of freedom of the conditional *t*-distribution is insignificant at 1% and 5% levels while estimating of the shape parameter of GED is highly insignificant at 1% level.

Table 4-9: Results of Coefficients Estimation of AR(1)-GARCH(1,1) Family Models for LOP Returns with Normal Distribution.

	AR-GARCH	AR-EGARCH	AR-GJR	AR-APARCH	AR-CGARCH	AR-ACGARCH
Mean equation						
Const (φ_0)	0.0079	0.0042	0.0089	0.0039	0.0072	0.0071
AR(1) (ϕ_1)	0.1222	0.1647	0.1321	0.1631**	0.1187	0.1576*
Variance equation						
Const (ω)	0.0012	-1.6357**	0.0042***	0.0325	0.0049	0.0209
ARCH (α)	0.4234***	0.5799**	0.0204	0.2595	0.7261	0.00009
GARCH (β)	0.4601***	0.7726***	0.0344	0.6162***	0.1256	0.5608***
EGARCH (δ)	-	-0.1321	-	-	-	-
GJR (γ)	-	-	0.7251**	-	-	-
APARCH (δ)	-	-	-	0.6707	-	-
APARCH (γ)	-	-	-	0.3794	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.9695***	1.0030***
CGARCH/ ACGARCH (θ)	-	-	-	-	-0.2562	0.0292
ACGARCH (γ)	-	-	-	-	-	0.3906**
AIC	-2.1609	**-2.1918**	-2.1789	-2.1843	-2.1580	-2.1576
SIC	-2.0687	**-2.0812**	-2.0682	-2.0552	-2.0289	-2.0101
HQ	-2.1235	**-2.1469**	-2.1339	-2.1319	-2.1056	-2.09776
Diagnostic tests						
Q(10)	14.2740	13.8620	15.8000*	13.4300	13.752	11.0590
$Q^2(10)$	7.5346	8.6863	8.6177	7.8570	8.4452	10.4410
JB	5.7810*	4.7354*	2.2230	4.5330	4.6540*	8.2430**
ARCH(1)						
F-statistic	0.0819	0.5583	0.3119	0.0179	0.0264	0.0267
nR^2	0.0829	0.5631	0.3151	0.0181	0.0267	0.0270
ARCH(5)						
F-statistic	0.7910	0.9708	0.6592	0.9197	0.7685	1.2888
nR^2	4.0027	4.8877	3.3507	4.6378	3.8936	6.4269
ARCH(10)						
F-statistic	0.7167	0.7209	0.8932	0.6822	0.8611	1.0630
nR^2	7.3432	7.3838	9.0493	7.0050	8.7418	10.655

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

Table 4-10: Results of Coefficients Estimation of AR(1)-GARCH(1,1) Family Models for LOP Returns with student-*t* Distribution.

	AR-GARCH	AR-EGARCH	AR-GJR	AR-APARCH	AR-CGARCH	AR-ACGARCH
Mean equation						
Const (φ_0)	0.008**	0.0043	0.0089	0.0028	0.0095	0.007
AR(1) (ϕ_1)	0.1230	0.1662	0.1322	0.1556***	0.1375	0.172*
Variance equation						
Const (ω)	0.0012	-1.952**	0.004***	0.0409	0.0087	0.009
ARCH (α)	0.4237***	0.5947**	0.0204	0.2329**	0.2583	0.045
GARCH (β)	0.4527**	0.712***	0.0344	0.6672***	0.3714	0.5814***
EGARCH (δ)	-	-0.1482	-	-	-	-
GJR (γ)	-	-	0.7252**	-	-	-
APARCH (δ)	-	-	-	0.4989	-	-
APARCH (γ)	-	-	-	0.4072	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.9439***	0.996***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.1628	0.026
ACGARCH (γ)	-	-	-	-	-	0.417**
T-DIST. DOF	70.8949	340.84	347.2609	201.911	23.012	26.796
AIC	-2.1494	**-2.1787**	-2.1671	-2.1731	-2.131459	-2.148404
SIC	-2.0387	**-2.0496**	-2.0379	-2.0255	-1.983892	-1.982391
HQ	-2.1045	**-2.1263**	-2.1147	-2.1132	-2.071578	-2.081038
Diagnostic tests						
Q(10)	14.277	14.322	15.800*	13.518	13.740	10.708
$Q^2(10)$	7.3846	8.9053	8.6196	8.7698	7.6883	10.936
JB	5.7498*	4.4975	2.2234	4.779*	6.837**	7.919**
ARCH(1)						
F-statistic	0.0788	0.6913	0.3121	0.0223	0.1219	0.0279
nR^2	0.0797	0.6967	0.3153	0.0226	0.1234	0.0282
ARCH(5)						
F-statistic	0.7698	1.0130	0.6594	1.1879	0.9609	1.3718
nR^2	3.8997	5.0939	3.3521	5.9415	4.8397	6.8234
ARCH(10)						
F-statistic	0.7025	0.7341	0.8933	0.7999	0.7474	1.0929
nR^2	7.2038	7.5129	9.0503	8.1519	7.6425	10.934

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

Table 4-11: Results of Coefficients Estimation of AR(1)-GARCH(1,1)Family Models for LOP Returns with GE Distribution.

	AR-GARCH	AR-EGARCH	AR-GJR	AR-APARCH	AR-CGARCH	AR-ACGARCH
Mean equation						
Const (φ_0)	0.0087	0.0034	0.0086	0.0036	0.009	0.0074
AR(1) (ϕ_1)	0.1175	0.1672*	0.1352	0.1692***	0.1264	0.1658*
Variance equation						
Const (ω)	0.0012	-1.663**	0.0042***	0.0569	0.0088	0.01490
ARCH (α)	0.4247***	0.5710**	0.0173	0.2482**	0.2405	0.0852
GARCH (β)	0.4498**	0.7656***	0.0363	0.5884***	0.4078	0.6127***
EGARCH (δ)	-	-0.1405	-	-	-	-
GJR (γ)	-	-	0.7276**	-	-	-
APARCH (δ)	-	-	-	0.5177	-	-
APARCH (γ)	-	-	-	0.4469	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.9362***	1.004***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.1801	0.0377
ACGARCH (γ)	-	-	-	-	-	0.4496***
GED parameter	1.88***	2.21***	2.06***	2.32***	1.83***	1.87***
AIC	-2.1499	-2.1819	-2.1673	**-2.1834**	-2.1310	-2.1482
SIC	-2.0392	**-2.0528**	-2.0381	-2.0358	-1.9834	-1.9822
HQ	-2.1049	**-2.1295**	-2.1149	-2.1235	-2.0711	-2.0808
Diagnostic tests						
Q(10)	14.368	14.001	15.825*	13.575	13.992	10.672
$Q^2(10)$	7.2534	8.9843	8.7491	7.7153	7.4774	11.478
JB	5.6860*	4.6900*	2.2623**	4.317**	6.513**	7.872**
ARCH(1)						
F-statistic	0.0731	0.5719	0.2934	0.0223	0.1102	0.0342
nR^2	0.0739	0.5768	0.2964	0.0225	0.1115	0.0346
ARCH(5)						
F-statistic	0.7317	1.0181	0.6743	0.9049	0.8800	1.5039
nR^2	3.7110	5.1187	3.4263	4.5657	4.4433	7.4513
ARCH(10)						
F-statistic	0.6863	0.7484	0.9024	0.6572	0.7196	1.1359
nR^2	7.0447	7.6522	9.1369	6.7595	7.3714	11.333

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

4.6.2 Diagnostic Checking of the Residuals of Fitted AR-GARCH Models

The results of the diagnostic tests for standardized residuals ($\frac{\hat{\varepsilon}_t}{\hat{\sigma}_t}$) and squared standardized residuals of AR-GARCH Models in the lower parts of Tables 4-9 to 4-11 can be summarized as follows

- Ljung-Box statistics up to 10^{th} order on the standardized residuals indicate that substantially residuals are independent for AR-GARCH, AR-EGARCH, AR-GJR, AR-PARCH, AR-CGARCH AND AR-ACGARCH models under the three error distributions with the *p*-values are more than the significance 5% level. The Ljung-Box tests up to 10^{th} order for the squared of residuals are not significant either for all used models suggest that the squared of residuals are independent which confirm the no precense of ARCH effect (conditional heteroskedasticity) in the residuals.

- The Jarque–Bera statistics indicate that the AR-GARCH, AR-EGARCH, AR-GJR, AR-PARCH, AR-CGARCH and AR-ACGARCH models under the three error distribution cannot reject null hypothesis for normality at the 1% level suggesting that all the residuals seem to be distributed normal.

- the Lagranger multiplier (LM) test to test the null hypothesis of no conditional heteroskedasticity in the residuals from the AR-GARCH family models with three error distributions is applied with results of F-statistic and nR^2 up to 10 lags. The results clearly indicate that conditional heteroskedasticity does not exist in the squared of residuals. Consequently, the null hypotheses are not rejected, and there are no ARCH effects. All the *p*-values are statistically insignificant at the 1% significance level.

- In the model estimation stage, the AIC, SIC and HQIC statistics from the AR-EGARCH model are smaller than the values of other models under the three assumption of error distribution. More specifically, the AR-EGARCH model has the highest values of AIC, SIC and HQ under *t*-distribution and GED while these criteria are smaller under normal distribution. Thus the best fitting model for Libyan crude oil price returns is AR-EGARCH model whit normal distribution.

4.6.3 Estimation Results for Volatility Models of Nigerian Oil Price Returns

From Tables 4-12 to 4-14 of the results of estimation for AR-GARCH class models to model Nigerian oil price returns we can see that the estimated coefficient of the constant term in the mean equation are statistically insignificant for all models under all the error distributions, except the constant in the AR-GARCH and AR-ACGARCH models with GED is significant at the 1% level. The AR(1) coefficients, (ϕ_1), in the conditional mean are statistically significant at the 10% level in the most models with the three error distributions. Except the AR(1) coefficient of AR-GARCH model with normal and GED distributions, AR-GJR model with *t*-distribution and GED and AR-CGARCH model with GED are statistically insignificant

The constant (ω) in variance equation for all GARCH-class models is positive under three distributions. The only exception in the EGARCH model for the three error distributions the constant is negative because the EGARCH model does not have any restrictions on its coefficients. Moreover, the estimated coefficient of constant for the APARCH, CGARCH and ACGARCH models are insignificant at any acceptable level under the three error distributions in addition to GARCH model with student-t distribution.

In GARCH model under the three error distributions the estimates of α and β are highly statistically significant at the 1% level, except the estimates of β under GED is insignificant at any acceptable level. The GARCH models satisfy the stability condition and $\alpha + \beta < 1$ under all distributions. The estimated conditional variance persistence, $\alpha + \beta$ is high and ranges from 0.9678 to 0.9559 and closed to unity indicating that the volatility tomorrow is highly dependent on the volatility today. The estimated number of the degree of freedom of the conditional *t*-distribution in the GARCH model is insignificant at the 1%, 5% and 10% levels while estimating of the shape parameter of GED is highly insignificant at the 1% significance level which implies that the returns of Nigerian market are conditionally non-normally distributed.

All the parameter estimates of the variance equation for the EGARCH(1,1) model are statistically significant for all error distributions. Moreover, the estimate of the coefficient β coefficients in the EGARCH with normal, student-*t* and GE distributions is statistically significant at the 1% level and less than 1 satisfies the assumption of stability condition. The degree of the persistence property in EGARCH model ranges from low of 0.66 under GED to the high of 0.74 with student-*t* distribution. The asymmetric parameter δ in the EGARCH(1,1) model is negative indicating that the leverage effect exists for the Nigerian returns and the negative shocks (bad news) have a greater impact on volatility under different distribution assumptions. However, this is statistically significant at the 1% level, suggesting that the Nigerian market exhibits a leverage effect. The estimated number of the degree of freedom of the *t*-distribution in the EGARCH model is insignificant at all levels while estimating of the shape parameter of GED is highly significant at the 1% level.

The asymmetric leverage coefficient (γ) of the GJR-GARCH model is positive, such that negative shocks increase the volatility more than the positive shocks and this coefficient is significant at the 10% level under the three error distributions indicating that the leverage effect exists. In contrast, we can see that under the three assumption of the error term, the coefficients α and β as well as the estimated number of the degree of freedom of the conditional *t*-distribution in the GJR model are insignificant at the 1%, 5% and 10% levels, except the coefficient α under the assumption of normality. Furthermore, the shape parameter of GED is highly significant at the 1%level.

The estimated coefficients α and β of APARCH model include are significantly different from 0 at the 1% level under the conditional normal and student-*t* distributions only. The asymmetry coefficient γ is positive under normal and student-*t* distributions means negative shocks will reduce the volatility on the returns. Moreover, the asymmetry coefficient is insignificant at the 1 % and 5% levels. This indicates that the Nigerian market does not exhibit a leverage effect. But under the assumption of GED, the asymmetry coefficient γ is negative and is highly significant at the 1% level indicating that the negative shocks give rise to higher volatility than positive shocks. The estimated of power parameter under the assumption of the three error distributions and the estimated number of the degree of freedom of the conditional *t*-distribution are insignificant. In contrast, the parameter of shape parameter for GED is highly significant at the 1% level.

The estimated coefficients α and β in both CGARCH and ACGARCH specifications satisfy the stability condition and $\alpha + \beta < 1$ under all error distributions. Also $\alpha + \beta$ ranges from the low of 0.0.2710 for CGARCH to the high of 0.0.6081 for ACGARCH indicating that the degree of persistence is slow and may vary across different error distribution assumptions. For the stationarity assumption the coefficient (ρ) must be less than one, for CGARCH model under all the error distribution the coefficient $\rho < 1$. While in ACGARCH model the value of ρ under the three error distributions equal unity indicating potential instability. However, the estimated coefficient for long run volatility component (ρ) of CGARCH models is positive, highly significant and less than unity indicating that permanent component in the conditional variance is very strong. The asymmetric coefficient estimates γ for ACGARCH model is positive and statistically significant at the 1% level under the three error distributions suggesting significant leverage effect indicating Nigerian market is more sensitive to negative shocks instead of positive shocks. The estimated number of the degree of freedom of the conditional *t*-distribution is insignificant at 1% and 5% levels while estimating of the shape parameter of GED is highly insignificant at 1% level.

Table 4- 12: Results of Coefficients Estimation of AR(1)-GARCH(1,1) Family Models for NOP Returns with Normal Distribution.

	AR-GARCH	AR-EGARCH	AR-GJR	AR-APARCH	AR-CGARCH	AR-ACGARCH
Mean equation						
Const (φ_0)	0.0051	0.0023	0.0028	0.0023	0.0055	0.0064
AR(1) (ϕ_1)	0.1285	0.1470**	0.1486**	0.1500**	0.1332*	0.1486**
Variance equation						
Const (ω)	0.00054*	-0.911***	0.0009*	0.0148	0.0117	0.0038
ARCH (α)	0.2164***	0.3508*	0.0852	0.1710***	0.0657	0.1565**
GARCH (β)	0.7395***	0.8703***	0.7237***	0.7370***	0.4531	0.7584*
EGARCH (δ)	-	-0.1296**	-	-	-	-
GJR (γ)	-	-	0.1032*	-	-	-
APARCH (δ)	-	-	-	0.9050	-	-
APARCH (γ)	-	-	-	0.493*	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.9612***	1.0161***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.1784	0.054**
ACGARCH (γ)	-	-	-	-	-	0.4578***
AIC	-1.9807	-1.9969	-1.9833	-1.9849	-1.9655	**-2.0001**
SIC	-1.9086	**-1.9105**	-1.8968	-1.8841	-1.8646	-1.8848
HQ	-1.9516	**-1.9621**	-1.9485	-1.9443	-1.9249	-1.9537
Diagnostic tests						
Q(10)	9.8802	10.073	9.6374	9.994	9.9232	9.1925
$Q^2(10)$	9.2581	12.984	11.454	13.37	9.2593	10.579
JB	13.621***	10.099***	11.589***	9.621***	14.289***	11.498***
ARCH(1)						
F-statistic	0.0697	0.1014	0.0164	4.23E-05	0.0014	0.0200
nR^2	0.0703	0.1022	0.0165	4.27E-05	0.0014	0.0202
ARCH(5)						
F-statistic	0.6072	0.6822	0.5318	0.7250	0.6537	0.8219
nR^2	3.0745	3.4485	2.6969	3.6618	3.3067	4.1427
ARCH(10)						
F-statistic	0.8427	1.0781	0.9952	1.1447	0.8233	0.9919
nR^2	8.5218	10.791	9.9973	11.42	8.3327	9.9652

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

Table 4-13: Results of Coefficients Estimation of AR(1)-GARCH(1,1) Family Models for NOP Returns with student-*t* Distribution.

	AR-GARCH	AR-EGARCH	AR-GJR	AR-APARCH	AR-CGARCH	AR-ACGARCH
Mean equation						
Const (φ_0)	0.0071	0.0031	0.0086	0.0024	0.0088	0.0069
AR(1) (ϕ_1)	0.1278*	0.142**	0.1172	0.1457**	0.1284*	0.1475**
Variance equation						
Const (ω)	0.0005	-0.902**	0.0061***	0.0182	0.0120 [	0.0043
ARCH (α)	0.2140***	0.352***	0.0129	0.1698**	0.1101	0.1540**
GARCH (β)	0.7478***	0.8720***	0.0218	0.7368***	0.1609	0.7615***
EGARCH (δ)	-	-0.1270**	-	-	-	-
GJR (γ)	-	-	0.2571*	-	-	-
APARCH (δ)	-	-	-	0.8269	-	-
APARCH (γ)	-	-	-	0.5090	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.9649***	1.0143***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.1682	0.0488**
ACGARCH (γ)	-	-	-	-	-	0.4427***
T-DIST. DOF	13.724	32.497	11.833	34.226	11.357	16.501
AIC	-1.9781	-1.9897	-1.9725	-1.9779	-1.9648	**-1.9971**
SIC	**-1.8916**	-1.8887	-1.8716	-1.8625	-1.8494	-1.8673
HQ	-1.9432	**-1.9489**	-1.9319	-1.9314	-1.9183	-1.9448
Diagnostic tests						
Q(10)	9.8246	10.061	9.4051	10.053	9.6679	9.1457
$Q^2(10)$	9.1150	12.805	25.650***	13.689	9.7983	10.829
JB	13.551***	10.14***	10.889***	9.428***	15.679***	11.636***
ARCH(1)						
F-statistic	0.1159	0.0857	0.5083	0.0008	0.0438	0.0057
nR^2	0.1169	0.0864	0.5114	0.0008	0.0442	0.0058
ARCH(5)						
F-statistic	0.5982	0.6707	1.1972	0.7572	0.7866	0.8847
nR^2	3.0297	3.3913	5.9863	3.8216	3.9676	4.4531
ARCH(10)						
F-statistic	0.8364	1.0644	2.0507**	1.1725	0.8658	1.0233
nR^2	8.4597	10.661	19.699**	11.689	8.7464	10.267

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

Table 4-14: Results of Coefficients Estimation of AR(1)-GARCH(1,1)Family Models for NOP Returns with GE Distribution.

	AR-GARCH	AR-EGARCH	AR-GJR	AR-APGARCH	AR-CGARCH	AR-ACGARCH
Mean equation						
Const (φ_0)	0.0148**	0.0039	0.0099	0.0074	0.0094	0.0085***
AR(1) (ϕ_1)	0.0671	0.1333*	0.0939	0.1549***	0.1050	0.1332*
Variance equation						
Const (ω)	0.0066***	-0.907**	0.0059***	0.3325	0.0111	0.0048
ARCH (α)	0.3073**	0.352**	0.0123	0.0711	0.0939	0.1580**
GARCH (β)	0.6605	0.8716***	0.0333	0.3514	0.2125	0.7461***
EGARCH (δ)	-	-0.1229**	-	-	-	-
GJR (γ)	-	-	0.4433*	-	-	-
APARCH (δ)	-	-	-	0.3043	-	-
APARCH (γ)	-	-	-	-0.999***	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.9575***	1.0139***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.1701	0.0439**
ACGARCH (γ)	-	-	-	-	-	0.4554***
GED parameter	1.4496***	1.8083***	1.5889***	1.6026***	1.5981***	1.7014***
AIC	-1.9619	-1.9905	-1.9741	-1.9145	-1.9660	**-1.9978**
SIC	-1.8754	**-1.8895**	-1.8732	-1.7992	-1.8507	-1.8681
HQ	-1.9270	**-1.9498**	-1.9335	-1.8680	-1.9196	-1.9456
Diagnostic tests						
Q(10)	10.1990	10.1170	9.4420	9.5741	10.087	8.9639
$Q^2(10)$	18.6360**	12.9090	25.1760***	31.4570***	9.8367	10.3460
JB	12.8770***	10.20***	10.4590***	6.8740**	15.1680***	11.1810***
ARCH(1)						
F-statistic	0.1139	0.0642	0.3604	7.6754*	0.0056	0.0069
nR^2	0.1148	0.0647	0.3628	7.4988*	0.0056	0.0069
ARCH(5)						
F-statistic	0.9478	0.6667	1.1474	2.1243	0.6653	0.7078
nR^2	4.7644	3.3714	5.7433	10.418	3.3643	3.5761
ARCH(10)						
F-statistic	1.5003	1.0754	2.0312**	2.8062***	0.8622	0.9763
nR^2	14.748	10.766	19.529**	26.139***	8.7112	9.8153

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

4.6.4 Diagnostic Checking of the Residuals of Fitted AR-GARCH Models

The results of the diagnostic tests for standardized residuals and squared standardized residuals of AR-GARCH Models for NOP returns in the lower parts of Tables 4-12 to 4-14 can be summarized as follows

- Ljung-Box statistics up to 10^{th} order on the standardized residuals show that substantially residuals are independent for all used models under the three error distributions with the *p*-values are more than the significance 10% level. The Ljung-Box tests up to 10^{th} order for the squared of residuals are not significant either for all used models suggest that the squared of residuals are independent which confirm the no precense of ARCH effect (conditional heteroskedasticity) in the residuals. The only exception in the cases of the AR-GJR model with student-*t* distrbution and both AR-GJR and AR-APARCH models under GED, the ARCH effects present in their squared standardized residuals at the 1% significance level.

- The correspondent *p*-values of the Jarque–Bera statistics indicate that the most of the AR-GARCH class models reject the null hypothesis of residuals are normally distributed at 1% level under the three distributions. Except the *p*-value of the AR-APARCH with GED is more than 1% meaning we have enough evidence to accept the null hypothesis of residuals are normally distributed.

- the Lagranger multiplier (LM) test is app;ied to test for the null hypothesis of no conditional heteroskedasticity in the residuals from the AR-GARCH models with three error distributions. The results with F-statistic and nR^2 up to 10 lags clearly indicate that the conditional heteroskedasticity does not exist in the squared of residuals. Consequently, the null hypotheses are not rejected, and there are no ARCH effects. All the *p*-values are statistically insignificant at the 1% significance level. The only exception in the AR-APGARCH model with GED under the LM test with five lags shows ARCH effects.

- In the model estimation stage, the AIC suggesting that the AR-ACGARCH model has a small values compare to the same model under other distribution. However, we have excluded this model because it showed potential instability. The SIC and HQIC statistics from the AR-EGARCH model are smaller than the values of other models under the three assumption of error distribution. Thus, the best fitting model for NOP market returns is AR-EGARCH model whit normal distribution based on both SIC and HQIC.

4.6.5 Estimation Results for Volatility Models of OPEC Returns

From Tables 4-15 to 4-17 of the results of estimation for AR-GARCH family models to model OPEC oil price returns we can see that the estimated coefficient of the constant term in the mean equation are statistically insignificant in most models under all assumptions of error distributions. Except, in the case of AR-CGARCH model under all error distribution are statistically significant at the 1% level and AR-EGARCH, AR-GJR and AR-APARCH models with student-*t* distribution are statistically significant at 10% level, while in AR-GJR model with GED is statistically significant at 1% level. With regard to the estimated the AR(1) coefficients, (ϕ_1), in the conditional mean are statistically significant at the 5% level for all models used under the three error distributions, except in AR-CGARCH model under all error distribution and AR-APARCH model with student-*t* distribution are statistically insignificant.

The constant (ω) in variance equation for all GARCH-class models is positive under three distributions. The only exception in the EGARCH model for the three error distributions the constant is negative because the EGARCH model does not have any restrictions on its coefficients. The estimated coefficients of a constant for the EGARCH, GJR, CGARCH and ACGARCH models are statistically significant at the 1% level under the three error distributions, while in the GARCH and APARCH models these estimated coefficients of constant are insignificant at any acceptable level under the three error distributions.

In GARCH model under the three error distributions the estimates of α and β are statistically significant at the 1% level, except the estimates of α under student-*t* distribution and GED are significant at the 5% level. The GARCH models satisfy the stability condition and $\alpha + \beta < 1$ under all distributions. The estimated conditional variance persistence, $\alpha + \beta$ is high and ranges from 0.8974 to 0.8699 indicating that the volatility tomorrow is highly dependent on the volatility today. The estimated number of the degree of freedom of the conditional *t*-distribution in the GARCH model is insignificant at the 1%, 5% and 10% levels while estimating of the shape parameter of GED is highly insignificant at the 1% significance level which implies that the returns of OPEC are conditionally non-normally distributed

The estimates of β for the EGARCH(1,1) model are statistically significant for all error distributions. While the estimates parameter of α are statistically insignificant for all error distributions. The estimate of the coefficient β must be $|\beta_1| < 1$ to ensure stationary of EGARCH. Therefore the β coefficients in the EGARCH(1,1) with normal, student-*t* and GE distributions highly statistically significant at the 1% level. The persistence in EGARCH model is calculated as $\hat{\beta}$ which ranges from low of 0.68 under student *t*-distribution to the high of 0.76 normal distribution. It is interesting to note that the conditional variance persistence significantly reduced when heavy-tailed conditional distributions are considered and. play an important role in the reduction of volatility persistence. The asymmetric parameter δ of shocks in the EGARCH model is negative, thus the leverage effect in the OPEC returns exists and the negative shocks have a greater impact on volatility rather than the positive shocks of the same magnitude under different distribution assumptions. However, the estimates of this coefficient are statistically significant at the 1% level, indicating that the asymmetry effect of shocks on OPEC market is considerable. Moreover, the estimated number of the degree of freedom of the conditional *t*-distribution in the EGARCH model is insignificant while estimating of the shape parameter of GED is highly significant at the 1% level.

In GJR-GARCH model, the estimators of coefficients α are negative and do not achieve the usual restrictions on this parameter (i.e. > 0) except, in the case under the assumption of GED this coefficient is positive and significant at the 1% level. In contrast, the estimators of coefficients β are positive and highly significant at the 1% level only under normal and student-*t* distributions. While under GED this coefficient is negative and does not achieve the usual restrictions. The asymmetric leverage coefficient (γ) of the GJR-GARCH model is positive, such that negative shocks increase the conditional variance more than the positive shocks and this coefficient is significant at the 5% level only under the normal and student-*t* distributions suggesting that the leverage effect exists. The estimated numbers of the degree of freedom of the conditional *t*-distribution in the GJR-GARCH model are insignificant at the 1%, 5% and 10% levels while the shape parameter of GED is highly significant at the 1% level.

The estimated coefficients of α, for APARCH model are insignificant under the three error distributions. While the coefficient β are positive and significant at the 1% under normal and GE distributions and this parameter is negative under student-*t* and does not achieve the usual restriction. The asymmetry coefficient γ is positive, close to unity and insignificant under both normal and GE distributions indicating that the OPEC market does not exhibit a leverage effect. The estimated of power parameter under the assumption of the three error distributions and the estimated number of the degree of freedom of the conditional *t*-distribution are insignificant. While the shape parameter of GED which is highly significant at the 1% level.

The estimated coefficients α and β of CGARCH specification are statistically significant at the 1% level, while in the ACGARCH are insignificant. However, these coefficients satisfy the stability condition and $\alpha + \beta < 1$ under all error distributions. Moreover, for the assumption of stationary the coefficient ρ is less than 1. The estimated coefficient for long run volatility component (ρ) of CGARCH and ACGARCH specifications is positive, highly significant and less than unity indicating that permanent component in the conditional variance is very strong. In addition, the magnitudes of $\alpha + \beta$ are lesser compared with ρ values suggesting that the long-run volatility component is more persistent than the short-run. In contrast, the asymmetric coefficient estimates γ for ACGARCH model is positive and become statistically significant at the 5% level under the three error distributions suggesting significant leverage effect and OPEC market is more sensitive to negative news instead of good news. The estimated number of the degree of freedom of the conditional *t*-distribution is insignificant at the 1% and 5% levels while estimating of the shape parameter of GED is highly insignificant at the 1% level.

Table 4-15: Results of Coefficients Estimation of AR(1)-GARCH(1,1) Family Models for OPEC Returns with Normal Distribution.

	AR-GARCH	**AR-EGARCH**	**AR-GJR**	**AR-APARCH**	**AR-CGARCH**	**AR-ACGARCH**
Mean equation						
const (φ_0)	0.0054	0.0016	0.0031	0.002	0.0097*	0.0035
AR(1) (ϕ_1)	0.1808**	0.2127***	0.1918***	0.207***	0.0742	0.1731***
Variance equation						
Const (ω)	0.0009	-1.2671***	0.0024***	0.0189	0.0095***	0.0070***
ARCH (α)	0.1499***	0.1516	-0.0732	0.107	0.1744***	0.1232
GARCH (β)	0.7475***	0.7649***	0.5843***	0.688***	0.776***	0.5371
EGARCH (δ)	-	-0.2021***	-	-	-	-
GJR (γ)	-	-	0.3786***	-	-	-
APARCH (δ)	-	-	-	1.0239	-	-
APARCH (γ)	-	-	-	1.00	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.8747***	0.8956***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.1873***	0.0906
ACGARCH (γ)	-	-	-	-	-	0.2869**
AIC	-1.9965	-2.0182	**-2.0226**	-2.0146	-2.0092	-1.9954
SIC	-1.9244	-1.9317	**-1.9361**	-1.9137	-1.9083	-1.8801
HQ	-1.9674	-1.9833	**-1.9877**	-1.9739	-1.9686	-1.9489
Diagnostic tests						
Q(10)	8.4546	9.1808	7.9509	8.978	10.232	7.0426
$Q^2(10)$	8.9727	11.745	13.705	12.27	14.914*	9.1421
JB	9.791***	5.782*	5.484*	6.420**	6.947**	7.353**
ARCH(1)						
F-statistic	0.3206	0.1629	0.2605	0.359	0.8590	0.0441
nR^2	0.3228	0.1642	0.2624	0.362	0.8631	0.0444
ARCH(5)						
F-statistic	0.2991	0.8094	1.1747	0.864	1.0131	0.4541
nR^2	1.5247	4.0805	5.8765	4.353	5.0856	2.3066
ARCH(10)						
F-statistic	0.9296	1.0869	1.2745	1.122	1.6356*	0.9232
nR^2	9.3649	10.875	12.650	11.21	15.987	9.3025

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

Table 4-16: Results of Coefficients Estimation of AR(1)-GARCH(1,1) Family Models for OPEC Returns with student-*t* Distribution.

	AR-GARCH	**AR-EGARCH**	**AR-GJR**	**AR-APARCH**	**AR-CGARCH**	**AR-ACGARCH**
Mean equation						
Const (φ_0)	0.0083	0.0048*	0.0094*	0.0109*	0.0145***	0.0104
AR(1) (ϕ_1)	0.1679**	0.203***	-	0.1096	0.0571	0.1468**
Variance equation						
Const (ω)	0.0010	-1.6300**	0.0026***	0.0061	0.0096***	0.0071***
ARCH (α)	0.1453**	0.1059	-0.0558	0.2327	0.1539***	0.0618
GARCH (β)	0.7351***	0.682***	0.5467***	-0.0880	0.819***	0.2592
EGARCH (δ)	-	-0.25***	-	-	-	-
GJR (γ)	-	-	0.3501**	-	-	-
APARCH (δ)	-	-	-	2.0125	-	-
APARCH (γ)	-	-	-	0.6608	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.8465***	0.9258***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.2089**	0.0659
ACGARCH (γ)	-	-	-	-	-	0.3021*
T-DIST. DOF	10.817	12.470	10.104	8.9704	9.1669	11.888
AIC	-1.9970	-2.0155	-1.9938	-2.0209	**-2.0214**	-1.9915
SIC	-1.9105	**-1.9146**	-1.9075	-1.9057	-1.9061	-1.8617
HQ	-1.9622	**-1.9749**	-1.9590	-1.9745	-1.9740	-1.9392
Diagnostic tests						
Q(10)	8.8719	9.3383	16.405*	7.6334	11.223	7.6309
$Q^2(10)$	9.0423	11.746	13.329	17.582**	11.120	9.3953
JB	9.877***	4.891*	7.116**	6.594***	9.393***	7.168**
ARCH(1)						
F-statistic	0.4816	0.0838	0.0002	1.2807	0.5739	0.0129
nR^2	0.4847	0.0845	0.0002	1.2845	0.5773	0.0129
ARCH(5)						
F-statistic	0.2997	0.9426	1.0408	1.6102	0.3968	0.4727
nR^2	1.5276	4.7387	5.2215	7.9820	2.0180	2.4006
ARCH(10)						
F-statistic	0.9565	1.1125	1.2915	1.5577	1.1394	0.0129
nR^2	9.6242	11.119	12.809	15.276	11.375	0.0129

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

Table 4-17: Results of Coefficients Estimation of AR(1)-GARCH(1,1)Family Models for OPEC Returns with GE Distribution.

	AR-GARCH	**AR-EGARCH**	**AR-GJR**	**AR-APGARCH**	**AR-CGARCH**	**AR-ACGARCH**
Mean equation						
Const (φ_0)	0.0096	0.0056	0.0191***	0.0056	0.0154***	0.0099
AR(1) (ϕ_1)	0.1461**	0.1903***	0.1628***	0.1805**	0.0477	0.1402**
Variance equation						
Const (ω)	0.0011	-1.560**	0.0166***	0.0195	0.0094***	0.0071***
ARCH (α)	0.1484**	0.1157	0.0840***	0.1095	0.1531***	0.1168
GARCH (β)	0.7215***	0.7008***	-0.981***	0.6517***	0.819***	0.4505
EGARCH (δ)	-	-0.235***	-	-	-	-
GJR (γ)	-	-	0.0161	-	-	-
APARCH (δ)	-	-	-	1.0605	-	-
APARCH (γ)	-	-	-	0.9999	-	-
CGARCH/ ACGARCH (ρ)	-	-	-	-	0.8400***	0.9185***
CGARCH/ ACGARCH (θ)	-	-	-	-	0.2072*	0.0731
ACGARCH (γ)	-	-	-	-	-	0.3167**
GED parameter	1.5294***	1.6275***	1.3247***	1.6388***	1.446***	1.5672***
AIC	-2.0019	-2.0182	-1.9834	-2.0141	**-2.0201**	-1.9991
SIC	-1.9155	**-1.9173**	-1.8825	-1.8987	-1.9138	-1.8694
HQ	-1.9671	-1.9775	-1.9428	-1.9676	**-1.9827**	-1.9468
Diagnostic tests						
Q(10)	9.5974	9.3099	10.896	9.1085	11.539	8.0914
$Q^2(10)$	9.1223	11.565	16.566*	12.278	11.112	8.5800
JB	10.247***	5.199*	10.889***	6.509**	9.665***	6.993**
ARCH(1)						
F-statistic	0.5409	0.0625	1.7518	0.3416	0.4965	0.0772
nR^2	0.5443	0.0630	1.7536	0.3439	0.4997	0.0778
ARCH(5)						
F-statistic	0.3041	0.8697	1.6814	0.8694	0.3586	0.4219
nR^2	1.5498	4.3792	8.3223	4.3774	1.8256	2.1446
ARCH(10)						
F-statistic	0.9706	1.0957	2.0084**	1.1346	1.1367	0.8729
nR^2	9.7605	10.959	19.327**	11.329	11.349	8.8149

Notes: The numbers in square brackets are *p*-values of the statistics. *, ** and *** indicates rejection at the 10%, 5% and 1% ssignificant levels.

4.6.6 Diagnostic Checking of the Residuals of Fitted AR-GARCH Models

The results of the diagnostic tests for standardized residuals ($\frac{\hat{\varepsilon}_t}{\hat{\sigma}_t}$) and squared standardized residuals of AR-GARCH Models in the lower parts of Tables 4-15 to 4-17 can be summarized as follows

- Ljung-Box statistics up to 10^{th} order on the standardized residuals are statistically insignificant indicating that the residuals are independent for all AR-GARCH models used under the three error distributions. Except, the standardized residuals of the AR-GJR model with student t distribution are dependent at the 10% level. The *p*-values of Ljung-Box Q(10)-statistics up to 10^{th} order for the squared of residuals are more than the significance 10% level which mean strong evidence that the squared of residuals are independent and confirm the no precense of ARCH effect (conditional heteroskedasticity) in the residuals. The only exception in the cases of the AR-CGARCH model with normal distrbution and AR-GJR with GED, the ARCH effects present in their squared standardized residuals at the 10% significance level. While the ARCH effects present in the squared standardized residuals of AR-APARCH under student-t distribution at the 5% significance level.

- The correspondent *p*-values of the Jarque–Bera statistics indicate that the null hypothesis of residuals are normally distributed rejected at the 1% level for AR-GARCH-N, AR-GARCH-*t*, AR-GARCH-GED, AR-CGARCH-t, AR-CGARCH-GED and AR-GJR-GED. While the *p*-values for other models are the more than 1% suggesting that we have enough evidence to accept the null hypothesis of residuals are normally distributed.

- the Lagranger multiplier (LM) test is carried out for testing the null hypothesis of no conditional heteroskedasticity in the squared residuals from the AR-GARCH family models with three error distributions. the results of F-statistics and nR^2 up to 10 lag indicating that the conditional heteroskedasticity does not exist. Consequently, the null hypotheses are not rejected, and there are no ARCH effects. All the *p*-values are statistically insignificant at the 1% significance level. The only exception in AR-CGARCH-N and AR-APARCH-GED models with ten lags shows ARCH effects.

- In-sample estimation stage, the AIC, SIC and HQIC suggesting that the AR-GJR-GARCH model with normal distribution has a small values compare to other models. However, we have excluded this model because it showed instability. Moreover, we get mixed results because each information criterion suggested a different model. The AIC indicates that the CGARCH model whit student-*t* the best fitting model for OPEC market returns. While, the SIC and HQIC suggest the AR-EGARCH with GED and normal respectively. Therefore, we select the AR-EGARCH model with GED as the optimal model for the returns of OPEC oil prices based on SIC.

4.6.7 The Best Conditional Mean and Conditional Variance Model for the Libyan, Nigerian and OPEC Markets in Sample Period

Estimates of conditional mean and conditional variance of oil price returns in sample period for the Libyan, Nigerian and OPEC markets are based on estimating six types of AR-GARCH family under three assumptions of error distribution in order to determine the best model describing the data. The outputs in Tables 4-9 to 4-17 show that the AR(1)-EGARCH(1,1) process is the better model at characterizing the dynamics of oil prices returns in the three markets. However, the results suggest that the specification of AR-EGARCH model with normal distribution is an adequate to capture the volatility in oil prices in Libya and Nigeria. Alternatively, the AR-EGARCH process with GED is the optimal model for the returns of OPEC.

The findings also confirm the existence of leverage effect implying that the conditional variance in oil prices of the three markets does not respond to equal magnitude of bad and good news equally. More specifically, the series encounters the leverage effect on oil price shocks. This implies that the downward changes (shocks) in the oil market are follow by larger volatilities than upward changes of the same magnitude (Cheong, 2009). Moreover, the results show that the asymmetric parameter in the AR-EGARCH model is negative indicating that the negative shocks (bad news) have a greater effect on volatility rather than the positive shocks (good news) in the three markets. However, the results exhibit that the asymmetric coefficient in the AR-GARCH model is significantly different from zero only in the cases of Nigeria and OPEC. This is implies that there is strong evidence of a leverage effect in these oil markets, except the Libyan oil market.

4.7 Breakpoint Tests for the Conditional Variance

Conditional variance series may undergo a change under the effects of economic events, political changes, natural disasters and wars. Failure to pay attention to these changes can lead to many negative consequences, ranging from making mistakes at the start of the prediction process to identifying the incorrect model. Consequently, in this section, structural break tests, including Bai-Perron test and Chow test are applied on the basis of conditional variance series which derived from the best AR-GARCH family models in the Libyan, Nigerian and OPEC markets in order to test the null hypothesis of no structural break in the variance equation. However, after the EGARCH(1,1) model has been estimated and selected as the best volatility model for all variance equations in Libya, Nigeria and OPEC, the estimated conditional variances series from this model have been generated and examined for potential structural changes. These series are illustrated in figure 4-9 below.

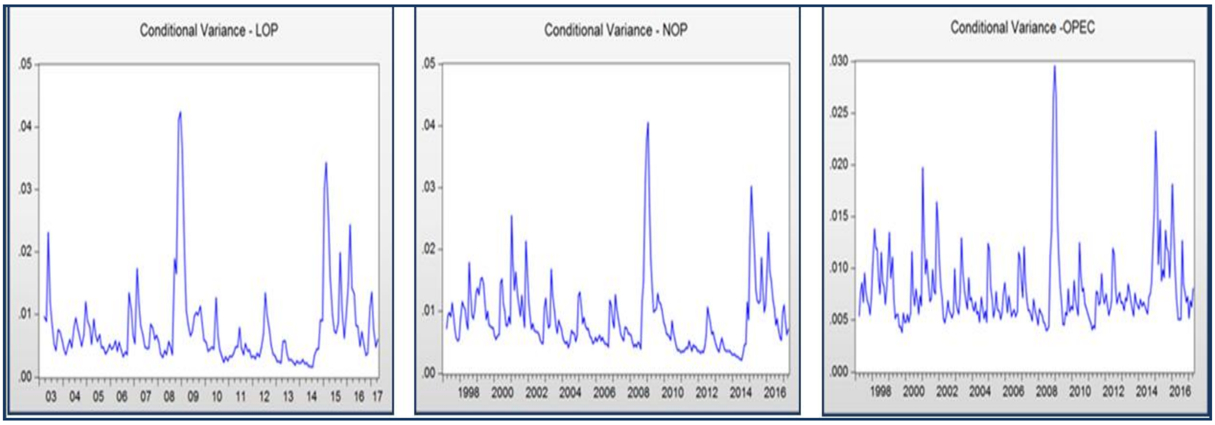


Figure 4-9. Estimated Conditional Volatility for LOP, NOP and OPEC Using an EGARCH(1,1) Model.

Figure 4-9 depicts the estimated volatility of oil price for Libya, Nigeria and OPEC. A quick examination of these graphs reveals evidence of remarkable spikes which surprisingly compatible to the global financial crisis. This is implying that, during the 2007-2009 periods, the global financial crisis greatly influenced the volatility of crude oil prices. Moreover, the estimated volatility of the EGARCH process showed high price volatility and periods of volatility clustering in the three oil markets. EGARCH volatility in the three markets maybe was increasing of major price shocks, which spurred speculation and led to volatility clustering; however, it declined during periods of price retreat. This means that oil markets have been constantly experiencing major uncertainties and have been affected by repeated shocks.

After AR(1)-EGARCH(1,1) models have been estimated, EGARCH variances for Libya, Nigeria and OPEC are subject to Bai–Perron and Chow structural change tests. To this end, the conditional variance is regressed on a constant and then structural break testing procedure is carried out. However, if a structural break is identified, a dummy variable identical to its date should be added and then the variance equation of the initial EGARCH model should be re-estimated. The results of Bai–Perron and Chow tests are presented in Table 4-18.

Table 4-18: Bai-Perron and Chow Breakpoint Tests in EGARCH Variances.

EGARCH(1,1) variances						
	Bai-Perron test			Chow test		
	Break test	F-Stat	critical values**	Break date	F-Stat	Prob.
Libya	0 vs. 1	2.4267	8.58	11/2008	1.0887	0.2982
Nigeria	0 vs. 1	1.5537	8.58	11/2008	0.0477	0.8273
				01/2009	0.9544	0.3271
OPEC	0 vs. 1	1.7642	8.58	11/2008	3.4565	0.0642

* Significant at the 0.05 level.

** Bai-perron (Econmetric jornal, 2003) critical values.

As a result of the Bai-Perron test, the F-statistics are smaller than the critical value so that we cannot reject the null hypothesis l=0 versus the alternative hypothesis l+1 = 1 break; therefore, no structural break was detected in the EGARCH variance series for Libya, Nigeria and OPEC.

The break date in Chow test should be known, therefore, it determined from notable spikes that appeared through visual inspection for the plots of the estimated conditional variance that given in Figure 4-9, which are confirmed by applying unit root tests with breakpoint for the estimated conditional variance data. Furthermore, the results of Chow test indicate that the null hypothesis that no break at specified date which is 11/2008 in the Libyan case is accepted at the 5% level. Moreover, we obtained the same results in both Nigeria and OPEC cases where the alternative hypothesis is rejected at the specified points and the results showed that the structural changes are insignificant in the volatility dynamics of the three oil markets in-sample analysis.

4.8 Forecast Evaluation

In this section we aim to evaluate the out-of-sample forecasting accuracies of the different conditional mean and conditional variance models used in this study for modelling the returns of crude oil prices. Thus, we perform out-of-sample predictive performance to evaluate various ARMA-GARCH class models. The last 12 months for the three time series under study covering the period from May 2017 to April, 2018 are used and their error functions include RMSE, MAE, MAPE and TIC are calculated. Tables from 4-19 to 4-21 report the comparison of out-of-sample forecasting performance of the different AR-GARCH-class models for the Libyan, Nigerian and OPEC oil price returns.

4.8.1 The Out-of-Sample Forecasting Evaluation for Libyan Oil Price Returns

As indicated in the estimation and diagnostic stages, the AR-EGARCH-N model appears to fit well for Libyan oil price returns. Nonetheless, there is no guarantee that it will perform better in forecasting stage. From the comparison of out-of-sample ahead forecasts for Performance evaluation of AR-GARCH family models for Libyan oil price returns in Table 4-19 we can say that the AR-CGARCH-GED model performs best on the three error criteria include RMSE, MAE and TIC. In terms of MAPE, the AR-GARCH-*t* produces the smallest value. Following Chai and Draxler (2014), the best out-of-sample forecasting model is selected based on RMSE and MAE as a standard statistical metric. In this case, the forecasting results have clearly shown that the CGARCH-GED model for the Libyan oil price returns is the best model for prediction.

Table 4-19: Comparison of Out-of-sample Forecasting Performance of AR-GARCH Models for Libyan Oil Prices Returns.

	Measuring the Performance			
	RMSE	**MAE**	**MAPE**	**TIC**
AR- GARCH -N	0.0612	0.0541	84.7160	0.8488
AR- EGARCH-N	0.0626	0.0562	92.3865	0.9136
AR- GJR -N	0.0609	0.0538	84.3263	0.8337
AR-APARCH-N	0.0627	0.0563	92.9147	0.9186
AR-CGARCH-N	0.0615	0.0545	86.2228	0.8612
AR-ACGARCH-N	0.0616	0.0548	86.4747	0.8623
AR- GARCH -*t*	0.0611	0.0540	**84.2730**	0.8432
AR- EGARCH-*t*	0.0625	0.0561	92.0428	0.9104
AR- GJR -*t*	0.0609	0.0538	84.3262	0.8338
AR-APARCH-*t*	0.0631	0.0569	95.1692	0.9402
AR-CGARCH-t	0.0609	0.0537	84.3652	0.8255
AR-ACGARCH-t	0.0614	0.0544	85.4926	0.8539
AR- GARCH - GED	0.0610	0.0538	84.2799	0.8369
AR- EGARCH- GED	0.0629	0.0566	93.9335	0.9279
AR- GJR - GED	0.0611	0.0539	84.3154	0.8396
AR-APARCH- GED	0.0628	0.0565	93.6456	0.9251
AR-CGARCH- GED	**0.0608**	**0.0536**	84.3414	**0.8249**
AR-ACGARCH-GED	0.0615	0.0545	85.9557	0.8579

Note: The error statistics correspond to the logarithmic returns. The values in bold face refer to the smallest.

For brevity, we only show the results of the out-of-sample forecasts derived from the best model. Therefore, we use the AR-CGARCH-GED model to illustrate multistep ahead forecasts, thus, Table 4-20 below contains the forecasts and standard errors of the associated forecast errors for the monthly Libyan oil prices returns and their volatilities covering the period from May 2017 to April 2018, In addition, the actual returns and actual Libyan oil prices are also given.

Table 4-20: Out-of-sample Forecasts for Libyan oil prices.

Step	Actual\ Return	Forecast\ Return	Standard error	Forecast\ Volatility	Actual\ Libyan oil price	Forecast\ Libyan oil price
May\ 2017	- 0.0428	0.0109	0.0664	0.0043	48.90	51.60
June\ 2017	-0.0860	0.0028	0.0696	0.0047	44.87	49.04
July\ 2017	0.0455	-0.0025	0.0841	0.0069	46.96	44.75
August\ 2017	0.0689	0.0140	0.0728	0.0052	50.31	47.62
September\ 2017	0.0904	0.0170	0.0708	0.0049	55.07	51.17
October\ 2017	0.0252	0.0197	0.0768	0.0058	56.48	56.16
November\ 2017	0.0864	0.0115	0.0621	0.0038	61.58	57.13
December\ 2017	0.0242	0.0192	0.0743	0.0054	63.09	62.77
January\ 2018	0.0783	0.0113	0.0604	0.0036	68.23	63.81
February\ 2018	-0.0583	0.0182	0.0700	0.0048	64.36	69.48
March\ 2018	0.0082	0.0009	0.0768	0.0058	64.89	64.42
April\ 2018	0.08192	0.0093	0.0610	0.0036	70.43	65.49

The out-of-sample forecasts from the AR-CGARCH-GED in Table 4-20 are likely to underestimate the volatilities during the period May 2017 to April 2018. Moreover, the forecasts of Libyan oil prices and their retunes obtained from AR-CGARCH-GED are closer to the actual values. However, we can see that the AR-CHARCH-GED model fits fairly well with Libyan oil price data. Furthermore the forecast of Libyan crude oil price with indicates an average price of crude oil around 56 USD/barrel with a relatively small volatility in the out-of-sample period. These results reflect a very good forecast model for the Libyan oil market. Finally, Figure 4-10 shows the 1-step to 12-step ahead out-of-sample forecasts and their tow standard error limits for Libyan oil prices and their returns using AR-CGARCH-GED model.

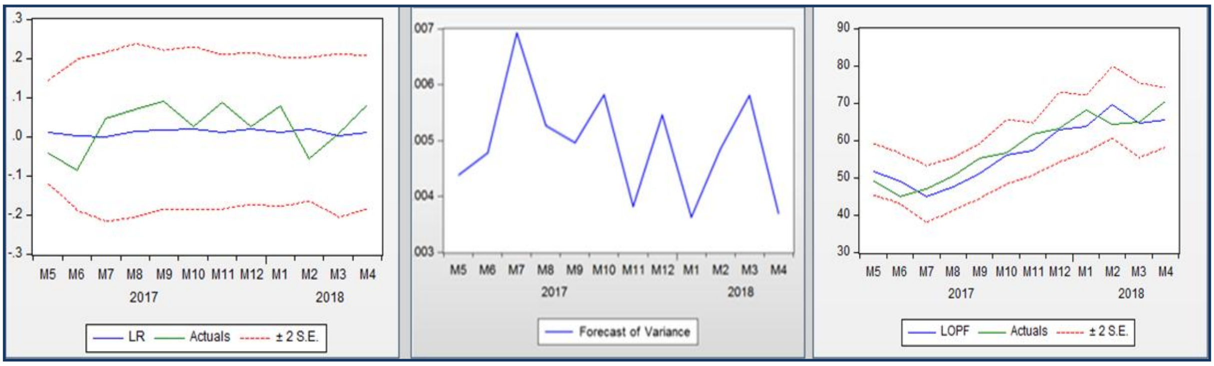


Figure 4-10: Plot of Out-of-sample Forecasts for Libyan Oil Prices using AR-CGARCH-GED Model.

4.8.2 The Out-of-Sample Forecasting Evaluation for Nigerian Oil Price Returns

As indicated in the estimation and diagnostic stages, the AR-EGARCH-N model appears to fit well for the Nigerian oil price returns based on SIC and HQIC. However, from the comparison of out-of-sample forecasts for performance evaluation of AR-GARCH family models for Nigerian oil price returns in Table 4-21 we can say that the AR-GARCH-GED model is superior to all other models on the all error criteria. The forecasting results have clearly shown that the AR-GARCH-GED model for Nigerian oil price returns is the best model for prediction.

Table 4-21: Comparisons of Out-of-sample Forecasting Performance of AR-GARCH Models for Nigerian Oil Prices Returns.

	Measuring the Performance			
	RMSE	**MAE**	**MAPE**	**TIC**
AR- GARCH -N	0.0602	0.0539	92.307	0.8939
AR- EGARCH-N	0.0613	0.0554	96.888	0.9472
AR- GJR -N	0.0611	0.0551	96.045	0.9368
AR-APARCH-N	0.0613	0.0554	96.943	0.9476
AR-CGARCH-N	0.0601	0.0537	91.668	0.8865
AR-ACGARCH-N	0.0598	0.0533	90.333	0.8713
AR- GARCH -*t*	0.0595	0.0529	89.091	0.8588
AR- EGARCH-*t*	0.0610	0.0549	95.529	0.9309
AR- GJR -*t*	0.0591	0.0521	86.681	0.8345
AR-APARCH-*t*	0.0613	0.0553	96.676	0.9447
AR-CGARCH-t	0.0590	0.0520	86.375	0.8313
AR-ACGARCH-t	0.0596	0.0530	89.492	0.8624
AR- GARCH - GED	**0.0574**	**0.0489**	**76.580**	**0.7466**
AR- EGARCH- GED	0.0607	0.0545	94.243	0.9161
AR- GJR - GED	0.0586	0.0514	84.454	0.8135
AR-APARCH- GED	0.0595	0.0527	88.635	0.8532
AR-CGARCH- GED	0.0588	0.0516	85.265	0.8210
AR-ACGARCH-GED	0.0591	0.0522	86.912	0.8364

Note: The error statistics correspond to the logarithmic returns. The values in bold face refer to the smallest.

we use the AR-GARCH-GED model to show out-of-sample forecasts, thus, Table 4-22 below shows the forecasts and standard errors of the associated forecast errors for the monthly Nigerian oil prices returns and their volatilities covering the period from May 2017 to April 2018, In addition, the actual returns and actual Nigerian oil prices are also given.

Table 4-22: Out-of-sample Forecasts for Nigerian oil prices.

Step	Actual\ Return	Forecast\ Return	Standard error	Forecast\ Volatility	Actual\ Nigerian oil price	Forecast\ Nigerian oil price
May\ 2017	-0.0433	0.0096	0.0812	0.0065	50.77	53.53
June\ 2017	-0.0788	0.0027	0.1122	0.0060	46.92	50.90
July\ 2017	0.03641	-0.0010	0.1115	0.0064	48.65	46.87
August\ 2017	0.0604	0.0112	0.1099	0.0056	51.69	49.20
September\ 2017	0.0898	0.0137	01039	0.0052	56.55	52.40
October\ 2017	0.02480	0.0169	0.1041	0.0056	57.97	57.51
November\ 2017	0.0878	0.0099	0.1019	0.0047	63.29	58.55
December\ 2017	0.0211	0.0166	0.1004	0.0053	64.64	64.35
January\ 2018	0.0785	0.0095	0.0993	0.0045	69.92	65.26
February\ 2018	-0.0543	0.0157	0.0969	0.0048	66.02	71.02
March\ 2018	0.0154	0.0012	0.1014	0.0053	67.05	66.10
April\ 2018	0.0815	0.0090	0.0992	0.0045	72.75	67.65

The out-of-sample forecasts from the AR-GARCH-GED in Table 4-22 shows that the forecasts of Nigerian oil prices and their retunes are closer to the actual values. Furthermore the forecast of Nigerian crude oil price with indicates an average price of crude oil around 58 USD/barrel with a relatively small volatility in the out-of-sample period. Thus, this model somehow fit the Nigerian oil price data well. Finally, Figure 4-11 illustrates the 1-step to 12-step ahead out-of-sample forecasts and their tow standard error limits for Nigerian oil prices and their returns using AR-GARCH-GED model.

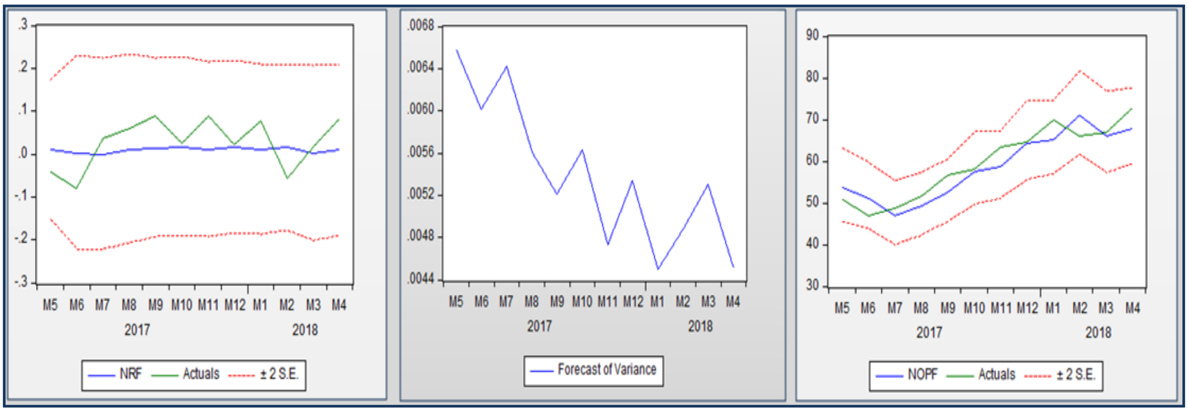


Figure 4-11: Plot of Out-of-sample Forecasts for Nigerian Oil Prices using AR-GARCH-GED Model.

4.8.3 The Out-of-Sample Forecasting Evaluation for OPEC Returns

As indicated in the estimation and diagnostic stages, the AR-CGARCH model with whit student-*t* appear to fit well for OPEC returns based on AIC. While, the SIC and HQIC suggest the AR-EGARCH with GED and normal respectively. However, from the comparison of out-of-sample forecasts for performance evaluation of AR-GARCH family models for OPEC returns in Table 4-23 we can say that the AR-EGARCH-t model is superior to all other models on the three error criteria include RMSE, MAE and TIC. In terms of MAPE, the AR-EGARCH-*N* produces the smallest value. The forecasting results have clearly shown that the AR-EGARCH-t model for OPEC oil price returns is the best model for prediction.

Table 4-23: Comparisons of Out-of-sample Forecasting Performance of AR-GARCH Models for OPEC.

	Measuring the Performance			
	RMSE	**MAE**	**MAPE**	**TIC**
AR- GARCH -N	0.0576	0.0515	88.875	0.8866
AR- EGARCH-N	0.0580	0.0519	**88.268**	0.9060
AR- GJR -N	0.0584	0.0525	91.775	0.9290
AR-APARCH-N	0.0553	0.0485	96.107	0.7577
AR-CGARCH-N	0.0562	0.0499	92.547	0.8129
AR-ACGARCH-N	0.0582	0.0523	90.550	0.9214
AR- GARCH -*t*	0.0567	0.0505	91.438	0.8364
AR- EGARCH-*t*	**0.0551**	**0.0481**	97.349	**0.7407**
AR- GJR -*t*	0.0562	0.0499	92.088	0.8177
AR-APARCH-*t*	0.0557	0.0492	94.014	0.7868
AR-CGARCH-t	0.0552	0.0484	96.234	0.7545
AR-ACGARCH-t	0.0554	0.0488	95.243	0.7685
AR- GARCH - GED	0.0556	0.0491	94.207	0.7838
AR- EGARCH- GED	0.0555	0.0490	94.619	0.7776
AR- GJR - GED	0.0558	0.0493	93.708	0.7915
AR-APARCH- GED	0.0558	0.0494	93.427	0.7959
AR-CGARCH- GED	0.0552	0.0482	96.890	0.7457
AR-ACGARCH-GED	0.0553	0.0483	96.630	0.7491

Note: The error statistics correspond to the logarithmic returns. The values in bold face refer to the smallest

we use the AR-EGARCH-t model is used to show the out-of-sample forecasts, thus, Table 4-24 shows the forecasts and standard errors of the associated forecast errors for the monthly OPEC prices returns and their volatilities covering the period from May 2017 to April 2018, In addition, the actual returns and actual OPEC prices are also given.

Table 4-24: Out-of-sample Forecasts for OPEC prices.

Step	Actual\ Return	Forecast\ Return	Standard error	Forecast\ Volatility	Actual\ OPEC price	Forecast\ OPEC price
May\ 2017	-0.0431	0.0080	0.0840	0.0070	49.20	51.78
June\ 2017	-0.0845	-0.0049	0.1235	0.0082	45.21	48.95
July\ 2017	0.0373	-0.0133	0.1351	0.0100	46.93	44.61
August\ 2017	0.0553	0.0114	0.1338	0.0077	49.60	47.47
September\ 2017	0.0745	0.01510	0.1198	0.0065	53.44	50.35
October\ 2017	0.0378	0.0190	0.1104	0.0056	55.50	54.46
November\ 2017	0.0902	0.0115	0.1023	0.0054	60.74	56.14
December\ 2017	0.0214	0.0222	0.1009	0.0047	62.06	62.10
January\ 2018	0.0743	0.0088	0.0981	0.0050	66.85	62.57
February\ 2018	-0.0517	0.0189	0.1086	0.0045	63.48	68.13
March\ 2018	0.0044	-0.0066	0.1086	0.0071	63.76	63.05
April\ 2018	0.0706	0.0047	0.1171	0.0065	68.43	64.06

The out-of-sample forecasts from the AR-EGARCH-t in Table 4-24 shows that the forecasts of OPEC prices and their retunes are closer to the actual values. However, the forecast of OPEC price with indicates an average price of crude oil around 58 USD/barrel with a relatively small volatility in the out-of-sample period. These results reflect a very good forecast model for OPEC market. Finally, Figure 4-12 illustrates the 1-step to 12-step ahead out-of-sample forecasts and their tow standard error limits for OPEC prices and their returns using AR-EGARCH-t model.

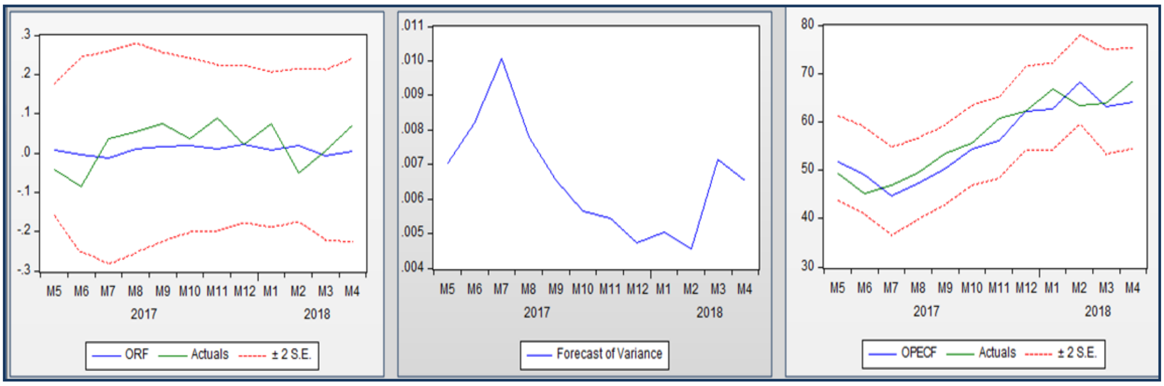


Figure 4-12: Plot of Out-of-sample Forecasts for OPEC Prices using AR-EGARCH-t Model.

As a conclusion, the forecasts of the Libyan, Nigerian and OPEC oil prices and their volatilities are crucial for all energy market participants, investors and policy makers in Libya and Nigeria or in the world, but forecasts of domestic oil prices have a particular importance due to possible effects of fluctuations in oil prices on commodity markets, on all aspects of energy markets, and on overall economic activity, inflation and GDP-growth in Libya and

Nigeria. Moreover, one of the direct applications of volatility is the the quantitative measurement of market risks such as value-at-risk. Economically, the risk of crude oil markets is a vital issue for financial institutions, including private or government investments, because a large amount of wealth can be lost due to a failure to supervise and control financial risks (Cheong, 2009).

4.9 A Discussion Between Comparative Analysis Results of Libya, Nigeria and OPEC

The empirical work of this chapter relates to the analysis and modeling of oil price returns for Libya, Nigeria and OPEC based on monthly data covering the period from January 1997 to April, 2018 to answer the first and second research question. The graphical representation of crude oil prices series under study suggested that the historical evolution of the prices in three markets is very similar. Despite the similarity in the historical development of oil prices under study, the results of the analysis showed slightly different results.

The outcomes of the Augmented Dickey-Fuller (ADF) and Phillip Peron (pp) test showed that all oil prices were non-stationary at the logarithm level, while they became stationary at their returns series. Therefore, all the individual series are treated as integrated of order one I~(1). To explore whether there exist structural breaks in the oil prices data, the study used unit root tests with breakpoints for two break specifications, innovation outlier and additive outlier models with unknown break date which chosen by minimizing the Dickey-Fuller t-statistic. All the returns series under study are considered non-trending data with intercept and the results of unit root with breaks indicating that the null hypothesis of a unit root is rejected at the 1% significant level, thus, all our return series are stationary with the selected break date 10/2008.

Based on the minimum value of SIC and HQI the an AR(1) model was selected as the appropriate conditional mean model for all returns series. By including structural breaks tests in mean and variance equations, in order to investigate break dates which could help us link them with specific event (e.g., financial crisis). The results of Bai-Perron and Chow breakpoint tests have not found any evidence of structural changes for the three returns series in both the mean and variance equations. The residuals of the AR(1) model for all returns showed a presence of ARCH effect. Therefore, several of AR-GARCH models with Normal distribution, student-t distribution and generalized error distribution (GED) are created. The results of the estimation for AR-GARCH family models for Libyan, Nigerian and OPEC returns lend support for high level of persistence in the conditional variance of all oil prices although the degree of persistence may vary across the symmetric and asymmetric models. In addition, the evidence of asymmetric effect to good and bad news appears mixed. Results showing that the Libyan oil price market exhibits a leverage effect in the AR-GJR and AR-ACGARCH models. While, the Nigerian oil price market exhibits a leverage effect in the asymmetric models include AR-EGARCH, AR-GJR, AR-APARCH and ACGARCH models. The prices of oil in OPEC exhibit a leverage effect in the EGARCH and ACGARCH models.

In the estimation stage the normal distribution provides a much better fit in sample for the three returns than any forms of the GARCH models with the student's t distribution and GED. From the values of the information criteria, the AR-EGARCH model with normal distribution was the best fitting model for returns of Libya and Nigeria. In contrast, the results in OPEC market are mixed because the AIC indicates that CGARCH process whit student-*t* the best fitting model for OPEC market returns. While, the SIC and HQIC suggest the AR-EGARCH with GED. The findingss of Bai-Perron and Chow breakpoint tests have not found any evidence of structural braks in the estimated variance series in the three markets. For investigating the forecasting capability of AR-GARCH models the last 12 months from our study covering the period from May 2017 to April, 2018 were used. The error functions of RMSE, MAE, MAPE and TIC were calculated and the comparison of out-of-sample forecasting performance has indicted that the best models for forecasting the returns of oil price were the CGARCH-GED model for Libyan market, the AR-GARCH-GED model for Nigerian market and the AR-EGARCH-t model for OPEC.

4.10 Summary

In this chapter, the returns of crude oil prices for Libyan, Nigerian and OPEC markets have been analysed to investigate the forecasting capability of the several estimated of ARMA(p, q)-GARCH(1,1) family models with three error distributions include normal, student-t and GE distributions. All the oil prices data were monthly and covered the period from January 2003 to April, 2018 for the Libyan market and the period from January 1997 to April, 2018 for both the Nigerian and OPEC markets. The construction of conditional mean and conditional variance functions for oil price returns series was based on the following steps: data source and graphical representation, descriptive statistics, detecting stationarity issue, examining the existence of structural breaks, model identification and estimation, diagnostic tests and finally forecasting capability.

The stationary detected using the visual examination of the correlogram, standard unit root tests and unit root tests with breakpoints include the modified Dickey-Fuller tests with breakpoints which allow for a structural break in the trend process under various specifications for the break. All the results obtained from detecting stationary property indicating that all the individual oil prices in the log-levels reported unit root, in contrast the tests rejected the null hypothesis of the unit root when we examined the returns series and all the returns series are stationary. Various ARMA models with different specifications are estimated in order to select a best ARMA model to fit each of our returns series as the mean equation. This selection was based on three information criteria including AIC, SIC and HIC. The AR(1) has been selected as the appropriate model for the Libyan, Nigerian and OPEC oil price returns. To investigate the existence of structural breaks in both the mean and variance equations Bai-Perron and Chow breakpoint tests have been carried out. The finding of these structural changes tests suggesting that the three oil prices markets under study showed no evidence of structural breaks in the important date in equation of the mean or conditional variance.

The residuals of mean equation have examined using various diagnostic tests included stationary condition, testing for uncorrelated, normality and heteroskedasticity. The results of the heteroskedasticity test indicating that the ARCH effect presented and the conditional heteroskedasticity can be modeled using GARCH models. Therefore, six hybrids of AR-GARCH family models include GARCH, EGARCH, GJR, PARCH, CGARCH and ACGARCH with normal, student-t and GE distributions for each returns series. Estimation of the parameters of these models and of the diagnostic tests on standardized residuals and squared standardized residuals were carried out. In the estimation stage the models with normal distribution provide a much better fit in sample for the three returns. From the values of the information criteria, the AR-EGARCH model with normal distribution was the best fitting model for Libyan and Nigerian, whilst, the AR-EGARCH-GED is the best for OPEC market. The results of the structural changes tests for the estimated conditional variance series of these models were insignificant and indicated to the absence for any structural breaks.

The evaluation of out-of-sample forecasting accuracies for different AR-GARCH-class models that used in this study for modelling the returns of crude oil prices for the Libyan, Nigerian and OPEC markets have been investigated based on four error functions include RMSE, MAE, MAPE and TIC. The results of the comparison of out-of-sample forecasting performance suggesting that the best models for prediction oil price returns are the CGARCH-GED model for the Libyan market, the AR-GARCH-GED model for the Nigerian market and the AR-EGARCH-t model for OPEC.

CHAPTER 5: Methodology and Theoretical Perspectives of Multivariate Time Series Analysis

5.0 Introduction

This chapter is divided into numerous sections that explain the methodology of multivariate time series analysis and several techniques which support what the study seeks to achieve in terms of answering questions 3, 4 and 5. The theoretical aspect which underpins the methodology is based on explaining in detail the vector autoregressive (VAR) model and its advantages and disadvantages. The concept of cointegration, the vector error correction (VECM) model and specification of the d terms in cointegrated processes are discussed. The Johansen's cointegration test and setting of the appropriate deterministic terms in cointegrated processes using the Pantula principle are also presented respectively. The Granger-causality test under VAR and the vector error correction models (VECM), impulse response analysis and forecast error variance decompositions (FEVD) are discussed in order to investigate the dynamic relationships among oil prices and selected macroeconomic variables.

5.1 Vector Autoregressive Model

Vector autoregressive model (VAR) is a multivariate time series consist a system of multiple single series. The model became known thanks to Sims (1980), who said that VAR is a very suitable tool for analysing the behaviour of the economic and financial time series, predict future values, studying the dynamic relationships among variables and structural analysis.

The natural extension of the univariate autoregressive process to dynamic multivariate time series is the vector autoregressive model of order p. The VAR model introduced by Sims (1980) describes a collection of k variables which are called endogenous variables over the same period ($t = 0, \pm 1, \pm 2, \ldots,$) as a linear function of their past values with an error term. Here, the term endogenous variable is used in econometric. It is similar to dependent variable where it is determined as a function in other variables. Moreover, the exogenous variable is similar to independent variable which is not influenced by other variables. The mathematical expression of the VAR(p) can be written as follows:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \dots + \phi_p r_{t-p} + \varepsilon_t \,; \qquad \varepsilon_t \sim i.i.d\,(0, \Sigma) \tag{5.1}$$

where $r_t = (r_{1t}, r_{2t}, \dots, r_{kt})'$ is an $(k \times 1)$ vector of time series variables, ϕ_0 is a $(k \times 1)$ vector of constants (intercepts), ϕ_i is a $(k \times k)$ matrix of coefficients, p is the lag number and ε_t is a $(k \times 1)$ vector of error are independently and identically distributed $(i.i.d)$ with zero mean and satisfying the conditions:

1. $E(\varepsilon_t) = 0$, for every error term.
2. $E(\varepsilon_t \acute{\varepsilon}_t) = \Sigma$, is the covariance matrix of error terms which is a $(k \times k)$ positive semi definite matrix. The VAR(p) model can be written in matrix notations as following

$$\begin{pmatrix} r_{1t} \\ r_{2t} \\ \vdots \\ r_{kt} \end{pmatrix} = \begin{pmatrix} \Phi_{10} \\ \Phi_{20} \\ \vdots \\ \Phi_{k0} \end{pmatrix} + \begin{pmatrix} \phi_{11}^{(1)} & \phi_{12}^{(1)} \cdots & \phi_{1k}^{(1)} \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} \cdots & \phi_{2k}^{(1)} \\ \vdots & \vdots \ \ddots & \vdots \\ \phi_{k1}^{(1)} & \phi_{k2}^{(1)} \cdots & \phi_{kk}^{(1)} \end{pmatrix} \begin{pmatrix} r_{1t-1} \\ r_{2t-1} \\ \vdots \\ r_{kt-1} \end{pmatrix} + \cdots + \begin{pmatrix} \phi_{11}^{(p)} & \phi_{12}^{(p)} \cdots & \phi_{1k}^{(p)} \\ \phi_{21}^{(p)} & \phi_{22}^{(p)} \cdots & \phi_{2k}^{(p)} \\ \vdots & \vdots \ \ddots & \vdots \\ \phi_{k1}^{(p)} & \phi_{k2}^{(p)} \cdots & \phi_{kk}^{(p)} \end{pmatrix} \begin{pmatrix} r_{1t-p} \\ r_{2t-p} \\ \vdots \\ r_{kt-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{kt} \end{pmatrix}$$

For instance, a bivariate VAR(2) model can be written as these forms

$$\begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \end{pmatrix} + \begin{pmatrix} \phi_{11}^{(1)} & \phi_{12}^{(1)} \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} \end{pmatrix} \begin{pmatrix} r_{1t-1} \\ r_{2t-1} \end{pmatrix} + \begin{pmatrix} \phi_{11}^{(2)} & \phi_{12}^{(2)} \\ \phi_{21}^{(2)} & \phi_{22}^{(2)} \end{pmatrix} \begin{pmatrix} r_{1t-2} \\ r_{2t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

or

$$r_{1t} = \phi_{10} + \phi_{11}^{(1)} r_{1t-1} + \phi_{12}^{(1)} r_{2t-1} + \phi_{11}^{(2)} r_{1t-2} + \phi_{12}^{(2)} r_{2t-2} + \varepsilon_{1t}$$

$$r_{2t} = \phi_{20} + \phi_{21}^{(1)} r_{1t-1} + \phi_{22}^{(1)} r_{2t-1} + \phi_{21}^{(2)} r_{1t-2} + \phi_{22}^{(2)} r_{2t-2} + \varepsilon_{2t}$$

The VAR (p) model in Eq. (5.1) can be written in lag operator notation as

$$\left(\mathrm{I} - \phi_1 B - \cdots - \phi_p B^p\right) r_t = \phi_0 + \varepsilon_t$$

$$= \phi(B) r_t = \phi_0 + \varepsilon_t (5.2)$$

where I is the $(k \times k)$ identity matrix and $\varphi(B) = \left(\mathrm{I} - \phi_1 B - \cdots - \phi_p B^p\right)$ is a matrix of VAR polynomial. The VAR model is stable or stationary if the roots of $\det(\mathrm{I} - \phi_1 B - \cdots - \phi_p B^p) = 0$ located outside the unit circle.

5.1.1 Vector Autoregressive Models Advantages

One of the most important advantages of the VAR model is that all variables in the model are treated as endogenous variables (Asteriou and Hall, 2011). For example, in regression models there is usually a problem in determining the identity of the exogenous and endogenous variable and it is difficult to decide which of the variables should be chosen as exogenous, but in the VAR model the right hand sides of the equations are always the same and consist lagged of the endogenous variables leading to the absence of such a problem.

According to Brooks (2008), in the univariate time series models, the variable is dependent only on the own lagged values and error terms. The VAR model is a more flexible model since the endogenous variable is affected by its lagged values as well as the lagged values of other endogenous variables in the system. However, the equations in the VAR model can simply be estimated using the ordinary least squared (OLS) method. Moreover, the VAR model do not need strong constraints of the kind required to identify underlying structural parameters and these models provide superior forecasts compared with univariate time series models and others. Brooks (2008) states that the results of McNees (1986) show that the forecasting of some macroeconomic indicators in the U.S by using the VAR model are more accurate than others. In addition, the VAR models are useful tool for structural inference and policy analysis which are used to study the dynamic relationships among the variables.

5.1.2 Vector Autoregressive Models Disadvantages

The first major weakness pointed out by Schlegel (1985) is that the large number of coefficients to be estimated in the VAR model, where new lagged values of each variable are added in system according to the selected order of VAR model which in turn produces a large number of parameters. Another issue related with the choice the optimal lag length for VAR model and to make a decision on the appropriate lag length usually we use different information criteria. The problem here is when the information criteria give different results and we forced to choose one of them. It is difficult to see which variables have major effect on the endogenous variable, since the VAR models require that all variables in the system must be stationary. If the stationarity condition has not been achieved, then VAR model should be converted into a vector error correction (VEC) model, which includes first difference and cointegration relationships.

5.1.3 The Optimal Lag Length Selection of VAR Model

The common procedure used to identify the optimal lag length for the VAR model is using the information criteria including AIC, SIC and HQ (Lutkepohl, 2005). The best model is the one with that minimize the information criteria. However, the general method for fitting VAR(p) models with orders p = 0, ..., $p_{\max}$ then select the value of p which minimizes some model is information criteria, therefore in this thesis the information criterion is preferred. Under the assumption of normality these information criteria are defined as following

1. Akaike criterion (AIC): $AIC = ln\left|\hat{\Sigma}(p)\right| + \frac{2}{T}pn^2$ (5.3)
2. Schwarz criterion (SIC): $\text{SIC} = \ln\left|\hat{\Sigma}(p)\right| + \frac{\ln(T)}{T}pn^2$ (5.4)
3. Hannan – Quinn criterion (HQ): $HQ = \ln\left|\hat{\Sigma}(p)\right| + \frac{2\ln(\ln(T))}{T}pn^2,$ (5.5)

where $\hat{\Sigma}(p) = \frac{1}{T}\sum_{t=1}^{T}(\hat{\varepsilon}_{t)}\ (\hat{\varepsilon}_t^{\prime})$ is the estimate of the variance – covariance matrix of residuals, T is the sample size and $n$is the total number of estimated coefficients in VAR model.

Lutkepohl (1991) reports that only under the consistency benchmark the criteria HQ and SIC are superior than AIC. Also, the small sample comparison of AIC, HQ, and SIC results of simulation study suggest that there is no strong reason to prefer a criterion for others in small sample size cases but in case of moderate sizes of sample sizes the AIC may provide superior outcomes in terms of forecast accuracy. However, Johansen (1991) and Gonzalo (1994) pointed out that the order selection of VAR model can influence proper inference about cointegrating analysis.

5.2 The Concept of Cointegration

The cointegration approach was introduced by Granger (1981) and Engle and Granger (1987). It is now widely used in numerous financial and econometric applications to study and test stationary linear relationship or cointegration relationship between nonstationary time series variables. Cointegration is considered as a common phenomenon that happens frequently in financial and economic time series, particularly when the time series exhibit stochastic trends integrated to the order of 1. In other words, cointegration is a statistical characteristic of some time series data related to the integration order and stationarity concepts. This means that if some variables have moved together in the long run, they are driven by a common stochastic trend and are called cointegrated. Formally, if $X_t = (x_{1t}, \ldots\ldots, x_{kt})'$ represents a $(k \times 1)$ vector of nonstationary or I(1) time series, X_t is called cointegrated if there exists a linear combination of them that is stationary such that for an $(k \times 1)$ vector $\beta = (\beta_1, \ldots\ldots, \beta_k)'$ then

$$Z_t = \beta' x_t = \beta_1 x_{1t} + \ldots. + \beta_k x_{kt} \sim \mathrm{I}(0) \tag{5.6}$$

The linear combination $Z_t = \beta' x_t$ is regularly motivated by the received knowledge of applied economics prevailing within the economic systems under investigation, and indicates a long-run relationship, with the vector β defined as a cointegrating vector which is not unique. Here, the term of long-term mean that the variables have a long-run stochastic trend.

According to Brooks (2008), the general rule concerning linear combination $\beta_1 x_{1t} + \beta_2 x_{2t}$ of two integrated variables x_{1t} and x_{2t} with orders of integration are b and d respectively, is that the integrated order of $\beta_1 x_{1t} + \beta_2 x_{2t}$ is highest order of b and d. With more clarity,

- If the variables $x_{1t} \sim \mathrm{I}(0)$, and $x_{2t} \sim \mathrm{I}(0)$, then $\beta_1 x_{1t} + \beta_2 x_{2t}$ will also be $\mathrm{I}(0)$.
- If the variables $x_{1t} \sim \mathrm{I}(0)$, and $x_{2t} \sim \mathrm{I}(1)$, then $\beta_1 x_{1t} + \beta_2 x_{2t}$ will also be $\mathrm{I}(1)$, here the highest order of integration $\mathrm{I}(1)$ dominatesthe lower order of integration I(0) and they cannot be cointegrated.
- If the variables $x_{1t} \sim \mathrm{I}(1)$, and $x_{2t} \sim \mathrm{I}(1)$, then $\beta_1 x_{1t} + \beta_2 x_{2t}$ will also be $\mathrm{I}(1)$ in the general situation.

5.3 The Vector Error Correction (VEC) Model

Johansen (1988) developed the VEC model which is generally applied if the set of variables are non-stationary and cointegrated. The VEC model is used for investigating the short-run and long-run relationship between underlying time series.

Suppose that, $X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t$, is a VAR($p$) model of a k-dimensional time series X_t and X_t is non-stationary and integrated of order one. The mathematical expression of VEC($p-1$) model for VAR(p) model can be written as follows:

$$\Delta X_t = \boldsymbol{\Pi} X_{t-1} + \phi_1^* \Delta X_{t-1} + \cdots + \phi_{p-1}^* \Delta X_{t-p+1} + \varepsilon_t \tag{5.7}$$

$$= \alpha \acute{\beta} X_{t-1} + \phi_1^* \Delta X_{t-1} + \cdots + \phi_{p-1}^* \Delta X_{t-p+1} + \varepsilon_t \tag{5.8}$$

Where Δ is the difference operator, $\phi_i^* = -(\phi_{i+1} + \cdots + \phi_p), i = 1, \ldots, p-1$ is a $(k \times k)$ coefficients matrix, $\boldsymbol{\Pi} = \alpha\acute{\beta}$ is a $(k \times k)$ coefficient matrix decomposed which is not unique that is meaning that it is possible to have a number co-integrating vectors, α and β are $(k \times r)$ matrices and

$$\boldsymbol{\Pi} = \alpha\acute{\beta} = \phi_p + \phi_{p-1} + \cdots + \phi_1 - \boldsymbol{I}, \tag{5.9}$$

where $\boldsymbol{I}$ is the identity matrix. However, the term $\boldsymbol{\Pi}X_{t-1}$ is referred as the error correction term which has a main role in cointegration analysis because it is concerned with long-run relationship among variables. The term $\phi_1^*\Delta X_{t-1} + \cdots + \phi_{p-1}^*\Delta X_{t-p+1}$ is concerned with short-run relationship among variables.

5.4 Specification of the Deterministic Terms in Cointegrated Processes

In this section, we introduce briefly the specification of deterministic term to be in the cointegrated VAR models. These specifications are proposed by Johansen (1992) and Perron and Campbell (1993) which are divided into two categories, a constant term of cointegration relationship and a constant of the differenced series term as well as a linear trend. Therefore, suppose that there are r cointegrating relationships. The VEC model can be written as

$$\Delta X_t = \mu_t + \alpha\acute{\beta}X_{t-1} + \phi_1^*\Delta X_{t-1} + \cdots + \phi_{p-1}^*\Delta X_{t-p+1} + \varepsilon_t \tag{5.10}$$

Inserting restrictions on the trend terms in Eq (5.10) produces five situations which are illustrated as follows

- **Model 1**: $\mu_t = 0$: In this situation, there are no constant or trend in the component series or in the cointegrating process. The VEC model becomes

$$\Delta X_t = \alpha\acute{\beta}X_{t-1} + \phi_1^*\Delta X_{t-1} + \cdots + \phi_{p-1}^*\Delta X_{t-p+1} + \varepsilon_t \tag{5.11}$$

Generally, in practice this assumption is an unreasonable and there is a little possibility that this model is not the best model because the constant part is usually necessary to calculate different units for measuring variables.

- **Model 2:** $\mu_t = \mu_0 = \alpha c_0$, where c_0 is a $(k \times 1)$ nonzero constant vector included in the cointegrating relations implies that, the first differenced returns in the cointegrating equation have different mean and here are no constant terms in the component series. This case is referred as a restricted constant case and the VEC model can be written as

$$\Delta X_t = \alpha\left(\acute{\beta} X_{t-1} + c_0\right) + \phi_1^* \Delta X_{t-1} + \cdots + \phi_{p-1}^* \Delta X_{t-p+1} + \varepsilon_t \tag{5.12}$$

- **Model 3**: Two constants are included; in the cointegrating equation and in the short-run term of the model. There are no linear terms included.

$$\Delta X_t = \mu_0 + \alpha\left(\acute{\beta} X_{t-1} + c_0\right) + \phi_1^* \Delta X_{t-1} + \cdots + \phi_{p-1}^* \Delta X_{t-p+1} + \varepsilon_t \tag{5.13}$$

- **Model 4**: There is a linear trend and constant in the cointegrating relation and the constant term and no trend in the component series.

- **Model 5:** In this case both linear trend terms and constant are present. All component series have a quadratic trend and constant, because the model is actually capable of generating quadratic trends in the means of the data (Lütkepohl, 2005). While the cointegrating relation in the model have a linear trend and constant. This case rarely occurs in practical analysis.

In practice, the decision to choose appropriate models to use in the Johansen approach, which will be discussed in the next section, is not easy task, and the results can be biased and misleading, because the critical values and the asymptotic distribution of the cointegration test will depend on the selected model. Therefore, there are two methods. The one of the possible method is visual diagnosis of the graph of time series at levels or in their returns, but the figures of data would give little information about the choice of models. The second method is called the Pantula principle was proposed by Johansen (1992) and Pantula (1989). However, in empirical works only models 2, 3 and 4 are of interest. Tsay (2005) indicates that model 1 is not regularly used in modelling economic time series data, while model 3 is helpful for modelling price data, but is not common in practice compared to model 4.

5.5 Testing for Cointegration

Testing for cointegration is a necessary procedure for checking if the modelling empirically meaningful relationships. In this study, the Johansen test (1991) is used to discover the cointegrating relationships between variables. This procedure is most commonly used in the analysis of common integration (Maddala and Kim, 1998). Therefore, we briefly describe this common test in the next subsection.

5.5.1 Johansen's Cointegration Test

The Johansen's test (JT) (Johannsen, 1988, 1991) and (Johannsen and Juselius 1990) is considered a superior test for cointegration, because it has all attractive statistical characteristics and can determine all cointegrating relations among variable. This test is used to test whether variables are integrating in the same order and they move together or not in the long run. The JT is based on the VAR model. Now, suppose that all individual variables of an $(k \times 1)$ vector X_t are $I(1)$. The VAR(p) model

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t \; ; \quad \varepsilon_t \sim i.i.d\,(0, \Sigma) \tag{5.14}$$

is called cointegrated of rank r if the matrix $\boldsymbol{\Pi} = \left(\phi_1 + \cdots + \phi_p - I_k\right)$ has rank r and $\boldsymbol{\Pi}$ can be presented as this form $\boldsymbol{\Pi} = \alpha\acute{\beta}$, where α and β are $(k \times r)$ matrices. The matrix β is usually defined as cointegrating vectors, α is referred as the loading matrix or speed, adjustment coefficients and the rank r of $\boldsymbol{\Pi}$ is the number of cointegrating vectors. Hence, to perform JT the VAR model must be transformed into a VEC model using series differencing and written as

$$\begin{aligned} \Delta X_t &= \boldsymbol{\Pi} X_{t-1} + \phi_1^* \Delta X_{t-1} + \cdots + \phi_{p-1}^* \Delta X_{t-p+1} + \varepsilon_t \\ &= \alpha\acute{\beta} X_{t-1} + \phi_1^* \Delta X_{t-1} + \cdots + \phi_{p-1}^* \Delta X_{t-p+1} + \varepsilon_t, \end{aligned} \tag{5.15}$$

with $\acute{\beta} X_{t-1} \sim I(0)$. Moreover, for getting a stationary error termε_t, the error correction term $\boldsymbol{\Pi} X_{t-1}$ should be stationary, in which case $\boldsymbol{\Pi} X_{t-1}$ must have $r < k$ cointegration relations. However, there are three cases in the VEC model which are based on the rank of $\boldsymbol{\Pi}$. These cases are summarized as following

- If the rank $(\boldsymbol{\Pi}) = 0$. This involves $\boldsymbol{\Pi} = 0$ and there is no cointegating relationship. In this case the VEC model is reduced to

$$\Delta X_t = \phi_1^* \Delta X_{t-1} + \cdots + \phi_{p-1}^* \Delta X_{t-p+1} + \varepsilon_t \tag{5.16}$$

Here, ΔX_t is stationary variables and follows a VAR model in differencing with order $p - 1$.

- If the rank $(\boldsymbol{\Pi}) = k$. This means that $|\boldsymbol{\Pi}| \neq 0, X_t$ is stationary and, hence, the VAR operator has no unit roots so that X_t is a stable VAR(p) process.

- If $0 < \text{rank}(\boldsymbol{\Pi}) = r < k$. In this situation $\boldsymbol{\Pi} = \alpha\acute{\beta}$, and $\text{Rank}(\alpha) = \text{Rank}(\beta) = r$, meaning that X_t is cointegrated with r cointegrated vectors.

The Johansen approach for testing cointegration examines the rank of the equation system ($\boldsymbol{\Pi}$) to determine the number of characteristic roots or eigenvalues which are denoted as λ. This approach specifies and estimates a VAR(p) model, and examines the rank of $\boldsymbol{\Pi}$ using maximum likelihood estimator of β (Lutkepohal, 1991; Harris, 1995). Johansen developed two cointegration likelihood ratio statistics, called the trace statistic denoted λ_{trace} and the maximum eigenvalue statistic denoted λ_{max} for the number of cointegration relations. Suppose that estimators of the eigenvalues of the matrix $\boldsymbol{\Pi}$ are $\hat{\lambda}_1 > \hat{\lambda}_1 > \cdots > \hat{\lambda}_k$. These likelihood-ratio statistics are calculated as following

$$\lambda_{trace} = -T\sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i) \tag{5.17}$$

$$\lambda_{max} = -T\ln(1-\hat{\lambda}_i) \tag{5.18}$$

It should be noted here that the formulation of the null hypothesis in the Johansen test in both cases differs subtly, and rejecting or accepting the initial hypothesis compares the test statistic with a specific critical value, compiled by Johansson and tabulated in Osterwald-Lenum (1992). To explain the hypothesis and the decisions in the Johansen test in both cases, assume that for bivariate model, these tests have carried out in two steps illustrated in the following Table 5-1.

Table 5-1: The Hypothesis and the Decisions in the Johansen Test.

Step 1		
Hypothesis	λ_{Trace}	λ_{Max}
Null (H_0)	$r = 0$	$r = 0$
Alternative	$r > 0$	$r = 1$
Accept H_0	Series are $I(1)$ and no cointegaration relations → stop	
Reject H_0	go to step 2	
Step 2		
Null(H_0)	$r \leq 1$	$r = 1$
Alternative	$r = 2$	$r = 2$
Accept H_0	Series are $I(1)$ and cointegrated	
Reject H_0	Series are $I(0)$	

In fact, there is no strong reason to prefer one test to the other, but in the literature there are some attempts to compare the performance of these tests. For example, Toda (1994) notes that the comparison of a Monte Carlo study for the characteristics of small samples for both tests indicates that these tests are similarly superior, but that the trace tests work better in some cases where the power is low . Lütkepohl and Trenler (2001) compare the characteristics of trace and the maximum eigenvalue tests for the cointegrating rank of a VAR(p) model. They report that both tests are variants of a type of likelihood ratio and work under several assumptions concerning the deterministic part of the generation process of the data. The results have found that, the trace and maximum eigenvalue tests have similar properties. However, the comparison for small samples, in case $(T = 100)$, suggested that in some situations the trace test tends to be more powerful compared to the maximum eigenvalue test. Their general recommendation was to use the trace test and there is nothing wrong with applying both tests simultaneously in practice. However, the key problems of the procedure of Johansen as reported by Maddala and Kim (1998, pp.220) "are sensitivity to misspecification of the lag length, and substantial size distortions in the tests for the second and subsequent cointegrating vectors when the ratio of data points to the number parameters is small (of the order of 5 or less)".

5.5.2 The Pantula Principle - Deterministic Functions in the Johansen Test

The procedure which has been used in this study to choose both the cointegrating rank and the appropriate specification of the deterministic function simultaneously is based on the Pantula principle (Pantula, 1989). The idea of this principle is to apply all Johansen's tests related to the relevant deterministic functions starting from the most restricted model (model 1) to the least restrictive model (model 5) and stopping when the null hypothesis is not rejected for the first time. More specifically, the Pantula principle begins with the most restrictive model (Model 1 and the null hypothesis of no cointegrating vectors or $r = 0$). Then, we should compare the Johansen's test statistic for this model to its critical value. If we reject the null hypothesis in model 1, we move over the next restrictive model (model 2) to the least restrictive one (model 5 and the null hypothesis of $r = k - 1$), and only stop when the first time the null hypothesis is not rejected indicating to the better model should be used to describe the system.

5.6 Structural Analysis

Because the VAR and VEC models characterize the links between a set of data, they are usually used to analyse particular aspects of relationships among variables of interest. Also, these models in higher orders have many parameters that may be difficult to explain due to the complicated interactions and causality among data in the system. Therefore, the dynamic characteristics of VAR and VEC models are usually summarised using different types of structural analysis. Here, the three major types of structural analysis are called Granger causality tests, impulse response functions, and forecast error variance decompositions. The following section provides a brief description of all these types of structural analysis.

5.6.1 Granger Causality

One of the major uses of the VAR models is prediction. Consequently, the structure of the VAR model provides information on a variable or set of variables that predicts other variables. Granger (1969) introduced the concepts of causality of a variable's forecasting ability, which can be summarized in words as follows. A variable r_{1t} is said not to Granger-cause another variable r_{2t} if r_{1t} cannot help to forecast future r_{2t} values. In contrast, r_{1t} is said to Granger-cause r_{2t} if it is found to be helpful to forecast r_{2t}.

- **Granger Causality Based on Bivariate VAR Models**

Suppose that VAR model is a bivariate case of order p for $r_t = (r_{1t}, r_{2t})'$, r_{2t} does not Granger-cause r_{1t} if all the coefficient matrices of VAR(p) model $\phi_1, \dots, \phi_p$ ae lower triangular. That is, the VAR(p) model has the matrix form

$$\begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \end{pmatrix} + \begin{pmatrix} \phi_{11}^{(1)} & 0 \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} \end{pmatrix} \begin{pmatrix} r_{1t-1} \\ r_{2t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \phi_{11}^{(p)} & 0 \\ \phi_{21}^{(p)} & \varphi_{22}^{(p)} \end{pmatrix} \begin{pmatrix} r_{1t-p} \\ r_{2t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

So that all parameters on the lag values of r_{2t} are equal to zero in the equation forr_{1t}. In the same way, r_{1t} does not Granger- cause r_{2t} if all the coefficients on the lag values of r_{1t} are equal to zero in the equation for r_{2t}. It should be noted here that if the coefficient matrices of VAR(p) model $\phi_1, \dots, \phi_p$ are diagonal in this case r_{2t} fails to Granger-cause r_{1t} and r_{1t} fails to Granger-cause r_{2t}.

In general, the test for Granger-causality in multivariate VAR(p) models follows those for bivariate models. Usually these tests are performed using the standard Wald's F or χ^2 statistic test. However, in the literature there are many tests for Granger-causality (see, e.g., Geweke, Meese and Dent, 1983). In the next subsection, we will introduce the main tests used in this thesis for testing the causality relationships among oil prices, Libya and Nigeria indicators.

- **Pairwise Granger Causality Tests**

Pairwise Granger causality test is based on bivariate VAR(p) model; therefore, two variables in this case will be analyzed together for testing causal direction relationships, VAR(p) model with two variables r_{1t} and r_{2t} will be estimated as follows

$$r_{1t} = \Phi_{10} + \Phi_{11}^{(1)} r_{1t-1} + \cdots + \Phi_{11}^{(p)} r_{1t-p} + \Phi_{12}^{(1)} r_{2t-1} + \cdots + \Phi_{12}^{(p)} r_{2t-p} + \varepsilon_{1t} \qquad (5.19)$$

$$r_{2t} = \Phi_{20} + \Phi_{22}^{(1)} r_{2t-1} + \cdots + \Phi_{22}^{(p)} r_{2t-p} + \Phi_{21}^{(1)} r_{1t-1} + \cdots + \Phi_{21}^{(p)} r_{1t-p} + \varepsilon_{2t} \qquad (5.20)$$

Pairwise Granger causality tests between (all possible) pairs of the group of variables. The calculated F-statistics for testing the joint hypothesis

$$H_{01}: \Phi_{12}^{(i)} = 0\,, i = 1, \dots. p \quad vs \quad H_{11}: \Phi_{12}^{(i)} \neq 0$$

For testing that r_{2t} does not Granger-cause r_{1t}, similarly,

$$H_{02}: \Phi_{21}^{(i)} = 0\,, i = 1, \dots. p \quad vs \quad H_{12}: \Phi_{21}^{(i)} \neq 0$$

For testing that r_{1t} does not Granger-cause r_{2t}. Hence, the F statistic for the Wald test is calculated as following

$$F = \frac{(SSE_r - SSE_u)/p}{SSE_u/(T-2p-1)} \sim F(p, T-2p-1), \qquad (5.21)$$

where SSE_r is the sum of squared residuals under the null hypostasis, SSE_u is the sum of squared residuals from VAR(p) model equations and T is the number of observations. However, if calculated F is greater than F-critical value, then the null hypotheses are rejected in each case, indicating there is Granger causality between the two variables. Generally, in testing Granger causality relationships there are four possible outcomes which can summarize as following:

- No causality relationship among variables.
- Unidirectional Granger causality from variable r_{2t} to variable r_{1t}.
- Unidirectional Granger causality from variable r_{1t} to r_{2t} and
- Bi-directional causality relationship among variables.

Pairwise Granger causality test results can be displayed as in Table 5-2 below.

Table 5-2: The Pairwise Granger Causality Test Results.

The decision	Rejection $H_{02}: \Phi_{21}^{(i)} = 0$	Acceptance $H_{02}: \Phi_{21}^{(i)} = 0$
Rejection $H_{01}: \Phi_{12}^{(i)} = 0$	$r_{2t} \Rightarrow r_{1t}$ $r_{1t} \Rightarrow r_{2t}$ (Bidirectional Granger causality)	$r_{2t} \Rightarrow r_{1t}$ $r_{1t} \nRightarrow r_{2t}$ (r_{2t} Granger causes r_{1t})
Acceptance $H_{01}: \Phi_{12}^{(i)} = 0$	$r_{2t} \nRightarrow r_{1t}$ $r_{1t} \Rightarrow r_{2t}$ (r_{1t} Granger causes r_{2t})	$r_{2t} \nRightarrow r_{1t}$ $r_{1t} \nRightarrow r_{2t}$ (no Granger causality)

- **The VAR Granger Causality/Block Exogeneity Wald Tests: The Multivariate Case**

Here, we are interested to investigate the Granger Causality among multiple series adopted on the multivariate VAR/VEC model. The Granger Causality/Block Exogeneity Wald tests are used to investigate this causal relationship. However, under this system, an endogenous variable can be considered as exogenous. The chi-square (Wald) statistics is used for testing the joint significance of each of the other lagged endogenous variables in each equation of the system, also, joint significance of all other lagged endogenous variables in each equation of the VAR process.

5.6.2. Impulse Response Function

Recall that in the univariate case, the AR model can be written in the form of an MA model. Similarly in the multivariate case, the VAR (p) in Eq. (5.1) also can be represented as a linear function of the previous errors as following

$$r_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \cdots, \tag{5.22}$$

where $\mu = \left(\mathrm{I} - \phi_1 - \cdots - \phi_p\right)^{-1} \phi_0$ and Ψ_s are the $(k \times k)$ moving average matrices. The elements of coefficient matrices Ψ_s are called the impulse response functions of r_t which mean effects of ε_{t-s} shocks on r_t. The Ψ_s is determined recursive substitution using

$$\Psi_s = \sum_{j=1}^{p-1} \Psi_{s-j}\, \phi_j,\ \ s = 0,1,2,\ldots \tag{5.23}$$

The impulse response function is the (i, j)-th element, ψ_{ij}^{s} of the matrix Ψ_s which can be written as follows

$$\psi_{ij}^{s} = \frac{\partial r_{i,t+s}}{\partial \varepsilon_{i,t}} = \frac{\partial r_{i,t}}{\partial \varepsilon_{i,t-s}}, \quad i, j = 1, \ldots, k \tag{5.24}$$

Also, the impulse responses functions are sometimes referred to as forecast error impulse responses in literature. In addition, the response of one variable to a unit shock or a one standard deviation unit shocks, in case the variables series have different scales, is sometimes graphically presented to get a visual impression of the dynamic relationships among variables in the system.

5.6.3 Forecast Error Variance Decompositions (FEVD)

The forecast error variance decomposition measures how much of the forecast error variance of each of the variables can be interpreted by exogenous shocks to the other variables. In other words, the forecast variance decomposition determines the proportion of the variation in r_{jt} due to the shock ε_{jt} versus shocks of other variables ε_{it} for $i \neq j$. The results of FEVD can be introduced in a table or a graph (Lütkepohl, 2005). More specifically, for known VAR coefficients the h-step ahead forecast error vector can be written as

$$r_{t+h} - r_t(h) = \sum_{s=0}^{h-1} \Psi_s\, \varepsilon_{T+h-s} \tag{5.25}$$

with $r_t(h)$ being the optimal h-step forecast at period t for r_{t+h}. Therefore, for a specific variable $r_{i,T+h}$ the forecast error is

$$r_{i,t+h} - r_{i,t}(h) = \sum_{s=0}^{h-1} \psi_{i1}^{s}\, \varepsilon_{1,T+h-s} + \cdots + \sum_{s=0}^{h-1} \psi_{ik}^{s}\, \varepsilon_{k,T+h-s} \tag{5.26}$$

The variance of the h-step forecast error is

$$var\,(r_{i,t+h} - r_{i,t}(h)) = \sigma_{\varepsilon_1}^2 \sum_{s=0}^{h-1} (\psi_{i1}^{s})^2 + \cdots + \sigma_{\varepsilon_k}^2 \sum_{s=0}^{h-1} (\psi_{ik}^{s})^2, \tag{5.27}$$

where $\sigma_{\varepsilon_j}^2$ is the variance of ε_{jt}. In this case, the portion of $var\,(r_{i,t+h} - r_{i,t}(h))$ due to shock ε_j is

$$FEVD_{i,j}(h) = \frac{\sigma_{\varepsilon_j}^2 \sum_{s=0}^{h-1} (\psi_{ij}^{s})^2}{\sigma_{\varepsilon_1}^2 \sum_{s=0}^{h-1} (\psi_{i1}^{s})^2 + \cdots + \sigma_{\varepsilon_k}^2 \sum_{s=0}^{h-1} (\psi_{ik}^{s})^2} \tag{5.28}$$

5.7 Summary

This chapter has provided the methodology and the theoretical perspectives for multivariate time series analysis, beginning with the vector autoregressive (VAR) model which was used for stationary time series data. The advantages and disadvantages of the VAR model are explained in detail. In addition, this chapter provided a detailed discussion related which the concept of cointegration, the vector error correction (VECM) model and specification of the terms in cointegrated processes, which should be used if there is a cointegration relationship among the variables. The Johansen's cointegration test and setting of the appropriate deterministic terms in cointegrated processes using the Pantula principle are presented in order to investigate the cointegration relationship in the long run among the variables. Different types of structural analysis under the VAR and the VEC frameworks are presented in this chapter including the Granger-causality tests under the vector autoregressive (VAR) and vector error correction (VECM) models. Impulse response analysis and forecast error variance decompositions (FEVD) are explained in order to investigate the dynamic links among oil prices and selected macroeconomic indicators.

CHAPTER 6: Empirical Applications of Relationships among Oil prices, GDP, Exchange Rate and Inflation

6.0 Introduction

This chapter identifies the details of the empirical outcomes which obtained through analyzing the data of variables and applying the methodology of multivariate time series analysis. The analysis seeks to address the objectives 3, 4 and 5 of the study, in order to investigate the dynamic relationships among crude oil prices and some macroeconomic variables in Libya and Nigeria. The third objective is to study whether domestic oil prices fluctuations would affect GDP, exchange rate and inflation in the short run and long run in the above mentioned countries. The fourth objective is to identify a suitable econometric-time series model that allow us to determine the dynamic relationships between oil price, GDP, exchange rate and inflation in the previously countries. The final objective is detecting the possible existence of causality relationships between oil price, GDP, exchange rate and inflation in Libya and Nigeria. All the results are obtained using the statistical program EViews.

Figure 6-1 shows in a schematic manner the structure of the analysis for constructing multivariate time series, the VAR and the VEC models, which are required for investigating the dynamic relationships between oil prices and selected macroeconomic indicators of each country in the sample. According to this figure, the first step after data transformed to natural logarithm form is applying the unit root tests to detect stationarity of our variables for all sample countries using graphical methods, ACFs and PACFs, the augmented Dickey-Fuller test and Phillip Perron tests. If the variables are not stationary, then we used the data in Logarithmic differences in order to get returns series. Furthermore, figure 6-1 displays that the next step is to identify the order of VAR(p) model and then test for checking whether there is cointegration among variables or not by employing the Johansen's cointegration test in the each sample countries. If the cointegration exists among variables, the VEC model with order $p-1$ should be build. On the other hand, if the results of cointegration test indicating that there is no cointegration relationship between the variables the VAR(p)) model will be employed for stationary data in the level, while if the data are stationary after the first logarithms differences the VAR model with order $p-1$ should be used. Furthermore, figure 6-1 shows that after choosing the appropriate lag for the VAR/VECM model, then estimate the coefficients of the model and diagnostic tests the fitted model. Additionally, the Granger-causality tests can be used to verify the causal relationship between variables. Finally, estimate impulse response functions and forecast error variance decompositions in order to examine the dynamic relationships among the variables or use the model for forecasting purposes.

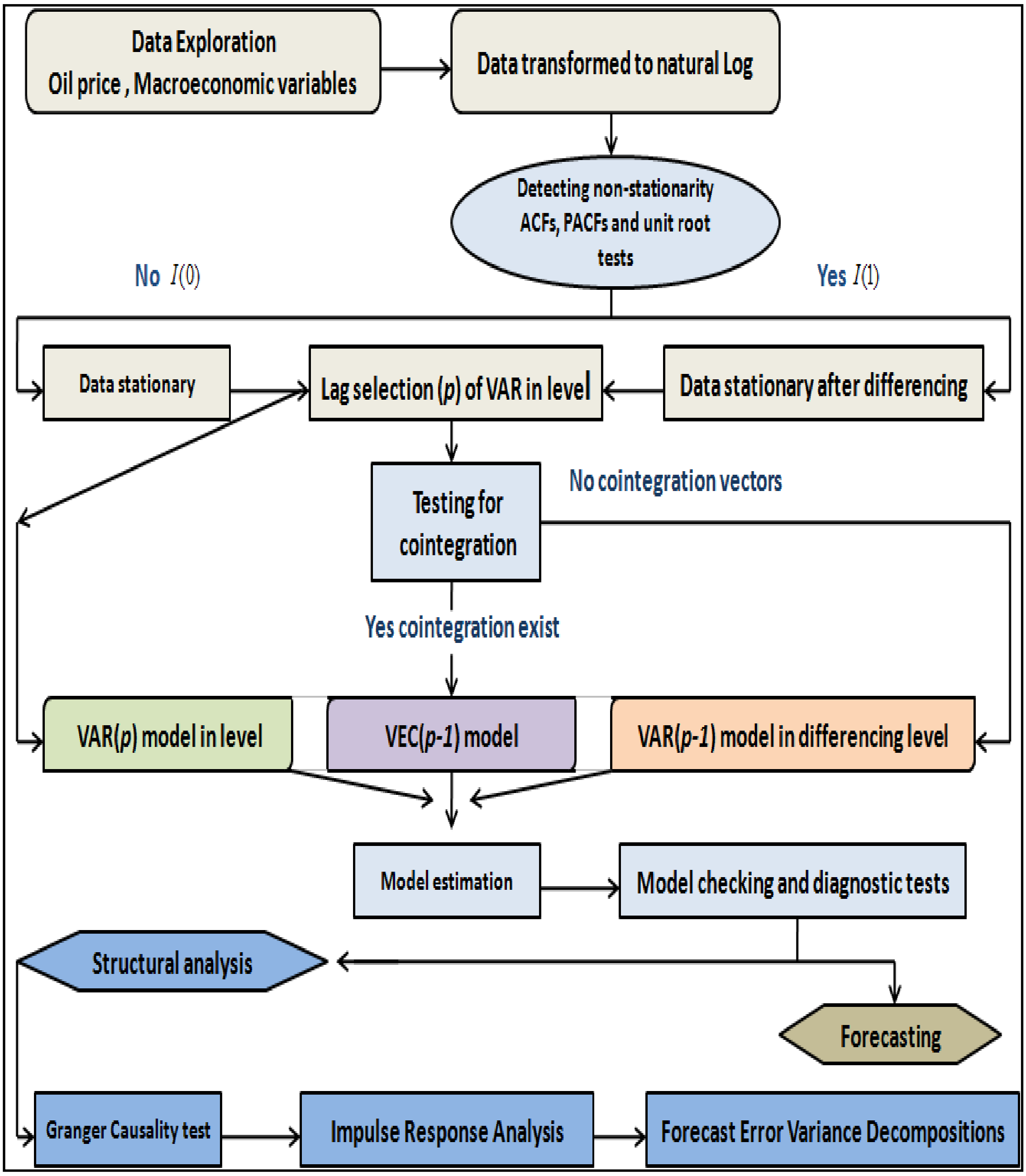


Figure 6-1: Framework for Specification and Estimation of Building VAR and VEC Models in a Schematic Way (Source: By Author).

6.1 Data Description and Sources

In this section, the nature of the selected macroeconomic variables for both Libya and Nigeria with their sources is reviewed in order to investigate the dynamic relationship among these selected indictors and crude oil prices. In our analysis, secondary data have been collected from various sources including: Central Bank of Libya, Central Bank of Nigeria, Organization Petroleum Export Countries (OPEC), United Nations, World Bank Database and the Statistics Portal. The data of oil prices and the macroeconomic indicators under consideration are annual data covering the period from 1970 to 2017 and measured in US dollars. Consequently, brief descriptions of the selected macroeconomic indicators for Libya and Nigeria are given below;

- **Libyan and Nigerian spot oil prices (LOP and NOP)**

  Oil prices that are included in this analysis are domestic Libyan and Nigerian crude oil prices. All these prices are annual covering the period from 1970 to 2017 and taken from the next sources.

  Source: OPEC. Libyan, Nigerian and OPEC oil price - various years-annual statistical bulletin. http://www.opec.org/opec_web/en/publications/202.htm

  Source: Libyan Central Bank, Oil Price. Economics Report, Various Issues. http://www.cbl.gov.ly/eg/

  Source: Central Bank of Nigeria, Crude Oil Price. https://www.cbn.gov.ng/rates/crudeoil.asp

  Source: Statista. OPEC oil price annually 1960-2018. https://www.statista.com/statistics/262858/change-in-opec-crude-oil-prices-since-1960/

- **Gross domestic product at current prices** (**GDP** in $/Billions)

  The Gross domestic product is defined as the value of all final goods and services produced within a nation in a given year. The data of GDP are annual covering the period from 1970 to 2017 for both Libya and Nigeria. These data - are obtained from the next source.

Source: United Nations. National Accounts Main Aggregates Database. Basic Data Selection. https://unstats.un.org/unsd/snaama/Index

- **Exchange rate (ER** units of national currency/$)

The exchange rate is defined as the annual average of the price of one national's' currency conversions to the US dollar, based on average annual market exchange rates. The data of exchange rates for Libya and Nigeria are annual data between 1970 and 2017 obtained from the next sources.

Source: United Nations. National Accounts Main Aggregates Database. Basic Data Selection. https://unstats.un.org/unsd/snaama/Index

Source: OPEC, Exchange rate- various years-annual statistical bulletins. http://www.opec.org/opec_web/en/publications/202.htm

Source: Libyan Central Bank, Exchange Rate. Economics Report-Various Issues. http://www.cbl.gov.ly/eg/

Source: Central Bank of Nigeria, Monthly Average Exchange Rates of the Naira https://www.cbn.gov.ng/rates/exrate.asp

- **Inflation Rate** (**IN**F, percent change annual %)

The inflation rate is measured by the consumer price index (CPI) reflects the annual percentage change in the cost to the average consumer of goods and services. The time series data of CPI for Libya and Nigeria are annual between 1970 and 2017 obtained from the next source.

Source: The World Bank Group. https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?locations=LY-NGhttps://www.indexmundi.com/facts/libya/consumer-price-indexhttps://www.indexmundi.com/facts/nigeria/consumer-price-index

6.1.1 Justification of Variable Selection and Period of Analysis

In general, the choice of the macroeconomic indicators is difficult but is very important, because the measures of economic activity and inflation are fundamental to analyses oil price activity (ThankGod and Maxwell, 2013). The selection of these economic indicators is fundamentally driven by similar studies, in particular Hamilton (1983), Burbidge and Harrison (1984) and Cologni and Manera (2008) have used as a standard, which have been conducted in developing countries and in line with economic theory.

One of the major obstacles to research in developing economies is the availability of data. In particular, the time series data of a country such as Libya is not easy to get. Thus, the selection of these macroeconomic variables for study is based on the availability of data is - sufficiently long. Moreover, some macroeconomic indicators are usually calculated on an annual or quarterly basis such as the GDP which is very difficult to find it in monthly form. Consequently, we are following several studies (Hamilton, 1983; Lorde et al., 2009; Bekhet and Yusop, 2009; Bouchaour and AL-Zeaud, 2012; Wilson et al., 2014) which used annual data to investigate the dynamic relationships among oil prices and various macroeconomic indicators.

6.2 Empirical Analysis of Libya

6.2.1. Graphical Representations of Variables

Figure 6-2 below illustrates the historical evolution of the time series of oil prices and Libyan variables in level during the period from 1970 to 2017.

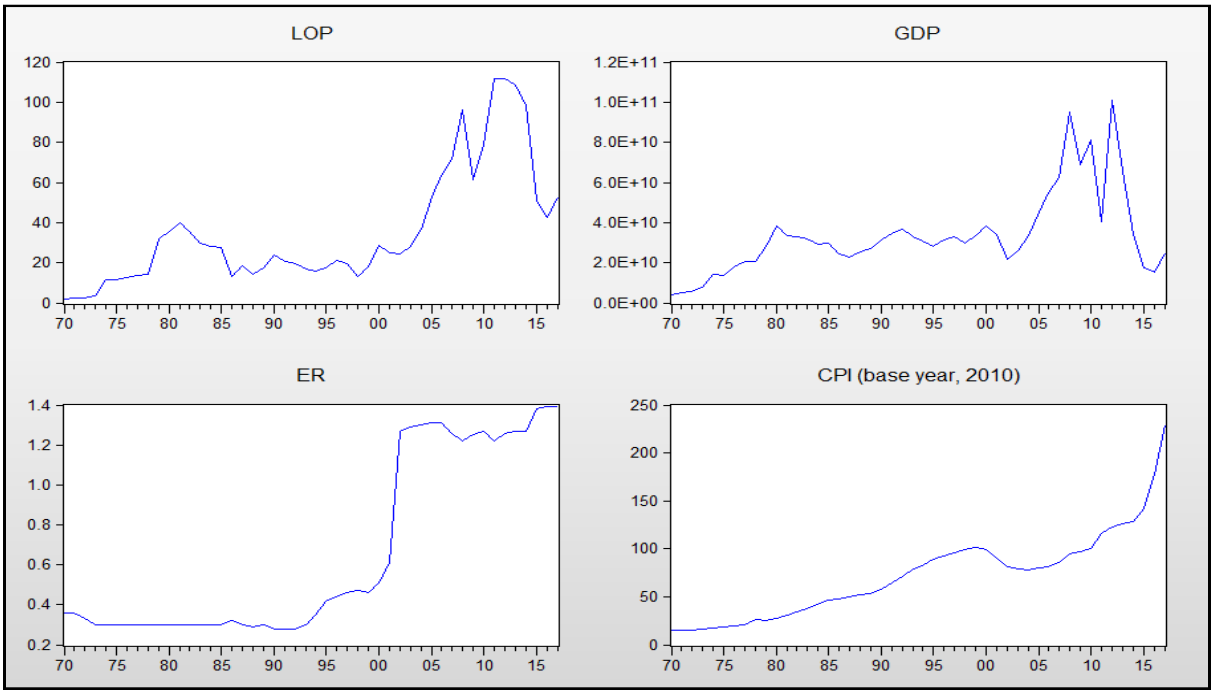


Figure 6-2: A Combined Graph for Annual LOP, GDP, ER and CPI for Libya Covering the Period from 1970 to 2017 in Level.

From the visual inspection of all series for Libyan variables, we can say that, our first impression is Libyan crude oil price series and Libyan variables seem to consistently move together. However, from 1974 to 1980 there was an oil boom where Libyan oil prices reached over \$53/b at the end of 1980. Since 1981, crude oil prices have declined to around \$13/b in 1998. From 2000, prices of oil increased again to almost \$96/bin 2008. After 2008, prices decreased and then highest prices have been occurred from 2011 until 2014. In 2017 the price of Libyan oil fluctuated slightly to reach \$52/b.

The historical pattern of GDP, exchange rate and CPI series appear to have behaviour with approximately a steady increase trend until 2008. The exchange rate in Libya increased an average of \$0.66 per one Libyan currency per year over the period of analysis.

In short, all of the variables of interest in this research virtually share the similar movement pattern during the period of sample. A steady upward trend appears to dominate the pre-2008 period in all series data. Figure 6-2 illustrates that all our time series data are non-stationary at all levels. All variables during empirical analysis are converted to the natural logarithmic form in order to smooth the series, and then the first differences are taken to achieve stationartity and defined as following

ΔLLOP = $ln(\text{LOP}_t) - ln(\text{LOP}_{t-1})$, is Libyan crude oil price.

ΔLGDP = $ln(\text{GDP}_t) - ln(\text{GDP}_{t-1})$, is Libyan economic growth.

ΔLER = $ln(\text{ER}_t) - ln(\text{ER}_{t-1})$, is the exchange rate.

ΔLCPI = INF = $ln(\text{CPI}_t) - ln(\text{CPI}_{t-1})$, is the Libyan CPI, inflation.

Figures 6-3 shows the plot of all variables after taking the first difference of the logarithmic prices. However, most of them after transformation into the first differences of natural log-values appear to fluctuate around their mean levels, which are close to zero. They suggest that all the variables seem to have constant means and variances and the possibility of integration order is one for all the variables to be stationary.

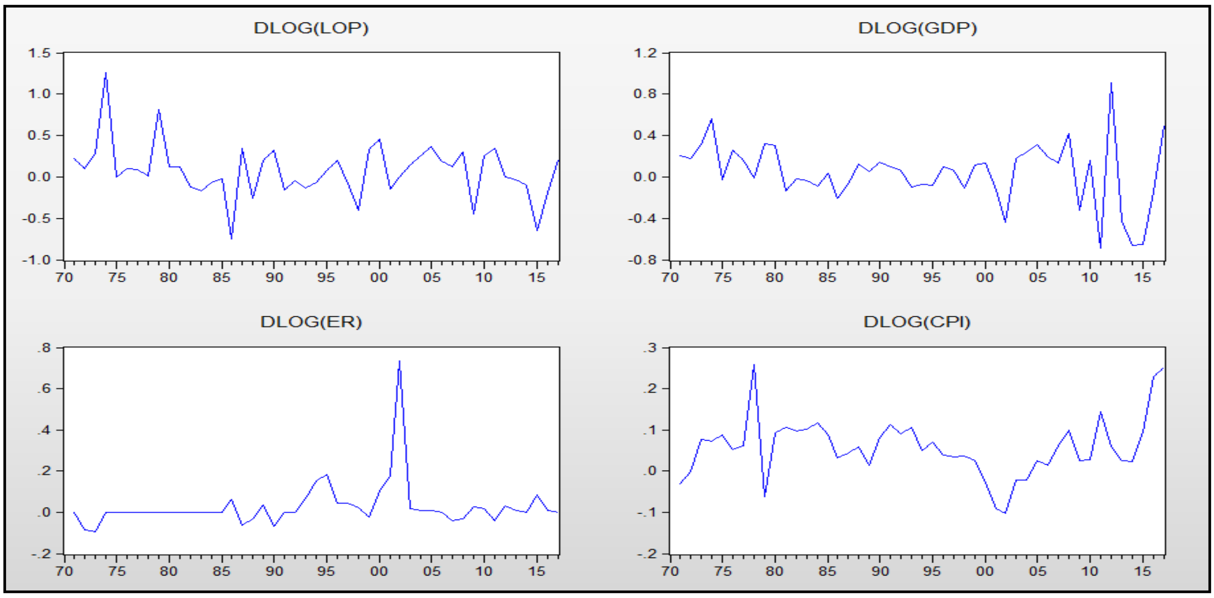


Figure 6-3: A Combined Graph for Libyan Variables Covering the Period from 1970 to 2017 after Transformation in the First Differencing Log Level.

Although the plots above give us a rough idea about the stationarity properties of the series dada we need more formal unit root tests to check the stationary. The next sections of analysis provide additional details on the statistical characteristics of all the selected macroeconomic variables in this study.

6.2.2 Descriptive Statistics

Table 6-1 blew presents descriptive statistics of all the variables at the levels and after transformation for Libya.

Table 6-1: Descriptive Statistics of Oil Prices and the Libyan Variables in Levels and the First log Differencing.

	Variables / Libyan case							
Descriptive Statistics	In level				In the first log differences			
	LOP	GDP	ER	CPI	ΔLLOP	ΔLGDP	ΔLER	ΔLCPI
Mean	35.30	3.37E+10	0.66	71.84	0.07	0.03	0.03	0.05
Std. Dev.	29.96	2.07E+10	0.45	45.24	0.33	0.31	0.12	0.07
Skewness	1.33	1.52	0.66	0.98	0.59	-0.22	4.57	0.54
Kurtosis	3.81	5.49	1.536	4.59	6.08	4.17	27.31	4.40
Jarque-Bera	15.54***	30.96***	7.85**	12.88***	21.31***	3.07	1320.87***	6.18 ***
P-value	0.00	0.00	0.019	0.00	0.00	0.26	0.00	0.04

*** and ** indicate rejection at 1% and 5% significance levels.

The basic statistics of the variables in their levels and first log differences for Libya reflect the historical evolution of the data being studied, including the mean, standard deviation, kurtosis, skewness, and the Jarque-Bera statistics.

Based on the dispersion values of series in level which are obtained from the standard deviation statistics (row two in Table 6-1), the exchange rate (ER) is less volatile in comparison with the LOP, GDP and CPI. All of the macroeconomic variables in Libya have right tails with positive skewness values. Furthermore, the values of kurtosis are greater than 3 suggesting that the distribution of oil prices and the Libyan macroeconomic variables are leptokurtic. The only exception for the distribution of the exchange rate is platykurtic. The *p*-values of the Jarque-Bera tests indicate that most variables for Libya are not normally distributed. Except, the exchange rate (ER) variable is accepted the null hypothesis of normality of the Jarque -Bera- test at the 1% significance level.

Comparatively for the data in the first log differences, the oil prices data (ΔLLOP), exchange rate (ΔLER) and inflation (ΔLCPI) have positive skewness values with right tails, while, the GDP variable has a negatively skewed. Thus, all variables series are leptokurtic, since all the estimated values of kurtosis exceed 3. Additionally, the null hypothesis of normality of the Jarque-Bera test is rejected at the 1% significance level, except, the GDP (ΔLGDP) and iflation rate (ΔLCPI) are normally distributed.

6.2.3 Detecting Stationarity

For detecting stationarity of all series under study, we compute the autocorrelations and partial autocorrelations coefficients for all data in log levels and in the first log differencing. The combined graphs (see Appendix B, graphs B1 to B2) present the correlogram of the sample ACFs and PACFs plots of all individual series of Libya.

The inspection of the sample ACFs and the sample PACFs plots suggest that all the series decay extremely slowly in log level. This means that all the series are non-stationary. Alternatively, the sample ACFs and the sample PACFs plots suggest that all the variables in first log differences are stationary.

The results of ACFs and PACFs for oil prices, GDP, exchange rate and inflation in Libya indicate that the appropriate order of integration is one for all variables to be stationary. However, to make sure about stationarity issue the ADF and PP unit root tests have been carried out for all variables individually in log levels and in the first log differences levels. The plots of Libyan oil prices and the macroecnomic variables in log level (see graph B3 in Appendix B) are suggestive of the presence of trend and the most of variables fluctuate around non-zero sample mean, indicating to the inclusion of intercept and trend in unit root tests. While the figures of their first log differenced (see graph 6-2) suggesting that their movements are around sample mean of almost zero, as a result, no constant is chosen for non-stationarity tests. The optimal lag length in standard unit root test is chosen automatically in EViews using SIC with maximum lag 9. The results of unit root tests are shown in the following subsection.

- **Outcomes of Standared Unit Root Tests**

Table 6-2 below summarises the results of ADF and PP unit root tests to both log levels and their differences of Libyan variables series.

Table 6-2: Results of Standard Unit Root Tests of Oil prices and Libyan Variables in Log Levels and the First Log Differencing.

Variable	ADF (intercept and liner trend)		PP (intercept and liner trend)		Variable	ADF (None)		PP (None)	
	t-Stat	*Prob.	t-Stat	*Prob.		t-Stat	*Prob.	t-Stat	*Prob.
in log level					**in first log differences**				
LLOP	-2.5803	0.2907	-2.5989	0.2827	ΔLLOP	-6.1905***	0.0000	-6.1904***	0.0000
LGDP	-2.5719	0.2943	-2.5260	0.3149	ΔLGDP	-6.5345***	0.0000	-6.5314***	0.0000
LER	-2.0014	0.5854	-2.0527	0.5579	ΔLER	-4.8932***	0.0000	-4.8932***	0.0000
LCPI	-1.6814	0.7435	-1.4907	0.8188	ΔLCPI	-2.3941**	0.0176	-2.2211**	0.0268
critic values:	1% -4.1658		5% -3.5085		**critic values**	1% -2.6162			5% -1.9481

Null Hypothesis: data has a unit root and lag length selected automatic based on Schwarz information criterion with max=9 and *MacKinnon (1996) one-sided p-values. *** and ** refer to the rejection at 1% and 5% significant levels.

From the results of ADF and PP tests in Table 6-2, we can see that, LOP, GDP, exchange rate and CPI in log levels have a unit root and the null hypothesises are accepted by comparing calculated t-statistics and test critical values at the 1% and 5% significance levels. Thus, all the calculated t-statistics are less than the critical values in absolute values and the *p*-values are greater than the 1% and 5% significance levels. On the other hand, the results of all the variables in the first difference levels indicate that the null hypothesis of a unit root are rejected and statistics tests provide *p*-values smaller than the 1% significance level, suggesting the alternative hypothesis are accepted and all the first log difference series under study are stationary. The only exception of is related with the inflation (CPI) variables in the first log difference series, is stationary at the 5% level.

The results obtained from standard unit root tests, ADF and PP indicate that Libyan oil price, GDP, exchange rate and inflation are non-stationary at the 1% level of significance and all the individual variables have the same order of integration I(1). Based on this we can proceed under the assumption that each time series can best be described as stationary or I(0) in the first log differences at the 5% significance level. However, since the variables are integrated of order I(1), we are interested to investigate whether our variables in Libya are cointegating or have a common stochastic trend. Thus, the Johansen method (1988) has carried out in the next sections.

6.2.4. The Optimal Lag Length Selection

The common procedure can be used to identify the optimal lag length for the VAR model is using the information criterion including AIC, SIC and HQ. The values of the three criteria are calculated under the estimated VAR model for different lags from 1 to 5. Here, the limited number of observations in the model led to the consideration of models that do not exceed a maximum of 5 lags. Table 6-3 presents below the results of these choices for VAR models for Libyan oil prices and other macroeconomic variables in log level for Libya.

Table 6-3: VAR Lag Order Selection Criteria for Oil Prices and Libyan Data.

Endogenous variables: LLOP , LGDP, LER and LCPI
Exogenous variables: C

Lag	AIC	SIC	HQ
0	4.8893	5.0531	4.9497
1	-3.3002	-1.8257	-2.7565
2	-3.6062*	-2.7871*	-3.3042*
3	-2.9016	-0.7718	-2.1162
4	-2.5518	0.2333	-1.5247
5	-2.3655	1.0748	-1.0968

* indicates lag order selected by the criterion.

As can be seen from Table 6-3, the results of the comparison between the information criteria of VAR lag order selection for oil prices with Libyan variables, suggesting that the appropriate number of lag is lag 2 based on the AIC, SIC and HQ.

6.2.5 Specification of the Deterministic Terms - the Pantula Principle

After estimating the VAR models in order to select the appropriate lag length, the next stage is to identify which deterministic components including a constant term and/or a trend (five situations, see chapter 5) will be contained in the VEC model or in the cointegrated processes. In fact, the appropriate deterministic terms are often not easy to determine. Therefore, as described in the methodology chapter (see chapter 5), this study uses Pantula (1989) principle which proposed by Johansen (1992) for selecting the optimal deterministic terms in the model. Since models 2, 3 and 4 are of interest and occur often in practice, we will consider only these models as possible.

6.2.6 Johansen Cointegration Test

To test cointegrating relationships between oil prices and all of variables under study, we carry out the Johansen cointegration test including both trace test and maximum eigenvalue test for the three plausible models (2, 3 and 4) which are estimated with a lag length of 1 in the VEC model, which is the optimal lag in VAR model minus one. The results of Johansen test with the Pantula principle are reported in Table 6-4 below.

Table 6-4: Results of Johansen Cointegration Tests and the Pantula Principle for Oil Prices and Libyan Variables.

Null Hypothesis	**Model 2** None\ Intercept – No Trend			**Model 3** Linear \ Intercept – No Trend			**Model 4** Linear \ Intercept – Linear		
	Test Statistic	Critical Value 0.05	P-value**	Test Statistic	Critical Value 0.05	P-value**	Test Statistic	Critical Value 0.05	P-value**
Trace test									
None	63.1655	54.0790	0.0063	45.1468*	47.8561	0.0879	62.9321	63.8761	0.0599
At most 1	31.8055	35.1927	0.1109	16.9873	29.7970	0.6410	30.6405	42.9152	0.4647
At most 2	12.5940	20.2618	0.3971	4.6942	15.4947	0.8404	16.1515	25.8721	0.4805
At most 3	4.3663	9.1645	0.3603	0.0402	3.8414	0.8410	4.4094	12.5179	0.6823
Number of Cointegrating Relations		1			0			0	
Maximum Eigenvalue test									
None	31.3599	28.5880	0.0215	28.1595	27.5843	0.0422	32.2916	32.1183	0.0476
At most 1	19.2115*	22.2996	0.1278	12.2930	21.1316	0.5190	14.4889	25.8232	0.6800
At most 2	8.2276	15.8921	0.5208	4.6540	14.2646	0.7847	11.7421	19.3870	0.4395
At most 3	4.3663	9.1645	0.3603	0.0402	3.8414	0.8410	4.4094	12.517	0.6823
Number of Cointegrating Relations		1			1			1	

Endogenous variables are LLOP LGDP LER LCPI. Lag length of 1 is used.
* denotes the first time that the null hypothesis cannot be rejected at the 0.05 level.
**MacKinnon-Haug-Michelis (1999) p-values.

Table 6-4 summarises the trace statistics and max-eigenvalue statistics under models 2, 3 and 4 with number of cointegration relations (r) by employing the Johansen procedure. The principle of pantula includes performing the Johansen test from the most restrictive model (model 2) to the least restrictive model (model 4), and then compares the trace and max-eigenvalue statistics to their corresponding critical values at each step. The pantula principle will indicate the optimal model when the null hypothesis cannot rejected at the first time.

Pantula principle starts with the most restrictive model (Model 2, null hypothesis no cointegration or r = 0 and the alternative hypothesis > 0). The statistic of trace test in model 2 is 63.1655, which is greater than - 54.0790 at the 5% level of significant. Thus, the null hypothesis of no cointegration is rejected and instead we accept that the alternative hypothesis that one or more cointegrating vectors have existed. Then we move to the next restrictive model (Model 3), the null hypothesis of no cointegration is accepted at the 5% level. Therefore, under the least restrictive one (model 3) the procedure stops at 45.1468 because this is the first time the null hypothesis cannot be rejected and model 3 is appropriate for the Johansen cointegration test. Moreover, the trace test statistic in model 3 suggests that the null hypothesis of no cointegration relations among variables is accepted and is no cointegration vector at the 5% level. Although the trace test statistics for models 1 indicate that there is one cointegration relationship at the 5% level of significance.

On the other hand, Pantula principle starts with the most restrictive model (Model 2, null hypothesis no cointegration), the max test statistic in model 2 is 31.3599 which is greater than 28.5880 at the 5% level of significant. Thus, the null hypothesis of no cointegration is rejected and instead we accept that the alternative hypothesis that one or more cointegrating vectors have existed. Then we move to the next restrictive model (Model 3), again the null hypothesis of no cointegration is rejected also under the least restrictive model (model 4) the null hypothesis of no cointegration is rejected at the 5% level. Since all three models reject the null hypothesis of zero cointegrating vectors, and the alternative hypothesis of at least one cointegrating vector has existed , we continue with row 2, where the null hypothesis is r = 1 and the alternative hypothesis $r > 1$. Therefore, procedure stops at 19.2115 because this is the first time that the null hypothesis cannot be rejected and model 2 is appropriate for the Johansen cointegration test and this model is the best model for describing the system.

However, the trace test statistic in model 3 suggests that there is no cointegration relationship at the 5% level of significance. While, the max test statistic in model 2 indicates that is one cointegration relationship between Libyan variables. In this case, our analysis is based on the results obtained from the max-eigenvalue test. Therefore, we can conclude that the model 2 specification, which is no intercept in the VAR, and there is only an intercept (no trend) in cointegrating equation is the best model to describe the given data. Additionally, the results of the the max-eigenvalue test suggests that the Libyan variables are integrated at one cointegrating vector in the VEC system and there is indeed a long-run relationship among oil prices, GDP, exchange rate and inflation rate at the 5% level. Moreover, there may be a causality relationship exist between two variables and these interrelationships can be examined through Granger causality test.

6.2.7 Estimating the Parameters of the VEC Model

Due to the results of cointegration, a VEC model will need to estimate in order to investigate the short-run and long-run dynamics among oil prices and selected Libyan variables. The VEC model is estimated using ordinary least squares (OLS) with lag ength 1. The specified VEC(1) model is in this form

$$\Delta X_t = \alpha(c_0 + \acute{\beta} X_{t-1}) + \phi_1^* \Delta X_{t-1} + \varepsilon_t, \qquad (6.1)$$

where $\Delta X_t = (\Delta\text{LLOP},\ \Delta\text{LGDP},\ \Delta\text{LER},\ \Delta\text{LCIP})'$

However, Table 6-5 presents the results of the VEC model estimation which is divided into two parts; the first part reports the results of one cointegrating equation from Johansen procedure. The second part of the results report results of short-run parameters from VAR model in the lagged first differences of all the endogenous variables in the system with the error correction terms.

Table 6-5: Parameter Estimation of a VEC(1) Model for Oil Prices and Libyan Variables.

Long-run parameters						
Cointegrating Eq:		C	LLOP(-1)	LGDP(-1)	LER(-1)	LCPI(-1)
CointEq1	coefficient	19.5489	1.0000	-1.0114	-0.7568	0.3698
(*β*)	Standard error	2.8142		0.1296	0.1212	0.1509

short-run parameters					
Error Correction:		ΔLLOP	ΔLGDP	ΔLER	ΔLCPI
CointEq1 (*α*)	coefficient	-0.4457	-0.2969	0.0980	0.0879
	Standard error	0.1273	0.1215	0.0502	0.0286
ΔLLOP (-1)	coefficient	0.1675	0.3895	-0.0346	-0.0206
	p-value	0.3142	0.0173**	0.5964	0.5793
ΔLGDP (-1)	coefficient	-0.0295	-0.3676	0.0514	0.0507
	p-value	0.8831	0.0605	0.5169	0.2644
ΔLER (-1)	coefficient	0.6399	0.1121	0.2184	-0.0215
	p-value	0.1106	0.7661	0.1659	0.8085
ΔLCPI (-1)	coefficient	2.7451	2.1724	-0.4557	0.3057
	p-value	0.0012***	0.0063***	0.1516	0.0930

*** and ** rejection at 1% and 5% significance levels.

Table 6-5 presents the estimated long run relationships between Libyan variables with their standard error in the first part. The cointegration equation (CointEq1 (*β*)), is estimated as

LNOP(-1) + 19.54897- 1.0114 LGDP(-1) - 0.7568 LER(-1) + 0.3698 LCPI(-1) = 0, which can be rewritten as:

LNOP(-1) = - 19.54897+ 1.0114 LGDP(-1) + 0.7568 LER(-1) - 0.3698 LCPI(-1) (6.2)

The long run equation shows that there is a significant relationship between LLOP, LGDP, LER and LCPI respectively. This result indicates that there are positive relationships between Libyan oil prices, GDP and ER in the long run. Whilst, the Libyan oil prices have a negative and significant impact on inflation. The second part of the Table 6-5 shows the matrix of short run parameters of the estimated VEC Model. The estimated results of ΔLLOP equation shows that there are insignificant positive relationships between ΔLLOP and the first lag of ΔLLOP (-1) and of ΔLER (-1) mean that the Libyan oil price will increase itself in one lag period. However, there is also insignificant but negative relationship between ΔLLOP and the first lag of LGDP. Moreover, there is a significant and positive relationship between ΔLLOP and ΔLCPI at 1% level. From the other equations, there exist negative links between the first lag period of LLOP and both ΔLER and ΔLLCPI, whilst, the positive relationship exists between ΔLGDP, and Libyan oil price (ΔLLOP) in first lag period. The residuals correlation matrix of the fitted VEC(1) model are presented in Table 6-6.

Table 6-6: Estimated Correlation Matrix from VEC(1) Model in the Libyan Case.

	LLOP	LGDP	LER	LCPI
LLOP	1			
LGDP	0.4505	1		
LER	0.0355	-0.1853	1	
LCPI	0.1630	0.0818	-0.3696	1

The result in Table 6-6 from the estimated correlation matrix of VEC(1) model for Libyan oil prices and Libyan variables, clearly shows positive relations between Libyan oil prices (LLOP) and all Libyan variables under study (LGDP, LER and LCPI).

6.2.8 Model Diagnostic Checking

- **Stationarity Condition:**

The fitted model VEC(1) must satisfied the stationary condition, in other words, the roots of the determinate equation $|\mathbf{I} - \varphi_1 L| = 0$ are greater than one in absolute value, or in other words all the eigenvalues are less than one. Figure 6-4 below shows that the inverse roots of AR characteristic polynomial lie inside the unit circle. Therefore, the VEC(1) model is stationary and checking for stability check does not show that our fitted models are misspecified.

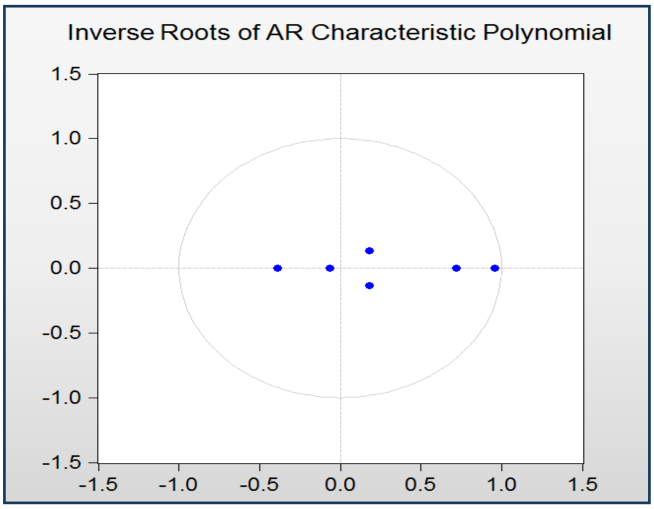


Figure 6-4: The Inverse AR Roots of VEC(1) Model for Libyan Variables.

- **Residual Diagnostics**

Figure 6-5 illustrates the plots of the residuals series of the fitted VEC(1) model. Here, the two horizontal lines point to the two standard errors. From these plots, we can say that there are many residuals exceed the two standard errors this may be suggestion for non-normality feature which is not sufficiently captured by this model.

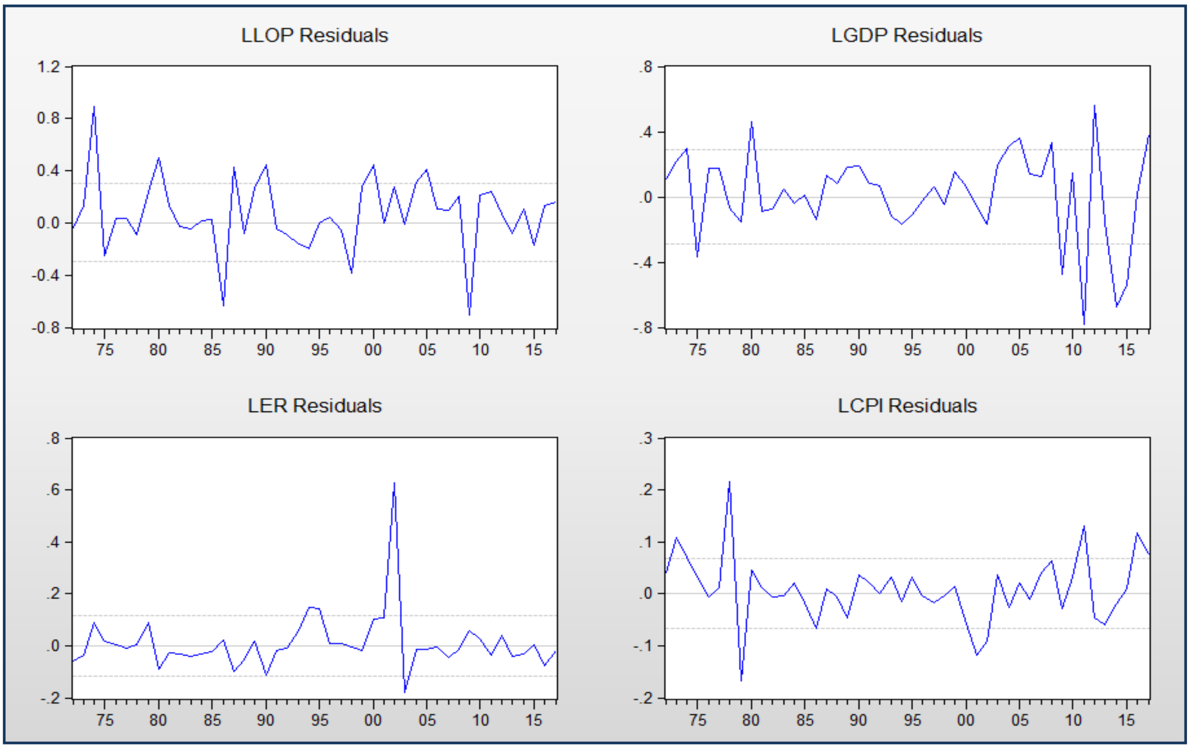


Figure 6-5: Residuals of A Fitted VEC(1) Model for Oil Prices and Libyan Variables.

- **Test for Autocorrelations of Residuals**

Figure 6-6 displays the autocorrelation functions of the VEC model, here we have chosen lag=15. However, the visual inspection of the resulting plots of the autocorrelation functions indicates that all the autocorrelation coefficient within the approximate confidence bounds. Consequently, there are no significant autocorrelations which is considered as a good result.

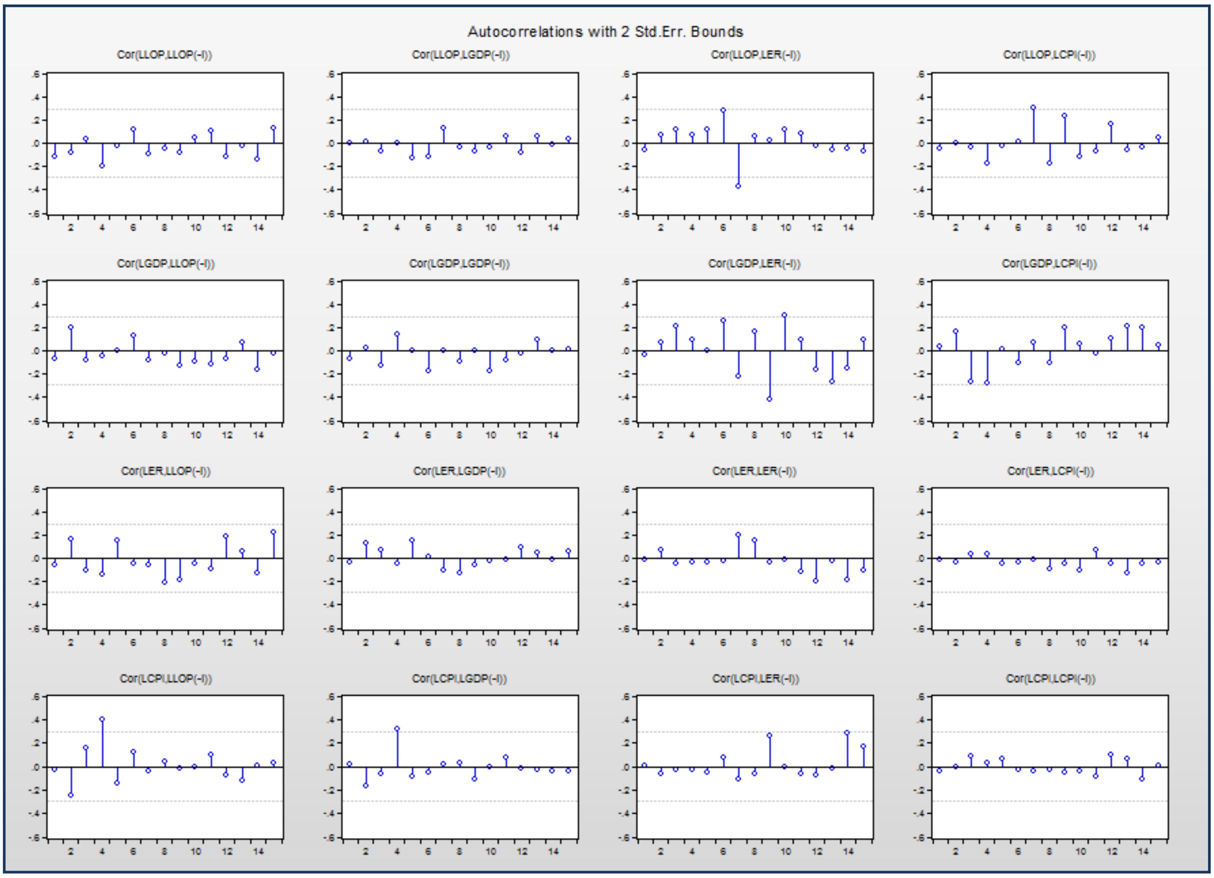


Figure 6-6: Plots of the Autocorrelation Functions of VEC(1) Model for Oil prices and Libyan Variables.

- **Multivariate Ljung–Box Portmanteau Test**

The multivariate Ljung–Box portmanteau tests have been performed for testing the null hypothesis, there is no autocorrelations in the VEC(1) residuals up to lag 12. The results of this test are reported in Table 6-7 below.

Table 6-7: Portmanteau Tests for Autocorrelations of VEC(1) Residuals for Oil Prices and Libyan Data.

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.
1	1.816374	NA*	1.856738	NA*
2	12.02755	0.9977	12.53205	0.9966
3	20.13058	0.9995	21.20042	0.9990
4	36.98301	0.9936	39.65784	0.9845
5	41.23659	0.9997	44.43014	0.9989
6	51.33258	0.9999	56.04054	0.9991
7	64.42740	0.9998	71.48571	0.9979
8	71.22977	1.0000	79.72015	0.9995
9	92.39868	0.9995	106.0383	0.9876
10	102.6518	0.9997	119.1394	0.9892
11	108.5420	1.0000	126.8809	0.9966
12	119.8255	1.0000	142.1468	0.9955

*The test is valid only for lags larger than the VAR lag order.

From Table 6-7, we can see that the null hypothesis of the Portmanteau test, is no autocorrelation in residuals of all residual series in the VEC(1) model have been accepted and there are no significant autocorrelation up to lag 12. However, the *p*-values of the Q-statistic and its adjusted Q-statistic are greater than 0.5 significance level which are indicate that there is inadequate evidence of presence of autocorrelations regarding the five residual series from the VEC model appear to be white noise.

- **Normality Test of Residuals**

For testing the normality of the VEC residuals for oil price and Libyan macroeconomic indicators, Jarque–Bera (JB) test and graphical methods including the histogram and QQ-plots have been applied. Results of these digenetic are presented in Table 6-8 as well as figures from 6-7 and 6-8 respectively.

Table 6-8: Results of Normality Test for VEC(1) Residuals of Oil Prices and Libyan Data.

residuals	**Jarque-Bera**	***p*-value**
LLOP	6.1871**	0.0453
LGDP	39.090***	0.0000
LER	588.0447***	0.0000
LCPI	25.5103***	0.0000
Joint	658.8329***	0.0000

Null Hypothesis: residuals are multivariate normal.*** and ** rejection at 1% and 5% significance levels.

From Table 6-8 for the results of Jarque–Bera tests of the VEC model for individual residuals case and in joint case for Libya, we can say that, the null hypothesis of the individual residuals are normal is rejected for LGDP, LER and LCPI residuals series at the 1% significance level, while it is accepted for LLOP residual and it is normally distributed at 1% level. The *p*-value of the joint statistics of Jarque–Bera is less than 1% significance level. Therefore, the null hypothesis for residuals are multivariate normal is rejected in the Libyan context.

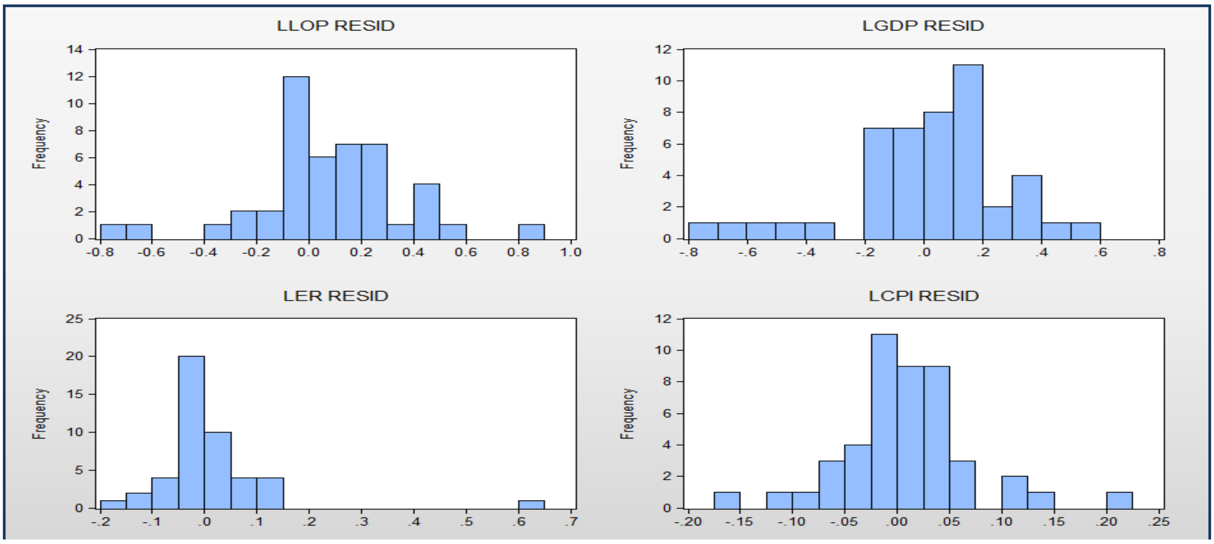


Figure 6-7: The Histogram Plots for Individual Residuals of VEC(1) Model for Oil Prices and Libyan Variables.

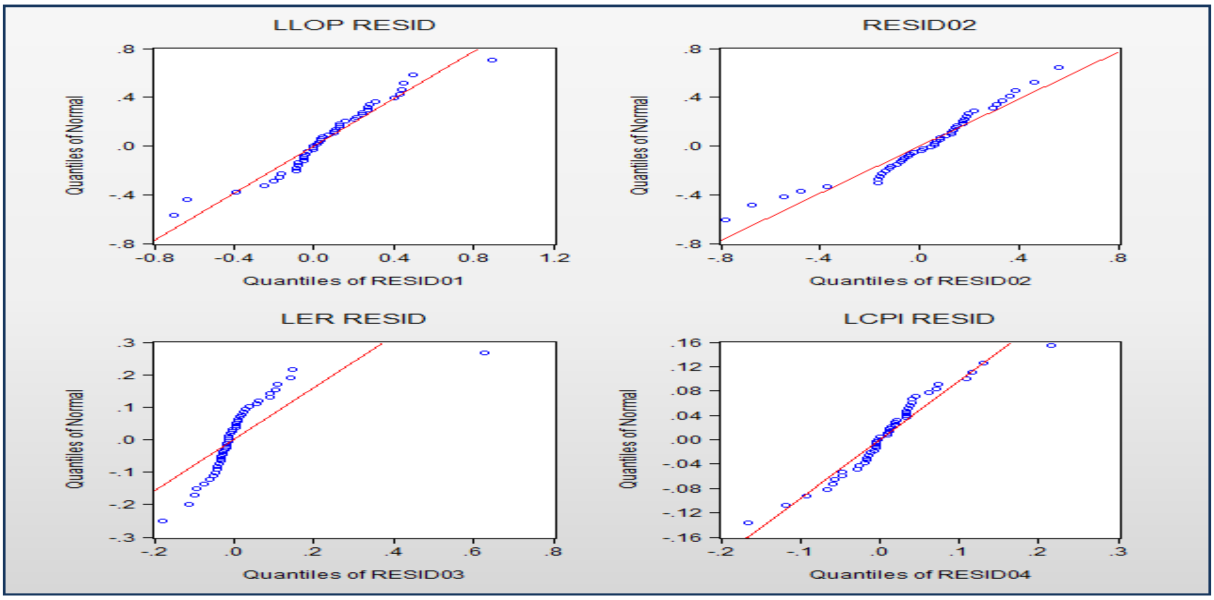


Figure 6-8: The Q-Q Plots for Individual Residuals of VEC(1) Model for Oil Prices and Libyan Variables.

Figures 6-7 and 6-8 present the histogram and the QQ-plots of the residuals series from the VEC model. According to these plots we can see that the residuals series of oil prices LLOP is approximately normally distributed, while the plots of residuals for LGDP, LER and LCPI suggest not normally distributed because the positive excess kurtosis and left-skewed distribution for LGDP, and right-skewed distribution for both LER and LCPI residuals have been appeared. Finally, this graphical diagnosis applies almost to the results obtained from Jarque–Bera tests. Based on all of the above, it can be said that the issue of non-normality with fat tails is typical for residuals obtained from modelling oil returns of price is due to the nature of the data. Particularly, there are many empirical studies that find evidence that crude oil prices series, their returns as well other financial time series are characterised by fat tail distribution (Morana, 2001; Narayan and Narayan, 2007). However, the size of the samples may have an effect for non-normality like in the Libyan variables which were annual and the sample size was small. Juselius (2006) indicates that a very large size of the sample is required to obtain skewness and kurtosis asymptotically normal.

- **Heteroskedasticity Tes to f Residuals**

The heteroscedasticity test was applied for testing the heteroskedastity issue of the residuals. Table 6-9 below is outlined the results of this test, according to the *p*-value of the heteroskedasticity test statistics, we can say that there is no precence of the heteroskedastity effect in the residuals of the VEC model at the 5% level of significance.

Table 6-9: Heteroskedasticity Test of VEC(1) Residuals of Oil Prices and Libyan Data.

Residuals of Libyan variables	
Chi-sq test-statistic	***P*-value**
272.7407	0.0719

6.2.9 Pairwise Granger Causality Test

In this subsection, we are interested to examine the directional causal relationship among oil prices and Libyan macroeconomic indicators using bivariate VAR models. A requirement for the pairwise Granger causality test is that the data are stationary, so we have to use the variables in the first log differenced form data ($\Delta LLOP$, $\Delta LGDP$, ΔLER and $\Delta LCPI$) in this test. To identify the optimal lag length of bivariate VAR framework are chosen based on

AIC, SIC and HQ information criterion. The results of these information criterions are contained in Table 6-10 between oil prices and all other variables.

Table 6--10: The Optimal Lag Length of Bivariate VAR Models for Oil Prices and Libyan Data.

Lag	1	2	3	4	5	6	7	8	9	10
Bivariate variables: ΔLLOP and ΔLGDP										
AIC	0.6083*	0.6680	0.7803	0.8730	1.04730	1.1416	1.0953	1.2068	1.3816	1.4863
SIC	0.8669*	1.0989	1.3837	1.6487	1.9953	2.2620	2.3882	2.6720	3.0192	3.2962
HQ	0.7003*	0.8213	0.9950	1.1490	1.3846	1.5402	1.5553	1.7281	1.9643	2.1302
Bivariate variables: ΔLLOP and ΔLER										
AIC	-1.0569*	-0.9156	-0.8226	-0.7120	-0.5926	-0.4388	-0.4658	-0.4663	-0.3643	-0.2073
SIC	-0.7983*	-0.4846	-0.2193	- 0.0636	0.3553	0.6815	0.8269	0.9988	1.2732	0.2183
HQ	-0.9649*	-0.7622	-0.6080	-0.4360	-0.2553	-0.0402	-0.0059	0.0549	1.6026	0.4366
Bivariate variables: ΔLLOP and ΔLCPI										
AIC	-2.0829	-2.5961*	-2.5377	-2.4242	-2.3623	-2.1864	-2.0799	-1.8955	-2.1012	-2.0511
SIC	-1.8244	-2.1067*	-1.9928	-1.6485	-1.4142	-1.0659	-0.7871	-0.4303	-0.4636	-1.5186
HQ	-1.9909	-2.3844*	-2.3814	-2.1482	-2.0250	-1.7877	-1.6199	-1.3742	-0.2411	-1.4071

* indicates lag order selected by the criterion.

From Table 6-10 we can see that, based on different estimated bivariate VAR models between oil prices (ΔLLOP) and Libyan variables (ΔLGDP, ΔLER and ΔLCPI) the lag 1 is selected as the optimal lag for all bivariate variables. The only exception is in the case of pair of ΔLLOP and ΔLCPI the best lag here is 2. These choices are based on the three information criteria, AIC, SC and HQ. Moreover, all the bivariate VAR models with optimal lag are diagnostic until satisfy stable condition and no autocorrelation in the residuals. Consequently, the standard pairwise Granger causality test is applied for analysing the dynamic bivariate interactions between oil prices and Libyan variables. Table 6-11 below shows the findings of the Granger causality test. The null hypothesis of the test is that there is no causality among oil price (ΔLLOP) and Libyan macroeconomic variables, and the F test statistics and the corresponding *p*-values are presented in the second and third columns.

Table 6-11: Results of Pair-wise Granger Causality Test for Oil Prices and Libyan Data.

Null Hypothesis:	F-Statistic	*p*-value
ΔLGDP does not Granger Cause ΔLLOP	1.8134	0.1851
ΔLLOP does not Granger Cause ΔLGDP	2.1541	0.1495
ΔLER does not Granger Cause ΔLLOP	0.0448	0.8333
ΔLLOP does not Granger Cause ΔLER	0.0538	0.8176
ΔLCPI does not Granger Cause ΔLLOP	1.4222	0.2531
ΔLLOP does not Granger Cause ΔLCPI	1.0319	0.3656

*** and ** indicate rejection at the 1% and 5% significant levels.

According to the obtained results in Table 6-11, there are no bidirectional or unidirectional causality relationships are found among oil prices and any individual of Libyan variables. However, the Granger causalities between Libyan oil price and Libyan variables are statistically insignificant.

6.2.10 VEC Granger Causality/Block Exogeneity Wald Tests

Granger Causality/Block Exogeneity Wald Tests has been applied to detect whether the lags of any variables can Granger-cause any other variables in the VEC (1) model. Under this test endogenous variables can be treated as exogenous. The Wald statistics used to test the null hypothesis that the dependent variable is not Granger-cause by the independent variables. Results are reported in Table 6-12.

Table 6-12: VEC Granger Causality/Block Exogeneity Wald Tests for Oil Prices and Libyan Data.

Dependent variable	Excluded			
ΔLLOP	ΔLGDP	ΔLER	ΔLCPI	All
Chi-sq	0.0218	2.6591	12.0638***	13.2408***
P-value	0.8824	0.1030	0.0005	0.0041
ΔLGDP	ΔLLOP	ΔLER	ΔLCPI	All
Chi-sq	6.1557**	0.0896	8.2889***	11.7536***
P-value	0.0131	0.7646	0.0040	0.0083
ΔLER	ΔLLOP	ΔLGDP	ΔLCPI	All
Chi-sq	0.2849	0.4273	2.1352	2.1778
P-value	0.5935	0.5133	0.1440	0.5363
ΔLCPI	ΔLLOP	ΔLGDP	ΔLER	All
Chi-sq	0.3123	1.2801	0.0594	1.4385
P-value	0.5763	0.2579	0.8073	0.6965

** and *** rejection at 5% and 1% significance levels.

In Table 6-12, the causality test is performed separately by variable and then an equation is analysed for each one of our four Libyan indicators, and, one by one, they are used as the dependent variable of the equation, which is dependent on the other three independent variables. Moreover, two hypotheses should be checked, if the lags coefficients of each of independent variables are equal to zero and also if the joint-coefficients of all the independent variables are equal to zero. The decision for both hypotheses is there is a causality relationship between the variables if their *p*-values are less than 1% or 5%.

However, the first equation under analysis has ΔLLOP as the dependent variable, as shown in Table 6-12. We analyse whether the lags of the independent variables ΔLGDP, ΔLER and ΔLCPI Granger causes the value of the LOP variable. We can check that the hypothesises that the lags of ΔLGDP and ΔLER are equal to zero are accepted, as their *p*-values are 0.8824 and 0.1030 which are more than 0.05, which meaning that these variables does not , indeed, cause ΔLLOP. Nevertheless, we cannot conclude the same for ΔLCPI because the hypothesis that the lag of ΔLCPI is equal to zero is rejected, as its *p*-value is less than 0.01, which means that this independent variable does, indeed, cause ΔLLOP. Therefore, we can conclude that there is a unidirectional causality relationship among ΔLLOP and ΔLCPI, meaning that the inflation in the regression equation of Libyan oil price (ΔLLOP) appear to be useful for predicting the future values of ΔLLOP. Moreover, inflation does a modestly better job at predicting Libyan oil prices than did GDP and exchange rate. Then, when we check the *p*-value for the joint hypothesis that all the lagged coefficients from all the independent variables cause an influence on ΔLLOP, thus, we can say that they jointly cause an effect on our dependent variable.

Moving on to our second equation, we now see the *p*-values from Table 6-12 for ΔLLOP. We conclude whether its null hypothesis is rejected. The *p*-value is less than 0.05, which meaning that the null hypothesis is rejected, and this independent variable does cause ΔLGDP. The same logic is true for ΔLCPI. Nevertheless, we cannot say the same for ΔLER. As a result, we can conclude that there is a unidirectional causality relationship among ΔLLOP and ΔLGDP and a unidirectional causality relationship running from ΔLCPI to ΔLGDP. Furthermore, the *p*-value for the joint hypothesis that all the lagged coefficients from all the independent variables cause an influence on ΔLGDP, we can then say that they jointly cause an effect on our dependent variable.

When testing our third equation, the null hypothesis of each independent variable is accepted. The variable ΔLER does not have a causality relationship with ΔLLOP, ΔLGDP, and ΔLCPI. Also, this equation shows that joint lagged coefficients also do not cause our dependent variable. Finally, the last equation to be tested is that related to the causality relationship among ΔLCPI and ΔLLOP, ΔLGDP and ΔLER. As the lagged coefficients' *p*-values presented in Table 6-12 are all above 0.05, we can say that there is no Granger causality relationships among this dependent variable and each of the equation's independent variables.

6.2.11 Impulse Response Functions

In this section, the study is most concerned with the responses of Libyan oil prices, GDP, exchange rate and inflation to a shock to Libyan oil price. For exploring the response of each variable to Libyan oil price shocks the plotting of the response to one standard deviation functions under the VEC(1) model are carried out for up to 10 periods and the result is presented in figure 6-9.

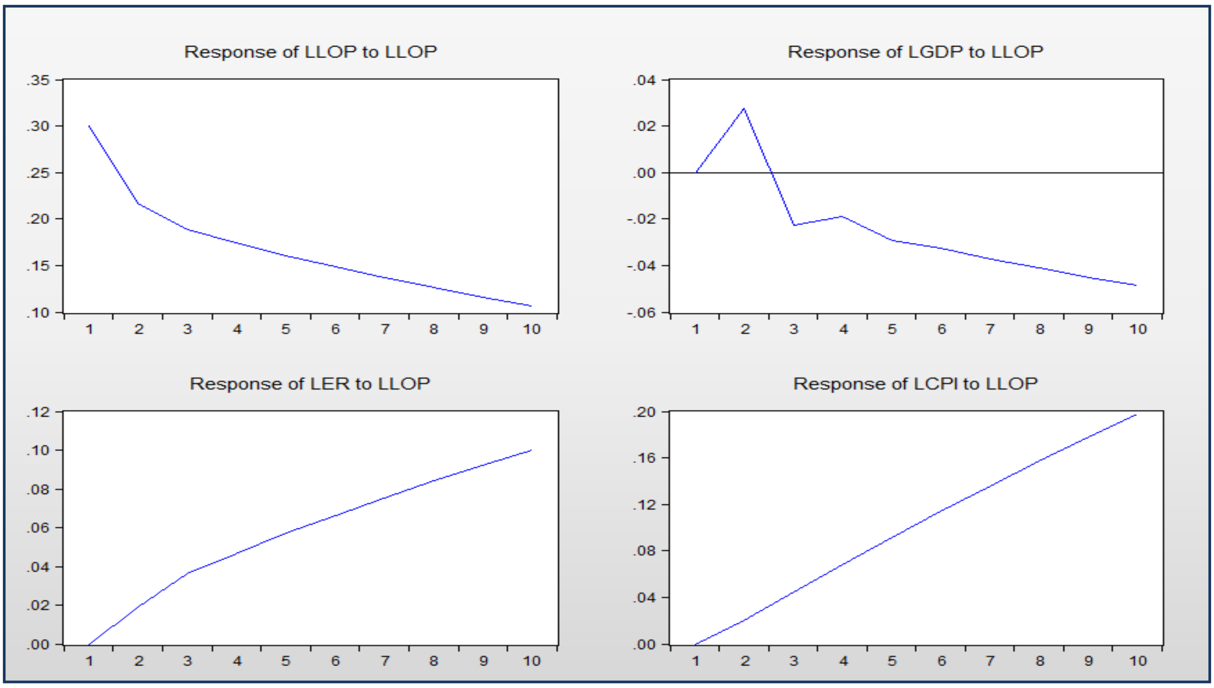


Figure 6-9: Impulse Response Functions (IRF) of Libyan Variables to LLOP.

Figure 6-9 is a combined graph illustrates the response of Libyan macroeconomic variables (LLOP, LGDP, LER and LCPI) to a shock of Libyan oil price which are obtained from the estimated VEC(1) framework, in order to investigate the magnitude of the impact of oil price on these variables.

In general, the results of the estimated impulse response functions suggest a statistically significant impact of any shock of Libyan oil price on Libyan variables over the specified period. However, the estimated effects of Libyan oil price are generally long term. More specifically, the top row shows the responses of Libyan oil price (LLOP) and GDP (LGDP) to a one standard deviation of Libyan oil price shock, is clear from figure 6-9 that the shock of one standard deviation to Libyan oil price temporary increases itself. This positive response decreases gradually after the first year, and then after the third year gradually falls and remains in the positive region. In general, there is a positive influence of oil price to itself both in the short-run and in the long-run. Moreover, a one shock to oil prices temporary increases LGDP of Libya from the first year to the second year. Libyan oil price shocks have a positive impact on the LGDP in the short-run (1–2 years). Nevertheless, the positive response of the GDP to oil price shocks declines suddenly after the second period to the negative region and then remains in the negative region in the long-run. As a result, oil shocks to the Libyan's GDP will have a negative effect in the long-run and short-run.

The second row shows the responses of exchange rate and inflation (LCPI) to Libyan oil prices. As can be seen from figure 6-9 the impulse response functions imply that the innovations in oil price significantly affect the LER and LCPI in Libya. The result of IRF suggests that the Libyan oil prices affect these indicators positively in the short-run and long-run. On the other hand, reaction of LER and LCPI to oil prices shocks continuously expands in the positive direction. We can safely say that oil price is more profoundly auto-influenced by its values in the short and long-term. Moreover, the Libyan macroeconomic variables show short and long-run responses to the price of national crude oil. However, findings of the impulse response functions suggest that shocks in Libyan oil price have a major impact on the macroeconomic variables of Libya.

6.2.12 Variance Decomposition (VDC)

In fact, the study is most concerned with the portion of the prediction error variance in oil prices, GDP, exchange rate and inflation which are explained by shocks to Libyan oil price. If shocks to Libyan oil price explain significant portions of the forecast error variance in oil prices, GDP, exchange rate and inflation, then oil prices have an impact on the Libyan macroeconomic variables. However, if shocks to Libyan oil price do not explain significant portions of the prediction error variance in oil prices, GDP, exchange rate and inflation, then oil prices have no impact on the Libyan macroeconomic variables. Therefore, VDC gives the contributions of shock to the variance of the *n*-period ahead prediction error for each variable in the system. Table 6-13 shows the portion of the variance in the prediction error of oil prices, GDP, exchange rate and LCPI, inflation that is attributable to its own shocks and to shocks to the other variables in the VEC model.

Table 6-13: Variance Decomposition of Forecast Error Variance of Oil Prices, GDP, Exchange rate and Inflation.

	Explained by shocks in				
Period	S.E.	LLOP	LGDP	LER	LCPI
Variance Decomposition of LLOP					
1	0.2997	100.0000	0.0000	0.0000	0.0000
2	0.4646	84.2281	3.2074	0.9726	11.5917
3	0.5984	76.1088	6.0357	1.2337	16.6215
4	0.7098	71.4930	7.8404	1.3411	19.3253
Variance Decomposition of LGDP					
1	0.2862	20.3037	79.6963	0.0000	0.0000
2	0.4253	25.5709	65.4754	0.1168	8.8366
3	0.5627	22.7297	64.0395	0.1003	13.1303
4	0.6752	21.7171	62.7126	0.1375	15.4326
Variance Decomposition of LER					
1	0.1182	0.1263	5.0884	94.7852	0.0000
2	0.1924	0.5086	6.9168	90.7883	1.7862
3	0.2531	1.0079	9.4653	86.9073	2.6193
4	0.3042	1.5325	11.4447	84.1065	2.9160
Variance Decomposition of LCPI					
1	0.0674	2.6572	0.0087	14.7063	82.6276
2	0.1191	7.0139	0.3047	18.8161	73.8651
3	0.1740	11.1000	1.7295	20.0951	67.0752
4	0.2313	14.4462	3.3947	20.3210	61.8379

Table 6-13 displays the point estimates of the proportion of forecast error variance in oil price, GDP, exchange rate and inflation which are explained by shocks to oil prices with standard errors at horizons 1, 2, 3, and 4 years to convey the dynamics of the VEC system. The source of this forecast error is the variation in the current and future values of the shocks to each variable in the VEC model. According to Wheeler (1999), the estimates of the proportion of prediction error variance are judged as significant if the point estimates are at least twice as large as their estimated standard errors. According to the VDC results for Libyan oil price, most of the Libyan oil price movements come from itself, which contributed about 100% in the first year declining to 71.49% in the fourth year. This suggests that Libyan oil price changes can influence Libyan macroeconomic variables but movements in Libyan macroeconomic variables have little impact on oil prices. Moreover, the inflation (LCPI) variable contributes in the third and fourth years about 16.62% and 19.32% to the variation in

Libyan oil price. The implication of this results is that, Libyan oil price tend to be highly responsive to variations in its past values. Libyan macroeconomic variables on the other hand explain less of the variation in Libyan oil price.

For GDP; the most of GDP changes come from itself and Libyan oil price as well as inflation (LCPI). At the first year 79.69% of the variability in GDP is explained by itself, while 30.30% is explained by Libyan oil price. After four years 62.71% is explained by GDP, while 21.71% and 15.43% are by Libyan oil price and inflation. In the long term, the effects of Libyan oil prices on GDP decrease.

The VDC of the variability of exchange rate comes from itself. Shocks to Libyan oil price are explained about 0.12% of shocks to the exchange rate in the first year rising slightly increased to 1.01 in the third and fourth years. The implication of this result is that Libyan oil prices have small effect on exchange rate in Libya in the short-run term. Finally, Table 6-13 shows that the major source of shocks in inflation rate was variability in inflation itself. However; Libyan oil prices explained only 2.65% to changes in inflation in the first year and slightly increased to 14.44 in the fourth year.

6.3 Empirical Analysis of Nigeria

6.3.1. Graphical Representations of Variables

Figure 6-10 below shows the historical evolution of the time series of oil prices and Nigerian variables in level during the period from 1970 to 2017.

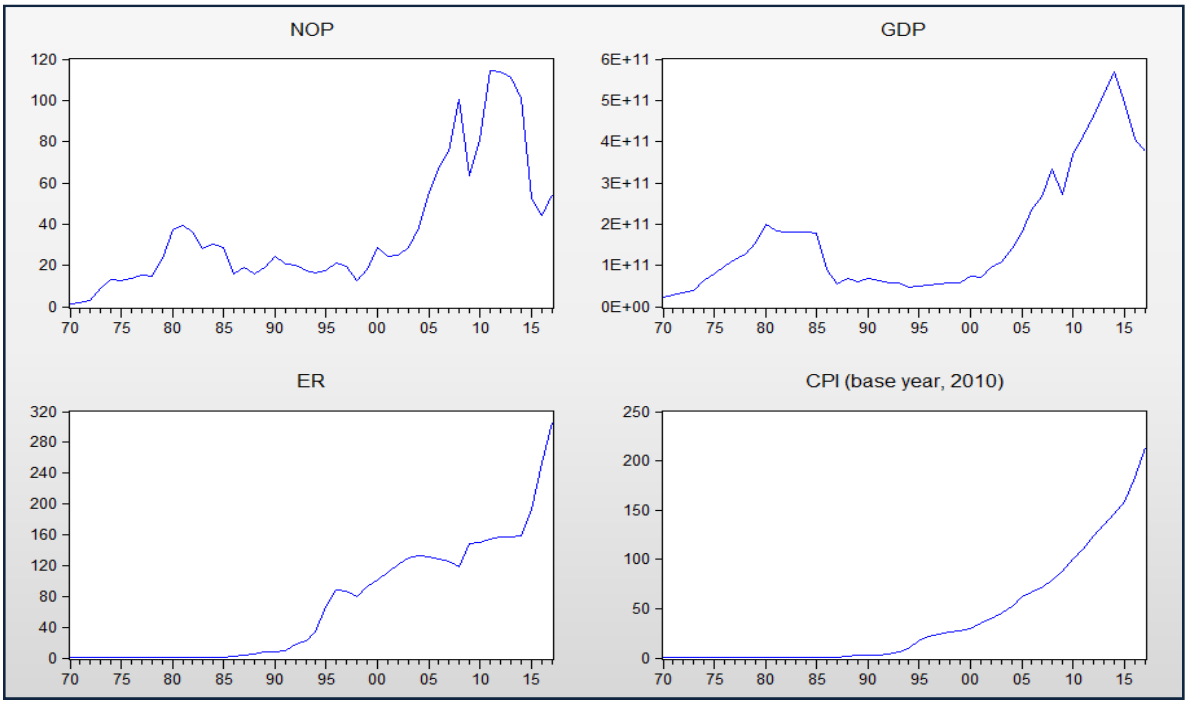


Figure 6-10: A Combined Graph for Annual NOP, GDP, ER and CPI in Nigeria Covering the Period from 1970 to 2017 in Level.

Through visual inspection of the time series of Nigerian oil prices, GDP, ER and CPI we can say that Nigerian oil prices and Nigerian variables seem to move together over time. However, the prices of oil are fluctuated in different periods between increase and decrease. Moreover, the trend appears clear in the historical pattern of Nigerian oil prices. Furthermore, the pattern of GDP, exchange rate and inflation, CPI data in Nigerian appear to have a pattern with approximately a steady increase trend. The exchange rate in Nigeria increased an average of $69 per one Nigerian currency per year. In summary, all of the macroeconomic variables of interest in this research virtually share the related historical patterns during the period of sample. A steady upward trend appears to dominate the pre-2008 period in all series data in Nigeria. In addition, the plots illustrate that the all our time series data are non-stationary at all levels. Therefore, all oil prices and Nigerian variables during analysis are converted to the natural logarithmic form in order to smooth the series and then the first differences are taken to achieve stationartity and defined as following

ΔLNOP = $ln(\mathrm{NOP_t}) - ln(\mathrm{NOP_{t-1}})$, is Nigerian crude oil price.

ΔLGDP = $ln(\mathrm{GDP_t}) - ln(\mathrm{GDP_{t-1}})$, is Nigerian economic growth.

ΔLER = $ln(\mathrm{ER_t}) - ln(\mathrm{ER_{t-1}})$, is the exchange rate.

ΔLCPI = INF = $ln(\text{CPI}_t) - ln(\text{CPI}_{t-1})$, is the Nigerian CPI, inflation.

Figure 6-11 illustrates the plots of all Nigerian variables after taking the first difference of the logarithmic prices. However, the variables after transformation into the first differences of natural log-values appear to fluctuate around their mean levels, which are close to zero. They suggest that all the variables seem to have constant means and variances and the possibility of integration order is one to be stationary.

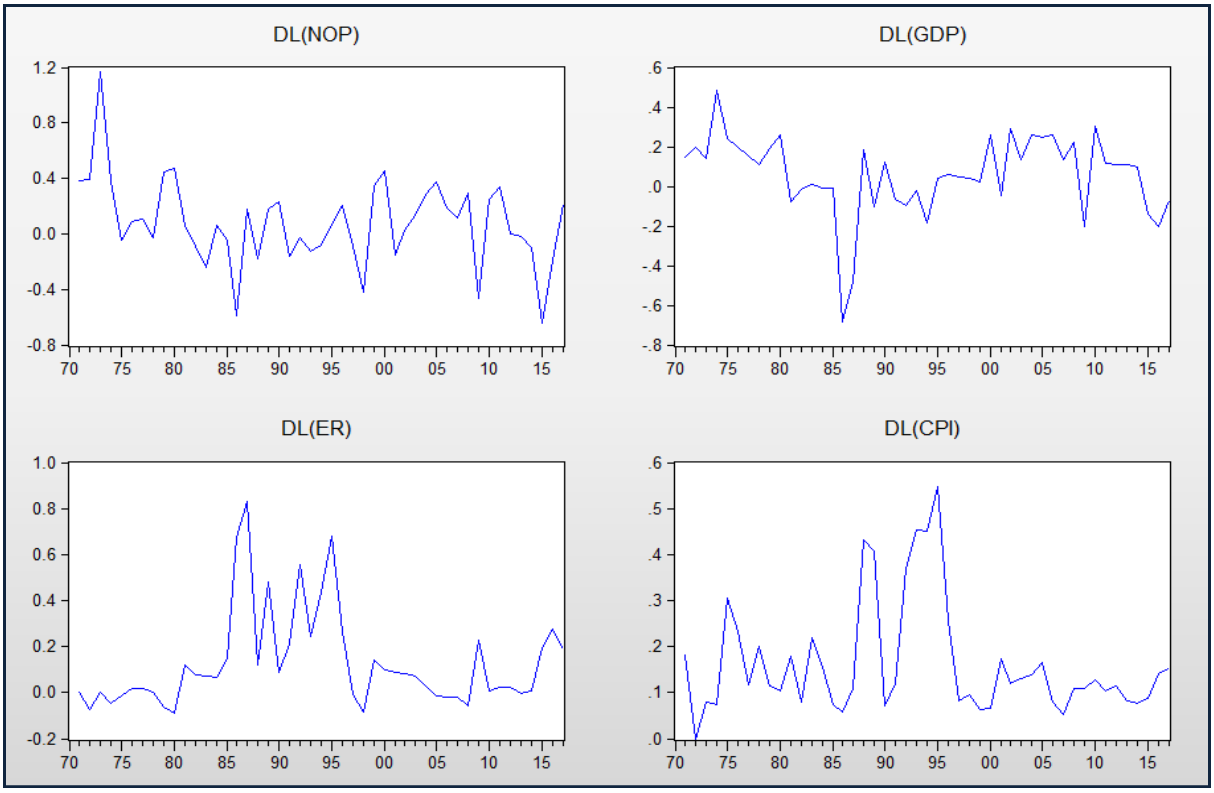


Figure 6-11: A Combined Graph for Nigerian Variables Covering the Period from 1970 to 2017 after Transformation.

6.3.2 Descriptive Statistics

Table 6-14 blew presents descriptive statistics of all the variables at the levels and after transformation in Nigerian case.

Table 6-14: Descriptive Statistics of Oil Prices and the Nigerian Variables in Levels and the First log Differencing.

	Variables / Nigerian case							
Descriptive Statistics	In level				In the first log differences			
	NOP	GDP	ER	CPI	ΔLNOP	ΔLGDP	ΔLER	ΔLCPI
Mean	34.08	1.68E+11	69.01	39.47	0.08	0.06	0.03	0.16
Std. Dev.	29.32	1.48E+11	77.40	55.65	0.34	0.21	0.21	0.12
Skewness	1.33	1.23	0.92	1.49	0.94	-1.25	1.71	1.57
Kurtosis	3.80	3.37	3.27	4.32	7.13	5.97	5.35	4.62
Jarque-Bera	15.53***	12.34***	6.88***	21.470	40.38***	29.60***	33.73***	24.59***
P-value	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00

*** and ** indicaterejection at 1% and 5% significance level.

Based on the dispersion values of series in level which are obtained from the standard deviation statistics (row two in Table 6-14), the GDP is more volatile in comparison with the Nigerian oil prices, ER and inflaton, CPI. However, all of the macroeconomic variables in Nigeria have right tails with positive skewness values. Moreover, the values of kurtosis are greater than 3 suggesting that the distribution of oil prices and the Nigerian macroeconomic variables are leptokurtic. The *p*-values of the Jarque-Bera tests indicate that most of variables for Nigeria are not normally distributed. Except, the exchange rate (ER) variable is accepted the null hypothesis of normality of the Jarque-Bera test at the 1% significance level.

Comparatively for the return series, oil prices data (Δ LNOP), exchange rate (Δ LER) and inflation have positive skewness values with right tails, while, the Δ LGDP is a negatively skewed. All return series are leptokurtic, since all the estimated values of kurtosis exceed 3. The null hypotheses of normality of the Bera-Jarque test are rejected at the 1% significance level indicating that the return series are not normally distributed.

6.3.3 Detecting Stationarity

The combined graphs (see Appendix B, graphs B4 to B5) present the correlogram of the sample ACFs and PACFs plots of all individual series of Nigeria. The inspection of the sample ACFs and the sample PACFs plots suggest that all the series decay extremely slowly in log level. This means that all the series are non-stationary. In contrast, the sample ACFs and the sample PACFs plots suggest that all returns are stationary. Moreover, the results of ACFs and PACFs for oil prices, GDP, exchange rate and inflation, CPI in Nigeria, indicate that the appropriate order of integration is one for all variables to be stationary. However, the ADF and PP unit root tests have been carried out for all variables individually in log levels and in returns series.

Since, the plots of oil prices and Nigerian variables in log level (see graph B6 in Appendix B) are suggestive of the presence of trend and the most of variables fluctuate around non-zero sample mean, indicating to the inclusion of intercept and trend in unit root tests. While the figures of their first log differenced (see graph 6-11) suggesting that their movements are around sample mean of almost zero, as a result, no constant is chosen for non-stationarity tests. The best lag length in unit root test is chosen using SIC with maximum lag 9. The results of unit root tests are shown in Table 6-15.

- **Outcomes of Standared Unit Root Tests**

Table 6-15 below shows the results of ADF and PP unit root tests to both log levels and their returns of Nigerian variables series.

Table 6-15: Results of Standard Unit Root Tests of Oil prices and Nigerian Variables in Log Levels and the First Log Differencing.

Variable	ADF (intercept and liner trend)		PP (intercept and liner trend)		Variable	ADF (None)		PP (None)	
	t-Stat	*Prob.	t-Stat	*Prob.		t-Stat	*Prob.	t-Stat	*Prob.
in log level					**in first log differences**				
LNOP	-3.1525	0.1066	-3.1578	0.1155	Δ LNOP	-5.0376***	0.0000	-5.0376***	0.0000
LGDP	-1.2826	0.8801	-1.7173	0.7278	ΔLGDP	-4.3505***	0.0000	-4.3789***	0.0000
LER	-1.6724	0.7474	-1.5803	0.7858	ΔLER	-3.0234***	0.0033	-2.9501***	0.0040
LCPI	-1.7533	0.7108	1.1140	0.9157	ΔLCPI	-2.0209**	0.0226	-2.0119**	0.0347
critic values: 1%	-4.1658		5%	-3.5085	**critic values** 1%	-2.6162		5%	-1.9481

Null Hypothesis: data has a unit root and lag length selected automatic based on Schwarz information criterion with max=9 and *MacKinnon (1996) one-sided p-values. *** and ** refer to the rejection at 1% and 5% significant levels.

From Table 6-15, we can see that, oil prices (LNOP), GDP, exchange rate and CPI in log levels have a unit root and the null hypothesises are accepted at the 1% significance level. Thus, all the calculated t-statistics are less than the critical values in absolute values and the *p*-values are greater than the 1% and 5% significance levels. In contrast, the results of all the variables in the first difference levels suggest that the null hypothesis of a unit root are rejected and statistics tests provide *p*-values smaller than the 1% significance level, suggesting the alternative hypothesis are accepted and all the returns series are stationary. The only exception of is related with the inflation (CPI) variables in the first log difference series, is stationary at the 5% level.

The results obtained from standard unit root tests, ADF and PP show that Nigerian oil prices, exchange rate and CPI are non-stationary at the 1% level of significance and all the individual variables have the same order of integration I(1). Therefore, we can proceed under the assumption that each time series can best be described as stationary or I(0) in returns series. However, to investigate whether the Nigerian variables are cointegating or have a common stochastic trend. Thus, the Johansen method has carried out in the next steps.

6.3.4 The Optimal Lag Length Selection

Table 6-16 presents below the results of the choices for VAR lag order for oil prices (LNOP) and other macroeconomic variables in log level for Nigeria.

Table 6-16: VAR Lag Order Selection Criteria for Oil Prices and Nigerian Data.

Endogenous variables: LNOP, LGDP, LER and LCPI
Exogenous variables: C

Lag	AIC	SIC	HQ
0	5.7944	5.9599	5.8551
1	-4.0691	-2.6839	-3.6274
2	-4.1734*	-3.2417*	-3.7658*
3	-4.1440	-1.9926	-3.3554
4	-3.7287	-0.9154	-2.6975
5	-3.7305	-0.2552	-2.4567

* indicates lag order selected by the criterion.

As can be seen from Table 6-16, the results of the comparison between the information criteria of VAR lag order selection for oil prices with Nigerian variables, suggesting that the optimal lag length is lag 2 based on the AIC, SC and HQ.

6.3.5 Specification of the Deterministic Terms - the Pantula principle

For selecting the optimal deterministic terms in the VEC model the Pantula principle has been carried out by employing the Johansen test under models 2, 3 and 4 to compare the trace and max-eigenvalue statistics to their corresponding critical values at each step. The Pantula principle and cointegration test results are explained in the next section.

6.3.6 Johansen Cointegration Test

To test cointegrating links between oil prices and Nigerian variables, we carry out the Johansen cointegration test including both trace test and maximum eigenvalue test for the three plausible models (2, 3 and 4) which are estimated with a lag length of 1 in the VEC model, which is the optimal lag in VAR model minus one. The results of Johansen test, reported in Table 6-17 below.

Table 6-17: Results of Johansen Cointegration Tests and The Pantula Principle for Oil Prices and Nigerian Variables.

Null Hypothesis	**Model 2** None\ Intercept – No Trend			**Model 3** Linear \ Intercept – No Trend			**Model 4** Linear \ Intercept – Linear		
	Test Statistic	Critical Value 0.05	P-value**	Test Statistic	Critical Value 0.05	P-value**	Test Statistic	Critical Value 0.05	P-value**
Trace test									
None	67.4945	54.0790	0.0020	53.8089	47.8561	0.0125	69.5147	63.8761	0.0156
At most 1	35.8475	35.1927	0.0425	26.1224*	29.7970	0.1251	41.4418	42.9152	0.0697
At most 2	16.8341	20.2618	0.1388	10.6601	15.4947	0.2333	21.1958	25.8721	0.1713
At most 3	7.2550	9.1645	0.1136	2.9403	3.8414	0.0864	6.7837	12.5179	0.3676
Number of Cointegrating Relations	2			1			1		
Maximum Eigenvalue test									
None	31.6470	28.5880	0.0197	28.0728*	32.1183	0.1442	27.6864	27.5843	0.0485
At most 1	19.0134	22.2996	0.1352	20.2459	25.8232	0.2293	15.4623	21.1316	0.2578
At most 2	9.5790	15.8921	0.3743	14.4120	19.3870	0.2277	7.7197	14.2646	0.4079
At most 3	7.2550	9.1645	0.1136	6.7837	12.5179	0.3676	2.94037	3.8414	0.0864
Number of Cointegrating Relations	1			0			1		

Endogenous variables are LNOP LGDP LER LCPI. Lag length of 1 is used.
 * denotes the first time that the null hypothesis cannot be rejected at the 0.05 level.
**MacKinnon-Haug-Michelis (1999) p-values.

Table 6-17 summarises the trace statistics and max-eigenvalue statistics under models 2, 3 and 4 with number of cointegration relations (r) by employing the Johansen procedure. The Pantula principle will indicate the optimal model when the null hypothesis cannot rejected at the first time.

Pantula principle starts with the most restrictive model (Model 2, null hypothesis no cointegration or r = 0 and the alternative hypothesis> 0). The statistic of trace test in model 2 is 67.4945, which is greater than 54.0790 at the 5% level of significant. Thus, the null hypothesis of no cointegration is rejected and instead we accept that the alternative hypothesis that one or more cointegrating vectors have existed. Then we move to the next restrictive model (Model 3), again the null hypothesis of no cointegration is rejected at the 5% level. Morover, under the least restrictive one, model 4, the null hypothesis of no cointegration is rejected at the 5% level. Since all three models reject the null hypothesis of zero cointegrating vectors, and the alternative hypothesis of at least one cointegrating vector has existed , we continue with row 2, where the null hypothesis is r = 1 and the alternative hypothesis $r > 1$. We start with the most restrictive model (Model 2), the statistic of trace test in model 2 is 35.8475, which is greater than 35.1927 at the 5% level of significant. Thus, the null hypothesis of one cointegration is rejected. However, the procedure stops at 26.1224 in model 3 because this is the first time that the null hypothesis cannot be rejected and model 3 is appropriate for the Johansen cointegration test and this model is the best model for describing the system. However, the trace test statistic in model 3 suggests that there is one cointegration relationship at the 5% level of significance. On the other hand, for max test statistics Pantula principle starts with the most restrictive model (Model 2, null hypothesis no cointegration), the max test statistic in model 2 is 31.6470 which is greater than 28.5880 at the 5% level of significant. Thus, the null hypothesis of no cointegration is rejected. Then we move to the next restrictive model (Model 3), here the procedure stops at 28.0728 because this is the first time that the null hypothesis cannot be rejected and model 2 is the best model for the Johansen cointegration test and this model is the appropriate for describing our data.

However, the trace test statistic in model 3 suggests that there is one cointegration relationship at the 5% level of significance. While, the max test statistic in the same model indicates that is no cointegration relationship between Nigerian variables. In this situation, our analysis is based on the outcomes obtained from the trace test. Therefore, we can conclude that the model 3 specification, which is has two contains, an intercept in the VAR, and there is an intercept in the cointegrating equation is the best model to describe the given data.

Additionally, the results of the trace test suggests that the Nigerian variables are integrated at one cointegrating vector in the VEC system and there is indeed a long-run relationship among oil prices, GDP, exchange rate and inflation rate at the 5% level. Moreover, there may be a causality relationship exist between two variables and these interrelationships can be examined through Granger causality test.

6.3.7 Estimating the Parameters of the VEC Model

Due to the results of cointegration, the VEC model will need to estimate, in order to investigate the short-run and long-run dynamics among oil prices and other Nigerian variables. The VEC model is estimated using ordinary least squares (OLS) with lag length 1 and under the assumption of model 3. The specified VEC(1) model for oil prices and Nigerian variables is in this form

$$\Delta X_t = \mu_0 + \alpha \left(c_0 + \acute{\beta} X_{t-1}\right) + \Phi_1^* \Delta X_{t-1} + \varepsilon_t, \tag{6.3}$$

where $\Delta X_t = (\Delta \mathrm{LNOP},\ \Delta \mathrm{LGDP},\ \Delta \mathrm{LER},\ \Delta \mathrm{LCPI})'$.

The results of the VEC model estimation is divided into two parts. The first part reports the results of one cointegrating equation from Johansen procedure. The second part of the results report results of short-run parameters from the VAR model in the lagged first differences of all the endogenous variables in the system with the error correction terms. However, Table 6-18 presents the results of estimation for VEC(1) model for our variables under study.

Table 6-18: Parameter Estimation of a VEC(1) Model for Oil Prices and Nigerian Variables.

Long-run parameters						
Cointegrating Eq:		C	LNOP(-1)	LGDP(-1)	LER(-1)	LCPI(-1)
CointEq1	coefficient	-3.4874	1.0000	-0.0234	1.2676	-1.4197
(*β*)	Standard error	6.6261		0.2298	0.3358	0.3537

short-run parameters					
Error Correction:		ΔLNOP	ΔLGDP	ΔLER	ΔLCPI
CointEq1 (*α*)	coefficient	-0.3434	0.1241	-0.0328	0.1284
	Standard error	0.1425	0.0883	0.0856	0.0452
C	coefficient	-0.0161	0.0498	0.0909*	0.0918***
	p-value	0.8500	0.3483	0.0812	0.0015
ΔLNOP (-1)	coefficient	0.4305**	0.2523**	-0.1642	-0.0922
	p-value	0.0266	0.0355	0.1516	0.1280
ΔLGDP (-1)	coefficient	0.0795	-0.1683	-0.2107	0.0031
	p-value	0.8742	0.5894	0.4862	0.9844
ΔLER (-1)	coefficient	0.102500	-0.3546	0.2452	0.1115
	p-value	0.8321	0.2405	0.4003	0.4686
ΔLCPI (-1)	coefficient	0.2337	0.2644	0.2147	0.3883
	p-value	0.6250	0.3742	0.4557	0.0137**

***, ** and * rejection at 1%, 5% and 10% significance levels.

Table 6-18 presents the estimated long run co-integrating relationships among the Nigerian variables with their standard error in the first part. This cointegration equation, CointEq1 (*β)*, is estimated as

LNOP(-1) - 3.4874 - 0.0234 LGDP(-1) + 1.2676 LER(-1) - 1.4197 LCPI(-1) = 0, which can be rewritten as:

$$LNOP(-1) = 3.4874 + 0.0234\ LGDP(-1) - 1.2676\ LER(-1) + 1.4197\ LCPI(-1) \quad (6.4)$$

The long run equation shows that that there is a significant relationship between LNOP, LGDP, LER and LCPI respectively. This result shows that there is a positive relationship among Nigerian oil prices and GDP, in the long run. Whilst, the Nigerian oil prices have a negative and significant impact on exchange rate. Moreover, the relationship among oil prices and inflation (LCPI) is positive. The second part of the Table 6-18 shows the estimated VEC Model for the short run. The estimated results of coefficients in the ΔLNOP equation inferred that, there is a positive and significant relationship between LNOP and its first differencing lag at the 5% level. The ΔLGDP, ΔLER and ΔLCPI have a positive relationship of LNOP function but insignificant. In the equation of ΔLGDP we can say that, there is a positive and significant effect of coefficient of the ΔLNOP (-1). Furthermore, in the equations of ΔLER and ΔLCPI there are positive but insignificant relationships with the first lag of ΔLNOP variable. However, estimates of the short-run coefficients are less robust than those of long-run coefficients to misspecification of the number of lags.

The residuals correlation matrix of the fitted VEC(1) model are presented in Table 6-19 below.

Table 6-19: Estimated Correlation Matrix from the VEC(1) model in the Nigerian Case.

	LNOP	LGDP	LER	LCPI
LNOP	1			
LGDP	0.61	1		
LER	-0.27	-0.75	1	
LCPI	0.004	-0.11	0.38	1

The results in Table 6-19 from the estimated correlation matrix of the VEC(1) model for oil prices and Nigerian variables, suggest positive correlations between Nigerian oil price (LNOP) and both LGDP and LCPI. While, the correlation between changes in LNOP and exchange rate (LER) is negative. However, this result is consistent with the findings obtained from the estimation of the long-term function.

6.3.8 Model Diagnostic Checking

- **Stationarity Condition:**

Figure 6-12 below shows that the inverse roots of AR characteristic polynomial are less than one (the one point is 0.99), indicating that the VEC(1) model is stationary and checking for stability check does not show that our fitted model is misspecified.

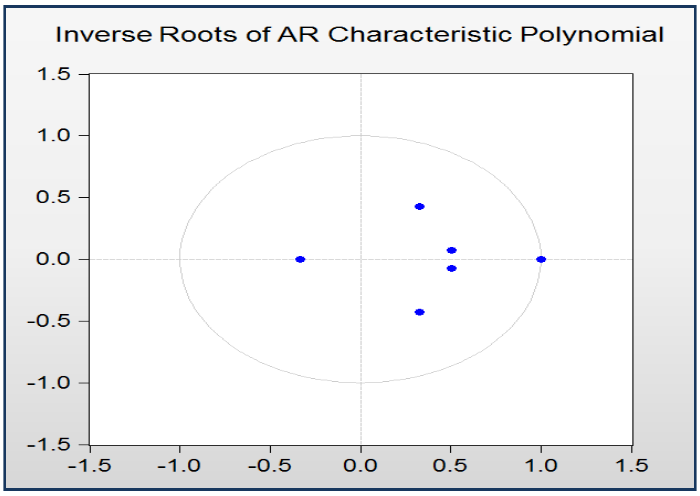


Figure 6-12: The Inverse AR Roots of VEC(1) Model for Nigerian Variables.

- **Residual Diagnostics**

Figure 6-13 illustrates the plots of the residuals series of the fitted VEC(1) model. Here the two horizontal lines point to the two standard errors. From these plots, we can say that there are many residuals exceed the two standard errors; this may be suggestion for non-normality feature which is not sufficiently captured by this model.

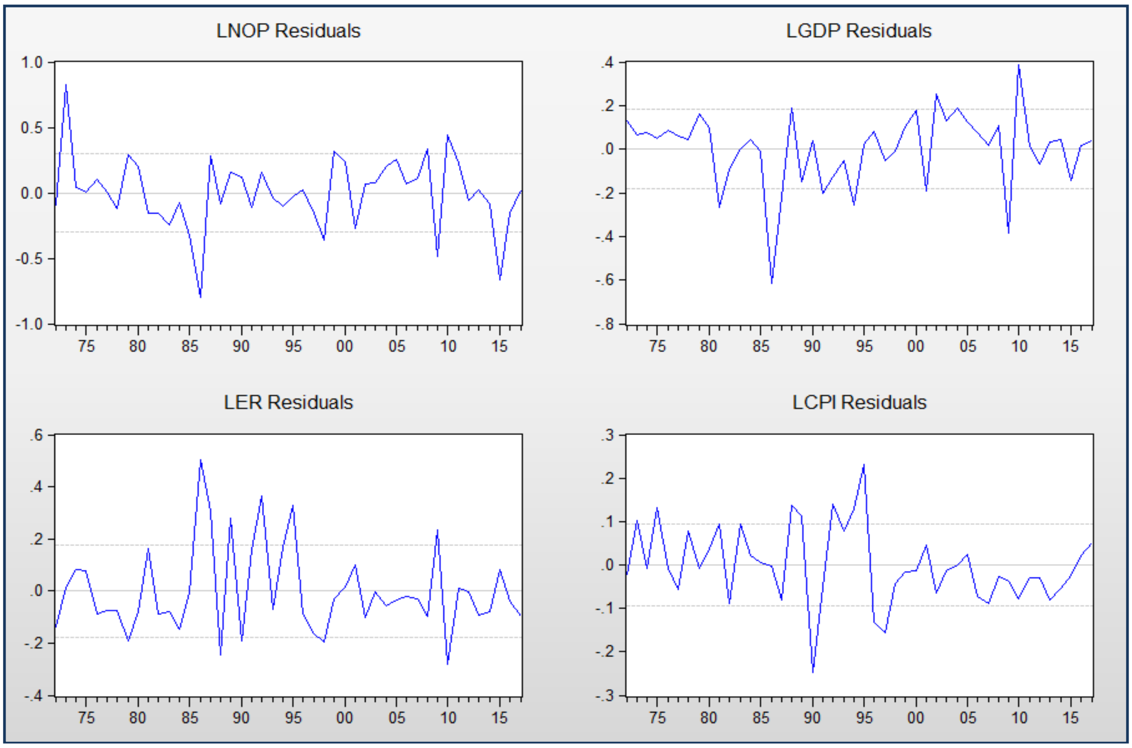


Figure 6-13: Residuals of A Fitted VEC(1) Model for Oil Prices and Nigerian Variables.

- **Test for Autocorrelations of residuals**

Figure 6-14 displays the autocorrelation functions of the VEC(1) model, here we have selected lag=15. However, the autocorrelation functions indicate that all the autocorrelation coefficient within the approximate confidence bounds. As a result, there are no significant autocorrelations.

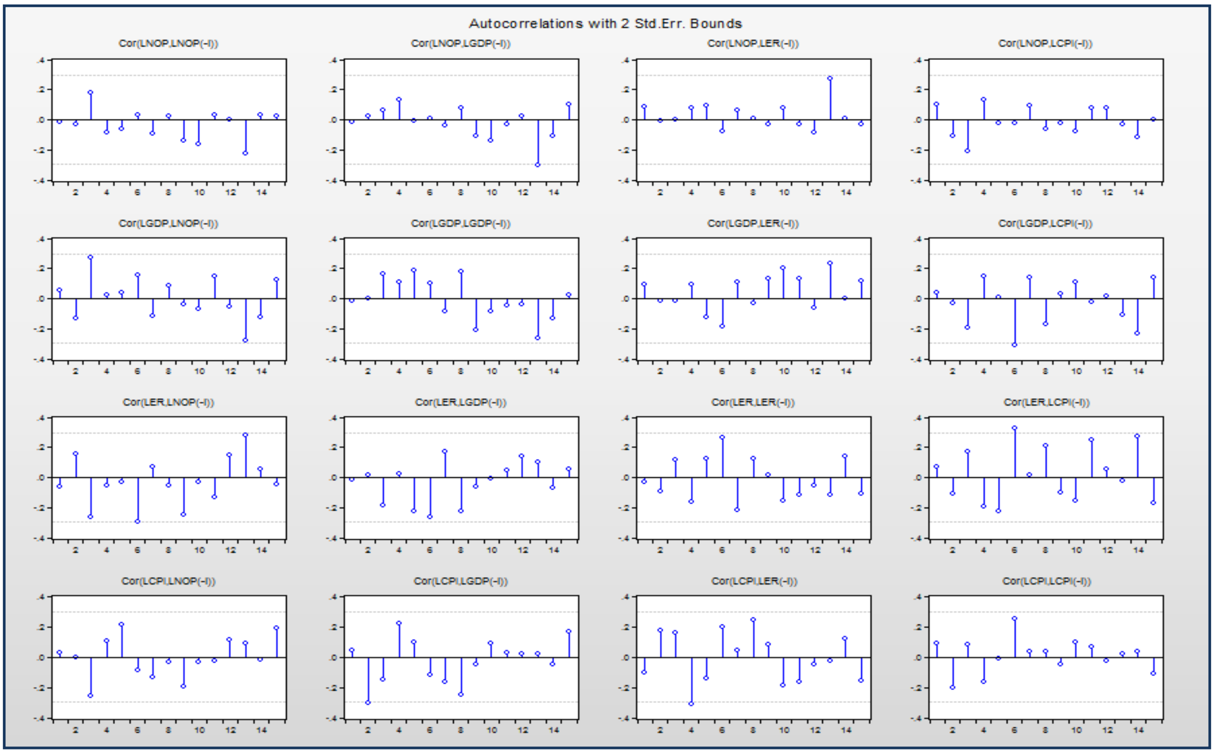


Figure 6-14: Plots of the Autocorrelation Functions of VEC(1) Model for Oil Prices and Nigerian Variables.

- **Multivariate Portmanteau test**

The multivariate Ljung–Box portmanteau tests have been carried out for testing the null hypothesis, there is no autocorrelations in VEC residuals up to lag 12. The result of this test is reported in Table 6-20 below.

Table 6-20: Portmanteau Tests for Autocorrelations of VEC(1) Residuals for Oil Prices and Nigerian Data.

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.
1	4.0804	NA*	4.1711	NA*
2	20.6630	0.8391	21.5074	0.8036
3	33.1977	0.8829	34.9166	0.8344
4	49.0698	0.8423	52.3004	0.7498
5	68.3368	0.7221	73.9170	0.5463
6	84.0127	0.7113	91.9443	0.4820
7	96.9352	0.7687	107.1862	0.5040
8	108.2067	0.8428	120.8307	0.5638
9	125.9459	0.7966	142.8848	0.4164
10	137.4459	0.8548	157.5793	0.4495
11	154.6457	0.8246	180.1847	0.3191
12	160.4373	0.9282	188.0204	0.4859

*The test is valid only for lags larger than the VAR lag order.

From Table 6-20, we can see that the null hypothesis of the Portmanteau test, is no autocorrelation in residuals of all residual series in the VEC(1) model has been accepted and there are no significant autocorrelation up to lag 12. However, the *p*-values of the Q-statistic and its adjusted Q-statistic are greater than the 5% significance level which are indicate that there is inadequate evidence of presence of autocorrelations regarding the four residual series from the VEC(1) model for Nigeria which appear to be white noise.

- **Normality Test of Residuals**

For testing the normality of VEC(1) residuals for oil price and Nigerian macroeconomic indicators, Jarque–Bera (JB) test and graphical methods including the histogram and QQ-plots have been applied. Results of these digenetic are presented in Table 6-21 as well as figures 6-15 and 6-16 respectively

Table 6-21: Results of Normality Test for VEC(1) Residuals of Oil Prices and Nigerian Data.

residuals	**Jarque-Bera**	***p*-value**
LNOP	6.5958	0.0370
LGDP	3.9468	0.1390
LER	14.3923	0.0007
LCPI	0.5582	0.7564
Joint	25.4932	0.0013

Null Hypothesis: residuals are multivariate normal.

From the outcome of Jarque–Bera test of the VEC(1) model for individual residuals case and in joint case in Table 6-21, we can say that, the null hypothesis of the individual residuals are normal is rejected for LER residuals series at the 1% significance level. While it is accepted for LNOP residual and it is normally distributed at 1% level and also it is accepted for both LGDP and LCPI residuals. Moreover, the *p*-value of the joint statistics of Jarque–Bera is less than 1% significance level. Therefore, the null hypothesis for residuals are multivariate normal is rejected in the Nigerian case.

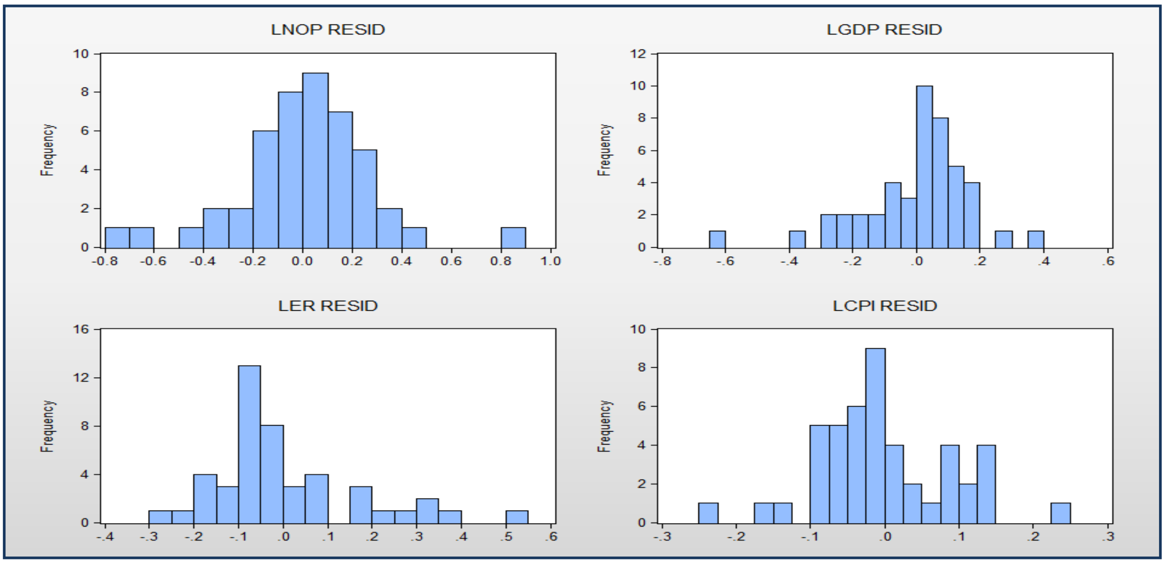


Figure 6-15: The Histogram Plots for Individual Residuals of VEC(1) Model for Oil Prices and Nigerian Variables.

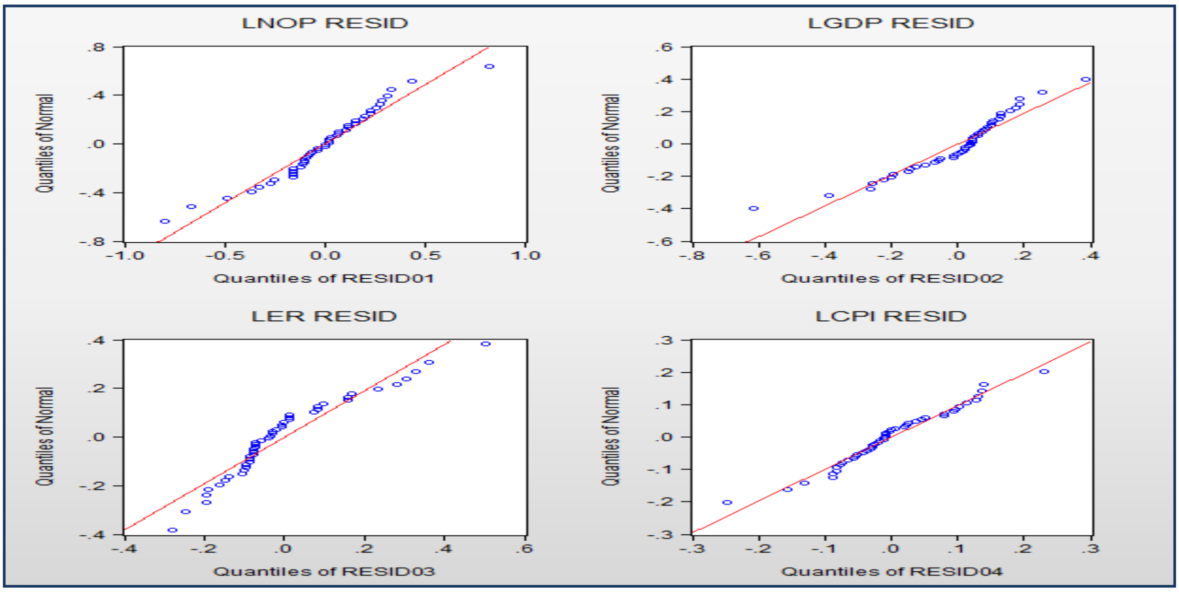


Figure 6-16: The Q-Q Plots for Individual Residuals of VEC(1) Model for Oil Prices and Nigerian Variables.

Figures 6-15 and 6-16 present the histogram and the QQ-plots of the five residual series from VEC(1) model for Nigerian variables. According to these plots we can see that the residual series of all individual variables approximately normally distributed and this graphical diagnosis applies almost to the results obtained from Jarque–Bera tests.

Figures 6-7 and 6-8 present the histogram and the QQ-plots of the residuals series from the VEC(1) model for Nigeria. According to these plots we can see that the residuals of Nigerian oil prices LNOP and LCPI are approximately normally distributed, while the plots of residuals for LGDP and LER suggest not normally distributed because the right-skewed distribution for LGDP as well as the positive excess kurtosis and left-skewed distribution for LER residuals have been appeared. Finally, this graphical diagnosis applies almost to the results obtained from Jarque–Bera tests.

- **Heteroskedasticity Test of Residuals**

According to the *p*-value of the heteroskedasticity test statistics in Table 6-22, we can say that there is no precence of the heteroskedastity effect in the residuals of the VEC(1) model at the 5% level of significance.

Table 6-22: Heteroskedasticity Test of VEC(1) Residuals of Oil Prices and Nigerian Data.

Residuals of Nigerian variables	
Chi-sq test-statistic	***P*-value**
194.5617	0.2169

6.3.9 Pairwise Granger Causality Test

In this subsection, we are interested to study the directional causal relationship between domestic oil prices and Nigerian macroeconomic variables using bivariate VAR models. A requirement for the pairwise Granger causality test is that the data are stationary, so we have to use returns series in this test. To identify the optimal lag length of bivariate VAR model are selected based on AIC, SIC and HQ information criterion. The results of these information criterions are contained in Table 6-23 between oil prices and all other variables.

Table 6-23: The Optimal Lag Length of Bivariate VAR Models for Oil Prices and Nigerian Data.

Lag	1	2	3	4	5	6	7	8	9	10
Bivariate variables: ΔLNOP and ΔLGDP										
AIC	-0.5561*	-0.4515	-0.4122	-0.2824	-0.0856	0.1035	0.1592	0.3008	0.2443	0.4394
SIC	-0.3819*	-0.1032	0.1101	0.4142	0.7851	1.1484	1.3782	1.6940	1.8117	2.1809
HQ	-0.4947*	-0.3287	-0.2280	-0.0368	0.2213	0.4718	0.5889	0.7920	0.7969	1.0533
Bivariate variables: ΔLNOP and ΔLER										
AIC	-0.1916*	-0.0296	0.0022	0.1844	0.3005	0.4707	0.5826	0.6659	0.8102	0.9086
SIC	0.0695*	0.4056	0.6118	0.9681	1.2584	1.6027	1.8888	2.1462	2.4646	2.7372
HQ	-0.0995*	0.1238	0.2171	0.4607	0.6382	0.8698	1.0431	1.1878	1.3934	1.5532
Bivariate variables: ΔLNOP and ΔLCPI										
AIC	-1.3100*	-1.2821	-1.1586	-0.9919	-0.8224	-0.7218	-0.5955	-0.4336	-0.4700	-0.2794
SIC	-1.0487*	-0.8467	-0.5490	-0.2082	0.1353	0.4101	0.7106	1.0466	1.1844	1.5491
HQ	-1.2179*	-1.1286	-0.9437	-0.7156	-0.4847	-0.3227	-0.1350	0.0882	0.1132	0.3652

* indicates lag order selected by the criterion.

Table 6-23 shows the results for all pairs of oil prices (ΔLNOP) and Nigerian indicators (ΔLGDP, ΔLER and ΔLCPI). The three information criterion, AIC, SC and HQ suggest lag 1 as the optimal lag for all bivariate variables. All bivariate VAR models with optimal lag are diagnostic until satisfy stable condition and no autocorrelation in the residuals. Consequently, the standard pairwise Granger causality test is applied for analysing the dynamic bivariate interactions between oil prices and Nigerian variables.

Table 6-24 below displays the outcomes of the Granger causality test. The null hypothesis is that there is no causality among oil price (ΔLNOP) and Nigerian macroeconomic variables, and the F test statistics with the corresponding *p*-values are presented in the second and third columns.

Table 6-24: Results of Pair-wise Granger Causality Test for Oil Prices and Nigerian Data.

Null Hypothesis:	F-Statistic	*p*-value
ΔLGDP does not Granger Cause ΔLNOP	0.0002	0.9864
ΔLNOP does not Granger Cause ΔLGDP	6.4185**	0.0150
ΔLER does not Granger Cause ΔLNOP	0.0967	0.7572
ΔLNOP does not Granger Cause ΔLER	7.2679**	0.0100
ΔLCPI does not Granger Cause ΔLNOP	0.1032	0.7495
ΔLNOP does not Granger Cause ΔLCPI	0.6190	0.4357

*** and** indicate rejection at the 1% and 5% significant levels.

According to the obtained results in Table 6-24, there are no bidirectional causality relationships are found among oil prices and any individual of Nigerian macroeconomic variables. However, Table 6-24 shows that the unidirectional causality is existed between ΔLNOP and ΔLGDP at the 5% significance level. Moreover, oil prices (ΔLNOP) has a unidirectional causality to the ER (ΔLER) at the 5% significance level. These results indicate that, any changes in oil price of Nigerian market would influence the Nigerian macroeconomic variables (i.e. GDP and ER).

6.3.10 VEC Granger Causality/Block Exogeneity Wald Tests

The Wald statistics have been used to test the null hypothesis that the dependent variable is not Granger-cause by the independent variables. Results are reported in Table 6-25.

Table 6-25: VEC Granger Causality/Block Exogeneity Wald Tests for Oil Prices and Nigerian Data.

Dependent variable	Excluded			
ΔLNOP	ΔLGDP	ΔLER	ΔLCPI	All
Chi-sq	0.0253	0.0455	0.2425	0.7300
P-value	0.8734	0.8310	0.6223	0.8661
ΔLGDP	ΔLNOP	ΔLER	ΔLCPI	All
Chi-sq	4.7381**	1.4192	0.8076	5.3478
P-value	0.0295	0.2335	0.3688	0.1480
ΔLER	ΔLNOP	ΔLGDP	ΔLCPI	All
Chi-sq	2.1370	0.4940	0.5673	4.6025
P-value	0.1438	0.4821	0.4513	0.2033
ΔLCPI	ΔLNOP	ΔLGDP	ΔLER	All
Chi-sq	2.4157	0.0003	0.5355	7.4417
P-value	0.1201	0.9843	0.4643	0.0591

** rejection at the 5% significance level.

The results of GCBEW in Table 6-25 of NOP and Nigerian variables indicate that the first equation under analysis has ΔLNOP as the dependent variable, the hypothesises that the lags of ΔLGDP, ΔLER and ΔLCPI are equal to zero are accepted, as their *p*-values are 0.8734, 0.8310 and 0.6223 which are more than 0.05, which mean that these independent variables does not, indeed, cause ΔLNOP. Therefore, we can conclude that there is no a directional causality relationship among ΔLLOP and other Nigerian variables. Moreover, the *p*-value for the joint hypothesis that all the lagged coefficients from all the independent variables

(ΔLGDP, ΔLER and ΔLCPI) does not cause ΔLNOP is accepted, which means that the rest of the variables have no causal relationship.

Moving on to our second equation for ΔLGDP, we now see the *p*-values from Table 6-25 for ΔLNOP. We conclude whether its null hypothesis is rejected. The *p*-value is less than 0.05, which indicating that the null hypothesis is rejected, and that this independent variable (ΔLNOP) does cause ΔLGDP. Moreover, this result meaning that the lagged coefficient of Nigerian oil price (ΔLNOP) in the regression equation of ΔLGDP appears to be useful for forecasting the future values of ΔLGDP. The null hypothesis of the excluded variables ΔLER and ΔLCPI are accepted. Thus, these variables do not granger cause ΔLGDP. Also, this equation shows that a joint lagged coefficient of the excluded variables also does not cause our dependent variable.

When checking our third equation for the dependent variable (ΔLER), the null hypothesis of each independent variable is accepted. The variable Δ LER does not have a causality relationship with ΔLNOP, ΔLGDP, and ΔLCPI. Also, this equation shows that joint lagged coefficients of these variables also does not cause our dependent variable.

Finally, the last equation to be tested is that related to the causality relationship between ΔLCPI and ΔLNOP, ΔLGDP and ΔLER. As the lagged coefficients, *p*-values presented in Table 6-25 are all above 0.05, we can say that there are no Granger causality relationships among this dependent variable and each of the equation’s independent variables.

6.3.11 Impulse Response Functions

Figure 6-17 below presents the responses of oil prices, GDP, exchange rate and LCPI, inflation to a shock to Nigerian oil price under the VEC(1) model for up to 10 periods.

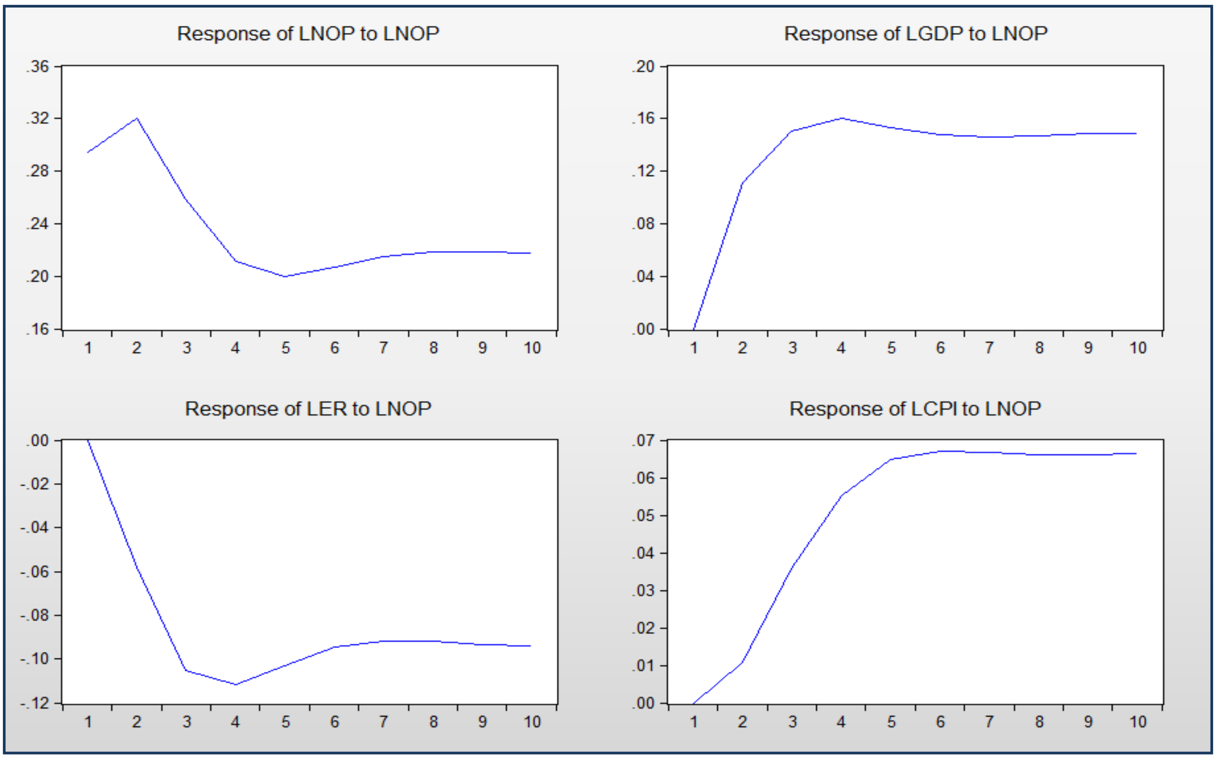


Figure 6-17: Impulse Response Functions (IRF) of Nigerian Variables to LNOP.

Figure 6-17 is a combined graph shows the response of Nigerian variables (LNOP, LGDP, LER and LCPI) to a shock of Nigerian oil price (LNOP) which are obtained from the estimated VEC(1) model, in order to investigate the magnitude of the impact of Nigerian oil price on these variables.

In general, the results of the estimated impulse response functions suggest a statistically significant impact of any shock of Nigerian oil price on Nigerian variables over the specified period. However, the estimated effects of Nigerian oil price are generally long term. More specifically, the top row shows the responses of Nigerian oil price (LNOP) and GDP (LGDP) to a one standard deviation of Nigerian oil price (LNOP) shock, is clear from figure 6-17 that a shock to LNOP temporary increases itself from the first year until the fourth year. Moreover, this response gradually decreases after the fourth year, and then stable up to the tenth period. This impact remains in the positive region, but never becomes negative. This shows the importance that Nigerian oil price shocks have impacts on the Nigerian oil market in both short-run and in the long-run.

The response function of LGDP indicates that Nigerian oil price shock has a significant positive impact on GDP throughout the first three years and the impact becomes relatively stable up to the tenth period. This shows that changes of Nigerian oil price affect Nigerian economic activity in the short-run and in the long-run.

The second row shows the result of responses of exchange rate and inflation (LCPI) to Nigerian oil prices. As can be seen from figure 6-17 the impulse response functions imply that the innovations in oil price significantly affect the LER and LCPI in Nigeria. The result of IRF suggests that the Nigeria oil prices affect LER negatively from the first year to the tenth year. On the other hand, reaction of LCPI to oil prices shocks continuously in the positive direction in the short-run and long-run. Consequently, we can say that the Nigerian macroeconomic variables show long-term responses to the price of national crude oil in Nigeria.

6.3.12 Variance Decomposition (VDC)

Table 6-26 displays the portion of the variance in the prediction error of Nigerian oil prices, GDP, exchange rate and inflation, CPI that is attributable to its own shocks and to shocks to the other variables in the VEC(1) model.

Table 6-26: Variance Decomposition of Forecast Error Variance of Oil Prices, GDP, Exchange rate and Inflation.

	Explained by shocks in				
Period	S.E.	LNOP	LGDP	LER	LCPI
Variance Decomposition of LNOP					
1	0.2947	100.0000	0.0000	0.0000	0.0000
2	0.4613	97.3276	1.0156	0.0116	1.6450
3	0.5744	91.8291	3.3552	0.0884	4.7271
4	0.6626	86.4903	5.8442	0.1977	7.4676
Variance Decomposition of LGDP					
1	0.1827	38.2871	61.7128	0.0000	0.0000
2	0.3167	58.5039	41.1384	0.3055	0.0521
3	0.4387	66.4081	33.2885	0.2124	0.0908
4	0.5399	69.5027	30.0887	0.1729	0.2355
Variance Decomposition of LER					
1	0.1770	7.4605	55.4093	37.1301	0.0000
2	0.3291	20.2429	50.2116	29.1209	0.4244
3	0.4708	27.6266	46.1927	25.7768	0.4037
4	0.5971	30.3983	45.2210	24.0968	0.2838
Variance Decomposition of LCPI					
1	0.0935	0.0016	2.1729	20.9843	76.8410
2	0.1671	0.0167	10.6535	30.2313	59.0983
3	0.2403	0.0317	20.8252	34.7767	44.3663
4	0.3121	0.1028	28.5461	36.8360	34.5149

Table 6-26 presents the point estimates of the proportion of forecast error variance in Nigerian oil prices, GDP, exchange rate and inflation (CPI) which are explained by shocks to oil prices and standard errors at horizons 1, 2, 3, and 4 years to convey the dynamics of the VEC model.

Table 6-26 shows that 100% of the changes of Nigerian oil price come from its values in the first year declining to almost 86% in the fourth year. While LGDP gave 5.8%, exchange rate contributes 0.19 % and LCPI gave 7.4% to the variation in Nigerian oil price in the fourth year. The implication of these results is that, the price of Nigerian crude oil tends to be highly responsive to movements in its past values. Nigerian macroeconomic variables explain less of the changes in Nigerian oil price.

The VDC of the variability of GDP comes from itself and Nigerian oil price. Shocks to Nigerian oil price are explained about 38.28% of shocks to the LGDP in the first year rising to 69.50% in the fourth year. The implication of this result is that Nigerian oil prices have a significant effect on GDP in Nigeria in the long-run.

For exchange rate; the most of ER changes come from GDP and itself at the first year 55.4% of the variability in ER is explained by GDP, while 37.1% is explained by itself. After four years 45.22% is explained by GDP and 30.3% is explained by NOP, while 24.09% is by its values. The implication of this result is that Nigerian oil prices have a key effect on exchange rate in Nigeria in the long-term. Finally, Table 6-26 indicates that the major source of shocks in inflation was variability in inflation itself and ER. However; Nigerian oil prices explained only .001% to changes in inflation in the first year and slightly increased to 0.10% in the fourth year, whilst, the ER has a significant effect on inflation in Nigeria. The results of the VDC suggest that Nigerian oil prices variations can impact Nigerian macroeconomic variables but changes in Nigerian macroeconomic variables have small influence on Nigerian oil prices.

6.4 A Discussion Between Comparative Analysis Results of Libya and Nigeria

The results of the analysis of the two countries under this study showed that all of the variables of interesthave a slightly convergent pattern through the period of sample. The descriptive statistics of oil price data in the Libyan, Nigerian markets as well as the macroeconomic variables in these countries suggest that the empirical distribution of all the variables is leptokurtic. The only exception for the distribution of Libyan exchange rate is platykurtic. On the other hand, all return series are leptokurtic in both Libya and Nigeria.

The outcomes obtained from ADF and PP tests show that all oil prices (LOP and NOP) and other variables (GDP, ER and CPI) in log level for the two countries are non-stationary and have the same order of integration I(1). Moreover, the return series are stationary or I(0) at the 5% level in Libya and Nigeria. The Johansen cointegration tests indicate that there is one long-run relationship among oil prices and macroeconomic variables in both Libya and Nigeria during the sample period of 1970-2017.

Due to the finding of long-term relationships from cointegration tests among the variables, the VEC(1) model has been estimated for Libya and Nigeria in order to investigate the short-run and the and long-run dynamics. The estimated correlations from the VEC(1) in Libya show significant and positive relations between Libyan oil prices and all Libyan variables. Furthermore, in Nigeria, the estimated correlations suggest positive relationships between Nigerian oil price and both LGDP and LCPI. While, the link between changes in Nigerian oil prices and exchange rate is negative.

The results of pair-wise Granger causality test based on the estimated bivariate VAR model suggest that there are no causality relationships among Libyan oil prices and any individual variable of Libya in the short-run. On the other hand, we get different results of Granger causality test which were obtained through VECM equations and they show unidirectional causality relationship running from inflation to Libyan oil prices. Moreover, there is a unidirectional causality relationship among Libyan oil prices and GDP of Libya. In Nigeria, the pair-wise Granger causality test shows that the unidirectional causality is existed between Nigerian oil prices and both GDP and exchange rate. The results of Granger causality test which obtained through VEC(1) model correspond with the results of pair-wise Granger causality test based on the bivariate VAR and indicated that only unidirectional causality is existed between Nigerian oil prices and GDP, meaning that the past values of Nigerian oil prices appear to be useful for forecasting the future values of GDP. The results of the estimated impulse response functions suggest a statistically significant impact of any shock of national oil prices on both Libyan and Nigerian variables in long-run. The findings show that there is a positive impact of oil price to itself, exchange rate and inflation, while the response of GDP to Libyan oil price shocks has changed from positive to negative in the long-run. Furthermore, in the Nigerian case, the results indicate that the responses of Nigerian oil price, GDP and inflation to Nigerian oil price shocks are positive, while Nigeria oil prices affect the exchange negatively.

The results of variance decomposition show that the most of the Libyan and Nigerian oil prices changes come from their self suggesting that oil prices movements changes are not affected by the changes in the macroeconomic variables in Libya and Nigeria. Moreover, the domestic oil prices have a major impact on GDP in both Libya and Nigeria. These results indicate that the prices of Libyan and Nigerian crude oil appear to be significant to the economy activities during the period of analysis. However, some of Libyan and Nigerian macroeconomic variables show long-term responses to the domestic crude oil price. This implies that oil price modelling in Libya and Nigeria would have been substantially incomplete from an analytical accurate and policy making perspectives if the macroeconomic aspects are not considered.

6.5 Summary

This chapter has investigated the dynamic relationships between crude oil prices and selected macroeconomic indicators for two African developing countries, including Libya and Nigeria from 1970 to 2017. Our analysis is based on the variable of oil price as an important factor affecting economic variables. Other explanatory variables used in this analysis are Gross domestic product, exchange rate and inflation. The analysis has been based on the VEC modelling frameworks. The data has been subjected to - standard unit root tests and found to be non-stationary in log level. All our VECM models treat all the variables in the first log difference. The length of lags for the VAR and VECM are chosen in the two cases based on the information criteria.

The standard Johansen cointegration test has been applied and suggested that there is an evidence of a long-run relationship among oil prices, GDP, exchange rates and inflation in the cases of both Libya and Nigeria. The VEC(1) models for Libya and Nigerian respectively estimated using ordinary least squares estimation. The residuals of these models have been examined using numerous checking tests included stationary condition, testing for uncorrelated, normality and heteroskedasticity to ensure that the estimated VEC models are not spurious. The results have tended to indicate that the equations are well-specified. The results of the matrix of correlations from the VECM concluded that the domestic oil prices have significant and positive correlations with GDP and inflation in both Libya and Nigeria. Moreover, Libyan oil prices have positive relations with exchange rate, while the relationship between Nigerian oil prices and exchange rate in Nigeria is negative.

For studying the causality relationships among the variables, the analysis is based on two Granger causality tests. The first test is pair-wise Granger causality test based on bivariate VAR model to study a short-run causal relationship between each two variables. The findings of directional Granger causality tests in Libya have been indicated that there is no directional causality relationships are found among national oil prices and any individual variables. On the other hand, a unidirectional relation has been existed between domestic oil prices and both GDP and exchange rate in Nigeria. The second test is Granger causality Wald test under

VEC models. The results of this test gave a different result from the results of the pair-wise Granger causality test in the Libyan case, where the results showed that the first lagged of the inflation variable is important and appear to be useful for forecasting the future values of Libyan oil prices. Furthermore, the results indicated that there is a unidirectional causality relationship running from the Libyan oil prices to GDP in the long-run. Moreover, the findings of Granger causality Wald test corresponded with the results of the pair-wise Granger causality test t and suggested that there is a causal relationship between Nigerian oil prices and GDP in Nigeria.

The findings of the impulse response functions suggested significant impacts of domestic oil prices shocks on the macroeconomic variables in Libya and Nigeria in the short and long term. From the variance decompositions analysis, it was found that the most sources of shocks in oil prices was variability in oil prices itself in the both countries. For Libya, the shocks of Libyan oil price are necessary to explain variability is happen in GDP, but in the long term, the effects of Libyan oil prices on GDP decrease. Additionally, the Libyan oil prices have small effects on exchange rate and inflation. For Nigeria, Nigerian oil price shocks have a significant effect on GDP and exchange rate in the long-run, whilst, the shocks of Nigerian price have a little effect on inflation. The results of the VDC suggest that the changes of Libyan oil price and Nigerian oil prices can impact most of the macroeconomic variables in Libya and Nigeria, but changes in the macroeconomic variables have small influence on oil prices.

CHAPTER 7: Discussion of the Results and Implications

7.0 Introduction

Based on the methodologies developed in Chapter 3 and 5, the research has applied different univariate and multivariate time series models with various statistical tests, comprising standard unit root tests, unit root tests with a breakpoint, Johansen cointegration tests, and Granger causality tests in order to achieve the proposed research objectives. Therefore, this chapter discusses the main findings of this study and their implications that obtained through the empirical analysis of the time series data in the preceding chapters (chapters 4 and 6) within the context of relevant literature, in order to answer the research questions which have been formulated as following:

RQ1: Do structural breaks exist in the oil price time series data?
RQ2: Which time series models are more suitable for describing and forecasting crude oil price returns in Libya, Nigeria and OPEC markets?
RQ3: Are there any relationships between domestic oil price and GDP, exchange rates and inflation in Libya and Nigeria in the short run and long run?
RQ4: What form of time series modelling is suitable for exploring the relationship between oil prices and selected macroeconomic indicators for Libya and Nigeria?
RQ5: Are there any long run causality relationship and short run causality effects running between oil price, GDP, exchange rate and inflation in Libya and Nigeria?

7.1 Discussion of the Results

This section discuses and summarises the empirical findings of the research based on the previous questions and findings that have been achieved in this research. To answer the first and second question, which are focused on the investigation of a structural break, modelling and forecasting issues of spot price of crude oil; the research was based on monthly data on domestic prices of crude oil for Libya and Nigeria as well as OPEC prices, which are divided into two parts. The first part is called the in-sample data covered the interval from January 2003 to April 2017 for the Libyan market and the period from January 1997 to April 2017 for the Nigerian and OPEC markets. The second one is out-of-sample data that expanded from May, 2017 to April 2018. Given the difficulty of obtaining monthly data for the macroeconomic variables used in this research, the researcher was forced to use annual data to study the dynamic relationships among oil prices, GDP, exchange rate and inflation in

Libya and Nigeria to answer the third, fourth and fifth of the research questions. These annual data covered the period from 1970 to 2017.

- **RQ1**: **Do structural breaks exist in the oil price time series data?**

To answer this question we have begun to study the historical evolution of crude oil prices in the three markets under study. Thus, the graphical presentation of these time series showed a similar history in terms of increase or decrease in prices. All time series data for oil prices showed the following characteristics, the presence of trends and changes in their statistical properties, which suggested non-constant means and variations. All the prices were converted to the logarithmic form and then the first difference was taken in order to obtain the series of returns. Returns series of Libya, Nigeria and OPEC appeared to have no trend and seem to be stationary over time. However, our results related to the study of historical development and the descriptive statistics of oil price data and their returns for the Libyan, Nigerian and OPEC markets coincided with results of several empirical studies that found evidence that crude oil price and its return, likewise other financial time data, were characterised by fat tail distribution, volatility clustering and asymmetry (Morana, 2001; Sadorsky, 2006; Narayan and Narayan, 2007; Wei et al., 2010).

Our investigation depending on the autocorrelation functions and standard unit root tests including the augmented Dickey Fuller test (1981) and Phillips and Perron (1988) test, they found that all the prices of oil in logarithm level were are non-stationary I(1), while their returns were stationary. However, our results coincided with several empirical studies that have been concerned with the study of non-stationary in oil prices, for example see (Pindyck, 1999; Xie et al., 2006; Hamilton, 2009; Yazizet et al., 2011; Kang and Yoon, 2013). These studies showed that oil prices are non-stationary because the issue of non-stationary is common when dealing with financial and economic data.

Ignoring the detection of structural breaks when analysing the data can affect unit root results (Maslyuk and Smyth, 2008). Therefore, the method outlined in Perron (1989), Vogelsang and Perron (1998) has been applied to assess whether Libyan, Nigerian and OPEC crude oil prices contain a unit root with one structural break, employing unit root test with breakpoints for two break specifications, innovational outlier and additive outlier based on different assumptions of trend and break specifications, which include non-trending data with intercept break, trending data with intercept break, intercept and trend break and with trend break.

Moreover, the break date is unknown and selected by minimizing the Dickey-Fuller t-statistic.

Our empirical findings from unit root test with breakpoints under the assumptions of innovational models and additive models showed that oil prices of Libya, Nigeria and OPEC have a unit root with a structural break. Furthermore, the estimated break dates for the three prices were different and mixed. Given that our empirical analysis is concerned with modeling oil price returns, we have treated them as non-trending data. Thus, under the assumption of innovational outlier and additive outlier breaks, for non-trending data with intercept break, the tests rejected the null hypothesis of a unit root suggesting that all returns series are stationary with a structural change. However, the estimated break date was 10/2008 for returns of Libya, Nigeria and OPEC; this date could be linked to the global financial crisis. However, our results from carrying out standard unit root tests and unit root tests with structural changes suggested that crude oil prices were nonstationary, while the returns series were stationary with a structural break. Moreover, structural breaks were indeed present in the dynamic of oil prices series and their returns in the Libyan, Nigerian and OPEC markets.

- **RQ2**: **Which time series models are more suitable for describing and forecasting crude oil price returns in Libya, Nigeria and OPEC markets?**

To answer this question we have built various ARMA models to identify the mean equations of our returns series. The results of comparison between ARMA models showed that the AR(1) model has the lowest value of SIC, and this model was selected as the best fit model for Libyan, Nigerian and OPEC oil price returns. Moreover, we have continued our empirical analysis by testing for structural breaks in the AR(1) mean equation based on Bai-Perron (1998) and Chow (1960) breakpoint tests. In Bai-Perron test the break dates are estimated when the null hypothesis $l=0$ versus alternative hypothesis $l+1 = 1$ break was rejected. However, we cannot reject the null hypothesis of Bai-Perron test and no structural breaks were detected in the mean equations of all returns series. Moreover, the results of Chow test with breakpoint October 2008, which was identified by using unit root tests with breakpoints indicating that the three returns series do not exhipt structural breaks in mean equation. Then, we also tested for ARCH effects, the null hypothesis of no conditional heteroskedasticity in the residuals from the AR(1) models of the three returns series were rejected indicating that the volatility clustering were exhibited in the Libyan, Nigerian and OPEC returns data. However, we also tested for structural breaks in the variance of each market. The squared residuals of the estimated mean equation model (i.e. AR(1) models), were used and the results of both Bai-Perron and Chow tests suggested that the three returns series exhibited no structural breaks in variance equation and the GARCH models can be used to characterise the conditional variance of oil prices returns.

Since no structural changes were detected in all returns series under study, we proceeded our modelling with fitting AR(1) model and GARCH family models without any structural breaks in the mean or variance equations. Therefore, various hybrid models of AR-GARCH family in the first order including AR-GARCH, AR-EGARCH, AR-GJR-GARCH, AR-PARCH, ARCGARCH and AR-ACGARCH with three error distributions, namely normal distribution, student-t distribution and generalized error distribution (GED) were created in order to select the best describe and forecast Libyan, Nigerian and OPEC returns.

Our results showed that, the AR-GARCH family models for modelling Libyan, Nigerian and OPEC returns lend support for high level of persistence in the volatility. We also found evidence of volatility clustering and leverage effect to good and bad news in the asymmetric models in the three oil price markets. The evidence of leverage effect in oil price returns, implying that the volatility of returns in the Libyan, Nigerian and OPEC oil markets do not have equal response to the same magnitude of positive and negative shocks. Moreover, our results are consistent with the results of Kang et al. (2009), Wei et al. (2010) and Mohammadi and Su (2010), which dealt with the two major crude oil markets, WTI and Brent. Generally, almost all the AR-GARCH family models performed better in normal distribution than in student`s-*t* and generalized error distributions for returns in-sample analysis for the three markets under study, therefore, AR-GARCH models with normal process was adequate enough to capture the variability in returns in these markets. Model selection was done using AIC, SIC and HQIC across the error distributions. Results suggested that the best fitting model for Libyan and Nigerian crude oil price returns is AR(1)-EGARCH(1,1) model whit normal distribution. While the results of OPEC returns based on SIC and HQIC suggested the AR(1)-EGARCH(1,1) with GED, thus, the generalized error assumption improved the fitness of AR(1)-EGARCH(1,1) model. Moreover, breakpoint tests have been applied for EGARCH conditional variance series. The results of these tests indicated that there is no structural break in the conditional variance. Cheong (2009) and Marzo and Zagaglia (2010) obtained different results. The results of Cheong (2009) for model selection based on SIC suggested the AR(1)-GARCH(1,1) with student-*t* as the best model for WTI and Brent markets. In contrast, the empirical analysis of Marzo and Zagaglia (2010) showed that a good in-sample fit based on SIC suggested the GJR-GARCH with student-t as the best model for future prices on crude oil. These results of GARCH models with student-*t* distribution are capable to capture the leptokurtosis of the empirical distribution of the returns.

The result of out-of-sample forecasts of returns was used in determining the predictive abilities of the used models by using the RMSE, MAE, MAPE and TIC. This result indicated that the AR-CGARCH-GED model was the best model for forecasting oil returns for the Libyan market, the AR-GARCH-GED model for the Nigerian market and the AR-EGARCH-t model for OPEC. Our results on the modeling of Nigerian oil returns were similar to the results presented by Marzo and Zagaglia (2010), where AR-GARCH-GE model proposed to forecast oil prices. In contrast, the empirical results of Wang and Wu (2012) selected the EGARCH and GJR models for modeling oil price fluctuations. Moreover, in the most of the practical studies of comparing out-of-sample forecasting performance for crude oil prices movements the results were mixed.

- **RQ3**: **Are there any relationships between domestic oil price and GDP, exchange rates and inflation in Libya and Nigeria in the short run and long run?**

To answer this question the study carried out the Johansen's cointegration tests (Johansen, 1988; Johansen and Juselius, 1990) to test the existence of cointegrating relationships among the prices of domestic crude oil and GDP, exchange rate and inflation for both the countries under this study. All variables through empirical analysis are converted to the natural logarithmic form and then the first differences were taken to achieve stationartity. Our results of ACFs, PACFs, ADF and PP tests for oil prices, GDP, exchange rate and inflation of Libya and Nigeria indicated that the appropriate order of integration is one for all variables to be stationary. More specifically the null hypothesis of a unit root were rejected and all the first log difference series under study were stationary or I(0). However, since the variables are integrated of order I(1), we interested to investigate whether our variables for both countries are cointegating or move together or not in the long-run. Thus, the Johansen method (1988) including both trace test and maximum eigenvalue test carried out based on the VEC model with order one for the three plausible models (2, 3 and 4) to achieve the test hypotheses which are there are no significant long-run relationships between oil prices and GDP, exchange rate and inflation in Libya and Nigeria.

- **Short-Run and Long-Run Relationships for Libya**

Before applying the Johansen test, the study was based on the Pantula principle to select the appropriate deterministic terms which should be contained in the VEC model. However, examining the Johansen's cointegration test of Libya based on the max-eigenvalue test, evidence from the data suggests that the Libyan oil prices and GDP, exchange rate and inflation were related, thus, this research rejected the null hypothesis of cointegration is there are no cointegrating relationship among the Libyan oil prices and the Libyan macroeconomic variables. Moreover, the findings of the max-eigenvalue test showed that the Libyan variables are integrated at one cointegrating relationship in the VEC model. Therefore, there is a long-run relationship between Libyan data.

- **Short-Run and Long-Run Relationships for Nigeria**

Exploring the Johansen's cointegration tests of the Nigerian variables, evidence from the variables shwoed that the prices of the Nigerian crude oil, GDP, exchange rate and inflation were related, consequently, this research rejected the null hypothesis of cointegration is there are no cointegrating relationships among Nigerian indicators. More specifically, the results of the trace and max test with the specification of model 3 showed that the Nigerian data are integrated at one cointegrating relationship in the VEC model and there is a long-run relationship between Nigerian variables.

These results of Libya and Nigeria are consistent with the results of Olomola and Adejumo (2006) and Aliyu (2009), who rejected the hypothesis of no cointegration between oil price and Nigerian variables in the long-run. Olomola and Adejumo (2006) using the Johansen and Juselius (1990) method to detect that there is a relationship between oil price, output (real GDP), inflation, the real exchange rate and the money supply. The results of the maximal eigenvalue and the trace tests showed that a long-run relationship exists among the variables of interest. Furthermore, the results of our study confirm the results of Aliyu (2009) regarding the existence of long-run relationships among oil prices and Nigerian indicators. Although this study used the international oil price (UK Brent), GDP and exchange rate, which slightly different from our selected data because it does not include inflation variable, the outcomes of Johansen's cointegration test suggested that the presence of cointegrating relationship among the three variables in the Nigerian economy. Moreover, the short-term causal relationships can be examined through Granger causality test based on VAR framework.

- **RQ4**: **What form of time series modelling is suitable for exploring the relationship between oil prices and selected macroeconomic indicators for Libya and Nigeria?**

Given the results we obtained from the cointegration test, the long-term relationships were found between our variables in both Libya and Nigeria, thus the most appropriate model in this case is the vector error correction (VEC) model which uses to study the short and long-term relationship among the variables.

- **VEC(1) model in Libyan case**

The VEC model with order one have been estimated using ordinary least squares (OLS) method in order to investigate the short and long-run dynamics among Libyan variables. However, the long-run equation suggested that there is a relationship between Libyan oil prices and Libyan variables. The results indicated that there is significant positive relationships between Libyan oil prices and both GDP and exchange rate. This means that the increase in Libyan oil prices level could lead to increase of GDP and exchange rate in Libya. On the other hand, the Libyan oil prices have a negative impact on inflation. Moreover, the findings of short term parameters estimates showed insignificant positive relationships between Libyan oil price and itself, exchange rate and inflation. While, the relationship between Libyan oil price and GDP is negative in the short-run. The empirical results of the estimated correlation matrix showed that the positive links between Libyan oil price and all Libyan variables under study.

- **VEC(1) model in Nigerian case**

Due to the results of cointegration in the Nigerian case, the VEC(1) model was estimated using ordinary least squares (OLS) to study short and long-run dynamics among oil prices and Nigerian variables. The results of long run relationship among the variables showed that thereis a significant relationship between Nigerian oil prices and Nigerian data. The result indicated that there is a positive relationship among Nigerian oil prices and both GDP and inflation variables. Whilst, the Nigerian oil prices have a negative and significant impact on exchange rate. It thus, implies that the increased Nigerian oil prices drive the GDP and inflation up in the long run. Alternatively, the result of short-run parameters estimates suggested a positive effect between Nigerian oil prices and its first lag, GDP, exchange rate and inflation.

The findings of the correlation matrix indicated that there are positive links between Nigerian oil price and both GDP and inflation. While, the effect of changes in Nigerian oil price on exchange rate is negative. However, this outcome is consistent with the findings obtained from the estimation of the long-term function.

- **RQ5**: **Are there any long run causality relationship and short run causality effects running between oil price, GDP, exchange rate and inflation in Libya and Nigeria?**

Usually, the VAR model is used when the data are non- cointegration, whilst the VEC model is applied when the data have cointegrating relationship. Thus, the analysis based on the VAR model to study short-run Granger-causality relationships among variables in Libya and Nigeria using pairwise Granger causality test. Moreover, the study used the VECM based on there being a long-run relationship for Libya and Nigeria, therefore, the Block Exogeneity Wald causality test applied to investigate a long-run Granger causality relationship for the variables in Libya and Nigeria. The study employed all the previous statstical tests to to answer the fifth question of the research. The pairwise Granger causality test under the vector autoregression model (VAR) showed that there are no causality relationships have been found among Libyan oil price and Libyan macroeconomic variables in the short-run. The absence of causal relationships suggests that the prices of Libyan crude oil do not have any significant impact on the main macroeconomic variables in Libya. In other words, Libyan oil prices do not matter for GDP, exchange rate and inflation in the short period for Libya.

However, the results of pairwise Granger causality test based on the VAR model fail the clarification of the causality relationship among Libyan oil prices and Libyan variables. Consequently, the study employed the Block Exogeneity Wald test based on the VECM to detect the causal relationships among Libyan variables. The outcomes of the Block Exogeneity Wald test to test the hypothesis that a lagged coefficient of endogenous variables does not Granger cause the dependent variable showed that there is a unidirectional causality relationship running from inflation to Libyan oil prices. Moreover, Libyan oil prices appear to be useful for forecasting the future values of GDP and there is a unidirectional causality relationship running from Libyan oil prices to GDP in Libya.

In the Nigerian case, the findings of pairwise Granger causality tests indicated that the unidirectional causality is existed from Nigerian oil prices to GDP and from Nigerian oil prices to exchange rate whereas there is no causal relationship between Nigerian oil price changes and inflation. Furthermore, the findings of Block Exogeneity Wald test confirms the results by used the pairwise Granger causality test for Nigeria which is that there is a unidirectional causal relationship between Nigerian oil prices and GDP.

Nevertheless, results from previous studies differ in terms of the directions of causalities. For instance, Hooker (1996) found strong evidence that oil prices no longer Granger-cause many macroeconomic variables in U.S. Amano and Van Norden (1998) found unidirectional causality relationships from oil prices to real exchange rate. Bekhet and Yusop (2009) found a unidirectional Granger causality from crude oil price to GDP in Malaysia. Moreover, the results of Ran et al. (2010) suggested that the price of oil does not Granger cause the GDP of Hong Kong. Moreover, Aliyu (2009), Thankgod and Maxwell (2013) and Okoli et al. (2018) applied the pairwise Granger causality among Nigerian data. Aliyu (2009) found a unidirectional causality emanates from oil prices to real GDP. While a bidirectional causality runs from oil price to exchange rate. Thankgod and Maxwell (2013) used nominal oil price, inflation rate, real GDP and real exchange rate to detect the Granger causality relationships. The findings of this study showed that only a unidirectional causality found from oil prices to exchange rate. Okoli et al. (2018) showed that there is bidirectional causality running between the real gross domestic product and oil prices. In addition, unidirectional causality is existed between exchange rate and oil prices, whereas there is no causal relationship between oil price volatility and inflation rate. Our results for Nigeria are consistent with the findings of Anjanaraju and Marathe (2017), which exhibited that there are no Granger causality relationships among oil prices and inflation of China and USA.

Furthermore, we have been explored the dynamic relationships using impulse response functions and variance decomposition of the VEC(1) models in order to explain the impact of a standard deviation shock in the error term of the oil prices on other selected macroeconomic variables included in these models in both Libya and Nigeria. The results of impulse response functions for up to ten years have shown similar findings for domestic oil prices and both their self and inflation in Libya and Nigeria. Thus, the shocks of domestic crude oil pieces have positive effect on their self and inflation variables of Libya and Nigeria. On the other hand, oil prices shocks affect exchange rate negatively in Nigeria. While, the impact of oil price shocks on the exchange rate in Libya is positive. The effect of oil price shocks on GDP in both Libya and Nigeria is positive, but in the Libyan case it moved from the positive to the negative in the long term while it continued in the positive in the Nigerian case. Moreover, the results concluded that shocks of oil prices have major impacts on the three macroeconomic variables in the short and long run in both Libya and Nigeria.

Our results on the impact of oil price shocks are with those of Chang and Wong (2003) who showed that oil price shocks have positive effect on inflation, and oil price shock causes inflationary pressure on the economy. However, shocks of oil price a delayed negative impact on real GDP. These finding is consistent with those of Hamilton (1983) and Mork (1989), who find oil price shocks decrease real GDP (or GNP). The results of Okoli et al. (2018) showed that oil price shocks have a positive impact on its own shocks, real GDP. However, inflation does not respond much to changes in oil price while shocks of oil price have a negative effect on exchange rate in Nigeria.

The results of variance decomposition suggested that Libyan oil price movements are explained by its past values. However, Libyan oil price shocks do significantly affect and they are necessary to explain fluctuations of the GDP in the short-run. Moreover, the result of the variance decomposition of exchange rate and inflation rate showed that shocks of Libyan oil price have small effects on exchange rate and inflation in Libya over the period covered by the study. Furthermore, the findings of variance decomposition in Nigeria are little similar with those obtained in Libya. However, the results suggested that shocks of Nigerian oil price have significant effects in explaining the volatility of itself, GDP and exchange rate in long-term. In addition, the findings demonstrated that changes in Nigeria oil prices have small impact on inflation rate in Nigeria.

Results from previous studies differ in terms of the variance decomposition analysis. For instance, Chang and Wong (2003) showed that the results of the VDC suggested that oil price shocks are not major sours of volatility of the GDP and inflation. Our results of variance decomposition are consistent with a study of Lorde et al. (2009) and Bouchaour and Zeaud (2012) who found that the shocks of oil price is a major component of forecast variation for GDP. However, Olomola and Adejumo (2006) indicated that that oil price shock does not significantly affect GDP in Nigeria. In addition, the previous studies of Amano and Van Norden (1998), Olomola and Adejumo (2006) and Bouchaour and Zeaud (2012) found that oil price shocks significantly affect the real exchange rate. Moreover, findings of Olomola and Adejumo (2006) and Bouchaour and Zeaud (2012) showed that shocks of oil prices do not affect the inflation, which are consistent with our results for Libya and Nigeria.

7.2 Implications

Oil price fluctuations are a significant and interesting subject for studying, because increases in prices of crude oil are often an indication of inflationary pressures in the economy which in turn may indicate the future of investments of all types. Therefore, this thesis employed methodology of time series analysis for modelling crude oil prices and to examine the dynamic relationships among fluctuations in oil prices and key macroeconomic indicators in Libya and Nigeria. Based on the results obtained from the practical analysis in this study, the researcher presents some implications of these results in this section.

Understanding, modelling and forecasting the fluctuations of crude oil price are important issues as they have implications for the economies of countries. Therefore, using the results of forecasts for crude oil prices in the Libyan, Nigerian and OPEC markets is very important for financial and economic policy makers in these two countries and in the world, since it provides forecasting of the future prices for crude oil. But given the level of risk related with investing in oil markets, governments, investors, and financial analysts should consider alternative error assumptions while specifying the conditional variance model for the purpose of forecasting, because the choice of less contributing error distributions may also lead to loss of efficiencies in the model. Investors should also not ignore the effect of news while building models to get predictions, because ignoring these effects may lead to serious biases and misleading results.

Knowledge of the relationship between domestic crude oil prices and macroeconomic variables in Libya and Nigeria is very important for the development of the oil markets in these two countries to achieve economic activities, in which authorities in these two countries are required to follow the movements of the local and global oil markets to take better decisions to develop their oil and economic sectors. However, results from the VEC model show that crude oil prices and oil prices volatility both play significant roles in affecting macroeconomic variables in Libya and Nigeria. Moreover, this research indicated that there are long-term relationships among domestic oil prices and macroeconomic indicators including GDP, exchange rate and inflation in Libya and Nigeria, which allows local and foreign investors to make successful investment decisions. An understanding of the relationships among these variables will assist investors and economists to manage their investment portfolios in a more effective manner.

The results of this thesis displayed that the causal relationship among the prices of crude oil and the exchange rate in Nigeria should be a necessary part of the design of exchange rate policies for Nigeria. The government of Nigeria should be cautious in their enforcement of exchange rates policies as it can impact stock markets in the short term. Moreover, monetary policies may have a main effect on crude oil and other commodity prices inflation (Taghizadeh-Hesary and Yoshino, 2015). On the other hand, monetary policies play a major role in determining prices in general and in the changes of economic growth (Sims, 1992). Therefore, findings of study the causality relationship between domestic crude oil prices and macroeconomic variables that includes GDP and exchange rates in Libya and Nigeria can be given to regulators who are concerned with the performance of oil market, and for economic sectors, financial institutions or individual investors who are interested in managing the risks of oil and financial markets. Since our results suggest a potentially important role for crude oil prices in future research on modelling the GDP or exchange rate in these countries.

The results show that oil price shocks had an impact on the macroeconomic variables of Libya and Nigeria. However, the size and magnitude of this impact varies for each country. Furthermore, oil prices shock had an impact on GDP in both Libya and Nigeria. Moreover, the results suggest that changes in oil prices affect most of the macroeconomic variables but, changes in the macroeconomic variables have little influence on oil prices. The positive response of GDP to Libyan oil price shocks became negative in the long term. Consequently, the positive to negative relationship among oil prices and the GDP, especially in Libya is possibly dependent on the strong interactions among oil revenue, government expenditure and economic output. Oil revenue increase is usually followed by expansion in both fiscal and monetary policy activities of the government, which also lead to higher prices. Moreover, since governments are the key channel through which oil and energy wealth is transferred through the economy, differences in government revenue, brought about by changes in oil prices, can lead to a fluctuant monetary policies and , therefore, to macroeconomic instability. Indeed, as a result of the wars and political upheavals that Libya has gone through since 2011 until now, in addition to changes in prices of oil, this will lead to to serious economic difficulties due to unsustainable government spending in periods of booms and stability. Therefore, there should be prudent management of oil and energy wealth tto avoid sudden economic effects caused by fluctuations in oil prices (Lorde et al., 2009). Therefore, the Libyan and Nigerian governments advise that the current and long-term needs should be carefully balanced to enhance the well-being of current and future generations, while ensuring macroeconomic stability and efficient spending of oil and energy resources and strengthening the non-energy sector at the same time. Consequently, the major challenge facing the financial authorities is to resist the temptation to burst spending in booms, strike a balance among current consumption and long-term goals, and build support for prudent energy wealth management.

The variance decompositions for domestic oil prices in Libya and Nigeria suggest that the most of the forecast error variance of oil prices is explained by its own shocks. These results imply that Libya and Nigeria are not big enough to largely affect world oil market, while the macroeconomic variables shocks are of no importance in explaining oil price fluctuations. Moreover, oil shocks have a very small impact on consumer price index confirms that oil prices hikes are not necessarily inflationary.

However, our results imply that the price of Libyan and Nigerian crude oil appears to be a significant key variable and a major determinant that influence economic growth in Libya and Nigeria during the period of analysis. However, some of Libyan and Nigerian macroeconomic variables show long-term responses to the domestic crude oil price. This implies that oil price modelling in Libya and Nigeria would have been substantially incomplete from an analytical accurate and policy making perspectives if the macroeconomic aspects are not considered. Therfore, policymakers should seek to understand the fluctuations of crude oil price, taking into account their impact on macroeconomic variables when formulating economic policy. However, the main policy implications from these findings are that policymakers should always take into account fluctuations in crude oil prices when considering policy changes, that is, policy makers should monitor and predict future oil prices and take these expectations into account when adopting a particular monetary policy.

7.3 Summary

This chapter discussed the empirical findings of this thesis, according to the general aims and questions. It also referred to the results of the previous literature on modelling and forecasting oil price changes and explored the dynamic relationships among oil prices and some macroeconomic variables including Libya and Nigeria. Furthermore, this chapter discussed the findings about employing various AR-GARCH family models, the VAR and the VECM models. Finally, the chapter discussed some implications of these results.

CHAPTER 8: Conclusion and Recommendations

8.0 Introduction

Crude oil is a commodity of energy goods has an important strategic role for the global economy. Understanding the behaviour of crude oil price fluctuations became an important issue. Therefore, the aims of this thesis are to understand and model the behaviour of oil price fluctuations and also to examine their impacts on some macroeconomic variables in both Libya and Nigeria.

In chapter 7, we interpreted and discussed the findings of research from data analysis in the previous chapters 4 and 6. The discussions were centred on modelling and forecasting crude oil price returns for three oil markets, Libyan, Nigerian and OPEC using several AR-GARCH models under normal distribution, student-*t* distribution and generalized error distribution (GED). The discussion also focused on studying the dynamic relationships among oil price changes and the selected macroeconomic indicators including GDP, exchange rates and inflation for Libya and Nigeria. Thus, the analysis based on Johansen cointegration test, VAR/VEC models, Granger causality tests, impulse response functions and the forecast variance decompositions. This chapter starts with a summary of the results depending on the objectives of the study that have been carried out. The discussion of the limitation of the research and policy recommendations are other points addressed in this chapter. Finally, some future works are presented for future studies.

8.1 Summary of Finding through Achieving Research Objectives

This study offered an extensive empirical investigation of the modelling and forecasting spot oil price returns in Libyan, Nigerian and OPEC crude oil markets and their impact on macroeconomic activity in Libya and Nigeria using the appropriate time series models. We now examine carefully each of the main research objectives of this study whit the associated findings. The first research objective was to determine whether there exist structural breaks in the oil prices data for the Libyan, Nigerian and OPEC markets. To achieve this objective or answer its associated question, the researcher used monthly spot prices of crude oil in Libyan, Nigerian and OPEC markets covering the span from January 2003 to April, 2018 for Libya and the period from January 1997 to April, 2018 for Nigeria and OPEC. Our investigation began with some descriptive statistics of the oil prices data, and then examined the unit root behaviour. Most importantly, though, motivated by Salisu and Fasanya (2013) and Smyth

(2008) pointed that not considering the structural change in oil price analysis could lead to a misleading conclusion. To investigate the existence of a structural break, unit root tests which allow for structural changes in the time series data have applied. Thus, our results showed that the three returns series are stationary with a structural break occurred in 10/2008 which is corresponding to the economic event of the global financial crisis that occurred during 2007-2009. According to Maslyuk and Smyth (2008), there are not many studies on testing for the prices of oil that have applied unit root tests with structural breaks. Thus, our findings could contribute to the recent studies on modelling the prices of oil.

The second research objective was to identify the best conditional mean and conditional variance model to perform statistical time-series modelling and forecasting of crude oil prices returns for the Libyan, Nigerian and OPEC oil markets under different error distributions. To accomplish the second target, the research also employed the same time series data that were analysed in the first objective. Modelling of the conditional mean suggested that all oil returns are characterised by an AR(1) process. Due to the limited studies on testing structural breaks property before proceeding with modelling the conditional mean and the conditional variance in crude oil prices markets, we examined the existence of structural breaks in both mean and variance equations. Therfore, our results indicate that the three oil price returns exhibit no structural break in mean and variance equations. However, our returns series exhibit volatility clustering, thus, modelling the conditional variance was based on six hybrids of AR-GARCH family models include GARCH, EGARCH, GJR, APARCH, CGARCH and ACGARCH with normal, student-t and GE distributions for each returns series. Results showed that, in general, the AR-GARCH family models performed better in normal distribution than in student-*t* and generalized error distributions in-sample for all returns data. Generally, the results of estimation for AR-GARCH family models to model Libyan, Nigerian and OPEC oil price returns lend support for high level of persistence in the conditional variance. We found evidence of volatility clustering and leverage effect in the asymmetric models in the three oil price markets. The results of the comparison of out-of-sample forecasting performance suggested that the best models for forecasting oil returns were the AR-CGARCH-GED model for Libyan market, the AR-GARCH-GED model for Nigerian market and the AR-EGARCH-*t* model for OPEC.

The third research objective was to study whether domestic oil prices fluctuations would affect GDP, exchange rates and inflation in the short-run and long-run in Libya and Nigeria. The study used annual data covering the period from 1970 to 2017 and the Johansen cointegration method (Johansen, 1988; Johansen and Juselius, 1990) is employed to achieve this objective. The results of Johansen cointegration tests confirmed that there were a long-term relationship among prices of domestic crude oil, GDP, exchange rate and inflation in both Libya and Nigeria. From the long run cointegration equation for Libya, the Libyan oil price is positively affects the GDP and exchange rate, while, the Libyan oil prices have a negative impact on inflation in the long-run. From the long run cointegration equation for Nigeria, the Nigerian oil price is positively affects the GDP and inflation, while, the Nigerian oil prices have a negative and significant effect on the exchange rate.

The forth research objective was to identify a suitable econometric-time series model that allows us to determine the dynamic relationships between oil prices, GDP, exchange rate and inflation in the previously mentioned countries. Achievement of this objective is based on the result of the cointegration test. If there are no log-run cointegrating relationships, the non-stationary variables converted to stationary by first differencing and then use a vector autoregression (VAR) model to examine the short-run relationship among variables. For non-stationary variables and cointegrated relationships, the vector error correction (VECM) model should be estimated to examine the short-run and long-run relationship among variables. Therefore, the VEC(1) model estimated for both Libya and Nigeria.

The fifth research objective was detected the possible existence of causality relationships between oil price, GDP, exchange rate and inflation in Libya and Nigeria. To achieve this objective, the study applied Granger causality tests under the VAR and VEC models. The findings of the causality tests exhibited that there was no bidirectional causality relationship among oil prices and any individual of variables in both Libya and Nigeria, but only unidirectional causality relationship running from the Libyan oil prices to the Libyan GDP. The results of causality tests in Nigeria showed that there are also unidirectional Granger-causality relationships from the Nigerian oil price to the GDP and exchange rate. Moreover, the findings of the impulse response functions suggest significant impacts of domestic oil prices shocks on the macroeconomic variables in Libya and Nigeria in the short and long term. The results of the variance decompositions analysis indicate that the changes in Libyan oil prices can impact Libyan GDP. While Nigerian oil price shocks could affect most of macroeconomic variables in Nigeria. However, the variance decompositions analysis showed that the most sources of shocks in oil prices was variability in oil prices itself in the both countries.

Consequently, there is no mutual agreement between researchers regarding the investigation of the interactions among crude oil prices and GDP, exchange rates and inflation. These issues require further empirical research for enriching the literature and contributing to the development of knowledge in the study of the behavior of crude oil prices and its relationship with macroeconomic variables not only in the countries under this study.

8.2 Recommendations

Based on the empirical outcomes obtained from this project, the following recommendations have been presented:

- The use of the results of this study related to modeling oil price fluctuations in the markets of Libya, Nigeria and OPEC is very important for financial and economic policy makers, decision makers, investors and governments in these two countries and in the world, since it provides the prediction of crude oil prices that can help them in making rational economic decisions, because persisting changes in volatility in the crude oil market can expose producers, intermediates and consumers to risks; also high volatility can induces mistrust in the market.

- As Libyan, Nigerian and OPEC oil markets may have undergone important structural changes during theri normal course in general, it is necessary to analyse the effects of structural breaks. Therefore, we suggest for similar future studies on modelling the prices of crude oil that including the period before and after the period which used in this study that may be taken into account structural changes analysis.

- Due to the level of risk related with investing in crude oil markets, governments, investors, and financial analysts should consider alternative error assumptions while specifying the best volatility model, because the choice of less contributing error distributions may also lead to loss of efficiencies in the model. Investors should also not ignore the effect of good and bad news while building models in modelling oil prices, because ignoring these effects may lead to serious biases and misleading results.

- Understanduing the links between domestic crude oil prices and macroeconomic indicators in Libya and Nigeria is very important for the development of the oil markets in these two countries to achieve economic activities. Therefore, the long-term relationship between domestic oil prices, GDP, exchange rate and inflation in Libya and Nigeria allows to local and foreign investors to make successful investment decisions. An understanding of the links among these indicators will assist investors and economists manage their investment portfolios in more effective methods.

- The absence of the causal link between the Libyan oil price and the exchange rate implies that Libyan government should not depeend on the foreign exchange from oil price to sustain her reserve. Thus, the Libyan government should diversify the economy from resource production and oil export to other non-oil activities that would generate foreign exchange for reserve building.

- Understanding the causal relationship among the prices of crude oil and the exchange rates in Nigeria is very important issue. Therefore, Nigerian government should be cautious in their implementation of exchange rate policies as it can impact stock markets in the short term.

- Libyan and Nigerian policymakers should seek to understand the changes of crude oil price, taking into account their impact on macroeconomic variables when formulating economic policy. Thus, they should always take into account fluctuations in crude oil prices when considering policy changes, that is, policy makers should monitor and predict oil prices and take these expectations into account when adopting a particular monetary policy.

- Libyan and Nigeria governments should macrolevel some economic plans were put into effect to realize profound fiscal, economic, and legal changes, thus, they need to expand the economy into other different sectors of the economy. The main objectives of these plans should ensure fiscal discipline, and establish a suitable environment for economic growth. Furthermore, it is necessary for these countries to s to reduce dependence on crude oil revenues, liberate the exchange rates, ensure the freedom of the Central Bank, and change the organizational and legal structures to create a suitable environment for economic activities, develop free market economy, and decrease the load on the shoulders of public sector.

8.3 Limitations of the Study

This study has some limitations due to the unavailability of some data, especially in the Libyan case. Therefore, the study limits itself to modelling the behaviour of crude oil price for Libya, Nigeria and OPEC as well as exploring the dynamic relationships among domestic oil prices and three macroeconomic variables of Libya and Nigeria. However, the results obtained only constitute a small portion of the domain of the applied research. Further research on modelling national and international crude oil prices and on the relationship between oil prices and a host of many other macroeconomic indicators are required. Considering the fluctuations of oil prices, higher frequency data with a long period such as daily data could also be used in order to obtain better results. In addition, other macroeconomic variables such as stock market indices, interest rates and unemployment should be included for further research on studying the links among the prices of crude oil and macroeconomy. Furthermore, non-marketing variables which may cause oil prices to fluctuate such as political instability, speculations military conflicts, climate changes and natural disasters can be included for study the dynamic relationship between oil price changes and these non-marketing indicators.

8.4 Suggested Future Work

From the empirical results obtained in this thesis, a number of future research ideas are suggested. These future ideas can be beneficial for researchers and those interested in future studies in analysing and modelling the prices of crude oil. The future works are saummarised as follows.

- The researcher proposes that the study may be expanded for modelling Libyan, Nigerian and OPEC oil prices using a longer time period and different statistical techniques such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVM) models and compare the results with AR-GARCH-class models that used in this thesis.

- If the researcher is able to obtain suitable data for both oil price variables and macroeconomic variables, (e.g. monthly data) it is possible to use multivariate time series models such as the VAR and VECM for the purposes of forecasting and compare their performance with the models of univariate time series used in this thesis.

- Future research can use the VAR and VECM techniques to investigate the linkage between the prices of crude oil and macroeconomy for Libya and Nigeria by adding other macroeconomic indicators such as interest rates, stock market indices and government expenditure.
- Future work can study the relationship among oil price fluctuations and non-marketing variables such as political instability, climate changes and natural disasters in both Libya and Nigeria or in oil importing and oil exporting countries in general.

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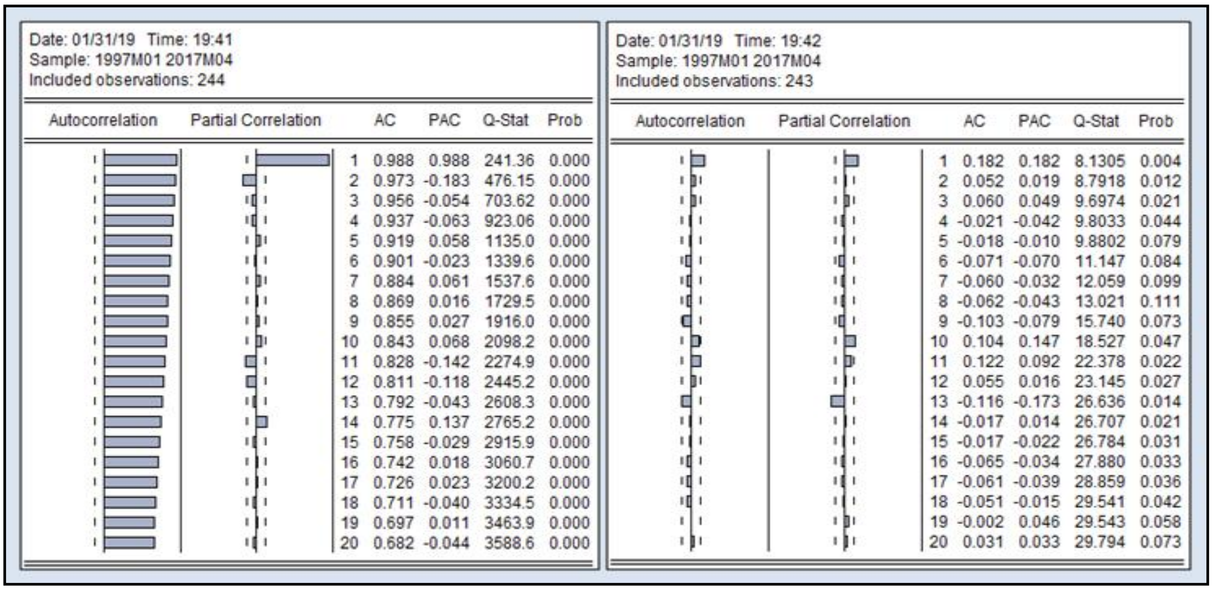
Appendix (A)



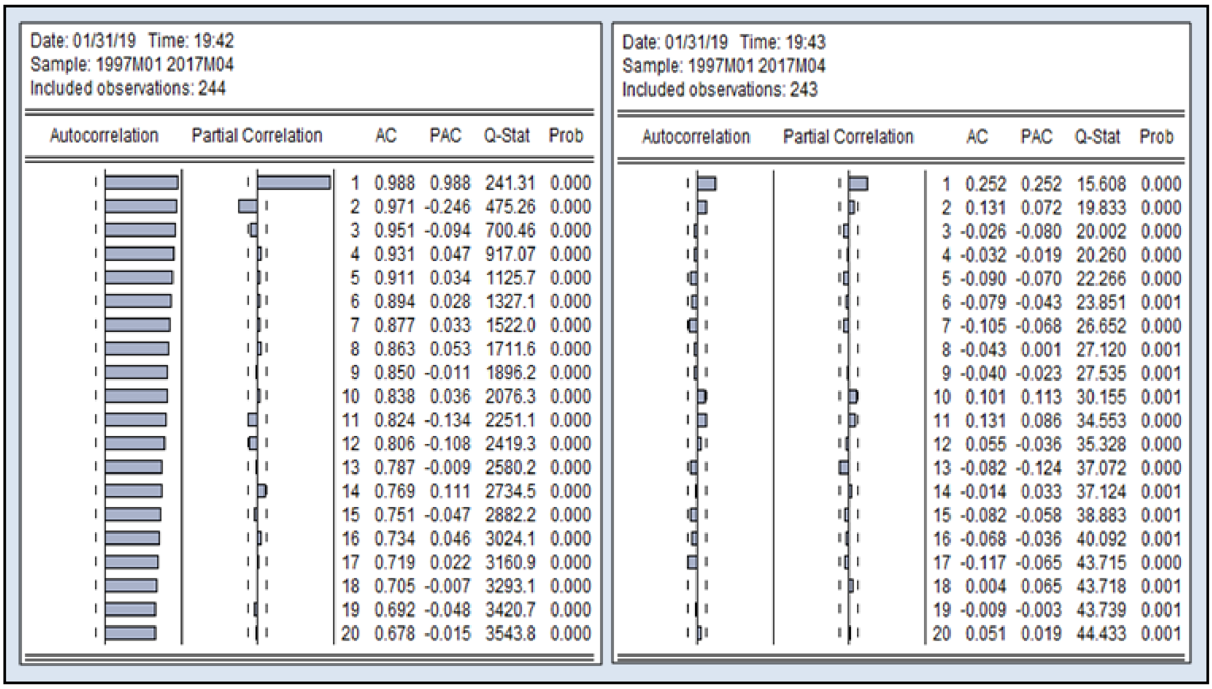
Date: 01/31/19 Time: 19:41
Sample: 1997M01 2017M04
Included observations: 244

Lag	AC	PAC	Q-Stat	Prob
1	0.988	0.988	241.36	0.000
2	0.973	-0.183	476.15	0.000
3	0.956	-0.054	703.62	0.000
4	0.937	-0.063	923.06	0.000
5	0.919	0.058	1135.0	0.000
6	0.901	-0.023	1339.6	0.000
7	0.884	0.061	1537.6	0.000
8	0.869	0.016	1729.5	0.000
9	0.855	0.027	1916.0	0.000
10	0.843	0.068	2098.2	0.000
11	0.828	-0.142	2274.9	0.000
12	0.811	-0.118	2445.2	0.000
13	0.792	-0.043	2608.3	0.000
14	0.775	0.137	2765.2	0.000
15	0.758	-0.029	2915.9	0.000
16	0.742	0.018	3060.7	0.000
17	0.726	0.023	3200.2	0.000
18	0.711	-0.040	3334.5	0.000
19	0.697	0.011	3463.9	0.000
20	0.682	-0.044	3588.6	0.000

Date: 01/31/19 Time: 19:42
Sample: 1997M01 2017M04
Included observations: 243

Lag	AC	PAC	Q-Stat	Prob
1	0.182	0.182	8.1305	0.004
2	0.052	0.019	8.7918	0.012
3	0.060	0.049	9.6974	0.021
4	-0.021	-0.042	9.8033	0.044
5	-0.018	-0.010	9.8802	0.079
6	-0.071	-0.070	11.147	0.084
7	-0.060	-0.032	12.059	0.099
8	-0.062	-0.043	13.021	0.111
9	-0.103	-0.079	15.740	0.073
10	0.104	0.147	18.527	0.047
11	0.122	0.092	22.378	0.022
12	0.055	0.016	23.145	0.027
13	-0.116	-0.173	26.636	0.014
14	-0.017	0.014	26.707	0.021
15	-0.017	-0.022	26.784	0.031
16	-0.065	-0.034	27.880	0.033
17	-0.061	-0.039	28.859	0.036
18	-0.051	-0.015	29.541	0.042
19	-0.002	0.046	29.543	0.058
20	0.031	0.033	29.794	0.073

Figure A1: Plots of Correlogram of ACFs and PACFs for Monthly Oil Prices of Nigeria in Logarithm Level and its Returns in Sample.



Date: 01/31/19 Time: 19:42
Sample: 1997M01 2017M04
Included observations: 244

Lag	AC	PAC	Q-Stat	Prob
1	0.988	0.988	241.31	0.000
2	0.971	-0.246	475.26	0.000
3	0.951	-0.094	700.46	0.000
4	0.931	0.047	917.07	0.000
5	0.911	0.034	1125.7	0.000
6	0.894	0.028	1327.1	0.000
7	0.877	0.033	1522.0	0.000
8	0.863	0.053	1711.6	0.000
9	0.850	-0.011	1896.2	0.000
10	0.838	0.036	2076.3	0.000
11	0.824	-0.134	2251.1	0.000
12	0.806	-0.108	2419.3	0.000
13	0.787	-0.009	2580.2	0.000
14	0.769	0.111	2734.5	0.000
15	0.751	-0.047	2882.2	0.000
16	0.734	0.046	3024.1	0.000
17	0.719	0.022	3160.9	0.000
18	0.705	-0.007	3293.1	0.000
19	0.692	-0.048	3420.7	0.000
20	0.678	-0.015	3543.8	0.000

Date: 01/31/19 Time: 19:43
Sample: 1997M01 2017M04
Included observations: 243

Lag	AC	PAC	Q-Stat	Prob
1	0.252	0.252	15.608	0.000
2	0.131	0.072	19.833	0.000
3	-0.026	-0.080	20.002	0.000
4	-0.032	-0.019	20.260	0.000
5	-0.090	-0.070	22.266	0.000
6	-0.079	-0.043	23.851	0.001
7	-0.105	-0.068	26.652	0.000
8	-0.043	0.001	27.120	0.001
9	-0.040	-0.023	27.535	0.001
10	0.101	0.113	30.155	0.001
11	0.131	0.086	34.553	0.000
12	0.055	-0.036	35.328	0.000
13	-0.082	-0.124	37.072	0.000
14	-0.014	0.033	37.124	0.001
15	-0.082	-0.058	38.883	0.001
16	-0.068	-0.036	40.092	0.001
17	-0.117	-0.065	43.715	0.000
18	0.004	0.065	43.718	0.001
19	-0.009	-0.003	43.739	0.001
20	0.051	0.019	44.433	0.001

Figure A2: Plots of Correlogram of ACFs and PACFs for Monthly Oil prices of OPEC in Logarithm Level and its Returns in Sample.

Date: 02/01/19 Time: 14:16
Sample: 1997M03 2017M04
Included observations: 242
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.009	-0.009	0.0178	
		2	0.006	0.006	0.0268	0.870
		3	0.065	0.065	1.0605	0.588
		4	-0.036	-0.035	1.3832	0.709
		5	0.002	0.001	1.3846	0.847
		6	-0.062	-0.066	2.3546	0.798
		7	-0.040	-0.037	2.7585	0.838
		8	-0.032	-0.034	3.0227	0.883
		9	-0.122	-0.115	6.7639	0.562
		10	0.103	0.103	9.4518	0.397
		11	0.096	0.103	11.789	0.299
		12	0.054	0.068	12.551	0.324
		13	-0.135	-0.168	17.258	0.140
		14	0.010	-0.008	17.283	0.187
		15	0.000	-0.017	17.283	0.241
		16	-0.066	-0.041	18.427	0.241
		17	-0.042	-0.045	18.885	0.275
		18	-0.043	-0.033	19.362	0.308
		19	0.007	0.040	19.375	0.369
		20	0.031	0.044	19.633	0.417

Date: 02/01/19 Time: 14:17
Sample: 1997M03 2017M04
Included observations: 242
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.022	-0.022	0.1240	
		2	0.085	0.085	1.9189	0.166
		3	-0.051	-0.048	2.5637	0.278
		4	-0.012	-0.021	2.5995	0.458
		5	-0.069	-0.062	3.7857	0.436
		6	-0.038	-0.041	4.1483	0.528
		7	-0.087	-0.081	6.0689	0.416
		8	-0.005	-0.009	6.0758	0.531
		9	-0.065	-0.060	7.1605	0.519
		10	0.084	0.070	8.9605	0.441
		11	0.099	0.107	11.471	0.322
		12	0.047	0.024	12.045	0.360
		13	-0.109	-0.131	15.104	0.236
		14	0.032	0.017	15.362	0.285
		15	-0.070	-0.043	16.649	0.275
		16	-0.032	-0.042	16.918	0.324
		17	-0.113	-0.091	20.298	0.207
		18	0.037	0.040	20.649	0.242
		19	-0.020	0.005	20.751	0.292
		20	0.061	0.035	21.748	0.297

Figure A3: Plots of Correlogram Examining the ACF, PACF and the Ljung-Box Test on the Residuals of AR (1) for Returns of NOP and OPEC Markets.

Date: 02/01/19 Time: 14:16
Sample: 1997M03 2017M04
Included observations: 242
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.253	0.253	15.732	
		2	0.127	0.067	19.696	0.000
		3	0.039	-0.008	20.077	0.000
		4	0.020	0.005	20.180	0.000
		5	0.058	0.055	21.030	0.000
		6	-0.032	-0.064	21.280	0.001
		7	0.143	0.167	26.430	0.000
		8	0.036	-0.031	26.765	0.000
		9	-0.004	-0.036	26.768	0.001
		10	0.132	0.152	31.210	0.000
		11	-0.050	-0.125	31.853	0.000
		12	-0.026	-0.032	32.026	0.001
		13	0.085	0.161	33.875	0.001
		14	0.018	-0.077	33.962	0.001
		15	-0.002	-0.037	33.964	0.002
		16	-0.114	-0.056	37.364	0.001
		17	0.025	0.015	37.524	0.002
		18	-0.008	0.007	37.542	0.003
		19	-0.080	-0.053	39.243	0.003
		20	-0.054	-0.095	40.023	0.003

Date: 02/01/19 Time: 14:18
Sample: 1997M03 2017M04
Included observations: 242
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.210	0.210	10.846	
		2	0.179	0.141	18.758	0.000
		3	0.077	0.016	20.228	0.000
		4	0.087	0.048	22.122	0.000
		5	0.095	0.062	24.367	0.000
		6	-0.094	-0.152	26.555	0.000
		7	0.088	0.114	28.499	0.000
		8	0.002	-0.007	28.500	0.000
		9	-0.038	-0.076	28.874	0.000
		10	-0.003	0.027	28.876	0.001
		11	-0.112	-0.102	32.060	0.000
		12	0.053	0.068	32.774	0.001
		13	0.012	0.060	32.809	0.001
		14	0.007	-0.028	32.820	0.002
		15	-0.013	-0.023	32.861	0.003
		16	-0.057	-0.032	33.707	0.004
		17	0.033	0.012	33.993	0.005
		18	0.001	0.044	33.993	0.008
		19	-0.050	-0.072	34.650	0.010
		20	-0.013	-0.007	34.692	0.015

Figure A4: Plots of the Correlogram for Examining the ACF, PACF and the Ljung-Box Test on the Squared of Residuals of AR (1) for LOP, NOP and OPEC Markets.

Estimation of Mean Equations

Dependent Variable: D(LOG(LOP))
Method: Least Squares
Date: 07/27/18 Time: 20:56
Sample (adjusted): 2003M03 2017M04
Included observations: 170 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002666	0.009324	0.285948	0.7753
AR(1)	0.278337	0.074062	3.758152	0.0002

R-squared	0.077550	Mean dependent var	0.002721
Adjusted R-squared	0.072059	S.D. dependent var	0.091079
S.E. of regression	0.087737	Akaike info criterion	-2.017261
Sum squared resid	1.293214	Schwarz criterion	-1.980370
Log likelihood	173.4672	Hannan-Quinn criter.	-2.002291
F-statistic	14.12371	Durbin-Watson stat	2.032751
Prob(F-statistic)	0.000236		

Inverted AR Roots	.28

Dependent Variable: D(LOG(NOP))
Method: Least Squares
Date: 07/27/18 Time: 20:59
Sample (adjusted): 1997M03 2017M04
Included observations: 242 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003817	0.007254	0.526142	0.5993
AR(1)	0.181825	0.063298	2.872530	0.0044

R-squared	0.033238	Mean dependent var	0.003701
Adjusted R-squared	0.029210	S.D. dependent var	0.093705
S.E. of regression	0.092327	Akaike info criterion	-1.918738
Sum squared resid	2.045809	Schwarz criterion	-1.889904
Log likelihood	234.1674	Hannan-Quinn criter.	-1.907123
F-statistic	8.251430	Durbin-Watson stat	2.012255
Prob(F-statistic)	0.004437		

Inverted AR Roots	.18

Dependent Variable: D(LOG(OPEC))
Method: Least Squares
Date: 07/27/18 Time: 21:01
Sample (adjusted): 1997M03 2017M04
Included observations: 242 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004002	0.007791	0.513602	0.6080
AR(1)	0.251922	0.062216	4.049186	0.0001

R-squared	0.063948	Mean dependent var	0.003800
Adjusted R-squared	0.060047	S.D. dependent var	0.093520
S.E. of regression	0.090668	Akaike info criterion	-1.954988
Sum squared resid	1.972976	Schwarz criterion	-1.926154
Log likelihood	238.5536	Hannan-Quinn criter.	-1.943373
F-statistic	16.39590	Durbin-Watson stat	2.042256
Prob(F-statistic)	0.000069		

Inverted AR Roots	.25

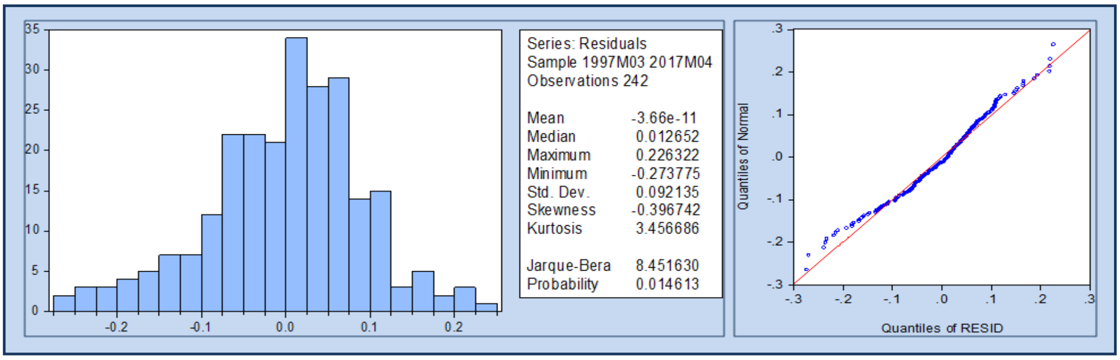


Figure A5: Histogram, Normality Test and QQ-Plot of AR(1) Residuals for NOP Returns.

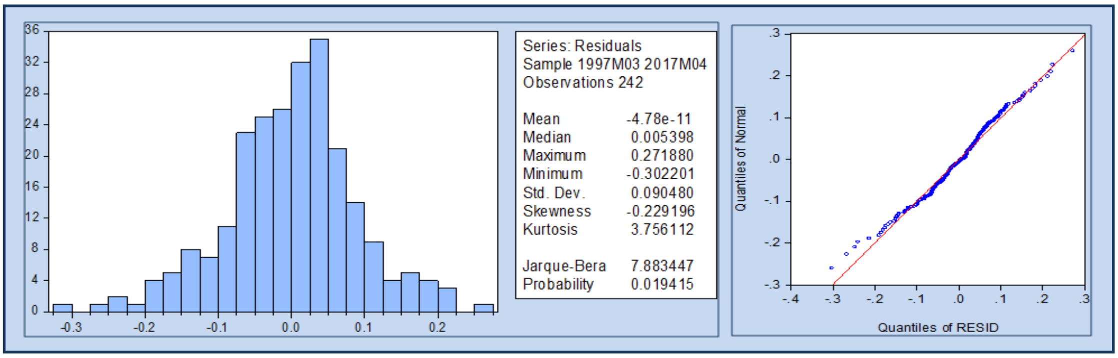


Figure A6: Histogram, Normality Test and QQ-Plot of AR(1) Residuals for OPEC Returns.

Results of Coefficients Estimation of AR(1)-GARCH(1,1) Model for LOP Returns with Normal Distribution.

Dependent Variable: LR
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 08/20/19 Time: 20:47
Sample (adjusted): 2003M03 2017M04
Included observations: 170 after adjustments
Convergence achieved after 23 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.007973	0.006504	1.225850	0.2203
AR(1)	0.122299	0.100010	1.222867	0.2214
		Variance Equation		
C	0.001172	0.000802	1.462015	0.1437
RESID(-1)^2	0.423431	0.154722	2.736718	0.0062
GARCH(-1)	0.460113	0.174969	2.629682	0.0085

R-squared	0.050581	Mean dependent var	0.002721
Adjusted R-squared	0.044930	S.D. dependent var	0.091079
S.E. of regression	0.089010	Akaike info criterion	-2.160964
Sum squared resid	1.331023	Schwarz criterion	-2.068735
Log likelihood	188.6820	Hannan-Quinn criter.	-2.123539
Durbin-Watson stat	1.686881		
Inverted AR Roots	.12		

Results of Coefficients Estimation of AR(1)-GARCH(1,1) Model for LOP Returns with Student-t Distribution.

Dependent Variable: LR
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/20/19 Time: 20:50
Sample (adjusted): 2003M03 2017M04
Included observations: 170 after adjustments
Convergence achieved after 35 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.008330	0.006531	1.275420	0.2022
AR(1)	0.123032	0.102379	1.201734	0.2295
		Variance Equation		
C	0.001218	0.000851	1.430264	0.1526
RESID(-1)^2	0.423725	0.160641	2.637719	0.0083
GARCH(-1)	0.452654	0.182517	2.480060	0.0131
T-DIST. DOF	70.89496	520.4851	0.136209	0.8917

R-squared	0.050451	Mean dependent var	0.002721
Adjusted R-squared	0.044799	S.D. dependent var	0.091079
S.E. of regression	0.089016	Akaike info criterion	-2.149399
Sum squared resid	1.331205	Schwarz criterion	-2.038724
Log likelihood	188.6990	Hannan-Quinn criter.	-2.104489
Durbin-Watson stat	1.687831		
Inverted AR Roots	.12		

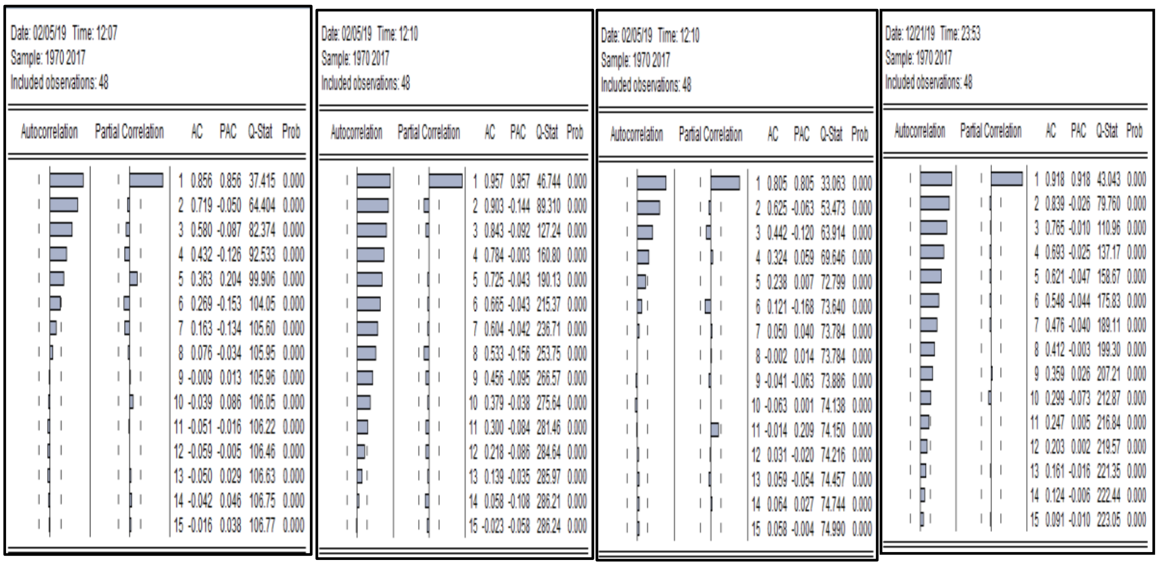
Results of Coefficients Estimation of AR(1)-GARCH(1,1) Model for LOP Returns with GE Distribution.

Dependent Variable: LR
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
Date: 08/20/19 Time: 20:51
Sample (adjusted): 2003M03 2017M04
Included observations: 170 after adjustments
Convergence achieved after 54 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.008732	0.006500	1.343315	0.1792
AR(1)	0.117529	0.101504	1.157883	0.2469
		Variance Equation		
C	0.001232	0.000873	1.411652	0.1581
RESID(-1)^2	0.424702	0.163348	2.599989	0.0093
GARCH(-1)	0.449776	0.187291	2.401479	0.0163
GED PARAMETER	1.882353	0.379105	4.965251	0.0000

R-squared	0.048231	Mean dependent var	0.002721
Adjusted R-squared	0.042566	S.D. dependent var	0.091079
S.E. of regression	0.089120	Akaike info criterion	-2.149891
Sum squared resid	1.334318	Schwarz criterion	-2.039215
Log likelihood	188.7407	Hannan-Quinn criter.	-2.104980
Durbin-Watson stat	1.675090		
Inverted AR Roots	.12		

Appendix (B)



Date: 02/05/19 Time: 12:07
Sample: 1970 2017
Included observations: 48

	AC	PAC	Q-Stat	Prob
1	0.856	0.856	37.415	0.000
2	0.719	-0.050	64.404	0.000
3	0.580	-0.087	82.374	0.000
4	0.432	-0.126	92.533	0.000
5	0.363	0.204	99.906	0.000
6	0.269	-0.153	104.05	0.000
7	0.163	-0.134	105.60	0.000
8	0.076	-0.034	105.95	0.000
9	-0.009	0.013	105.96	0.000
10	-0.039	0.086	106.05	0.000
11	-0.051	-0.016	106.22	0.000
12	-0.059	-0.005	106.46	0.000
13	-0.050	0.029	106.63	0.000
14	-0.042	0.046	106.75	0.000
15	-0.016	0.038	106.77	0.000

Date: 02/05/19 Time: 12:10
Sample: 1970 2017
Included observations: 48

	AC	PAC	Q-Stat	Prob
1	0.957	0.957	46.744	0.000
2	0.903	-0.144	89.310	0.000
3	0.843	-0.092	127.24	0.000
4	0.784	-0.003	160.80	0.000
5	0.725	-0.043	190.13	0.000
6	0.665	-0.043	215.37	0.000
7	0.604	-0.042	236.71	0.000
8	0.533	-0.156	253.75	0.000
9	0.456	-0.095	266.57	0.000
10	0.379	-0.038	275.64	0.000
11	0.300	-0.084	281.46	0.000
12	0.218	-0.086	284.64	0.000
13	0.139	-0.035	285.97	0.000
14	0.058	-0.108	286.21	0.000
15	-0.023	-0.058	286.24	0.000

Date: 02/05/19 Time: 12:10
Sample: 1970 2017
Included observations: 48

	AC	PAC	Q-Stat	Prob
1	0.805	0.805	33.063	0.000
2	0.625	-0.063	53.473	0.000
3	0.442	-0.120	63.914	0.000
4	0.324	0.059	69.646	0.000
5	0.238	0.007	72.799	0.000
6	0.121	-0.168	73.640	0.000
7	0.050	0.040	73.784	0.000
8	-0.002	0.014	73.784	0.000
9	-0.041	-0.063	73.886	0.000
10	-0.063	0.001	74.138	0.000
11	-0.014	0.209	74.150	0.000
12	0.031	-0.020	74.216	0.000
13	0.059	-0.054	74.457	0.000
14	0.064	0.027	74.744	0.000
15	0.058	-0.004	74.990	0.000

Date: 12/21/19 Time: 23:53
Sample: 1970 2017
Included observations: 48

	AC	PAC	Q-Stat	Prob
1	0.918	0.918	43.043	0.000
2	0.839	-0.026	79.760	0.000
3	0.765	-0.010	110.96	0.000
4	0.693	-0.025	137.17	0.000
5	0.621	-0.047	158.67	0.000
6	0.548	-0.044	175.83	0.000
7	0.476	-0.040	189.11	0.000
8	0.412	-0.003	199.30	0.000
9	0.359	0.026	207.21	0.000
10	0.299	-0.073	212.87	0.000
11	0.247	0.005	216.84	0.000
12	0.203	0.002	219.57	0.000
13	0.161	-0.016	221.35	0.000
14	0.124	-0.006	222.44	0.000
15	0.091	-0.010	223.05	0.000

Figure B1: A Combined Graph of Correlogram of ACF and PACF for LOP, GDP, ER and CPI for Libya in Log Level.

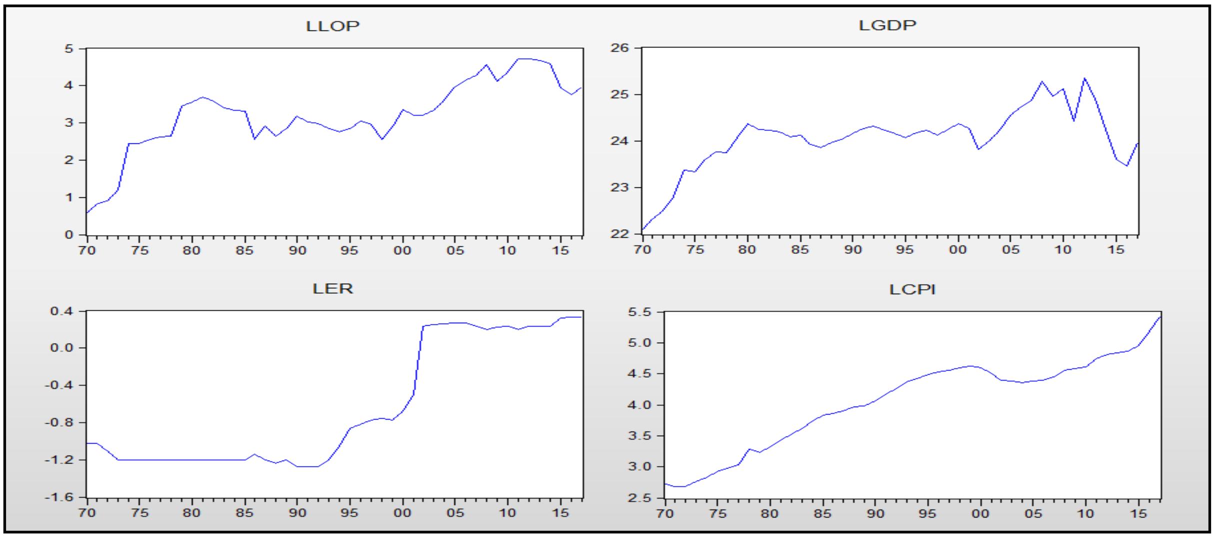
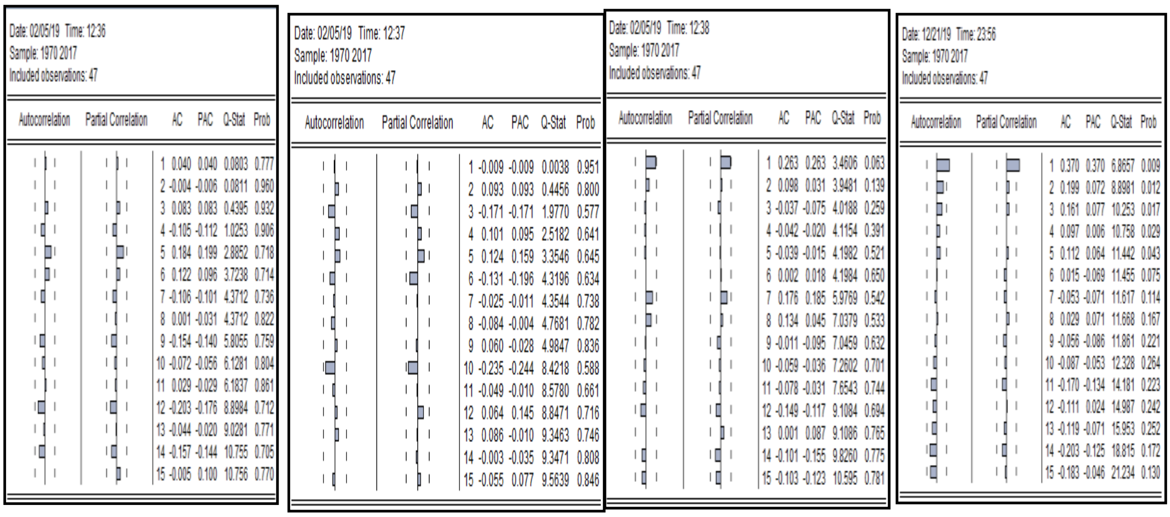


Figure B3: A Combined Graph for LOP, GDP, ER and LCPI for Libya Covering the Period from 1970 to 2017 in Log Level.



Date: 02/05/19 Time: 12:36
Sample: 1970 2017
Included observations: 47

Lag	AC	PAC	Q-Stat	Prob
1	0.040	0.040	0.0803	0.777
2	-0.004	-0.006	0.0811	0.960
3	0.083	0.083	0.4395	0.932
4	-0.105	-0.112	1.0253	0.906
5	0.184	0.199	2.8852	0.718
6	0.122	0.096	3.7238	0.714
7	-0.106	-0.101	4.3712	0.736
8	0.001	-0.031	4.3712	0.822
9	-0.154	-0.140	5.8055	0.759
10	-0.072	-0.056	6.1281	0.804
11	0.029	-0.029	6.1837	0.861
12	-0.203	-0.176	8.8984	0.712
13	-0.044	-0.020	9.0281	0.771
14	-0.157	-0.144	10.755	0.705
15	-0.005	0.100	10.756	0.770

Date: 02/05/19 Time: 12:37
Sample: 1970 2017
Included observations: 47

Lag	AC	PAC	Q-Stat	Prob
1	-0.009	-0.009	0.0038	0.951
2	0.093	0.093	0.4456	0.800
3	-0.171	-0.171	1.9770	0.577
4	0.101	0.095	2.5182	0.641
5	0.124	0.159	3.3546	0.645
6	-0.131	-0.196	4.3196	0.634
7	-0.025	-0.011	4.3544	0.738
8	-0.084	-0.004	4.7681	0.782
9	0.060	-0.028	4.9847	0.836
10	-0.235	-0.244	8.4218	0.588
11	-0.049	-0.010	8.5780	0.661
12	0.064	0.145	8.8471	0.716
13	0.086	-0.010	9.3463	0.746
14	-0.003	-0.035	9.3471	0.808
15	-0.055	0.077	9.5639	0.846

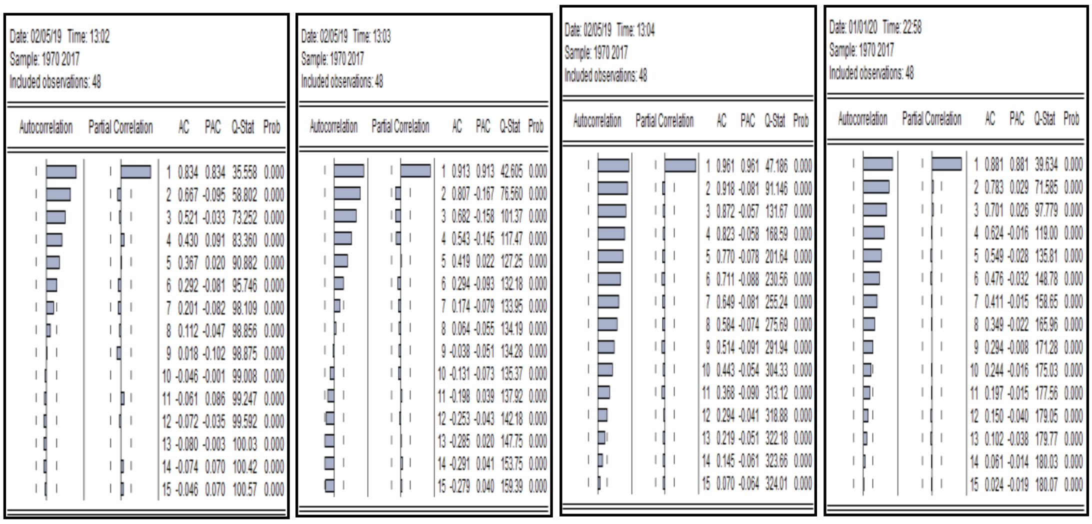
Date: 02/05/19 Time: 12:38
Sample: 1970 2017
Included observations: 47

Lag	AC	PAC	Q-Stat	Prob
1	0.263	0.263	3.4606	0.063
2	0.098	0.031	3.9481	0.139
3	-0.037	-0.075	4.0188	0.259
4	-0.042	-0.020	4.1154	0.391
5	-0.039	-0.015	4.1982	0.521
6	0.002	0.018	4.1984	0.650
7	0.176	0.185	5.9769	0.542
8	0.134	0.045	7.0379	0.533
9	-0.011	-0.095	7.0459	0.632
10	-0.059	-0.036	7.2602	0.701
11	-0.078	-0.031	7.6543	0.744
12	-0.149	-0.117	9.1084	0.694
13	0.001	0.087	9.1086	0.765
14	-0.101	-0.155	9.8260	0.775
15	-0.103	-0.123	10.595	0.781

Date: 12/21/19 Time: 23:56
Sample: 1970 2017
Included observations: 47

Lag	AC	PAC	Q-Stat	Prob
1	0.370	0.370	6.8657	0.009
2	0.199	0.072	8.8981	0.012
3	0.161	0.077	10.253	0.017
4	0.097	0.006	10.758	0.029
5	0.112	0.064	11.442	0.043
6	0.015	-0.069	11.455	0.075
7	-0.053	-0.071	11.617	0.114
8	0.029	0.071	11.668	0.167
9	-0.056	-0.086	11.861	0.221
10	-0.087	-0.053	12.328	0.264
11	-0.170	-0.134	14.181	0.223
12	-0.111	0.024	14.987	0.242
13	-0.119	-0.071	15.953	0.252
14	-0.203	-0.125	18.815	0.172
15	-0.183	-0.046	21.234	0.130

Figure B2: A Combined Graph of Correlogram of ACF and PACF for LOP, GDP, ER and CPI for Libya n in the Firs Log Differencing Level.



Date: 02/05/19 Time: 13:02
Sample: 1970 2017
Included observations: 48

Lag	AC	PAC	Q-Stat	Prob
1	0.834	0.834	35.558	0.000
2	0.667	-0.095	58.802	0.000
3	0.521	-0.033	73.252	0.000
4	0.430	0.091	83.360	0.000
5	0.367	0.020	90.882	0.000
6	0.292	-0.081	95.746	0.000
7	0.201	-0.082	98.109	0.000
8	0.112	-0.047	98.856	0.000
9	0.018	-0.102	98.875	0.000
10	-0.046	-0.001	99.008	0.000
11	-0.061	0.086	99.247	0.000
12	-0.072	-0.035	99.592	0.000
13	-0.080	-0.003	100.03	0.000
14	-0.074	0.070	100.42	0.000
15	-0.046	0.070	100.57	0.000

Date: 02/05/19 Time: 13:03
Sample: 1970 2017
Included observations: 48

Lag	AC	PAC	Q-Stat	Prob
1	0.913	0.913	42.605	0.000
2	0.807	-0.167	76.560	0.000
3	0.682	-0.158	101.37	0.000
4	0.543	-0.145	117.47	0.000
5	0.419	0.022	127.25	0.000
6	0.294	-0.093	132.18	0.000
7	0.174	-0.079	133.95	0.000
8	0.064	-0.055	134.19	0.000
9	-0.038	-0.051	134.28	0.000
10	-0.131	-0.073	135.37	0.000
11	-0.198	0.039	137.92	0.000
12	-0.253	-0.043	142.18	0.000
13	-0.285	0.020	147.75	0.000
14	-0.291	0.041	153.75	0.000
15	-0.279	0.040	159.39	0.000

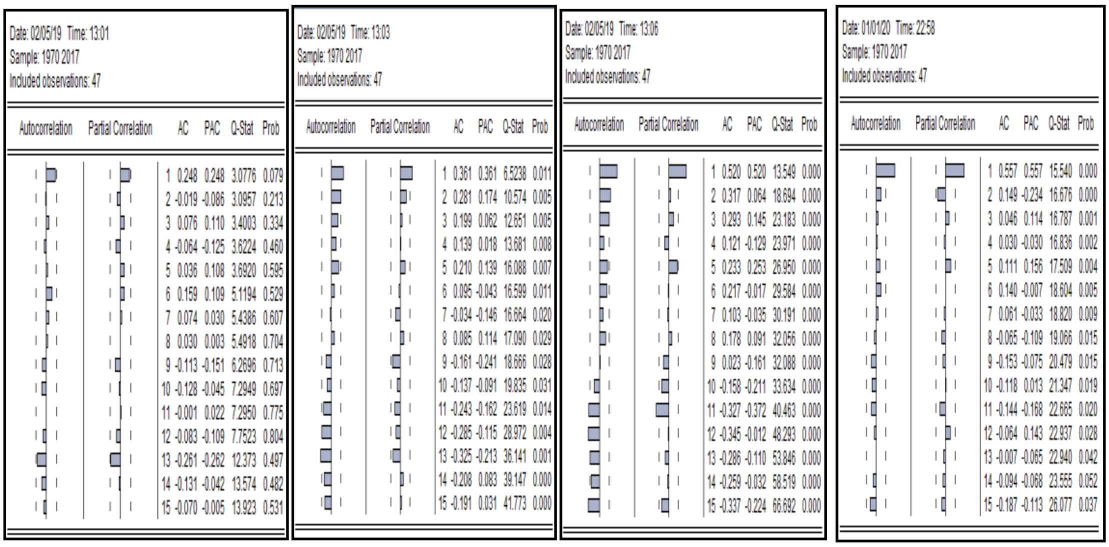
Date: 02/05/19 Time: 13:04
Sample: 1970 2017
Included observations: 48

Lag	AC	PAC	Q-Stat	Prob
1	0.961	0.961	47.186	0.000
2	0.918	-0.081	91.146	0.000
3	0.872	-0.057	131.67	0.000
4	0.823	-0.058	168.59	0.000
5	0.770	-0.078	201.64	0.000
6	0.711	-0.088	230.56	0.000
7	0.649	-0.081	255.24	0.000
8	0.584	-0.074	275.69	0.000
9	0.514	-0.091	291.94	0.000
10	0.443	-0.054	304.33	0.000
11	0.368	-0.090	313.12	0.000
12	0.294	-0.041	318.88	0.000
13	0.219	-0.051	322.18	0.000
14	0.145	-0.061	323.66	0.000
15	0.070	-0.064	324.01	0.000

Date: 01/01/20 Time: 22:58
Sample: 1970 2017
Included observations: 48

Lag	AC	PAC	Q-Stat	Prob
1	0.881	0.881	39.634	0.000
2	0.783	0.029	71.585	0.000
3	0.701	0.026	97.779	0.000
4	0.624	-0.016	119.00	0.000
5	0.549	-0.028	135.81	0.000
6	0.476	-0.032	148.78	0.000
7	0.411	-0.015	158.65	0.000
8	0.349	-0.022	165.96	0.000
9	0.294	-0.008	171.28	0.000
10	0.244	-0.016	175.03	0.000
11	0.197	-0.015	177.56	0.000
12	0.150	-0.040	179.05	0.000
13	0.102	-0.038	179.77	0.000
14	0.061	-0.014	180.03	0.000
15	0.024	-0.019	180.07	0.000

Figure B4: A Combined Graph of Correlogram of ACF and PACF for NOP, GDP, ER and CPI for Nigeria Log Level.



Date: 02/05/19 Time: 13:01
Sample: 1970 2017
Included observations: 47

	AC	PAC	Q-Stat	Prob
1	0.248	0.248	3.0776	0.079
2	-0.019	-0.086	3.0957	0.213
3	0.076	0.110	3.4003	0.334
4	-0.064	-0.125	3.6224	0.460
5	0.036	0.108	3.6920	0.595
6	0.159	0.109	5.1194	0.529
7	0.074	0.030	5.4386	0.607
8	0.030	0.003	5.4918	0.704
9	-0.113	-0.151	6.2696	0.713
10	-0.128	-0.045	7.2949	0.697
11	-0.001	0.022	7.2950	0.775
12	-0.083	-0.109	7.7523	0.804
13	-0.261	-0.262	12.373	0.497
14	-0.131	-0.042	13.574	0.482
15	-0.070	-0.005	13.923	0.531

Date: 02/05/19 Time: 13:03
Sample: 1970 2017
Included observations: 47

	AC	PAC	Q-Stat	Prob
1	0.361	0.361	6.5238	0.011
2	0.281	0.174	10.574	0.005
3	0.199	0.062	12.651	0.005
4	0.139	0.018	13.681	0.008
5	0.210	0.139	16.088	0.007
6	0.095	-0.043	16.599	0.011
7	-0.034	-0.146	16.664	0.020
8	0.085	0.114	17.090	0.029
9	-0.161	-0.241	18.666	0.028
10	-0.137	-0.091	19.835	0.031
11	-0.243	-0.162	23.619	0.014
12	-0.285	-0.115	28.972	0.004
13	-0.325	-0.213	36.141	0.001
14	-0.208	0.083	39.147	0.000
15	-0.191	0.031	41.773	0.000

Date: 02/05/19 Time: 13:06
Sample: 1970 2017
Included observations: 47

	AC	PAC	Q-Stat	Prob
1	0.520	0.520	13.549	0.000
2	0.317	0.064	18.694	0.000
3	0.293	0.145	23.183	0.000
4	0.121	-0.129	23.971	0.000
5	0.233	0.253	26.950	0.000
6	0.217	-0.017	29.584	0.000
7	0.103	-0.035	30.191	0.000
8	0.178	0.091	32.056	0.000
9	0.023	-0.161	32.088	0.000
10	-0.158	-0.211	33.634	0.000
11	-0.327	-0.372	40.463	0.000
12	-0.345	-0.012	48.293	0.000
13	-0.286	-0.110	53.846	0.000
14	-0.259	-0.032	58.519	0.000
15	-0.337	-0.224	66.692	0.000

Date: 01/01/20 Time: 22:58
Sample: 1970 2017
Included observations: 47

	AC	PAC	Q-Stat	Prob
1	0.557	0.557	15.540	0.000
2	0.149	-0.234	16.676	0.000
3	0.046	0.114	16.787	0.001
4	0.030	-0.030	16.836	0.002
5	0.111	0.156	17.509	0.004
6	0.140	-0.007	18.604	0.005
7	0.061	-0.033	18.820	0.009
8	-0.065	-0.109	19.066	0.015
9	-0.153	-0.075	20.479	0.015
10	-0.118	0.013	21.347	0.019
11	-0.144	-0.168	22.665	0.020
12	-0.064	0.143	22.937	0.028
13	-0.007	-0.065	22.940	0.042
14	-0.094	-0.068	23.555	0.052
15	-0.187	-0.113	26.077	0.037

Figure B5: A Combined Graph of Correlogram of ACF and PACF for NOP, GDP, ER and CPI for Nigerian in the Firs Log Differencing Level.

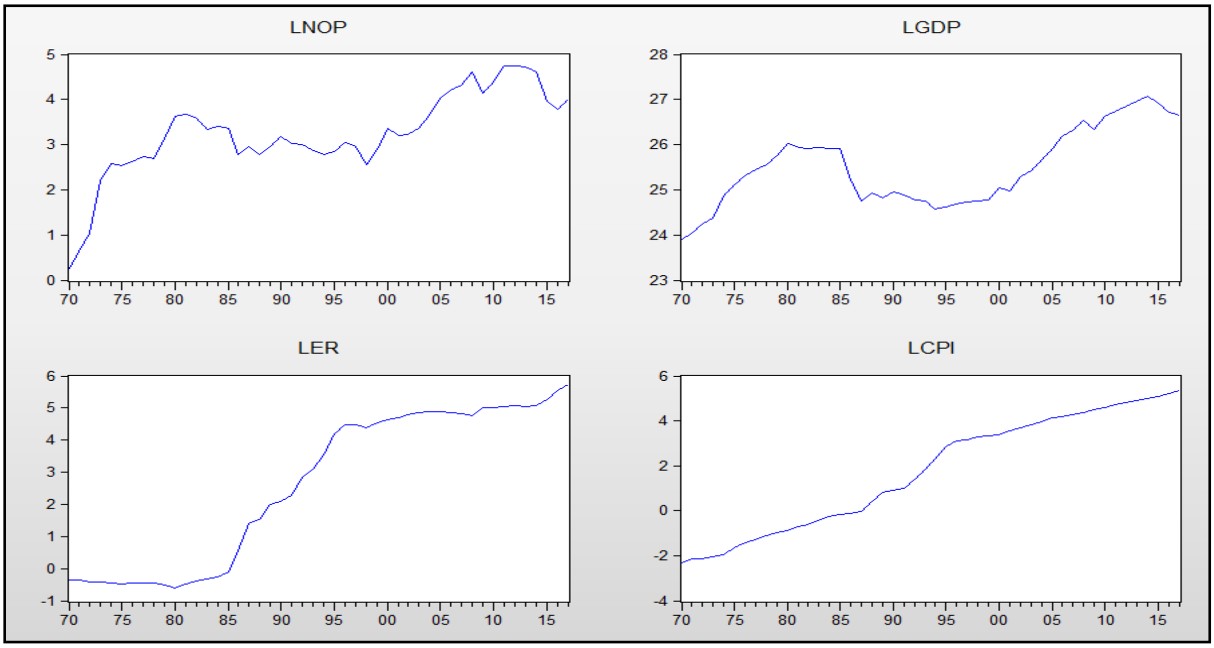


Figure B6: A Combined Graph for LOP, GDP, ER and CPI for Nigerian Covering the Period from 1970 to 2017 in Log Level.

Optimal Lag Lengths of the VAR Model for Libya

VAR Lag Order Selection Criteria
Endogenous variables: LLOP LGDP LER LCPI
Exogenous variables: C
Date: 12/22/19 Time: 01:26
Sample: 1970 2017
Included observations: 43

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-101.1212	NA	0.001561	4.889360	5.053193	4.949777
1	106.9555	14.89713	4.44e-07	-3.300255	-1.825762	-2.756508
2	97.53524	351.1138*	3.20e-07*	-3.606290*	-2.787128*	-3.304208*
3	114.3861	10.36835	6.98e-07	-2.901681	-0.771857	-2.116268
4	122.8646	10.25297	1.10e-06	-2.551840	0.233314	-1.524761
5	134.8601	12.27454	1.59e-06	-2.365588	1.074896	-1.096843

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Optimal Lag Lengths of the VAR Model for Nigeria

VAR Lag Order Selection Criteria
Endogenous variables: LNOP LGDP LER LCPI
Exogenous variables: C
Date: 02/24/20 Time: 15:50
Sample: 1970 2017
Included observations: 43

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-117.6841	NA	0.004476	5.794480	5.959973	5.855140
1	105.4524	393.1452	1.85e-07	-4.069161	-2.683995	-3.627490
2	123.6419	28.58358*	1.73e-07*	-4.173426*	-3.241700*	-3.765864*
3	139.0244	21.24240	1.78e-07	-4.144017	-1.992617	-3.355444
4	146.3046	8.666961	3.00e-07	-3.728791	-0.915421	-2.697580
5	162.3418	16.03720	3.60e-07	-3.730563	-0.255223	-2.456713

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen's Cointegration Test for Libyan Variables

Date: 08/22/19 Time: 14:52
Sample (adjusted): 1972 2017
Included observations: 46 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: LLOP LOPEC LGDP LER IN
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.547687	85.84704	88.80380	0.0802
At most 1	0.389111	49.35153	63.87610	0.4430
At most 2	0.280187	26.68092	42.91525	0.6994
At most 3	0.152479	11.55777	25.87211	0.8415
At most 4	0.082237	3.947550	12.51798	0.7497

Trace test indicates no cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.547687	36.49552	38.33101	0.0800
At most 1	0.389111	22.67060	32.11832	0.4424
At most 2	0.280187	15.12316	25.82321	0.6234
At most 3	0.152479	7.610216	19.38704	0.8549
At most 4	0.082237	3.947550	12.51798	0.7497

Max-eigenvalue test indicates no cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Johansen's Cointegration Test for Nigerian Variables

Date: 02/24/20 Time: 17:29
Sample (adjusted): 1972 2017
Included observations: 46 after adjustments
Trend assumption: Linear deterministic trend
Series: LNOP LGDP LER LCPI
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.452219	53.80894	47.85613	0.0125
At most 1	0.285475	26.12249	29.79707	0.1251
At most 2	0.154495	10.66014	15.49471	0.2333
At most 3	0.061921	2.940374	3.841466	0.0864

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.452219	28.07288	32.11832	0.1442
At most 1	0.285475	20.24598	25.82321	0.2293
At most 2	0.154495	14.41207	19.38704	0.2277
At most 3	0.061921	6.783787	12.51798	0.3676

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

VAE Model Estimates for Libya

Vector Error Correction Estimates
Date: 01/04/20 Time: 00:37
Sample (adjusted): 1972 2017
Included observations: 46 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LLOP(-1)	1.000000
LGDP(-1)	-1.011446 (0.12966) [-7.80073]
LER(-1)	-0.756852 (0.12121) [-6.24428]
LCPI(-1)	0.369808 (0.15093) [2.45027]
C	19.54897 (2.81423) [6.94647]

Error Correction:	D(LLOP)	D(LGDP)	D(LER)	D(LCPI)
CointEq1	-0.445748 (0.12732) [-3.50101]	-0.296939 (0.12155) [-2.44284]	0.098076 (0.05024) [1.95217]	0.087921 (0.02864) [3.06963]
D(LLOP(-1))	0.167584 (0.16447) [1.01893]	0.389586 (0.15702) [2.48108]	-0.034644 (0.06490) [-0.53382]	-0.020678 (0.03700) [-0.55887]
D(LGDP(-1))	-0.029516 (0.19955) [-0.14791]	-0.367692 (0.19052) [-1.92996]	0.051475 (0.07874) [0.65372]	0.050792 (0.04489) [1.13144]
D(LER(-1))	0.639942 (0.39243) [1.63070]	0.112174 (0.37466) [0.29940]	0.218437 (0.15485) [1.41063]	-0.021533 (0.08828) [-0.24391]
D(LCPI(-1))	2.745141 (0.79035) [3.47330]	2.172434 (0.75457) [2.87905]	-0.455713 (0.31187) [-1.46124]	0.305777 (0.17780) [1.71979]
R-squared	0.259223	0.212166	0.121431	0.210117
Adj. R-squared	0.186952	0.135304	0.035717	0.133055
Sum sq. resids	3.685057	3.358877	0.573775	0.186492
S.E. equation	0.299799	0.286223	0.118298	0.067443
F-statistic	3.586829	2.760351	1.416705	2.726603
Log likelihood	-7.210996	-5.079378	35.56450	61.41303
Akaike AIC	0.530913	0.438234	-1.328891	-2.452741
Schwarz SC	0.729678	0.636999	-1.130126	-2.253975
Mean dependent	0.068725	0.035624	0.029369	0.059776
S.D. dependent	0.332485	0.307803	0.120469	0.072434

VEC Model Estimates for Nigeria

Vector Error Correction Estimates
Date: 02/25/20 Time: 16:34
Sample (adjusted): 1972 2017
Included observations: 46 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LNOP(-1)	1.000000
LGDP(-1)	-0.023491 (0.22987) [-0.10220]
LER(-1)	1.267602 (0.33585) [3.77433]
LCPI(-1)	-1.419776 (0.35378) [-4.01314]
C	-3.487428 (6.62619) [-0.59505]

Error Correction:	D(LNOP)	D(LGDP)	D(LER)	D(LCPI)
CointEq1	-0.343406 (0.14250) [-2.40992]	0.124141 (0.08834) [1.40528]	-0.032862 (0.08560) [-0.38392]	0.128477 (0.04524) [2.84018]
D(LNOP(-1))	0.430549 (0.18703) [2.30206]	0.252380 (0.11594) [2.17673]	-0.164235 (0.11235) [-1.46187]	-0.092280 (0.05937) [-1.55427]
D(LGDP(-1))	0.079526 (0.49912) [0.15933]	-0.168335 (0.30942) [-0.54404]	-0.210731 (0.29982) [-0.70287]	0.003127 (0.15844) [0.01973]
D(LER(-1))	0.102500 (0.48021) [0.21345]	-0.354655 (0.29770) [-1.19133]	0.245230 (0.28846) [0.85014]	0.111559 (0.15244) [0.73181]
D(LCPI(-1))	0.233740 (0.47456) [0.49254]	0.264400 (0.29420) [0.89872]	0.214717 (0.28507) [0.75322]	0.388334 (0.15065) [2.57772]
C	-0.016112 (0.08466) [-0.19033]	0.049806 (0.05248) [0.94901]	0.090986 (0.05085) [1.78920]	0.091875 (0.02687) [3.41868]
R-squared	0.199948	0.289438	0.395732	0.501778
Adj. R-squared	0.099941	0.200617	0.320199	0.439500
Sum sq. resids	3.475731	1.335781	1.254154	0.350266
S.E. equation	0.294777	0.182742	0.177070	0.093577
F-statistic	1.999344	3.258688	5.239168	8.057085
Log likelihood	-5.865929	16.12871	17.57897	46.91604
Akaike AIC	0.515910	-0.440379	-0.503434	-1.778958
Schwarz SC	0.754428	-0.201860	-0.264915	-1.540440
Mean dependent	0.073016	0.056645	0.131856	0.162678
S.D. dependent	0.310712	0.204390	0.214761	0.124992

VEC Granger Causality/Block Exogeneity Wald Tests for Libya

VEC Granger Causality/Block Exogeneity Wald Tests
Date: 01/04/20 Time: 01:43
Sample: 1970 2017
Included observations: 46

Dependent variable: D(LLOP)

Excluded	Chi-sq	df	Prob.
D(LGDP)	0.021877	1	0.8824
D(LER)	2.659196	1	0.1030
D(LCPI)	12.06384	1	0.0005
All	13.24087	3	0.0041

Dependent variable: D(LGDP)

Excluded	Chi-sq	df	Prob.
D(LLOP)	6.155738	1	0.0131
D(LER)	0.089640	1	0.7646
D(LCPI)	8.288944	1	0.0040
All	11.75365	3	0.0083

Dependent variable: D(LER)

Excluded	Chi-sq	df	Prob.
D(LLOP)	0.284959	1	0.5935
D(LGDP)	0.427346	1	0.5133
D(LCPI)	2.135211	1	0.1440
All	2.177834	3	0.5363

Dependent variable: D(LCPI)

Excluded	Chi-sq	df	Prob.
D(LLOP)	0.312336	1	0.5763
D(LGDP)	1.280147	1	0.2579
D(LER)	0.059494	1	0.8073
All	1.438533	3	0.6965

VEC Granger Causality/Block Exogeneity Wald Tests for Nigeria

VEC Granger Causality/Block Exogeneity Wald Tests
Date: 02/26/20 Time: 15:26
Sample: 1970 2017
Included observations: 46

Dependent variable: D(LNOP)

Excluded	Chi-sq	df	Prob.
D(LGDP)	0.025387	1	0.8734
D(LER)	0.045560	1	0.8310
D(LCPI)	0.242594	1	0.6223
All	0.730088	3	0.8661

Dependent variable: D(LGDP)

Excluded	Chi-sq	df	Prob.
D(LNOP)	4.738148	1	0.0295
D(LER)	1.419266	1	0.2335
D(LCPI)	0.807692	1	0.3688
All	5.347842	3	0.1480

Dependent variable: D(LER)

Excluded	Chi-sq	df	Prob.
D(LNOP)	2.137063	1	0.1438
D(LGDP)	0.494021	1	0.4821
D(LCPI)	0.567335	1	0.4513
All	4.602589	3	0.2033

Dependent variable: D(LCPI)

Excluded	Chi-sq	df	Prob.
D(LNOP)	2.415771	1	0.1201
D(LGDP)	0.000389	1	0.9843
D(LER)	0.535543	1	0.4643
All	7.441704	3	0.0591