MARKET EFFICIENCY, VOLATILITY BEHAVIOUR AND ASSET PRICING ANALYSIS OF THE OIL & GAS COMPANIES QUOTED ON THE LONDON STOCK EXCHANGE

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Abstract

This research assessed market efficiency, volatility behaviour, asset pricing, and oil price risk exposure of the oil and gas companies quoted on the London Stock Exchange with the aim of providing fresh evidence on the pricing dynamics in this sector. In market efficiency analysis, efficient market hypothesis (EMH) and random walk hypothesis were tested using a mix of statistical tools such as Autocorrelation Function, Ljung-Box Q-Statistics, Runs Test, Variance Ratio Test, and BDS test for independence. To confirm the results from these parametric and non-parametric tools, technical trading and filter rules, and moving average based rules were also employed to assess the possibility of making abnormal profit from the stocks under study. In seasonality analysis, stock returns were tested for the day-of-the-week and month-of-the-year effects. Volatility processes, estimation, and forecasting were undertaken using both asymmetric and symmetric volatility models such as GARCH (1,1) and Threshold ARCH or TARCH (1,1,1) to investigate the volatility behaviour of stock returns. To determine the effect of an exogenous variable on volatility, Brent crude oil price was used in the models formulated as a variance regressor for the assessment of its impact on volatility. The models were then used to forecast the price volatility taking note of the forecasting errors for the determination of the most effective forecasting model. International oil price risk exposure of the oil and gas sector was measured using a multi-factor asset pricing model similar to that developed by Fama and French (1993). Factors used in the asset pricing model are assessed for statistical significance and relevance in the pricing of oil and gas stocks. Data used in the study were mainly the adjusted daily closing prices of oil and gas companies quoted on the exchange. Five indices of FTSE All Share, FTSE 100, FTSE UK Oil and Gas, FTSE UK Oil and Gas Producers, and FTSE AIM SS Oil and Gas were also included in the analysis. Our findings suggest that technical trading rules cannot be used to gain abnormal returns, which could be regarded as a sign for weak form market efficiency. The results from seasonality analysis have not shown any day-of-the-week or monthly effect in stock returns. The pattern of stock returns' volatility can be estimated and forecasted, although the relationship between risk and return cannot be generalised. On a similar note, the relationship between volatility attributes and the efficient market hypothesis cannot be clearly established. However, we have established that volatility modelling can significantly measure the quantum of risk in the oil and gas sector. Market risk, oil price risk, size and book-to-market related factors in asset pricing models were found to be relevant in the determination of asset prices of the oil and gas companies.

Keywords: Information efficiency, seasonality analysis, volatility, systematic risk, asset pricing, and forecasting.

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

The process of effective capital formation in every economy centres on the operations of stock markets. The information efficiency and operational efficiency of stock markets are regarded as the determinants of market effectiveness. According to Brown (2011), a stock market where prices reflect all available information is deemed to be information efficient. In other words, the changes in the prices of stocks are due to the changes in information about that stock. The study of market efficiency continues to be popular and relevant in the field of finance. Brown (2011) believes that economists, academic researchers, regulators and all, market participants are responsible for the contemporary global financial crisis because of their irrational trust on the 'Efficient Market Hypothesis' and failure to forecast correctly the volatility of asset prices.

A large number of researchers have contributed to the debate on market efficiency, making this one of the most widely researched areas in the field of finance. Roberts (1959) has stated categorically that in the history of finance, markets and stock prices are the most extensively studied areas, resulting in various theories of the behaviour of stock markets and techniques that indicate the future direction of stock prices. The advent of a formal model of market efficiency by Fama (1970) increased the interest in the study of the stock market and share price behaviour. A number of stock markets have been investigated for information efficiency by many researchers using several techniques. Tung and Marsden (1998) have described the inferences from the findings of many studies as contentious, despite the huge importance of stock markets to the development of every economy. They went further, associating the cause of the contentious results to a lack of proper control of the variables in these studies. Alexeev and Tapon (2011) have supported the view that the outcomes from stock market research are controversial and linked the reason for this to an unwarranted preference by researchers to use stock market indices instead of price data from individual stocks. Quirin et al. (2000) attributed the cause of inconsistency to the use of analytical tools on cross-sectional data representing various industries, characterised by distinct features such as accounting policies, business risks, industrial regulations, sets of shareholders and government policies. In line with this reasoning, Brown (2011) supports the view of many observers that financial economists are, in particular, responsible for the recent global financial meltdown because of their illogical reliance on controversial models or understandings of the efficient market hypothesis. Brown (2011) argued that the effect of the controversy on the examination of the efficient market hypothesis had resulted in the inability of practitioners, investors, regulators and academics to predict the development and collapse of the recent bubbles in asset prices. Most of the studies conducted on developed markets have shown that the markets are efficient by ascertaining random walk processes in their share prices (Mollah, 2007; Adelegan, 2003). The previous studies conducted on these developed markets are mostly on all-share indices and for that reason, information efficiency could not be traced to individual industries or sectors of the markets (see also Alexeev and Tapon, 2011). In view of some of these arguments, this research will address the issue of market efficiency with more control of the variables of the study and the employment of various tools in the quest to overcome a number of weaknesses in the prior studies in this area. We shall focus on the information efficiency of the UK oil and gas sector. Firstly, we plan to look at the randomness of returns and then extend the analysis by applying trading and filter rules and moving average-based strategies to see the relative performance of these investment strategies.

Volatility modelling and forecasting are also areas that require further research for empirical evidence and to identify whether theoretical models can explain the extent of day-to-day fluctuations in stock returns (Taylor, 2005). Koopman et al. (2005) stress the growing popularity of volatility modelling in the field of finance. Basu and Bundick (2012) have stated that, due to high level of uncertainties, the foundation of education, experience and expertise used by professionals to analyse stock markets in order to advise investors is not yielding the desired results. Basu and Bundick (2012) have further mentioned that there is a need to explore more about the business environment and stock markets, and this can be achieved by the study of variability in asset prices (volatility). Empirical research has provided evidence of the existence of a significant relationship between market volatility and expected returns. Pindyck (1983) has explained the cause of the collapse of stock prices during the 1970s as being due to an increase in volatility during the period. Researchers such as French et al. (1987) and Shawky et al. (1995) have also supported the argument that volatility can determine stock returns. Shawky et al. (1995) conducted a study on the value-weighted daily return series of the Standard & Poor’s 500 (S&P 500), the New York Stock Exchange (NYSE), the

American Stock Exchange (AMEX) and the National Association of Securities Dealers Automated Quotations (NASDAQ) from the Centre for Research in Security Prices (CRSP) market portfolio, which contains all of the stocks listed on these indices. Based on their findings, they conclude that the markets experience the presence of two regimes, where periods of rising prices are characterised by low volatility and periods of declining prices are characterised by high volatility. In this research, conditional volatility modelling and forecasting will be adopted to explain the volatility of the UK oil and gas sector. Exogenous factors (variance regressors) will be incorporated into the modelling process to assess their significance. Other issues in volatility processes, such as information asymmetric effects and volatility clustering, will be addressed.

The importance of asset pricing models in any research on the behaviour of stock prices or returns cannot be overemphasised. The fact that investors are always concerned about the expected returns from their investments based on a given risk has also contributed to the need for effective asset pricing models. Scholars have made various attempts to capture the relationship between asset risk and return, which has resulted in the advent of models such as the mean-variance asset pricing model developed by Markowitz (1952). The Capital Asset Pricing Model (CAPM), devised by Sharpe (1964), Lintner (1965) and Mossin (1966), was also developed as a single-factor model on the assumption that asset return is determined by market systematic risk, since it is claimed that unsystematic risks of individual assets are eliminated by diversification in an efficient portfolio. The weaknesses observed in these early models, such as the failure of CAPM to consider size, value and momentum anomalies, have resulted in modifications to the single-factor model. Multi-factor asset pricing models, such as Fama and French's (1993) three-factor and Fama, French and Carhart's (1997) four-factor asset pricing models, have been developed to consider more relevant factors in the determination of asset price. In recent years, the impact of other commodity prices, such as international crude oil, has also been incorporated into multi-factor asset pricing models to find the best explanation of a stock's price dynamics. We also plan to adopt the multi-factor asset pricing model of Fama-French-Carhart (1997), augmented by the price of oil, as represented by the OPEC Basket Price (a benchmark of oil price constituted by OPEC as the average price from the Saharan Blend (Algeria), Girassol (Angola), Oriente (Ecuador), Iran Heavy (Islamic Republic of Iran), Basra Light (Iraq), Kuwait Export (Kuwait), Es Sider (Libya), Bonny Light (Nigeria), Qatar Marine (Qatar), Arab Light (Saudi Arabia), Murban (UAE) and Merey (Venezuela)) in order to achieve the objectives of the research.

1.2 Statement of the Problem

The efforts by financial experts, practitioners, market regulators and scholars to improve capital market investment decisions have persisted over many decades. Earlier studies by scholars, such as those of Bachelier (1900), Graham and Dodd (1934), Kendall (1953), Roberts (1959), Cootner (1964), Samuelson (1965), Jensen (1967), Fama (1970), Rubinstein (1975), Marsh (1979), Tailor (1988) and Brock et al. (1992), have made a remarkable contribution to the explanation of the behaviour of stock markets for improved investment decisions. On the same note, recent studies, such as those by Laopodis (2004), Ferson et al. (2005), Lim et al. (2008), Skogsvik (2008), Balsara et al. (2007), Bettman et al. (2009), Hatemi-J (2009), Borges (2010) and Alexeev and Tapon (2011), have tried to improve the existing inferences and overcome some of the identified weaknesses of the models employed. Despite the conviction of Borges (2010) that the acceptability of the Efficient Market Hypothesis (EMH) in the determination of the behaviour of stock markets has strong ramifications for financial theories and investment strategies, the outcome of a large number of studies on the validity of EMH and many other theories has not led to an acceptable consensus worldwide. The global financial sector has witnessed many crises since the economic depression of the 1930s. This is a clear indication that more needs to be done by scholars to find the best answers to the investment puzzles in stock markets.

1.3 Aim and Objectives

1.3.1 Aim

The research is aimed at exploring the price dynamics of oil and gas stocks quoted on the London Stock Exchange by investigating their information efficiency and volatility behaviour and the suitability of asset pricing models for analysing them.

1.3.2 Objectives

1. To examine the features of weak form market efficiency in the UK oil and gas sector and explore the relevance of technical trading rules.

2. To study the demeanour of UK oil stock returns during different time periods by conducting a seasonality analysis. Days of the week (DOTW) and months of the year (MOTY) effects will be mainly investigated.

3. To conduct an analysis of volatility modelling and forecasting with a view to determining the volatility behaviour of oil and gas stocks on the London Stock Exchange. The modelling and forecasting processes will involve conditional volatility using various ARCH and GARCH model types.

4. To investigate the suitability of a multi-factor asset pricing model augmented with an international crude oil price for the assessment of the relevance of market risk, firm size, book-to-market, Carhart's momentum and crude oil price risk factors in the determination of oil and gas asset prices.

1.4 Justification of the Study

The oil and gas sector has been classified as one of the most crucial industries in the world. The international oil and gas market is estimated to be worth over $1,600 billion ($1.6 trillion) per annum in production and distribution of oil-related products, and over $1,100 billion ($1.1 trillion) per annum in crude oil alone (International Energy Agency, 2014). The increase in the impact of oil activities on the environment and the desire to reduce global warming has also contributed to the amount of attention paid to the industry (Lanza et al, 2005). In this regard, it is imperative to investigate the drivers of oil stock prices and come up with a better explanation of the behaviour of risks and returns to make appropriate investment decisions.

On the London Stock Exchange, the oil and gas sector is the second largest sector by market capitalisation after the banking sector. The banking sector had a market capitalisation of over £658 billion while that of the oil and gas sector was over £656 billion at 31st October, 2014. The sector (oil and gas) accounts for over 15% of the total market capitalisation of the London stock exchange. The two sectors of banking and oil industry account for over 32% of the total market capitalisation of the exchange. It is, therefore, justifiable to design a comprehensive study of this nature of the oil and gas industry to provide sufficient information to investors for investment decision-making.

1.5 Originality and Contribution to Knowledge

1.5.1 Originality

The main aim of the research is to study the volatility behaviour and to review the market efficiency of the UK oil and gas sector. Evidence will also be gathered on the relationship between volatility processes and market efficiency. This is an industry-based investigation and has been justified by the challenges associated with having a cross-sectional examination of various industries with distinct features. The findings of studies on stock markets have been regarded by scholars such as Mittal and Jain (2009) and Mollah (2007) as some of the most contentious in the field of finance. It is also proposed that in order to improve the understanding of equity returns and their risk-return relationship, there should be more control of the variables of a study (Tung and Marsden, 1998). In our effort to address the issues raised above, this research is designed to consider only the oil and gas industry. The research study will be among the few undertaken to examine the volatility and market efficiency of this sector.

Alexeev and Tapon (2011) have opined that in order to achieve the best results of an information efficiency empirical investigation, individual stock returns should be examined instead of market indices. This study will also individually examine all of the oil and gas stocks, the sector indices and the overall market index for comparison purposes. To improve the robustness of its findings, data series for up to 20 years, ranging from 1992 to 2012, are considered. There is no doubt that in recent years, the global financial markets have been highly volatile, particularly due to the 2007/2008 crisis. Investors' confidence in both investment performance and the strategies of the important oil and gas sector has certainly been affected. A study to investigate the volatility and market efficiency of the UK oil and gas sector at this moment will provide welcome evidence that takes into account the contemporary issues. Moreover, scholars such as Taylor (2005) suggest that additional empirical studies are needed to test the theoretical models of changes in volatility.

The application of advanced econometric tools and the critical evaluation of their strengths and weaknesses in this study will make the findings of the research useful to both investors and financial analysts.

Finally, the study will also be important because its dataset covers a period of a stock market boom (2001–2007), an economic recession period (2008–2009) and an economic stability period (2010–2012).

1.5.2 Contribution to Knowledge

The main contribution of this research is to identify the behaviour of oil and gas stocks on the London Stock Exchange and to provide fresh evidence of investment strategies for oil and gas investors, regulators and policymakers. The response of the oil and gas market to the most recent events, such as the recent economic crisis, will also be evaluated.

The study will employ various analytical tools on the same set of data, which will provide a unique framework for the critical evaluation of statistical tools used in similar studies.

Apparently, a similar study has not been undertaken, where information efficiency, volatility and asset pricing modelling are investigated at the same time with regard to London-quoted oil and gas stocks.

The findings of the research will be relevant to contemporary financial matters because the dataset includes one of the longest stock market boom periods (2001–2007) and the worst economic recession (2008–2009) since the Great Depression. Volatility and market efficiency will be analysed on the same set of data, making the contribution of the research highly relevant.

1.6 Structure of the Thesis

The thesis is organised into eleven chapters, out of which five (chapters 6 to 10) cover the key areas of the research namely, a descriptive analysis, market efficiency, a seasonality analysis, volatility processes and asset pricing models respectively. The first five chapters consist of the introduction, an overview of the economic theory, and the structure and operations of the London Stock Exchange. An explanation of the Exchange's oil and gas sector and the research methodology adopted is also provided. Chapter 1 gives the background of the study, against which the motivation and the outline of the objectives to be achieved are explained. In Chapter 2, the competitive nature of the market and its economic importance to the UK are discussed. Chapter 3 gives an outline of the market structure and the details of the trading operations in the Exchange. Chapter 4 consists of a description of the oil and gas sector and its importance to the development of the Exchange. Chapter 5 provides details of the research approach, and the methods and data analysis techniques adopted. Chapter 11, the final chapter of the thesis, provides the overall conclusions from the study.

CHAPTER 2

ECONOMIC THEORY OF THE LONDON STOCK EXCHANGE

2.1 Introduction

This chapter explains the economic and competitive forces in the London Stock Exchange. It gives an overview of the mechanisms that dictate the operations and behaviour of the market. The competitiveness of the market is deemed to affect the practicability of some of the theoretical frameworks adopted in this study. In particular, the assessment of the validity of the Efficient Market Hypothesis could be deficient if the market is not competitive.

Competitive characteristics or elements such as pricing methods, level of transaction costs, transparency and regulatory bureaucracy are studied in the following subsections to determine the level of operational competitiveness in the London stock exchange. The perception of the meaning of 'competition' in an exchange has been described as ambiguous. It is seen in different ways. Requirements include the presence of fair rivalry between market participants in the same economic environment and of a market structure that enables fragmentation for the equal involvement of all participants. In addition, the market should be of sufficient size so that no single participant can influence the pricing of assets, there should be no differential laws and regulations controlling the participants and generally it must be considered as a 'level playing ground'. It must also have free entry and exit and instant perfect information to all participants. Also, the equities traded must be homogenous in terms of risk and return assessment.

The emphasis of the chapter is to examine competition from both within and outside the Exchange by focusing on the level of restrictions on market participants, regulatory flexibility, fair pricing, levels of transaction costs, activities of market makers, brokers and institutional investors, transparency and generally the equality of opportunity given to every participant. In relation to competition among the top stock exchanges in the world, the competitiveness of the London market will be viewed from the angle of its ability to attract new companies for listing, potential investors and other market participants.

2.2 London Stock Exchange and the UK Economy

The London Stock Exchange (LSE) plays a significant role in the UK economy and its development. The UK economy is the world's fifth largest by nominal gross domestic product (GDP) at over US$ 2.85 trillion and the world's eighth largest by purchasing power parity (PPP) at over US$ 2.64 trillion, (International Monetary Fund (IMF), 2015). It is also the fourth largest exporter and importer in the world. It has the second largest flow of inward foreign direct investment which directly reflects the role of the London Stock Exchange in attracting foreign capital. The economy is generally characterized as a free but partially controlled market and among the most globalized in the world. As the first economy that witnessed the industrial revolution in the mid-18th century, it has a remarkable influence on the overall global economy with its capital city of London being one of the largest financial centres in the world. Unsurprisingly, the Exchange remains one of the largest security markets in the world based on parameters such as market capitalisation, number of listed companies (both foreign and local) and incentives to small and growing companies seeking share quotations, (Lees, 2012). In 1986, the exchange had undertaken a major restructuring of its market structure in activities referred to as 'Big-Bang' and that became a blueprint for other exchanges in the world. The key changes during the 'Big-Bang' era encompass the permission of 100% external ownership of the Exchange, abolition of fixed commissions and charges, distinction between the functions of stock brokers and that of stock jobbers, introduction of the fully automated trading systems and changes in the regulatory framework of the Exchange. The Exchange also become a private limited company under the Companies Act (1985) and stopped individual members from having voting rights as part of the deregulation that took place during the period. It was reported that, not long after the 'Big-Bang' deregulation, the New York Stock Exchange (NYSE) undertook a similar reorganisation. For this reason, the London Stock Exchange is also referred to as a 'pace-setter' in the operational or business model of global financial exchanges.

The London Stock Exchange had a market capitalisation of over US$6.06 trillion (£4.09 (GBP) trillion) as at the end of December 2014 which was more than 200% of the country's nominal GDP. As of March 2015, there are 2,426 companies from over 100 countries that are listed on the exchange. 44% (or 1,088 companies) are listed on the Alternative Investment Market (AIM) and 1,338 companies are listed on the main market. According to the published Annual Report (2014) of the London Stock Exchange Group (LSEG), the capital market segment has generated revenues of over £309 million representing about 26% of the group's total income for the year ended March 2014. The income from the capital market is derived from the three segments of primary listing, secondary trading and other service activities. The primary segment generates income mainly from admission fees for new listings, for raising additional capital and from annual charges levied on all listed companies. From the secondary segment of the market, fees on transactions (value traded) in existing UK equities and bonds are mainly the source of income. Membership fees from firms and other market players such as stock brokers, stock jobbers, market makers, clearing firms or houses, issuing security firms, advisers and underwriters to access the trading markets constitute part of the other activities that generates income for the market. Pricing procedures and the level of other fees are among the attributes to be explored in order to assess the competitiveness of the Exchange.

LSE remains attractive to investors because of its dynamic nature especially after the 1986 Big-Bang deregulation that created the automated trading system in which face-to-face trading was substituted for computer-based trading, the AIM for small and growing companies and the techMARK exchange for high-tech and healthcare companies. The extent of competitiveness in the London stock exchange would have a significant impact on the global financial position.

2.3 Competitive Attributes of the London Stock Exchange

In the context of stock exchanges, the level of competition in their operations is determined by the characteristics of competitive elements which are considered to be a reflection of the transparency and effectiveness in policy formulations of the Exchange. The most influential elements considered in this chapter are discussed in the following subsections.

2.3.1 Pricing and Trading Volume Information Disclosure

Millenium IT (an information technology firm owned by the LSE) provides most of the trading facilities and services at the London stock exchange that are used in the pricing of listed securities. The trading services are designed to cover different segments of the market based on the nature of its trading activities. For instance, SETS (Stock Exchange Electronic Trading Service) provides a platform as an electronic order book giving executable price quotations for the constituents of the FTSE 100 (a share index that constitutes the top 100 companies that have the highest market capitalisation on the LSE), FTSE 250 (a share index that constitutes the 101^{st} to 350^{th} companies in market capitalisation on the LSE) and FTSE SmallCap (a share index that constitutes the 351^{st} to 619^{th} companies in market capitalisation on the LSE) indices, highly liquid AIM securities, Irish and London secondary listed securities. SETSqx (with the support of market makers) is a similar platform to SETS but delivers non-electronically executable quotations and covers main market securities that are not traded by SETS. There is also SETSqx (without the support of market makers) which is an electronic order book auction for the main market securities that are not traded via SETS and not supported by market makers. Stock Exchange Automated Quotations or SEAQ is another trading platform or facility that provides a non-electronically executable quotations for sterling bonds and convertibles with market maker support. There are numerous trading facilities such as the ones listed above in the Exchange that allow the execution of trading activities which directly deals with the pricing of securities.

The disclosure of information with regard to the pricing procedures and trading volume is a key element that signifies the extent of transparency and competitiveness of the Exchange. The information include the details of the trading schedule with the timings, basis of calculating both the opening and closing prices, price monitoring activities, market maker activities, settlement processes and trading volume. The rules of the London Stock Exchange contain a section that provides the requirements or standards for the disclosure of information. The standards in the rules have emphasized that market participants should ensure information disclosed or released in the Exchange is in all respects accurate, timely, complete and not misleading. The trading volume information also plays an important role in determining the market forces of demand and supply and thus the security price. Presently, the Exchange also displays on its website the information on five-day trading volume of every listed security and that enhances transparency. The turnover volume and value including the number of trades undertaken are also published on daily, monthly and yearly basis on the Exchange’s website. However, the monopolistic status of Millenium IT that provides the facilities for trading services may hinder the competitiveness that is expected from the market. The firm is the major provider of the automated trading facilities or platforms on the Exchange and being without a competitor that could affect the effectiveness of the services. Although appropriate rules exist, it is always difficult to ascertain if there is full and effective compliance.

2.3.2 Settlement and Clearing Processes

Member firms are expected by the 'Rules of the Exchange' to ensure that every transaction effected by them is duly cleared and settled at a reasonable time. It does not matter whether the member-firm acted as a principal or an agent. Clearing member firms are expected to clear all trades after each transaction provided they are part of a clearing membership agreement with any relevant central counter party (a firm that takes the risk of being a selling party to a matched buyer and also being a buying party to a matched seller) in a given central counter party security. It is a process that occurs after the electronic trading of matching buyers and sellers using trading facilities has taken place. After the matching of buyers and sellers (electronic trading), clearing firms would take the risk of being buyers and sellers and, if there is a default from any of the actual parties, the clearing firm must buy or sell the stock. Settlement occurs after clearance and it is the process of delivering the title of ownership of the financial instruments to the actual owner which is usually after three days in terms of equity stocks. The settlement should comply with the terms agreed during the time of the trade or transaction. In both the clearing and settlement processes, participating members are expected to comply with the provisions of the rules in order to make sure the market is efficient. Since 2014 the Financial Conduct Authority (FCA) under which the LSE operates has placed an obligation on the Exchange to ensure adequate supervision of the activities of any member-firm that uses its facilities. The efforts of the FCA are meant to provide equal opportunities to all market players as well as enhance the competitiveness of the Exchange.

2.3.3 Pricing Initial Public Offerings (IPOs) and Transaction Costs

The issue of pricing procedure for Initial Public Offerings (IPOs) in the London Stock Exchange is considered an important element in the determination of the exchange's competitiveness. An IPO is the first public issue of equity shares by a company seeking a quotation on a stock exchange. It is also referred to as a flotation in the UK markets and provides an opportunity of transforming a private company (Ltd status) to a publicly listed company (Plc status). It is an important process that involves a number of participants such as banks, accountants, underwriting firms, financial advisers, consultants and legal firms. The London's IPO market has been very vibrant over the years compared to other world major stock exchanges. According to the LSE Group's Annual Report (2014), the exchange had raised about £6.5 billion as equity capital for new companies from IPOs in the year ended 2014, so generating about £39.9 million in income for the Exchange. The Alternative Investment Market (AIM) is another segment of the LSE that showed evidence of high new share issue activity. In the year ended 2014, over 100 small and growing companies were floated on the market contributing a significant proportion of the £39.9 million generated from IPOs by the exchange in 2014.

The process of pricing and valuing IPOs is seen as a significant element in assessing the competitiveness of an exchange. The concern of whether IPOs are traded at an issue price below or above the real value of companies, thereby giving undue benefits to some individuals and institutions, depends on the transparency in the exchange. Financial institutions acting as issue managers could over-value companies that are preparing IPOs in order to secure business deals from the firms. Similarly, company managers can also set the issue price of IPOs at less than the true value if they are also potential owners of the floated companies, so that they pay less for ownership. In a publication entitled *'Leadership in a changing global economy: the future of London's IPO market'* by the London Stock Exchange Group (2011), it was confirmed that there were comments on the lack of transparency in London's IPO market which gives an added advantage to some individuals and results in the sudden rise of share prices immediately after flotation. However, the report has concluded that the basis of those comments were unsubstantiated and opined that London's IPOs are more fairly priced compared to other international stock exchanges such as New York (NYSE) and Hong Kong (HKEx). On the same note, the report recommends a way forward by supporting the establishment of more avenues for pre-IPO engagement and research where stakeholders can have enough time to assess companies in the pipeline for an IPO. Scholars have also argued that the fee structure of IPOs is more dependent on the current financial position of companies than on their long term stability. This has contributed to security issuing houses over-valuing company shares to maximize the fees paid to them. To improve fairness in the pricing of IPOs, the exchange should ensure transparency in all the processes of floating a company by involving investors (representation from investor clubs, unions or associations) in the valuation of companies.

Transaction costs such as brokerage commissions and other trading fees incurred when selling or buying shares in the secondary market and stamp duty charged during the flotation of shares are considered to be high in the London stock exchange. According to Financial News (2015), LSE transaction costs are almost four times higher than that in some competitor exchanges such as BATS Europe (a recognised pan-European investment exchange in the UK and subsidiary of BATS Global Markets that is based in Kansas, United States). Hawkins and McCrae (2002) explain that the key components of transaction costs include the brokerage commission and bid-ask spread. The brokerage commission in the LSE ranges between 0% for institutional investors and 5% for smallest private investors. The bid-ask spread varies according to the type of securities, market segments and method of trade (via order book, off order book, electronically or non-electronically). According to London Stock Exchange (2001), the total transaction costs in the Exchange in the first quarter of 2001 was 0.72% including stamp duty. The LSEG (2011) report on the future of London's IPO market also confirms that the stamp duty on the transaction value of shares (0.5% of the transaction value) in the LSE and in the South Korea Exchange has the highest rates in the world, exposing these markets to competitive disadvantage. It is arguable that the competitiveness of an exchange is improved if trading costs are not set at a level that is too high. The assessment of the market efficiency of the London Stock Exchange in this research would be affected by the level of transaction costs that exist in the market. It is for this reason that we plan to incorporate or consider these costs in the empirical tests employed.

2.3.4 Membership and Annual Fees

On admission, new member firms (such as brokers, advisers, market makers and underwriters) of the London Stock Exchange are required to pay a fixed admission fee of £10,000 which entitles the firms to operate for the next 12 months without paying annual fees. Existing member firms pay a flat rate of £12,500 in annual fees although an annual credit of £2,500 is given against the fees charged for the use of trading services for equities and exchange traded products. The membership of the exchange allows the member firms to undertake various trading services under relevant regulations in the market. In its effort to improve the competitiveness of the exchange, LSE has made some changes to the membership structure of fees which include payment of flat rate annual fees instead of using annual headcount declarations of activities to calculate yearly fees, the introduction of a 20% discount on annual fees and an annual credit of £2,500 on fees for the use of trading services. It is believed that these changes would enhance transparency and also reduce administrative bureaucracy. In contrast to LSE, the membership fees of the New York Stock Exchange (NYSE) are not fixed but are determined by the forces of demand and supply which range between $4,000 and $2,500,000 per annum. In the case of low demand for membership of the NYSE by potential member firms, the fee could be significantly lower than that of the London Stock Exchange. In the Tokyo Stock Exchange (TSE), basic annual fees for membership are JPY400,000 (£2,200) per trading participant which is also lower than that of the LSE. At the Frankfurt Stock Exchange (FSE) membership annual fees are between €2,500 (£1,800) and €6,000 (£4,312).

In the face of efforts by the LSE to reduce its membership fees and the level of administrative bureaucracy, the exchange's annual fees remain the highest among many top stock exchanges in the world. Based on the comparison of fees between LSE, NYSE, TSE and FSE made above, the LSE would have a competitive disadvantage because, with the globalization of stock exchange activity, competent market participants may seek membership on less expensive exchanges.

2.3.5 Member Firms of the London Stock Exchange and their Activities

Most of the activities of the LSE are undertaken by its member firms. The members of the Exchange (referred to as 'member firms') are firms that specialise in areas such as stockbroking, market making, trading services, underwriting, listing of securities, provision of investment advice, market making, clearing and settlement services, share issue activities and other legal services. These services are usually rendered to clients (companies seeking equity capital, plus individual and institutional investors) using trading facilities available at various platforms of the Exchange. The firms are admitted as members based on certain criteria and requirements of the Exchange. As of May 2015, the London Stock Exchange has over 800 registered members that are allowed to operate in various market segments such as new equity capital market, fixed income market, derivatives markets and trading systems based on their expertise. In carrying out their duties, the admitted members need to have access to real time market data and trading facilities in order to render effective and competitive trading services. From their own part, the member firms ensure compliance with the 'London Stock Exchange Rules' and the timely payment of all applicable fees. In return, member firms are expected to operate in an environment characterised by having fair treatment and equal opportunities to all members. For the Exchange to be competitive, there must be perfect, free and instant information together with free entry and exit for all participants. However, the extent and strictness of 'Rules', the different sizes and specialisms of member firms and the high admission and annual fees may negatively affect the competitiveness of the Exchange. The Exchange has been characterised as having high admission and annual fees compared to some of the top world's stock exchanges. Having fixed fees and stamp duties can also affect member firms that are small in size. The specialist or professional segments of the market such as the Specialist Fund Market (SFM) and Professional Securities Market (PSM) where only member firms that possess the appropriate skills can operate may bring unfairness to other participating members. For instance, the listing of Islamic bonds on the Exchange which raised over US$ 51 billion to date may require only the services of member firms that have the knowledge of Islamic legal system and that may put other members at a disadvantage. The Exchange should provide a platform where all members can acquire the basic knowledge of dealing in specialist securities in order to have an equal opportunity of participation. In addition, fixed admission fees irrespective of a firm's size should be abolished and replaced by a system that recognises the different sizes of participating member firms.

2.3.6 Activities of Market Makers, Brokers and Institutional Investors

The activities of market makers, brokers and institutional investors remain contentious when it comes to the issue of whether all member firms are given equal opportunities of participation. Market makers or liquidity providers are firms that quote both the buy and sell prices of a stock and are prepared to buy or sell at any time in order to make profit from the bid-offer spread. Stockbrokers are known as agents or mediators that buy or sell stocks on behalf of individuals and institutional investors for a commission referred to as brokerage. Institutional investors are organisations that put together large funds for investment in securities and other assets. Pension funds administrators, unit trust and mutual funds managers, insurance companies and investment trusts companies can all be institutional investors. Market makers, stockbrokers and institutional investors are key players of every stock exchange and can equally be registered as members of that exchange. If a market lacks transparency, market makers can influence the price of securities to their advantage or that of institutional investors. On a similar note, institutional investors can gain undue advantage by having access to any market information that is not available to other investors. Therefore, the activities of these players are supposed to be monitored for the purpose of ensuring fair competition among all the participants. In the London Stock Exchange, there are established market making rules that are related to both order and off order book trading. The rules contain the registration process of a member firm as a market maker, obligations such as the minimum size of quotes and any exceptions to those obligations. The contentious issue is whether the rules are effectively complied with by all market participants.

2.3.7 Regulatory Framework

The structure of the financial market is mainly regulated by the Financial Services Act 1986 (FSA) which was superseded by the Financial Services and Markets Act 2000 (FSM) and also the Financial Conduct Authority (FCA) alongside the Prudential Regulatory Authority (PRA) in 2012. The Financial Conduct Authority (FCA) and the Prudential Regulatory Authority (PRA) are now responsible for the various statutory and regulatory provisions guiding the operations of the market. Formerly, this was undertaken by the Financial Services Authority (FSA). A new trading system or an exchange such as BATS Europe or the LSE itself has an option to choose between the various laws and regulations of operation in the United Kingdom. The choice depends on whether the trading system or the exchange is to conduct investment business or other financial services in the UK. For investment business, the exchange may select either to be authorised for operations or be exempted if it operates outside the UK under the former Financial Services Act. Before the introduction of the Financial Conduct Authority (FCA) and the Prudential Regulatory Authority (PRA), the authorisation could also be obtained directly from the Securities and Investment Board (SIB) (a body formed as a regulator to ensure compliance with most of the provisions of both the defunct Financial Services Act and Financial Services and Market Act) or indirectly by being a member of one of the Self Regulating Organisations (SRO) such as the Securities and Futures Authority (SFA) and the London Stock Exchange (LSE). As a former self-regulating organisation, the Securities and Futures Authority (SFA) governs all firms such as issuing houses and banks operating in the UK securities and futures markets with a primary role of protecting investors. Automated trading firms such as BEST, POSIT, TRADE and Instinet (firms that provide and manage automated trading systems in the Exchange before the acquisition of MilleniumIT by the London Stock Exchange Group) have chosen to be regulated indirectly by becoming members of both the Securities and Futures Authority (SFA) and the London Stock Exchange (LSE) as self-regulating organisations. A trading system can also select to be exempted from regulations under the Financial Services and Markets Act if it does not carry out investment business in the UK or outside the UK. The exemptions are obtained through becoming a member of any of the international securities SROs such as the International Securities Market Association (ISMA), Recognized Overseas Investment Exchanges or Recognized Investment Exchanges such as the National Association of Securities Dealers Automated Quotation (NASDAQ). The new Financial Conduct Authority (FCA) and the Prudential Regulatory Authority (PRA) have taken over the functions of the SIB and the SFA as well as the supervision of SROs which were under the former Financial Services Act in order to streamline the financial regulations in the UK.

The London Stock Exchange is a Self-Regulating Organisation (SRO) that has specific rules and regulations referred to as 'Rules of the Exchange' with which members must comply. The rules of the exchange provides the overall code of conduct in the London Stock Exchange and are the operational requirements for all member firms. Trading rules for both order and off order books are also specified. An order book is an official list of both buy and sell orders from potential buyers and sellers of a security while an off-order book refers to 'outside order book' or in other words, not recorded in the order book. In trading, member firms can decide to use order book trading strategy where the Exchange's trading system or facility is used to record and match buy and sell orders. They also have the option to boycott the Exchange's trading facility in selling or buying a security. Guidelines for market makers (MM) who are member firms such as J.P. Morgan Securities Plc, trading settlements and clearing processes are also provided. It also has the details of compliance procedures and default consequences for any member firm that fails to comply with the rules. Companies that are listed on the exchange are deemed to have been complying with one of the most respected sets of admission and disclosure requirements, (London Stock Exchange, 2015). Both potential and existing investors in those companies would also be expected to enjoy the benefit from the system that ensures the highest operational standards for investor confidence. The LSE admission and disclosure standards (rules and responsibilities with regard to admission of companies for trading and continuing obligations of member-firms and admitted companies in disclosure of information) are provided for companies based on the route into the main market or the Alternative Investment Market (AIM). Larger companies comply with higher or strict standards compared to the admission and disclosure standards of growing companies. Subsequent to the successful admission and listing of a company's equity on the Exchange, there are also numerous continuing obligations for quoted firms such as adherence to market guidance, payment of fees, compliance and appeals, time tabling for corporate actions, disciplinary procedures and compliance with changes in market procedures.

The assessment of the regulatory framework as a competitive element of the London stock exchange could indicate the strength of its competitiveness. The option to choose between various laws and regulations under which to operate by market participants could be seen as a flexibility that can improve competitiveness. However, the bureaucracy involved in the selection and administration processes could also hinder the attainment of that objective. The introduction of both Financial Conduct Authority (FCA) and Prudential Regulatory Authority (PRA) has reduced some of the bureaucratic upheavals at least by becoming the key regulators of the financial services industry.

2.3.8 Market Bureaucracy and Ease of Operations

According to reports by the London stock exchange, the management of the exchange has been undertaking a series of actions since the 1986 'Big-Bang' deregulation to reduce its level of bureaucracy and improve ease of operations. A technology roadmap project has been in the pipeline where significant resources are committed to transform the LSE for ease of operations. Part of the project includes the establishment of the 'Infolect market data system' which has already increased the trading speed to 15 times faster than before. The system provides tick-by-tick (change of a price from one trade to another) real time data that helps in the dissemination of pricing and other trading activities information. Ernst and Young (2009 p12) stated that the former CEO of the LSE, Clara Fuse, had made a declaration that "the heightened speed is critical for the LSE to remain competitive globally". Other transformations undertaken to minimise market bureaucracy and ensure ease of operations include the admission of various automated trading systems such as Instinet, BEST, POSIT and TRADE into the market (Lee, 1998). The success of these trading systems has made LSE become one of the most automated exchanges in the world. Regulatory and corporate governance flexibility was also ensured by the founding of the Alternative Investment Market (AIM) segment of the exchange. Small and growing companies seeking a listing are now facing less administrative bureaucracy and regulatory restrictions which enhances ease of operations in the market. According to the London Stock Exchange Group (LSEG)'s Annual Report (2014), there are almost 3,500 companies listed on AIM as of March 2014 and the market had raised over £85 billion of equity capital for small companies. However, the exchange has been described as having a complex regulatory and operational structure that consist of numerous requirements, standards and oversight functions.

2.3.9 Transparency and Competitive Practice

The disclosure of pricing procedures and quote information (allowing member firms to have access to the information and processes undertaken to match buy and sell orders such as access to order books) has been one of the key elements of transparency and competitive practice in stock exchanges. If trading information is published (by sending the information to Infolect market data system) immediately to all stakeholders (member firms), a level playing ground that promotes competitiveness would be ensured. The London Stock Exchange has standards that are related to disclosure of information as part of the continuing obligations of all market participants who are mainly the member firms. Some of the requirements include the disclosure of a timetable for corporate actions such as business acquisition that may affect existing investors to the stock situation analysis team of the Exchange. The argument of whether there is transparency in the disclosure of pricing information in the LSE has not been resolved. There are claims that IPOs in the Exchange lack transparency and that gives an added advantage to some individuals and institutions, (LSEG, 2011). Proposed actions such as the time extension of pre-IPO engagements with investors and other stakeholders could improve transparency in the Exchange. An important step in the implementation of a transparency directive effective from 20 January 2007 was also undertaken by the LSE to boost the level of transparency. The directive was designed by the European Commission to ensure that the same information disclosure framework exists between the European exchanges. It stipulates among others that firms should disclose information at regular intervals such as annually and half yearly or where interim management reports are expected for the first and third quarters of the year through the same channels of communication such as interim management reports to managers and directors together with annual or final reports to the shareholders. Stock exchanges have been claiming to act in a way that enhances transparency and competitive practice but whether this actually happens is another question to be answered.

2.4 Conclusion

The ambiguity of determining the level of competitiveness in the operations of a given stock exchange has made it difficult to easily identify whether the London Stock Exchange is competitive. Despite the difficulty we have assessed some competitive elements in the exchange that may provide an idea of the market's strengths and weaknesses. In our assessment, we have seen characteristics of both competitive and uncompetitive practice. The key elements that enhance the competitiveness of the LSE are the continued technology transformation, globalisation and flexibilities in choosing the regulations under which market participants can operate. In technology transformation, the exchange has ensured the successful implementation of various automated trading systems that facilitates competition among the systems as well as external competitive advantage. It was also found that the exchange has programmes in place to extend its globalisation to countries such as China, India and Russia as markets for companies seeking new share listings similar to the exchange's coverage in Italy. In contrast, signs of non-competitiveness were also observed and the most prominent are the high membership and annual fees, transaction costs and stamp duty on shares. The presence of these exorbitant charges may not provide a level playing ground for all the market participants. The existence of numerous laws and regulations guiding every aspect of trading and other activities in the exchange is another indication that such regulations are set without consideration to the international competition facing the exchange.

CHAPTER 3

STRUCTURE AND OPERATIONS OF THE LONDON STOCK EXCHANGE

3.1 Introduction

The chapter consists of a brief historical trend, market structure and the main operational activities of the London Stock Exchange. Major events in the history of the exchange are identified as key points in the review of its historical trend. In assessing the exchange's market structure, an overview of the overall London Stock Exchange Group (LSEG) and a review of the various market segments established for specific types of securities will also be provided. Lastly, some of the major operational activities of the exchange would be equally highlighted.

3.2 Brief Historical Trend of the London Stock Exchange

The history of the London Stock Exchange can be traced back over 300 years ago. The evidence of the existence of a market became obvious in 1698 when John Castaing was found to be listing some stocks and other commodities in the city centre of London for sale or exchange. Coffee houses were the meeting points for these transactions until 1748 when an accidental fire destroyed most of them. After the coffee houses were rebuilt and trading activities continued to be undertaken, major ideas that changed the trading style began to emanate. In 1761, stock brokers and jobbers met and formed a club for buying and selling stocks and at the same time protecting their interests. Stock brokers are agents that buy or sell stocks on behalf of individual and institutional investors while stock jobbers act as market makers that keep stocks to ensure smooth trading by dealing with the brokers. Subsequent to the formation of the club, they set up their trading activities in their preferred building at the Sweeting's Alley. The building included a dealing room and other facilities needed for convenient trading. Soon after that, members of the club referred to the building as 'The Stock Exchange' and gradual transformation continued until 1801 when the Exchange was officially established.

The London Stock Exchange (LSE) was formally founded in 1801 and it is presently part of the London Stock Exchange Group (LSEG). The group comprises of the Borsa Italiana, Italy's main stock exchange that was acquired in 2007, the Turquoise Exchange, which is a platform that provides access for secondary trading of various securities that are quoted in both the USA and all major European markets across 19 countries, MTS Market International Inc., which is a fixed income securities market that trades most European governments' bonds and the LSE itself. It has also acquired Millenium IT in 2009, which is a Sri Lanka-based information technology firm that specialises in the provision of electronic trading services and serves as the trading system base of the Exchange and the LCH Clearnet Group, which is a world leading clearing company. Therefore, Borsa Italiana, Turquoise, MTS, Millenium IT, LCH Clearnet Group and LSE are presently the subsidiaries of LSEG and each has a different structure that dictates its operations.

The historical trend of the London Stock Exchange can be seen in stages. Firstly, its transformation from an informal market to a formal exchange took place between 1693 and 1801. As highlighted above, LSE existed before 1801 as an informal market or meeting place where securities were traded between sellers and buyers. At that time, there were no intermediaries or any formal set up for the purpose of undertaking security transactions. A few wealthy individuals undertook private negotiations or agreements between themselves to buy or sell securities of joint-stock companies such as the East India Company and the Hudson's Bay Company which were mainly traded in London's informal securities market. Prior to 1689, there were only 15 joint-stock companies in the UK but the number started growing with a diversification of businesses. In 1695, the number of joint-stock companies increased to about 150 including the Bank of England which was formed in 1694. Due to these developments, the informal market witnessed an influx of many investors and other market intermediaries which warranted the need for a formal set-up with appropriate facilities to handle the activities of the market. As a response to those needs, the LSE was formally established in 1801 with structures and facilities that could underpin the rapid development of the market.

Secondly, the exchange experienced another significant transformation from dealing in mainly short term securities to trading in long term securities between 1801 and 1851. It was more of a short term money market after its formation in 1801 and took about 50 years to witness a shift that allowed the exchange to become more of a long term capital market as defined by the intensity of its relationship with money and capital market institutions.

Evidence of this shift was seen in the development of the railway industry where the value of its long term securities increased in 1845 by a factor of 12 compared to its value in 1835. Similarly, the proportion of corporate debt to total financial assets in the Exchange increased to 16% in 1850 from just 7% in 1760. This advance resulted in more institutions such as brokers, institutional investors and financial advisers beginning to play a role in the market activities. It has also witnessed the introduction of further rules and regulatory authorities that helped to improve the formal dealings in the market. During this period most of the securities were domestic with little involvement in international business. However, the continued growth of the exchange encouraged international communities to take an interest in the activities of the London Stock Exchange.

Between 1850 and 1914, the exchange began another journey from a domestic market to a more international structure by attracting significant interest from international investors and institutions even though that was surpassed by the demands from local investors and institutions. The evolution of communication facilities such as the telegraph and the telephone contributed positively in the beginning to the process of the internationalisation of the exchange. The organisational structure of the Exchange had to change to accommodate these developments and thus a distinction was particularly made between owners and managers or members of the Exchange. Michie (1999) opined that the growth and sophistication in the classes of participants in the market have led to the present state of its modernisation. Major political and economic events such as the First World

War (1914-1918) and the Second World War (1939-1945) have also affected the development of the exchange.

The history of the LSE would not be complete without mentioning the 'Big Bang' and 'Black Hole' episodes. In 1986, the LSE undertook significant reforms that became the most recognised in the history of the exchange. The transformation was termed 'Big Bang' and some of the key changes included the removal of fixed commission charges by brokers on transactions, separating the functions of stock jobbers from that of stock brokers, regulatory changes and the introduction of an electronic system (computer-based) of trading as opposed to face-to-face trading. During the period, the Exchange was also converted to a private limited company under the provisions of the Companies Act 1985. Following the Big Bang, the market structure had to further change due to the increase in the number of both foreign and local institutions operating in the market. Scholars have argued that the 'Big Bang' was an event that eased the operations in the market and also enhanced its competitiveness.

The need for financial integration among stock exchanges resulted in another set of changes in 2001 referred to as the 'Black Hole', which reflected the challenges facing the sustainability of all stock exchanges. Any stock exchange that sought to be successful needed to reorganise its structure and operations in order to face the challenges of globalisation. The London Stock Exchange was not an exception and therefore witnessed massive improvement in its automated trading systems, most particularly with the Stock Exchange Electronic Trading Service (SETS) that was established in 1997. In 2007, the

Exchange acquired Borsa Italiana and thus created the London Stock Exchange Group (LSEG). The LSEG also acquired a 60% shareholding of the Turquoise Global Holdings Limited (TGHL) in 2009. This was an investment firm established in 2008 by a consortium of nine investment banks including Citi, Credit Suisse, Merrill Lynch, Morgan Stanley, Goldman Sachs, UBS, BNP Paribas, Societe Generale and Deutsche Bank. MTS was also a subsidiary acquired by the group and serves as a market for European fixed income securities and has about 25 years of innovation in that sector.

Today, the London Stock Exchange is considered to be one of the most advanced exchanges in the world despite the fact that the Amsterdam securities exchange was the world's principal point of security trading in the seventeenth century, although not recognised as a formal organisation at that time. A similar market location recognised as prominent was that of Paris. However, the effect of the French revolution and Napoleonic wars had resulted in the temporary disintegration of the Amsterdam and Paris stock markets and favoured the growth and development of the London Stock Exchange.

3.3 Market Structure of the Exchange

The London Stock Exchange as one of the subsidiaries of the LSE Group (LSEG) has its own distinct structure. This structure can be explained by the composition of various firms that are its members, including platforms for raising equity capital, fixed income markets, derivatives market and the trading systems which provide services in the Exchange. The LSE is operated by registered member firms such as stock brokers, investment banks, market makers and providers of trading facilities. The firms have to meet the Exchange's membership requirements and pay the appropriate admission fees before being admitted as member firms of the LSE. They are allowed to directly undertake trading activities in the Exchange or indirectly by using any of the Exchange's trading platforms. As of May 2015, there were over 800 firms operating as members of the LSE and these formed a network of over 350 trading participants in the Exchange.

The platforms for raising equity capital in the Exchange consist of the Main Market, the Alternative Investment Market (AIM), the Professional Securities Market (PSM) and the Specialist Fund Market (SFM). The Main Market is the flagship bearer of the London Stock Exchange and it is where most of the international companies are quoted. It has listing requirements and other operational guidelines that are considered to be the most comprehensive in the world. The more established equity securities of large companies are listed on the main market. In hierarchical order, the Alternative Investment Market (AIM) is a segment of the LSE that follows the Main Market in operational significance. Securities of both local and international growing companies that are less established in comparison to those of the Main Market are listed on the Alternative Investment Market (AIM). The Professional Securities Market (PSM) serves as a segment for listing specialised securities of a complex nature for professional investors in the market. It comprises different types of more sophisticated securities, debt instruments such as Islamic bonds and other depository receipts certificates. The PSM was invented to serve the specific needs of issuers of listing securities that have special or unique features such as that of marine companies. Both AIM and PSM have specific listing requirements and operational guidelines similar to that of the main market. Specialised investment funds are traded in another separate market termed the 'Specialist Fund Market (SFM)'. It is a segment that allows specialised investment firms to target institutional or highly knowledgeable individual investors. A high-technology company can issue its securities on the SFM for industry knowledgeable investors to invest. In all these segments, the member firms of the LSE provide the services to the trading activities of every market. The role of the member firms in handling the specialised segments of the market has contributed to the transformation and internationalisation of the London Stock Exchange. It has about 2,426 companies listed as of March 2015 with a market value of over £4.09 trillion making it among the top four stock exchanges in the world. The listed companies represent 47 different industries or sectors and 114 sub-sectors. Out of the total listed companies, 1609 companies are incorporated in the Great Britain while 817 companies are incorporated in countries other than the United Kingdom. From the total number of 2,426 companies, 1280 companies are listed on the Main Market. Only 641 companies are qualified for inclusion in the FTSE All Share Index which captures about 98% of the total market capitalisation of the UK's Main Market while the remaining 639 companies feature in other FTSE indices based on any given selection criteria. 1088 companies are listed on the Alternative Investment Market (AIM), 35 companies on the Professional Securities Market (PSM) and 23 companies on the Specialist Fund Market (SFM).

The fixed income market provides a place for the trading of gilts (UK government fixed interest bonds), conventional corporate bonds, retail bonds (more flexible bonds that are accessible to private investors) and Islamic bonds. The gilts are UK government bonds denominated in sterling and issued by Her Majesty (HM) Treasury. The market makers or dealers of the gilt securities are referred to as 'Gilt-Edged Market Makers (GEMMs)'. The GEMMs are also registered as members of the London stock exchange. Conventional corporate bonds can also be issued on the main market or the professional securities market as simple bonds, Eurobonds, complex asset-backed bonds, convertible bonds, exchangeable bonds or high yield bonds. The LSE has been described as being a 'deep pool of capital' which provides bonds issuers with easy access to global capital at very competitive trading fees. In order to ensure greater accessibility to fixed income securities, the Exchange introduced an Order Book for Retail Bonds (ORB) in 2010. The ORB is an electronic order book for retail bonds that allows private investors to buy and sell fixed income securities more easily. The flexibility and lower requirements for transactions in these bonds are the key features of retail bonds. Islamic bonds (Sukuk) are fixed income securities that are issued based on the Islamic legal system (Sharia). To date, LSE has raised over US$ 51 billion from these type of securities.

The LSE also has a segment for derivatives financial instruments that gives member firms the opportunity to raise funds from innovative financial instruments such as Russian depository receipts and dividend derivatives. Derivative contracts such as Options, Swaps and Futures in equity and bond securities are also listed on the Exchange's derivatives market.

Effective trading systems are needed to provide services that can easily co-ordinate and monitor all the trading activities taking place in the various market segments highlighted above. In the London Stock Exchange, the trading systems are provided by the facilities of Millenium IT which specialises in the provision of electronic trading services to stock exchanges. It serves as the system that provides domestic and European trading services as well as international trading services in the Exchange. These services are part of the key operations of the Exchange presented in the next sub section.

3.4 Operational Activities of the London Stock Exchange

The key operations of the London Stock Exchange revolves around the admission of firms as members of the Exchange, the listing and pricing of new securities, the secondary trading of listed securities, clearing and settlement procedures, domestic, European and international trading services and other day-to-day operations such as the provision of regulatory oversight functions. The admission process of new members and the oversight functions on their activities by the Exchange are part of its important operational activities. Potential new members such as brokers and market makers (companies only) interested in undertaking a trading activity in the market would be expected to complete a form and send an application to the Exchange. In the application, a potential member can also indicate clearly the area of its operation such as market making. The Exchange has a membership team that scrutinise an application based on the set criteria for approval. If approved, the Exchange also provides an oversight function to ensure that every member complies with the rules of the Exchange.

The listing and pricing of securities are other key areas of the Exchange's operations. It is responsible for the admission of a company's securities being traded in the market. The responsibility of approving company prospectuses and entering them on the 'Official List' lies with the UK Listing Authority (UKLA) as a unit of the Financial Conduct Authority (FCA). The Exchange continues to supervise the activities and stock dealings of all companies admitted or listed. The procedures for listing of new companies comprised the pre-float preparation (where companies prepare prospectuses, business plans, ownership structure and also meet all the requirements of the Exchange), the listing process (where companies appoint member firms of the Exchange as issuers, advisers, underwriters and follow the step-by-step guidelines for admission) and the passporting into the market where capital can be raised. It is part of the key operations of the Exchange to provide adequate supervision of all market players. In the pricing of securities, the Exchange has established both electronic and non-electronic trading systems that facilitate effective pricing with the support of its numerous member firms. An avenue for clearing and settlement of trading after pricing was also provided by the Exchange and the importance of its oversight functions cannot be overemphasised. This function of the Exchange covers all domestic, European and international trading services. Disciplinary powers can be exercised on any member firm for non-compliance with applicable laws and regulations.

A brief overview of the stages of the trading process at the London Stock Exchange is presented in Table 3.1 below.

Table 3.1 Stages of Trading Process at the London Stock Exchange

<table>
<tr><th colspan="2">Stage</th><th>Description</th></tr>
<tr><td colspan="2">Placement of buy or sell orders through stock brokers</td><td>A buyer or seller of securities usually place an order through stock brokers. The brokers present the orders in the Exchange as agents of their clients (buyers and sellers) for a commission. These orders are the initial inputs for the electronic trading.</td></tr>
<tr><td colspan="2">Electronic trading by automated trading system</td><td>Computerised system of matching buy and sell orders of securities</td></tr>
<tr><td rowspan="3">Post trade</td><td>Clearing Procedures</td><td>After matching buy and sell orders, the trade is cleared by a central counterparty (clearing house) that takes the risk of standing as the buyer of the sell orders and the seller of the buy orders. If there is any default by the actual parties of the orders, the clearing house ensures that there will not be any disruption to the process. The clearing house keeps a record of any variation after matching the orders due to a default.</td></tr>
<tr><td>Settlement Procedures</td><td>Settlement involves the payment for the securities traded by both the central counterparty and the actual buyers. At this point, the transfer of ownership of financial securities takes place. The title of ownership would have to be held by the custodian of securities in the Exchange pending the clearing of cheques (usually three working days).</td></tr>
<tr><td>Custody and transfer of ownership</td><td>The Exchange's Central Securities Depositories (CSDs) are the custodians of securities for safekeeping and other administrative services before the final transfer of certificates. These CSDs are also member firms of the Exchange</td></tr>
</table>

Source: London Stock Exchange Group (2013)

3.5 Conclusion

The London Stock Exchange has remained a focal point for international financial activities due to its diverse market structure and effective operations. In its effort to extend its operations to various parts of the world, new business environments such as China, Russia and India are being targeted. The Exchange's strategy of seeking to provide the most effective trading services in the world has contributed to the increase in the rate of its business partnerships with prominent organisations across the globe.

CHAPTER 4

OIL AND GAS SECTOR OF THE LONDON STOCK EXCHANGE

4.1 Introduction

This chapter explores the composition of the oil and gas sector within the London Stock Exchange. An overview of the sector's market performance and its significance in the development of the exchange will also be explored.

4.2 Oil and Gas Sector

The oil and gas related sectors represent 2 of the 47 sectors or industries of the London Stock Exchange. It consists of oil and gas producers, and oil equipment, services and distribution firms. The oil and gas producers' sector has two sub-sectors of exploration/production and integrated oil & gas while the oil equipment, services and distribution has only one sub-sector of oil equipment and services. There are a total number of 170 listed oil and gas companies that are worth over £656 billion, in which 152 companies are oil and gas producing companies worth over £553 billion. The remaining 18 companies fall under the oil equipment, services and distribution sector with a market value of over £102 billion. All the companies are listed between the Main Market, the Alternative Investment Market (AIM) and the Professional Securities Market (PSM). The oil and gas sector accounts for over 15% of the total market capitalisation of the entire London Stock Exchange that stands at over £4,000,000 million.

4.2.1 Oil and Gas Producers

The oil and gas producers constitute the exploration, production and integrated oil services companies that account for over 89% of the total companies in the sector. Out of the 152 companies in the oil producing sector, 46 companies with a market value of more than £546 billion are quoted on the main market. A considerable number of 105 companies with a combined market value of not more than £8 billion are quoted on the Alternative Investment Market (AIM). GAIL (India) Company was the only one found to be listed on the Professional Securities Market (PSM). In an estimate by Oil & Gas UK (2014), the sector produces about 1.43 million barrels of oil from over 380 producing fields every day, making it to be the 19^{th} among the world oil producing countries. Over the last forty-five years, there have been over 3,000 companies that are involved in the production and distribution of oil products in the United Kingdom. Out of the 46 oil producing companies quoted on the main market of the London stock exchange, only 17 companies are incorporated in the Great Britain. These are BG Group Plc, BP Plc , Cadogan Petroleum Plc, Cairn Energy Plc, Enquest Plc, Fortune Oil Plc, JKX Oil and Gas Plc, Nostrum Oil & Gas Plc, Ophir Energy Plc, Premier Oil Plc, Royal Dutch Shell Plc, Ruspetro Plc, Salamander Energy Plc, Soco International Plc , Tullow Oil Plc and XPlorer Plc. All the listed companies above are included in the sample of the study except Nostrum Oil & Gas Plc and XPlorer Plc which were listed after the earmarked period of study on 20 June, 2014 and 11 July 2013 respectively. 30 companies (incorporated in both the UK and other countries) are found to be exploration and production companies while 16 companies are classified under integrated oil and gas services.

4.2.2 Oil Equipment, Services and Distribution

The oil and gas equipment, services and distribution sector constitute a segment that accounts for about 11% of the total companies in the oil and gas sector. There are only 18 companies under the oil equipment, services and distribution, out of which 10 companies worth £102 billion are quoted on the Main Market while 8 companies worth £672 million are quoted on the Alternative Investment Market (AIM). None of the oil equipment, services and distribution companies is listed on either the Professional Securities Market (PSM) or the Specialist Fund Market (SFM). Out of the 10 oil equipment and services companies quoted on the main market of the London stock exchange, only 4 companies are incorporated in Great Britain. These 4 companies are Amec Plc, Gulf Marine Services Plc, Hunting Plc and Wood Group (John) Plc. All the 4 companies listed above are included in the sample of the study except Gulf Marine Services Plc, which was only recently quoted on the market on 19 March, 2014.

4.3 Oil and Gas Companies Quoted on the Alternative Investment Market

The majority of the oil and gas companies quoted on the London stock exchange are listed on the AIM segment of the market. There are 113 oil and gas companies listed on AIM out of the total of 170 oil and gas companies on the London Stock Exchange. Surprisingly, even though the oil and gas companies on AIM represent over 66% percent of the total oil companies on the London Stock Exchange. Market capitalisation of the oil and gas companies quoted on AIM amounts to £8 billion which represents only 1.2% of the total oil and gas companies' market capitalisation of £656 billion. A preliminary analysis of the oil and gas companies quoted on AIM has indicated that most of the oil companies are inactive in the trading market. In other words, they are characterised by significant zero returns (unchanging prices) due to factors such as temporary trading suspension. Based on these facts, we have decided not to include the individual oil and gas companies quoted on the Alternative Investment Market (AIM) in the sample of this study. However, we have included the FTSE AIM Supersector (SS) Oil and Gas index that represents the overall oil companies on AIM as part of the sample for investigation.

4.4 Overview of the Market Performance of the Oil and Gas Sector

The oil and gas sector has over £656 billion of market capitalisation as at 31st October, 2014 which represents about 15% of the entire London Stock Exchange market capitalisation of £4,000,000 million. The sector also comprises the two sectors of Oil and Gas Producers, and Oil Equipment, Services and Distribution, out of the total 47 industrial sectors of the London stock exchange. It is the second largest sector by market capitalisation in London stock exchange after the banking sector. The banking sector has a market capitalisation of over £658 billion while that of the oil and gas sector was over £656 billion as at 31st October, 2014. The two sectors of banking and oil industry account for over 32 percent of the total market capitalisation of the London Stock Exchange.

According to the Oil & Gas UK (2014), the oil and gas sector in the UK remains the largest industrial investor that pays the highest tax to the Exchequer. In 2012, it was recorded to have generated a turnover of over £35 billion in its supply chain which showed an increase of about £11.4 billion between 2008 and 2012. Across the whole United Kingdom, the oil and gas sector had provided over 440,000 roles in 2012. Over 77% percent of the employment opportunities were provided by exploration (production) companies.

CHAPTER 5

RESEARCH METHODOLOGY AND FRAMEWORK

5.1 Introduction

This chapter explains the overall research methodology employed to achieve the aim and objectives of the research. The research philosophy, design, questions, hypotheses, theoretical framework, data collection procedure and analysis techniques are the key elements that defined the research approach adopted. We try to provide insight and justification of the approach for an appropriate understanding of how to achieve the research objectives.

5.2 Research Philosophy

Johnson and Clark (2006) have emphasized the need for every researcher to understand the philosophical approach underlying a given research study in order to appreciate the philosophical commitment to be adhered to as well as the justification of why alternative approaches were not selected. In the light of these suggestions, we identify our philosophical approach in conducting this research as 'positivism' from the domain of ontology and epistemology theories, which are the main concepts that determine the type of research philosophy. Ontology is seen as the research philosophy that attempts to study the nature of reality, being and characteristics associated with existing entities. Some features of the nature of reality could be explained by answering questions in relation to whether they are external, internal, objective, subjective, multiples, singles, their relatedness with other variables or outside environment, their value and etc. Saunders et al (2012) described the two major facets of ontology as ‘objectivism’ and ‘subjectivism’. Objectivism is explained as the research position to study meaningful realities based on the assumption of objectivity, while subjectivism is a research position to study social entities that are deemed to be determined by the perception of social actors. Epistemology provides a research position similar to that of a natural scientist that possesses an acceptable body of knowledge for use in collecting, measuring and analysing facts from the existing realities. Ferrier (1854) had explained epistemology as a branch of philosophy that is concerned with the theory, nature and scope of knowledge and how it relates to subjects of reality. Realism, interpretivism and positivism are seen as the key aspects of epistemology (Saunders et al, 2012). Realism is a research philosophy based on the assumption and belief that existing entities or subjects have features of reality that are independent of the researcher’s mind. Realism can be seen as having opposite meaning and status to ‘idealism’. Interpretivism as a philosophical position attempts to separate the nature of social entities or subjects from a defined theoretical base. It emanated as a criticism of positivism which tries to define the behaviour of observable reality based on theoretical phenomena or an established and accepted generalisation similar to the position of a natural scientist.

As stated earlier, the research philosophy adopted in this study has been identified as ‘Positivism’. The nature of the study involves an investigation of whether observable variables such as changes in asset prices are generated based on formulated hypotheses and theories. Therefore, we intend to undertake testing of hypotheses and applicability of theories developed by various eminent scholars in justifying the behaviour of asset returns. Our objective is to verify and provide sufficient information to investors and other stakeholders with regard to how to utilise the existing theories in their investing decisions. In addition, we adhere to the philosophical ethics and commitment in respect of the adopted positivism approach by upholding the independence and objectivity of the collected data and the applied statistical tools for data analysis. We shall present our results in detail and make interpretations objectively.

5.3 Research Design

The adoption of a positivism research philosophy and the nature of our data, data collection and analysis procedures have resulted in the employment of a quantitative method research design. It presents a plan of how to answer our research questions and test the tentative statements of the research hypotheses. The focus is mainly on using secondary data to test the validity of numerous theories in the form of a deductive approach. The strategy is similar to that of an experimental research study using statistical techniques to measure the numeric significance of whether to accept or reject the underline hypotheses. The steps of our strategy are explained in the following paragraphs.

Theoretical frameworks from previous studies form the basis for this research study of an investigation into the market efficiency, volatility processes and asset pricing analysis of the oil and gas companies quoted on the London stock exchange. Market efficiency hypotheses were tested to see the randomness of returns using various statistical tools on the secondary data of stock prices. We also plan to employ technical trading rule strategies to assess whether investors can make abnormal profit from the stocks in order to substantiate the results of the market efficiency tests conducted. Seasonality analysis (day-of-the-week effect in the data) will also be undertaken to examine the possibility of predicting the returns of any day within the week. If the existence of seasonality in the data is established, then the results will be considered as further evidence to reject the market efficiency hypotheses. Due to the developing interest in the analysis of risk by investors and other analysts, we intend to investigate the volatility behaviour of the oil and gas sector by using both asymmetric and symmetric models. Volatility processes, estimation and forecasts are to be undertaken using the simple GARCH (1,1) symmetric model and the Threshold ARCH (1,1) asymmetric model. The results from the models' estimation are then used in forecasting volatility and their power or accuracy measured by error statistics. It is also part of this study to make a comparison between volatility patterns observed from the entire market of the London stock exchange and the oil and gas sector of the market. The impact of the Brent crude oil price as an exogenous factor in the volatility equation or model is also to be tested. The Brent crude oil price is used as a benchmark for the international oil price and hence is considered more appropriate to be used in our study. Asset pricing analysis constitutes another area of our investigation. A multi-factor asset pricing model augmented with an international oil price represented by the OPEC Basket Price is developed and tested on London-quoted oil and gas stocks. Emphasis will be given to the significance of the independent variables used in the model for investors to be well informed about factors that determine the asset prices of stocks and indices earmarked for this study.

Time series data of the oil and gas stocks quoted on the LSE will be collected from Datastream available in the Department of Accounting and Finance of the Aberdeen Business School (ABS), Robert Gordon University, Aberdeen, United Kingdom. Indices such as Oil and Gas Producers' Index, Oil and Gas Index, FTSE 100 Index, and FTSE All-Share Index will also be included in the sample data. FTSE AIM SS Oil and Gas Share Index representing oil and gas companies quoted on the second tier of the LSE. International oil prices represented by Brent Crude Oil Price and OPEC Basket Price are to be included in circumstances where exogenous factors are to be considered mostly in the GARCH and asset pricing modelling.

EViews, OxMetrics (PcGive and G@RCH), TSP (Time Series Processor), Excel, MiniTab and SPSS statistical software packages are to be utilised for the analysis of time series data. The outcomes expected from the analysis consist of descriptive statistics (including graphical presentation and normality tests), results from market efficiency tests, seasonality tests, volatility modelling, volatility forecasting and asset pricing models. In our literature review we also aimed to use NVivo software for a thorough review and effective synthesis.

There are three principal hypotheses which emerge out of this study. There are also various sub-hypotheses that emerge from the principal hypotheses in the course of the study. The sub-hypotheses are mostly incorporated in the statistical tools to be applied where significance levels (including the use of critical values) and p-values from the coefficients' values are used to accept or reject the given null hypotheses.

The results and findings of our work will be reported in a way to provide an investment decision tool for the use of both potential and existing investors. Finance professionals and investment analysts are also expected to benefit from the inferences.

5.4 Research Questions and Hypotheses

5.4.1 Research Questions

The study is guided by the following research questions. It is believed that appropriate answers to these questions will be the pathway for the attainment of the research objectives. The questions are also linked to the research hypotheses in a way that answers are seen as further evidence for the rejection or acceptance of the formulated hypotheses.

In order to test whether oil and gas investors can make abnormal gain from the use of technical trading rules, the first research question was formulated to provide that information. If the trading rules are found to be generating abnormal gain, then the weak form market efficiency would be rejected.

1. Can investors use technical trading rules to gain abnormal returns from the United Kingdom oil and gas sector?

Investors are mostly concerned with risk and returns of their investments. In trying to establish the relationship between risk and returns, our second research question was meant to inquire about any existing relationship between the risk and returns in the oil and gas stocks of the LSE.

2. What is the relationship between volatility (risk) and returns in the UK oil and gas sector?

We plan to investigate the relationship between volatility attributes and efficient market hypothesis as part of our effort to explore the price dynamics of the oil and gas sector. The third research question was framed to assess whether volatility behaviour can provide any evidence of the efficient market hypothesis.

3. Can volatility attributes provide evidence to an Efficient Market Hypothesis in the UK oil and gas sector?

We also consider the importance of measuring the quantum of investment risk and therefore the fourth research question was for assessing the extent of how volatility estimation can measure the underlying risk in oil and gas stock returns.

4. To what extent can the volatility analysis measure the quantum of risk in the United Kingdom oil and gas sector?

The effect of seasonality in stock returns has been investigated in various markets by researchers. In that regard, we also plan to include seasonality analysis in our study and thus, the fifth research question was formulated.

5. Is there any evidence of seasonality in the prices of oil and gas stocks quoted on the London stock exchange?

In our plan to assess the relevance of the factors suggested by Fama-French-Carhart and oil price risk exposure in the determination of oil and gas asset's price, we have decided to employ a multifactor asset pricing model. The model is expected to provide an answer to the following research question.

6. What is the role of market risk, firm's size, book-to-market ratio, and momentum in the asset pricing of oil and gas stocks?

5.4.2 Research Hypotheses

The first null hypothesis was derived to test the assumptions of Efficient Market Hypothesis on the LSE oil and gas sector. In particular, the weak form market efficiency would be tested.

H1 – The prices of oil and gas companies quoted on the London stock exchange do not fluctuate according to Random Walk and Efficient Market Hypotheses.

In null hypothesis 1, Random Walk Theory developed by Bachelier (1900) and the Efficient Market Hypothesis (EMH) developed by Fama (1970) will be tested on the oil and gas sector of the London stock exchange. If the hypothesis is accepted, then technical analysis might be considered to have an impact but, if rejected, then technical analysis in forecasting future prices is irrelevant. Random walk theory suggests that stock returns take a random movement and therefore prediction is not possible. Similarly, the efficient market hypothesis postulates that all relevant information are fully reflected in stock prices and therefore making it impossible for investors to make any abnormal gain. Both random walk theory and efficient market hypothesis are confirmed if technical analysis cannot provide investors with any abnormal gain.

The second null hypothesis was formulated to basically explore the nature of volatility behaviour of the LSE oil and gas stock returns.

H2 – Volatility behaviour or patterns of London-quoted oil and gas stock returns cannot be an indication for future investment prospects.

In null hypothesis 2, volatility attributes are investigated using basically the Autoregressive Conditional Heteroscedasticity (ARCH) model developed by Engle (1982), the Generalized ARCH (GARCH) model developed by Bollerslev (1986) and the Threshold ARCH (TARCH) model developed by Glosten et al (1993). The null hypothesis is to be tested by the results generated from the models mentioned above. If the null hypothesis is accepted, then the result is considered as further evidence supporting the Efficient Market Hypothesis in which volatility behaviour reflects only the information in the market. If the null hypothesis is rejected, then it is deemed as evidence that abnormal returns can be obtained by using volatility models.

Finally, the third null hypothesis was articulated to test the validity of the proposition of Fama-French-Carhart's multifactor asset pricing model.

H3 – Asset pricing dynamics of London-quoted oil and gas companies do not follow the propositions of the capital asset pricing model and other multifactor pricing models.

In null hypothesis 3, risk factors in capital asset pricing model developed by Sharpe (1964), Fama and French's (1993) three factor model, and Fama-French-Carhart's (1993) four factor will be tested for statistical significance in the London-quoted oil and gas companies. If the coefficients of the risk factors in the models are found to be statistically significant, then the null hypothesis will be rejected and if found insignificant it will be accepted.

5.5 Theoretical Framework

The theoretical framework to adopt in this research is based on the three main hypotheses of the study. The hypotheses are formulated under the key areas of market efficiency, volatility processes and asset pricing modelling to provide answers to the research questions. To test for market efficiency, we plan to employ the theoretical frameworks of the random walk theory (Bachelier, 1900) and the efficient market hypothesis (Fama, 1970) as explained in sub sections 5.5.1 and 5.5.2. In volatility modelling and forecasting, the theoretical frameworks of the autoregressive conditional heteroscedasticity model (Engle, 1982), the generalized autoregressive conditional heteroscedasticity model (Bollerslev, 1986), and the threshold autoregressive conditional heteroscedasticity model (Glosten et al, 1993) will be employed as explained in sub sections 5.5.3, 5.5.4 and 5.5.5. The theoretical frameworks to adopt in asset pricing analysis are that of the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; and Mossin, 1966), the Fama and French three-factor model (Fama and French, 1993), and Fama-French-Carhart's four factor model (Fama et al, 1997) as explained in sub sections 5.5.6, 5.5.7 and 5.5.8 below. Mathematical notations of the models are given in detail under appropriate chapters where analysis is undertaken.

5.5.1 Random Walk Theory – Bachelier (1900)

The theory of random walk was originated by Bachelier in 1900 from his PhD work titled 'The theory of speculation'. It was argued that the return from market speculation is equals to zero because there is no useful information in the historic price movement of a stock. The finding was initially criticized and ignored until some 60 years later when scholars such as Paul Samuelson and Eugene Fama revisited it. The theory was then regarded as a breakthrough in the field of finance. This explains stock price movement as a 'random walk' responding to new information in the market that cannot be predicted. Since then, scholars have been testing the validity of the theory using various methods and in different markets. We have also decided to adopt this theory as a theoretical framework to test its validity in the current data of the London stock exchange oil and gas sector using numerous statistical tools.

5.5.2 Efficient Market Hypothesis – Fama (1970)

A further development to the random walk theory is witnessed in the advent of the Efficient Market Hypothesis initiated by Roberts (1967). The hypothesis suggests that financial markets are efficient if prices fully reflect all available information, (Fama, 1970). Fama improved the work of Roberts (1967) by undertaken a joint hypothetical test and categorising the hypothesis of market efficiency into weak form market efficiency, semi-strong market efficiency and strong market efficiency. The classification was based on the type of information available where prices in a weak form efficient market are expected to fully reflect past information on price movement, where a semi-strong form efficient market fully reflects all publicly available information and where a strong form efficient market fully reflects both publicly and privately available information. It was another revolution in finance where scholars attempt to assess the validity of EMH in different ways. In achieving our research objective of exploring the dynamics of oil and gas stocks' returns, a review of the market efficiency hypothesis will not only complete our study but also provide a basis for further investigation.

5.5.3 Autoregressive Conditional Heteroscedasticity (ARCH) Model – Engle (1982)

The Autoregressive Conditional Heteroscedasticity (ARCH) model was developed by Engle (1982) as an alternative to models that are based on homoscedasticity assumption. Homoscedasticity assumes that the variances of the error term of a linear regression model should be constant. In contrast to that, the variances of the error term of stock returns are discovered to be changing over time, with this phenomenon termed as 'heteroscedasticity'. In the presence of heteroscedasticity, the results from the ordinary least squares model will be biased and unrealistic. In an attempt to overcome this problem, autoregressive conditional heteroscedasticity (ARCH) specification was designed to model the time-varying variances in the process of model estimation. The ARCH model is considered as advancement to conventional regression models. We shall employ the ARCH model in the analysis of our time series data.

5.5.4 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model – Bollerslev (1986)

Bollerslev (1986) discovered some limitations in the ARCH model and proposed a generalisation of the ARCH specification which was accepted in the field of finance as the Generalized-ARCH (GARCH) model. In the initial ARCH specification, the variances of the error terms are assigned to be specific and conditional to time in a way that a highly volatile period could have high variance as well as a low volatile period having low variance based on time. However, the swing between high and low volatility could not happen at a predetermined time especially if the times of occurrence are also stochastic in nature. In a nut-shell, the ARCH model's variance of the residuals at a given time depends on the value of the squared error terms of the previous period from the mean equation. Bollerslev (1986) suggested the inclusion of lagged terms of the variance itself as the determinant of the present variance. The new model (GARCH) hence becomes more robust and has been adopted by scholars in the field of finance. We shall use the GARCH specification in modelling the conditional variance of the London-quoted oil and gas stocks and the selected FTSE indices.

5.5.5 Threshold Autoregressive Conditional Heteroscedasticity (TARCH) Model – Glosten, Jagannathan, and Runkle (1993)

Threshold-ARCH (TARCH) or GJR-GARCH is an asymmetric version of GARCH based on the assumption that the impact of negative information (bad news) on volatility is higher than that of positive information (good news). Studies have shown that asymmetric volatility models are more powerful than symmetric models. In that regard, we intend to also employ the model in volatility estimation and forecasting.

5.5.6 Capital Asset Pricing Model (CAPM) – Sharpe (1964), Lintner (1965), and Mossin (1966)

The Capital asset pricing model is a theoretical asset pricing technique developed from the work of Harry Markowitz on portfolio theory by Sharpe (1964), Lintner (1965) and Mossin (1966) independently. The model became one of the most important models in the determination of an asset's required rate of return. According to the model, the expected return of a given asset is a function of risk free rate of return (time value of money) and a market risk premium (based on a systematic risk measure (beta)). Many other multi-factor models that are used presently were developed from the basic assumptions of the CAPM either in a way to overcome its limitation or just as a supplement. In our asset's return estimation, we shall test the risk factor recognised by the capital asset pricing model.

5.5.7 Fama and French (1993)'s Three Factor Asset Pricing Model

Fama and French (1993) suggested an improvement to the single factor model like the CAPM by incorporating a firm's size (by market capitalisation) and value (by book-to-market ratio) factors based on the assumption that small size stocks and low value stocks outperform big size stocks and high value stocks in the market. These factors are to be formulated and tested for statistical significance in the asset pricing modelling of the London-quoted oil and gas stocks under investigation in this study.

5.5.8 Fama, French and Carhart (1997)'s Four Factor Model

Fama-French-Carhart's four factor model is an extension of the Fama and French three factor model with an additional factor of momentum. A momentum factor represents the tendency of an asset's price to continue rising if it is increasing and also to continue falling if it is decreasing. This phenomenon is classified as momentum and used as an explanatory variable in asset price modelling. Scholars such as Mohanty et al (2014) have also integrated additional variables (usually commodity prices) in the multi-factor model. We intend to adopt Mohanty et al (2014)'s methodology by including an international oil price denoted by the OPEC Basket Price in the Fama-French-Carhart's four factor model in order to assess the impact of all variables in the asset pricing of London-quoted oil and gas stocks.

5.6 Population and Sample

The study distinguishes between target population, study population and sample. The target population is the entire group on which the study aims to draw its inferences. All the quoted stocks of the London Stock Exchange (LSE) are the target population of the study. Unfortunately, the entire elements of the target population cannot be assessed contemporaneously. In order to overcome that barrier and conform to the intentions of the research, a study population was extracted. The study population is the group of stocks on which variables are assessable and inferences can be made rightfully.

The total number of oil and gas companies quoted on the London stock exchange from year 1992 to 2012 is considered to be the study population of this research. This comprises companies from both the oil and gas producers and oil equipment services and distribution sectors of the London stock exchange. According to the London Stock Exchange (2012), there were a total number of 152 oil and gas producers and 18 oil equipment services and distribution companies. Over seventy percent (107 companies) of the total oil and gas producers are small growing companies listed on the Alternative Investment Market (AIM- a sub-market of LSE), while about thirty percent (45 companies) of the companies are listed on the main market of the London stock exchange. Forty-four percent (8 companies) of the oil equipment services and distribution sector are listed on the AIM and fifty six percent (10 companies) are listed on the main market of the LSE.

The study will consider only the oil and gas companies quoted on the main market of the London stock exchange that are actively trading. This represents the sample of the study and it involves both the oil and gas producers and oil equipment and services companies. However, we have excluded companies that are listed after December 2012 and included FTSE indices comprising of FTSE All Share, FTSE 100, FTSE UK Oil and Gas, FTSE UK Oil and Gas Producers and FTSE AIM SS Oil and Gas to represent all the eighteen (18) oil and gas companies quoted.

The companies under study are depicted in Table 1.1 below:

Table 5.1 – Sample of the Study

	Company	Market	Sector	Date of Listing / Admission to trading	Time Series of Stock Prices under Study (31.12.1992 to 31.12.2012)*	Market Capitalisation (in millions) as at 31.12.2012	Data-stream Codes
1.	FTSE All Share	LSE-Main	Index	10 Apr 1962	20 Years	£3,093.41 (Index)	FTALLSH(PI)
2.	FTSE 100	LSE-Main	Index	31 Jan 1978	20 Years	£5,897.81 (Index)	FTSE100(PI)
3.	FTSE UK Oil & Gas	LSE-Main	Index	31 Dec 1993	19 Years	£635.73 (Index)	F1UKO1L(PI)
4.	FTSE UK Oil & Gas Prod.	LSE-Main	Index	31 Dec 1993	19 Years	£518.56 (Index)	F3UKOGL(PI)
5.	FTSE AIM SS Oil & Gas	LSE-AIM	Index	29 Dec 2000	12 Years	£3,319.79 (Index)	FTI202£(PI)
6.	Amec Plc	LSE-Main	OilES	22 Dec 1982	20 Years	£3,016.08	901788
7.	BG Group Plc	LSE-Main	OilGP	05 Dec 1986	20 Years	£34,442.36	911488
8.	BP Plc	LSE-Main	OilGP	20 Dec 1964	20 Years	£81,310.13	900995
9.	Cairn Energy	LSE-Main	OilGP	21 Dec 1988	20 Years	£1,597.43	910146
10.	Dragon Oil	LSE-Main	OilGP	30 Jun 1986	20 Years	£2,735.94	974981
11.	Fortune Oil	LSE-Main	OilGP	27 Sep 1989	20 Years	£199.71	910419
12.	Hunting Plc	LSE-Main	OilES	29 Jul 1970	20 Years	£1,162.28	917509
13.	Premier Oil	LSE-Main	OilGP	21 Feb 1973	20 Years	£1,780.46	900997
14.	Royal Dutch Shell 'B'	LSE-Main	OilGP	30 Dec 1964	20 Years	£56,935.27	900998
15.	Tullow Oil Plc	LSE-Main	OilGP	04 Oct 1989	20 Years	£11,446.88	506343
16.	Aminex Plc	LSE-Main	OilGP	05 Jul 1995	18 Years	£33.16	135251
17.	JKX Oil & Gas Plc	LSE-Main	OilGP	11 Jul 1995	18 Years	£133.04	139998
18.	Soco International	LSE-Main	OilGP	28 May 1997	16 Years	£1,187.63	897311
19.	Wood Group (John)	LSE-Main	OilES	28 May 2002	11 Years	£2,711.12	258098
20.	Afren Plc	LSE-Main	OilGP	11 Mar 2005	8 Years	£1,424.92	30398Q
21.	Hardy Oil & Gas Plc	LSE-Main	OilGP	06 Jun 2005	8 Years	£65.73	31131U
22.	Royal Dutch Shell 'A'	LSE-Main	OilGP	20 Jul 2005	8 Years	£79,477.81	902178
23.	Petrofac Ltd	LSE-Main	OilES	03 Oct 2005	7 Years	£5,613.82	31946M
24.	Lamprell Plc	LSE-Main	OilES	10 Oct 2006	6 Years	£244.74	41248W
25.	Salamander Energy	LSE-Main	OilGP	29 Nov 2006	6 Years	£488.18	414296
26.	Endeavor International	LSE-Main	OilGP	14 Dec 2007	5 Years	£143.24	51429N
27.	Kentz Corporation Ltd	LSE-Main	OilES	04 Feb 2008	5 Years	£455.06	51596W
28.	Heritage Oil Plc	LSE-Main	OilGP	28 Mar 2008	5 Years	£550.2	51846T
29.	Cadogan Petroleum	LSE-Main	OilGP	17 Jun 2008	4 Years	£33.22	36198N
30.	Exillon Energy	LSE-Main	OilGP	16 Dec 2009	3 Years	£274.57	68552K
31.	Enquest	LSE-Main	OilGP	05 Apr 2010	3 Years	£963.19	69033U
32.	Essar Energy	LSE-Main	OilGP	03 May 2010	3 Years	£1,557.61	69286X
33.	Genel Energy Plc	LSE-Main	OilGP	16 Jun 2011	2 Years	£2,185.94	77278X
34.	Ophir Energy Plc	LSE-Main	OilGP	07 Jul 2011	2 Years	£2,018.02	77404V
35.	Ruspetro Plc	LSE-Main	OilGP	18 Jan 2012	1 Year	£263.37	86735D

Source: London Stock Exchange (2012); Thomson Reuters Datastream (2012).*The data has also been extended to June and December 2014 in asset pricing and seasonality (monthly effect) analyses respectively.

5.7 Data Collection and Analysis

This section explains the data collection methods and statistical tools employed in data analysis.

5.7.1 Data Collection Methods

The main data used in the entire research is secondary data of time series values of oil and gas stocks quoted on the main market of the London Stock Exchange. The data was downloaded from the Datastream available in the Department of Accounting and Finance of the Aberdeen Business School, Robert Gordon University, Aberdeen, United Kingdom.

5.7.2 Data Analysis Techniques

We plan to apply numerous statistical tools in order to achieve the objectives of the research. In chapter 6 presenting descriptive statistics, the following data analysis techniques are to be employed.

i. Graphical presentation of all the data series under study.
ii. Descriptive statistics consisting of mean, median, maximum, minimum and standard deviation values.
iii. Normality test consisting of graphical approach (histogram, box-plot, and Q-Q plot), numerical method (skewness, kurtosis, and Jacque bera statistics) and formal tests (Lilliefors (LF) test, Cramervon Mises (W2) test, Watson (U2) test, Anderson Darling (AD) test and Kolmogorov-Smirnov (KS) test).

iv. Stationarity test (unit root) consisting of Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests.

In chapter 7 presenting weak form market efficiency tests and trading rule strategies, we plan to employ the following statistical tools.

i. Autocorrelation function and Ljung-Box Q-statistics.
ii. Runs test.
iii. Variance ratio test.
iv. Brock, Dechert, and Scheinkman (BDS) Test.
v. Trading and filter rules based on autocorrelation persistence.
vi. Moving average trading rule results and graphical presentation of performance.

In chapter 8 presenting seasonality analysis, we plan to use the following statistical tools.

i. F-Test, Kruskall-Wallis, and Tukey tests on the day-of-the-week return series under study.
ii. Generalised ARCH (1,1) regression modelling for the test of the day-of-the-week effect on the return series under study

In chapter 9 presenting volatility processes, estimation and forecasting, we employ the following tools.

i. Test for ARCH effect in the residuals of the series under study using a regression model.

ii. Application of ARCH (1) and GARCH (1,1) models for symmetric volatility.
iii. Application of Threshold-ARCH (TARCH)(1,1) model for asymmetric volatility.
iv. Regressing Brent Crude Oil Price as an exogenous variable in GARCH (1,1) model.
v. Forecasting and estimating forecasting errors using the models estimated above.

In chapter 10 presenting asset pricing models and oil price risk exposure, we plan to adopt Fama-French-Carhart's Four Factor asset pricing model augmented with an international crude oil price denoted by the OPEC Basket Price.

5.8 Conclusion

The research approach and design are broadly discussed in this chapter based on a quantitative research philosophy. The subsequent chapters present the actual results of our investigation in line with the adopted research methodology. Limitations of the overall research strategy observed in the course of undertaking the study will be presented in the last chapter of the thesis.

CHAPTER 6

DESCRIPTIVE STATISTICS, DISTRIBUTION ANALYSIS AND STATIONARITY TEST OF THE OIL AND GAS STOCK RETURNS

6.1 Introduction

A good quantitative analysis starts with the description of the nature and behaviour of the sample data. This chapter presents the comprehensive analysis of the features that characterised the data in this study. In stock market analysis, the most commonly used data are the stock prices from stock exchanges and stock returns that are usually calculated as the log-difference in prices. Stock returns are usually tested for normal distribution because the basic postulation of many statistical tools and tests are confined around the normality assumption. It is therefore imperative to analyse the statistical characteristics and the distribution pattern of the stock returns earmarked for this study. This will guide the appropriate selection of the statistical and econometric tools to employ in the study. Visual tools would also be employed to identify the nature of stock returns of oil companies listed on the London stock exchange. Descriptive statistics to be used are the mean, median, maximum, minimum and standard deviation, while a normality test is to be accomplished by graphical methods, numerical methods and formal or standard normality tests. Tools to employ in graphical methods would include histograms, boxplots and Q-Q-plots. Numerical methods are mainly the estimated skewness, kurtosis and the Jacque bera statistic. The formal or standard normality tests to be employed are the Lilliefors (LF) test, Anderson-Darling (AD) test, Watson (U_2) test, Cramer- von Mises (W_2) test, and

Kolmogorov Smirnov (KS) test. The results derived from these tests will certainly dictate the mix of parametric or non-parametric analytical tools to be employed in the study. The return series in this study are classified into three categories of the index returns, companies with returns data for more than ten years and companies with less than ten years returns data.

6.2 Review of Related Literature on Descriptive Statistics, Distribution of Stock Returns and Stationarity Tests

6.2.1 Background

The inquisitive attitude of researchers on the nature of stock return distribution started after the description of a normal white noise process by Bachelier (1900). Many finance scholars support the view that the statistical properties and distribution of stock returns exhibit a defined pattern. Researchers are interested on the distribution pattern of stock returns because conventional asset pricing models, risk management models and numerous economic tools and techniques are based on a specific pattern of normal distribution, (Amado,1994; Balaban et al, 2005). Officer (1972) explained that an appropriate method to describe the nature of a random variable such as stock returns is to analyse the pattern of its distribution. Most of the findings of these analyses concluded that stock returns were not normally distributed. In other words, the return distribution does not pass the normality hypothesis, which is generally accepted as a conventional hypothesis by scholars to test the behaviour of a distribution function. However, some scholars believe that no statistical tool can possess the power to predetermine the nature of stock return distribution. Officer (1972) showed the existence of 'fat tails' in the distribution of stock returns. Teichmoeller (1971) also discovered that daily returns are not normally distributed and have 'fatter tails'. On a similar note, Brown and Warner (1985) provided more evidence to ascertain the inferences of Fama (1976) that the distribution of stock returns is fat tailed in relation to normal distribution. Many finance theories such as the capital asset pricing model (CAPM) by Sharpe (1964) and the Black-Scholes' option pricing model are formulated based on normality assumptions. Peiro (1994) argued that the distribution of stock returns is a deviation from normal distribution. He examined six stock markets (New York, Tokyo, London, Frankfurt, Paris, and Madrid) to establish the statistical characteristics of the distribution of stock returns. His findings suggest a clear rejection of the normality assumption.

Although a significant number of studies in finance has confirmed that the distribution of stock returns are not normally distributed, it is imperative to test whether return distributions are similar to alternative distributions such as Mandelbrot's stable paretian distribution, (Fama, 1963). This chapter will examine the nature of the return distribution of UK oil and gas stocks regarding the normality assumption and other alternative distributions.

6.2.2 Normal (Gaussian) Distribution

Aparicio and Estrada (2001) state that the assumption of stock returns being normally distributed has been rejected with strong empirical evidence. In their article, they tested the normality hypothesis on thirteen European markets using daily stock returns and unsurprisingly rejected the assumption in all of the markets. The same data was used to test the distribution of monthly stock returns and strong evidence was found in favour of normal distribution.

Balaban et al (2005) investigated thirty two sector indices including the FTSE All Share and the FTSE 100 of the London stock exchange to establish the evidence on return distributions. Out of the study sample, only the monthly returns of the indices for investment companies and general retailers are found to be normally distributed. Similarly, it was discovered that the 10-day returns of the life assurance, automobiles, health and food sectors indices have depicted normal distribution. This could be due to homogenous consumer behaviour over products and services at a given specific time periods. However, the scholars have not provided any empirical support for their argument that the homogenous behaviour of consumers could be the reason for normality distribution in the monthly returns of some sector-indices. On that note, Aparicio and Estrada (2001) believe that stock returns can only have normal distribution if information arrives at the market linearly and investors respond to the same information linearly. The UK oil and gas sector was among the thirty two sectors examined by Balaban et al (2005) using the parameters of stable paretian distribution since the scholars believed that financial returns are leptokurtic and can be conveniently modelled by stable distribution. The statistical parameter of characteristics exponent (α) was used to determine the shape of the distribution in their study, and the results from both the short and long horizon holding periods of the oil and gas sector deviate significantly from normal distribution with short-term horizons having stronger deviation. Behr and Potter (2009) studied the S&P 500 returns for 135 years and divided the period into three sub-periods of Pre-World War I, World War II and Post-World War II periods to establish whether the stock returns are normally distributed. The findings of the scholars suggest that stock return distributions are incompatible with the assumptions of normal distribution.

The rejection of normality distribution in stock returns and the apprehension that many test statistics will become irrelevant due to their dependence on normality distribution has contributed to various attempts made by researchers to justify normality distribution in stock returns. Drezner et al (2010) used a modified Kolmogorov-Smirnov test which is an improvement on the conventional Kolmogorov-Smirnov test to test for normal distribution. The conventional Kolmogorov-Smirnov test uses a sample of normal distribution with a mean and variance that would be compared to a set of data under test for the determination of normality. The modified Kolmogorov-Smirnov test selects a sample mean and variance of the normality distribution that give the closest fit to the set of data under test. It is expanding the reference normal distribution to increase the chances of capturing the data under test within the region of normal distribution. The modified Kolmogorov-Smirnov test minimizes the KS-Statistic and, by comparison with the conventional Kolmogorov-Smirnov test, it is a better test for data that has wider deviation from normal distribution. However, the modified Kolmogorov-Smirnov test fails to identify non-normality in any set of data that has a distribution closer or similar to normal distribution. Agrawal (2009) tested for the impact of sample size on the distributional features of stock returns. The test was conducted on Nifty index representing the companies quoted on the National Stock Exchange (NSE) in Delhi, India and the Sensex index representing the companies quoted on Bombay Stock Exchange (BSE). Statistical tools employed for normality test were the Kolmogorov-Smirnov test, Anderson-

Darling test, and Jacque-Bera statistics. The results indicated a high possibility of a sample size affecting the normality distribution of stock returns with a large sample size having a deviation from normal distribution and a short sample size having normal distribution. The findings that monthly stock returns are normally distributed are similar to the findings of Stokie (1982). Stokie examined the distribution of monthly stock returns of key Australian companies and discovered compliance with the assumption of normal distribution. An important point was highlighted by Agrawal (2009) that researchers and other analysts should examine the statistical characteristics of data prior to the selection of any model for stock market analysis. Some scholars assessed the power of statistical tools used in testing normality by making comparisons among the tools. Razali and Wah (2010) compared the statistical power of the Shapiro-Wilk (SW) test, the Kolmogorov-Smirnov (KS) test, the Lilliefors (LF) tests and the Anderson-Darling (AD) test by using Monte Carlo Simulation on sample data to generate numerous alternative distributions of symmetry and asymmetry. The power of each test was derived by comparing their normality statistic with relevant critical values. According to Razali and Wah (2010), the Shapiro-Wilk (SW) test is the most powerful normality test in all types of distribution and sample sizes. The Kolmogorov-Smirnov (KS) test is the least powerful test compared to the Anderson-Darling (AD) test and the Lilliefors (LF) test. The power of the Anderson-Darling (AD) test is almost identical to that of the Shapiro-Wilk (SW) test. This study considers conducting normality test on the UK oil stock returns and indices using a mix of the tests listed above.

The significance of the normality test is rooted in the fact that all parametric statistical tools are built on the assumption of normal distribution and as a result of which interpretation of analysis becomes void if the data is not normally distributed. Statistical methods used in testing normality range from basic and simplest methods to the most advanced or formal methods. Graphical methods are seen as the simplest where data is plotted graphically and observation made to identify any fitness or deviation to normal distribution. Many scholars refer to the graphical methods as 'visual econometrics' and it includes the basic quantile-quantile (Q-Q) plot, the histogram plot and the box-plot which will all be employed in this study. Razali and Wah (2010) have described the graphical method as insufficient for final conclusion. To reinforce the graphical methods, numerical methods are adopted. Numerical methods are the measurement of the graphical area (shape) of the normality distribution. It includes skewness which in simple terms measures the horizontal size from both the positive and negative area of the normal distribution, kurtosis which measures the vertical size or height of the normal distribution and the Jacque-bera statistic which combines both the skewness and kurtosis in its assumptions. Skewness, Kurtosis and Jacque-bera statistic are the most used normality test tools in the literature. However, in recent times more advanced methods are used, for example, the Anderson-Darling (AD), Shapiro-Wilk (SW), Lilliefors (LF) and Kolmogorov-Smirnov (KS) tests among others. The majority of the findings by researchers using different types of normality tests have shown that daily stock returns of large size sample data are not normally distributed. Few researchers have seen evidence of normal distribution in monthly stock returns which was attributed to short size sample data.

6.2.3 Non-Normal Distribution

Time series of daily stock returns are generally found to be not normally distributed. The majority of the empirical studies suggest the non-normality of stock returns and this has forced researchers to use other type of analytical framework. Mandelbrot (1963) described that stock returns come from the family of stable paretian distribution, which generalizes the normal distribution assumptions. The family of stable paretian distribution comes with four parameters of tail index ($\propto$), skewness (β), scale (γ), and location (δ). Scholars such as Fama (1963), Fama and Roll (1971), Peiro (1994), Mittnik et al (1999), Paolella (2001), and Balaban et al (2005) have all tested the Mandelbrot theory of stable paretian hypothesis on different stock return series in order to uphold or reject it. Fama (1963) made further examination of the findings of Mandelbrot's stable paretian hypothesis and discovered that the statistical properties of stable paretian distribution were derived from the test conducted on a few different classes of speculative stock prices that are not statistically adjusted for smoothness. Fama added that any test on similar data for stable paretian distribution would yield a positive result. Fama and Roll (1971) conducted a test on statistically adjusted speculative prices by forming closed-formed densities of probabilities of stable parameters to overcome the problem with stable paretian distribution identified by Fama (1963). In addition, two statistical tests of goodness-of-fit and a test of stability property were recommended for data analysis. Findings showed that the family parameters of stable paretian hypothesis performed better than other distributions. Mittnik et al (1999) confirmed the findings of Fama (1963) and Fama and Roll (1971) that the only limitation of the stable paretian hypothesis is a lack of closed-form or clear expression of its probability density function; otherwise it can be seen as the best description of stock returns distribution because of its assumption of normality in a modified way with heavy tails and large skewness. Paolella (2001) suggested a simpler method of testing the stable paretian assumption by using estimates to explain the behaviour of parameters. Part of the findings from the study was the discovery of a high power of student's t test and mixed normal options in the explanation of stock returns distribution. As discussed earlier, Balaban et al (2005) used symmetric stable paretian distribution to explain the statistical distribution of UK stock returns. Surprisingly, some sector indices indicated normality in their return distributions, while others including the oil and gas sector are departures from normality. The conclusion of Balaban et al (2005) coincides with that of many researchers on the suggestion for the modification of asset pricing models to recognize the departure of data distribution from normality.

The search for the definitive explanation of stock returns distribution have resulted in an attempt by a significant number of studies to empirically test alternative distributions against financial time series or stock returns. Kanellopoulou and Panas (2008) investigated whether the Levy-Stable distribution can explain the distribution of stock returns. The choice of the Levy-Stable distribution was because it recognizes the observed kurtosis, skewness and fat tails at the same time. Kanellopoulou and Panas (2008) tested the Paris market's stock returns against the Levy-Stable distribution and discovered high peaks and large or fat tails in their distribution patterns. Skewness appeared to be at different values of both positive and negative signs. Empirical results have shown that the Levy-Stable distribution estimates generated from the data are consistent with a stable distribution, which are also invaluable when long memory process is investigated. It was concluded that the Paris market's stock returns are characterized by long memory dependence or process, which clearly rejects the efficient market hypothesis.

Cont (2001) argued that the empirical evidence and statistical attributes supporting non-normal distribution of stock returns are insufficient to categorically determine the form of stock returns distribution out of numerous parametric distributions suggested in the literature. The scholar listed the parametric distributions that may explain the distribution of stock returns as normal distribution, student's t distribution, hyperbolic distribution, normal inverse Gaussian distribution, exponential distribution, and stable distribution.

Behr and Potter (2009) pointed out that even though normal distribution fails to reflect the distribution of stock returns, researchers are still conducting studies on normal and alternative distributions. In their article, the scholars tested the Gaussian mixture, the generalised logF, and the generalised hyperbolic models on monthly stock returns of the S&P 500 index between 1871 and 2005. The results show some fitness between the distribution of the data and the three alternative distributions presented. However, on conducting the same test on the daily returns of the series, there was inconsistency and departure from the alternative distribution. The findings are not different from those of other scholars since it was explained in the literature that monthly returns are closer to normality and daily returns show a total departure from normality.

The non-normality of stock returns has been described as the cause of continuing research on the distribution of stock returns. Researchers are still seeking answers to questions about the normality or non-normality of stock return distributions. This study takes on this challenge and aims to explore the nature of the distribution of the stock returns series under investigation.

6.2.4 Properties of the Distribution of Stock Returns

Cont (2001) outlined the empirical properties of financial asset returns and explained how some of the prevailing properties undermine the validity of various statistical techniques used to analyse stock returns. The return series of financial assets such as stocks, market indices, exchange rates and other forms of financial instruments have common statistical properties as identified by Cont (2001) and summarized below.

Time series of stock returns are usually characterised by the absence of autocorrelation. In other words, there is no correlation between the discrete values of returns over time. This feature supports the random walk theory in some way and consistent with the efficient market hypothesis. More of these theories are to be discussed in subsequent chapters of this study. Some studies have shown the presence of autocorrelation in high frequency data. Cont (2001) stated that autocorrelation exists within intra-day data of twenty minutes interval.

Stock returns are also described as a mean reverting series referred to as volatility clustering. A cluster of low changes follows a cluster of high changes. Expressed in a different way, low changes are followed by low changes of opposite signs and high changes are followed by high changes of opposite signs.

The negative changes in stock returns usually outweigh the positive changes. Cont (2001) referred to that as 'gain/loss asymmetry'. This is explained by Agrawal (2009) who opined that if returns are calculated by percentage changes in prices, the data would automatically have asymmetric distribution because a decrease cannot be below hundred percent of the original price but an increase can be up to infinity. It could also be explained by the inferences from financial market analysis that suggest higher impact on returns as a result of negative (bad) news compared to impact as a result of positive (good) news.

Stock returns are also shown to have a high degree of variability. When examined from visual econometrics, the charts of returns are always unstable in the same direction over time and as such breaks, outliers and location shifts can easily be identified.

Officer (1972) opined that the pattern of stock returns distribution cannot be predetermined to fit any specific distribution by statistical tools. Findings from the test conducted by Officer have suggested the existence of some stable distribution properties. Fat tails were also discovered to be prominent. Aparicio and Estrada (2001) also confirmed from the results of their analysis that stock returns distribution have fat tails and high peaks which comes from high kurtosis of the distribution. Another feature used to describe the properties of stock returns distribution is skewness in terms of the symmetry of the distribution. Peiro (1999) believes that albeit skewness has been used by many scholars to portray the characteristics of stock returns but the findings are still not distinct or strong enough for any generalisation to be made. Ekholm and Pasternack (2005) stated that stock returns are negatively skewed as documented by significant literature in finance. The scholars went further to justify the negative skewness as a product of asymmetries in the information disclosure system of firms. In other words, firms disclose both scheduled and unscheduled information discriminately. However, scholars such as Aparicio and Estrada (2001) have tested for distribution and found skewness of different signs and values.

Cont (2001) also highlighted a few characteristics of the distribution of stock returns. A heavy tail feature was among the characteristics identified and it was stated that the distribution of stock returns exhibits a heavy Pareto-like tail with a finite index which is higher than two and less than five. It was further stated that the distribution pattern of stock returns changes with change in the time frame or the scale on which returns are calculated. Empirical evidence has shown that unconditional distribution of daily stock returns is a departure from normality while monthly stock returns depict a distribution closer to normality. High frequency data are also examined to have a distinctive distribution pattern. Agrawal (2009) investigated this assertion by using both daily and monthly returns and discovered that sample size has an impact on the pattern of distribution.

6.2.5 Factors Responsible for the Distribution of Stock Returns

Balaban et. al (2005) attributed the features of stock return distribution to investor behaviour. It was argued by the scholars that normal distribution can be attained in stock returns if there are homogenous responses to information or investment needs by investors. Empirical evidence has not been provided by the scholars to support their argument.

Aparicio and Estrada (2001) believe that information asymmetry is the factor responsible for the non-normal distribution of stock returns. The arrival of information into the market as well as the use of such information by market participants is not linearly transmitted.

Agrawal (2009) conducted a test on sample sizes and concluded that long period sample sizes of stock returns are responsible for non-normal distribution. Short period sample sizes of stock returns are tested to be closer to the normal distribution.

Cont (2001) has supported the position of Agrawal (2009) by the explanation of 'gain/loss asymmetry'. Cont (2001) stated that negative changes are higher than positive changes in stock returns because the investors' reactions to bad news is higher than if it is to good news. The origin of stock prices as a product from a stochastic process could be seen as another justification for the non-normal distribution of stock returns.

6.2.6 Stationary and Non-Stationary Time Series

Stationarity of a time series has been defined as a situation in which the properties of a series including the mean, variance, covariance and periodic variations are constant over time. If the statistical variables are changing or time varying, the series is said to be non-stationary. Chatfield (2004) stated that most of the probability theories underlying estimation models are based on unchanging statistical properties. The contribution of Dickey and Fuller (1979) had resulted in a research outburst in unit root testing for stationarity.

Dickey and Fuller (1979) developed the basic test for identifying stationarity. The Augmented Dickey Fuller test is a parametric modification of the Dickey and Fuller test designed to address the existence of higher order autocorrelation. The KPSS (Kwiatkowski, Phillips, Schmidt, and Shin) test was also developed by Kwiatkowski et al (1992) where the series under test is assumed to be trend stationary under the null. Phillips-Perron (1988) developed a test as a non-parametric modification of the Dickey Fuller test to consider high order autocorrelation in the white noise. The ERS (Elliot, Rothenberg, and Stock Point Optimal) test was developed by Elliot et al (1996) and the NP (Ng and Perron) test was developed by Ng and Perron (2001) as a modification of the Phillips-Perron test. The tests are designed to detect the existence of unit root in a series for proper selection of statistical tools for estimation and to avoid spurious regression results.

The power of the numerous unit root tests was also examined by scholars such as Fuller et al (1994) and Maddala and Wu (1999). Fuller et al (1994) compared the power of various unit root tests in a first order autoregressive process using Monte Carlo simulation and concluded that Ordinary Least Squares (OLS) methods are the least powerful with the ERS (Elliot, Rothenberg, and Stock Point Optimal) test being the most powerful. Halkos and Kevork (2005) compared the performance and power of unit root tests under the three methods of the absence of autocorrelation in the error term of a model, the series accepting the random walk hypothesis and a rejection of the random walk hypothesis, using a Monte Carlo simulation. Part of the conclusion made was that, if there is no anticipation of autocorrelation in the error term of the model, the simple Dickey Fuller test should be employed instead of the Augmented Dickey Fuller and the Phillips-Perron tests. This signifies that, if autocorrelation is expected in the error term, the Augmented Dickey Fuller test is the right parametric measure, while the Phillips-Perron test can be employed as the right non-parametric measure.

In order to be robust in our analysis, the research employs the Augmented Dickey Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Dickey Fuller – Generalized Least Squares (DF-GLS) tests.

6.2.7 Summary of Literature and Research Objectives

The non-normal distribution of daily stock returns is well documented in many empirical studies. Scholars explained the alternative distributions of daily stock returns in various forms such as fat-tailed, scaled t, paretian, chi-square, logistic, leptokurtosis, and exponential distributions. Numerous explanations were also given as the justification for the non-normality distribution. Information asymmetry has been seen as one of the factors that lead to deviation of daily stock returns from normality. It is believed that even if there is homogenous information investors' reaction is not homogenous. Sample sizes have been seen as another cause for the asymmetrical distribution in daily stock returns. It was explained that large sample sizes depict deviation from normal distribution while short samples sizes show compliance to normal distribution assumptions. On the same note, empirical evidences were gathered by few researchers that monthly stock returns have distributions closer to normal or Gaussian. It was concluded that since the form of data distribution can determined the type of statistical model to be employed, scholars should conduct distribution analysis on financial time series before model estimation and forecasting.

The objective of this chapter is to analyse the financial data series earmarked for this research in order to explore the statistical characteristics including the distribution of the data for appropriate selection of financial estimation models. The analysis would also enhance our understanding and appreciation of the models selected.

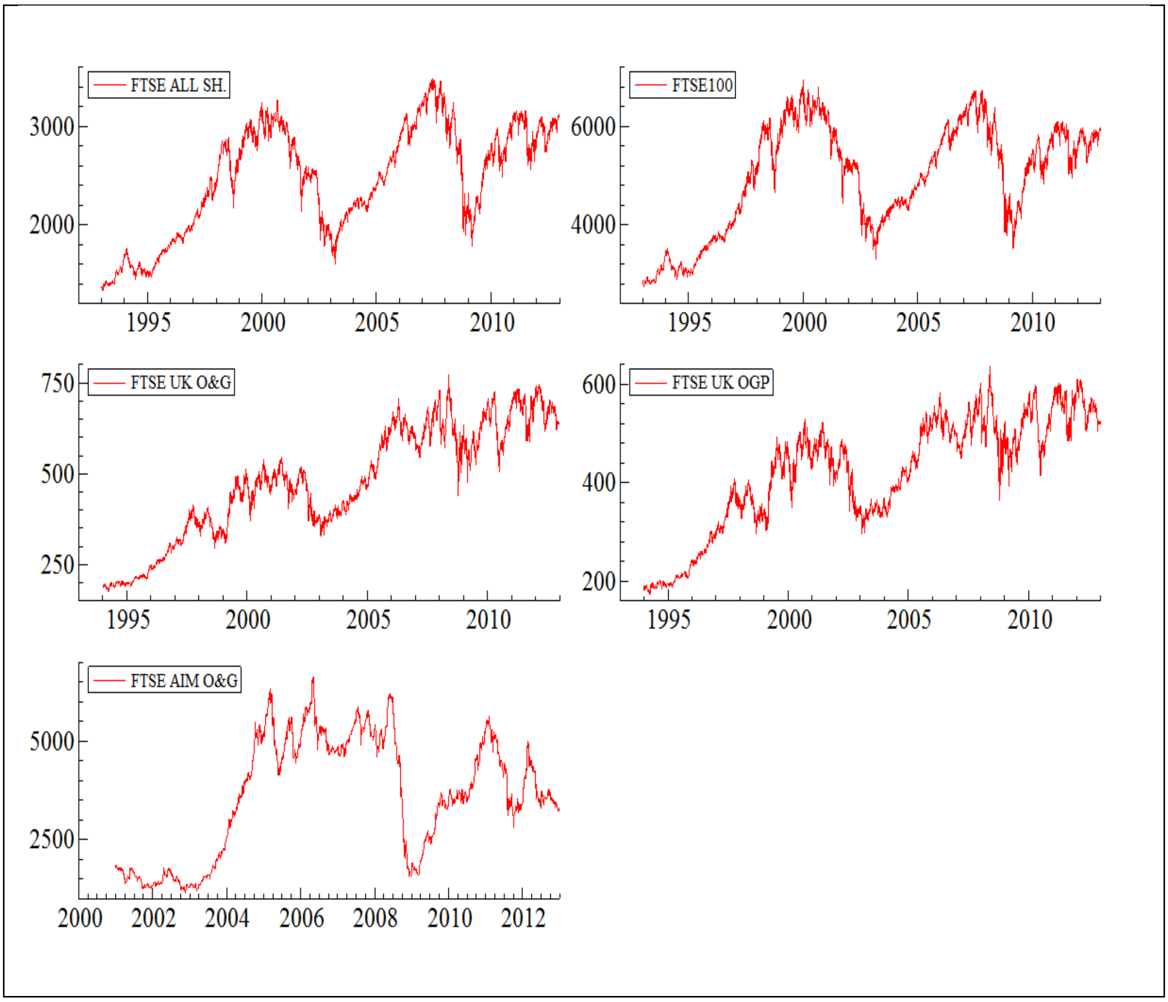
6.3 Descriptive Statistics and the Statistical Distribution of the Oil and Gas Stock Returns and Indices under Study

6.3.1 Stock Prices of the Oil and Gas Companies and Indices

The original data for this study are stock prices and indices sourced from Datastream UK. These series are adjusted for dividends, rights issue, bonuses and stock splits. The period of time series is mainly from January 1, 1993 to December 31, 2012. For those stocks or indices not listed or active as at

January 1, 1993, only the available series are considered for the study. The data is classified into three categories based on the type of series and sub periods. Firstly, the indices are considered separately and includes FTSE All Share, FTSE 100, FTSE UK Oil and Gas, FTSE UK Oil and Gas Producers, and FTSE AIM Super Sector (SS) Oil and Gas. The second category consists of all oil and gas companies that have time series data of more than ten years available for study. The third category consists of the most recently listed or active oil and gas companies that have a time series of less than ten years available.

Table 6.1.1 - Graphical Presentation of the Indices' Series under study

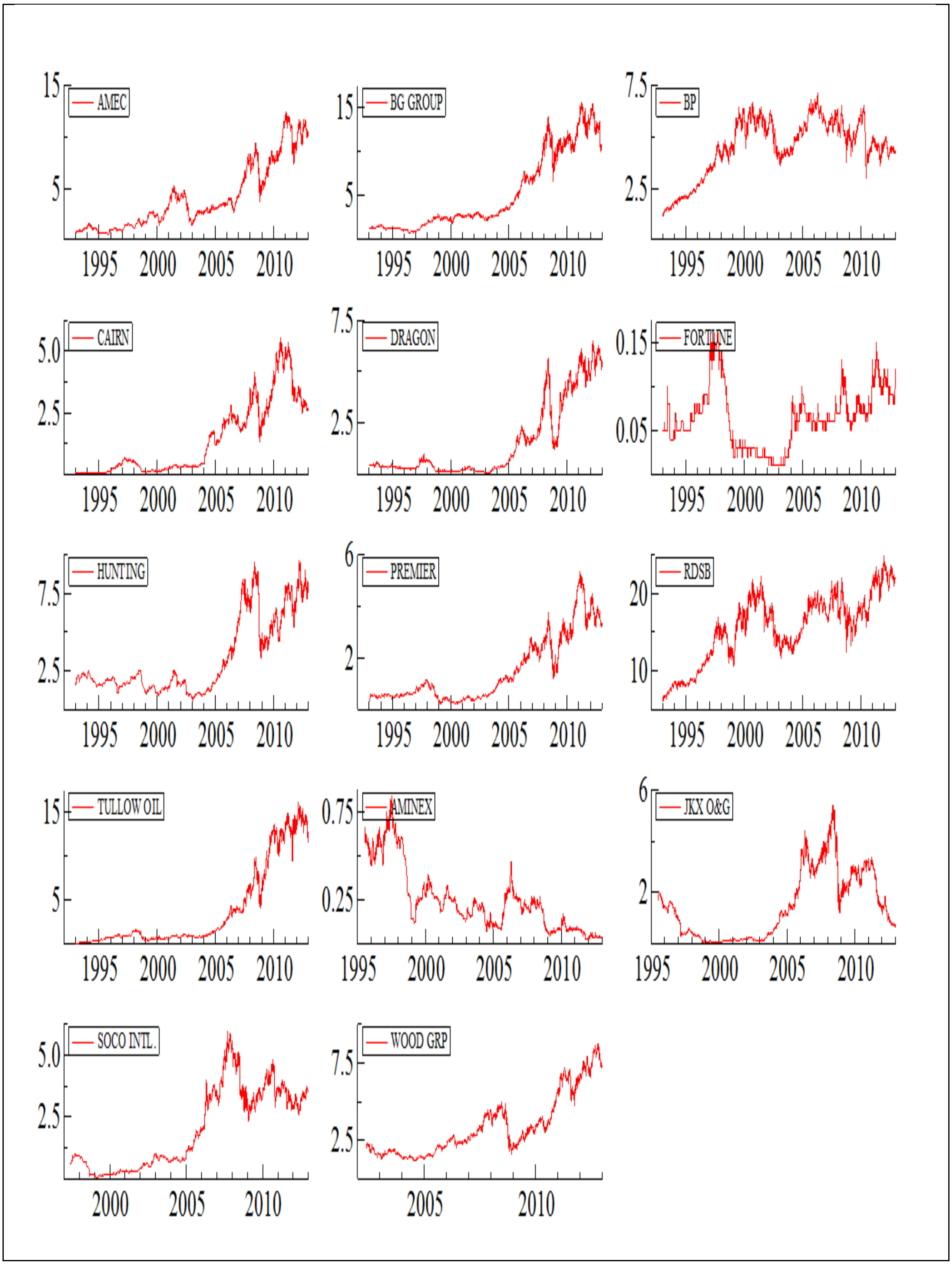


Source: Author (2015)

Table 6.1.1 portrays the graphical presentation of stock indices of the first category of our data. The FTSE All Share, FTSE 100, FTSE UK Oil and Gas, FTSE UK Oil and Gas Producers, and FTSE AIM SS Oil and Gas indices are plotted on line graphs to enable sight observations of the series behaviour for the proper identification of their characteristics. The charts from the plotted series have shown some signs of conventional characteristics of time series data. Common to the majority of the indices, there is a drift or an intercept noticeable except in the FTSE AIM SS Oil and Gas. Trends are observed in the FTSE UK Oil and Gas, and FTSE UK Oil and Gas Producers index series. FTSE All Share and FTSE 100 Share indices have not shown sign of trends, with FTSE AIM SS Oil and Gas index having neither an intercept nor a trend. Non stationarity is obvious in the graphs of the indices, where the series cannot be seen to generate constant mean or reversion around the mean even in the long run. The graphs of FTSE UK Oil and Gas index and the FTSE UK Oil and Gas Producers index show intercept and trend which suggest a random walk with a drift (slow steady movement) and deterministic trend. FTSE AIM SS Oil and Gas index does not show any sign of intercept and trend is described as a full random walk process. FTSE All Share and FTSE 100 Share indices have an intercept noticeable and the process is described as a random walk with drift. The presence of drift and trend in the series will be tested using the 'drift or intercept', 'trend' and 'none' specifications in the stationarity test model developed by Dickey Fuller (1979). The series is not reverting to their mean even in the long run, which signifies that the variance will be changing as a result of a change in time. There is a clear indication that the series is not stationary.

The line graphs have also indicated signs of stability in the series of the indices for the FTSE UK Oil and Gas and FTSE UK Oil and Gas Producers. Powerful breaks are observed in the FTSE All Share and FTSE 100 Share indices during the same period between 2003 and 2004, while the break in the FTSE AIM SS Oil and Gas index occurred around 2009. The graphs have shown the same pattern of movement for FTSE All Share and FTSE 100 Share indices. It shows that the top hundred companies representing the FTSE 100 share index could be the driving force of the entire London stock exchange.

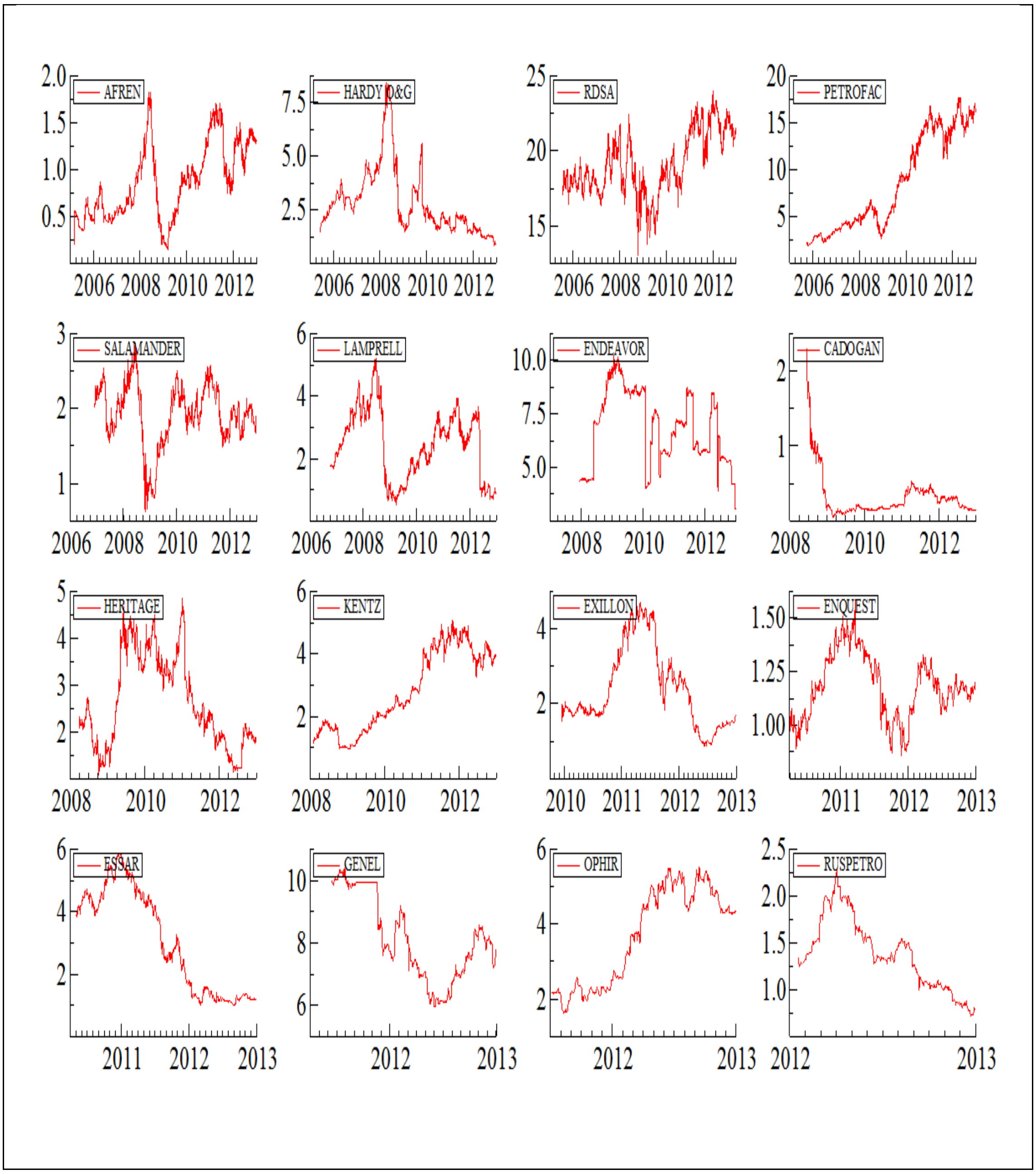
Table 6.1.2 - Graphical Presentation of Stock Prices of Companies with More Than 10 Years Series under study



Source: Author (2015)

Table 6.1.2 represents the graphical price series of the second category data set consisting of oil and gas companies that have time series data of more than ten years. Trends are observed with no intercepts in the time series of Amec Plc, BG Group Plc, Cairn Plc, Dragon Plc, Hunting Plc, Premier Plc, Tullow Oil Plc, Soco Intl. Plc, and Wood Group Plc. The series can be described as having random walk with a deterministic trend due to the absence of any constant mean generated. The price series of Fortune Plc and JKX Oil and Gas Plc depicted a random walk without trend or intercept indicating a full random walk process. BP Plc. and Aminex Plc price series have a constant but without a trend showing random walk with a drift and the RDSB Plc series has both trend and constant indicating a random walk with a drift and deterministic trend. In general, most of the series in this category of data set had lower prices or trading inactivity prior to 2005 as shown by the graphical presentation. The series of Fortune Plc prices appears to be unchanging over a long period which resulted in significant zero returns over the period of the study.

Table 6.1.3 – Graphical Presentation of Stock Prices of Companies with Less Than 10 Years Series under study



Source: Author (2015)

The final data set of this study constitutes the oil and gas companies with less than ten years' time series of prices and returns. The prices are presented graphically in Table 6.1.3 and, as with the observations made on the first and second data sets, all the stock price series indicate a random walk process either with a drift (constant), a deterministic trend or the combination of the two. However, most of the series in this category appears to be a full random walk process without a drift or deterministic trend. Afren Plc, Lamprell Plc, Cadogan Plc, Heritage Plc, Kentz Plc, Exillon Plc, Genel Plc and Ophir Plc have price series from a full random walk process. Random walk with a drift and deterministic trend is observed in Hardy Oil and Gas Plc, Royal Dutch Shell 'A' (RDSA) Plc, Essar Plc and Ruspetro Plc. Stock prices of Salamander Plc, Endeavor Plc and Enquest Plc depict random walk with only a drift, while that of Petrofac Plc suggests random walk with a deterministic trend.

In conclusion, the price series of oil and gas stocks quoted on the main market of the London stock exchange appear non-stationary due to a time varying mean of the individual series over the period of the study. The non-stationarity of the series provides an indication of a random walk process. A full random walk process does not come with either a drift (constant) or deterministic trend. It is a process where the change in Y_t is purely random and can be represented as $Y_t = Y_{t-1} + \varepsilon_t$, where ε_t represents ΔY_t. A random walk process could be with a drift (constant) where in forecasting tomorrow's price (P_{t+1}) can be determined by today's price (P_t) plus the difference between today's price and yesterday's price (P_{t-1}). Mathematically, this is represented by $P_{t+1} = P_t + (P_t - P_{t-1})$, which is similar to $Y_t = Y_{t-1} + \delta + u_t$, where δ is the difference between Y_t and Y_{t-1}, and u_t as the error term. A random walk process could also be with a deterministic trend ($Y_t = Y_{t-1} + \beta_2 t + u_t$) or with both a drift and deterministic trend at the same time ($Y_t = Y_{t-1} + \delta + \beta_2 t + u_t$). The stocks and indices under study have indicated all the characteristics discussed above. However, the application of some estimation models including the ordinary least square regression model on a non-stationary time series is believed to produce spurious results. In this regard, the non-stationary price series is converted to a stationary time series by using the first or higher order differencing of the price series (returns).

6.3.2 Stock Returns of the Oil and Gas Companies and Indices

The returns of the oil and gas stocks and indices are calculated using the log difference as expressed below:

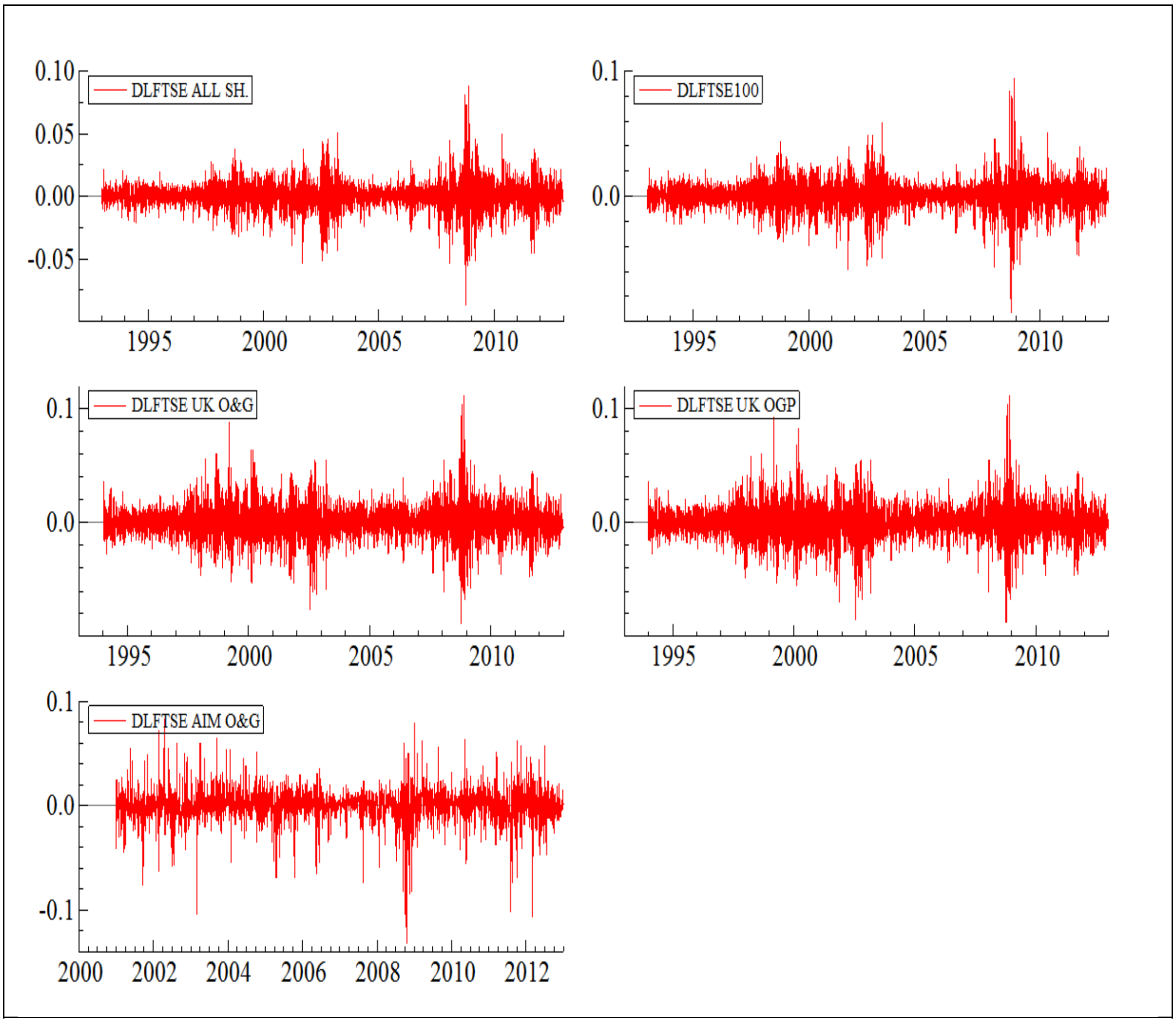
$$Rt = log(^{P_t}/_{P_{t-1}})$$

Where P_t = Price at time 't', (P_{t-1}) = One lagged price, R_t = Return at time 't'.

The use of log returns instead of simple percentages of price changes was mainly to eliminate the inequalities in the use of percentage where a decrease of a stock price (P_t) cannot be beyond hundred per cent (100%) of that price (P_t) because there is no negative stock price while an increase in the same value can be to infinity. In other words, log returns creates normalization by equating variables in comparable metric form for proper analysis of relationship between the variables. Log returns are also considered to be continuous or time-additive where returns are compounded based on the time series of prices.

The graphical presentation of oil and gas stock return and FTSE indices return series are shown in the tables below for visual analysis for observing seasonal behaviour and outliers or irregularities.

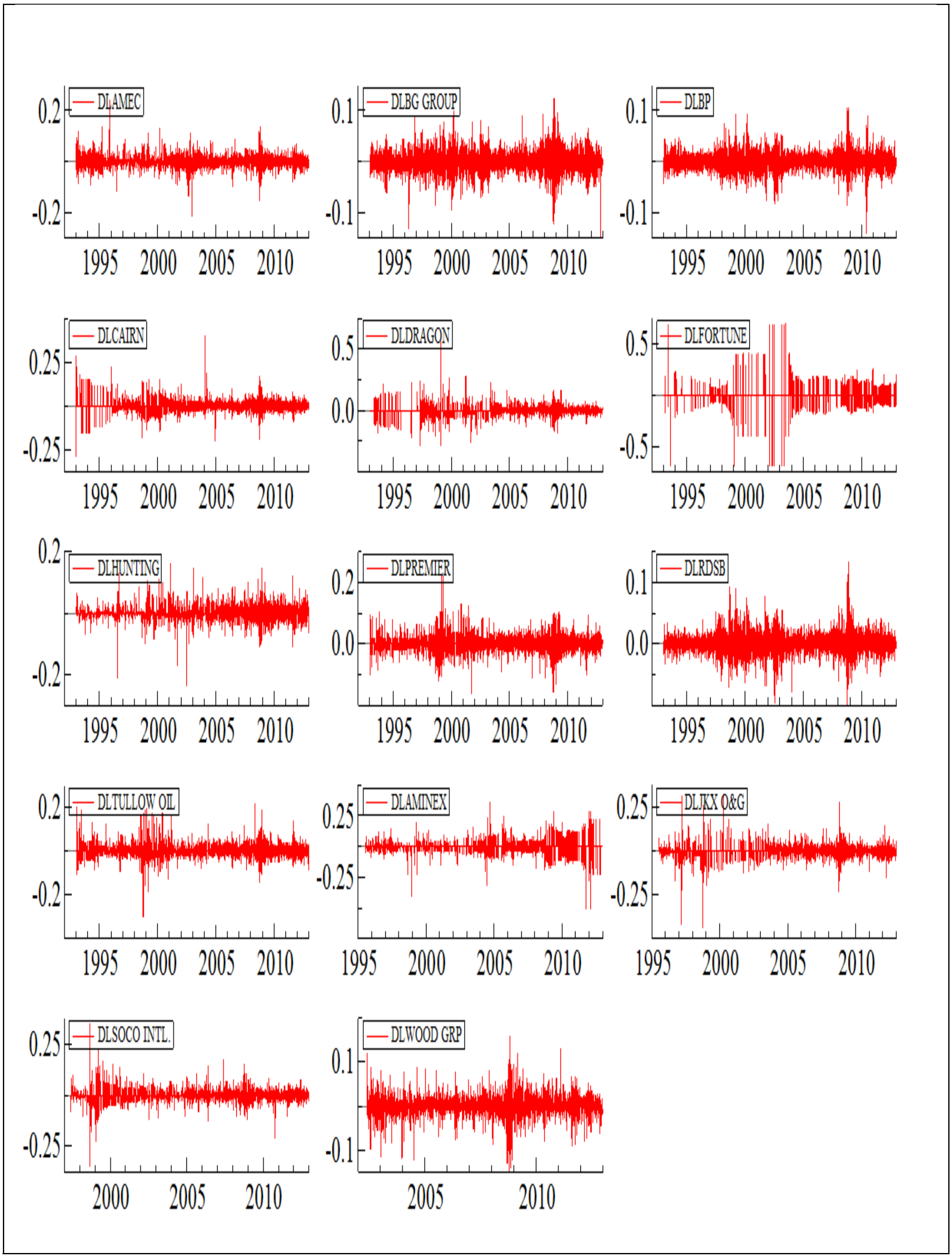
Table 6.2.1 - Graphical Presentation of the Indexes' Return Series under study



Source: Author (2015)

Table 6.2.1 presents the return series of the FTSE All Share, FTSE 100, FTSE UK Oil and Gas, FTSE UK Oil and Gas Producers and FTSE AIM Oil and Gas indices. The daily returns or changes in prices seem to revolve around the constant mean. There are outliers observed in the FTSE All Share, FTSE 100, FTSE UK Oil and Gas and FTSE UK Oil and Gas Producers indices during the same period in 2003 and 2009. Further analysis will highlight the behaviour of returns of these series.

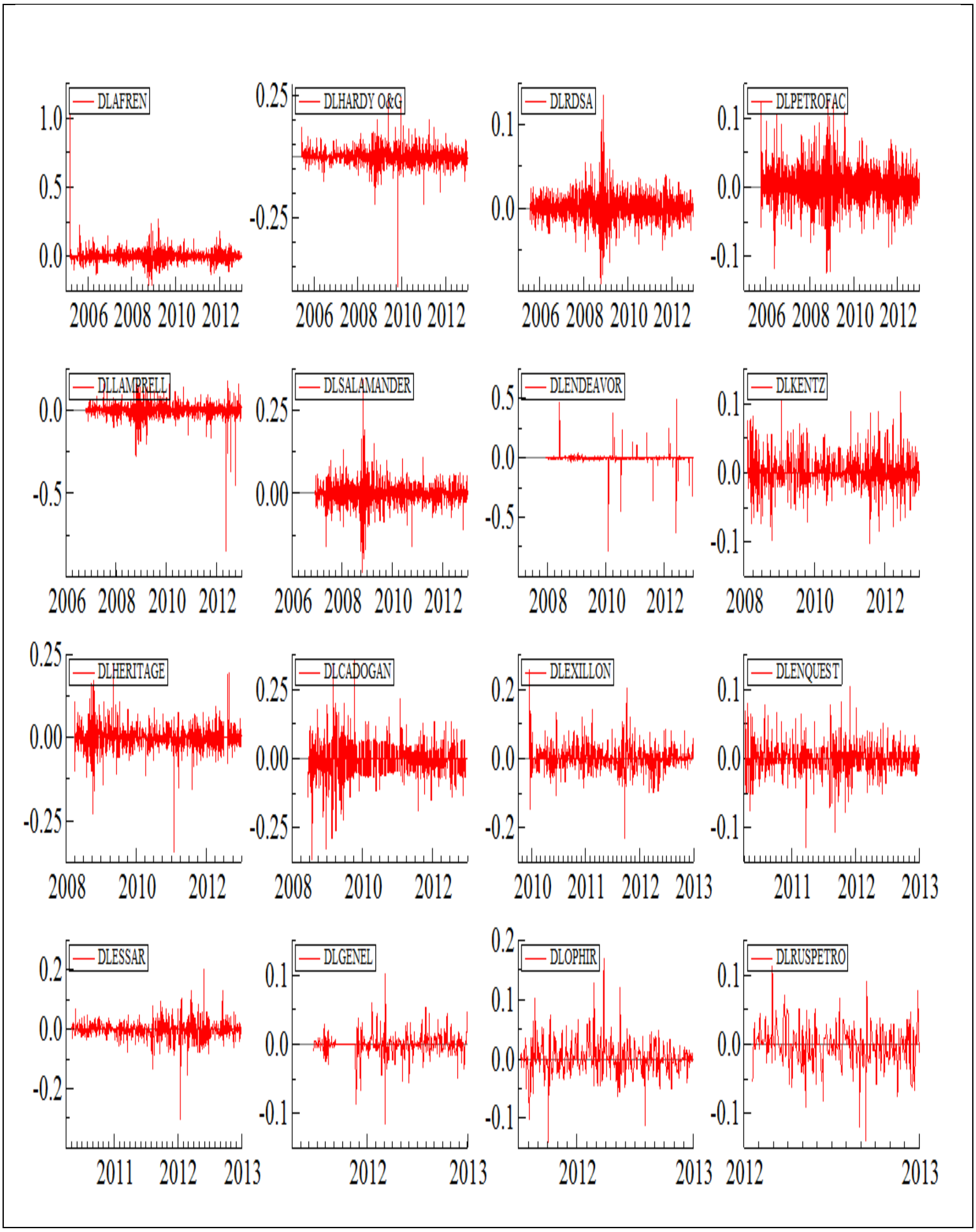
Table 6.2.2 - Graphical Presentation of Stock Returns of Companies with More Than 10 Years Series under study



Source: Author (2015)

Table 6.2.2 presents the oil and gas stock returns with more than ten (10) years series and the existence of a constant mean and variance is obvious which is a sign that the return series are stationary. An observation as a point of concern to this study was that in almost all the series shocks were observed around 2003 and 2009 similar to the outliers pointed out in the FTSE indices return series. However, there is an indication of significant inactivity or unchanging prices (zero returns) in Fortune Plc between the period 1993 and 2008; in Dragon Plc between the period 1993 and 1997; in Cairn Plc between 1993 and 1996; and in JKX Oil and Gas Plc between 2000 and 2003. Having a stationary time series from these stock returns will enable us to employ various financial models on the stocks for estimation and forecasting.

Table 6.2.3 – Graphical Presentation of Stock Returns of Companies with Less Than 10 Years Series under study



Source: Author (2015)

Table 6.2.3 presents the stock returns of companies with less than ten years series under study. Statistical properties seem to be constant indicating that the series are stationary. The irregularities observed in this data set are more conspicuous than the data sets of FTSE indices and stocks with more than ten years series. At this point of the research, it will be difficult to conclude of whether the instability was because companies are newly listed on the market. Specifically, the outliers found in each return series are more than the few identified in the other data sets. It is also prominent that the level of unchanging prices (zero returns) in the series of this data set is high as well. The overall model estimation and forecasting to be conducted in this research, essentially for volatility estimation, will measure the extent of changes or risks in the return of the series.

6.3.3 Descriptive Statistics of the Oil and Gas Stocks Returns and Indices

This section describes the statistical properties (descriptive statistics) of each return series under study. These statistics include mean, median, maximum, minimum, and standard deviation. The statistical properties of the return series are presented in Tables 6.3.1, 6.3.2, and 6.3.3 based on the categorical data sets of the study shown below.

Table 6.3.1 – Descriptive Statistics of the Indexes Return Series under study

	FTSE All Share	FTSE 100	FTSE UK O&G	FTSE UK O&G Prod.	FTSE AIM SS O&G
Mean	0.000157	0.000140	0.000244	0.000207	0.000188
Median	0.000186	2.01E-05	0.000000	0.000000	9.12E-05
Maximum	0.088107	0.093843	0.111159	0.111476	0.083357
Minimum	-0.087099	-0.092656	-0.088086	-0.087633	-0.132510
Std. Dev.	0.010791	0.011586	0.014881	0.015389	0.016173
Observations	5217	5217	4956	4956	3131

Source: Author (2015)

Table 6.3.1 portrays the descriptive statistics of the returns of the five FTSE share indices using daily data under consideration. The mean returns show that the FTSE UK Oil and Gas index has the highest average return of 0.000244, followed by that of the FTSE UK Oil and Gas Producers with 0.000207 and then the FTSE AIM SS Oil and Gas with 0.000188 and the FTSE All Share with 0.000157. The FTSE 100 Share index has the lowest average return of 0.000140 in that order. This postulates that the investors acquired higher risk-adjusted returns from an oil and gas sector portfolio (assuming all companies are represented) than the portfolio representing the entire market (FTSE All Share index). It is also noted that investment in oil and gas producing companies during the period of study might not have resulted in a return higher than that from the overall oil and gas sector (production and equipment services companies). The median represents the middle values or average of the middle values of the return series. FTSE UK Oil and Gas Producers index recorded the maximum return of 0.111476, while the FTSE AIM SS Oil and Gas index had the minimum return of -0.132510 among the indices.

Standard deviation is an important statistical feature that measures the extent of variability or dispersion in the return series. This measure is used by investors to assess the magnitude of risk involved in an investment. Standard deviation is calculated by:

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

Finance theory postulates that the relationship between the standard deviation (risk) and return should be positive, where higher returns are associated with higher risk. The FTSE Aim SS Oil and Gas index return has the highest standard deviation of 0.016173 when its average return was not the highest among the FTSE indices. Similarly, the FTSE All Share index return has the lowest standard deviation as this is the most diversified portfolio when its average return was not the lowest

Table 6.3.2– Descriptive Statistics of Stock Returns of Companies with More Than 10 years Series under study

	Amec Plc	**BG Group**	**BP Plc**	**Cairn Energy**	**Dragon Oil**
Mean	0.000516	0.000386	0.000236	0.000804	0.000482
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.238411	0.123090	0.105892	0.405465	0.559616
Minimum	-0.213574	-0.147277	-0.140773	-0.287682	-0.287682
Std. Dev.	0.021678	0.019852	0.016928	0.029078	0.035096
Observations	5217	5217	5217	5217	5217
	Fortune Oil	**Hunting Plc**	**Premier Oil**	**RDS 'B'**	**Tullow Oil**
Mean	0.000133	0.000304	0.000385	0.000231	0.000927
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.693147	0.162859	0.223144	0.132139	0.215748
Minimum	-0.693147	-0.235566	-0.162519	-0.098147	-0.305382
Std. Dev.	0.063994	0.020242	0.024307	0.016422	0.026708
Observations	5217	5217	5217	5217	5217
	Aminex Plc	**JKX O&G**	**Soco Internl.**	**Wood Group (John)**	
Mean	-0.000593	-0.000172	0.000419	0.000470	
Median	0.000000	0.000000	0.000000	0.000000	
Maximum	0.367725	0.312375	0.348307	0.158824	
Minimum	-0.510826	-0.435318	-0.348307	-0.146603	
Std. Dev.	0.042613	0.032481	0.028256	0.025217	
Observations	4563	4559	4068	2764	

Source: Author (2015)

Table 6.3.2 presents the statistical properties of oil and gas companies with more than ten years series. Cairn Energy return series had the highest average return (mean) of 0.000804 with a standard deviation (risk) of 0.029078 which was not the highest among the fourteen stocks in this data set. The lowest average returns of -0.000593 was observed in the Aminex Plc stock return series with a standard deviation of 0.042613 which was not the lowest in the data set. Tullow Oil Plc, Amec Plc, Dragon Oil Plc and Wood Group (John) Plc were stocks with highest average returns after Cairn Energy Plc at 0.000927, 0.000516, 0.000482, 0.000470 and standard deviation of 0.026708, 0.021678, 0.035096, and 0.025217 respectively. Negative average returns were only observed in the Aminex Plc and JKX Oil and Gas Plc stock returns without having the lowest standard deviations. Fortune Oil Plc stock returns recorded the highest standard deviation of 0.063994 and its average return was 0.000133.

Table 6.3.3 – Descriptive Statistics of Stock Returns of Companies with Less Than 10 years Series under study

	Afren Plc	**Hardy O&G**	**RDS 'A'**	**Petrofac Ltd**	**Lamprell Plc**
Mean	0.000923	-0.000238	9.13E-05	0.001110	-0.000390
Median	0.000000	0.000000	7.83E-05	0.000000	0.000000
Maximum	1.029619	0.256878	0.136519	0.126971	0.184429
Minimum	-0.213574	-0.534298	-0.091990	-0.124563	-0.842788
Std. Dev.	0.045291	0.032954	0.015733	0.025712	0.047310
Observations	2036	1975	1943	1890	1624
	Salamander	**Endeavor Intl.**	**Kentz Corp.**	**Heritage Oil**	**Cadogan Petr.**
Mean	-3.86E-05	-0.000261	0.000950	-7.29E-05	-0.002364
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.345502	0.500081	0.118808	0.220576	0.356675
Minimum	-0.237959	-0.782546	-0.102105	-0.343361	-0.365460
Std. Dev.	0.033841	0.043498	0.021502	0.036373	0.059006
Observations	1588	1316	1280	1241	1184
	Exillon Energy	**Enquest**	**Essar Energy**	**Genel Energy Plc**	**Ophir Energy**
Mean	0.000133	0.000298	-0.001704	-0.000618	0.001815
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.257829	0.104261	0.202237	0.102963	0.171245
Minimum	-0.228952	-0.128992	-0.303307	-0.114334	-0.139113
Std. Dev.	0.035000	0.022917	0.033226	0.017755	0.029152
Observations	793	715	695	402	387
	Ruspetro Plc				
Mean	-0.002131				
Median	0.000000				
Maximum	0.112619				
Minimum	-0.139762				
Std. Dev.	0.031249				
Observations	248				

Source: Author (2015)

Table 6.3.3 portrays the descriptive statistics of sixteen oil and gas companies with less than ten years of data. Nine out of the sixteen stocks recorded negative average returns (mean) over the period of the study. Hardy Oil and Gas Plc, Lamprell Plc, Salamander Plc, Endeavor Intl. Plc, Heritage Oil Plc, Cadogan Petroleum Plc, Essar Energy Plc, Genel Energy Plc and Ruspetro Plc stocks have negative average returns. Stocks of Afren Plc, Royal Dutch Shell 'A' Plc (RDSA), Petrofac Plc, Kentz Corp. Plc, Exillon Energy Plc, Enquest Plc, Essar Energy Plc and Ophir Energy Plc recorded positive average returns. Cadogan Petroleum Plc had the highest negative return within the period while Ophir Energy had the highest positive return. The standard deviation showed higher variability of returns from the average mean in Cadogan Petroleum Plc's returns at 0.059006, and lowest variability (standard deviation) noted in RDS 'A' stock returns at 0.015733.

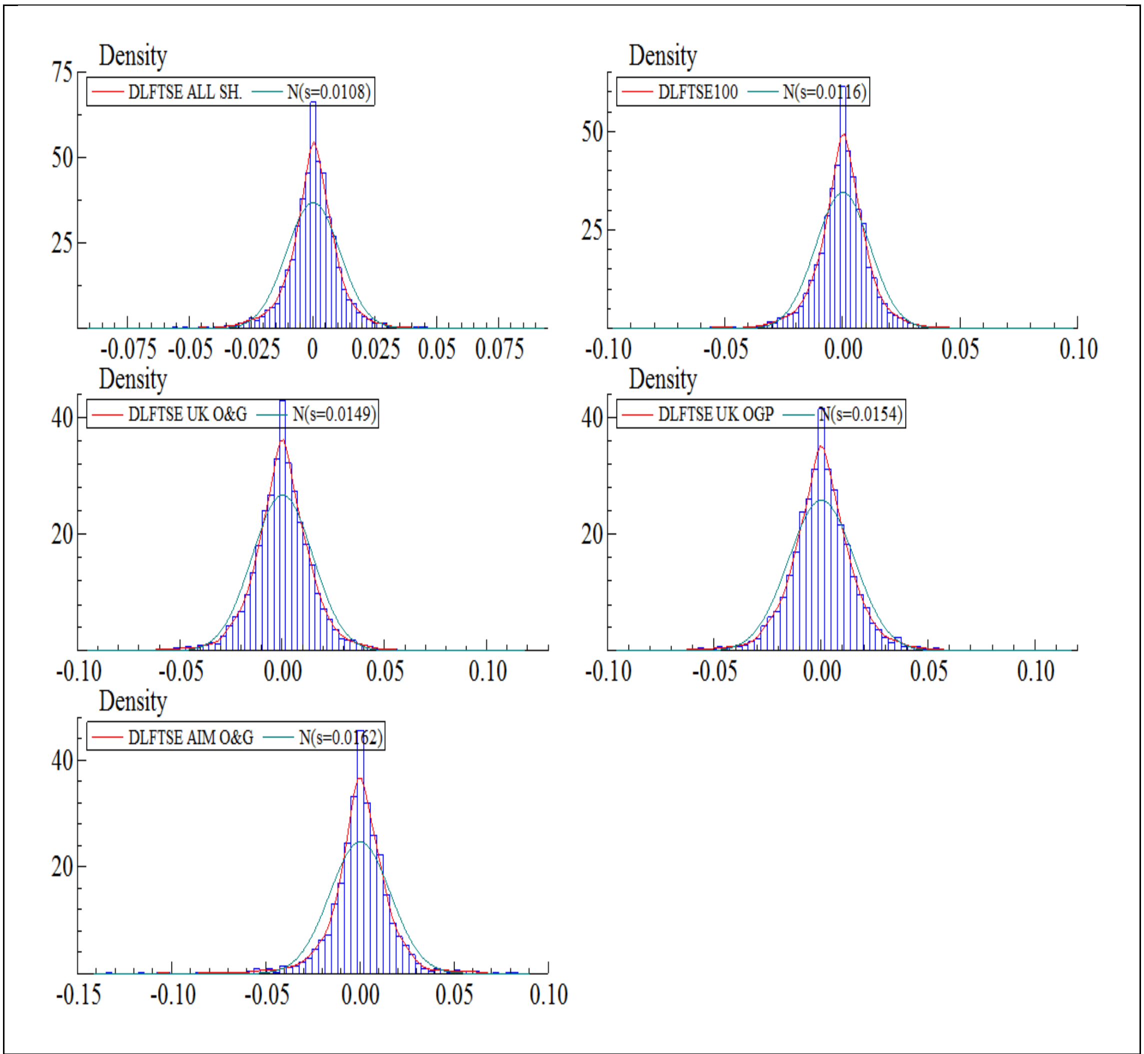
6.3.4 Normality Tests on the Oil and Gas Stocks Returns and Indices

The distributions of the return series under study are analysed using the normality test to assess the features of their skewness and the kurtosis and establish whether they possess the characteristics of either normal or non-normal distribution. In addition to graphical and numerical methods, more advanced methods were also used to explain the distribution pattern of the series.

6.3.4.1 Graphical Methods

In graphical methods, the skewness and kurtosis of the data series are presented against that of a normal distribution (reference) to observe any compliance or deviation. A histogram with density and normal reference, a box-plot, and Q-Quantiles methods are employed. The histogram with density and normal reference represents the range of stock returns in blocks based on the number of occurrences or observations (x_t). The green lines in the graphs represent the supposed normal distribution while red lines represent the actual distribution of the research data series. A box plot is another convenient way of graphical presentation of statistical properties and distribution. A box is plotted representing a normal distribution from a data set where the centre of the box is the mean. Lines outside the box are called whiskers and outliers are easily identified beyond the whiskers. The Quantile-Quantile (QQ) plot tests whether a data set follows a given distribution with a single line representing the actual data. In a normal QQ plot, the actual data line is plotted on normal distribution lines.

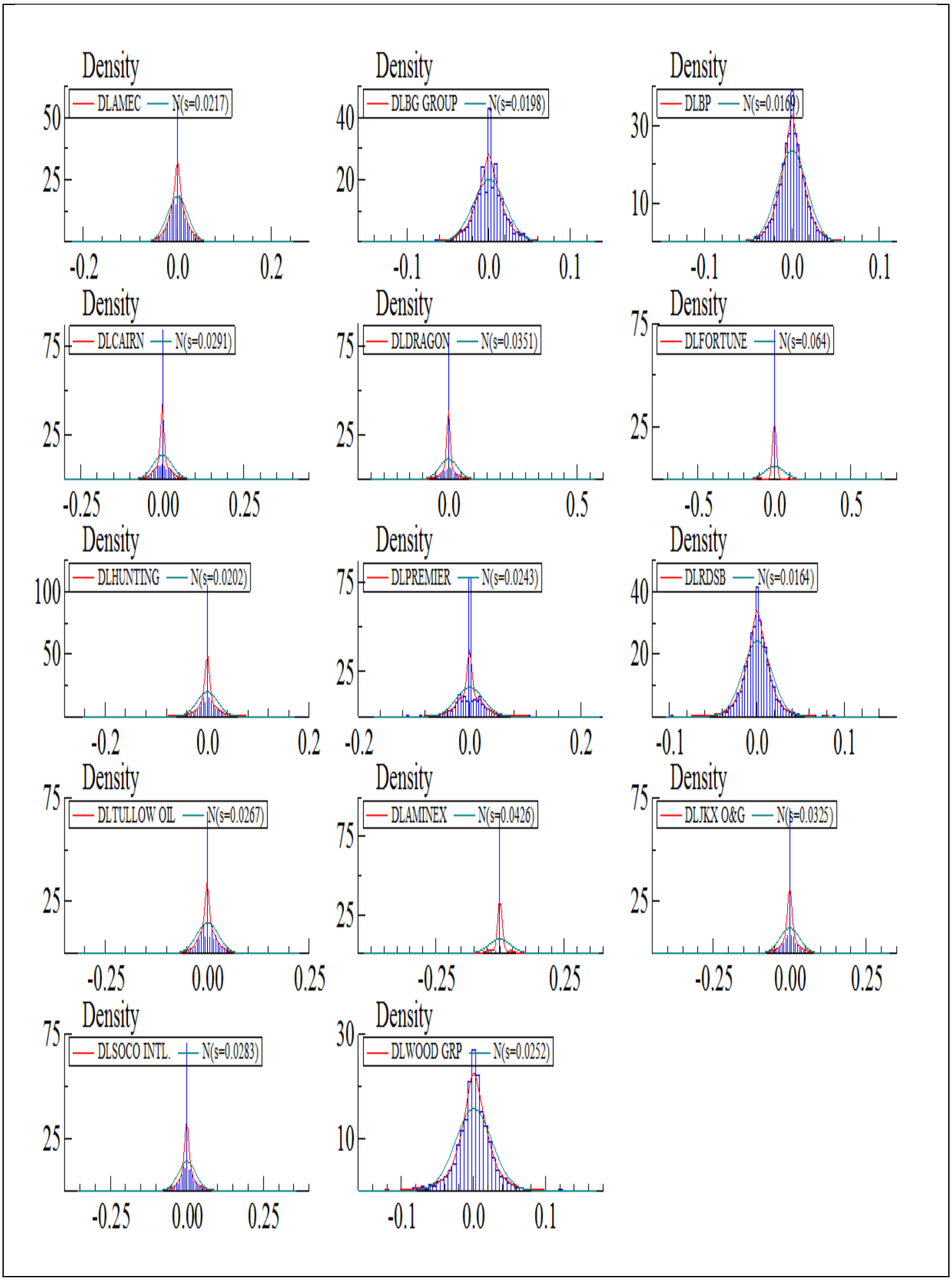
Table 6.4.1 – Histogram with Density and Normality Reference of Indexes' Return Series under study



Source: Author (2015)

Table 6.4.1 shows the distribution pattern of the FTSE indices' return series using a histogram with density and normal reference. High kurtosis was observed in all the indices as compared to the kurtosis of a normal distribution. Although, skewness is not exactly at a point shown by normal distribution green lines, the deviation was not high. At this stage, it can only be seen that the distributions of the FTSE All Share, FTSE 100, FTSE UK Oil and Gas, FTSE UK Oil and Gas Producers and FTSE AIM Oil and Gas indices return series are a deviation from normality with a high kurtosis observed.

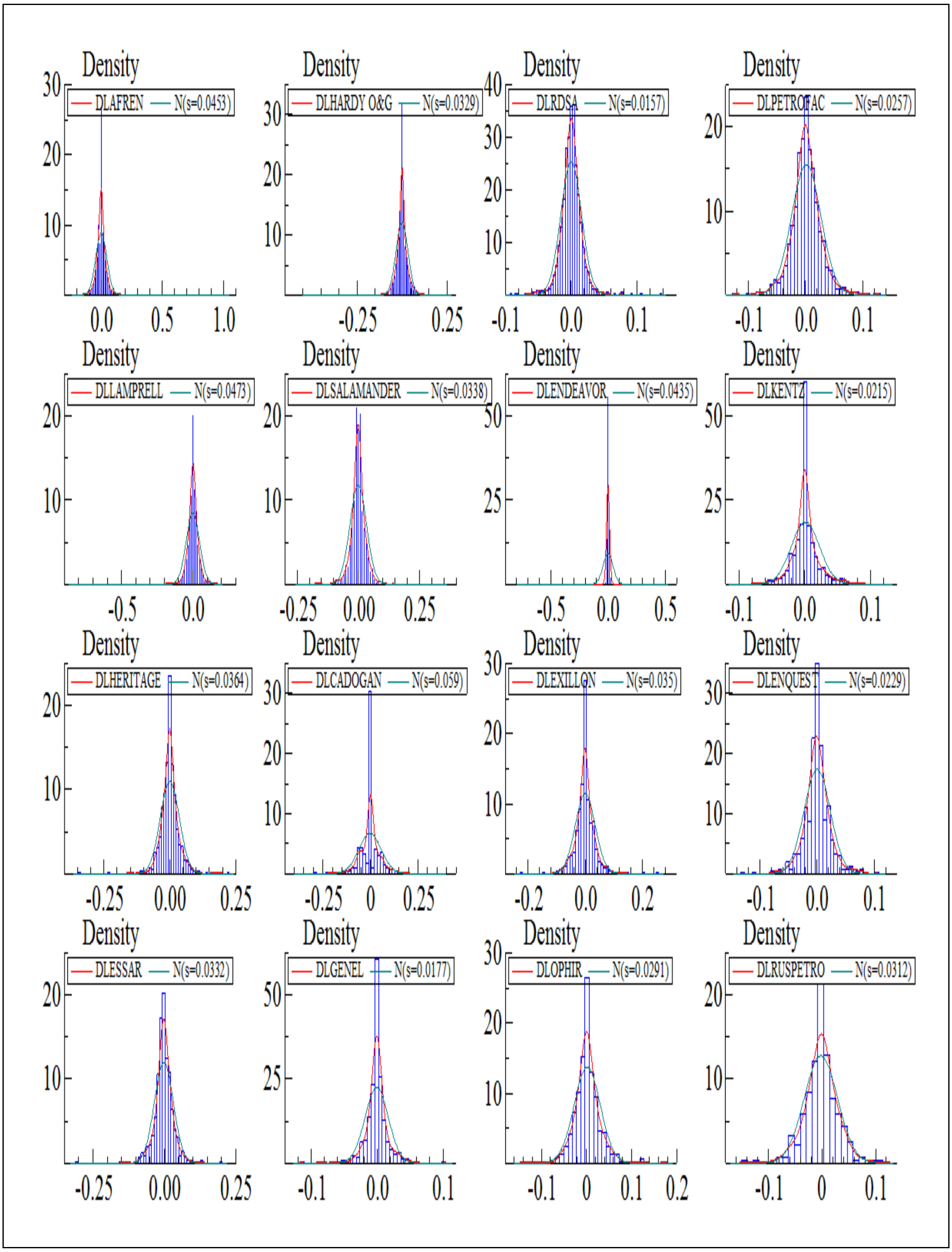
Table 6.4.2 – Histogram with Density and Normality Reference of Stock Returns of Companies with More Than 10 Years Series under study



Source: Author (2015)

Table 6.4.2 presents the histogram with density and normality reference of the category of companies in this study with more than 10 years series. According to the graphs, all the series show deviation from normality at different levels. BG Group Plc, BP Plc, RDS 'B' Plc and the Wood Group Plc had their kurtosis higher than that of referenced normal distribution with skewness having a slight deviation from the normality point. The picture depicted by Amec Plc, Cairn Energy Plc, Dragon Plc, Fortune Plc, Hunting Plc, Premier Plc, Tullow Oil, Aminex Plc and JKX Oil and Gas Plc can be described as sceptical at this level. It is to be elaborated further by both numerical and formal methods of normality test.

Table 6.4.3 – Histogram with Density and Normality Reference of Stock Returns of Companies with Less Than 10 Years Series under study



Source: Author (2015)

Table 6.4.3 presented the histogram with density and normality reference of stock returns of companies with less than 10 years series. Similar to the graphs of series presented earlier, high kurtosis above normality was observed. Skewness was also seen to be a deviation from normality. The distribution pattern of Endeavor Plc and Cadogan Plc were regarded as sceptical due to extreme outliers observed. Further analysis is required for a conclusion to be made.

Appendix 1 (Table 6.5.1) shows the Box Plot of the FTSE indices return series under study. The blue-box plotted depicts an area of normal distribution, while the red spots indicate actual data. The distributions of the FTSE indices return series are outside the area of normality. The actual series are mostly on the whiskers with some outliers detected.

Appendix 2 (Table 6.5.2) presents the Box Plot of companies with more than 10 years series and, despite the actual series being out of the normal distribution box, various outliers are equally detected. A normal distribution box could not be constructed from the data of Dragon Plc, Fortune Plc and Aminex Plc.

Appendix 3 (Table 6.5.3) exhibits the Box Plot of stock returns of companies with less than 10 years series and the common feature observed in these series was the existence of extreme values of outliers. It is not surprising that the stock return series are not within the normality box. The outliers observed in the return series of stocks such as Afren Plc, Hardy Oil and Gas Plc, Lamprell Plc, Heritage Plc, Cadogan Petroleum Plc, Exillon Plc and Essar Plc are all for consideration in modelling and forecasting. Robust models would be employed where necessary to address this concern.

Appendix 4 (Table 6.6.1) presents the QQ plot of the FTSE indices' return series. The red lines represent the actual series while green lines are plotted on the assumption of normal distribution. In this case, two probability distributions of normality and actual data series are plotted for comparison. It is clear from observations made on the graphs that actual data series are slightly skewed in both positive and negative directions away from normality. It can also be seen that the tails of the FTSE indices return series are heavier than that of normal distribution.

Appendix 5 (Table 6.6.2) presents the QQ plot of oil companies with return series of more than ten (10) years. The characteristics are similar to those observed in the QQ plot of the FTSE indices return series. Slight skewness and heavy tails are dominant features of the actual series. Significant zero returns or inactivity are noted in the series of Fortune Plc and Aminex Plc.

Appendix 6 (Table 6.6.3) shows the QQ plot of companies with less than 10 years series under study. From the plots, all the series show deviation from normal distribution with heavy tails observed. Zero returns (inactivity) are observed in the return series of Endeavor Plc and Cadogan Plc.

6.3.4.2 Numerical Methods

The numerical methods considered for normality test and assessment of other characteristics of the research data probability distribution are skewness, kurtosis and Jacque-Bera statistic.

Skewness is simply the measure of asymmetry in the distribution of a data series. It is about the symmetry around the sample mean of a given data series and is given by:

$$\text{Skewness} = \frac{\sum_{i=1}^{n}(x_i - \mu)3}{N\sigma^3}$$

Skewness of zero (0) value indicates a symmetrical distribution, while positive skewness means asymmetrical distribution has a long tail to the right (skewed positively) or to the left (skewed negatively) if skewness has negative value. It is conventionally assumed that a skewness of >1 or < -1 indicates a strong deviation from being symmetrical.

Kurtosis is a measure of the peak (height) of the probability distribution. Gaussian distribution is expected to have a kurtosis equal to 3. Excess kurtosis is determined by deducting 3 from the overall kurtosis (EK = K-3). It is given by:

$$\text{Kurtosis} = \frac{\sum_{i=1}^{n}(x_i - \mu)4}{\sigma^4}$$

Negative kurtosis indicates flatter distribution, while positive kurtosis denotes peaked distribution.

Jacque-Bera statistic tests whether both the skewness and kurtosis are the same with that of normal distribution. It is given as:

Jacque-Bera = $\frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$

S = Skewness, K = Kurtosis.

The null and alternative hypotheses are:

H_0 : Normal distribution

H_1 : Non-normal distribution

Significance level (ρ) of 5% and 1% are used to accept or reject the hypotheses. Using 2% degrees of freedom, the statistic can be used to test for chi-square distribution.

Table 6.7.1 – Skewness, Kurtosis, and Jacque-Bera Statistic of Indexes Return Series under study

	FTSE All Share	FTSE 100	FTSE UK O&G	FTSE UK O&G Prod	FTSE AIM SS O&G
Skewness	-0.230121	-0.157194	0.072763	0.057754	-0.858220
Kurtosis	9.715615	9.272656	7.499790	7.413048	10.50695
Excess Kurtosis	6.7156	6.2727	4.4998	4.4130	7.5070
Jacque – Bera Stat.	9849.545	8574.369	4185.608	4024.341	7736.249
Probability	0.000000	0.000000	0.000000	0.000000	0.000000

Source: Author (2015)

Table 6.7.1 shows the skewness, kurtosis, and Jacque-Bera statistic of the FTSE indices return series. FTSE All Share, FTSE 100 and FTSE AIM SS Oil and Gas indices return series are negatively skewed with skewness of -0.230121, -0.157194, and -0.858220 respectively. FTSE UK Oil and Gas and FTSE UK Oil and Gas Producers indices return series are positively skewed with skewness of 0.072763 and 0.057754 respectively. The skewness values are not less than -1 and greater than 1 and therefore not to show a strong deviation from symmetrical distribution. Excess kurtosis was recorded in all the series with the highest at 7.5070 suggesting a slight deviation from that of normal distribution.

Jacque-Bera statistic's null hypothesis of normal distribution was strongly rejected at both the 5% and 1% significance level for all the series. The alternative hypothesis of non-normal distribution is accepted.

Table 6.7.2 – Skewness, Kurtosis, and Jacque-Bera Statistic of Stock Returns of Companies with More Than 10 years Series under study

	Amec Plc	**BG Group Plc**	**BP Plc**	**Cairn Energy Plc**	**Dragon Oil Plc**
Skewness	0.180549	-0.079972	-0.020532	0.914705	0.779906
Kurtosis	12.57404	6.646250	7.351447	22.48178	26.38318
Excess Kurtosis	9.5740	3.6462	4.3514	19.482	23.383
Jacque – Bera Stat.	19953.43	2895.591	4116.382	83229.98	119383.7
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Fortune Oil	**Hunting Plc**	**Premier Oil**	**RDS 'B' Plc**	**Tullow Oil Plc**
Skewness	-0.120350	-0.191022	0.336821	0.105473	0.509788
Kurtosis	50.88975	16.28953	9.978643	7.757852	14.87789
Excess Kurtosis	47.890	13.290	6.9786	4.7579	11.878
Jacque – Bera Stat.	498546.6	38422.65	10685.12	4930.425	30894.14
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Aminex Plc	**JKX O&G Plc**	**Soco Intl. Plc**	**Wood (John) Group Plc**	
Skewness	-0.568339	-0.486766	-0.486220	-0.238983	
Kurtosis	24.28697	26.74168	27.09140	7.553424	
Excess Kurtosis	21.280	23.742	24.091	4.5534	

Jacque – Bera Stat.	86397.97	107253.3	98537.34	2414.138	
Probability	0.000000	0.000000	0.000000	0.000000	

Source: Author (2015)

Table 6.7.2 shows the skewness, kurtosis and Jacque-Bera statistic of stock returns with more than 10 years series. BG Group Plc, BP Plc, Fortune Oil Plc, Hunting Plc, Aminex Plc, JKX Oil and Gas Plc, Soco Intl. Plc and Wood Group Plc return series are negatively skewed with skewness of -0.079972, -0.020532, -0.120350, -0.191022, -0.568339, -0.486766, -0.486220, and -0.238983 respectively. Cairn Energy Plc, Dragon Oil Plc, Premier Oil Plc, RDS 'B' Plc, and Tullow Oil Plc return series are positively skewed with skewness of 0.914705, 0779906, 0.336821, 0.105473, and 0.509788 respectively. The skewness values are neither less than -1 nor greater than 1 and therefore do not show a strong deviation from symmetrical distribution. Excess kurtosis was recorded in all the series with the highest recorded in Fortune Oil Plc at 47.890, followed by Soco Intl. Plc at 24.091, JKX O&G Plc at 23.742, Dragon Oil Plc at 23.383, Aminex Plc at 21.280, Cairn Energy Plc at 19.482, Hunting Plc at 13.290 and Tullow Oil Plc at 11.878. These stock returns with extreme kurtosis are deemed to have a leptokurtosis distribution.

Jacque-Bera statistic's null hypothesis of normal distribution was strongly rejected at both the 5% and 1% significance level for all the series. The alternative hypothesis of non-normal distribution is accepted.

Table 6.7.3 – Skewness, Kurtosis, and Jacque-Bera Statistic of Stock Returns of Companies with Less Than 10 years Series under study

	Afren Plc	**Hardy O&G Plc**	**RDS 'A' Plc**	**Petrofac Plc**	**Lamprell Plc**
Skewness	5.990967	-1.785837	0.298040	0.057651	-4.583030
Kurtosis	135.8592	43.52064	10.78380	6.056701	74.46898
Excess Kurtosis	132.86	40.521	7.7838	3.0567	71.469
Jacque – Bera Stat.	1509620.	136166.3	4933.830	736.8416	351313.9
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Salamander Plc	**Endeavor Intl. Plc**	**Kentz Corp. Plc**	**Heritage Oil Plc**	**Cadogan Petroleum Plc**
Skewness	0.595314	-5.434037	0.341588	-0.261858	-0.242248
Kurtosis	18.51511	160.6660	7.199762	15.06397	9.218145
Excess Kurtosis	15.515	157.67	4.1998	12.064	6.2181
Jacque – Bera Stat.	16021.34	1369556.	965.5859	7539.785	1919.070
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Exillon Energy Plc	**Enquest Plc**	**Essar Energy Plc**	**Genel Energy Plc**	**Ophir Energy Plc**
Skewness	0.587455	-0.073841	-0.831949	-0.617295	0.507924
Kurtosis	11.47697	6.655585	16.04639	12.84782	8.933786
Excess Kurtosis	8.4770	3.6556	13.046	9.8478	5.9338
Jacque – Bera Stat.	2419.955	398.7647	5009.124	1649.938	584.3984
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Ruspetro Plc				
Skewness	-0.368145				
Kurtosis	5.596321				
Excess Kurtosis	2.5963				
Jacque – Bera Stat.	75.25770				
Probability	0.000000				

Source: Author (2015)

Table 6.7.3 shows the skewness, kurtosis and Jacque-Bera statistic of stock returns with less than 10 years series. Most of the stock return series are negatively skewed at greater than -1 except Endeavor Intl. Plc at -5.434037, Lamprell Plc at -4.583030 and Hardy O&G Plc at -1.785837. Since the values are less than -1, a strong deviation to a symmetrical distribution is established. Others are positively skewed at less than 1 except Afren Plc which recorded 5.990967, that was significantly greater than 1 and strongly asymmetrical. Excess kurtosis was recorded in all the series with the highest recorded in Endeavor Intl. Plc at 157.67, followed by Afren Plc at 132.86, Lamprell Plc at 71.469, Hardy Oil and Gas Plc at 40.521, Salamander Plc at 15.515, and Essar Plc at 13.046. These stock returns with extreme kurtosis are deemed to have leptokurtosis distribution as well.

Jacque-Bera statistic's null hypothesis of normal distribution was strongly rejected at both the 5% and 1% significance level for all the series. The alternative hypothesis of non-normal distribution is accepted.

6.3.4.3 Formal Normality Tests

Formal normality tests are empirical distribution tests for normality in which a comparison is made between empirical distribution and a specified theoretical distribution function. It is possible to use specified parameters to test for other distributions such as chi-square, logistic, exponential and gamma. Some of the prominent formal tests were invented by Lilliefors (1967), Anderson-Darling (1952), Watson (1961), Cramervon Mises (1928-1930), Shapiro-Wilk (1965) and Kolmogorov-Smirnov (1948). These tests are equally employed for distribution analysis in this research. The test-statistics have null and alternative hypotheses as:

H_0 : Normal distribution

H_1 : Non-normal distribution

A significance level (ρ) of 5% and 1% are used to accept or reject the hypotheses.

Table 6.8.1 – Lilliefors (LF), Anderson-Darling (AD), Watson (U_2), Cramervon Mises (W_2), Shapiro-Wilk (SW), and Kolmogorov-Smirnov tests of Indexes Return Series under study

	FTSE All Share	FTSE 100	FTSE UK O&G	FTSE UK O&G Prod	FTSE AIM SS O&G
Lilliefors (LF) Test: Value P-value	0.079399 0.0000	0.071941 0.0000	0.054731 0.0000	0.055226 0.0000	0.090429 0.0000
Cramervon Mises (W2) Test: Value P-value	13.18311 0.0000	11.24395 0.0000	6.843159 0.0000	7.124952 0.0000	9.643597 0.0000
Watson (U2) Test: Value P-value	13.06517 0.0000	11.17768 0.0000	6.842826 0.0000	7.124548 0.0000	9.486204 0.0000
Anderson-Darling (AD) Test: Value P-value	74.84743 0.0000	64.37471 0.0000	40.17333 0.0000	41.83033 0.0000	55.65134 0.0000
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.079 0.000	0.072 0.000	0.055 0.000	0.055 0.000	0.090 0.000

Source: Author (2015)

Table 6.8.1 presents the statistical results of the Lilliefors (LF), Anderson-Darling (AD), Watson (U_2), Cramervon Mises (W_2), Shapiro-Wilk (SW), and Kolmogorov-Smirnov tests on FTSE indices return series under study. The statistics' null hypotheses of normal distribution were strongly rejected at both the 5% and 1% significance level for all the series. The alternative hypothesis of non-normal distribution is accepted.

Table 6.8.2 – Lilliefors (LF), Anderson-Darling (AD), Watson (U2), Cramervon Mises (W_2), Shapiro-Wilk (SW), and Kolmogorov-Smirnov tests of Stock Returns of Companies with More Than 10 Years Series under study

	Amec Plc	**BG Group Plc**	**BP Plc**	**Cairn Energy Plc**	**Dragon Oil Plc**
Lilliefors (LF) Test: Value P-value	0.090429 0.0000	0.245964 0.0000	0.056444 0.0000	0.241715 0.0000	0.264125 0.0000
Cramervon Mises (W2) Test: Value P-value	9.643597 0.0000	72.66503 0.0000	7.343239 0.0000	82.71455 0.0000	121.2500 0.0000
Watson (U2) Test: Value P-value	9.486204 0.0000	66.72308 0.0000	7.343229 0.0000	82.54600 0.0000	121.2311 0.0000
Anderson-Darling (AD) Test: Value P-value	55.65134 0.0000	394.7976 0.0000	41.68704 0.0000	387.6891 0.0000	561.7367 0.0000
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.106 0.000	0.072 0.000	0.056 0.000	0.242 0.000	0.264 0.000
	Fortune Oil Plc	**Hunting Plc**	**Premier Oil Plc**	**RDS 'B' Plc**	**Tullow Oil Plc**
Lilliefors (LF) Test: Value P-value	0.446391 0.0000	0.200062 0.0000	0.186792 0.0000	0.060744 0.0000	0.174188 0.0000
Cramervon Mises (W2) Test: Value P-value	307.4243 0.0000	63.72180 0.0000	36.42461 0.0000	8.942711 0.0000	42.08531 0.0000
Watson (U2) Test: Value P-value	307.4199 0.0000	63.69716 0.0000	36.35764 0.0000	8.942338 0.0000	41.91285 0.0000
Anderson-Darling (AD) Test: Value P-value	1378.791 0.0000	299.7097 0.0000	169.4253 0.0000	51.65318 0.0000	204.5932 0.0000
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.446 0.000	0.200 0.000	0.187 0.000	0.061 0.000	0.174 0.000

	Aminex Plc	JKX O&G Plc	Soco Intl. Plc	Wood (John) Group Plc	
Lilliefors (LF) Test: Value P-value	0.380046 0.0000	0.219532 0.0000	0.192991 0.0000	0.078266 0.0000	
Cramervon Mises (W2) Test: Value P-value	177.5365 0.0000	70.54040 0.0000	50.65713 0.0000	6.586382 0.0000	
Watson (U2) Test: Value P-value	177.5360 0.0000	70.53912 0.0000	50.65554 0.0000	6.540304 0.0000	
Anderson-Darling (AD) Test: Value P-value	797.6681 0.0000	330.1835 0.0000	242.0170 0.0000	37.39265 0.0000	
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.380 0.000	0.220 0.000	0.193 0.000	0.078 0.000	

Source: Author (2015)

Table 6.8.2 presents the statistical results of the Lilliefors (LF), Anderson-Darling (AD), Watson (U_2), Cramervon Mises (W_2), Shapiro-Wilk (SW), and Kolmogorov-Smirnov tests on oil and gas companies with more than ten years return series for the study. The statistics' null hypotheses of normal distribution were strongly rejected at both the 5% and 1% significance level for all the series. The alternative hypothesis of non-normal distribution is accepted.

Table 6.8.3 – Lilliefors (LF), Anderson-Darling (AD), Watson (U_2), Cramervon Mises (W_2), Shapiro-Wilk (SW), and Kolmogorov-Smirnov tests of Stock Returns of Companies with Less Than 10 Years Series under study

	Afren Plc	**Hardy O&G Plc**	**RDS 'A' Plc**	**Petrofac Plc**	**Lamprell Plc**
Lilliefors (LF) Test: Value P-value	0.147620 0.0000	0.118424 0.0000	0.067599 0.0000	0.060282 0.0000	0.122571 0.0000
Cramervon Mises (W2) Test: Value P-value	14.44659 0.0000	10.99713 0.0000	3.838633 0.0000	2.715446 0.0000	11.18587 0.0000
Watson (U2) Test: Value P-value	14.37433 0.0000	10.99606 0.0000	3.837120 0.0000	2.712397 0.0000	11.09637 0.0000
Anderson-Darling (AD) Test: Value P-value	75.81094 0.0000	55.91510 0.0000	24.07580 0.0000	15.74652 0.0000	62.78420 0.0000
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.148 0.000	0.118 0.000	0.068 0.000	0.060 0.000	0.123 0.000

	Salamander Plc	**Endeavor Intl. Plc**	**Kentz Corp. Plc**	**Heritage Oil Plc**	**Cadogan Petr. Plc**
Lilliefors (LF) Test: Value P-value	0.106774 0.0000	0.351830 0.0000	0.159028 0.0000	0.099089 0.0000	0.232195 0.0000
Cramervon Mises (W2) Test: Value P-value	8.290968 0.0000	64.73604 0.0000	9.562198 0.0000	5.191911 0.0000	12.04804 0.0000
Watson (U2) Test: Value P-value	8.290915 0.0000	64.71395 0.0000	9.503115 0.0000	5.174596 0.0000	12.04449 0.0000
Anderson-Darling (AD) Test: Value P-value	45.96910 0.0000	324.4696 0.0000	46.42829 0.0000	28.14814 0.0000	54.05676 0.0000
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.107 0.000	0.352 0.000	0.159 0.000	0.099 0.000	0.232 0.000

	Exillon Energy Plc	Enquest Plc	Essar Energy Plc	Genel Energy Plc	Ophir Energy Plc
Lilliefors (LF) Test: Value P-value	0.121943 0.0000	0.120565 0.0000	0.106621 0.0000	0.139446 0.0000	0.095378 0.0000
Cramervon Mises (W2) Test: Value P-value	3.765565 0.0000	2.066792 0.0000	2.432168 0.0000	3.580084 0.0000	1.206988 0.0000
Watson (U2) Test: Value P-value	3.743406 0.0000	2.065533 0.0000	2.426306 0.0000	3.575119 0.0000	1.192256 0.0000
Anderson-Darling (AD) Test: Value P-value	18.95053 0.0000	10.86342 0.0000	13.21155 0.0000	18.11805 0.0000	6.453790 0.0000
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.122 0.000	0.121 0.000	0.107 0.000	0.139 0.000	0.095 0.000

	Ruspetro Plc
Lilliefors (LF) Test: Value P-value	0.087664 0.0001
Cramervon Mises (W2) Test: Value P-value	0.435424 0.0000
Watson (U2) Test: Value P-value	0.428673 0.0000
Anderson-Darling (AD) Test: Value P-value	2.316897 0.0000
Kolmogorov-Smirnov (KS) Test: Statistic P-value	0.088 0.000

Source: Author (2015)

Table 6.8.3 presents the statistical results of the Lilliefors (LF), Anderson-Darling (AD), Watson (U_2), Cramervon Mises (W_2), Shapiro-Wilk (SW) and

Kolmogorov-Smirnov tests on oil and gas companies with less than ten years return series for the study. The statistics' null hypotheses of normal distribution were strongly rejected at both the 5% and 1% significance level for all the series.

6.3.5 Discussion of Findings

This section summarises the findings from the descriptive statistics and distribution analysis of the stock return series under study.

Firstly, the adjusted stocks and the five FTSE indices price series downloaded from Datastream are classified based on type of series (stock or index) and sub-periods. The series are plotted graphically for sight observations. Intercepts or drifts are observed in all the indices except the FTSE AIM SS Oil and Gas while trends are observed in only the FTSE Oil and Gas and FTSE Oil and Gas Producers indices. Random walk processes (full random walk, random walk with a drift, intercept or both) were observed in the series where statistical properties are time varying and non-stationary. It was also discovered that the oil and gas indices are more stable than the FTSE All Share and FTSE 100 Share indices where powerful breaks were observed within the same period. The patterns of the FTSE All Share and FTSE 100 Share indices are the same over the period of study. Similarly, the oil and gas companies with the longest series showed the same pattern observed in the FTSE indices. In addition, zero returns or unchanging prices were significant prior to 2005. Most of the companies with the shortest series depict a full random walk process with more significant zero returns or unchanging prices over the period.

Secondly, the distribution pattern of the time series were comprehensively analysed using graphical, numerical and formal methods. The results show the distribution of the oil and gas stock returns under study as a deviation to the assumptions of normal distribution which is similar to the findings of many researchers such as Peiro (1994), Aparicio and Estrada (2001), Behr and Potter (2009), and Cont (2001). However, in our investigation, it was discovered that the deviation or inconsistency with normal distribution is stronger in individual stock returns of oil and gas companies compared to both market and oil sector indices. The distribution pattern of the series depict high kurtosis in most of the return series described as leptokurtic distribution as found by Balaban et al (2005). Heavy tails were also discovered in the majority of the series which coincided with the findings of Officer (1972), Teichmoeller (1971) and Fama (1976). Both positive and negative skewness were discovered which is contrary to the findings of some scholars that stock returns are negatively or positively skewed.

6.4 Stationarity Tests of the Oil and Gas Stock Returns and Indices

The statistical properties of a given data series need to be consistent for effective modelling and forecasting. Most of the estimation models are designed on the assumption that the mean, variance and co-variance of a series are not time-varying. In unit root testing the existence of unit root in a series is used to determine whether the series is stationary or non-stationary. A unit root exists in a stochastic process where the only parameter used is equal to 1 when white noise (ε) is independently and identically distributed (*iid*). Consider:

$$Y_t = \alpha Y_{t-1} + \varepsilon_t \quad \text{where; } \alpha = 1,\ \varepsilon_t \sim iid\ (0, \sigma^2)$$

Financial time series are usually attained through a stochastic process. However, the returns used are products of first order differencing which converts the series to stationary. Dickey and Fuller (1979) have invented prominent unit root tests that examine the following null and alternative as follows:

H_0 : $\alpha = 1$ (unit root) – series is non-stationary.

H_1 : $\alpha < 1$ (no unit root) – series is stationary.

If the null hypothesis is accepted, it is assumed that the series is non-stationary (continuation of stochastic process) and, if it is rejected, the series is said to be stationary. Augmented Dickey Fuller (ADF), Dickey Fuller – Generalized Least Squares (DF-GLS) and Phillips-Perron (PP) tests are based on those hypotheses of unit root. However, the stationarity test developed by Kwiatkowski et al. (1992) referred to as Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test has the reverse of unit root null and alternative hypotheses for examination. Therefore, KPSS tests the following hypotheses.

H_0 : series is stationary.

H_1 : series is non-stationary.

If the asymptotic critical values are less than the KPSS test statistic (T-Stat), the null hypothesis is rejected. Brooks (2014) has recommended the examination of the two null hypotheses of unit root (ADF, PP and DF-GLS) and stationarity (KPSS) for robust results.

In that case, the study has employed four tests of the Augmented Dickey Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Dickey Fuller – Generalized Least Squares (DF-GLS) tests for testing whether the return series are stationary.

6.4.1 Augmented Dickey Fuller (ADF)

The Augmented Dickey Fuller test is an improved version of the Dicker Fuller unit root test for more power to handle large and sophisticated time series data. ADF considers three (3) forms of time series eg, time series with an intercept, trend and intercept or without trend and intercept.

The behaviour of return (log P_t – log P_{t-1}) series for this research as explained in earlier sections of this chapter depicts neither intercept nor trend. As such, ADF is estimated on that basis.

6.4.2 Phillips-Perron (PP)

The Phillips-Perron (PP) test also modifies the Dicker Fuller test of unit root testing by considering the possibility that the process generating 'Y_t' can have higher order of autocorrelation more than what the test equation recognises. Most importantly, it makes non-parametric correction to the t-test statistic equation for autocorrelation and heteroscedasticity. The white noise is considered for both autocorrelation and heteroscedasticity. It also considers the three forms of time series considered by ADF. Phillips-Perron is more robust in the treatment of serial correlation and heteroscedasticity than ADF.

6.4.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS)

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is used to test whether a time series is stationary around its deterministic trend. It differs from the other unit root tests because of the assumption that time series follow a deterministic trend. Its statistic is based on the residuals generated from ordinary least squares regression of the dependent variable (y_t) on the independent variable (y_{t-1}).

6.4.4 Dickey Fuller - Generalized Least Squares (DF-GLS)

The Dickey Fuller - Generalized Least Squares (DF-GLS) test was developed by Elliott et al. (1996). It was a modification of the Augmented Dicker Fuller (ADF) test using the concept of Generalized Least Squares (GLS). The GLS is meant to deal with the existence of autocorrelation and heteroscedasticity in the time series which overcomes the limitation of Ordinary Least Squares (OLS) regression. In DF-GLS test, ADF test is simply estimated on GLS detrended (y_t) (the series of (y_t) regressed on a constant and a linear trend) for the elimination of autocorrelation and hetroscedasticity effect. In the estimation for ADF, the GLS detrended (y_t) is used as the dependent variable while its generated residuals in the detrending used as an independent variable.

Estimates for ADF and PP are made on the basis that the time series are without an intercept and a trend while that of KPSS and DF-GLS with an intercept and a trend.

Table 6.9.1 Stationarity Test of the Indices Return Series under Study using Augmented Dickey Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Dickey Fuller – Generalized Least Squares (DF-GLS) Tests

		Augmented Dickey Fuller (ADF)		Phillips-Perron (PP)		Kwiatkowski-Phillips-Schmidt-Shin (KPSS)		Dickey Fuller – Generalized Least Squares (DF-GLS)	
		T-Stat	P-Value	T-Stat	P-Value	T-Stat	ACV*	T-Stat	TCV*
1.	FTSE All Share	-34.335	0.0000	-72.592	0.0001	0.0587	0.146	-34.161	-2.890
2.	FTSE 100	-32.945	0.0000	-74.294	0.0001	0.0625	0.146	-34.853	-2.890
3.	FTSE UK Oil & Gas	-36.099	0.0000	-71.008	0.0001	0.0223	0.146	-36.023	-2.890
4.	FTSE UK O&G Prod.	-36.367	0.0000	-71.609	0.0001	0.0264	0.146	-36.304	-2.890
5.	FTSE AIM SS O&G	-34.287	0.0000	-48.457	0.0001	0.1054	0.146	-34.286	-2.890

*ACV and TCV stand for Asymptotic Critical Value and Test Critical Value at 5% significance level.

Source: Author (2015)

Table 6.9.1 presents the results (t-statistics and p-values) from both the Augmented Dicker Fuller (ADF) and Phillips-Perron (PP) tests on the FTSE indices for the research. Using the significance level of 5% and 1%, the p-values of less than 0.05 and 0.01 generated from both tests strongly rejected the null hypotheses of 'unit root' on which the alternative hypothesis of 'no unit root' is accepted. The KPSS test results show asymptotic critical values being higher than its t-statistic values in all the series and therefore the null hypothesis of 'series is stationary' cannot be rejected. In the DF-GLS test results, the test critical values are found to be significantly less than the t-statistic values in all the series which strongly reject the null hypothesis of 'unit root'. Hence, the series are found to be stationary in which the mean, variance and covariance are constant over the given period of investigation.

Table 6.9.2 Stationarity Test of Stock Returns of Companies with More Than 10 Years Series under Study using Augmented Dickey Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Dickey Fuller – Generalized Least Squares (DF-GLS) Tests

		Augmented Dickey Fuller (ADF)		**Phillips-Perron (PP)**		**Kwiatkowski-Phillips-Schmidt-Shin (KPSS)**		**Dickey Fuller – Generalized Least Squares (DF-GLS)**	
		T-Stat	**P-Value**	**T-Stat**	**P-Value**	**T-Stat**	**ACV***	**T-Stat**	**TCV***
1.	Amec Plc	-68.087	0.0001	-68.179	0.0001	0.0294	0.146	-67.885	-2.890
2.	BG Group	-46.089	0.0001	-77.983	0.0001	0.0961	0.146	-46.056	-2.890
3.	BP Plc	-45.904	0.0001	-72.663	0.0001	0.0264	0.146	-45.905	-2.890
4.	Cairn Energy	-70.985	0.0001	-70.974	0.0001	0.0870	0.146	-70.958	-2.890
5.	Dragon Oil	-74.159	0.0001	-74.461	0.0001	0.0760	0.146	-73.243	-2.890
6.	Fortune Oil	-47.937	0.0001	-100.15	0.0001	0.0568	0.146	-81.986	-2.890
7.	Hunting Plc	-65.487	0.0001	-65.750	0.0001	0.0608	0.146	-65.421	-2.890
8.	Premier Oil	-35.768	0.0000	-66.924	0.0001	0.0664	0.146	-35.740	-2.890
9.	RDS 'B'	-34.221	0.0000	-73.319	0.0001	0.0347	0.146	-33.737	-2.890
10.	Tullow Oil	-70.073	0.0001	-70.096	0.0001	0.0994	0.146	-70.111	-2.890
11.	Aminex Plc	-73.703	0.0001	-74.062	0.0001	0.0299	0.146	-73.718	-2.890
12.	JKX O&G	-61.941	0.0001	-61.771	0.0001	0.3707	0.146	-60.917	-2.890
13.	Soco Intl.	-59.746	0.0001	-59.777	0.0001	0.1651	0.146	-2.3083	-2.890
14.	Wood Grp. (John)	-52.168	0.0001	-52.516	0.0001	0.0468	0.146	-1.8147	-2.890

*ACV and TCV stand for Asymptotic Critical Value and Test Critical Value at 5% significance level.

Source: Author (2015)

Table 6.9.2 depicts the results (t-statistics and p-values) from both the Augmented Dicker Fuller (ADF) and Phillips-Perron (PP) tests on stock returns of oil and gas companies with more than 10 years series under our consideration. Using the significance level of 5% and 1%, the p-values of less than 0.05 and 0.01 generated from both tests strongly rejected the null hypothesis of 'unit root' on which the alternate hypothesis of 'no unit root' is accepted. The KPSS test results show asymptotic critical values being higher than its t-statistic values in all the series except in JKX Oil and Gas and Soco International where t-statistic values are less than the asymptotic critical values. In the majority of the series the null hypothesis of 'series is stationary' cannot be rejected while in JKX Oil and Gas and Soco International, the null hypothesis is rejected (the null hypothesis was found to be accepted after conducting the test on the second difference of the series). In the DF-GLS test results, the test critical values are found to be significantly less than the t-statistic values in all the series except in Soco International and Wood Group

(John) which strongly reject the null hypothesis of 'unit root'. The estimation results of Soco International, JKX Oil and Gas and Wood Group (John) are interpreted with caution although the series are already stationary by the results of ADF and PP tests and could also be stationary by KPSS and DF-GLS if subjected to further differencing. On general terms, the series are found to be stationary in which the mean, variance and covariance are constant over the given period of investigation because

Table 6.9.3 Stationarity Test of Stock Returns of Companies with Less Than 10 Years Series under Study using Augmented Dickey Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Dickey Fuller – Generalized Least Squares (DF-GLS) Tests

		Augmented Dickey Fuller (ADF)		**Phillips-Perron (PP)**		**Kwiatkowski-Phillips-Schmidt-Shin (KPSS)**		**Dickey Fuller – Generalized Least Squares (DF-GLS)**	
		T-Stat	**P-Value**	**T-Stat**	**P-Value**	**T-Stat**	**ACV***	**T-Stat**	**TCV***
1.	Afren Plc	-49.249	0.0001	-49.390	0.0001	0.0583	0.146	-3.4305	-2.890
2.	Hardy O&G	-43.260	0.0001	-43.353	0.0001	0.0517	0.146	-2.2292	-2.890
3.	RDS 'A'	-20.874	0.0000	-44.947	0.0001	0.0176	0.146	-19.104	-2.890
4.	Petrofac Ltd	-44.660	0.0001	-44.901	0.0001	0.0472	0.146	-2.0714	-2.890
5.	Lamprell Plc	-37.911	0.0000	-37.912	0.0000	0.0827	0.146	-37.719	-2.890
6.	Salamander	-37.438	0.0000	-37.441	0.0000	0.0331	0.146	-37.242	-2.890
7.	Endeavor Intl.	-24.148	0.0000	-35.969	0.0000	0.0407	0.146	-24.213	-2.890
8.	Kentz Corp.	-33.176	0.0000	-33.168	0.0000	0.0902	0.146	-2.0542	-2.890
9.	Heritage Oil	-36.232	0.0000	-36.309	0.0000	0.0763	0.146	-1.7800	-2.890
10.	Cadogan Petr.	-27.573	0.0000	-36.828	0.0000	0.2596	0.146	-2.3207	-2.890
11.	Exillon Energy	-26.630	0.0000	-26.591	0.0000	0.1467	0.146	-26.639	-2.890
12.	Enquest	-28.436	0.0000	-29.434	0.0000	0.0910	0.146	-1.6752	-2.890
13.	Essar Energy	-27.426	0.0000	-27.414	0.0000	0.1321	0.146	-27.519	-2.890
14.	Genel Energy Plc	-18.929	0.0000	-18.923	0.0000	0.0861	0.146	-17.101	-2.890
15.	Ophir Energy	-19.601	0.0000	-19.636	0.0000	0.1137	0.146	-19.638	-2.892
16.	Ruspetro	-12.660	0.0000	-15.018	0.0000	0.0871	0.146	-3.0506	-2.921

*ACV and TCV stand for Asymptotic Critical Value and Test Critical Value at 5% significance level.

Source: Author (2015)

Table 6.9.3 shows the results (t-statistics and p-values) from both the Augmented Dicker Fuller (ADF) and Phillips-Perron (PP) tests on stock returns of oil and gas companies with less than 10 years series under our study. Using the significance level of 5% and 1%, the p-values of less than 0.05 and 0.01 generated from both tests strongly rejected the null hypothesis of 'unit root' and on which the alternate hypothesis of 'no unit root' is accepted. The KPSS test results show asymptotic critical values being higher than its t-statistic values in all the series except in Cadogan Petroleum where t-statistic values are less than the asymptotic critical values. In all the series except Cadogan Petroleum the null hypothesis of 'series is stationary' cannot be rejected. In the DF-GLS test results, the test critical values are found to be significantly less than the t-statistic values in all the series which strongly reject the null hypothesis of 'unit root'. However, an exception was recorded in Hardy Oil and Gas, Kentz Corporation, Heritage Oil, Cadogan Petroleum and Enquest where test critical values are found to be slightly greater than the t-statistic values. The inconsistency could be due to the shortness of the time series and nature of DF-GLS test since the series are already stationary by the results of ADF and PP tests and could also be stationary by the DF-GLS if subjected to further differencing. On general terms, the series are found to be stationary in which the mean, variance and covariance are constant over the given period of investigation.

6.5 Conclusion

Based on our findings, it was observed that the oil and gas indices are more stable and close to the assumptions of normal distribution than individual stocks such as BP Plc. It will therefore be easier to model and forecast the FTSE UK Oil and Gas and the FTSE UK Oil and Gas Producers indices than individual stock returns. Since FTSE indices are traded on the London stock exchange, oil and gas investors are advised to invest in the sector indices rather than individual stocks for more control of risks and returns.

On the same note, oil companies with a longer existence on the stock exchange such as BG Group Plc, BP Plc, RDS ‘B’ Plc and Wood Group Plc are more consistent compared to recently listed companies such as Hardy Oil and Gas Plc, Salamander Plc and Ruspetro Plc. Investors are to note that risk would be higher in the newly listed oil and gas companies and may not provide returns commensurate with the risks involved. The unit root and stationary tests conducted have shown that the majority of the return series at first differencing are stationary and all can equally be stationary at second or further differencing.

CHAPTER 7

ANALYSIS OF INFORMATION EFFICIENCY

7.1 Introduction

Capital market efficiency has been one of the most studied areas in the field of finance. The proposition of whether stock prices are predictable, are serially correlated and follow a random walk, has been the main focus of research. The quest to improve investment strategies in the capital markets also depend on the pricing behaviour of securities in the secondary market. Mittal and Jain (2009) also stated in their study that market participants such as investors, brokers, regulators and financial analysts are all interested in the behaviour of stock markets explained by their information or market efficiency. The concept of market efficiency or the efficient market hypothesis (EMH) was defined by Fama (1970) as a situation when stock prices fully reflect all relevant available information. Milionis (2007) observed that scholars like Black (1986), Beaver (1981) and Rubinstein (1975) have all defined market efficiency in different ways but that of Fama (1970) turned out to be more accepted and was adopted as a theoretical framework by various scholars. Fama (1970) classifies market efficiency into three types of weak form, semi-strong form and strong form of market efficiency. Capital markets are weak form efficient if current stock prices fully reflect a past pattern of price movements. In that case, profit advantage cannot be achieved by studying the past pattern of price movements. Semi-strong form market efficiency arises when the current stock prices fully reflect all publicly available information such as announcement of earnings, dividends, and stock split information. If the market is semi-strong form efficient, abnormal profit cannot be obtained by a few individuals from the publicly available information because the prices have reflected that information accordingly. Strong form market efficiency arises when the current stock prices fully reflect both publicly and privately available information. In general terms market efficiency means that current and past information are already reflected in the market via the stock prices and future prices can only be determined by new information which cannot be predicted, (Adelegan, 2003). The validity of the efficient market hypothesis has been tested by numerous scholars especially with regard to developed markets, (Al-loughani and Chappell, 1997).

In testing the market efficiency hypothesis, various techniques were employed by researchers to find out whether stock exchanges are efficient. Interestingly, the outcome of the previous studies conducted on market efficiency remains contentious, (Tung and Marsden, 1998; Mollah, 2007; Mittal and Jain, 2009). Academics such as Tung and Marsden (1998) explained the reason for the conflicting results was due to a lack of control of the variables of study. Alexeev and Tapon (2011) explained that the reason for the conflicting results was due to the use of stock market indices by researchers instead of data series from individual stocks. In the same way, Quirin et al (2000) accredited the inconsistencies to the varied cross-sectional studies on several industries with diverse characteristics, business environments, competition, accounting policies, taxation, regulations and nature of investors. Generally, most of the previous studies on market efficiency asserted that developed markets are weak form efficient and future share returns are independent and follow a random walk, (Mollah, 2007; Adelegan, 2003). However, most of the market efficiency investigations were conducted on share indices, without any similar effort on specific industries and individual stocks.

7.2 Review of Literature on Market (Information) Efficiency and Trading Rules

7.2.1 Weak Form Market Efficiency

The concept of weak form market efficiency originated from the Efficient Market Hypothesis (EMH) developed by Fama (1970). Subsequently various scholars tested the validity of the hypothesis on a large number of stock markets. Roberts (1959) stated that prior to Fama (1970)'s work on market efficiency, the study of markets or stock prices behaviour was based on empirical analysis of the physical processes of share price movements such as patterns, waves and tides; in other words, it was referred to as technical analysis. Brock et al (1992) confirmed that the use of technical analysis in explaining the pattern of stock price movements was as old as the market itself. However, researchers have diverted their attention to the efficient market hypothesis after Fama (1970)'s theory on market efficiency.

Hudson et al (1996) conducted a weak form efficiency test on stocks prices in the UK between 1935 and 1994 using the same technical trading rules employed by Brock et al (1992) to assess whether historical movement of past prices can be used to generate a future profit that was higher than that from a simple buy and hold strategy. Brock et al (1992) employed moving average and trading-range breakout rules on the US Dow Jones Index to confirm the forecasting power of technical analysis in obtaining excess returns from the market. They found evidence of abnormal return from the employed trading rules and concluded that the Dow Jones Index does not follow a random walk process. Hudson et al (1996) also applied the same technique on the Financial Times Industrial Ordinary Index of the UK and, contrary to the findings of Brock et al (1992), affirmed that the use of technical trading rules cannot assist investors to make excess return, unless a long term series of stock indices are to be considered. In other words, a short term series may provide evidence for randomness, while a long term series may show the existence of serial correlation. However, the use of long term series may affect the reliability of trading rules as a practical investment strategy.

Al-loughani and Chappell (1997) tested the Random Walk Hypothesis on the FTSE 30 Share index using the Dickey-Fuller tests, the Lagrange Multiplier test, the Brock, Dechert and Scheinkman (BDS) statistic and the GARCH-M model statistical tools for the period June 30, 1983 to November 16, 1989. Their results did not find the market to be weak form efficient mainly because the series were found to possess traces of serial correlation. The application of the BDS statistic also showed that the series were also characterized by conditional heteroscedasticity which might have resulted in the rejection of the weak form efficiency. Milionis and Moschos (2000) reviewed the empirical work of Al-loughani and Chappell (1997) and suggested that the results do not support their interpretation. Milionis and Moschos (2000) argued that Al-loughani and Chappell (1997) assigned successive logarithmic values to the FTSE 30 index in a stochastic process of random walk. In that process, successive returns of the FTSE index are required to be independently and identically distributed for the expected returns to be constant. Therefore, a random walk hypothesis test is an integrated test of both weak form market efficiency and constancy of expected returns. The rejection of the random walk hypothesis does not mean the absolute rejection of the weak form market efficiency hypothesis. Milionis and Moschos (2000) concluded that the London stock exchange is weak form efficient.

Buguk and Brorsen (2003) had tested for weak form market efficiency in the Istanbul stock exchange between 1992 and 1999 using the Augmented Dickey-Fuller test, the rank and sign-based variance ratio test, the GPH fractional integration test and the LOMAC single variance ratio test. Results from all the four (4) tests employed are consistent with the random walk hypothesis which led to the conclusion that the Istanbul stock exchange is weak form efficient.

The Chinese stock market has two major exchanges with four (4) classes of shares, Shanghai and Shenzhen stock exchanges. The Shanghai Stock Exchange (SHSE) is located in the city of Shanghai while the Shenzhen Stock Exchange (SHZE) is located in the southern city of Shenzhen. Both the SHSE and SHZE trade in class A and B shares. Class A shares are traded in the Chinese local currency, Yuan Renminbi, meant for only local investors while class B shares are traded in foreign currencies for both local and limited foreign investors, (Charles and Darne, 2009). Balsara et al (2007) analysed the indices of daily stock prices for class A and B shares both on the Shanghai and Shenzhen exchanges in order to test for weak form efficiency by examining the random walk model and technical trading rules. Analytical tools such as the variance ratio test, the ARIMA forecasting model, the moving average crossover rule, the channel breakout rule and the Bollinger band breakout rule were employed in the study, and their findings suggested that Chinese stock markets are consistent with the random walk hypothesis. However, the technical trading rules applied showed signs of positive returns on buy trades in Chinese stock markets which is a contradiction of the motion of weak form efficiency.

Lim et al (2008) also used a mix of tests such as serial correlation tests, runs test, variance ratio tests, unit root tests and spectral analysis to ascertain the market efficiency in some Asian stock exchanges. Lim et al (2008) conducted similar research to that of Cajueiro and Tabak (2006) by employing the rolling bicorrelation test statistic to compare the efficiency of stock markets in China, Korea and Taiwan with different price limits. Conclusions were made that restrictive price limits and price limits per stock exchange are not barriers to market efficiency. In other words, market efficiency is determined by events that destabilise the market and the time needed to adjust prices to a new equilibrium level but not price limits.

Jain and Mittal (2009) also tested for weak form efficiency on Indian stock exchanges using three representative indices of S&P NNX 500, CNX 100 and BSE 200 and various tools such as unit root test, runs test, and various serial correlation tests. They reported that the Indian stock market based on the indices analysed is weak form efficient.

Researchers have also tested the impact of factors such as transaction cost on weak form market efficiency. Among those scholars is Liu (2010) who tested for the impact of explicit transaction costs in the context of brokerage commission deregulation in Japan on the weak form efficiency of Japanese equity markets and Japanese stocks listed in the United States. He reported that the randomness of return increases significantly for the Japanese markets after the brokerage commission deregulation in Japan.

Alexeev and Tapon (2011) argued that testing for weak form efficiency can best be achieved by using the data series of individual stock instead of stock market indices. A model-based bootstrap and modified chart pattern recognition algorithm were applied to all the stocks quoted on the Toronto Stock Exchange (TSX) between August 1980 and August 2010. Inferences were made from the result of the test that the null hypothesis of weak form efficiency on the Toronto stock exchange cannot be rejected.

7.2.2 Semi-Strong Form Market Efficiency

Several variables of financial information that are publicly available have been tested for relevance on the market values of quoted companies and findings from some of these studies were equally reviewed in this section. Basu (1977) selected and tested the price-earnings (P/E) ratio as an indicator of the future investment performance of a security. Empirically, (P/E) ratios of over 1200 industrial firms quoted on the New York Stock Exchange (NYSE) were tested within the period September 1956 to August 1971. Portfolios of companies under study were created based on similar (P/E) ratios and their risk-return relationship was compared for evaluation of performance in the capital market. Results have shown that (P/E) ratios may be indicators of future investment performance due to high investor expectations. Conclusions were made by Basu (1977) that security price behaviour is not in line with the efficient market hypothesis and thus the (P/E) ratio is not fully reflected in the security price. Investors can use (P/E) ratios to gain abnormal returns from the market.

Marsh (1979) tested for the impact of a rights issue announcement on the market price of all companies that made right issues between July 1962 and December 1975 on the London stock exchange. He reported that the United Kingdom market is semi strong form efficient and as such the right issues by companies do not have any significant impact on post rights issue announcement prices.

Groenewold and Kang (1993) conducted a test for the semi-strong form of market efficiency using macroeconomic data on Australian share market between 1980 and 1988. The researchers set a model where share prices are dependent variables to the money supply, real government expenditure and the price level as the independent variables. All the variables in the model were used in log-difference form and the results have indicated that none of the variables can predict the market price of companies quoted on the Australian market. Despite the evidence that the Australian market is semi-strong efficient, Groenewold and Kang (1993) believed that there should be more research to analyse the semi strong form efficiency of the Australian stock market.

Toutkoushian (1996) studied whether the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the NASDAQ exchange are semi-strong form efficient with regard to information on insider transactions. It was tested whether investors can gain excess return by replicating insider transactions that were made publicly available in the market. The results shown indicated support for semi strong efficiency by suggesting that investors can gain excess returns by replicating publicly available insider transactions depending on the intensity of insider trading, volume of transactions, and the speed by which information of insider transactions is disseminated.

Hatemi-J and Morgan (2009) have also contributed to the existing evidence of the semi strong form market efficiency school of thought by testing whether the Australian stock market is semi strong efficient with regard to interest rate and exchange rate shocks during the period 1994-2006. Leveraged bootstrap distributions were used in a case of non-normal autoregressive conditional heteroskedasticity (ARCH) to overcome the limitation of using standard estimation methods on non-normal data with the effect of (ARCH). The results from the tests have shown that the Australian market is not semi strong form efficient with regard to both interest rate and exchange rate fluctuations because investors can use the fluctuations to gain abnormal return from the market.

Skogsvik (2008) tested whether the Swedish stock market was efficient with regard to variables in the financial statement information that was publicly available for the period between 1970 and 1994. It was noted that financial statement information was helpful in generating abnormal profit which suggested that the Swedish stock market did not seem to be semi strong form efficient. Alexakis et al (2010) also confirmed the findings of Skogsvik (2008) by ascertaining the usefulness of accounting information in predicting the Athens stock market prices between 1993 and 2006.

Tung and Marsden (1998) believe that a lack of control of the variables of study while testing for market efficiency had caused significant controversial results and conclusions among researchers. Tung and Marsden (1998) employed a new dimension of investigating market efficiency by adopting controlled laboratory experiments. An electronic market shell with stock market activities and price adjustments were developed. Market models were considered and tested in the artificial market shell as tested in actual markets by previous researchers. Results from the study have shown that information quality is an important factor in attaining abnormal profit from the market. The study also supports the semi-strong market efficiency and rejected the strong market efficiency hypothesis.

7.2.3 Strong Form Market Efficiency

On a similar note, the strong form market efficiency hypothesis has been empirically tested in several markets. Finnerty (1976) investigated insider transactions and their abnormal profit by analysing stock transactions of firms quoted on the New York Stock Exchange (NYSE) from January, 1969 to December, 1972. The scholar discovered that private information can be used by insiders to gain abnormal returns which suggested market inefficiency in strong form. Scholars such as Jaffe (1974), Pratt and DeVere (1970), Rogoff (1964) and Glass (1966) have also supported the hypothesis that investors do earn abnormal return from using privately available information, so rejecting the strong form market efficiency hypothesis.

Ferreira (1995) and Del Brio et al (2002) also have the same opinion that insiders can use private information to secure above average profit from stock market trading. On a contrary view, Lin and Rozeff (1995) discovered that about 85 percent to 88 percent of private information is reflected or incorporated into the prices of stocks within one full trading day, so supporting the semi strong form market efficiency hypothesis.

7.2.4 Trading Rules and Abnormal Returns

Technical trading rules are tools used to explore the past behaviour of stock prices in order to predict future stock prices. If the rules yield an abnormal profit from investment, it is assumed that the movement of stock prices follow a predictable pattern or a random process if its current movement is independent of past movement. The advent of the Efficient Market Hypothesis by Fama (1970) has opined that the trading rules cannot provide any clue as to the behaviour of stock prices because prices reflect all relevant information and therefore there is no chance of making accurate prediction. To confirm the Efficient Market Hypothesis, scholars have continued to test the power of various technical trading rules in 'beating the market' as one of the ways of testing market efficiency.

Brock et al (1992) have tested the performance of the simplest and most famous trading rules using moving average and trading range breaks on a very long series of the Dow Jones index ranging from 1897 to 1986. The overall results confirmed the possibility of realising abnormal profit from the movement of stock prices. It provides strong support for the usefulness of technical trading rules and hence concluded that they have predictive ability with regard to the Dow Jones Index.

Hudson et al (1996) replicated the study by Brock et al (1992) on the UK data to assess whether the technical trading rules can also yield abnormal profit in the UK despite the costly trading environment. The same methodology employed by Brock et al (1992) was employed on the UK longest daily series of the Financial Times Industrial Ordinary Share Index from July 1935 to January 1994. The results generated have also shown predictive power in the trading rules but concluded that it was difficult to make any abnormal profit due to high transaction costs in the market.

On the same note, Mills (1997) also investigated the predictive ability of simple trading rules (moving average) on the FTSE 30 Share index for the period 1935 to 1994. Mills also discovered that the trading rules generated returns higher than that from a buy and hold investment strategy for most of the study period. It was also stated that the trading rules only worked when the market was driftless prior to 1980. The results were explained by the scholar as consistent to that of Brock et al (1992).

Ratner and Leal (1999) have extended the test of technical trading strategies to the emerging markets of Latin America and Asia. Variable Length Moving Average (VMA) trading rules were applied to ten emerging markets over the period 1982 to 1995. Total trading returns after transaction costs were compared with total returns of a buy and hold strategy from every country. The markets in Mexico, Thailand and Taiwan showed evidence of predictability in the trading rules because of the high returns generated. There was no strong evidence of trading rule predictability in the other markets. The study used inflation adjusted stock returns instead of the nominal returns used by many scholars.

Coutts and Cheung (2000) investigated whether the moving average oscillator and the trading range break out trading rules have predictive power in the Hang Seng Index of the Hong Kong Stock Exchange for the period 1985 to 1997. Although, the trading range break out rule was found to be stronger than the moving average oscillator, both rules would fail to provide abnormal profit if transaction costs are taking into consideration.

Milionis and Papanagiotou (2008) have conducted research on the variation of the moving average trading rule performances based on the length of longer moving average periods. The analysis was carried out on the NYSE and the Athens Stock Exchange daily data for the period April 1993 to April 2005. Significant variability of performance between the different lengths of the moving average trading rules was observed. Shorter length moving averages had enhanced performance compared to longer length moving average trading rules. It was also discovered that seventy five percent of the trading signals by moving average trading rules are not realistic. The possibility of enhancing the performance of the moving average trading rules by inclusion of more information variables such as filters and volume of trade could be explored.

7.2.5 Summary of Literature and Research Objectives

The literature reviewed in this chapter has confirmed the view of scholars such as Al-loughani and Chappell (1997) that the area of market efficiency is one of the most studied in the field of finance. The theories of Random Walk developed by Bachelier (1900) about the behaviour of stock prices and the Efficient Market Hypothesis by Fama (1970) have been used as a theoretical basis by numerous researchers to explain the dynamics of stock market returns. In line with that, various stock exchanges and stock market data have been tested to review the random walk or efficient market hypotheses using a large range of parametric and non-parametric statistical tools. This provides an accurate explanation to stakeholders that can ensure optimum investment decisions. However, the debate on market efficiency is not settled because there are so many conflicting results from stock market studies as argued by Mollah (2007). Tung and Marsden (1998) have argued that some of the conflicting results are caused by improper generalisation, data handling and misapplication of statistical tools.

Our study is aimed at conducting a comprehensive investigation of market efficiency in the oil and gas sector in comparison to the behaviour of the entire market. Our approach can simply be described as 'specific-to-general' because our emphasis starts from individual stock series to market indices in order to capture all the relevant characteristics that are important in the explanation of stock price behaviour. The statistical tools employed ranges from traditional to advanced tools in order to generate results that can facilitate robust inferences. Specifically, we examine extensively the weak form of market efficiency in the oil and gas sector in comparison to that of the entire market as represented by FTSE All Share and FTSE 100 Share indices. We shall firstly apply the basic tests to see the randomness of returns. If daily returns are fluctuating randomly, the market can be classified as weak form efficient. If we find symptoms of persistence or non-randomness, the market cannot be classified as inefficient. We shall extend the analysis by applying technical trading and filter rule tests and moving average tests. This will assess whether investors can make abnormal gains from their investments before arriving at a deduction about the weak form market efficiency under investigation.

7.3 Tests of Random Walk Hypothesis

7.3.1 Autocorrelation Function and Ljung-Box Q-Statistic Tests

The autocorrelation function is used to examine the correlation between daily stock returns and could be helpful to make inferences on whether the returns can be predicted. The argument of whether oil and gas stock returns on the London Stock Exchange follow the Random Walk Hypothesis (RWH) will partly be tested by the Autocorrelation Function results generated for up to 10 lags of the series. The Autocorrelation Function is mathematically given as:

$$\rho(k) = \frac{Cov(r_t, r_{t-k})}{\sqrt{Var(r_t)}\sqrt{Var(r_{t-k})}} = \frac{E\,[(r_t - \mu)(r_{t-k} - \mu)]}{E\,[(r_t - \mu)^2]}$$

Where;

$\rho(k)$ = Autocorrelation coefficient

r_t = Return at time (t)

r_{t-k} = Return at lag (k)

$Cov(r_t, r_{t-k})$ = Covariance between current and lagged returns

$Var(r_t)$ = Variance of return at time (t)

$Var(r_{t-k})$ = Variance of return at lag (k)

The null and alternative hypotheses to be tested are:

H_0: $\rho(k) = 0$

H_1: $\rho(k) \neq 0$

If $\rho(k) =$ 0, there is no serial correlation between variables in the series and the error term of the model is independent and identically distributed *(iid)* or $(u_t = \varepsilon_t)$ based on the $(u_t = \rho u_{t-1} + \varepsilon_t)$ equation. In that case, it can be said that stock returns follow a random walk and future returns cannot be predicted based on past returns. If $\rho(k) =$ 1, positive serial correlation occurs and where $\rho(k)$ = -1, then negative serial correlation exists. In both cases, the future stock returns can be predicted to some extent and the random walk hypothesis rejected. The random walk hypothesis is tested by interpreting the values of $\rho(k)$ as being significantly different from zero. The significant deviation from zero at each lag is measured using a band of 95% level of confidence interval $(\pm 1.96 \times \frac{1}{\sqrt{N}})$ on which the null hypothesis of the random walk is rejected or accepted. If the $\rho(k)$ value falls outside the 95% level of confidence interval, then it is deemed as significantly different from zero and the null hypothesis (H_0: $\rho(k)$ = 0) rejected. The autocorrelation coefficient band using 95% level of confidence interval for all the series is presented in Table 7.1.4 (Appendix 7).

To improve the robustness of the Autocorrelation Function analysis, the Ljung-Box Q-Statistic Test will be employed to test whether the summation of autocorrelation coefficients from selected lags is equal to zero. The test is developed from the portmanteau Box-Pierce Q-Statistic by Box and Pierce (1970), and given as:

$$Q_k = N \sum_{k=1}^{m} \rho^2 \, (k)$$

Where;

Q_k = Ljung-Box Q-Statistic Coefficient

N = Complete Sample Size

m = Maximum Lag Length

$\rho^2(k)$ = Autocorrelation Coefficient at lag k

The Ljung-Box Q-Statistic Test is considered to be more powerful than Autocorrelation Function and it has p-values on which the null hypothesis of autocorrelation can be rejected or accepted based on 1% or 5% significance level. If the p-value is less than 0.05, the null hypothesis that autocorrelation equals zero ($\rho(k)$ = 0) is rejected at 5% level and the random walk hypothesis rejected as well.

Table 7.1.1 Autocorrelation Function and Ljung-Box Q-Statistic Tests of the Indices Return Series (Full Sample)

FTSE All Share Index				FTSE 100 Index		
Lag	AC	Q-Stat	P-value	AC	Q-Stat	P-value
1	-0.004	0.0797	0.778	-0.020	2.0417	0.153
2	-0.039*	8.0329	0.018	-0.048*	13.968	0.001
3	-0.070*	33.425	0.000	-0.077*	44.649	0.000
4	0.058*	50.868	0.000	0.054*	59.950	0.000
5	-0.045*	61.559	0.000	-0.050*	73.001	0.000
6	-0.037*	68.791	0.000	-0.039*	81.053	0.000
7	0.014	69.792	0.000	0.011	81.702	0.000
8	0.040*	78.230	0.000	0.038*	89.405	0.000
9	0.001	78.235	0.000	-0.001	89.407	0.000
10	-0.012	79.031	0.000	`-0.015	90.618	0.000
FTSE UK Oil & Gas Index				**FTSE UK Oil & Gas Producers Index**		
Lag	AC	Q-Stat	P-value	AC	Q-Stat	P-value
1	0.002	0.0188	0.891	-0.005	0.1060	0.745
2	-0.054*	14.478	0.001	-0.061*	18.670	0.000
3	-0.070*	38.569	0.000	-0.067*	40.682	0.000
4	0.052*	52.059	0.000	0.050*	53.055	0.000
5	-0.028*	55.954	0.000	-0.030*	57.380	0.000
6	-0.021	58.135	0.000	-0.020	59.436	0.000
7	0.007	58.396	0.000	0.015	60.609	0.000
8	-0.012	59.066	0.000	-0.013	61.495	0.000
9	-0.009	59.454	0.000	-0.008	61.804	0.000
10	-0.009	59.835	0.000	-0.013	62.599	0.000
FTSE AIM SS Oil and Gas Index						
Lag	AC	Q-Stat	P-value			
1	0.159*	78.822	0.000			
2	0.080*	98.752	0.000			
3	-0.006	98.874	0.000			
4	0.057*	109.09	0.000			
5	0.026	111.17	0.000			
6	0.020	112.46	0.000			
7	0.008	112.65	0.000			
8	-0.000	112.65	0.000			
9	0.001	112.65	0.000			
10	0.035*	116.57	0.000			

* indicates significance at 5% level

Source: Author (2015)

Table 7.1.1 presents the autocorrelation coefficients and the associated Ljung-Box Q-Statistic applied on the daily data of the indices' return series. Autocorrelation coefficients are interpreted using the band of 95% level of confidence interval while the Ljung-Box Q-Statistic is interpreted using p-values at 5% level of significance. The FTSE All Share Index and the FTSE 100 Share Index have shown a significant deviation from zero autocorrelation coefficient in 6 out of 10 lags (indicated by asterisks). These are the coefficients outside the respective band as shown in Appendix 7 (Table 7.1.4.) and therefore the null hypothesis of $\rho(k) = 0$ can be rejected. For the Ljung-Box Q-Statistic, the p-values are significant at 5% level for all the lags except the first-order correlation. Autocorrelation coefficient in the FTSE UK Oil and Gas, the FTSE UK Oil and Gas Producers and the FTSE AIM SS Oil and Gas Indices was found to be significant in less than 5 of the 10 lags. However, the p-values from the Q-Statistic test are significant for all lags except first-order or lag 1 coefficient. Our conclusion will be made based on the results from the Ljung-Box Q-Statistic test since it is assumed to be more powerful due to its consideration for the overall correlation coefficients from lags.

The results show persistence in return series and presence of serial correlation. This is an indication of non-random returns but it is not a sufficient condition to classify the market as weak form inefficient. Further tests will be conducted for robustness and results from non-parametric tests such as runs test will also be considered prior to making inferences about the information efficiency of the oil and gas sector under this study.

Table 7.1.2 Autocorrelation Function and Ljung-Box Q-Statistic of Companies with More Than 10 Years Data (Full Sample).

Amec Plc					BG Group Plc		
Lag	**AC**	**Q-Stat**	**P-value**		**AC**	**Q-Stat**	**P-value**
1	-0.020	2.0417	0.153		-0.041*	8.7113	0.003
2	-0.048*	13.968	0.001		-0.031*	13.837	0.001
3	-0.077*	44.649	0.000		-0.064*	35.069	0.000
4	0.054*	59.950	0.000		-0.014	36.056	0.000
5	-0.050*	73.001	0.000		0.010	36.537	0.000
6	-0.039*	81.053	0.000		-0.003	36.600	0.000
7	0.011	81.702	0.000		-0.015	37.744	0.000
8	0.038*	89.405	0.000		-0.013	38.639	0.000
9	-0.001	89.407	0.000		-0.007	38.921	0.000
10	-0.015	90.618	0.000		-0.028*	43.141	0.000
BP Plc					**Cairn Energy Plc**		
Lag	**AC**	**Q-Stat**	**P-value**		**AC**	**Q-Stat**	**P-value**
1	-0.004	0.0671	0.796		0.016	1.4064	0.236
2	-0.051*	13.521	0.001		0.012	2.1650	0.339
3	-0.061*	33.075	0.000		-0.018	3.9053	0.272
4	0.040*	41.519	0.000		0.011	4.5620	0.335
5	-0.013	42.444	0.000		0.005	4.7096	0.452
6	-0.012	43.144	0.000		-0.007	4.9868	0.546
7	0.024	46.121	0.000		-0.016	6.3461	0.500
8	-0.027*	49.928	0.000		-0.008	6.6919	0.570
9	0.018	51.640	0.000		-0.020	8.8613	0.450
10	-0.007	51.929	0.000		0.005	8.9903	0.533
Dragon Oil Plc					**Fortune Oil Plc**		
Lag	**AC**	**Q-Stat**	**P-value**		**AC**	**Q-Stat**	**P-value**
1	-0.027*	3.7650	0.052		-0.157*	129.30	0.000
2	-0.002	3.7810	0.151		-0.000	129.30	0.000
3	-0.021	6.0294	0.110		-0.070*	155.00	0.000
4	-0.005	6.1411	0.189		0.003	155.05	0.000
5	-0.005	6.2705	0.281		-0.015	156.19	0.000
6	-0.027*	10.124	0.120		-0.012	156.89	0.000
7	0.004	10.219	0.177		-0.046*	168.09	0.000
8	-0.012	10.980	0.203		-0.013	169.03	0.000
9	-0.004	11.075	0.271		-0.021	171.40	0.000
10	-0.024	13.993	0.173		-0.018	173.04	0.000
Hunting Plc					**Premier Oil Plc**		
Lag	**AC**	**Q-Stat**	**P-value**		**AC**	**Q-Stat**	**P-value**
1	-0.157*	129.30	0.000		0.073*	27.852	0.000
2	-0.000	129.30	0.000		-0.037*	35.071	0.000
3	-0.070*	155.00	0.000		-0.049*	47.728	0.000
4	0.003	155.05	0.000		0.037*	55.039	0.000
5	-0.015	156.19	0.000		-0.009	55.496	0.000
6	-0.012	156.89	0.000		-0.003	55.540	0.000
7	-0.046*	168.09	0.000		-0.013	56.402	0.000
8	-0.013	169.03	0.000		0.001	56.410	0.000
9	-0.021	171.40	0.000		-0.012	57.148	0.000
10	-0.018	173.04	0.000		0.001	57.160	0.000
Royal Dutch Shell ‘B’ Plc					**Tullow Oil Plc**		
Lag	**AC**	**Q-Stat**	**P-value**		**AC**	**Q-Stat**	**P-value**
1	0.004	0.0816	0.775		0.029*	4.3675	0.037
2	-0.066*	22.704	0.000		0.000	4.3681	0.113
3	-0.040*	31.011	0.000		0.006	4.5784	0.205
4	0.055*	46.799	0.000		0.009	4.9634	0.291
5	-0.047*	58.139	0.000		-0.013	5.8619	0.320
6	-0.025	61.344	0.000		0.020	8.0357	0.236
7	0.010	61.844	0.000		-0.010	8.5723	0.285

8	-0.008	62.201	0.000		-0.028*	12.703	0.122
9	-0.018	63.909	0.000		0.002	12.717	0.176
10	-0.006	64.093	0.000		0.006	12.912	0.229
Aminex Plc					**JKX Oil and Gas Plc**		
Lag	**AC**	**Q-Stat**	**P-value**		**AC**	**Q-Stat**	**P-value**
1	-0.087*	34.870	0.000		0.086*	33.414	0.000
2	0.018	36.391	0.000		-0.001	33.416	0.000
3	0.019	38.104	0.000		0.012	34.034	0.000
4	0.009	38.476	0.000		-0.003	34.086	0.000
5	-0.002	38.488	0.000		-0.015	35.086	0.000
6	-0.036*	44.477	0.000		-0.040*	42.256	0.000
7	-0.025	47.267	0.000		0.017	43.511	0.000
8	-0.008	47.583	0.000		-0.009	43.849	0.000
9	-0.007	47.785	0.000		-0.016	45.092	0.000
10	-0.029*	51.680	0.000		-0.014	46.037	0.000
Soco Intl. Plc					**Wood Group (John) Plc**		
Lag	**AC**	**Q-Stat**	**P-value**		**AC**	**Q-Stat**	**P-value**
1	0.062*	6.0550	0.014		0.011	0.3338	0.563
2	-0.028	7.3174	0.026		-0.029	2.7130	0.258
3	-0.055*	12.199	0.007		-0.044*	7.9572	0.047
4	-0.046*	15.531	0.004		-0.006	8.0491	0.090
5	-0.077*	25.043	0.000		-0.037*	11.839	0.037
6	0.016	25.456	0.000		-0.023	13.318	0.038
7	0.092*	39.078	0.000		0.020	14.467	0.043
8	-0.064*	45.600	0.000		0.005	14.537	0.069
9	-0.075*	54.626	0.000		-0.017	15.349	0.082
10	-0.049*	58.411	0.000		0.004	15.386	0.119

* indicates significance at 5% level

Source: Author (2015)

Table 7.1.2 contains the results from the Autocorrelation Function and Ljung-Box Q-Statistic on the oil and gas companies listed on the London stock exchange for over 10 years. The results suggest that most of the stock series in this category (except Cairn Energy, Tullow Oil and Dragon) show serial correlation at most of the lags. This information on serial correlation could be used to develop trading strategies to earn abnormal returns. Technical trading rules will be employed in the subsequent sections of this chapter to check the possibility of earning abnormal returns using past information on serial correlation.

Table 7.1.3 Autocorrelation Function and Ljung-Box Q-Statistic Tests of Companies with Less Than 10 Years Data (Full Sample)

Afren Plc					Hardy Oil and Gas Plc		
Lag	AC	Q-Stat	P-value		AC	Q-Stat	P-value
1	0.059*	7.0395	0.008		0.030	1.7706	0.183
2	-0.020	7.8716	0.020		0.033	3.9096	0.142
3	-0.019	8.5725	0.036		-0.019	4.5999	0.204
4	0.016	9.0762	0.059		0.021	5.4705	0.242
5	-0.002	9.0864	0.106		0.031	7.3763	0.194
6	-0.029	10.800	0.095		-0.015	7.8433	0.250
7	0.004	10.837	0.146		0.031	9.7569	0.203
8	0.026	12.270	0.140		-0.005	9.8037	0.279
9	-0.034	14.621	0.102		0.047*	14.111	0.118
10	-0.030	16.507	0.086		-0.006	14.189	0.165
Royal Dutch Shell 'A' Plc					Petrofac Plc		
Lag	AC	Q-Stat	P-value		AC	Q-Stat	P-value
1	-0.019	0.7347	0.391		-0.023	1.0195	0.313
2	-0.042	4.1582	0.125		0.012	1.2926	0.524
3	-0.048*	8.6023	0.035		-0.061*	8.2846	0.040
4	0.116	34.872	0.000		-0.029	9.8396	0.043
5	-0.053*	40.271	0.000		-0.058*	16.276	0.006
6	-0.032	42.246	0.000		0.005	16.325	0.012
7	0.016	42.737	0.000		0.022	17.278	0.016
8	-0.015	43.151	0.000		0.025	18.477	0.018
9	-0.065*	51.378	0.000		-0.039	21.419	0.011
10	0.051*	56.402	0.000		-0.019	22.125	0.014
Lamprell Plc					Salamander Plc		
Lag	AC	Q-Stat	P-value		AC	Q-Stat	P-value
1	0.060*	5.9175	0.015		0.062*	6.0550	0.014
2	-0.009	6.0626	0.048		-0.028	7.3174	0.026
3	-0.010	6.2196	0.101		-0.055*	12.199	0.007
4	0.027	7.3655	0.118		-0.046	15.531	0.004
5	-0.016	7.7701	0.169		-0.077	25.043	0.000
6	0.024	8.7424	0.189		0.016	25.456	0.000
7	-0.011	8.9568	0.256		0.092*	39.078	0.000
8	0.040	11.605	0.170		-0.064*	45.600	0.000
9	-0.012	11.841	0.222		-0.075*	54.626	0.000
10	0.009	11.971	0.287		-0.049*	58.411	0.000
Endeavor Intl. Plc					Kentz Corp. Plc		
Lag	AC	Q-Stat	P-value		AC	Q-Stat	P-value
1	0.017	0.3932	0.531		0.078*	7.7353	0.005
2	-0.025	1.1937	0.551		-0.011	7.8876	0.019
3	-0.134*	24.874	0.000		0.004	7.9127	0.048
4	-0.005	24.901	0.000		-0.052	11.383	0.023
5	-0.000	24.902	0.000		-0.001	11.386	0.044
6	0.009	25.007	0.000		0.013	11.615	0.071
7	0.000	25.007	0.001		0.007	11.673	0.112
8	-0.010	25.134	0.001		-0.034	13.125	0.108
9	-0.003	25.146	0.003		-0.026	13.984	0.123
10	-0.000	25.147	0.005		0.022	14.638	0.146
Heritage Oil Plc					Cadogan Petroleum Plc		
Lag	AC	Q-Stat	P-value		AC	Q-Stat	P-value
1	-0.025	0.7950	0.373		-0.069*	5.6778	0.017
2	0.025	1.5948	0.451		-0.087*	14.725	0.001
3	-0.091*	11.806	0.008		0.051	17.783	0.000
4	0.043	14.070	0.007		0.017	18.121	0.001
5	-0.040	16.083	0.007		0.088*	27.441	0.000
6	0.007	16.143	0.013		-0.011	27.592	0.000
7	-0.033	17.491	0.014		0.025	28.322	0.000

8	0.015	17.757	0.023	-0.005	28.350	0.000
9	-0.044	20.156	0.017	-0.042	30.495	0.000
10	0.027	21.082	0.021	-0.023	31.129	0.001
Exillon Energy Plc				**Enquest Plc**		
Lag	**AC**	**Q-Stat**	**P-value**	**AC**	**Q-Stat**	**P-value**
1	0.055	2.3650	0.124	-0.056	2.2886	0.130
2	-0.026	2.8875	0.236	0.014	2.4362	0.296
3	-0.031	3.6366	0.303	-0.007	2.4748	0.480
4	0.010	3.7125	0.446	-0.050	4.2569	0.372
5	-0.056	6.2572	0.282	-0.014	4.3995	0.493
6	-0.004	6.2695	0.394	-0.061*	7.1263	0.309
7	0.091*	12.911	0.074	-0.094*	13.515	0.061
8	-0.033	13.768	0.088	0.012	13.626	0.092
9	0.017	13.992	0.123	-0.039	14.727	0.099
10	-0.049	15.936	0.101	-0.038	15.749	0.107
Essar Energy Plc				**Genel Energy Plc**		
Lag	**AC**	**Q-Stat**	**P-value**	**AC**	**Q-Stat**	**P-value**
1	-0.044	1.3341	0.248	0.044	0.7750	0.379
2	0.051	3.1633	0.206	-0.012	0.8358	0.658
3	-0.058	5.5067	0.138	0.044	1.6175	0.655
4	-0.029	6.0933	0.192	-0.026	1.8952	0.755
5	0.023	6.4665	0.263	-0.025	2.1566	0.827
6	0.021	6.7715	0.342	-0.029	2.4922	0.869
7	-0.001	6.7720	0.453	-0.058	3.8760	0.794
8	-0.013	6.8920	0.548	-0.036	4.4109	0.818
9	0.004	6.9008	0.647	0.098*	8.3924	0.495
10	-0.071	10.455	0.401	0.067	10.271	0.417
Ophir Energy Plc				**Ruspetro Plc**		
Lag	**AC**	**Q-Stat**	**P-value**	**AC**	**Q-Stat**	**P-value**
1	-0.003	0.0032	0.955	0.044	0.4965	0.481
2	0.104*	4.2643	0.119	-0.157*	6.7454	0.034
3	0.024	4.4978	0.212	0.025	6.9011	0.075
4	0.019	4.6395	0.326	0.117	10.361	0.035
5	-0.117	10.069	0.073	0.063	11.365	0.045
6	0.060	11.507	0.074	-0.069	12.574	0.050
7	-0.045	12.309	0.091	0.016	12.642	0.081
8	0.074	14.473	0.070	-0.003	12.645	0.125
9	0.012	14.526	0.105	0.055	13.437	0.144
10	0.020	14.682	0.144	-0.029	13.659	0.189

* indicates significance at 5% level

Source: Author (2015)

Table 7.1.3 presents the results of the Autocorrelation Function and Ljung-Box Q-Statistic tests on stocks that have time series data of less than 10 years. Afren Plc, Hardy Oil and Gas Plc, Petrofac Ltd, Lamprell Plc, Kentz Corp. Plc, Exillon Energy Plc, Enquest Plc, Essar Energy Plc, Genel Energy Plc, Ophir Energy Plc and Ruspetro Plc stocks are identified with insignificant autocorrelation coefficients that fall within the band of 95% level of confidence interval. The p-values generated from the Q-Statistic are also insignificant or higher than 5% in most of the lags. The null hypothesis of 'no serial correlation' cannot be rejected in this instance. The evidence of the absence of serial correlation suggests that these stocks fluctuate randomly.

The main findings of these results is that there is less persistence in the returns of companies which were listed and started trading in the last ten years. In other words, the longer is the time series, the greater is the probability of finding persistence. This could be due to certain events which affect the market for a short time but the presence of those events in longer series affects the overall results.

Appendix 7 (Table 7.1.4) presents the band of 95% level of confidence interval calculated for every stock using the assumption of normal distribution $(\pm 1.96 \times \frac{1}{\sqrt{N}})$. The significance of Autocorrelation Function coefficients are judged based on whether they fall within or outside the band as explained earlier.

7.3.2 Runs Test

Runs test is a non-parametric (or distribution-free) test developed by Bradley (1968) for detecting randomness or non-randomness in a time series. The run test is associated with two mutually exclusive values of 'increase' and 'decrease'. A run is a sequence of non-stop 'increasing values' or 'decreasing values' at a given time and the length of the run is the number of occurrences of the values. A number above the mean or median of a series is regarded as an increase or positive, while any number below the mean or median of the same series is regarded as a decrease or negative.

Figure 7.1 Illustration of a Run Process

(+++++)(-----)(+++)(------)(+)(-)(+++++)(----)(+++++)(--)(++++++)

Figure 7.1 presents a series with 11 runs and the length of each run as 5, 5, 3, 6, 1, 1, 5, 4, 5, 2, and 6 respectively. The mean and standard deviation of the runs are given as:

Mean (Expected Runs): $\bar{R} = \frac{2N_1N_2}{N} + 1$

Standard deviation: $\sigma_R = \sqrt{\frac{2N_1N_2(2N_1N_2-N)}{(N)^2(N-1)}}$

Where;

N = Total number of observations (N_1+N_2)

N_1 = Number of values above the series mean

N_2 = Number of values below the series mean

R = Number of actual runs

If N_1>10, and N_2>10, then the runs distribution is expected to be normally distributed and the null hypothesis is rejected if 'R' falls outside the standardised normality band (± 1.96) at 95% level of confidence interval.

The null and alternative hypotheses to be tested are:

H_0: The series is generated from a random process

H_1: The series is not generated from a random process

In other words, the null hypothesis signifies zero autocorrelation while the alternative hypothesis implies significant autocorrelation. To standardise the results obtained on the assumption of normal distribution at 95% level of confidence interval, Z-Statistic coefficients are used to reject or accept the null hypothesis. If (Z > 1.96) in absolute terms, the null hypothesis is rejected and vice versa. Z-Statistic is given as:

$$Z = \frac{R - \bar{R}}{\sigma_R}$$

Where (R) is the actual run, $(\bar{R})$ as the mean of the runs and (σ_R) as the standard deviation.

Table 7.2.1 Runs Test of the Indices Return Series

	Obs. N_1+N_2	N_1 Above	N_2 Below	Actual Runs-R	Expected Runs- $\bar{R}$	Std. Dev.	Z-Stat	P-Value
FTSE All Share	5217	2623	2594	2585	2609.42	36.1	-0.676	0.499
FTSE 100	5217	2576	2641	2629	2609.10	36.1	0.551	0.581
FTSE UK O&G	4956	2396	2560	2407	2476.29	35.1	-1.971	0.049
FTSE UK O&G Prd	4956	2387	2569	2425	2475.66	35.1	-1.441	0.150
FTSE AIM SS O&G	3131	1553	1578	1398	1566.40	27.9	-6.020	0.000

Source: Author (2015)

Table 7.2.1 presents the runs test results of the indices return series. The Z-Statistics of all the series are less than 1.96 except for the FTSE UK Oil and Gas and the FTSE AIM SS Oil and Gas indices that have Z-Statistic values greater than 1.96 at -1.971 and -6.020 respectively. Hence, the null hypothesis of randomness is rejected at 5% significance level in the FTSE UK Oil and Gas and the FTSE AIM SS Oil and Gas indices. The null hypothesis of randomness is accepted in the FTSE All Share, the FTSE 100, and the FTSE UK Oil and Gas Producers indices because their Z-Statistics are less than 1.96.

The result is contradictory to that of the Autocorrelation Function and Ljung-Box Q-Statistics which show evidence of serial correlation and rejection of Random Walk Hypothesis in all the FTSE indices under study. Only the results of the FTSE UK Oil and Gas and the FTSE AIM SS Oil and Gas indices are consistent with that of the Autocorrelation Function and Ljung-Box Q-Statistics. Due to some of these inconsistencies, inferences will be made about the Random Walk and Market Efficiency Hypotheses at the end of this chapter after various tests including whether abnormal profit can be obtained by technical trading rules have been conducted.

Table 7.2.2 Runs Test of Companies with More Than 10 Years Series under study

	Obs. N_1+N_2	**N_1 Above**	**N_2 Below**	**Actual Runs-R**	**Expected Runs-$\bar{R}$**	**Std. Dev.**	**Z-Stat**	**P-Value**
Amec Plc	5217	2116	3101	2297	2516.51	34.8	-6.304	0.000
BG Group Plc	5217	2273	2944	2584	2566.35	35.5	0.497	0.619
BP Plc	5217	2358	2859	2523	2585.44	35.7	-1.745	0.081
Cairn Energy Plc	5217	1405	3812	1714	2054.23	28.4	-11.97	0.000
Dragon Oil Plc	5217	1270	3947	1436	1922.68	26.6	-18.29	0.000
Fortune Oil Plc	5217	284	4933	539	538.080	7.43	0.124	0.901
Hunting Plc	5217	1596	3621	1778	2216.49	30.6	-14.29	0.000
Premier Oil Plc	5217	1667	3550	2026	2269.68	31.4	-7.759	0.000
RDSB Plc	5217	2708	2509	2569	2605.70	36.0	-1.018	0.309
Tullow Oil Plc	5217	1761	3456	2099	2334.15	32.2	-7.280	0.000
Aminex Plc	4563	3967	596	1009	1037.31	15.3	-1.846	0.065
JKX O&G Plc	4559	3254	1305	1569	1863.90	27.5	-10.69	0.000
Soco Intl. Plc	4068	1273	2795	1439	1750.28	27.4	-11.35	0.000
Wood Group Plc	2764	1268	1496	1388	1373.60	26.1	0.552	0.581

Source: Author (2015)

Table 7.2.2 shows the results from runs test conducted on stocks that are listed for more than ten years on the London stock exchange. The Z-Statistics are found to be greater than 1.96 in 11 stocks out of the total number of 14 stocks in this data classification. The null hypothesis of randomness is rejected in the 11 stocks, which indicates evidence of persistence in most of the series. BG Group Plc, Fortune Oil Plc, and Wood Group (John) Plc have Z-Statistics less than 1.96 and the null hypothesis of randomness is accepted. Abnormal profit can be obtained from technical trading rules on all the stocks except BG Group Plc, Fortune Oil Plc, and Wood Group (John) Plc due to the existence of serial correlation which opposes the assumptions of the Random Walk Hypothesis (RWH) and the Efficient Market Hypothesis (EMH).

The result is consistent with the Autocorrelation Function and Ljung-Box Q-Statistics results of the Wood Group Plc that accept the null hypothesis of randomness. From the results for Amec Plc, BP Plc, Dragon Oil Plc, Hunting Plc, Premier Oil Plc, Royal Dutch Shell 'B' Plc, Aminex Plc, JKX Oil and Gas Plc, and Soco Intl. Plc the null hypothesis of randomness is rejected by providing evidence of serial correlation. Inconsistencies were only observed in Cairn Energy Plc and Tullow Oil Plc in which the Autocorrelation Function shows evidence of randomness while Runs Test results show evidence of serial correlation. More information to reconcile the inconsistencies will be obtained from variance ratio tests, the BDS test and technical trading rules to be employed in subsequent sections.

Table 7.2.3 Runs Test of Companies with Less Than 10 Years Series under study

	Obs. N_1+N_2	**N_1 Above**	**N_2 Below**	**Actual Runs-R**	**Expected Runs- $\bar{R}$**	**Std. Dev.**	**Z-Stat**	**P-Value**
Afren Plc	2036	734	1302	855	939.77	20.7	-4.076	0.000
Hardy O&G Plc	1975	1151	824	970	961.42	21.6	0.397	0.692
RDSA Plc	1943	970	973	963	972.49	22.0	-0.431	0.666
Petrofac Plc	1890	885	1005	918	942.19	21.6	-1.118	0.264
Lamprell Plc	1624	928	696	786	796.42	19.7	-0.529	0.597
Salamander E. Plc	1588	896	692	774	781.89	19.5	-0.403	0.687
Endeavor Intl. Plc	1316	739	577	648	649.02	17.8	-0.058	0.954
Kentz Corp. Plc	1280	459	821	510	589.81	16.4	-4.852	0.000
Heritage Oil Plc	1241	686	555	601	614.58	17.4	-0.780	0.435
Cadogan Petr. Plc	1184	848	336	498	482.29	13.9	1.123	0.261
Exillon Energy Plc	793	301	492	355	374.49	13.2	-1.471	0.141
Enquest Plc	715	275	440	356	339.46	12.6	1.308	0.191

Essar Energy Plc	695	366	329	357	347.51	13.1	0.722	0.470
Genel Energy Plc	402	239	163	174	194.81	9.65	-2.156	0.031
Ophir Energy Plc	387	180	207	188	193.55	9.77	-0.569	0.570
Ruspetro Plc	248	139	109	119	123.18	7.74	-0.541	0.589

Source: Authors (2015)

Table 7.2.3 presents the results of runs test on companies that have shorter time series of less than 10 years representing 16 stocks of oil and gas companies. Afren Plc, Kentz Corp. Plc and Genel Energy Plc have a Z-Statistic value greater than 1.96 at -4.076, -4.852 and -2.156 respectively. Therefore, the null hypothesis of randomness is rejected for the three stocks which indicate evidence for serial correlation. The null hypothesis cannot be rejected in the remaining 13 stocks because their Z-Statistics are lower than 1.96. In these stocks, the series are not serially correlated and abnormal profit cannot be obtained from technical trading rules confirming the assumptions of the Random Walk Hypothesis.

7.3.3 Variance Ratio Test

The variance ratio test as adopted by Lo and Mackinlay (1988, 1989) is among the numerous approaches employed by scholars to ascertain the predictability of stock returns. The test compares variances of differences in the data returns calculated over different intervals. If the time series of data is assumed to follow random walks, the variance of q-period difference should be q times the variance of a one-period difference. In other words, return series are assumed to be generated from a random process if the variance of two periods is double the value of a single period variance. Variance ratio statistic for two-period or two-day returns is given by the formula:

$$VR(2) = \frac{Var\,[r_t(2)]}{2Var(r_t)}$$

Where;

$r_t(2) = r_t + r_{t+1}$

$r_t + r_{t+1}$ = Two-day return

The assumption of the variance ratio test is tested for significance using the following null and alternative hypotheses:

H_0 = variance ratio is equal to 1 (series follow random walk)

H_1 = variance ratio is not equal to 1 (series do not follow random walk)

Using the assumption of standard normal distribution, if the Z-statistic is greater the 1.96, the null hypothesis of random walk is rejected. In other words, if the p-values are less than 5% level of significance, the null hypothesis of random walk is rejected which suggests evidence of serial correlation.

Table 7.3.1 Variance Ratio Test of the Indices Return Series

FTSE All Share Index					FTSE 100 Index		
Period	Var. Ratio	z-Statistic	P-value		Var. Ratio	z-Statistic	P-value
2	0.994797	-0.244382	0.8069		0.983891	-0.779959	0.4354
4	0.921325	-1.918954	0.0550		0.890337	-2.759736	0.0058
8	0.855327	-2.162800	0.0306		0.800227	-3.091407	0.0020
16	0.837643	-1.630532	0.1030		0.762635	-2.471147	0.0135
32	0.818626	-1.280891	0.2002		0.719348	-2.055505	0.0398
FTSE UK Oil & Gas Index					FTSE UK Oil and Gas Prod. Index		
Period	Var. Ratio	z-Statistic	P-value		Var. Ratio	z-Statistic	P-value
2	0.986697	-0.556407	0.5779		0.985827	-0.632045	0.5274
4	0.913045	-1.929761	0.0536		0.900139	-2.384118	0.0171
8	0.889608	-1.526958	0.1268		0.863720	-2.039520	0.0414
16	0.842426	-1.467763	0.1422		0.808999	-1.928550	0.0538
32	0.755993	-1.594827	0.1108		0.722639	-1.964177	0.0495

FTSE AIM SS Oil and Gas Index					
Period	Var. Ratio	z-Statistic	P-value		
2	1.175389	6.052303	0.0000		
4	1.353821	6.734747	0.0000		
8	1.535350	6.608004	0.0000		
16	1.740953	6.392288	0.0000		
32	2.175804	7.308544	0.0000		

Source: Author (2015)

Table 7.3.1 presents the variance ratio test results comprising the variance ratio statistics, z-statistics and p-values generated from the FTSE indices under study using 5 periods (2, 4, 8, 16, 32). From the result, the null hypothesis of VR=1 (random walk process) is rejected in all periods of the FTSE AIM SS Oil and Gas index because p-values are less than 0.05 and z-statistics are greater than 1.96. Similar results were obtained in the FTSE 100 index and the FTSE UK Oil and Gas Producers' index where the majority of the p-values and z-statistics indicate evidence for the rejection of the null hypothesis of the random walk process which is a sign that signifies the existence of serial correlation. However, the null hypothesis of VR=1 (random walk process) is accepted in the FTSE All Share index and the FTSE UK Oil and Gas index because the z-statistics are less than 1.96 in most of the periods and the p-values are greater than 0.05, which is evidence that the indices follow random walk.

The result is consistent with the Autocorrelation Function and Ljung-Box Q-Statistics results on the FTSE AIM SS Oil and Gas index, the FTSE 100 index, and the FTSE UK Oil and Gas Producers index that also rejected the Random Walk Hypothesis but is inconsistent with the results on the FTSE All Share index and the FTSE UK Oil and Gas index. The consistency was also extended to the runs test results which accepts the Random Walk Hypothesis in the

FTSE All Share index and the FTSE UK Oil and Gas index. The BDS test and technical trading rules will provide more information to make appropriate inferences.

Table 7.3.2 Variance Ratio Test of Companies with More Than 10 Years Series under study

Amec Plc				BG Group Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.016194	0.567991	0.5700	0.990973	-0.308700	0.7575
4	0.997646	-0.044492	0.9645	0.943194	-1.044623	0.2962
8	0.936497	-0.763783	0.4450	0.861092	-1.622621	0.1047
16	0.866073	-1.106064	0.2687	0.724581	-2.173763	0.0297
32	0.901238	-0.574592	0.5656	0.572741	-2.349290	0.0188
BP Plc				Cairn Energy Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	0.977522	-1.064163	0.2873	0.994158	-0.218894	0.8267
4	0.884666	-2.938616	0.0033	0.985996	-0.273867	0.7842
8	0.847526	-2.449842	0.0143	0.939973	-0.729022	0.4660
16	0.825756	-1.890728	0.0587	0.874738	-1.028405	0.3038
32	0.785067	-1.642653	0.1005	0.899031	-0.577790	0.5634
Dragon Oil Plc				Fortune Oil Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.056173	1.919686	0.0549	0.755239	-9.829305	0.0000
4	1.076791	1.442562	0.1491	0.618617	-8.770264	0.0000
8	1.079463	0.973791	0.3302	0.510457	-7.748482	0.0000
16	0.994347	-0.047590	0.9620	0.431452	-6.443073	0.0000
32	1.046596	0.275999	0.7825	0.364978	-5.292614	0.0000
Hunting Plc				Premier Oil Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.008975	0.313403	0.7540	1.000855	0.036859	0.9706
4	0.985145	-0.279610	0.7798	0.951164	-1.086897	0.2771
8	0.967957	-0.396417	0.6918	0.931643	-0.954986	0.3396
16	0.979884	-0.174153	0.8617	0.891729	-1.020487	0.3075
32	1.047739	0.296418	0.7669	0.989225	-0.070049	0.9442
Royal Dutch Shell 'B' Plc				Tullow Oil Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	0.999673	-0.014811	0.9882	0.979235	-0.727341	0.4670
4	0.926072	-1.804571	0.0711	0.952427	-0.859976	0.3898
8	0.890710	-1.691923	0.0907	0.903549	-1.122019	0.2619
16	0.799973	-2.109470	0.0349	0.805977	-1.547779	0.1217
32	0.667413	-2.469019	0.0135	0.697424	-1.683574	0.0923
Aminex Plc				JKX Oil and Gas Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.038209	1.344073	0.1789	1.031629	0.940327	0.3470
4	1.031644	0.615153	0.5385	1.042671	0.707415	0.4793
8	1.027461	0.351051	0.7256	1.019300	0.206219	0.8366

16	0.983192	-0.152573	0.8787		0.908759	-0.653822	0.5132
32	0.968082	-0.209792	0.8338		0.936164	-0.324675	0.7454
Soco Intl. Plc					Wood Group (John) Plc		
Period	Var. Ratio	z-Statistic	P-value		Var. Ratio	z-Statistic	P-value
2	1.058328	1.904568	0.0568		1.036515	1.183386	0.2367
4	1.061870	1.109871	0.2671		0.974336	-0.446126	0.6555
8	0.991115	-0.103759	0.9174		0.896521	-1.178657	0.2385
16	0.895271	-0.839701	0.4011		0.824219	-1.383196	0.1666
32	0.833197	-0.937489	0.3485		0.773505	-1.246792	0.2125

Source: Author (2015)

Table 7.3.2 presents the variance ratio test results of stocks listed on the London stock exchange for over 10 years. The p-values and z-statistics generated in all series are found to be insignificant even at 1% except in Fortune Oil Plc where the z-statistics are significantly greater than 1.96 and the p-values are less than 0.05. This provides statistical evidence to accept the null hypothesis of VR=1 (the series follow random walk) in all the series except Fortune Oil. Based on the variance ratio test results, only Fortune Oil stock series is found to be serially correlated which conforms to the findings of the Autocorrelation Function and Ljung Box Q Statistics results. In this case technical trading rules may not yield any results because of the existence of random walk.

The results are consistent with that of runs test in most of the series because the random walk hypothesis was also accepted but are inconsistent with that of Autocorrelation and Q-Statistic results because of the rejection of the random walk hypothesis in most of the series. Conclusive inference about the weak form of market efficiency will be made after the application of the BDS test and technical trading rules in subsequent sections.

Table 7.3.3 Variance Ratio Test of Companies with Less Than 10 Years Series under study

	Afren Plc			Hardy Oil and Gas Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.042501	1.471151	0.1413	1.053531	1.134957	0.2564
4	1.029208	0.549847	0.5824	1.082970	1.015089	0.3101
8	0.955164	-0.548844	0.5831	1.186822	1.592534	0.1113
16	0.986741	-0.112152	0.9107	1.343011	2.139903	0.0324
32	1.121279	0.726270	0.4677	1.563342	2.581666	0.0098

	Royal Dutch Shell 'A' Plc			Petrofac Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	0.990886	-0.241894	0.8089	0.956703	-1.377110	0.1685
4	0.951467	-0.691959	0.4890	0.910537	-1.497848	0.1342
8	0.963366	-0.329585	0.7417	0.816102	-1.927254	0.0539
16	0.902204	-0.598407	0.5496	0.746314	-1.786877	0.0740
32	0.782433	-0.932997	0.3508	0.655572	-1.686967	0.0916

	Lamprell Plc			Salamander Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.026806	0.965151	0.3345	1.003684	0.094966	0.9243
4	1.049435	0.922452	0.3563	0.952044	-0.693959	0.4877
8	1.138529	1.591360	0.1115	0.895998	-1.019340	0.3080
16	1.223745	1.679991	0.0930	0.797964	-1.392065	0.1639
32	1.321955	1.680513	0.0929	0.838963	-0.801721	0.4227

	Endeavor Intl. Plc			Kentz Corp. Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.017542	1.195251	0.2320	1.072527	1.565430	0.1175
4	0.947531	-0.871551	0.3835	1.041662	0.486324	0.6267
8	0.851837	-1.051353	0.2931	0.957701	-0.315977	0.7520
16	0.782192	-1.179317	0.2383	0.886288	-0.590730	0.5547
32	0.821949	-0.798884	0.4244	0.817457	-0.697040	0.4858

	Heritage Oil Plc			Cadogan Petroleum Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	0.999136	-0.022204	0.9823	0.893044	-1.539844	0.1236
4	0.990806	-0.134065	0.8934	0.827965	-1.370711	0.1705
8	0.965993	-0.318560	0.7501	0.803242	-0.922051	0.3565
16	0.904224	-0.637389	0.5239	0.847906	-0.425301	0.6706
32	1.009987	0.047868	0.9618	0.955325	-0.085787	0.9316

	Exillon Energy Plc			Enquest Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	1.035666	0.785730	0.4320	0.943262	-1.376087	0.1688
4	1.063488	0.729293	0.4658	0.924235	-0.938902	0.3478
8	1.035181	0.258051	0.7964	0.786630	-1.709672	0.0873
16	0.983822	-0.079364	0.9367	0.588604	-2.296127	0.0217
32	1.179443	0.607415	0.5436	0.572336	-1.685793	0.0918

	Essar Energy Plc			Genel Energy Plc		
Period	Var. Ratio	z-Statistic	P-value	Var. Ratio	z-Statistic	P-value
2	0.990664	-0.194216	0.8460	1.045406	0.356339	0.7216
4	0.977372	-0.247254	0.8047	1.072291	0.357571	0.7207
8	1.009250	0.066111	0.9473	1.058093	0.224211	0.8226

16	1.061697	0.310938	0.7558		1.174846	0.538914	0.5899
32	1.257720	0.942271	0.3461		1.411368	1.000892	0.3169
Ophir Energy Plc					Ruspetro Plc		
Period	Var. Ratio	z-Statistic	P-value		Var. Ratio	z-Statistic	P-value
2	0.977796	-0.421442	0.6734		1.105781	1.264193	0.2062
4	1.019097	0.177306	0.8593		1.022674	0.153576	0.8779
8	0.995552	-0.025820	0.9794		1.184767	0.828742	0.4073
16	0.996355	-0.014372	0.9885		1.419405	1.305878	0.1916
32	1.005442	0.015044	0.9880		2.132571	2.496335	0.0125

Source: Author (2015)

Table 7.3.3 shows the variance ratio test results of stocks with shorter time series in the study. P-values are found to be insignificant even at 1% in all the stocks series which provide strong evidence for the acceptance of the null hypothesis of random walk. Z-Statistics are also significantly less than 1.96 which is another evidence for the acceptance of the hypothesis. It is therefore concluded that all the series follow a random walk and technical trading rules cannot yield any positive result. The result is similar to that obtained from 7.3.2 above.

In comparison to the results of the autocorrelation and runs tests, the autocorrelation and Q-Statistic results were found to be inconsistent with the variance ratio test results because of the rejection of the Random Walk Hypothesis by the autocorrelation function. The runs test results was found to be consistent with variance ratio test results in most of the series because the acceptance of random walk in most of the series by runs test. As stated earlier, further information will be acquired from the BDS test and trading rules to make inferences about the weak form of market efficiency of the oil and gas sector on the London stock exchange.

7.3.4 Brock, Dechert, and Scheinkman (BDS) Test

The BDS Independence Test is a non-linearity statistical model designed by Brock, Dechert, Scheinkman and LeBaron (1996) to test for time-based dependence in a given series. It can also test for deviations of a series from independence to provide more empirical evidence for or against serial dependence. In the test for dependence, the BDS test has the power to consider a wide-range of linearity, non-linearity and chaos dependence. In addition, the BDS tests whether the residuals of a series are independent and identically distributed (iid). The residuals from a fitted linear model such as the Autoregressive Moving Average (ARMA) can be tested for non-linear dependence. Statistically, the BDS test is calculated by considering a distance (ε) in a series and, from the distance (ε), a pair of points (X_s, X_t) is selected. Multiple pairs in the distance (ε) of the series will be ({X_s, X_t}, {X_{s+1}, X_{t+1}} {X_{s+2}, X_{t+2}},……….{X_{s+m-1}, X_{t+m-1}}), where '*m*' is the total consecutive points used in the distance (ε). To test whether the observations of the series are independent and identically distributed (iid), the probability (C_1 (ε)) of the distance between two points of a pair (X_s, X_t) at less than or equal to Epsilon will be constant. For all the pairs in a distance (ε) of the series, the probability will be the product of individual pairs and this is represented by:

$$Cm(\varepsilon) = C_1^{m}(\varepsilon)$$

Therefore, the BDS statistic is given as:

$$W_m(\varepsilon) = \frac{\sqrt{n[C_m(\varepsilon) - {C_1}^m(\varepsilon)]}}{\sigma_m(\varepsilon)}$$

Where;

$W_m(\varepsilon)$ = BDS Statistic

$\sigma_m(\varepsilon)$ = Estimate of Standard Deviation

n = Number of samples

$C_m(\varepsilon)$ = All pairs in a distance of the series

${C_1}^m(\varepsilon)$ = Product of individual pairs

It is further expected that this relationship may not be 100% correct, as a result of which provision for errors is made in the model. If the estimated error in the model is large, it is then not likely that it is caused by the variation in the random observations. The BDS test is designed to measure the quantum of errors in the model to determine the dependence of the series. According to Brooks (2008), the BDS test can be applied on raw or original data to explore the characteristics of a given series as well as on the residuals derived from an employed model (as a model diagnostic) to determine whether the residual series are *iid* or not.

The motivation for the employment of the BDS test in this study was because of its power to assess the linearity or non-linearity structure of a series in addition to being a measure of departure from randomness. In that course, the model diagnostic approach will be employed and the residuals derived from a fitted model would be tested for iid using the BDS test. The Autoregressive Moving Average (ARMA) model with one order of Autoregression (AR (1)) and MA (1) will be used to model the series under study and the generated residuals will be subjected to the BDS test. The results from the residual test for iid will indicate the extent of how the ARMA

(1,1) was able to capture the linearity in our series. If the residuals are found to be generated from white noise (random process), then the linear model of ARMA (1,1) would be said to be effective by capturing all the statistical properties in the series. On the same note, if the residuals are found to be correlated, then the linear model would be considered as ineffective in capturing all the statistical properties in the series. The BDS test is a pure hypothetical test and the hypotheses to be tested are:

H_0 = the series or data are pure noise

H_1= the series or data are not pure noise

The rejection or acceptance of the null hypothesis depends on the significance of the p-values and z-statistics at 5% level of significance (other level of significance can be chosen).

Provided below are the results from the BDS test conducted on the residuals from the ARMA (1,1) model using correlation dimension (number of points used from the data series) of 6, fraction of pairs Epsilon method (Epsilon computed as an equal fraction of all pairs in the sample points) and 0.7 Epsilon value (default Epsilon value for shorter dimension or points used).

Table 7.4.1 BDS Test for Independence on the Residuals from ARMA (1,1) Model on the Indices Return Series

FTSE All Share Index				FTSE 100 Index		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.022617	16.96209	0.0000	0.020885	16.13554	0.0000
3	0.048154	22.77809	0.0000	0.044251	21.50419	0.0000
4	0.068630	27.32063	0.0000	0.063001	25.69659	0.0000
5	0.082031	31.39503	0.0000	0.075298	29.44916	0.0000
6	0.088896	35.34984	0.0000	0.081570	33.05985	0.0000
FTSE UK Oil & Gas Index				FTSE UK Oil and Gas Prod. Index		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.018643	14.97870	0.0000	0.019212	15.31744	0.0000
3	0.036131	18.25548	0.0000	0.037252	18.68247	0.0000
4	0.049774	21.10603	0.0000	0.051770	21.79501	0.0000
5	0.056809	23.09705	0.0000	0.059567	24.05042	0.0000
6	0.060092	25.31772	0.0000	0.063581	26.60894	0.0000
FTSE AIM SS Oil and Gas Index						
Dimension	BDS Stat.	z-Statistic	P-value			
2	0.019082	11.12609	0.0000			
3	0.036289	13.32320	0.0000			
4	0.048435	14.94086	0.0000			
5	0.054072	16.01031	0.0000			
6	0.056229	17.27035	0.0000			

Source: Author (2015)

The BDS test results for independence on the residuals from ARMA (1,1) on the FTSE indices return series are presented in Table 7.4.1. The Z-statistics are higher than 1.96 and the p-values are also significant even at 1% level of significance. The null hypothesis of pure noise or random process is strongly rejected in the residuals which indicates the existence of serial correlation. It shows that the linear model of ARMA (1,1) could not capture all the statistical properties of the FTSE indices. In other words, the series are characterised by a non-linear structure.

The results are consistent with that of the variance ratio test even though it was not applied on residuals but on raw data of stock returns. The inconsistency observed between the results of the autocorrelation function and the variance ratio test will be the same for the BDS test when compared with the autocorrelation function and Ljung-Box Q-statistics.

Table 7.4.2 BDS Test for Independence on the Residuals from ARMA (1,1) Model on Companies with More Than 10 Years Series under study

Amec Plc				BG Group Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.022415	16.34770	0.0000	0.056497	32.35923	0.0000
3	0.040519	18.58370	0.0000	0.114644	41.12921	0.0000
4	0.053092	20.43169	0.0000	0.161823	48.49816	0.0000
5	0.059961	22.11850	0.0000	0.195143	55.80020	0.0000
6	0.062695	23.95712	0.0000	0.217080	63.99376	0.0000
BP Plc				Cairn Energy Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.016347	13.51304	0.0000	0.019044	10.75676	0.0000
3	0.031457	16.41471	0.0000	0.038947	13.81112	0.0000
4	0.042742	18.78848	0.0000	0.052300	15.52862	0.0000
5	0.047882	20.25682	0.0000	0.059922	17.01342	0.0000
6	0.050429	22.19077	0.0000	0.062222	18.25423	0.0000
Dragon Oil Plc				Fortune Oil Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.035716	17.79487	0.0000	0.100855	43.18680	0.0000
3	0.067636	21.10980	0.0000	0.168664	45.07940	0.0000
4	0.091863	23.94623	0.0000	0.209543	46.58759	0.0000
5	0.104670	26.02224	0.0000	0.230811	48.73474	0.0000
6	0.108670	27.83854	0.0000	0.238812	51.72851	0.0000
Hunting Plc				Premier Oil Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.029694	17.39053	0.0000	0.020936	14.51546	0.0000
3	0.052454	19.26466	0.0000	0.039130	17.07733	0.0000
4	0.069765	21.43011	0.0000	0.050587	18.54077	0.0000
5	0.080666	23.67057	0.0000	0.056429	19.84120	0.0000
6	0.086827	26.29949	0.0000	0.057532	20.97214	0.0000
Royal Dutch Shell ‘B’ Plc				Tullow Oil Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.023249	18.44916	0.0000	0.018721	12.26648	0.0000
3	0.043823	21.93197	0.0000	0.036231	14.93607	0.0000
4	0.060259	25.38037	0.0000	0.048015	16.61321	0.0000
5	0.069122	27.99183	0.0000	0.053838	17.85920	0.0000
6	0.072932	30.69006	0.0000	0.056135	19.29201	0.0000
Aminex Plc				JKX Oil and Gas Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.027007	11.36878	0.0000	0.025109	13.24832	0.0000
3	0.054321	14.27562	0.0000	0.047762	15.78861	0.0000
4	0.072279	15.80653	0.0000	0.063068	17.42017	0.0000
5	0.081473	16.92801	0.0000	0.070988	18.71143	0.0000

6	0.085797	18.29670	0.0000		0.073209	19.89766	0.0000
Soco Intl. Plc					Wood Group (John) Plc		
Dimension	BDS Stat.	z-Statistic	P-value		BDS Stat.	z-Statistic	P-value
2	0.020845	10.98213	0.0000		0.017716	9.733801	0.0000
3	0.037777	12.49638	0.0000		0.030790	10.66513	0.0000
4	0.050314	13.93809	0.0000		0.038493	11.21661	0.0000
5	0.055455	14.69403	0.0000		0.042482	11.89672	0.0000
6	0.057054	15.62536	0.0000		0.042827	12.45644	0.0000

Source: Author (2015)

Table 7.4.2 presents the BDS test results for independence on the residuals from ARMA (1,1) on stocks that have more than 10 years series on the stock market. The Z-statistics are higher than 1.96 and the p-values are also significant even at 1% level of significance. The null hypothesis of pure noise or random process is strongly rejected in the residuals which indicates the existence of serial correlation. It shows that the linear model of ARMA (1,1) could not capture all the statistical properties of oil and gas stock returns in this classification. In other words, the series are characterised by a non-linear structure or any other structure apart from linear structure.

The results are consistent with that of the variance ratio test even though it was not applied on residuals but on raw data of stock returns. The consistency and inconsistency observed between the results of the autocorrelation function and the variance ratio test will be the same for the BDS test when compared with the autocorrelation function and Ljung-Box Q-statistics. The only difference was noticed in the high z-statistics which is a sign of strong evidence to reject the null hypothesis.

Table 7.4.3 BDS Test for Independence on the Residuals from ARMA (1,1) Model on Companies with Less Than 10 Years Series under study

Afren Plc				Hardy Oil and Gas Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.021235	9.512638	0.0000	0.024794	10.88053	0.0000
3	0.045905	12.94734	0.0000	0.043837	12.10859	0.0000
4	0.065434	15.50315	0.0000	0.056356	13.07282	0.0000
5	0.078196	17.77854	0.0000	0.062236	13.84972	0.0000
6	0.082692	19.49748	0.0000	0.062945	14.52238	0.0000
Royal Dutch Shell 'A' Plc				Petrofac Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.025654	12.52017	0.0000	0.016907	8.167628	0.0000
3	0.044198	13.59122	0.0000	0.035149	10.71001	0.0000
4	0.056688	14.65691	0.0000	0.047510	12.18511	0.0000
5	0.062114	15.42714	0.0000	0.053139	13.10566	0.0000
6	0.062379	16.08403	0.0000	0.055100	14.12308	0.0000
Lamprell Plc				Salamander Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.025843	10.47357	0.0000	0.019979	7.895542	0.0000
3	0.048095	12.27059	0.0000	0.036596	9.087610	0.0000
4	0.059814	12.81845	0.0000	0.046975	9.779561	0.0000
5	0.067294	13.83815	0.0000	0.051720	10.31205	0.0000
6	0.070269	14.98450	0.0000	0.051823	10.69421	0.0000
Endeavor Intl. Plc				Kentz Corp. Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.014232	5.493628	0.0000	0.018849	5.915856	0.0000
3	0.024368	5.926074	0.0000	0.032650	6.430615	0.0000
4	0.032744	6.694771	0.0000	0.040140	6.618038	0.0000
5	0.036552	7.177794	0.0000	0.043082	6.791910	0.0000
6	0.036901	7.521813	0.0000	0.041676	6.788984	0.0000
Heritage Oil Plc				Cadogan Petroleum Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.019741	7.198322	0.0000	0.028700	9.117576	0.0000
3	0.038885	8.937523	0.0000	0.050690	10.14424	0.0000
4	0.049299	9.530218	0.0000	0.066557	11.19341	0.0000
5	0.054250	10.07670	0.0000	0.074242	11.98575	0.0000
6	0.054452	10.50256	0.0000	0.076436	12.80103	0.0000
Exillon Energy Plc				Enquest Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.017576	4.877145	0.0000	0.012620	3.522502	0.0004
3	0.033313	5.814501	0.0000	0.028166	4.937345	0.0000
4	0.041728	6.112170	0.0000	0.035239	5.176474	0.0000
5	0.050667	7.114895	0.0000	0.039844	5.603149	0.0000
6	0.053566	7.793070	0.0000	0.039177	5.700005	0.0000
Essar Energy Plc				Genel Energy Plc		
Dimension	BDS Stat.	z-Statistic	P-value	BDS Stat.	z-Statistic	P-value
2	0.019350	5.191772	0.0000	0.027005	4.560735	0.0000
3	0.046064	7.783114	0.0000	0.050603	5.347546	0.0000
4	0.062540	8.878950	0.0000	0.067531	5.956360	0.0000

5	0.073471	10.01242	0.0000		0.077740	6.536735	0.0000
6	0.078031	11.03129	0.0000		0.082705	7.163937	0.0000
Ophir Energy Plc					Ruspetro Plc		
Dimension	BDS Stat.	z-Statistic	P-value		BDS Stat.	z-Statistic	P-value
2	0.009225	1.940675	0.0523		0.012958	2.458134	0.0140
3	0.020477	2.705865	0.0068		0.014817	1.769455	0.0768
4	0.029244	3.239021	0.0012		0.020388	2.045567	0.0408
5	0.031644	3.356192	0.0008		0.023001	2.215232	0.0267
6	0.031044	3.407403	0.0007		0.023572	2.355245	0.0185

Source: Author (2015)

Table 7.4.3 shows the results of the BDS test for independence on the residuals from ARMA (1,1) on stocks that have less than 10 years series on the stock market. The Z-statistics are higher than 1.96 and the p-values are also significant even at 1% level of significance. The null hypothesis of pure noise or random process is strongly rejected in the residuals which indicates the existence of serial correlation. It shows that the linear model of ARMA (1,1) could not capture all the statistical properties of oil and gas stock returns in this classification. In other words, the series are characterised by a non-linear structure or any other structure apart from linearity.

Similarly, the results are consistent with that of the variance ratio test even though it was not applied on residuals but on raw data of stock returns. The consistency and inconsistency observed between the results of the autocorrelation function and the variance ratio test will be the same for the BDS test when compared with the Autocorrelation Function and Ljung-Box Q-statistics. The only difference was noticed in the high z-statistics which is a sign of strong evidence to reject the null hypothesis. The subsequent sections of this chapter will address the application of trading rules to support or reject the findings from both the parametric and non-parametric statistical tools employed to assess the weak form market efficiency of the oil and gas sector.

7.4 Technical Trading Filter Rules and Abnormal Profit

The presence of serial correlation in daily returns is an indication of non-randomness in returns but it is not a sufficient condition to classify a market as inefficient. A market can only be classified as inefficient if we can develop trading rules based on autocorrelation in past data and can earn abnormal profit by trading on those rules. It is important to take account of transaction costs in this process. The next section will test if (based on persistence in data) trading and filter rules earn abnormal profits.

7.4.1 Trading and Filter Rules based on Autocorrelation Persistence

A trading and filter rule strategy is developed on the basis of autocorrelation or persistence in returns and used in testing whether profit can be obtained from investment in oil and gas stocks that are higher than a buy and hold strategy. If there is a high positive autocorrelation at the first lag, any positive or negative stock returns will be expected to continue at that level into the immediate subsequent lags. Therefore, the trading strategy is to buy in any stock that has positive return in the current day if the return was also positive in the previous day and to sell the same stock if the previous day's return was negative and invest the proceeds (cash) in a risk free asset such as government treasury bills. The trading rule will be tested using a hypothetical investment of £1 as the opening or initial investment where the closing value of the investment over the sample period is given by:

$$J_T(Active) = e^{\left(\sum_{t=1}^{T} \alpha_t r_t + (1-\alpha_t) rf_t\right)}$$

Where;

$J_T(Active)$ = Closing value of £1 hypothetical investment using the trading rule

e = Exponential (or investment)

r_t = Return at period 't'

rf_t = Risk–free rate of return

$$\alpha_t = \begin{cases} 1 \ if \ r_{t-1} > 0 \\ 0 \ if \ r_{t-1} < 0 \\ \alpha_{t-1} \ if \ r_{t-1} = 0 \end{cases}$$

This shows that whenever r_{t-1} is positive, there will be no investment in the risk free asset because of the buy signal (investment in stock) and if r_{t-1} is negative there will be an investment in the risk free asset because of the sell signal (cash from sale). The previous action will be maintained (no present action) if r_{t-1} is equals to zero. The strategy generates a high number of trading transactions in each stock over the sample period. In order to reduce the trading transactions, filters to return thresholds are introduced to the trading rule similar to the work of Alexander (1961), where signals are only generated if return limits are reached. The filters used are 0.05%, 0.1%, 0.15%, 0.2%, 0.3%, 0.4%, 0.5%, 0.6%, 0.7%, 0.8%, 0.9%, and 1%. In each of the filters, the number of trading transactions, trading profit and break even cost are calculated for assessment.

The trading profit from the employed trading strategy or rule is compared with that from an ordinary buy and hold strategy to assess the power of the trading rule and weak form market efficiency. The buy and hold investment strategy is represented by the 'J_T(Static)' which is given as:

$$J_T(Static) = e^{(\sum_{t=1}^{T} r_t)}$$

Where $J_T(Static)$ is the buy and hold investment strategy and other parameters are as defined in the preceding paragraph.

Break-even cost is also calculated by dividing the difference between the terminal values of 'J_T(Active)' and 'J_T(Static)' by the number of trading transactions. For any trading profit to be considered higher than that of the buy and hold strategy, the break-even cost must be higher than relevant transaction cost. In other words, transaction cost must not exceed the break-even cost which is given by:

$$BC = \frac{\ln\big(J_T\,(Active)\big) - \ln(J_T\,(Static))}{s}$$

Where 'BC' stands for the break-even cost, 'ln' for the natural logarithm and 's' for the number of trading transactions.

The strategy is employed on the FTSE indices and the oil and gas stock series for three years from January, 2010 to December, 2012. Stocks that have less than three years series are excluded for the analysis. The results are presented in Table 5.5 below.

Table 7.5 Trading and Filter Rules based on Autocorrelation Persistence for Indexes and Oil and Gas Stock Series under study

FTSE All Share Index														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.101657	1.184276	1.180164	1.127262	1.074867	1.120892	1.191831	1.21425	1.166021	1.214219	1.221673	1.163727	1.05762	1.105039
		0.000193	0.000196	0.000068	-0.00007	0.000055	0.000279	0.0004	0.000262	0.00052	0.000612	0.000349	-0.00028	0.000024
		375	351	339	331	317	282	245	217	187	169	157	145	129
FTSE 100 Share Index														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.072951	1.068313	1.048606	1.093862	1.127651	1.072048	1.065441	1.21089	1.08986	1.089869	1.124942	1.107237	1.12481	1.111323
		-0.000011	-0.00006	0.000057	0.000153	-0.00003	-0.00002	0.00049	0.000067	0.000077	0.000264	0.000193	0.00031	0.00026
		381	365	341	325	315	292	247	233	203	179	163	151	135
FTSE UK Oil and Gas Index														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.912638	0.986217	0.939701	0.954348	1.020027	1.035775	1.032615	1.02603	1.088166	1.082953	1.161126	1.124351	1.05428	1.033482
		0.000203	0.000078	0.000123	0.000322	0.000382	0.000413	0.00041	0.000677	0.000731	0.001125	0.001059	0.00077	0.000715
		382	376	364	345	331	299	289	260	234	214	197	188	174
FTSE UK Oil and Gas Producers' Index														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.900381	0.977141	0.9738	0.977154	1.038724	1.023837	1.029693	1.01736	1.049335	1.084246	1.107038	1.086483	1.04062	1.041134
		0.000213	0.000211	0.000226	0.000415	0.000386	0.000443	0.00042	0.00058	0.000781	0.000939	0.000944	0.00075	0.000844
		384	372	362	344	333	303	291	264	238	220	199	193	172
FTSE UK AIM SS Oil and Gas														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.922307	1.846881	1.726036	1.631233	1.689039	1.808008	1.688541	1.6603	1.685111	1.57055	1.493596	1.311148	1.5105	1.769944
		0.001913	0.001806	0.001712	0.001945	0.002329	0.002248	0.00234	0.002609	0.002547	0.002498	0.001922	0.00303	0.004434
		363	347	333	311	289	269	251	231	209	193	183	163	147
AMEC														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.261194	1.240133	1.240133	1.248715	1.31522	1.421684	1.368866	1.36669	1.348752	1.221447	1.177931	1.119795	1.10806	1.051429
		-0.000049	-0.00004	-0.00003	0.000131	0.000388	0.000289	0.0003	0.000265	-0.00013	-0.00030	-0.00054	-0.0006	-0.00092
		343	343	331	319	309	283	269	253	239	225	219	207	196
BG GROUP														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.865236	0.800762	0.800762	0.812751	0.838938	0.850311	0.830495	0.97486	0.904033	0.836244	0.829725	0.766363	0.76083	0.797097
		-0.00021	-0.00021	-0.00018	-0.00009	-0.00005	-0.00013	0.00041	0.000161	-0.00013	-0.00017	-0.00052	-0.00059	-0.00039
		368	368	352	342	336	316	292	272	260	244	230	220	206

BP														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.685484	0.769183	0.769183	0.769183	0.760691	0.776714	0.818329	0.76396	0.657273	0.665167	0.693202	0.680832	0.71066	0.777476
		0.000322	0.000322	0.000322	0.000291	0.000355	0.000537	0.00035	-0.00014	-0.00010	0.000041	-0.00002	0.00015	0.000543
		358	358	358	358	352	330	310	308	292	274	258	246	232
CAIRN ENERGY														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.670918	0.816135	0.816135	0.816135	0.809928	0.848107	0.861699	0.79766	0.861579	0.902449	1.016762	0.954666	0.99654	0.845858
		0.000537	0.000537	0.000537	0.000519	0.000672	0.000734	0.00053	0.00082	0.001029	0.001575	0.001389	0.00166	0.001007
		365	365	365	363	349	341	327	305	288	264	254	238	230
DRAGON OIL														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.35443	2.05902	2.05902	2.05902	1.903635	1.740408	1.664509	1.67833	1.354631	1.3791	1.292716	1.171024	1.15977	1.115719
		0.001258	0.001258	0.001258	0.001047	0.000806	0.000708	0.00079	0.000001	0.000072	-0.00019	-0.00063	-0.00075	-0.00097
		333	333	333	325	311	291	273	265	250	244	230	208	198
FORTUNE OIL														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.571429	0.005709	0.005709	0.005709	0.005709	0.005709	0.005709	0.00571	0.005709	0.005709	0.005709	0.005709	0.00571	0.005709
		-0.043547	-0.04354	-0.04355	-0.04354	-0.04354	-0.04354	-0.0435	-0.04355	-0.04354	-0.04354	-0.04354	-0.04355	-0.04354
		129	129	129	129	129	129	129	129	129	129	129	129	129
HUNTING														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.322091	1.367726	1.367726	1.423174	1.346573	1.51762	1.44526	1.49899	1.601851	1.553153	1.538657	1.73351	1.69484	1.431444
		0.000091	0.000091	0.000205	0.000052	0.000409	0.000277	0.00042	0.000703	0.000622	0.000604	0.001183	0.00112	0.000366
		373	373	359	353	337	321	299	273	259	251	229	221	217
PREMIER OIL														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.10596	0.704465	0.704465	0.704465	0.675484	0.687234	0.575113	0.64786	0.733283	0.801862	0.773056	0.894069	0.90969	0.824583
		-0.001216	-0.00121	-0.00122	-0.00135	-0.00136	-0.00196	-0.0017	-0.00143	-0.00120	-0.00143	-0.00093	-0.00093	-0.00146
		371	371	371	363	349	333	309	287	267	249	227	211	201
ROYAL DUTCH SHELL ‘B’														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.166224	1.121494	1.100789	1.029607	1.054637	1.008386	1.026929	1.11476	1.225276	1.148336	1.223397	1.216259	1.15562	1.169827
		-0.000107	-0.00016	-0.00035	-0.00029	-0.00045	-0.00043	-0.0002	0.000203	-0.00006	0.000241	0.000237	-0.00005	0.00002
		367	361	355	339	317	293	267	243	223	199	177	169	155
TULLOW OIL														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.956061	1.244316	1.244316	1.224007	1.234721	1.06997	0.985613	0.8255	0.779178	0.823893	0.939416	0.853129	0.790141	0.869254
		0.000714	0.000714	0.000677	0.000709	0.000315	0.000088	-0.0004	-0.00066	-0.00050	-0.00006	-0.00044	-0.00074	-0.00039

		369	369	365	361	357	345	333	309	295	271	257	255	239
AMINEX														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.307692	0.009217	0.009217	0.009217	0.009217	0.009217	0.009217	0.00922	0.009217	0.009217	0.009217	0.009217	0.009217	0.009217
		-0.035797	-0.03579	-0.0358	-0.03579	-0.03579	-0.03579	-0.0358	-0.0358	-0.03579	-0.03579	-0.03579	-0.03579	-0.03579
		98	98	98	98	98	98	98	98	98	98	98	98	98
JKX OIL AND GAS														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.259649	1.264357	1.264357	1.264357	1.264357	1.264357	1.35006	1.20731	1.1649	1.161838	1.146529	1.146529	1.097543	0.952135
		0.004931	0.004931	0.004931	0.004931	0.004931	0.005301	0.00517	0.005088	0.005295	0.005562	0.005562	0.005653	0.005218
		321	321	321	321	321	311	297	295	283	267	267	255	249
SOCO INTERNATIONAL														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.034582	0.85205	0.85205	0.85205	0.85205	0.847029	0.809828	0.98603	0.955931	1.009086	1.05089	0.924184	0.943831	0.892805
		-0.00055	-0.00055	-0.00055	-0.00055	-0.00057	-0.00074	-0.0002	-0.00026	-0.00008	0.000057	-0.00043	-0.00037	-0.00061
		353	353	353	353	349	329	313	303	283	273	261	247	241
WOOD GROUP														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	2.283951	1.643601	1.643601	1.675917	1.663084	1.623511	1.499139	1.34007	1.442323	1.452534	1.691683	1.504198	1.631084	1.766541
		-0.000927	-0.00092	-0.00091	-0.00096	-0.00106	-0.00139	-0.0019	-0.00178	-0.00192	-0.00139	-0.00199	-0.00178	-0.00145
		355	355	339	329	321	301	279	258	235	215	209	189	177
AFREN														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.444444	1.476929	1.476929	1.476929	1.476929	1.476929	1.476929	1.50523	1.297878	1.363849	1.225585	1.338519	1.090865	1.195628
		0.000071	0.000071	0.000071	0.000071	0.000071	0.000071	0.00013	-0.00035	-0.00020	-0.00058	-0.00028	-0.00108	-0.00078
		315	315	315	315	315	315	311	305	285	281	267	259	241
HARDY OIL AND GAS														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.369919	0.300877	0.300877	0.300877	0.300877	0.300877	0.300877	0.30088	0.288579	0.382962	0.39663	0.380031	0.395551	0.406755
		-0.000571	-0.00057	-0.00057	-0.00057	-0.00057	-0.00057	-0.0006	-0.00069	0.000101	0.000208	0.000081	0.000204	0.000293
		362	362	362	362	362	362	362	358	342	336	332	328	324
ROYAL DUTCH SHELL 'A'														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.038466	1.135819	1.099581	1.100353	1.10709	1.112684	1.082095	1.06847	1.164264	1.147441	1.068724	1.046018	1.235139	1.146245
		0.000236	0.000157	0.000167	0.000192	0.000214	0.000141	0.00011	0.000482	0.000452	0.000141	0.000039	0.001077	0.000637
		380	346	346	334	322	291	263	237	221	203	187	161	155
PETROFAC														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.713536	1.180332	1.108462	1.181258	1.102714	1.062514	1.136543	1.03014	1.017837	0.988669	0.93559	1.06186	1.062297	1.059282

		-0.001021	-0.00120	-0.00106	-0.0013	-0.00144	-0.00132	-0.0017	-0.00179	-0.002	-0.00231	-0.00203	-0.00212	-0.00232
		365	361	351	339	331	311	303	291	275	261	235	225	207
SALAMANDER ENERGY														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.786008	1.418486	1.418486	1.418486	1.418486	1.418486	1.418486	1.43542	1.44633	1.518993	1.52096	1.337035	1.309804	1.253821
		0.001794	0.001794	0.001794	0.001794	0.001794	0.001794	0.00187	0.001948	0.002218	0.002436	0.002043	0.002059	0.001962
		329	329	329	329	329	329	323	313	297	271	260	248	238
LAMPRELL														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.500000	0.723453	0.723453	0.723453	0.734757	0.745108	0.839199	1.02669	1.109568	0.985865	0.962823	0.884707	0.830455	0.813209
		0.001059	0.001059	0.001059	0.001109	0.00117	0.001613	0.00242	0.002817	0.002433	0.002454	0.002186	0.002005	0.001938
		349	349	349	347	341	321	297	283	279	267	261	253	251
ENDEAVOR INTERNATIONAL CORPORATION														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.34668	0.644048	0.644048	0.644048	0.638905	0.639919	0.67792	0.45757	0.343079	0.206363	0.198932	0.208999	0.220203	0.295812
		0.001806	0.001806	0.001806	0.001825	0.001886	0.002184	0.00104	-0.00004	-0.00224	-0.00258	-0.00267	-0.00271	-0.00105
		343	343	343	335	325	307	267	247	231	215	189	167	151
CADOGAN PETROLEUM														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.823529	0.084787	0.084787	0.084787	0.084787	0.084787	0.084787	0.08479	0.084787	0.084787	0.084787	0.084787	0.084787	0.088248
		-0.009317	-0.00931	-0.00932	-0.00931	-0.00931	-0.00931	-0.0093	-0.00931	-0.00931	-0.00931	-0.00931	-0.00931	-0.00922
		244	244	244	244	244	244	244	244	244	244	244	244	242
HERITAGE OIL														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.536932	1.246944	1.246944	1.246944	1.246944	1.216578	1.207738	1.23429	1.215222	0.799662	0.762751	0.741289	0.72827	0.852508
		0.002709	0.002709	0.002709	0.002709	0.002647	0.002658	0.0028	0.002807	0.001398	0.001258	0.00119	0.00115	0.001827
		311	311	311	311	309	305	297	291	285	279	271	265	253
KENTZ														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	1.940299	3.693271	3.693271	3.693271	2.751829	2.849411	2.679485	2.28078	2.015881	2.063502	2.249837	2.209623	2.307702	2.237079
		0.002315	0.002315	0.002315	0.001304	0.001489	0.001356	0.00074	0.000193	0.000338	0.000892	0.000903	0.001376	0.001167
		278	278	278	268	258	238	218	198	182	166	144	126	122
EXILLON ENERGY														
Initial Invest.	***J_T(Static)***	***J_T(Active)***	**0.0005**	**0.001**	**0.0015**	**0.002**	**0.003**	**0.004**	**0.005**	**0.006**	**0.007**	**0.008**	**0.009**	**0.01**
1.000000	0.850000	3.036845	3.036845	3.036845	3.22187	3.127387	3.621514	3.80298	3.38374	3.318485	3.255568	3.048858	2.89889	2.672982
		0.004468	0.004468	0.004468	0.004917	0.004807	0.005553	0.00579	0.005504	0.005652	0.005714	0.005482	0.005551	0.005379
		285	285	285	271	271	261	259	251	241	235	233	221	213

Notes: The first column is the initial or opening investment of £1 used as the hypothetical investment in the study. J_T (Static) represents the terminal value of investment using buy and hold strategy in column 2. J_T (Active) in column 3 represents the terminal value of investment using trading rule without any filter. Subsequent columns present the terminal investments using the trading rules at various filters. Therefore, row 1 after the headings presents values of opening and terminal investments using buy and hold strategy, trading rule without filter, and trading rule with filters. Row 2 is the breakeven cost which is a limit that transaction cost must not exceed for profit to be considered as abnormal. Row 3 presents the number of transactions which under normal circumstance reduces as filters increase. **SOURCE: AUTHOR (2015)**

Table 7.5 presents the results of trading and filter rules based on autocorrelation persistence for indices and oil and gas stock series for the period of three years. Breakeven costs are used to assess whether the generated profit from the technical trading rule is higher than that from the simple buy and hold strategy on the assumption that transaction cost or commission must be paid on every transaction (see notes attached to the Table). It is interesting to note from the results that the breakeven cost per transaction in most of the stock series is very small (in some cases negative) which will definitely be lower than any transaction commission. In that case, the trading profit cannot be higher than that from the simple buy and hold strategy after considering the transaction cost. All the FTSE indices trading rule results have not shown any sign that there could be abnormal profit due to meagre breakeven cost except in the FTSE UK AIM SS Oil and Gas index which shows a possibility of making abnormal profit due to high breakeven cost. Other stocks that show similar results with that of the FTSE AIM SS Oil and Gas index are Dragon Oil, JKX Oil and Gas, Salamander Energy, Endeavor International Corporation, Heritage Oil, Kentz and Exillon Energy. The possible factor that might have affected the results of these few stocks is the level of liquidity in the market with regard to these particular stocks which can be seen from the unchanging number of transactions even after the filters are considered. If such illiquidity is confirmed, the theoretical abnormal profit cannot be made in reality because of inadequate or lack of buyers and sellers.

The employment of technical trading rules in this study was justified by the need to provide further information in addition to the conflicting results from the autocorrelation function and Q-Statistics, the runs test, the variance ratio test and the BDS test for appropriate inferences on the acceptance or rejection of random walk and weak form market efficiency hypotheses. Thereof, the technical trading and filter rules have not shown any signs of abnormal profit in most of the stocks series which is evidence of random walk and weak form market efficiency. Moving averages are also considered in the subsequent section as another trading strategy to assess the possibility of making abnormal profit from the series.

7.4.2 Moving Averages

The moving average trading rule is one of the simplest technical trading rules used by chartists to generate 'buy' and 'sell' signals based on the history of stock prices. According to Achelis (1995), a simple moving average is calculated as an average of stock prices over a given period 't' and changes over time due to inclusion of new daily stock prices. He also described the moving average as an agreement or consensus of investors' expectation over the averaging time. If the future stock price is above the moving average, investors are assumed to be optimistic about the company and that becomes a 'buy signal' while, if stock price is below the moving average, investors are assumed to be pessimistic about the company and that indicates a 'sell signal'. Moving averages could be simple (arithmetic) as explained above, exponential, triangular, variable and weighted. The difference between the various types of moving average depends on the weight given to the new variable (stock price) added to the moving average. In this study, only the simple moving average will be considered which happens to be the most prominent in the literature.

Brock et al (1992) employed the simple moving average and trading range break-out to investigate the predictive power of trading rules on the 90-year series of the Dow Jones Industrial Average (DJIA) index. Using the simple moving average, two moving averages of long and short periods were used to generate 'buy' and 'sell' signals. The strategy signals a 'buy' transaction if the short period moving average rises or crosses above the long period moving average and a 'sell' transaction if the short period moving average falls or crosses below the long period moving average. The simple moving average adopted by Brock et al (1992) encompasses the Variable Moving Average (VMA) and the Fixed Moving Average (FMA). In the Variable Moving Average (VMA) a day is classified as buy (sell) if the short moving average lies above (below) the long moving average. The Fixed Moving Average designates a buy (sell) signal immediately the short moving average crosses the long moving average from below (above). The use of both short and long period moving averages at the same time was justified by the scholars as an attempt to stabilise any high volatility in the series. Although, various combinations of short and long period moving averages such as 1-200, 2-200, 5-150 and 1-150 were used in the literature, Brock et al (1992) had emphasised the short and long periods to be '$S \leq 5'$ and $'L \geq 50'$ respectively as the most popular range employed by scholars, as cited by Taylor (2005).

This study employs the same moving average (Fixed Moving Average) methodology employed by Brock et al (1992) to test whether abnormal profit can be obtained from our series that show evidence of serial correlation. The parameters of short and long moving averages and the yardstick for investment decisions (buy and sell) are defined according to the representation of Mills (1998) as follows:

$$S_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} x_{t-i}$$

$$L_t(m) = \frac{1}{m}\sum_{i=0}^{m-1} x_{t-i}$$

$$S_t(n) > L_t(m) = Buy$$

$$S_t(n) < L_t(m) = Sell$$

Where;

$S_t(n)$ = Short period (n) moving average

$L_t(m) =$ Long period (m) moving average, in which $(m > n)$.

x_t = Variable at period 't' which represents stock price in our case.

Brock et al (1992) tested the significance of the difference between the trading rule and the buy and hold strategy returns using t-statistics defined as:

The t-statistics for the buy and sell mean returns = $\frac{\mu_r - \mu}{\left(\frac{\sigma^2}{N}+\frac{\sigma^2}{N_r}\right)^{1/2}}$

Where;

μ_r = Mean return for the buy or sell transactions

μ = Mean return for the buy and hold strategy (mean of the full sample)

$\sigma^2 =$ Variance of the full sample

N = Number of full sample

N_r = Number of signals (days) for the buy or sell transaction

The t-statistics for the (buy-sell) mean returns = $\dfrac{\mu_b - \mu_s}{\left(\frac{\sigma^2}{N_b} + \frac{\sigma^2}{N_s}\right)^{1/2}}$

Where;

μ_b = Mean return for the buy transactions

μ_s = Mean return for the sell transactions

σ^2 = Variance of the full sample

N_b = Number of signals (days) for the buy transactions

N_s = Number of signals (days) for the sell transactions

The critical values of the t-statistics calculated are used to assess the significance of the difference between the returns generated from the trading rules and the buy and hold investment strategy. If the t-statistics value is greater than its critical value, the difference between the trading rule and the buy and hold returns is assumed to be significant. In simple terms, the null hypothesis that the returns from trading rules (moving averages) are equal to those from the buy and hold strategy will be rejected if the t-statistics value is greater than its critical value. In that case, the trading rules investment strategy can result in abnormal gain which is an indication that the market is not weak form efficient. The number of buy and sell signals (days) are also used to determine whether the market is bullish or bearish. If the buy signals (days) are greater than the sell signals (days) the market is considered as bullish and bearish if vice versa. The test of significance of the difference between buy and sell mean returns assesses whether the opposing signals (days) are meaningful or not. Similarly, t-statistics (and critical values) are used to accept or reject the null hypothesis of equality. Rejection of the null hypothesis will mean that the values (buy and sell mean returns) are significantly different which demonstrates that the signals are meaningful.

We specifically employed ten combinations of short moving average, long moving average, and zero bandwidth or threshold ranging from (5,10,0) to (5,100,0) as Fixed Moving Averages (FMA) on the FTSE indices and oil and gas stock series for three years from January, 2010 to December, 2012.

Table 7.6.1 Descriptive Statistics of the Daily Returns Data Sample (2010-2012) for Moving Average Trading Rules

	N	Mean (B&H)	Std. Dev.	Skewness	Kurtosis
FTSE All Share	781	0.000146	0.010790	-0.179733	5.023554
FTSE 100	781	0.000110	0.011036	-0.143514	4.958961
FTSE UK O&G	781	-0.0000783	0.013088	-0.089951	3.949530
FTSE UK O&GP	781	-0.0000945	0.013083	-0.093243	3.963604
FTSE UK AIM	781	-0.0000370	0.016779	-0.727100	8.374857
Amec	781	0.000302	0.017815	-0.130370	4.671171
BG Group	781	-0.000131	0.018785	-0.594432	8.215809
BP	781	-0.000442	0.017977	-0.619007	10.44615
Cairn Energy	781	-0.000451	0.021103	-0.044317	4.490315
Dragon Oil	781	0.000458	0.020457	-0.206243	5.180657
Fortune Oil	781	0.000286	0.052192	0.338050	6.824401
Hunting	781	0.000391	0.022246	0.195726	5.134077
Premier Oil	781	0.000252	0.019799	-0.015543	5.509770
RDSB	781	0.000235	0.013094	-0.111025	4.136313
Tullow Oil	781	-0.0000439	0.021787	0.207256	6.167609
Aminex	781	-0.001038	0.066229	-0.886754	15.55957
JKX Oil & Gas	781	-0.001662	0.025801	-0.003198	6.799479
Soco Intl.	781	0.000085	0.022517	-1.205120	14.17334
Wood Group	781	0.001077	0.022342	-0.038334	5.886926
Afren	781	0.000554	0.031928	0.202485	6.367402
Hardy O&G	781	-0.001318	0.030893	0.120811	7.003875
RDSA	781	0.000150	0.012256	-0.17363	4.154584
Petrofac	781	0.000667	0.021385	-0.039987	4.178070
Salamander	781	-0.000304	0.023144	-0.370142	7.676936
Lamprell	781	-0.000743	0.050582	-7.358224	112.7479
Endeavor	781	-0.001329	0.053271	-5.852068	111.7277
Cadogan Petr.	781	-0.000249	0.042504	0.271748	5.398318
Heritage Oil	781	-0.000741	0.032106	-0.968899	24.58121
Kentz	781	0.000855	0.020107	0.442685	7.971614
Exillon Energy	781	-0.0000732	0.033206	0.162738	8.926945

Source: Author (2015)

Table 7.6.1 presents the summary statistics of the full sample of data (log differences of stock prices) earmarked for moving average trading rules. The 'N' column represents the total number of observations from the sample period which is also regarded as the total number of trading days given as 781 for all the series. The mean column represents the unconditional mean return from the buy and hold investment strategy over the full sample period. Sixteen out of thirty stocks or series recorded negative mean returns with the minimum at -0.166% from the JKX Oil and Gas stock. Wood Group (John) recorded the highest daily mean return at 0.1077%. Most of the series are found to be negatively skewed and similar to the findings of Mills (1997), Hudson et al (1996), and Brock et al (1992) even though the sample periods are different in all cases. The kurtosis has shown the sign of leptokurtic distribution especially in stocks such as BP Plc, Aminex Plc, Soco International Plc, Lamprell Plc, Endeavor International Plc and Heritage Oil Plc. The indices have kurtosis close to that of normal distribution '3', although that could be attributed to the size of the data.

Table 7.6.2 Test Results for the Moving Averages Trading Rules on Daily Returns Series from 2010-2012

FTSE All Share Index							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	426	345	0.000618	0.000463	0.000155	0.423	0.114
			(0.7263)	(0.4545)	(0.1983)		
(5,20,0)	428	321	0.000308	-0.00001	0.000318	0.129	0.114
			(0.2496)	(-0.2181)	(0.3992)		
(5,30,0)	447	299	0.000229	-0.00006	0.000289	0.084	0.114
			(0.1297)	(-0.2807)	(0.3585)		
(5,40,0)	414	285	0.000296	0.000775	-0.00047	0.172	0.114
			(0.2287)	(0.8424)	(-0.5768)		
(5,50,0)	421	275	0.000206	0.000035	0.000171	0.097	0.114
			(0.0920)	(-0.1467)	(0.2044)		
(5,60,0)	428	267	0.000309	0.000206	0.000103	0.187	0.114
			(0.2512)	(0.0784)	(0.1224)		
(5,70,0)	435	259	0.000209	-0.00009	0.000299	0.067	0.114
			(0.0976)	(-0.3050)	(0.3531)		
(5,80,0)	427	267	0.000048	-0.00036	0.000408	-0.074	0.114
			(-0.1509)	(-0.6615)	(0.4847)		
(5,90,0)	430	205	0.000091	-0.00035	0.000441	-0.033	0.114
			(-0.0849)	(-0.5858)	(0.4816)		
(5,100,0)	425	205	0.000141	-0.00022	0.000361	0.143	0.114
			(-0.0077)	(-0.4322)	(0.3934)		
Average			0.000245	0.000038	0.000207		
FTSE 100 Share Index							
			Buy Mean	Sell Mean	Buy-Sell	Trad. Rule	Buy and Hold

Moving Averages	N(Buy)	N(Sell)	Return	Return	Difference	Return	Return
(5,10,0)	418	353	0.000601	0.000491	0.00011	0.425	0.086
			(0.7341)	(0.5383)	(0.1379)		
(5,20,0)	427	321	0.000180	-0.00011	0.00029	0.038	0.086
			(0.1054)	(-0.3007)	(0.3557)		
(5,30,0)	445	301	0.000210	-0.00007	0.00028	0.091	0.086
			(0.1526)	(-0.2404)	(0.3400)		
(5,40,0)	400	299	0.000211	0.000111	0.0001	0.117	0.086
			(0.1488)	(0.0013)	(0.1185)		
(5,50,0)	420	277	0.000212	0.000145	0.000067	0.129	0.086
			(0.1527)	(0.0454)	(0.0784)		
(5,60,0)	423	272	0.000195	0.000008	0.000187	0.105	0.086
			(0.1276)	(-0.1313)	(0.2180)		
(5,70,0)	429	265	0.000210	0.000014	0.000196	0.093	0.086
			(0.1508)	(-0.1224)	(0.2273)		
(5,80,0)	423	271	0.000079	-0.00019	0.000269	-0.019	0.086
			(-0.0465)	(-0.3856)	(0.3133)		
(5,90,0)	418	213	0.000071	-0.00040	0.000471	-0.055	0.086
			(-0.0583)	(-0.5978)	(0.5070)		
(5,100,0)	414	214	0.000096	-0.00023	0.000326	-0.010	0.086
			(-0.0209)	(-0.3993)	(0.3509)		
Average			0.000206	-0.00002	0.000229		
FTSE UK Oil and Gas Index							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	400	371	0.000891	0.001191	-0.0003	0.798	-0.0611
			(1.2045)	(1.5380)	(-0.3180)		
(5,20,0)	409	338	0.000630	0.000850	-0.00022	0.550	-0.0611
			(0.8866)	(1.0893)	(-0.2286)		
(5,30,0)	414	326	0.000439	0.000709	-0.00027	0.413	-0.0611
			(0.6501)	(0.9122)	(-0.2786)		
(5,40,0)	422	317	0.000024	0.000229	-0.000205	0.083	-0.0611
			(0.1293)	(0.3525)	(-0.2107)		
(5,50,0)	379	317	0.000118	0.000395	-0.000277	0.169	-0.0611
			(0.2395)	(0.5430)	(-0.2780)		
(5,60,0)	378	317	0.000270	0.000576	-0.000306	0.284	-0.0611
			(0.4247)	(0.7506)	(-0.3069)		
(5,70,0)	375	319	0.000397	0.000606	-0.000209	0.341	-0.0611
			(0.5780)	(0.7868)	(-0.2096)		
(5,80,0)	365	327	0.000542	0.000745	-0.000203	0.442	-0.0611
			(0.7474)	(0.9550)	(-0.2036)		
(5,90,0)	377	228	0.000500	0.000467	0.000033	0.295	-0.0611
			(0.7045)	(0.5534)	(0.0300)		
(5,100,0)	369	233	0.000430	0.000379	0.000051	0.246	-0.0611
			(0.6148)	(0.4680)	(0.0465)		
Average			0.000424	0.000614	-0.000190		
FTSE UK Oil and Gas Producers' Index							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	402	369	0.000868	0.001213	-0.000345	0.796	-0.0738
			(1.1985)	(1.5820)	(-0.3657)		
(5,20,0)	412	335	0.000687	0.000965	-0.000278	0.606	-0.0738
			(0.9810)	(1.2399)	(-0.2888)		
(5,30,0)	410	330	0.000461	0.000759	-0.000298	0.439	-0.0738
			(0.6962)	(0.9936)	(-0.3079)		
(5,40,0)	420	318	0.000001	0.000256	-0.000255	0.081	-0.0738
			(0.1206)	(0.4027)	(-0.2622)		
(5,50,0)	375	321	0.000230	0.000553	-0.000323	0.263	-0.0738
			(0.3947)	(0.7464)	(-0.3246)		
(5,60,0)	375	320	0.000266	0.000597	-0.000331	0.290	-0.0738
			(0.4385)	(0.7963)	(-0.3324)		
(5,70,0)	373	321	0.000422	0.000663	-0.000241	0.370	-0.0738
			(0.6272)	(0.8733)	(-0.2419)		
(5,80,0)	365	329	0.000535	0.000761	-0.000226	0.445	-0.0738

			(0.7588)	(0.9948)	(-0.2272)		
(5,90,0)	372	232	0.000561	0.000532	0.000029	0.332	-0.0738
			(0.7953)	(0.6404)	(0.0264)		
(5,100,0)	368	233	0.000474	0.000453	0.000021	0.279	-0.0738
			(0.6872)	(0.5606)	(0.01917)		
Average			0.000450	0.000675	-0.000224		
FTSE UK AIM SS Oil and Gas Index							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	385	382	0.001621	0.001913	-0.000292	1.350	-0.0280
			(1.5868)	(1.8613)*	(-0.2409)		
(5,20,0)	369	377	0.001054	0.001185	-0.000131	0.835	-0.0280
			(1.0293)	(1.1613)	(-0.1066)		
(5,30,0)	352	383	0.001194	0.001239	-0.000045	0.894	-0.0280
			(1.1428)	(1.2190)	(-0.0363)		
(5,40,0)	357	375	0.000916	0.001021	-0.000105	0.709	-0.0280
			(0.8890)	(1.0036)	(-0.0846)		
(5,50,0)	348	380	0.001500	0.001567	-0.000067	1.110	-0.0280
			(1.4212)	(1.5284)	(-0.0538)		
(5,60,0)	312	381	0.001686	0.001472	0.000214	1.080	-0.0280
			(1.5332)	(1.4391)	(0.1670)		
(5,70,0)	303	390	0.001537	0.001283	0.000254	0.966	-0.0280
			(1.3860)	(1.2687)	(0.1976)		
(5,80,0)	304	389	0.001202	0.001029	0.000173	0.765	-0.0280
			(1.0923)	(1.0237)	(0.1346)		
(5,90,0)	304	385	0.000968	0.001032	-0.000064	0.691	-0.0280
			(0.8860)	(1.0231)	(-0.0497)		
(5,100,0)	294	386	0.001639	0.001447	0.000192	1.040	-0.0280
			(1.4598)	(1.4215)	(0.1478)		
Average			0.001331	0.001318	0.000012		
AMEC							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	442	319	0.000937	0.000420	0.000517	0.540	0.240
			(0.5988)	(0.0996)	(0.3950)		
(5,20,0)	435	323	0.000714	0.000175	0.000539	0.370	0.240
			(0.3865)	(-0.1077)	(0.4119)		
(5,30,0)	441	308	0.000735	0.000252	0.000483	0.400	0.240
			(0.4080)	(-0.0417)	(0.3651)		
(5,40,0)	422	305	0.000922	0.000414	0.000508	0.520	0.240
			(0.5760)	(0.0931)	(0.3794)		
(5,50,0)	431	298	0.001155	0.000783	0.000372	0.730	0.240
			(0.7979)	(0.3965)	(0.2771)		
(5,60,0)	439	280	0.000723	0.000281	0.000442	0.400	0.240
			(0.3961)	(-0.0169)	(0.3244)		
(5,70,0)	419	271	0.001182	0.001039	0.000143	0.780	0.240
			(0.8157)	(0.5867)	(0.1029)		
(5,80,0)	400	280	0.000971	0.000597	0.000374	0.560	0.240
			(0.6107)	(0.2377)	(0.2694)		
(5,90,0)	400	279	0.000881	0.000287	0.000594	0.430	0.240
			(0.5285)	(-0.0120)	(0.4274)		
(5,100,0)	408	271	0.000745	0.000117	0.000628	0.340	0.240
			(0.4070)	(-0.1472)	(0.4498)		
Average			0.001331	0.001318	0.000012		
BG GROUP							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	396	354	0.000381	0.000775	-0.000394	0.425	-0.102
			(0.4418)	(0.7527)	(-0.2867)		
(5,20,0)	410	338	0.000027	0.000432	-0.000405	0.157	-0.102
			(0.1379)	(0.4603)	(-0.2934)		
(5,30,0)	396	350	0.000073	0.000526	-0.000453	0.213	-0.102
			(0.1760)	(0.5437)	(-0.3286)		
(5,40,0)	390	347	0.000297	0.000752	-0.000455	0.376	-0.102
			(0.3674)	(0.7285)	(-0.3282)		
(5,50,0)	387	335	0.000201	0.000639	-0.000438	0.291	-0.102

			(0.2843)	(0.6276)	(-0.3124)		
(5,60,0)	392	330	0.000011	0.000426	-0.000415	0.145	-0.102
			(0.1221)	(0.4516)	(-0.2957)		
(5,70,0)	367	344	0.000333	0.000774	-0.000441	0.388	-0.102
			(0.3902)	(0.7445)	(-0.3128)		
(5,80,0)	356	306	0.000477	0.000869	-0.000392	0.435	-0.102
			(0.5061)	(0.7893)	(-0.2676)		
(5,90,0)	352	309	0.000476	0.000855	-0.000379	0.431	-0.102
			(0.5033)	(0.7810)	(-0.2588)		
(5,100,0)	335	279	0.000737	0.001095	-0.000358	0.552	-0.102
			(0.7074)	(0.9357)	(-0.2351)		
Average			0.000301	0.000714	-0.000413		
BP							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	326	443	0.000692	0.001394	-0.000702	0.843	-0.344
			(0.9566)	(1.7170)*	(-0.5351)		
(5,20,0)	388	359	0.000573	0.001471	-0.000898	0.750	-0.344
			(0.9090)	(1.6688)*	(-0.6821)		
(5,30,0)	399	341	0.000568	0.001657	-0.001089	0.791	-0.344
			(0.9130)	(1.7988)*	(-0.8214)		
(5,40,0)	388	350	0.000112	0.001128	-0.001016	0.438	-0.344
			(0.4961)	(1.3577)	(-0.7666)		
(5,50,0)	359	339	0.000503	0.001670	-0.001167	0.746	-0.344
			(0.8243)	(1.8063)*	(-0.8571)		
(5,60,0)	364	333	0.000547	0.001553	-0.001006	0.716	-0.344
			(0.8668)	(1.6956)*	(-0.7379)		
(5,70,0)	351	346	0.000548	0.001475	-0.000927	0.702	-0.344
			(0.8569)	(1.6512)*	(-0.6806)		
(5,80,0)	346	351	0.000449	0.001349	-0.0009	0.628	-0.344
			(0.7674)	(1.5503)	(-0.6608)		
(5,90,0)	344	258	0.000309	0.000319	-0.00001	0.188	-0.344
			(0.6455)	(0.5895)	(-0.0067)		
(5,100,0)	325	264	0.000112	-0.00004	0.000152	0.024	-0.344
			(0.4668)	(0.3141)	(0.1020)		
Average			0.000441	0.001197	-0.000756		
CAIRN ENERGY							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	367	402	-0.000155	0.000908	-0.001063	0.308	-0.352
			(0.2216)	(1.0491)	(-0.6977)		
(5,20,0)	362	388	-0.000229	0.000729	-0.000958	0.200	-0.352
			(0.1654)	(0.9002)	(-0.6212)		
(5,30,0)	325	423	0.000446	0.001280	-0.000834	0.686	-0.352
			(0.6439)	(1.3587)	(-0.5357)		
(5,40,0)	299	440	0.000003	0.000932	-0.000929	0.411	-0.352
			(0.3163)	(1.0994)	(-0.5873)		
(5,50,0)	249	445	-0.000686	0.000771	-0.001457	0.172	-0.352
			(-0.1530)	(0.9749)	(-0.8723)		
(5,60,0)	257	435	-0.000121	0.001094	-0.001215	0.444	-0.352
			(0.2174)	(1.2237)	(-0.7317)		
(5,70,0)	276	407	-0.000721	0.000723	-0.001444	0.095	-0.352
			(-0.1827)	(0.9099)	(-0.8775)		
(5,80,0)	299	381	-0.000387	0.000948	-0.001335	0.245	-0.352
			(0.0445)	(1.0608)	(-0.8188)		
(5,90,0)	227	371	-0.000796	0.001175	-0.001971	0.255	-0.352
			(-0.2168)	(1.2219)	(-1.1083)		
(5,100,0)	221	375	-0.001169	0.000923	-0.002092	0.087	-0.352
			(-0.4465)	(1.0363)	(-1.1689)		
Average			-0.000381	0.000948	-0.001329		
DRAGON OIL							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	431	335	0.001197	0.000833	0.000364	0.794	0.357
			(0.6020)	(0.2806)	(0.2442)		
(5,20,0)	409	348	0.000591	0.000020	0.000571	0.249	0.357

			(0.1065)	(-0.3322)	(0.3827)		
(5,30,0)	383	326	0.000869	0.000563	0.000306	0.516	0.357
			(0.3220)	(0.0778)	(0.1985)		
(5,40,0)	375	331	0.000550	0.000178	0.000372	0.264	0.357
			(0.07158)	(-0.2086)	(0.2411)		
(5,50,0)	353	340	0.000831	0.000448	0.000383	0.445	0.357
			(0.2842)	(-0.0075)	(0.2463)		
(5,60,0)	352	293	0.000658	0.000037	0.000621	0.242	0.357
			(0.1522)	(-0.3003)	(0.3838)		
(5,70,0)	352	340	0.000362	-0.00028	0.000642	0.019	0.357
			(-0.0730)	(-0.5552)	(0.4127)		
(5,80,0)	348	343	0.000080	-0.00057	0.00065	-0.169	0.357
			(-0.2866)	(-0.7757)	(0.4176)		
(5,90,0)	343	347	0.000199	-0.00042	0.000619	-0.077	0.357
			(-0.1954)	(-0.6652)	(0.3974)		
(5,100,0)	341	285	0.000482	-0.00017	0.000652	0.114	0.357
			(0.0180)	(-0.4435)	(0.3971)		
Average			0.000581	0.000063	0.000518		
FORTUNE OIL							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	521	244	0.000113	-0.00122	0.001333	-0.238	0.2231
			(-0.0585)	(-0.3934)	(0.3292)		
(5,20,0)	327	382	0.002459	0.001520	0.000939	1.380	0.2231
			(0.6320)	(0.3786)	(0.2388)		
(5,30,0)	279	432	0.001536	0.000166	0.00137	0.500	0.2231
			(0.3433)	(-0.0383)	(0.3417)		
(5,40,0)	238	473	0.002189	0.000347	0.001842	0.685	0.2231
			(0.4924)	(0.0200)	(0.4440)		
(5,50,0)	319	402	0.001280	0.000128	0.001152	0.459	0.2231
			(0.2866)	(-0.0493)	(0.2943)		
(5,60,0)	357	364	0.001058	0.000058	0.00100	0.398	0.2231
			(0.2315)	(-0.0688)	(0.2572)		
(5,70,0)	321	390	0.000880	-0.00019	0.00107	0.208	0.2231
			(0.1716)	(-0.1470)	(0.2720)		
(5,80,0)	256	440	0.001014	-0.00022	0.001234	0.162	0.2231
			(0.1936)	(-0.1626)	(0.3007)		
(5,90,0)	304	343	0.001680	0.000449	0.001231	0.665	0.2231
			(0.3950)	(0.0482)	(0.2994)		
(5,100,0)	313	334	0.001632	0.000462	0.00117	0.665	0.2231
			(0.3855)	(0.0515)	(0.2849)		
Average			0.001384	0.00015	0.001234		
HUNTING							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	394	366	0.001196	0.000289	0.000907	0.577	0.306
			(0.5855)	(-0.0723)	(0.5616)		
(5,20,0)	394	359	0.001670	0.000972	0.000698	1.000	0.306
			(0.9304)	(0.4095)	(0.4300)		
(5,30,0)	419	332	0.001546	0.000930	0.000616	0.956	0.306
			(0.8573)	(0.3698)	(0.3768)		
(5,40,0)	404	306	0.001312	0.000919	0.000393	0.811	0.306
			(0.6755)	(0.3519)	(0.2331)		
(5,50,0)	417	291	0.001177	0.000735	0.000442	0.704	0.306
			(0.5825)	(0.2251)	(0.2601)		
(5,60,0)	418	288	0.001004	0.000473	0.000531	0.555	0.306
			(0.4546)	(0.0534)	(0.3116)		
(5,70,0)	410	290	0.000791	0.000163	0.000628	0.371	0.306
			(0.2948)	(-0.1490)	(0.3679)		
(5,80,0)	411	289	0.000954	0.000399	0.000555	0.507	0.306
			(0.4153)	(0.0052)	(0.3249)		
(5,90,0)	400	234	0.000607	-0.00063	0.001237	0.094	0.306
			(0.1579)	(-0.6158)	(0.6756)		
(5,100,0)	387	246	0.000875	-0.00018	0.001055	0.292	0.306
			(0.3499)	(-0.3510)	(0.5815)		
Average			0.001113	0.000407	0.000706		

PREMIER OIL							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	431	340	0.001982	0.002028	-0.000046	1.540	0.197
			(1.4561)	(1.3805)	(-0.0320)		
(5,20,0)	378	370	0.001825	0.001243	0.000582	1.150	0.197
			(1.2679)	(0.7930)	(0.4019)		
(5,30,0)	395	351	0.001105	0.000684	0.000421	0.680	0.197
			(0.6977)	(0.3395)	(0.2898)		
(5,40,0)	425	315	0.001178	0.001033	0.000145	0.830	0.197
			(0.7759)	(0.5909)	(0.0985)		
(5,50,0)	341	351	0.001558	0.001084	0.000474	0.910	0.197
			(1.0162)	(0.6539)	(0.3148)		
(5,60,0)	354	338	0.001492	0.001117	0.000375	0.905	0.197
			(0.9774)	(0.6710)	(0.2490)		
(5,70,0)	367	324	0.001252	0.000833	0.000419	0.729	0.197
			(0.7980)	(0.4440)	(0.2776)		
(5,80,0)	380	310	0.001198	0.001015	0.000183	0.769	0.197
			(0.7639)	(0.5740)	(0.1207)		
(5,90,0)	376	314	0.001069	0.000833	0.000236	0.663	0.197
			(0.6574)	(0.4391)	(0.1559)		
(5,100,0)	361	320	0.000980	0.000558	0.000422	0.532	0.197
			(0.5777)	(0.2328)	(0.2776)		
Average			0.001363	0.001042	0.000321		

ROYAL DUTCH SHELL 'B'							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	409	340	0.001012	0.000481	0.000531	0.577	0.183
			(0.9722)	(0.2891)	(0.5525)		
(5,20,0)	414	333	0.000849	0.000330	0.000519	0.461	0.183
			(0.7713)	(0.1108)	(0.5384)		
(5,30,0)	424	320	0.000460	-0.00014	0.0006	0.148	0.183
			(0.2848)	(-0.4314)	(0.6188)		
(5,40,0)	418	322	0.000460	-0.00005	0.00051	0.173	0.183
			(0.2835)	(-0.3286)	(0.5252)		
(5,50,0)	376	316	0.000277	-0.00026	0.000537	0.019	0.183
			(0.0511)	(-0.5670)	(0.5373)		
(5,60,0)	376	315	0.000515	-0.00005	0.000565	0.176	0.183
			(0.3406)	(-0.3260)	(0.5649)		
(5,70,0)	364	326	0.000519	0.000026	0.000493	0.197	0.183
			(0.3417)	(-0.2420)	(0.4937)		
(5,80,0)	358	331	0.000490	0.000017	0.000473	0.169	0.183
			(0.3051)	(-0.2538)	(0.4737)		
(5,90,0)	367	322	0.000334	-0.00018	0.000514	0.064	0.183
			(0.1194)	(-0.4785)	(0.5140)		
(5,100,0)	366	238	0.000458	-0.00021	0.000668	0.117	0.183
			(0.2688)	(-0.4590)	(0.6126)		
Average			0.000537	-3.6E-06	0.000541		

TULLOW OIL							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	395	375	0.000860	0.001125	-0.000265	0.761	-0.034
			(0.6719)	(0.8539)	(-0.1687)		
(5,20,0)	399	349	0.000533	0.000465	0.000068	0.374	-0.034
			(0.4303)	(0.3627)	(0.0425)		
(5,30,0)	409	330	0.000546	0.000603	-0.000057	0.422	-0.034
			(0.4436)	(0.4522)	(-0.0353)		
(5,40,0)	402	336	0.000340	0.000417	-0.000077	0.276	-0.034
			(0.2870)	(0.3242)	(-0.0478)		
(5,50,0)	357	345	0.000225	0.000137	0.000088	0.127	-0.034
			(0.1931)	(0.1284)	(0.0535)		
(5,60,0)	350	351	0.000542	0.000460	0.000082	0.350	-0.034
			(0.4180)	(0.3599)	(0.0498)		
(5,70,0)	360	341	0.000178	0.000105	0.000073	0.099	-0.034
			(0.1598)	(0.1052)	(0.0443)		
(5,80,0)	368	334	-0.000199	-0.00003	-0.000169	-0.179	-0.034
			(-0.1125)	(0.0097)	(-0.1026)		

(5,90,0)	377	259	-0.000034	-0.00031	0.000276	-0.093	-0.034
			(0.0072)	(-0.1703)	(0.1569)		
(5,100,0)	381	254	-0.000301	-0.00052	0.000219	-0.246	-0.034
			(-0.1888)	(-0.3025)	(0.1240)		
Average			0.000269	0.000245	0.000023		
AMINEX							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	484	284	-0.001490	0.001871	-0.003361	-0.189	-0.810
			(-0.0303)	(0.1631)	(-0.1747)		
(5,20,0)	098	664	-0.006702	0.000786	-0.007488	-0.135	-0.810
			(-0.2053)	(0.1342)	(-0.2688)		
(5,30,0)	125	623	-0.001335	0.001743	-0.003078	0.919	-0.810
			(-0.0119)	(0.2011)	(-0.1220)		
(5,40,0)	142	588	-0.003918	0.001058	-0.004976	0.066	-0.810
			(-0.1226)	(0.1491)	(-0.2067)		
(5,50,0)	202	528	-0.000505	0.002039	-0.002544	0.974	-0.810
			(0.0262)	(0.2122)	(-0.1194)		
(5,60,0)	196	521	-0.001282	0.001626	-0.002908	0.595	-0.810
			(-0.0118)	(0.1829)	(-0.1348)		
(5,70,0)	234	401	-0.003190	0.000161	-0.003351	-0.680	-0.810
			(-0.1122)	(0.0758)	(-0.1582)		
(5,80,0)	199	435	-0.002305	0.000810	-0.003115	-0.106	-0.810
			(-0.0619)	(0.1200)	(-0.1414)		
(5,90,0)	239	384	-0.004819	-0.00088	-0.003939	-1.490	-0.810
			(-0.1987)	(0.0098)	(-0.1857)		
(5,100,0)	193	429	-0.007189	-0.00134	-0.005849	-1.960	-0.810
			(-0.2973)	(-0.0195)	(-0.2622)		
Average			-0.003273	0.000787	-0.004060		
JKX OIL AND GAS							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	284	487	0.000600	0.003094	-0.002494	1.670	-1.290
			(1.2652)	(3.1925)*	(-1.2946)		
(5,20,0)	279	458	-0.001216	0.001908	-0.003124	0.530	-1.290
			(0.2478)	(2.3510)*	(-1.5943)		
(5,30,0)	264	470	-0.000353	0.002423	-0.002776	1.040	-1.290
			(0.7126)	(2.7120)*	(-1.3988)		
(5,40,0)	280	452	-0.000756	0.002323	-0.003079	0.830	-1.290
			(0.5041)	(2.6133)*	(-1.5691)		
(5,50,0)	249	482	0.000442	0.002936	-0.002494	1.520	-1.290
			(1.1205)	(3.0766)*	(-1.2385)		
(5,60,0)	196	504	-0.000418	0.002327	-0.002745	1.090	-1.290
			(0.6035)	(2.7059)*	(-1.2638)		
(5,70,0)	197	503	-0.000807	0.002178	-0.002985	0.936	-1.290
			(0.4156)	(2.6032)*	(-1.3764)		
(5,80,0)	194	506	-0.000468	0.002300	-0.002768	1.070	-1.290
			(0.5768)	(2.6908)*	(-1.2704)		
(5,90,0)	191	456	-0.000862	0.002470	-0.003332	0.960	-1.290
			(0.3841)	(2.7173)*	(-1.4983)		
(5,100,0)	190	457	-0.000649	0.002555	-0.003204	1.040	-1.290
			(0.4853)	(2.7751)*	(-1.4385)		
Average			-0.000448	0.002451	-0.002900		
SOCO INTERNATIONAL							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	417	348	0.000293	0.000438	-0.000145	0.274	0.0660
			(0.1523)	(0.2432)	(-0.0886)		
(5,20,0)	398	357	0.000197	0.000243	-0.000046	0.165	0.0660
			(0.0807)	(0.1098)	(-0.0280)		
(5,30,0)	357	350	-0.000024	0.000411	-0.000435	0.135	0.0660
			(-0.0757)	(0.2250)	(-0.2568)		
(5,40,0)	352	352	0.000074	0.000467	-0.000393	0.191	0.0660
			(-0.0076)	(0.2642)	(-0.2315)		
(5,50,0)	359	343	-0.000489	-0.00021	-0.000279	-0.250	0.0660
			(-0.3997)	(-0.2022)	(-0.1641)		

(5,60,0)	365	334	-0.000218	0.000049	-0.000267	-0.060	0.0660
			(-0.2122)	(-0.0244)	(-0.1565)		
(5,70,0)	361	331	-0.000221	0.000055	-0.000276	-0.061	0.0660
			(-0.2135)	(-0.0203)	(-0.1610)		
(5,80,0)	342	338	-0.000489	-0.00024	-0.000249	-0.240	0.0660
			(-0.3931)	(-0.2216)	(-0.1441)		
(5,90,0)	340	340	-0.000196	0.000056	-0.000252	-0.047	0.0660
			(-0.1920)	(-0.0198)	(-0.1459)		
(5,100,0)	334	345	-0.000544	-0.00038	-0.000164	-0.310	0.0660
			(-0.4272)	(-0.3194)	(-0.0948)		
Average			-0.000161	0.000088	-0.000250		
WOOD GROUP							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	418	350	0.001654	-0.00011	0.001764	0.650	0.840
			(0.4261)	(-0.8259)	(1.0897)		
(5,20,0)	455	304	0.001757	0.000322	0.001435	0.890	0.840
			(0.5160)	(-0.4998)	(0.8670)		
(5,30,0)	474	278	0.002097	0.000940	0.001157	1.250	0.840
			(0.7840)	(-0.0878)	(0.6855)		
(5,40,0)	460	236	0.001934	0.000994	0.00094	1.120	0.840
			(0.6526)	(-0.0500)	(0.5254)		
(5,50,0)	478	217	0.001887	0.001136	0.000751	1.140	0.840
			(0.6242)	(0.0344)	(0.4106)		
(5,60,0)	483	212	0.001785	0.000975	0.00081	1.060	0.840
			(0.5474)	(-0.0589)	(0.4400)		
(5,70,0)	476	218	0.001480	0.000040	0.00144	0.713	0.840
			(0.3102)	(-0.6059)	(0.7881)		
(5,80,0)	477	216	0.001513	0.000068	0.001445	0.736	0.840
			(0.3358)	(-0.5874)	(0.7886)		
(5,90,0)	482	205	0.001318	0.000034	0.001284	0.627	0.840
			(0.1862)	(-0.5948)	(0.6892)		
(5,100,0)	480	156	0.001328	-0.00013	0.001458	0.617	0.840
			(0.1937)	(-0.6160)	(0.7080)		
Average			0.001675	0.000426	0.001248		
AFREN							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	415	349	0.001361	0.000957	0.000404	0.890	0.432
			(0.4160)	(0.1960)	(0.1742)		
(5,20,0)	427	335	0.002203	0.001849	0.000354	1.560	0.432
			(0.8581)	(0.6210)	(0.1519)		
(5,30,0)	414	322	0.001179	0.000452	0.000727	0.630	0.432
			(0.3219)	(-0.0482)	(0.3064)		
(5,40,0)	363	372	0.000991	0.000103	0.000888	0.397	0.432
			(0.2154)	(-0.2242)	(0.3769)		
(5,50,0)	429	269	0.001620	0.001270	0.00035	1.030	0.432
			(0.5555)	(0.3172)	(0.1409)		
(5,60,0)	404	292	0.002089	0.001680	0.000409	1.330	0.432
			(0.7845)	(0.5141)	(0.1667)		
(5,70,0)	404	292	0.002199	0.001832	0.000367	1.420	0.432
			(0.8407)	(0.5835)	(0.1496)		
(5,80,0)	403	294	0.001717	0.001151	0.000566	1.030	0.432
			(0.5938)	(0.2732)	(0.2311)		
(5,90,0)	408	279	0.001894	0.001730	0.000164	1.250	0.432
			(0.6870)	(0.5280)	(0.0661)		
(5,100,0)	412	262	0.001614	0.001311	0.000303	1.000	0.432
			(0.5452)	(0.3320)	(0.1200)		
Average			0.001686	0.001233	0.000453		
HARDY OIL AND GAS							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	356	414	0.002122	0.004369	-0.002247	0.025	-1.020
			(1.7412)*	(3.0280)*	(-1.0062)		
(5,20,0)	334	408	0.000785	0.002921	-0.002136	1.450	-1.020

			(1.0412)	(2.2463)*	(-0.9370)		
(5,30,0)	324	417	0.000617	0.002811	-0.002194	1.370	-1.020
			(0.9478)	(2.2036)*	(-0.9589)		
(5,40,0)	265	475	-0.000076	0.002048	-0.002124	0.950	-1.020
			(0.5655)	(1.8725)*	(-0.8967)		
(5,50,0)	243	383	-0.000189	0.001431	-0.00162	0.500	-1.020
			(0.4975)	(1.4264)	(-0.6393)		
(5,60,0)	242	383	0.000028	0.001632	-0.001604	0.630	-1.020
			(0.5922)	(1.5307)	(-0.6322)		
(5,70,0)	284	339	-0.001521	0.001365	-0.002886	0.030	-1.020
			(-0.0948)	(1.3352)	(-1.1613)		
(5,80,0)	312	310	-0.000628	0.001568	-0.002196	0.290	-1.020
			(0.3334)	(1.3916)	(-0.8864)		
(5,90,0)	250	372	-0.001087	0.001103	-0.00219	0.130	-1.020
			(0.1029)	(1.2439)	(-0.8668)		
(5,100,0)	258	363	-0.002263	0.000591	-0.002854	-0.360	-1.020
			(-0.4259)	(0.9727)	(-1.1345)		
Average			-0.000221	0.001983	-0.002205		
ROYAL DUTCH SHELL 'A'							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	424	325	0.000968	0.000716	0.000252	0.642	0.116
			(1.1064)	(0.6996)	(0.2788)		
(5,20,0)	411	336	0.000776	0.000448	0.000328	0.469	0.116
			(0.8381)	(0.3726)	(0.3638)		
(5,30,0)	427	317	0.000587	0.000256	0.000331	0.331	0.116
			(0.5924)	(0.1298)	(0.3642)		
(5,40,0)	416	324	0.000203	-0.00015	0.000353	0.035	0.116
			(0.0712)	(-0.3704)	(0.3887)		
(5,50,0)	378	314	0.000313	0.000003	0.00031	0.117	0.116
			(0.2122)	(-0.1794)	(0.3312)		
(5,60,0)	384	307	0.000396	0.000039	0.000357	0.164	0.116
			(0.3220)	(-0.1344)	(0.3804)		
(5,70,0)	379	312	0.000419	0.000061	0.000358	0.177	0.116
			(0.3506)	(-0.1084)	(0.3821)		
(5,80,0)	369	321	0.000400	0.000118	0.000282	0.185	0.116
			(0.3229)	(-0.0393)	(0.3014)		
(5,90,0)	374	316	0.000402	0.000128	0.000274	0.190	0.116
			(0.3269)	(-0.0269)	(0.2925)		
(5,100,0)	378	225	0.000477	0.000149	0.000328	0.213	0.116
			(0.4258)	(-0.0010)	(0.3178)		
Average			0.000494	0.000176	0.000317		
PETROFAC							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	440	330	0.001763	0.000659	0.001104	0.990	0.520
			(0.8597)	(-0.0056)	(0.7089)		
(5,20,0)	439	319	0.001665	0.000482	0.001183	0.884	0.520
			(0.7823)	(-0.1301)	(0.7519)		
(5,30,0)	464	287	0.001327	0.000141	0.001186	0.656	0.520
			(0.5265)	(-0.3563)	(0.7385)		
(5,40,0)	444	253	0.000736	0.000046	0.00069	0.315	0.520
			(0.0542)	(-0.4014)	(0.4096)		
(5,50,0)	463	231	0.000790	0.000099	0.000691	0.343	0.520
			(0.0980)	(-0.3546)	(0.4011)		
(5,60,0)	472	220	0.000623	-0.00053	0.001153	0.176	0.520
			(-0.0352)	(-0.7333)	(0.6604)		
(5,70,0)	481	210	0.000399	-0.00128	0.001679	-0.077	0.520
			(-0.2162)	(-1.1712)	(0.9492)		
(5,80,0)	466	216	0.000839	-0.00031	0.001149	0.323	0.520
			(0.1374)	(-0.5942)	(0.6527)		
(5,90,0)	461	220	0.000773	-0.00039	0.001163	0.270	0.520
			(0.0843)	(-0.6475)	(0.6636)		
(5,100,0)	457	223	0.000796	-0.00037	0.001166	0.279	0.520
			(0.1024)	(-0.6386)	(0.6674)		
Average			0.000971	-0.00014	0.001116		

SALAMANDER ENERGY							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	402	347	0.002847	0.003517	-0.00067	2.360	-0.237
			(2.2179)*	(2.5590)*	(-0.3950)		
(5,20,0)	362	384	0.000624	0.000934	-0.00031	0.580	-0.237
			(0.6306)	(0.8582)	(-0.1828)		
(5,30,0)	360	377	0.000407	0.000753	-0.000346	0.430	-0.237
			(0.4822)	(0.7282)	(-0.2028)		
(5,40,0)	300	435	-0.001509	-0.00073	-0.000779	-0.770	-0.237
			(-0.7665)	(-0.3076)	(-0.4484)		
(5,50,0)	272	453	-0.001213	-0.00051	-0.000703	-0.560	-0.237
			(-0.5578)	(-0.1507)	(-0.3959)		
(5,60,0)	334	380	-0.000489	-0.00007	-0.000419	-0.180	-0.237
			(-0.1222)	(0.1616)	(-0.2413)		
(5,70,0)	312	399	-0.000368	0.000056	-0.000424	-0.090	-0.237
			(-0.0412)	(0.2527)	(-0.2424)		
(5,80,0)	310	322	-0.000181	0.000077	-0.000258	-0.030	-0.237
			(0.0791)	(0.2485)	(-0.1400)		
(5,90,0)	314	317	0.000390	0.000468	-0.000078	0.270	-0.237
			(0.4487)	(0.5008)	(-0.0423)		
(5,100,0)	320	311	0.000207	0.000296	-0.000089	0.158	-0.237
			(0.3326)	(0.3866)	(-0.0482)		
Average			0.000071	0.000479	-0.000407		
LAMPRELL							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	408	363	0.001687	0.003716	-0.002029	2.037	-0.580
			(0.7864)	(1.3877)	(-0.5559)		
(5,20,0)	436	319	0.002056	0.004667	-0.002611	2.385	-0.580
			(0.9256)	(1.6096)	(-0.7006)		
(5,30,0)	384	314	0.001918	0.005125	-0.003207	2.345	-0.580
			(0.8440)	(1.7361)*	(-0.8333)		
(5,40,0)	389	308	0.000592	0.003523	-0.002931	1.315	-0.580
			(0.4252)	(1.2534)	(-0.7597)		
(5,50,0)	365	332	-0.000091	0.002475	-0.002566	0.788	-0.580
			(0.2032)	(0.9710)	(-0.6688)		
(5,60,0)	337	359	0.000572	0.002842	-0.00227	1.213	-0.580
			(0.3988)	(1.1115)	(-0.5916)		
(5,70,0)	334	361	0.000396	0.002658	-0.002262	1.091	-0.580
			(0.3444)	(1.0564)	(-0.5890)		
(5,80,0)	336	358	0.000191	0.002343	-0.002152	0.903	-0.580
			(0.2830)	(0.9558)	(-0.5601)		
(5,90,0)	328	359	-0.000407	0.001971	-0.002378	0.574	-0.580
			(0.1009)	(0.8414)	(-0.6154)		
(5,100,0)	324	321	-0.000332	0.002256	-0.002588	0.616	-0.580
			(0.1229)	(0.8942)	(-0.6497)		
Average			0.000658	0.003157	-0.002499		
ENDEAVOR INTERNATIONAL CORPORATION							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	443	323	0.003711	0.008307	-0.004596	4.327	-1.038
			(1.5906)	(2.7343)*	(-1.1791)		
(5,20,0)	376	383	0.003786	0.006458	-0.002672	3.896	-1.038
			(1.5297)	(2.3432)*	(-0.6909)		
(5,30,0)	352	378	0.003383	0.004011	-0.000628	2.707	-1.038
			(1.3778)	(1.5998)	(-0.1591)		
(5,40,0)	317	404	0.003904	0.003891	0.000013	2.809	-1.038
			(1.4750)	(1.5989)	(0.0032)		
(5,50,0)	304	415	0.002840	0.003770	-0.00093	2.428	-1.038
			(1.1576)	(1.5757)	(-0.2312)		
(5,60,0)	316	402	0.002734	0.003881	-0.001147	2.424	-1.038
			(1.1439)	(1.5932)	(-0.2863)		
(5,70,0)	242	405	0.003042	0.003950	-0.000908	2.335	-1.038
			(1.1152)	(1.6183)	(-0.2097)		
(5,80,0)	252	395	0.002726	0.003925	-0.001199	2.237	-1.038

			(1.0506)	(1.5974)	(-0.2791)		
(5,90,0)	247	399	0.001392	0.001908	-0.000516	1.105	-1.038
			(0.6997)	(0.9874)	(-0.1196)		
(5,100,0)	257	389	-0.001084	0.000356	-0.00144	-0.139	-1.038
			(0.0639)	(0.5097)	(-0.3362)		
Average			0.002643	0.004045	-0.001402		
CADOGAN PETROLEUM							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	213	558	0.004750	0.002161	0.002589	2.217	-0.194
			(1.5215)	(1.0229)	(0.7562)		
(5,20,0)	438	311	0.000780	0.001723	-0.000943	0.877	-0.194
			(0.4055)	(0.6919)	(-0.2991)		
(5,30,0)	251	494	0.001557	0.000931	0.000626	0.850	-0.194
			(0.5856)	(0.4829)	(0.19000)		
(5,40,0)	334	395	0.000868	0.000908	-0.00004	0.648	-0.194
			(0.4019)	(0.4408)	(-0.0126)		
(5,50,0)	314	415	0.002008	0.001685	0.000323	1.329	-0.194
			(0.7946)	(0.7490)	(0.1016)		
(5,60,0)	304	387	0.002149	0.001867	0.000282	1.375	-0.194
			(0.8345)	(0.8008)	(0.0865)		
(5,70,0)	326	365	0.001501	0.001530	-0.000029	1.047	-0.194
			(0.6244)	(0.6601)	(-0.0089)		
(5,80,0)	288	357	0.000971	0.001157	-0.000186	0.692	-0.194
			(0.4163)	(0.5177)	(-0.0552)		
(5,90,0)	344	345	0.002056	0.002250	-0.000194	1.482	-0.194
			(0.8380)	(0.9094)	(-0.0599)		
(5,100,0)	302	342	0.001939	0.002103	-0.000164	1.304	-0.194
			(0.7596)	(0.8534)	(-0.0488)		
Average			0.001857	0.001631	0.000226		
HERITAGE OIL							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	336	429	0.002999	0.004025	-0.001026	2.734	-0.578
			(1.7854)*	(2.4701)*	(-0.4386)		
(5,20,0)	407	355	0.000180	0.002195	-0.002015	0.852	-0.578
			(0.4692)	(1.4286)	(-0.8642)		
(5,30,0)	324	421	0.001129	0.002534	-0.001405	1.432	-0.578
			(0.8813)	(1.6870)*	(-0.5921)		
(5,40,0)	293	443	0.001163	0.002393	-0.00123	1.400	-0.578
			(0.8656)	(1.6411)	(-0.5087)		
(5,50,0)	247	459	0.001351	0.002371	-0.00102	1.421	-0.578
			(0.8925)	(1.6480)*	(-0.4025)		
(5,60,0)	237	466	0.001630	0.002448	-0.000818	1.527	-0.578
			(0.9957)	(1.6968)*	(-0.3193)		
(5,70,0)	231	471	-0.000282	0.001426	-0.001708	0.606	-0.578
			(0.1908)	(1.1569)	(-0.6622)		
(5,80,0)	226	475	-0.000357	0.001381	-0.001738	0.575	-0.578
			(0.1583)	(1.1358)	(-0.6698)		
(5,90,0)	207	419	-0.000090	0.001386	-0.001476	0.561	-0.578
			(0.2593)	(1.0940)	(-0.5411)		
(5,100,0)	202	379	-0.000446	0.001344	-0.00179	0.419	-0.578
			(0.1164)	(1.0373)	(-0.6399)		
Average			0.000727	0.002150	-0.001422		
KENTZ							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	392	379	0.002816	0.001267	0.001549	1.584	0.667
			(1.5756)	(0.3273)	(1.0693)		
(5,20,0)	362	392	0.001985	0.000279	0.001706	0.827	0.667
			(0.8838)	(-0.4628)	(1.1639)		
(5,30,0)	396	293	0.001560	0.000595	0.000965	0.792	0.667
			(0.5683)	(-0.1887)	(0.6228)		
(5,40,0)	374	309	0.000949	-0.00041	0.001359	0.229	0.667
			(0.0743)	(-0.9361)	(0.8791)		
(5,50,0)	379	303	0.000475	-0.00102	0.001495	-0.128	0.667

			(-0.3018)	(-1.3778)	(0.9648)		
(5,60,0)	398	283	0.000429	-0.00118	0.001609	-0.164	0.667
			(-0.3440)	(-1.4586)	(1.0291)		
(5,70,0)	423	257	0.000631	-0.00093	0.001561	0.0279	0.667
			(-0.1845)	(-1.2344)	(0.9816)		
(5,80,0)	452	226	0.000729	-0.00074	0.001469	0.161	0.667
			(-0.1060)	(-1.0502)	(0.8967)		
(5,90,0)	433	220	0.000967	-0.00043	0.001397	0.323	0.667
			(0.0929)	(-0.8372)	(0.8391)		
(5,100,0)	438	215	0.000681	-0.00100	0.001681	0.082	0.667
			(-0.1449)	(-1.1978)	(1.0039)		
Average			0.001122	-0.00035	0.001479		
EXILLON ENERGY							
Moving Averages	N(Buy)	N(Sell)	Buy Mean Return	Sell Mean Return	Buy-Sell Difference	Trad. Rule Return	Buy and Hold Return
(5,10,0)	399	358	0.003456	0.004133	-0.000677	2.858	-0.0571
			(1.7271)*	(1.9846)*	(-0.2800)		
(5,20,0)	403	331	0.001382	0.001770	-0.000388	1.142	-0.0571
			(0.7145)	(0.8463)	(-0.1575)		
(5,30,0)	423	308	0.002263	0.003203	-0.00094	1.943	-0.0571
			(1.1654)	(1.4663)	(-0.3779)		
(5,40,0)	423	304	0.002516	0.003634	-0.001118	2.169	-0.0571
			(1.2916)	(1.6514)*	(-0.4477)		
(5,50,0)	406	319	0.003168	0.004297	-0.001129	2.656	-0.0571
			(1.5953)	(1.9806)*	(-0.4544)		
(5,60,0)	359	334	0.002567	0.002846	-0.000279	1.872	-0.0571
			(1.2469)	(1.3446)	(-0.1105)		
(5,70,0)	361	332	0.002409	0.002706	-0.000297	1.768	-0.0571
			(1.1745)	(1.2774)	(-0.1176)		
(5,80,0)	351	342	0.002349	0.002496	-0.000147	1.678	-0.0571
			(1.1351)	(1.1932)	(-0.0582)		
(5,90,0)	349	335	0.003001	0.003458	-0.000457	2.205	-0.0571
			(1.4378)	(1.6282)	(-0.1799)		
(5,100,0)	345	337	0.003380	0.003630	-0.00025	2.389	-0.0571
			(1.6086)	(1.7111)*	(-0.0983)		
Average			0.002649	0.003217	-0.000568		

Notes: The first column of the table represents the combinations of short moving average, long moving average and zero bandwidth (5,10,0…………5,100,0) employed as a trading rule. N(Buy) and N(Sell) columns show the number of days in a buy or sell decision after their respective signals. Buy and sell mean returns are daily averages of the total return generated from the buy and sell transactions, while the values in parenthesis under them are t-statistics to be used in rejecting or accepting the null hypothesis of equality at 5% significant level. The significance of the difference between buy and sell returns are also measured in a separate column. The last two columns are the total trading returns from each rule (moving average) and corresponding buy and hold investment strategy returns over the same period. The last row of each stock computed the averages of buy mean returns, sell mean returns, and buy-sell difference of the trading rules employed.

Source: Author (2015)

The results in Table 7.6.2 show that the indices except the FTSE UK AIM SS Oil and Gas index have more buy decisions (days) than sell decisions (days) which is a sign of bullish condition. The FTSE UK AIM SS Oil and Gas index shows a sign of bearish condition due to higher sell-days than buy-days. The t-statistics generated in relation to the buy and sell mean returns of the indices are not more than their critical values to indicate the rejection of the null hypothesis that the returns from the trading rule and the buy and hold strategy are equal. Based on these results, the moving average trading rule cannot provide any result that is significantly different from the simple buy and hold strategy even after disregarding transaction cost.

Similar to the results of the indices, significant t-statistic values (higher than their critical value at 5% significant level) are only observed in the sell mean returns of BP, JKX Oil and Gas, Hardy Oil and Gas, Heritage Oil and Exillon Energy as indicated by the asterisks after the t-statistics parentheses. In these few cases, the null hypothesis of equality between sell mean returns and buy and hold strategy mean returns can be rejected. However, it cannot be concluded that the trading rules are influential since the buy mean returns are not significantly different from the buy and hold mean returns. In all the stocks N(Buys) are higher than N(Sells) indicating bullish conditions except in Cairn Energy, Aminex Plc, JKX Oil and Gas, Wood Group, Hardy Oil and Gas, Salamander Energy, and Heritage Oil which showed bearish conditions by having N(Sells) significantly higher than N(Buys).

The reliability of the trading rule results presented in Table 7.6.2 above has been tested by a stationarity test conducted on the moving average (10) trading rule return series (as a sample) in order to assess whether the series is stationary. If the series is non stationary, then the buy and sell mean returns used as a yardstick for assessing the performance of a trading rule strategy would not be realistic since the series is generated from a stochastic process. On the contrary, if the series is found to be stationary by rejecting the null hypothesis of unit root, then the trading rule buy or sell mean returns can be assumed to be constant over which it can be compared with the unconditional mean return of the buy and hold investment strategy. Results of the stationarity test are presented in Table 7.6.3 below.

Table 7.6.3 Stationarity Test Results of the Moving Average (10) Trading Rule Return Series

		Augmented Dickey Fuller (ADF) Test		Phillips-Perron (PP) Test	
		T-Stat	P-Value	T-Stat	P-Value
1.	FTSE All Share	-26.9298	0.00000	-27.8016	0.00000
2.	FTSE 100	-27.0434	0.00000	-27.6492	0.00000
3.	FTSE UK Oil & Gas	-27.5932	0.00000	-27.7400	0.00000
4.	FTSE UK O&G Prod.	-27.6836	0.00000	-27.7423	0.00000
5.	FTSE AIM SS O&G	-25.5402	0.00000	-25.5194	0.00000
6.	Amec Plc	-27.8926	0.00000	-28.7138	0.00000
7.	BG Group	-22.0363	0.00000	-21.4690	0.00000
8.	BP	-14.0095	0.00000	-14.0435	0.00000
9.	Cairn Energy	-25.0875	0.00000	-24.5480	0.00000
10.	Dragon Oil	-13.4671	0.00000	-12.2605	0.00000
11.	Fortune Oil	-35.6595	0.00000	-37.9720	0.00000
12.	Hunting	-20.2925	0.00000	-18.7155	0.00000
13.	Premier Oil	-9.34361	0.00000	-9.34839	0.00000
14.	Royal Dutch Shell 'B'	-13.6467	0.00000	-13.2590	0.00000
15.	Tullow Oil	-17.0608	0.00000	-17.0695	0.00000
16.	Aminex	-34.3535	0.00000	-35.6511	0.00000
17.	JKX Oil and Gas	-11.7874	0.00000	-12.0803	0.00000
18.	Soco International	-25.9464	0.00000	-25.8425	0.00000
19.	Wood Group (John)	-19.7088	0.00000	-18.4200	0.00000
20.	Afren	-18.8397	0.00000	-18.0106	0.00000
21.	Hardy Oil and Gas	-8.87303	0.00000	-8.83021	0.00000
22.	Royal Dutch Shell 'A'	-11.6946	0.00000	-11.5412	0.00000
23.	Petrofac	-15.3649	0.00000	-15.2286	0.00000
24.	Salamander Energy	-7.70000	0.00000	-7.00006	0.00000
25.	Lamprell	-16.1638	0.00000	-16.1279	0.00000
26.	Endeavor Intl. Corporation	-8.94127	0.00000	-8.87944	0.00000
27.	Cadogan Petroleum	-14.6592	0.00000	-14.2911	0.00000
28.	Heritage Oil	-8.20630	0.00000	-8.19145	0.00000
29.	Kentz	-8.70567	0.00000	-7.99142	0.00000
30.	Exillon Energy	-8.40783	0.00000	-7.41207	0.00000

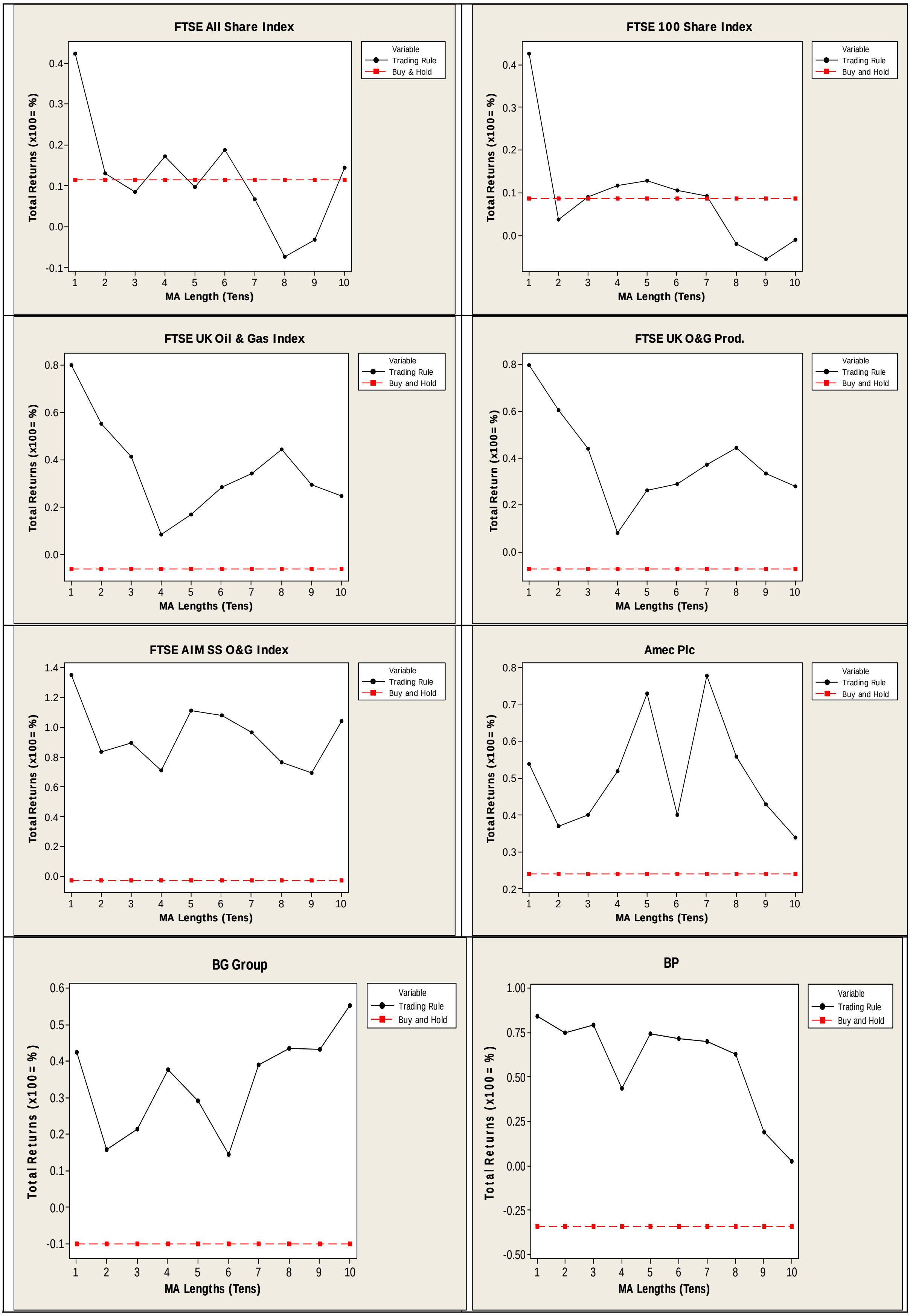
Source: Author (2015)

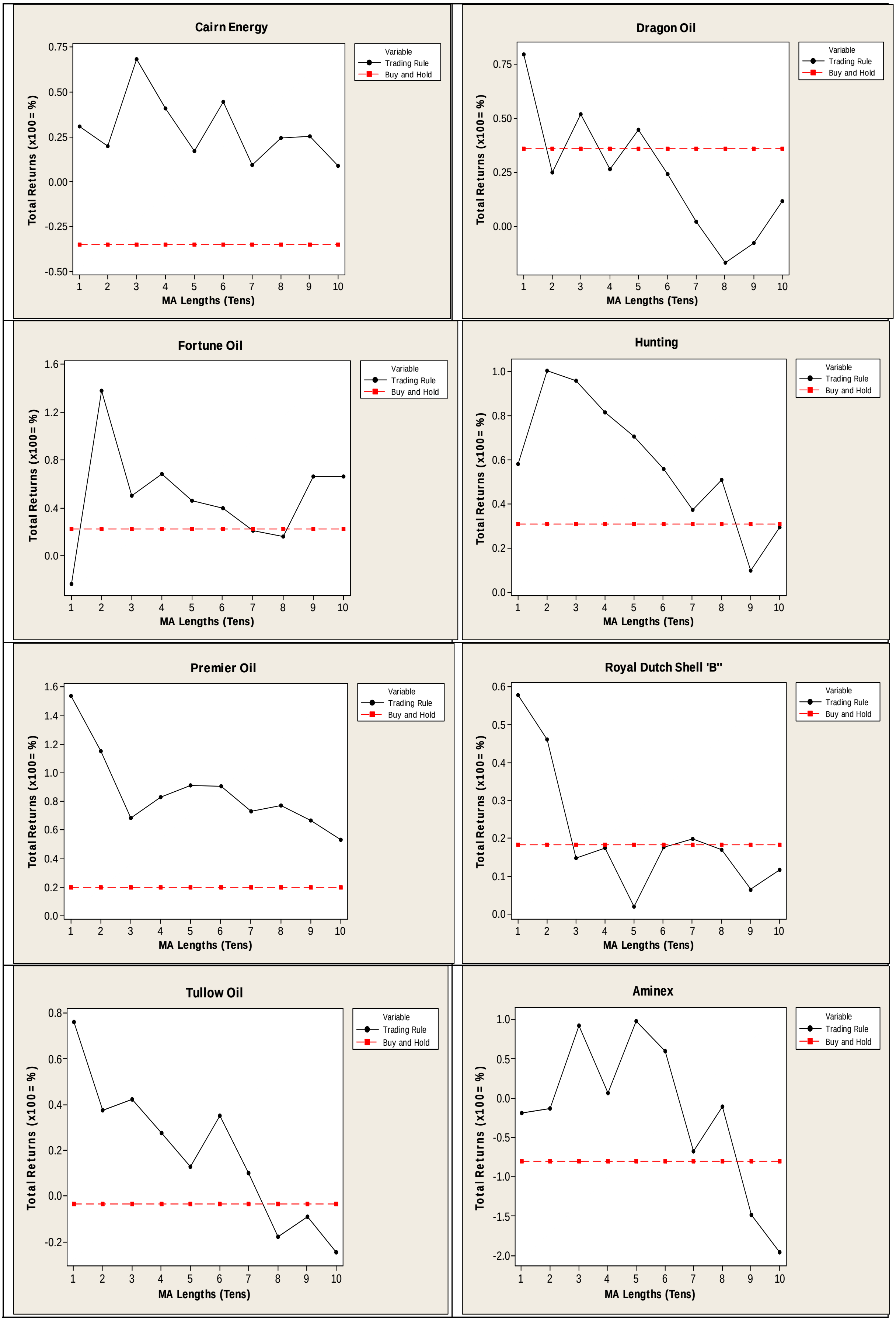
Table 7.6.3 shows the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root tests results on the return series generated from the moving average (10) trading rule. As mentioned earlier, the test was meant to assess whether the statistical properties used to measure the performance of a trading rule are generated from a stationary process or not. The null hypothesis that the 'series has a unit root' is rejected or accepted by the t-statistics and p-values of the ADF and PP tests generated. Based on the results presented in Table 7.6.3, both the t-statistics and p-values are highly significant even at 1% significance level, in which the null hypothesis of unit root is strongly rejected. It is therefore concluded that the moving average trading rule return series are stationary and its constant mean can be compared with the unconditional mean return of the buy and hold investment strategy.

We also employed the methodology of Milionis and Papanagiotou (2008) to assess the performance of the various combinations of moving averages used as trading rule. Milionis and Papanagiotou (2008) conducted a study to examine the performance of moving average trading rules based on the variation in the lengths of the moving averages. The aim of the study was partly achieved by qualitative observations of the moving averages in comparison to the buy and hold investment returns plotted on a graph. The scholars concluded from observation that shorter moving averages perform better than longer moving averages despite the fact that three out of four trading signals are false due to the discovery of non-stationary in some successive trading rule return series. It was also opined by the scholars that moving average trading rules can be improved by the inclusion of more information such as the volume of trade and filters.

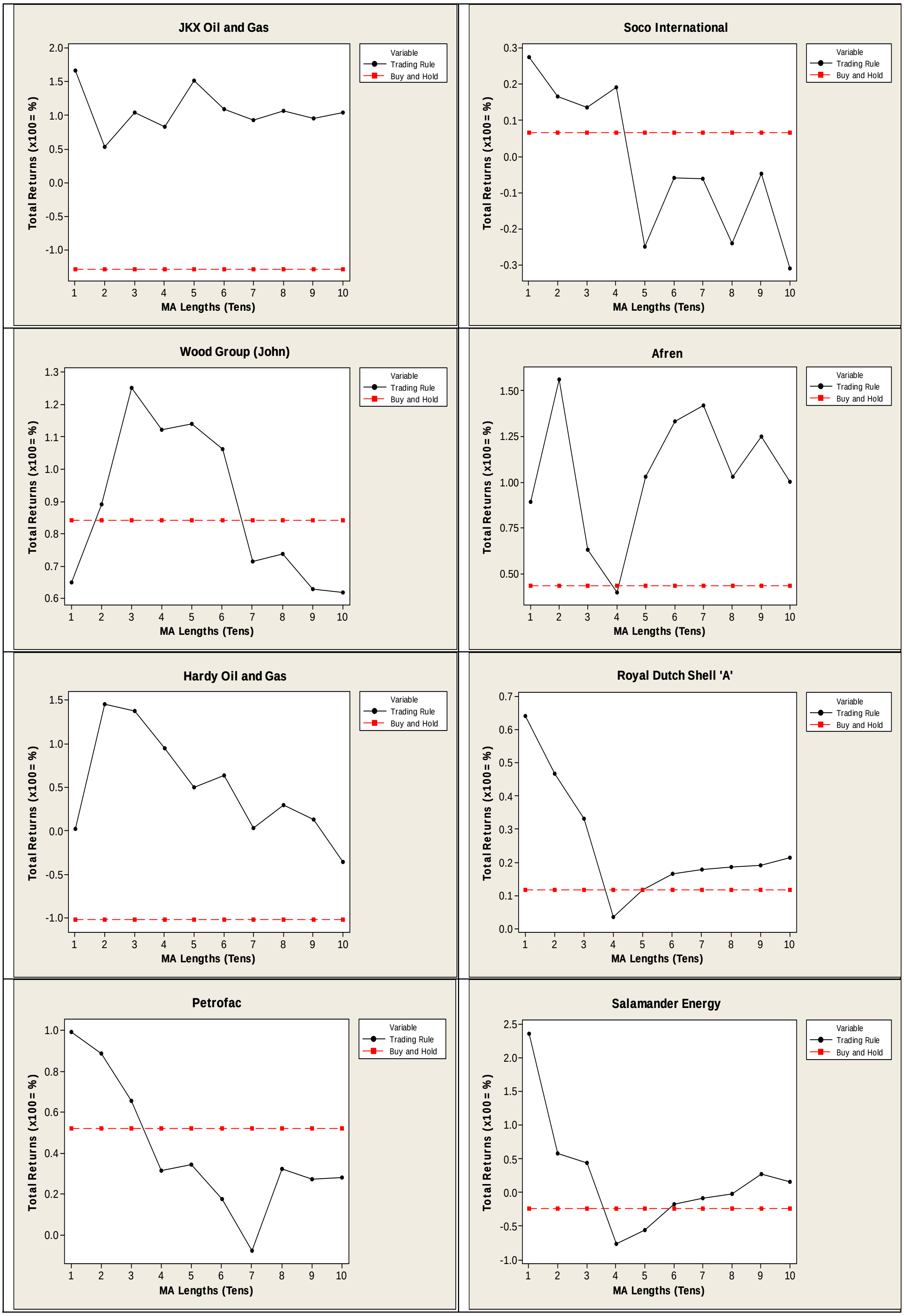
The graphical presentation of the returns generated by various moving average trading rules and a simple buy and hold investment strategy are made in Figure 7.1 for qualitative observations.

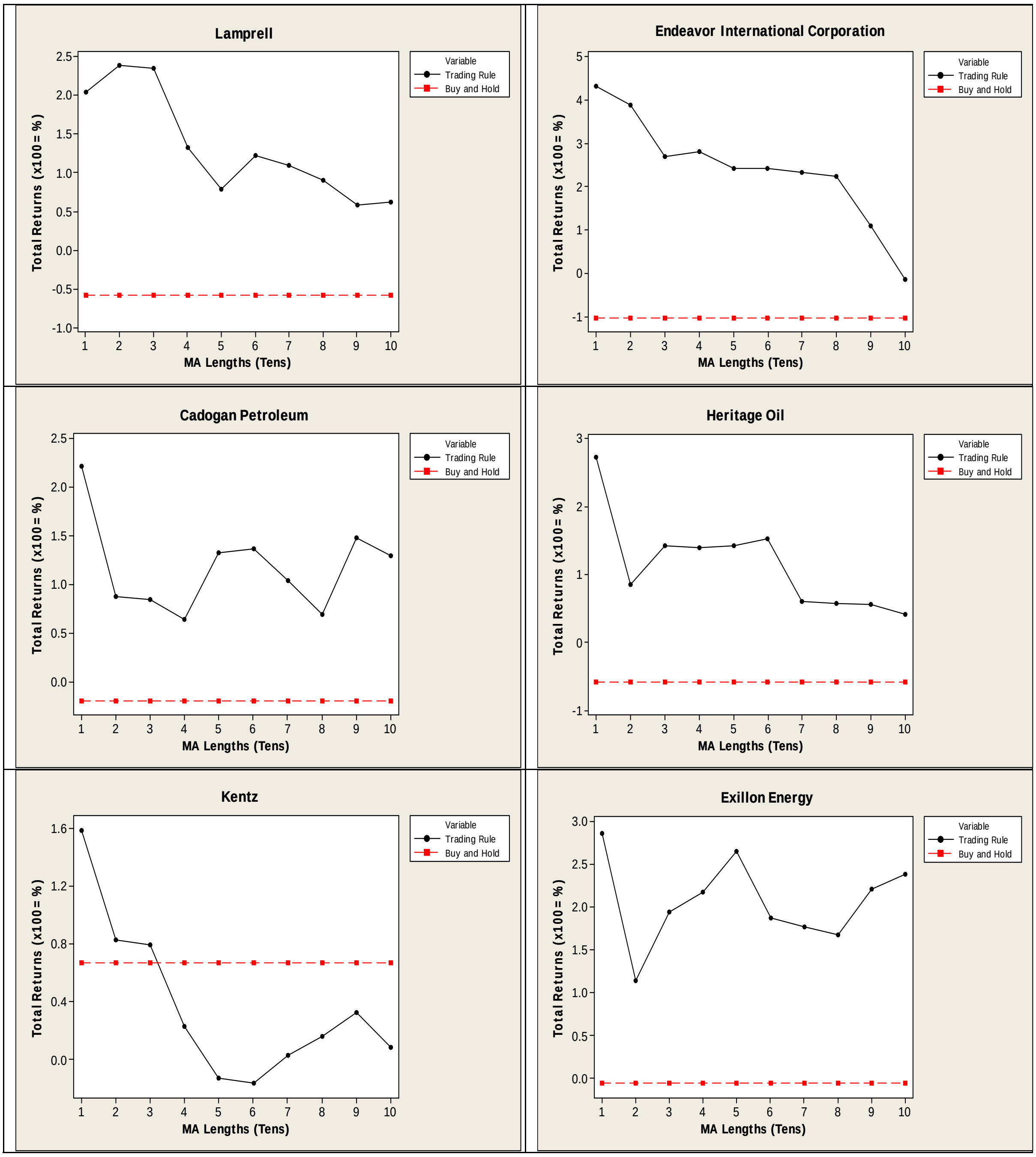
Figure 7.2 Performances of Moving Averages Trading Rules Returns against the Return from Simple Buy and Hold Investment Strategy





Cairn Energy
Dragon Oil
Fortune Oil
Hunting
Premier Oil
Royal Dutch Shell 'B"
Tullow Oil
Aminex
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold


JKX Oil and Gas
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold
Soco International
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold
Wood Group (John)
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold
Afren
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold
Hardy Oil and Gas
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold
Royal Dutch Shell 'A'
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold
Petrofac
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold
Salamander Energy
Total Returns (x100= %)
MA Lengths (Tens)
Variable
Trading Rule
Buy and Hold



Source: Author (2015)

Figure 7.1 showed the total returns generated by every moving average trading rule (ranging from '5,10,0' to '5,100,0') against the total return from the buy and hold strategy. It is obvious from the graphs above that the shorter moving average trading rule of '5,10,0' produced higher returns compared to the other longer moving average trading rules on the charts in all the FTSE share indices and the stocks of BP, Dragon oil, Premier Oil, Royal Dutch Shell 'B', Tullow Oil, JKX Oil and Gas, Soco International, Royal Dutch Shell 'A', Petrofac, Salamander Energy, Endeavor International, Cadogan Petroleum, Heritage Oil, Kentz and Exillon Energy. Other stocks such as Amec, BG Group, Cairn Energy and Wood Group that have not been mentioned above do not show superior performance of the shorter moving average trading rule. The moving average trading rules were completely found to outperform a simple buy and hold investment strategy in the FTSE UK Oil and Gas index, the FTSE UK Oil and Gas Producers index, the FTSE AIM SS Oil and Gas index and in the stocks of Amec, BG Group, BP, Cairn Energy, Premier Oil, JKX Oil and Gas, Hardy Oil and Gas, Lamprell Plc, Endeavor International Corporation, Cadogan Petroleum, Heritage Oil and Exillon Energy.

7.5 Discussion of Findings

The Autocorrelation and Q-Statistic tests were specifically employed to assess whether there is any evidence of serial correlation in the series which is another form of testing the random walk hypothesis. The results generated provide evidence of serial correlation in all the FTSE share indices and sixteen individual oil and gas companies out of the total number of thirty companies under study. By this result, the London stock exchange represented by the FTSE All Share index and the oil and gas sector represented by the FTSE Oil and Gas Share index and other major oil stocks do not follow the random walk, which is evidence to reject the weak form market efficiency hypothesis and confirms the predictability of stock returns. Similar to our findings, Hudson et al (1996) also discovered that technical trading rules have the ability to predict future stock prices on the London stock exchange due to the existence of serial correlation. However, the scholars stated that high trading costs would not allow any abnormal profit to be generated. Al-loughani and Chappell (1997) had also rejected the validity of weak form market efficiency on the FTSE 30 share index by establishing that the series does not follow random walk. Milionis and Moschos (2000) argued that the findings of Al-loughani and Chappell (1997) are plausible and concluded that, although the random walk hypothesis can be rejected, it is not possible to reject weak form market efficiency of the FTSE 30 Share index. Contrary to the findings in most of the existing literature such as Kendall et al (1953), Working (1934), Roberts (1959) and Osborne (1959,1962) that explain developed markets as weak form efficient, the findings of Brock et al (1992) also contradict that assertion by discovering the predictive power of technical trading rules in the Dow Jones index.

The runs test was employed as a non-parametric test in order to overcome the unrealistic assumption of normal distribution in daily stock returns by parametric tests which was also not found in our series (see chapter 4). The results generated show that the FTSE All Share, FTSE 100, and FTSE UK Oil and Gas Producers share indices are not serially correlated but follow random walk which suggests weak form market efficiency. According to the runs tests results, the London stock exchange and its oil and gas producers sector can be deemed as weak form efficient which is contrary to the results of the autocorrelation and Ljung-Box Q-Statistic tests. However, the runs test results on FTSE UK Oil and Gas and FTSE AIM SS Oil and Gas indices and of eight individual oil stocks are found to be consistent with the autocorrelation results. Our inferences will be concluded after the application of technical trading rules on the series to assess whether abnormal profit can be made due to the existence of serial correlation.

In recent years, conventional statistical tools such as the autocorrelation function used in testing random walk and weak form market efficiency hypotheses have been criticised by scholars based on the argument that the absence of serial correlation cannot exclusively suggest independence or market efficiency. The variance ratio test was among the new formal tests developed for random walk hypothesis and equally employed in this study. According to the variance ratio test results, the null hypothesis of random walk (VR=1) has been accepted in most of the series that are considered for investigation in this study. In simple terms, the results advocate that the oil and gas sector and the entire market of the London stock exchange are efficient in weak form. Charles and Darne (2009) also rejected the random walk hypothesis in five emerging markets of Latin America using variance ratio test. Smith and Ryoo (2003) had reassessed the weak form market efficiency of five European emerging markets in Greece, Hungary, Poland, Portugal, and Turkey using the variance ratio test. The random walk hypothesis was rejected in four of the five markets tested in the study.

The BDS test was also employed because of its power to detect whether the structure of the series is linear or non-linear in addition to randomness assessment. The residuals from a linear model of ARMA (1,1) were tested for randomness in order to assess the effectiveness of the model in capturing the linearity of the series. The results rejected the null hypothesis of white noise in all the residuals generated which is an indication that the series are not linear since linear models could not capture all the statistical properties of the series. On the same note the random walk hypothesis was rejected in all the series due to the existence of serial correlation in the residuals of the series. The results are also found to be completely consistent with that of the variance ratio test. However, our inferences will also consider the results from technical trading rules in the following section.

Technical trading rules were employed to assess whether oil and gas investors can make abnormal gains from their investments due to the signs of serial correlation found in the stock series under investigation. We tested the possibility of earning abnormal returns using trading and filter rules. Our findings in all the series suggested that the trading rule cannot provide sufficient profit to cover the brokerage cost associated with every transaction. We also employed moving average trading rules in a similar way as used by Brock et al (1992) to assess whether our findings are going to be different. However, despite the application of ten different combinations of the moving average trading rule, our t-statistics could not be significant enough for us to reject the null hypothesis that the returns from the trading rule are equal to that from the buy and hold strategy. In that case, we have to accept the null hypothesis that the returns generated from the moving average trading rule are not different from the returns of the buy and hold investment strategy. In order to confirm the authenticity of our results, we tested whether the return series generated from the moving average trading rule are stationary. The results from the unit root tests conducted on the moving average (10) trading rule return series confirmed that the series are stationary and therefore authenticate the use of constant statistical properties such as the mean to assess the power of the trading rule. We also tested the assertion of Milionis and Papanagiotou (2008) that shorter moving average trading rules perform better than longer moving average trading rules. We confirmed that assertion in some of our stock series and equally rejected it in others. We have not gone further to investigate the variation in performance among the different ranges of the moving averages.

7.6 Conclusion

This chapter investigated the weak-form market efficiency in the UK oil and gas sector. The Autocorrelation Function, the Ljung-Box Q-statistic, the variance ratio test, the BDS independence test and non-parametric runs test were specifically adopted to examine the Random Walk Hypothesis. The entire London stock exchange represented by the FTSE All Share and FTSE 100 Share indices was also investigated. The results generated from the statistical tools employed are not uniform in all the stock series under study. In other words, the rejection or acceptance of the null hypothesis of a random walk process of the individual stock series is different. In summary, the autocorrelation function and the Ljung Box Q-statistic have rejected the random walk hypothesis in all the FTSE share indices and sixteen stocks but accepted the hypothesis in fourteen stock series. The runs test which is a non-parametric test rejected the random walk hypothesis in only two FTSE share indices and fourteen stocks, while the hypothesis is accepted in nineteen stocks including three indices. The variance ratio test rejected the random walk hypothesis in three FTSE share indices and the Fortune Oil stock, while the hypothesis is accepted in all the remaining thirty one stock series. The BDS independence test rejected the random walk hypothesis in all the series under study. We have not found any stock series described by all the statistical tools in the same way. Results are more consistent between the runs test and the variance ratio test where stock series are classified as random or not at the same time. In the same way, the autocorrelation function, the Q-statistics and the BDS test have common features of rejecting the random walk hypothesis in most of the series. We have observed that other factors such as the lengths of time series, the assumptions of statistical tools, the parametric and non-parametric nature of the statistical tools and the analytical approach employed have a significant impact on the statistical results. We recommend that investment and financial analysts should employ a robust analytical approach prior to making inferences and generalisation.

To provide additional information to our random walk tests, we employed two technical trading rules that are among the most prominent in the literature as explained earlier to assess the possibility of utilising any non-randomness to generate abnormal gains. The evidence gathered from trading and filter rules based on positive autocorrelation persistence has not shown any sign or possibility that oil and gas investors can make abnormal gains, especially due to the consideration of transaction cost. In moving averages, we ignored transaction cost to see whether the profitability is affected by the high cost of transaction or not. On a similar note, the trading results have not shown any possibility of abnormal profit even prior to consideration of brokerage commission.

At this point, we concluded that the oil and gas sector as well as the entire market of the London stock exchange can be described as weak form efficient.

CHAPTER 8

SEASONALITY ANALYSIS

8.1 Introduction

This chapter investigates the existence of seasonality anomalies in the stock returns in the oil and gas sector in the London stock exchange. The analysis of seasonality in stock returns has been performed by many scholars over the years in order to establish whether there are calendar related anomalies in stock returns. If the proposition that calendar anomalies such as day-of-the-week, intraday, weekend and January effects exist in stock returns, then the random walk hypothesis would be rejected. This also contradicts the efficient market hypothesis because at that point future stock returns can be predicted. In other words, seasonality test or analysis would be considered as another tool for testing the predictability of stock returns or assessing the validity of the Efficient Market Hypothesis. In this chapter, we employ seasonality tests as a tool to provide further evidence on the predictability of stock returns of London-quoted oil and gas stocks and some market indices.

8.2 Literature Review on Seasonality Analysis

8.2.1 Calendar Anomalies

Yadav and Pope (1992) have been among the scholars that tested for the existence of calendar anomalies in stock markets. They investigated the existence of either intraweek or intraday seasonality in the pricing or returns of UK stock index future contracts using the distinctive settlement methods of the London stock exchange. The existence of seasonality was found in the UK stock market because of abnormal Monday returns discovered which could be due to the non-trading weekends. However, there was no evidence that the abnormal Monday returns could be attributed to the delay in the release of bad news until Friday as speculated by some scholars. In contrast to the findings of Yadav and Pope (1992), Mookerjee and Yu (1999) discovered abnormal returns on Thursdays from an investigation on the Shanghai and Shenzhen stock exchanges of China although these researchers have agreed that their findings are odd when compared to that of many scholars. Mookerjee and Yu (1999) found high mean returns on Thursdays instead of Fridays (negative returns are usually found on Mondays) as reported by most of the earlier studies and barriers to the changes in daily prices (limits on daily returns). The daily returns were also found to be positively correlated with risk (standard deviation figures). Most of the studies on the day-of-the-week effect were conducted in developed markets and, according to the majority of the inferences, the effect of seasonality was evidenced in such markets. In similar developments, Chang et al (1993) investigated the day-of-the-week effect in some European markets and the United States using classical or traditional methods adopted by various scholars and an approach with sample size and error term adjustments. Results showed the existence of day-of-the-week effect in the majority of the markets similar to most of the findings in the literature. Dicle and Levendis (2014) tested whether the day-of-the-week effect still exists by investigating up to fifty-one international markets from thirty three countries over the period between 2000 and 2007. Similar to the findings of Yadav and Pope (1992), Mookerjee and Yu (1999), and Chang et al (1993), they also found the existence of day-of-the-week effect in almost all the exchanges in these countries. Qadan (2013) also tested the existence of day-of-the-week effect on the recent United States data of the S&P 500 index using a threshold–ARCH model. The results of the test showed both stock returns and volumes on Monday to be lower than those of other days. In addition, they also reported that the investor's fear gauge as measured by volatility was higher on Mondays and lower on Fridays.

Further evidence on the day-of –the-week effect in the developed markets have also been recorded by the studies of Clare et al (1995), Dubois and Louvet (1996), and Steeley (2001). Steeley (2001) attributed the presence of seasonality in the UK equity market to the pattern of flow of market-wide news. Dubois and Louvet (1996) examined the day-of-the-week effect in eleven indices across nine countries over the period between 1969 and 1992. Lower returns were found at the beginning of the week and tend to increase towards the end of the week. Dubois and Louvet (1996) concluded that there is a strong evidence of day-of-the-week in European countries. The UK equity market was also investigated by Clare et al (1995) and found results similar to that of Dubois and Louvet (1996). Clare et al (1995) used a deterministic seasonal model (a method adopted by Franses (1991)) on the FTSE All Share index and discovered a significant seasonality effect in the market. In a slightly contrary view, Steeley (2001) has reported that weekend effects have vanished from UK markets in the 1990s. However, day-of-the-week effect can still be traced in the market if the stock return series data is divided according to the directions ((+) or (-) of the returns) of the market. In that case, Steeley (2001) concluded that the cause of the day-of-the-week effect was due to the pattern and nature of market-wide information classified as 'bad' or 'good' news.

The research on the day-of-the-week effect has also been extended to emerging markets. Al Ashikh (2012) investigated the day-of-the-week effect on the Saudi Arabian stock exchange and found evidence from both the analysis of mean returns and its variance that the market efficiency hypothesis can be rejected due to the existence of day-of-the week effect. Haroon and Shah (2013) have also examined the Karachi stock exchange in Pakistan for the existence of day-of-the-week effect. In contrast to the results reported by Al Ashikh (2012), Haroon and Shah (2013) discovered mixed results from the two (2) partitions of the period of study that is, sub-period I and II. Sub-period I negates the existence of day-of-the-week effect while sub-period II found evidence of the existence of day-of-the-week effect. Ogieva et al (2013) have also conducted an investigation on the Nigerian stock exchange for the existence of day-of-the-week effect and found evidence to reject the market efficiency hypothesis.

Other calendar anomalies such as a January effect have also been investigated extensively in the field of finance. Findings reported by scholars are similar to that of day-of-the-week effect where the majority of the studies found evidence for the seasonality effect in stock returns, although scholars such as Chien et al (2002) observed that the empirical evidence supporting a January effect could be due to the misapplication of statistical tools. He opined that, with high volatility in stock returns, the dummy variables in the regression model testing the existence of seasonality could generate significant coefficients. Studies like that of Haugen and Lakonishok (1988); Jaffe and Westerfield (1985); and Solnik and Bousquet (1990) have all documented evidence of a 'January effect' in the stock returns of various stock exchanges which may create doubt on the work of Fama (1970) on the Efficient Market Hypothesis (EMH).

8.2.2 Summary of Literature and Research Objectives

The interest of researchers in seasonality analysis was promoted by the fact that evidence gathered could be used to accept or reject the Efficient Market Hypothesis. Although, majority of the inferences made suggest the existence of seasonality, market inefficiency could not be confirmed especially due to the existence of transaction costs. Documented evidence in support of the seasonality presence in stock returns have also been criticised by some scholars who attributed the empirical evidence as the product of statistical misspecification. It was observed that existing studies have not provided sufficient and most reliable conclusions about the existence of seasonality in stock returns and any relating consequences to the proposition of the market efficiency.

We aim to investigate the existence of the day-of-the-week effect in the stock returns of the London-quoted oil and gas equity stocks and a few FTSE indices to provide further evidence to our previous chapters on the examination of market efficiency.

8.3 Seasonality Analysis on the Stock Returns of London-Quoted Oil and Gas Companies and Market Indices

In this section, we aim to investigate the existence of the day-of-the-week and monthly effects in the stock returns of London-quoted oil and gas stocks and some related FTSE measures such as the FTSE All Share, the FTSE 100, the FTSE UK Oil and Gas, the FTSE UK Oil and Gas Producers and the FTSE AIM SS indices. Our data for this analysis covers the periods from January 4, 2010 to December 31, 2012 for the day-of-the-week effect and January 2005 to December 2014 for the monthly effect.

Firstly, days of the week (Monday through Friday) stock returns of individual series were calculated using $(\log P_t \,/\log P_{t-1})$ and mean returns compared in order to test the null hypothesis of equality. The null hypotheses of equality between the discrete week's days' mean- returns are tested using both parametric and non-parametric statistical tools. The F-Test is employed as a parametric tool to test whether there is any significant difference between the week's days' mean-returns. If the F-Statistic value is found to be higher than the critical value (critical values for F-distribution) at a selected significance level, then the null hypothesis that $(\mu_M = \mu_T = \mu_W = \mu_{Th} = \mu_F)$ is rejected for the alternative hypothesis that $(\mu_M \neq \mu_T \neq \mu_W \neq \mu_{Th} \neq \mu_F)$. Kruskal-Wallis is a non-parametric test that is not based on any assumption about the underlying distribution. It performs the same function as the F-Test but without consideration for the distribution of samples tested. It rather tests whether the samples are from the same distribution. If the K-W Statistic value is found to be greater than its critical value, the null hypothesis of equality is rejected and accepted if vice versa. Pairwise test of the week's days' mean returns were also conducted using the Tukey test to make comparison between the pair means. If the Tukey test statistical values allows the null hypothesis of equality to be rejected then, the pair of means returns of two week-days are regarded as not equal which signifies the existence of a day-of-the-week effect.

The results of our F-test, Kruskal-Wallis test and Tukey test on the day-of-the-week return series are presented in Table 6.1 below

Table 8.1 F-Test, Kruskal-Wallis Test, and Tukey Test on the Day-Of-The-Week (DOTW) Return Series under study

		Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
FTSE All Sh.	Mean Return	-0.00022	0.000955	-0.000349	0.000503	-0.000170
	Observation	144	153	155	156	152
	F-Statistic	0.399011027				
	K-W Statistic	2.935440532				
	Tukey Stat:					
	Monday	0	1.315683	-0.14976	0.808005	0.050776
	Tuesday		0	-1.46544	-0.507678	-1.264907
	Wednesday			0	0.9577646	0.200536
	Thursday				0	-0.757229
FTSE100	Mean Return	-0.0002	0.001121	-0.000461	0.000429	-0.000346
	Observation	144	153	155	156	152
	F-Statistic	0.53241147				
	K-W Statistic	3.554102754				
	Tukey Stat:					
	Monday	0	1.449682	-0.28884	0.6895659	-0.162001
	Tuesday		0	-1.73852	-0.760116	-1.611683
	Wednesday			0	0.9784018	0.126835
	Thursday				0	-0.851567
FTSE UK O&G	Mean Return	2.71E-05	0.001402	-0.000862	-0.000437	-0.000512
	Observation	144	153	155	156	152
	F-Statistic	0.679264795				
	K-W Statistic	4.797923822				
	Tukey Stat:					
	Monday	0	1.2744	-0.82434	-0.429674	-0.49952
	Tuesday		0	-2.09874	-1.704074	-1.77392
	Wednesday			0	0.3946653	0.324819
	Thursday				0	-0.069846
FTSE UK OGP	Mean Return	2.58E-05	0.001401	-0.000870	-0.000481	-0.000539
	Observation	144	153	155	156	152
	F-Statistic	0.693737153				
	K-W Statistic	4.929917434				
	Tukey Stat:					
	Monday	0	1.27478	-0.83036	-0.469856	-0.52385
	Tuesday		0	-2.10514	-1.744636	-1.79863
	Wednesday			0	0.3605003	0.306507
	Thursday				0	-0.053994

FTSE AIM OG	Mean Return	-0.00208	-0.002526	-0.000564	0.000448	0.004435
	Observation	144	153	155	156	152
	F-Statistic	4.010797958				
	K-W Statistic	21.88855327				
	Tukey Stat:					
	Monday	0	-0.32516	1.092983	1.8245219	4.707024
	Tuesday		0	1.418146	2.1496856	5.032188
	Wednesday			0	0.7315391	3.614041
	Thursday				0	2.882502
AMEC	Mean Return	2.03E-05	0.001658	-0.000452	0.000266	0.000054
	Observation	144	153	155	156	152
	F-Statistic	0.297659605				
	K-W Statistic	1.424564284				
	Tukey Stat:					
	Monday	0	1.115047	-0.32156	0.1672951	0.022647
	Tuesday		0	-1.43661	-0.947752	-1.0924
	Wednesday			0	0.4888587	0.344211
	Thursday				0	-0.144648
BG GROUP	Mean Return	-0.00046	0.002049	-0.001622	-0.000833	0.000207
	Observation	144	153	155	156	152
	F-Statistic	0.810097929				
	K-W Statistic	4.736793417				
	Tukey Stat:					
	Monday	0	1.61868	-0.75162	-0.242484	0.429282
	Tuesday		0	-2.3703	-1.861164	-1.189398
	Wednesday			0	0.5091399	1.180906
	Thursday				0	0.671767
BP	Mean Return	0.000312	-0.000301	-0.000476	-0.000267	-0.001502
	Observation	144	153	155	156	152
	F-Statistic	0.195088866				
	K-W Statistic	3.140288403				
	Tukey Stat:					
	Monday	0	-0.41349	-0.53138	-0.39099	-1.223996
	Tuesday		0	-0.11789	0.0225037	-0.810503
	Wednesday			0	0.14039	-0.692616
	Thursday				0	-0.833006
CAIRN	Mean Return	-0.00187	0.000373	-0.000946	0.000046	-0.000003
	Observation	144	153	155	156	152
	F-Statistic	0.272821274				
	K-W Statistic	3.064199928				
	Tukey Stat:					
	Monday	0	1.291092	0.532656	1.1032085	1.074713
	Tuesday		0	-0.75844	-0.187883	-0.216379
	Wednesday			0	0.5705525	0.542057
	Thursday				0	-0.028495
DRAGON	Mean Return	-0.00018	0.000727	0.001819	0.000822	-0.000909
	Observation	144	153	155	156	152
	F-Statistic	0.381826186				
	K-W Statistic	0.825266994				
	Tukey Stat:					
	Monday	0	0.534847	1.182334	0.591457	-0.434915
	Tuesday		0	0.647487	0.0566104	-0.969761
	Wednesday			0	-0.590877	-1.617249
	Thursday				0	-1.026372
FORTUNE	Mean Return	-0.00477	0.001849	0.001681	-0.000523	0.002951
	Observation	144	153	155	156	152
	F-Statistic	0.49235208				
	K-W Statistic	1.628715356				
	Tukey Stat:					
	Monday	0	1.538968	1.499977	0.9878145	1.795065
	Tuesday		0	-0.03899	-0.551153	0.256097

	Wednesday			0	-0.512162	0.295088
	Thursday				0	0.80725
HUNTING	Mean Return	-0.0004	0.001374	-0.002310	0.001241	0.002091
	Observation	144	153	155	156	152
	F-Statistic	0.939621194				
	K-W Statistic	3.59337799				
	Tukey Stat:					
	Monday	0	0.968823	-1.03973	0.8966124	1.360206
	Tuesday		0	-2.00856	-0.072211	0.391383
	Wednesday			0	1.9363452	2.399938
	Thursday				0	0.463593
PREMIER	Mean Return	0.000532	-0.001777	0.000465	0.001146	0.000928
	Observation	144	153	155	156	152
	F-Statistic	0.520226882				
	K-W Statistic	2.792678369				
	Tukey Stat:					
	Monday	0	-1.415	-0.04113	0.3760816	0.242734
	Tuesday		0	1.373873	1.7910812	1.657734
	Wednesday			0	0.4172082	0.283861
	Thursday				0	-0.133348
RDSB	Mean Return	0.000286	0.002686	-0.000721	-0.000694	-0.000322
	Observation	144	153	155	156	152
	F-Statistic	1.753720054				
	K-W Statistic	7.569918787				
	Tukey Stat:					
	Monday	0	2.222766	-0.9326	-0.907989	-0.56335
	Tuesday		0	-3.15537	-3.130755	-2.786116
	Wednesday			0	0.0246099	0.369249
	Thursday				0	0.34464
TULLOW	Mean Return	-0.00059	0.000128	-0.001841	-0.000343	0.002437
	Observation	144	153	155	156	152
	F-Statistic	0.763607697				
	K-W Statistic	4.540064018				
	Tukey Stat:					
	Monday	0	0.401267	-0.69443	0.1390366	1.687078
	Tuesday		0	-1.09569	-0.262231	1.28581
	Wednesday			0	0.8334623	2.381503
	Thursday				0	1.548041
AMINEX	Mean Return	0.002376	-0.002853	0.006753	-0.008139	-0.003247
	Observation	144	153	155	156	152
	F-Statistic	1.112091933				
	K-W Statistic	2.539464198				
	Tukey Stat:					
	Monday	0	-0.9568	0.800705	-1.923947	-1.028971
	Tuesday		0	1.757506	-0.967147	-0.072171
	Wednesday			0	-2.724653	-1.829677
	Thursday				0	0.894976
JKX O&G	Mean Return	0.001148	-0.001855	-0.002311	-0.000286	-0.005110
	Observation	144	153	155	156	152
	F-Statistic	1.202895668				
	K-W Statistic	5.225484511				
	Tukey Stat:					
	Monday	0	-1.41191	-1.62629	-0.674319	-2.94217
	Tuesday		0	-0.21438	0.7375941	-1.530257
	Wednesday			0	0.9519699	-1.315882
	Thursday				0	-2.267852
SOCO INTL.	Mean Return	0.000307	-0.000432	-0.001115	0.000909	0.000786
	Observation	144	153	155	156	152
	F-Statistic	0.215608431				
	K-W Statistic	1.10832227				
	Tukey Stat:					

	Monday	0	-0.3982	-0.76594	0.3241272	0.258133
	Tuesday		0	-0.36774	0.7223266	0.656333
	Wednesday			0	1.0900714	1.024077
	Thursday				0	-0.065994
WOOD GRP	Mean Return	0.000259	0.002383	-0.000664	0.001247	0.002288
	Observation	144	153	155	156	152
	F-Statistic	0.510816937				
	K-W Statistic	6.860733061				
	Tukey Stat:					
	Monday	0	1.153157	-0.50062	0.5369051	1.101957
	Tuesday		0	-1.65378	-0.616251	-0.0512
	Wednesday			0	1.0375238	1.602575
	Thursday				0	0.565052
AFREN	Mean Return	-0.00047	0.002852	-0.000681	0.000786	0.000311
	Observation	144	153	155	156	152
	F-Statistic	0.287916093				
	K-W Statistic	1.345452187				
	Tukey Stat:					
	Monday	0	1.262706	-0.07933	0.4778316	0.29748
	Tuesday		0	-1.34204	-0.784875	-0.965226
	Wednesday			0	0.5571661	0.376814
	Thursday				0	-0.180352
HARDY O&G	Mean Return	-0.00463	-0.003579	0.001358	0.000717	-0.000903
	Observation	144	153	155	156	152
	F-Statistic	1.051237673				
	K-W Statistic	6.036124707				
	Tukey Stat:					
	Monday	0	0.413558	2.352295	2.1004191	1.464555
	Tuesday		0	1.938736	1.6868607	1.050997
	Wednesday			0	-0.251876	-0.88774
	Thursday				0	-0.635864
RDSA	Mean Return	-2.4E-05	0.002371	-0.000904	-0.000288	-0.000538
	Observation	144	153	155	156	152
	F-Statistic	1.682564012				
	K-W Statistic	8.202197593				
	Tukey Stat:					
	Monday	0	2.383797	-0.87633	-0.263021	-0.511184
	Tuesday		0	-3.26013	-2.646819	-2.894981
	Wednesday			0	0.6133119	0.365149
	Thursday				0	-0.248163
PETROFAC	Mean Return	0.000824	0.001232	-0.001067	0.002203	0.000233
	Observation	144	153	155	156	152
	F-Statistic	0.484073992				
	K-W Statistic	2.69118205				
	Tukey Stat:					
	Monday	0	0.231353	-1.07277	0.7819499	-0.335171
	Tuesday		0	-1.30412	0.5505969	-0.566524
	Wednesday			0	1.8547179	0.737597
	Thursday				0	-1.117121
SALAMANDER	Mean Return	0.000297	-0.002800	0.000733	-0.000046	0.000272
	Observation	144	153	155	156	152
	F-Statistic	0.556664052				
	K-W Statistic	1.9574156				
	Tukey Stat:					
	Monday	0	-1.62301	0.228108	-0.179823	-0.01321
	Tuesday		0	1.851119	1.4431875	1.609801
	Wednesday			0	-0.407931	-0.241318
	Thursday				0	0.166614
LAMPRELL	Mean Return	0.001513	0.000273	-0.007814	-0.000394	0.002843
	Observation	144	153	155	156	152
	F-Statistic	1.003828883				

	K-W Statistic	1.004767414				
	Tukey Stat:					
	Monday	0	-0.29729	-2.23656	-0.457288	0.318952
	Tuesday		0	-1.93927	-0.159997	0.616242
	Wednesday			0	1.7792744	2.555514
	Thursday				0	0.776239
ENDEAVOR	Mean Return	0.001918	-0.002845	-0.005402	0.002057	-0.002488
	Observation	144	153	155	156	152
	F-Statistic	0.548515069				
	K-W Statistic	0.274690258				
	Tukey Stat:					
	Monday	0	-1.08459	-1.667	0.0314785	-1.003476
	Tuesday		0	-0.5824	1.1160723	0.081118
	Wednesday			0	1.6984749	0.66352
	Thursday				0	-1.034955
CADOGAN	Mean Return	-0.00245	-0.002814	0.002441	-0.000277	0.001666
	Observation	144	153	155	156	152
	F-Statistic	0.452860858				
	K-W Statistic	2.068736118				
	Tukey Stat:					
	Monday	0	-0.10538	1.394441	0.6187843	1.173314
	Tuesday		0	1.499822	0.7241653	1.278695
	Wednesday			0	-0.775656	-0.221127
	Thursday				0	0.554529
HERITAGE	Mean Return	-0.00352	0.003045	-0.000644	-0.003062	0.000260
	Observation	144	153	155	156	152
	F-Statistic	1.009395797				
	K-W Statistic	4.067021843				
	Tukey Stat:					
	Monday	0	2.480671	1.086682	0.1734628	1.42843
	Tuesday		0	-1.39399	-2.307209	-1.052241
	Wednesday			0	-0.91322	0.341748
	Thursday				0	1.254967
KENTZ	Mean Return	-0.00064	0.001641	-0.001234	0.002753	0.001784
	Observation	144	153	155	156	152
	F-Statistic	1.069964819				
	K-W Statistic	11.79090978				
	Tukey Stat:					
	Monday	0	1.378884	-0.35562	2.049722	1.464866
	Tuesday		0	-1.7345	0.6708383	0.085983
	Wednesday			0	2.4053401	1.820484
	Thursday				0	-0.584856
EXILLON	Mean Return	-0.00166	-0.001154	0.001921	-0.000187	0.000595
	Observation	144	153	155	156	152
	F-Statistic	0.269798504				
	K-W Statistic	0.606926897				
	Tukey Stat:					
	Monday	0	0.186483	1.309531	0.5397565	0.825446
	Tuesday		0	1.123049	0.3532738	0.638963
	Wednesday			0	-0.769775	-0.484086
	Thursday					

NOTE: First column of the table shows both the indices and individual oil and gas companies on which the tests are performed. The details of the statistical tests conducted are depicted in column 2. Columns 3 through 7 of the table show the results against the days of the week (Monday to Friday). From the mean returns, the days with highest and lowest average returns can be deduced. F-Statistic, K-W Statistic, and Tukey Statistic have critical values at 95% critical value or 5% significance level of **2.38**, **9.48**, and **3.86** respectively.

Source: Author (2015)

From the results of the F-Test, the Kruskal Wallis test, and the Tukey tests in Table 8.1, the null hypothesis of equality cannot be rejected in all the series except the FTSE AIM SS Oil and Gas index. The statistical values derived from the tests employed are not greater than their respective critical values at 5% significance level and that suggests the non-existence of the day-of-the-week effect in the series under investigation. In the FTSE AIM SS Oil and Gas index, the F-Statistic is recorded at 4.0107 which is significantly higher than the critical value of 2.38 at 5% level. The non-parametric test of the Kruskal-Wallis statistic has a value of 21.888 which is also higher than the critical value of 9.48 at 5% level. The Tukey pairwise test suggests a significant difference between the mean-returns of Fridays and Mondays at 4.7070 and Fridays and Tuesdays at 5.0321 (both higher than a critical value of 3.86 at 5%) which indicate the rejection of the null hypothesis of equality and at the same time confirming the existence of the day-of-the-week-effect in the FTSE AIM SS Oil and Gas index.

The next step undertaken in our investigation of the day-of the-week effect is to create binary dummy variables for the week's days of Mondays through Fridays as independent variables while the return series of every week-day remains as dependent variables. The variables are subjected to a regression model based on the assumption of Autoregressive Conditional Heteroscedasticity (ARCH) developed by Engle (1982) in order to explore the relationship (deviations) between variables using coefficients generated from the regression model. The ARCH model was employed because the standard Ordinary Least Square (OLS) regression model's assumption of Homoscedasticity cannot be attained by the series of stock returns. In other words, the variances and covariances of stock returns are found to be changing over time and not homoscedastic (constant). Fama (1965) and Mandelbrot (1966) have discovered the existence of volatility clustering (large changes in returns followed by similar changes and small changes also followed by small changes) which give rise to changing conditional variance (heteroscedasticity). Lagged returns are also included in the model in order to overcome the problem of auto-correlation. In our effort to improve the model, we have employed the generalised version of ARCH model as suggested by Bollerslev (1986). The specifications of the models employed are given as:

$$\mathrm{R}_t = \alpha_M D_{Mt} + \alpha_T D_{Tt} + \alpha_W D_{Wt} + \alpha_{Th} D_{Tht} + \alpha_F D_{Ft} + \alpha_i R_{t-i} + \varepsilon_t$$

$$\sigma^2{}_t = \alpha_M D_{Mt} + \alpha_T D_{Tt} + \alpha_W D_{Wt} + \alpha_{Th} D_{Tht} + \alpha_F D_{Ft} + \alpha_1 u^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1}$$

Where R_t is the stock return series under investigation, D_{Mt}, D_{Tt}, D_{Wt}, D_{Tht}, D_{Ft} represent the binary dummy variables for Monday through Friday; for Monday returns the dummy variable is equal to 1 and all others are equal to zero. The coefficients attached to the dummy variables measure the average deviation of the week's days' mean return from other days' mean returns. If any coefficient is found to be significant, then the days' mean return attached to the coefficient has deviated from that of the others and thus, there is the existence of the day-of-the-week effect. A constant is not included in the regression model in order to avoid the dummy variable trap. The second equation is the generalised ARCH employed where $\sigma^2{}_t$ is the conditional variance, $\alpha_1 u^2{}_{t-1}$ is the ARCH term and $\beta_1 \sigma^2{}_{t-1}$ is the generalised ARCH term.

The coefficients of the ARCH and GARCH terms are referred to as alpha and beta respectively.

Details of the regression results are presented in Table 6.2 below.

Table 8.2 Generalised ARCH (1,1) Regression Results for the Test of Day-Of-The-Week (DOTW) Effect on the Return Series under study

		Monday	**Tuesday**	**Wednes.**	**Thursday**	**Friday**	**r (-1)**	**Alpha1**	**Beta1**
FTSE All Sh.	Coefficient	0.0001	0.0012	0.0002	0.0004	0.0004	0.0282	0.1262	0.8396
	Stand. Error	0.0008	0.0006	0.0006	0.0007	0.0008	0.0404	0.0258	0.0306
	z-Statistic	0.1455	1.9132	0.3663	0.5782	0.5114	0.6977	4.8895	27.352
	Probability	0.8842	0.0557	0.7141	0.5631	0.609	0.4853	0.0000*	0.0000*
FTSE100	Coefficient	0.0001	0.0013	0.0002	0.0004	0.0002	0.0105	0.1277	0.8375
	Stand. Error	0.0009	0.0007	0.0007	0.0008	0.0008	0.0405	0.0266	0.0317
	z-Statistic	0.1345	1.9170	0.3157	0.4732	0.2111	0.2600	4.8031	26.404
	Probability	0.8930	0.0552	0.7522	0.6361	0.8328	0.7949	0.0000*	0.0000*
FTSE UK O&G	Coefficient	0.0005	0.0014	-0.0003	-0.0002	0.0002	0.0063	0.0987	0.8660
	Stand. Error	0.0011	0.0008	0.0009	0.0009	0.0011	0.0407	0.0241	0.0359
	z-Statistic	0.4081	1.7698	-0.3415	-0.1876	-0.178	0.1551	4.0917	24.124
	Probability	0.6832	0.0768	0.7328	0.8512	0.8584	0.8768	0.0000*	0.0000*
FTSE UK OGP	Coefficient	0.0004	0.0014	-0.0003	-0.0002	0.0002	0.0047	0.0991	0.8650
	Stand. Error	0.0011	0.0008	0.0009	0.0009	0.0011	0.0406	0.0243	0.0363
	z-Statistic	0.3982	1.7753	-0.3195	-0.1973	-0.225	0.1170	4.0821	23.798
	Probability	0.6905	0.0758	0.7493	0.8436	0.8214	0.9069	0.0000*	0.0000*
FTSE AIM OG	Coefficient	-0.0032	-0.0004	0.0013	0.0002	0.0036	0.1573	0.1937	0.7650
	Stand. Error	0.0011	0.0010	0.0012	0.0010	0.0012	0.0415	0.0269	0.0277
	z-Statistic	-3.0299	-0.4022	1.1395	0.1678	2.9516	3.7945	7.2036	27.583
	Probability	0.0024*	0.6875	0.2545	0.8667	0.003*	0.001*	0.0000*	0.0000*
AMEC	Coefficient	-0.0001	0.0020	0.0008	-0.0003	0.0011	0.0064	0.1235	0.7835
	Stand. Error	0.0015	0.0012	0.0013	0.0012	0.0014	0.0417	0.0284	0.0482
	z-Statistic	-0.0564	1.5673	0.6311	-0.2409	0.8064	0.1544	4.3475	16.250
	Probability	0.9551	0.1170	0.5279	0.8097	0.4200	0.8773	0.0000*	0.0000*
BG GROUP	Coefficient	0.0006	0.0017	-0.0019	-0.0006	0.0001	0.0105	0.0627	0.7959
	Stand. Error	0.0018	0.0015	0.0015	0.0015	0.0017	0.0412	0.0277	0.0849
	z-Statistic	0.3371	1.1818	-1.2380	-0.3881	0.0811	0.2549	2.2622	9.3789
	Probability	0.7361	0.2373	0.2157	0.6979	0.9353	0.7988	0.023**	0.0000*
BP	Coefficient	0.0002	0.0012	0.0001	-0.0008	0.0003	0.0059	0.1089	0.8570
	Stand. Error	0.0014	0.0010	0.0011	0.0012	0.0014	0.0367	0.0150	0.0234
	z-Statistic	0.1760	1.2578	0.0750	-0.6432	-0.235	0.1619	7.2360	36.660
	Probability	0.8603	0.2085	0.9402	0.5201	0.8142	0.8714	0.0000*	0.0000*
CAIRN	Coefficient	-0.0007	0.0007	-0.0011	-0.0007	0.0002	0.0008	0.0508	0.9306
	Stand. Error	0.0018	0.0015	0.0016	0.0014	0.0018	0.0376	0.0144	0.0241
	T-Statistic	-0.3765	0.4543	-0.6764	-0.4705	0.0880	-0.022	3.5244	38.599
	Probability	0.7065	0.6496	0.4988	0.6380	0.9298	0.9820	0.0004*	0.0000*
DRAGON	Coefficient	0.0006	0.0002	0.0015	0.0016	0.0003	0.0725	0.0643	0.8905
	Stand. Error	0.0014	0.0017	0.0016	0.0017	0.0016	0.0411	0.0156	0.0304
	z-Statistic	0.4579	0.1119	0.9771	0.9369	-0.173	1.7633	4.1155	29.302
	Probability	0.6470	0.9109	0.3285	0.3488	0.8623	0.0778	0.0000*	0.0000*
FORTUNE	Coefficient	-0.0008	-0.0004	-0.0007	-0.0005	-0.008	-0.362	0.1059	0.7745
	Stand. Error	0.0030	0.0042	0.0046	0.0032	0.004	0.0429	0.0189	0.0305
	z-Statistic	-0.2501	-0.0970	-0.1535	-0.1639	-0.161	-8.444	5.5978	25.369
	Probability	0.8025	0.9227	0.8780	0.8698	0.8717	0.000*	0.0000*	0.0000*
HUNTING	Coefficient	-0.0004	0.0014	0.0000	0.0012	0.0021	0.0197	0.1820	0.4291
	Stand. Error	0.0016	0.0017	0.0020	0.0017	0.0016	0.0398	0.0382	0.1392

	z-Statistic	-0.2511	0.8065	0.0230	0.7141	1.3235	0.4950	4.7623	3.0830
	Probability	0.8018	0.4199	0.9817	0.4752	0.1857	0.6206	0.0000*	0.0020*
PREMIER	Coefficient	0.0007	-0.0013	0.0003	0.0019	0.0013	-0.033	0.0760	0.8881
	Stand. Error	0.0016	0.0014	0.0016	0.0014	0.0016	0.0385	0.0196	0.0253
	z-Statistic	0.4137	-0.9750	0.1626	1.3710	0.7896	-0.875	3.8770	35.032
	Probability	0.6791	0.3296	0.8708	0.1704	0.4298	0.3811	0.0001*	0.0000*
RDSB	Coefficient	0.0004	0.0016	0.0004	-0.0001	-0.001	-0.001	0.1004	0.8618
	Stand. Error	0.0011	0.0009	0.0009	0.0009	0.0011	0.0414	0.0250	0.0364
	z-Statistic	0.3888	1.8724	0.4015	-0.1147	-0.070	-0.035	4.0154	23.647
	Probability	0.6974	0.0612	0.6881	0.9087	0.9436	0.9716	0.0001*	0.0000*
TULLOW	Coefficient	0.0002	0.0006	-0.0015	-0.0013	0.0023	-0.007	0.0935	0.8460
	Stand. Error	0.0020	0.0015	0.0015	0.0016	0.0017	0.0410	0.0211	0.0371
	z-Statistic	0.1086	0.3896	-0.9966	-0.7654	1.3769	-0.183	4.4249	22.797
	Probability	0.9135	0.6968	0.3190	0.4441	0.1685	0.8542	0.0000*	0.0000*
AMINEX	Coefficient	-0.0005	0.0004	0.0036	-0.0081	-0.004	-0.218	0.1025	0.8201
	Stand. Error	0.0044	0.0056	0.0044	0.0049	0.0061	0.0427	0.0143	0.0161
	z-Statistic	-0.1062	0.0731	0.8267	-1.6461	-0.681	-5.110	7.1804	51.056
	Probability	0.9154	0.9417	0.4084	0.0997	0.4958	0.000*	0.0000*	0.0000*
JKX O&G	Coefficient	0.0028	-0.0027	-0.0016	-0.0002	-0.004	0.0815	0.0474	0.9396
	Stand. Error	0.0022	0.0017	0.0019	0.0018	0.0020	0.0364	0.0111	0.0109
	z-Statistic	1.3079	-1.5837	-0.8504	-0.1201	-2.033	2.2397	4.2677	86.453
	Probability	0.1909	0.1133	0.3951	0.9044	0.04**	0.02**	0.0000*	0.0000*
SOCO INTL.	Coefficient	-0.0028	-0.0009	-0.0002	0.0015	0.0011	-0.031	0.2076	0.3555
	Stand. Error	0.0016	0.0017	0.0018	0.0019	0.0020	0.0500	0.0440	0.1036
	z-Statistic	-1.7033	-0.4969	-0.1134	0.7904	0.5278	-0.634	4.7163	3.4316
	Probability	0.0885	0.6193	0.9097	0.4293	0.5977	0.5261	0.0000*	0.0006*
WOOD GRP	Coefficient	0.0002	0.0026	-0.0006	0.0006	0.0036	0.0445	0.0604	0.8889
	Stand. Error	0.0018	0.0016	0.0020	0.0016	0.0018	0.0361	0.0138	0.0285
	z-Statistic	0.1189	1.6251	-0.2886	0.3957	2.0092	1.2348	4.3799	31.244
	Probability	0.9054	0.1041	0.7729	0.6923	0.0445	0.2169	0.0000*	0.0000*
AFREN	Coefficient	0.0005	0.0038	-0.0020	0.0027	0.0014	0.0416	0.0638	0.9214
	Stand. Error	0.0026	0.0024	0.0023	0.0018	0.0025	0.0394	0.0111	0.0114
	z-Statistic	0.1964	1.6102	-0.8588	1.4797	0.5623	1.0551	5.7527	80.893
	Probability	0.8443	0.1073	0.3905	0.1389	0.5739	0.2914	0.0000*	0.0000*
HARDY O&G	Coefficient	-0.0015	-0.0037	-0.0002	-0.0043	0.0016	-0.091	0.1316	0.6442
	Stand. Error	0.0026	0.0025	0.0022	0.0023	0.0026	0.0464	0.0357	0.1103
	z-Statistic	-0.5625	-1.4622	-0.0753	-1.8934	0.6100	-1.979	3.6834	5.8429
	Probability	0.5738	0.1437	0.9399	0.0583	0.5419	0.04**	0.0002*	0.0000*
RDSA	Coefficient	0.0001	0.0014	-0.0001	0.0001	-0.003	0.0355	0.0939	0.8487
	Stand. Error	0.0011	0.0008	0.0009	0.0008	0.0010	0.0402	0.0245	0.0438
	z-Statistic	0.0604	1.6520	-0.1199	0.1349	-0.298	0.8833	3.8387	19.373
	Probability	0.9518	0.0985	0.9046	0.8927	0.7657	0.3771	0.0001*	0.0000*
PETROFAC	Coefficient	0.0021	0.0014	-0.0005	0.0014	0.0003	-0.046	0.0713	0.9066
	Stand. Error	0.0015	0.0015	0.0015	0.0015	0.0018	0.0363	0.0158	0.0201
	z-Statistic	1.3828	0.9510	-0.3302	0.8775	0.1455	-1.267	4.5070	45.165
	Probability	0.1667	0.3416	0.7412	0.3802	0.8843	0.2049	0.0000*	0.0000*
SALAMANDER	Coefficient	0.0002	0.0004	0.0027	0.0002	-0.005	0.0794	0.2946	0.0581
	Stand. Error	0.0020	0.0018	0.0016	0.0017	0.0017	0.0404	0.0565	0.0826
	z-Statistic	0.0766	0.2344	1.7155	0.1372	-0.290	1.9622	5.2128	0.7032
	Probability	0.9389	0.8147	0.0863	0.8909	0.7714	0.04**	0.0000*	0.4819
LAMPRELL	Coefficient	-0.0025	-0.0065	0.0028	-0.0025	0.0058	-0.084	-0.0062	1.0125
	Stand. Error	0.0026	0.0012	0.0001	0.0023	0.0022	0.0043	0.0002	0.0008
	z-Statistic	-0.9603	-5.2635	50.0250	-1.0775	2.592	-19.39	-28.715	1226.1
	Probability	0.3369	0.0000*	0.0000*	0.2813	0.009*	0.000*	0.000*	0.000*
ENDEAVOR	Coefficient	-0.0008	-0.0019	-0.0028	0.0022	-0.004	-0.005	0.0204	0.6597
	Stand. Error	0.0049	0.0049	0.0058	0.0121	0.0055	0.2054	0.0117	0.1868
	z-Statistic	-0.1600	-0.3938	-0.4909	0.1815	-0.878	-0.025	1.7441	3.5326
	Probability	0.8729	0.6938	0.6235	0.8560	0.3799	0.9798	0.0811	0.004*
CADOGAN	Coefficient	0.0003	-0.0038	-0.0033	-0.0013	0.0043	-0.176	0.1431	0.5097
	Stand. Error	0.0032	0.0034	0.0033	0.0031	0.0035	0.0453	0.0307	0.1161
	z-Statistic	0.1079	-1.1277	-0.9885	-0.4184	1.2397	-3.899	4.6588	4.3897
	Probability	0.9141	0.2595	0.3229	0.6756	0.2151	0.001*	0.000*	0.000*

HERITAGE	Coefficient	-0.0036	0.0038	-0.0028	-0.0023	0.0002	0.0651	0.0737	0.7030
	Stand. Error	0.0032	0.0025	0.0026	0.0027	0.0035	0.0419	0.0202	0.0401
	z-Statistic	-1.1405	1.4807	-1.0784	-0.8314	0.0652	1.5521	3.6587	17.538
	Probability	0.2541	0.1387	0.2808	0.4057	0.9481	0.1206	0.0003*	0.0000*
KENTZ	Coefficient	0.0009	0.0013	-0.0009	0.0028	0.0023	0.1139	0.0812	0.8718
	Stand. Error	0.0018	0.0015	0.0014	0.0013	0.0015	0.0360	0.0125	0.0215
	z-Statistic	0.4795	0.8965	-0.6315	2.2086	1.5204	3.1678	6.4743	40.604
	Probability	0.6316	0.3700	0.5277	0.027**	0.1284	0.001*	0.0000*	0.0000*
EXILLON	Coefficient	-0.0023	-0.0002	0.0025	0.0001	0.0046	0.0776	0.2585	0.6196
	Stand. Error	0.0025	0.0024	0.0022	0.0021	0.0022	0.0416	0.0437	0.0527
	z-Statistic	-0.9213	-0.0918	1.1319	0.0290	2.1434	1.8657	5.9150	11.747
	Probability	0.3569	0.9268	0.2577	0.9768	0.03**	0.0621	0.0000*	0.0000*

NOTE: * and ** denote level of significance at 1% and 5% respectively. The coefficients are deemed to be significant if their z-Statistic's value is greater than its critical value or if probability value is less than 0.01 and 0.05. Probability values are used for interpretation in this case.

Source: Author (2015)

The regression results are presented in Table 8.2 and most of the week's days' coefficients are not significant at both 1% and 5% levels of significance. This indicates the absence of a day-of-the-week effect in the stock returns. However, the FTSE AIM Oil and Gas index return series has significant Monday and Friday coefficients which are signs of a day-of-the-week effect as shown by the results of the F-Test, the Kruskal Wallis test, and the Tukey tests depicted in Table 8.1. Similarly, JKX Oil and Gas has recorded a significant coefficient on Friday at 5% level of significance. Lamprell Plc stock returns also have significant coefficients on Tuesday, Wednesday and Friday at 1% level of significance. In summary, only coefficients in three stocks (FTSE AIM Oil and Gas index, JKX Oil and Gas, Lamprell) were found to be significant which is indicative of the existence of a day-of-the-week effect. The results from JKX Oil and Gas index and Lamprell Plc contradict that of the F-Test, the Kruskal Wallis test, and the Tukey tests which showed no evidence of day-of-the-week anomalies. The coefficients of both the ARCH and GARCH terms represented in the results as 'Alpha 1' and 'Beta 1' were found to be strongly significant at 1% level which is an additional sign of model appropriateness.

In testing for the monthly effect, binary dummy variables were also created for the monthly (January through December) stock returns as 12 independent variables (constant parameter would not be included in order to avoid dummy variable trap). Both the dummy variables (independent variables) and the monthly return series (dependent variables) are subjected to a regression model using GARCH specifications. The specifications of the models employed are given as:

$$\mathrm{R}_t = \alpha_J D_{Jt} + \alpha_F D_{Ft} + \alpha_M D_{Mt} + \alpha_A D_{At} + \alpha_{My} D_{Myt} + \alpha_{Jn} D_{Jnt} + \alpha_{Jy} D_{Jyt} + \alpha_{Au} D_{Aut} + \alpha_S D_{St} + \alpha_O D_{Ot} + \alpha_N D_{Nt} + \alpha_D D_{Dt} + \alpha_i R_{t-i} + \varepsilon_t$$

$$\sigma^2{}_t = \alpha_J D_{Jt} + \alpha_F D_{Ft} + \alpha_M D_{Mt} + \alpha_A D_{At} + \alpha_{My} D_{Myt} + \alpha_{Jn} D_{Jnt} + \alpha_{Jy} D_{Jyt} + \alpha_{Au} D_{Aut} + \alpha_S D_{St} + \alpha_O D_{Ot} + \alpha_N D_{Nt} + \alpha_D D_{Dt} + \alpha_1 u^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1}$$

Where R_t is the monthly stock return series under investigation, $D_{Jt} + D_{Ft} + D_{Mt} + D_{At} + D_{Myt} + D_{Jnt} + D_{Jyt} + D_{Aut} + D_{St} + D_{Ot} + D_{Nt} + D_{Dt}$ represent the binary dummy variables for January through December; for January returns the dummy variable is equal to 1 and all others are equal to zero and it goes the same way for the remaining months. The coefficients attached to the dummy variables measure the average deviation of a given month's mean return from other months' mean returns. If any coefficient is found to be significant, then the monthly mean return attached to the coefficient has deviated from that of the others and thus, there is the existence of the monthly effect. The second equation is the generalised ARCH employed where $\sigma^2{}_t$ is the conditional variance, $\alpha_1 u^2{}_{t-1}$ is the ARCH term and $\beta_1 \sigma^2{}_{t-1}$ is the generalised ARCH term. The coefficients of the ARCH and GARCH terms are referred to as alpha and beta respectively.

Details of the regression results are presented in Table 8.3 below.

Table 8.3 Generalised ARCH (1,1) Regression Results for the Test of Monthly Effect on the Return Series under study

FTSE All Sh.		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0408	0.0070	-0.0039	0.0146	0.0232	0.0100	-0.0043
	Stand. Error	0.0060	0.0083	0.0080	0.0114	0.0051	0.0037	0.0047
	z-Statistic	6.8522	0.8371	-0.4810	1.2885	4.5330	2.6641	-0.9084
	Probability	0.0000*	0.4025	0.6305	0.1976	0.0000*	0.0077*	0.3637
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0017	0.0039	0.0086	0.0267	-0.012	1.5777	0.0133
	Stand. Error	0.0062	0.0065	0.0066	0.0063	0.0085	0.3758	0.0552
	z-Statistic	-0.2701	0.5985	1.3008	4.2321	-1.418	4.1981	0.2419
	Probability	0.7871	0.5495	0.1933	0.0000*	0.1560	0.0000*	0.8089
FTSE100		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0388	0.0047	-0.0028	0.0141	0.0254	0.0133	-0.0004
	Stand. Error	0.0070	0.0085	0.0103	0.0125	0.0067	0.0056	0.0055
	z-Statistic	5.5502	0.5515	-0.2753	1.1250	3.7766	2.3817	-0.0764
	Probability	0.0000*	0.5813	0.7831	0.2606	0.0002*	0.017**	0.9391
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0016	-0.0008	0.0081	0.0240	-0.009	1.2737	0.0222
	Stand. Error	0.0073	0.0084	0.0081	0.0079	0.0092	0.3665	0.0963
	z-Statistic	-0.2209	-0.0894	1.0022	3.0453	-1.048	3.4748	0.2307
	Probability	0.8251	0.9288	0.3162	0.0023*	0.2945	0.0005*	0.8175
FTSE UK O&G		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0230	-0.0001	-0.0114	0.0175	0.0341	-0.017	0.0121
	Stand. Error	0.0154	0.0118	0.0181	0.0199	0.0134	0.0125	0.0217
	z-Statistic	1.4933	-0.0052	-0.6313	0.8779	2.5459	-1.383	0.5561
	Probability	0.1354	0.9959	0.5279	0.3800	0.0109	0.1666	0.5781
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0076	-0.0267	-0.0099	0.0278	-0.013	0.4201	0.3737
	Stand. Error	0.0224	0.0150	0.0157	0.0164	0.0309	0.2717	0.2961
	z-Statistic	-0.3411	-1.7777	-0.6302	1.6973	-0.425	1.5465	1.2621
	Probability	0.7331	0.0755	0.5285	0.0896	0.6705	0.1220	0.2069
FTSE UK OGP		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0222	-0.0009	-0.0112	0.0157	0.0365	-0.016	0.0145
	Stand. Error	0.0147	0.0118	0.0185	0.0194	0.0130	0.0125	0.0206
	z-Statistic	1.5065	-0.0787	-0.6034	0.8058	2.8088	-1.285	0.7034
	Probability	0.1319	0.9373	0.5462	0.4204	0.0050*	0.1985	0.4818
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0097	-0.0261	-0.0118	0.0259	-0.013	0.4374	0.3564
	Stand. Error	0.0230	0.0149	0.0156	0.0152	0.0325	0.2701	0.2869
	z-Statistic	-0.4207	-1.7584	-0.7558	1.7040	-0.407	1.6194	1.2424
	Probability	0.6740	0.0787	0.4498	0.0884	0.6836	0.1054	0.2141
FTSE AIM OG		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0158	0.0145	-0.0040	-0.0113	-0.0038	-0.032	-0.0191
	Stand. Error	0.0684	0.0191	0.0316	0.0229	0.0217	0.0196	0.0377
	z-Statistic	0.2304	0.7571	-0.1260	-0.4948	-0.1771	-1.634	-0.5053
	Probability	0.8178	0.4490	0.8997	0.6208	0.8595	0.1021	0.6133
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0185	0.0131	0.0037	-0.0352	-0.022	0.3563	0.5448
	Stand. Error	0.0196	0.0245	0.0197	0.0265	0.0295	0.1757	0.1891
	z-Statistic	0.9463	0.5358	0.1858	-1.3244	-0.755	2.0280	2.8806
	Probability	0.3440	0.5921	0.8526	0.1854	0.4501	0.042**	0.0040
AMEC		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	-0.0101	0.0493	0.0001	0.0286	0.0237	0.0023	-0.0179
	Stand. Error	0.0444	0.0217	0.0253	0.0448	0.0433	0.0191	0.0290
	z-Statistic	-0.2274	2.2714	0.0031	0.6378	0.5470	0.1194	-0.6162
	Probability	0.8201	0.0231**	0.9975	0.5236	0.5844	0.9050	0.5378
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0157	-0.0022	-0.0027	0.0155	-0.018	0.0678	0.8735
	Stand. Error	0.0220	0.0286	0.0183	0.0250	0.0255	0.0710	0.0856

	z-Statistic	0.7151	-0.0756	-0.1480	0.6218	-0.706	0.9549	10.202
	Probability	0.4746	0.9398	0.8823	0.5341	0.4797	0.3396	0.0000*
BG GROUP		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0387	0.0116	0.0496	0.0314	0.0041	-0.009	0.0147
	Stand. Error	0.0206	0.0171	0.0196	0.0273	0.0289	0.0177	0.0201
	z-Statistic	1.8723	0.6778	2.5246	1.1497	0.1435	-0.540	0.7333
	Probability	0.0612	0.4979	0.0116	0.2503	0.8859	0.5887	0.4634
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0174	0.0055	-0.0178	-0.0124	-0.002	-0.0772	0.5346
	Stand. Error	0.0268	0.0308	0.0173	0.0182	0.0190	0.0722	0.7583
	z-Statistic	-0.6516	0.1792	-1.0261	-0.6835	-0.110	-1.0688	0.7050
	Probability	0.5147	0.8578	0.3048	0.4943	0.9122	0.2852	0.4808
BP		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0118	0.0045	-0.0088	0.0106	0.0189	-0.006	0.0065
	Stand. Error	0.0186	0.0132	0.0249	0.0151	0.0166	0.0201	0.0212
	z-Statistic	0.6345	0.3425	-0.3540	0.7054	1.1370	-0.333	0.3081
	Probability	0.5257	0.7320	0.7233	0.4806	0.2555	0.7385	0.7580
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0243	-0.0421	-0.0127	0.0510	-0.017	0.5463	0.1848
	Stand. Error	0.0198	0.0158	0.0189	0.0152	0.0401	0.2157	0.2707
	z-Statistic	-1.2270	-2.6575	-0.6741	3.3676	-0.429	2.5328	0.6830
	Probability	0.2198	0.0079*	0.5003	0.0008*	0.6674	0.011**	0.4946
CAIRN		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0442	-0.0382	-0.0018	0.0450	0.0321	0.0088	-0.0231
	Stand. Error	0.0303	0.0287	0.0568	0.0297	0.0589	0.0268	0.0593
	z-Statistic	1.4584	-1.3311	-0.0312	1.5152	0.5458	0.3283	-0.3895
	Probability	0.1447	0.1832	0.9751	0.1297	0.5852	0.7427	0.6969
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0006	0.0096	-0.0415	-0.0475	0.0320	0.0341	0.5523
	Stand. Error	0.0263	0.0566	0.0220	0.0285	0.0373	0.1084	0.4568
	z-Statistic	0.0232	0.1695	-1.8875	-1.6676	0.8584	0.3145	1.2090
	Probability	0.9815	0.8654	0.0591	0.0954	0.3907	0.7532	0.2267
DRAGON		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0279	0.0746	0.0491	0.0396	-0.0092	-0.077	0.0319
	Stand. Error	0.0339	0.0513	0.0337	0.0372	0.0332	0.0203	0.0178
	z-Statistic	0.8228	1.4546	1.4563	1.0662	-0.2785	-3.793	1.7914
	Probability	0.4106	0.1458	0.1453	0.2863	0.7807	0.0001*	0.0732
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0096	0.0232	-0.0520	0.0336	-0.019	0.5872	0.4351
	Stand. Error	0.0313	0.0477	0.0257	0.0224	0.0399	0.2921	0.2201
	z-Statistic	-0.3057	0.4870	-2.0259	1.4968	-0.495	2.0102	1.9765
	Probability	0.7599	0.6263	0.0428	0.1344	0.6206	0.044**	0.048**
FORTUNE		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0960	-0.1030	0.0505	-0.0361	0.0667	-0.027	-0.0145
	Stand. Error	0.0254	0.0362	0.0370	0.0326	0.0418	0.0399	0.0502
	z-Statistic	3.7838	-2.8421	1.3666	-1.1074	1.5981	-0.681	-0.2896
	Probability	0.0002*	0.0045*	0.1718	0.2681	0.1100	0.4956	0.7721
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0391	0.0672	-0.0211	0.0045	-0.045	-0.0731	0.5185
	Stand. Error	0.0503	0.0531	0.0406	0.0276	0.0583	0.0172	0.7418
	z-Statistic	-0.7775	1.2650	-0.5199	0.1643	-0.779	-4.2597	0.6989
	Probability	0.4368	0.2059	0.6031	0.8695	0.4355	0.0000*	0.4846
HUNTING		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0689	0.0354	0.0272	0.0781	-0.0298	-0.047	-0.0118
	Stand. Error	0.0134	0.0178	0.0177	0.0164	0.0148	0.0112	0.0108
	z-Statistic	5.1504	1.9935	1.5386	4.7462	-2.0092	-4.206	-1.0943
	Probability	0.0000*	0.0462**	0.1239	0.0000*	0.044**	0.0000*	0.2738
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0480	0.0422	-0.0133	0.0234	-0.010	0.2806	-1.0275
	Stand. Error	0.0108	0.0134	0.0117	0.0133	0.0186	0.0590	0.0234
	z-Statistic	4.4349	3.1587	-1.1420	1.7586	-0.545	4.7597	-43.932
	Probability	0.0000*	0.0016*	0.2534	0.0786	0.5851	0.0000*	0.0000*
PREMIER		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0215	0.0424	0.0075	0.0216	0.0222	-0.046	-0.0009

	Stand. Error	0.0453	0.0216	0.0480	0.0286	0.0279	0.0342	0.0308
	z-Statistic	0.4748	1.9677	0.1569	0.7581	0.7943	-1.364	-0.0279
	Probability	0.6349	0.0491	0.8753	0.4484	0.4270	0.1725	0.9778
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0463	-0.0219	-0.0229	0.0269	-0.002	0.4523	0.4092
	Stand. Error	0.0233	0.0244	0.0317	0.0216	0.0279	0.2459	0.2400
	z-Statistic	1.9910	-0.8948	-0.7203	1.2467	-0.103	1.8391	1.7050
	Probability	0.0465	0.3709	0.4714	0.2125	0.9179	0.0659	0.0882
RDSB		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0358	-0.0032	-0.0136	0.0012	0.0417	-0.019	0.0207
	Stand. Error	0.0196	0.0129	0.0152	0.0256	0.0246	0.0122	0.0137
	z-Statistic	1.8288	-0.2471	-0.8915	0.0457	1.6994	-1.627	1.5124
	Probability	0.0674	0.8048	0.3727	0.9635	0.0892	0.1037	0.1304
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0000	-0.0080	-0.0222	0.0154	-0.021	0.1234	0.8433
	Stand. Error	0.0210	0.0258	0.0185	0.0167	0.0360	0.0947	0.1283
	z-Statistic	0.0023	-0.3099	-1.2012	0.9257	-0.582	1.3024	6.5727
	Probability	0.9982	0.7567	0.2297	0.3546	0.5600	0.1928	0.0000*
TULLOW		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0281	-0.0007	0.0518	0.0494	-0.0245	0.0147	0.0361
	Stand. Error	0.0434	0.0299	0.0168	0.0427	0.0223	0.0268	0.0247
	z-Statistic	0.6486	-0.0222	3.0722	1.1552	-1.0955	0.5491	1.4573
	Probability	0.5166	0.9823	0.0021*	0.2480	0.2733	0.5829	0.1450
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0467	0.0113	0.0462	-0.0333	0.0240	0.3114	-0.3004
	Stand. Error	0.0252	0.0362	0.0271	0.0356	0.0367	0.1704	0.2587
	z-Statistic	-1.8558	0.3137	1.7064	-0.9343	0.6526	1.8277	-1.1612
	Probability	0.0635	0.7537	0.0879	0.3501	0.5140	0.0676	0.2456
AMINEX		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.1035	-0.0665	0.0415	0.0076	-0.0301	-0.114	-0.0038
	Stand. Error	0.0385	0.0446	0.0007	0.0455	0.0505	0.0395	0.0845
	z-Statistic	2.6894	-1.4930	58.3129	0.1668	-0.5964	-2.893	-0.0452
	Probability	0.0072*	0.1354	0.0000*	0.8675	0.5509	0.0038*	0.9640
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0540	0.0379	0.0068	-0.0056	-0.042	-0.0593	1.0810
	Stand. Error	0.0692	0.0654	0.0685	0.0510	0.0465	0.0204	0.0410
	z-Statistic	-0.7806	0.5798	0.0999	-0.1094	-0.904	-2.9102	26.355
	Probability	0.4350	0.5621	0.9204	0.9129	0.3660	0.0036*	0.0000*
JKX O&G		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0070	-0.0198	0.0199	0.0415	0.0010	-0.054	-0.0309
	Stand. Error	0.0482	0.0401	0.0377	0.0795	0.0451	0.0400	0.0520
	z-Statistic	0.1442	-0.4934	0.5266	0.5222	0.0214	-1.350	-0.5941
	Probability	0.8853	0.6217	0.5985	0.6015	0.9829	0.1768	0.5524
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0077	-0.0598	-0.0103	0.0104	-0.028	0.4527	0.2376
	Stand. Error	0.0242	0.0485	0.0475	0.0440	0.0774	0.2215	0.2403
	z-Statistic	-0.3177	-1.2328	-0.2172	0.2374	-0.366	2.0434	0.9886
	Probability	0.7507	0.2177	0.8280	0.8123	0.7144	0.041**	0.3229
SOCO INTL.		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0011	0.0228	0.0591	0.0006	0.0101	-0.010	-0.0177
	Stand. Error	0.0039	0.0389	0.0249	0.0156	0.0403	0.0401	0.0230
	z-Statistic	0.2807	0.5848	2.3741	0.0352	0.2519	-0.269	-0.7697
	Probability	0.7789	0.5587	0.017**	0.9719	0.8011	0.7875	0.4415
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0438	0.0199	-0.0084	-0.0351	-0.017	-0.1010	1.0605
	Stand. Error	0.0389	0.0301	0.0290	0.0266	0.0398	0.0527	0.0410
	z-Statistic	1.1263	0.6593	-0.2904	-1.3234	-0.447	-1.9170	25.877
	Probability	0.2600	0.5097	0.7715	0.1857	0.6545	0.0552	0.0000*
WOOD GRP		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	-0.0043	0.0630	0.0386	0.0333	0.0076	-0.019	0.0386
	Stand. Error	0.0257	0.0281	0.0278	0.0425	0.0313	0.0200	0.0405
	z-Statistic	-0.1654	2.2405	1.3887	0.7825	0.2427	-0.955	0.9533
	Probability	0.8686	0.0251**	0.1649	0.4339	0.8082	0.3393	0.3404
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**

	Coefficient	0.0289	0.0010	-0.0013	-0.0101	-0.006	0.3215	0.1257
	Stand. Error	0.0210	0.0298	0.0239	0.0345	0.0310	0.1795	0.3387
	z-Statistic	1.3764	0.0319	-0.0525	-0.2924	-0.217	1.7910	0.3712
	Probability	0.1687	0.9745	0.9581	0.7700	0.8278	0.0733	0.7105
AFREN		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0487	0.0684	0.0051	0.0737	-0.0252	-0.017	-0.0776
	Stand. Error	0.0925	0.0412	0.0574	0.0479	0.0572	0.0382	0.1045
	z-Statistic	0.5262	1.6618	0.0886	1.5379	-0.4405	-0.454	-0.7427
	Probability	0.5988	0.0966	0.9294	0.1241	0.6595	0.6497	0.4577
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0458	0.0243	-0.0018	0.0544	-0.012	0.2948	0.6667
	Stand. Error	0.0326	0.0498	0.0638	0.0613	0.0692	0.1751	0.1595
	z-Statistic	1.4056	0.4881	-0.0276	0.8882	-0.184	1.6833	4.1805
	Probability	0.1599	0.6255	0.9780	0.3744	0.8538	0.0923	0.0000*
HARDY O&G		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0317	0.0289	0.0698	0.0287	0.0688	0.0145	-0.0760
	Stand. Error	0.0606	0.0528	0.0471	0.0453	0.0413	0.0412	0.0913
	z-Statistic	0.5226	0.5478	1.4806	0.6346	1.6659	0.3509	-0.8329
	Probability	0.6013	0.5838	0.1387	0.5257	0.0957	0.7256	0.4049
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0067	0.0321	-0.0200	-0.0882	-0.036	-0.0785	1.0626
	Stand. Error	0.0438	0.0012	0.0362	0.0450	0.0476	0.0160	0.0366
	z-Statistic	0.1528	27.7045	-0.5536	-1.9588	-0.772	-4.9060	29.013
	Probability	0.8785	0.0000*	0.5799	0.0501	0.4398	0.0000*	0.0000*
RDSA		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0309	-0.0127	-0.0172	0.0045	0.0414	-0.008	0.0094
	Stand. Error	0.0208	0.0164	0.0151	0.0245	0.0199	0.0107	0.0121
	z-Statistic	1.4854	-0.7745	-1.1418	0.1853	2.0811	-0.772	0.7782
	Probability	0.1375	0.4386	0.2535	0.8530	0.0374	0.4398	0.4365
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0092	-0.0050	-0.0177	0.0145	-0.016	0.1855	0.7384
	Stand. Error	0.0186	0.0190	0.0269	0.0140	0.0196	0.1515	0.1952
	z-Statistic	0.4956	-0.2609	-0.6574	1.0342	-0.859	1.2247	3.7821
	Probability	0.6202	0.7942	0.5109	0.3010	0.3898	0.2207	0.0002*
PETROFAC		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0549	0.0179	0.0028	0.0897	-0.0071	-0.027	-0.0317
	Stand. Error	0.0477	0.0368	0.0245	0.0387	0.0695	0.0218	0.0374
	z-Statistic	1.1512	0.4879	0.1146	2.3206	-0.1028	-1.247	-0.8465
	Probability	0.2497	0.6256	0.9087	0.020**	0.9181	0.2122	0.3973
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0366	0.0521	0.0006	0.0163	-0.040	0.1448	0.7031
	Stand. Error	0.0245	0.0554	0.0352	0.0356	0.0243	0.1291	0.3062
	z-Statistic	1.4944	0.9410	0.0169	0.4578	-1.646	1.1216	2.2964
	Probability	0.1351	0.3467	0.9865	0.6471	0.0998	0.2620	0.021**
SALAMANDER		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0505	0.0142	0.0477	0.0260	0.0429	-0.106	-0.0384
	Stand. Error	0.0806	0.0520	0.0882	0.0543	0.0316	0.0432	0.0759
	z-Statistic	0.6268	0.2726	0.5410	0.4794	1.3589	-2.459	-0.5058
	Probability	0.5308	0.7852	0.5885	0.6317	0.1742	0.013**	0.6130
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0181	-0.0383	-0.0381	-0.0327	-0.045	0.0623	0.8178
	Stand. Error	0.0372	0.0536	0.0319	0.0644	0.0380	0.0747	0.2441
	z-Statistic	-0.4863	-0.7149	-1.1929	-0.5080	-1.205	0.8334	3.3496
	Probability	0.6267	0.4747	0.2329	0.6114	0.2282	0.4046	0.0008*
LAMPRELL		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.1146	-0.0120	0.0553	0.0028	0.1006	-0.138	0.0364
	Stand. Error	0.1298	0.0784	0.1626	0.2177	0.1474	0.0606	0.2057
	z-Statistic	0.8824	-0.1536	0.3401	0.0126	0.6824	-2.288	0.1769
	Probability	0.3776	0.8779	0.7338	0.9899	0.4950	0.022**	0.8596
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0326	0.0330	-0.0074	-0.1346	-0.145	-0.0375	0.5650
	Stand. Error	0.1073	0.1140	0.0814	0.0626	0.0704	0.0336	0.8210
	z-Statistic	-0.3038	0.2891	-0.0911	-2.1498	-2.061	-1.1190	0.6882
	Probability	0.7613	0.7725	0.9274	0.0316	0.039**	0.2632	0.4913

ENDEAVOR		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0968	0.1430	-0.0321	0.0327	0.0531	0.1160	0.1224
	Stand. Error	0.0397	0.0342	0.0632	0.0676	0.0295	0.0316	0.0643
	z-Statistic	2.4372	4.1838	-0.5081	0.4834	1.7979	3.6670	1.9045
	Probability	0.0148	0.0000*	0.6114	0.6288	0.0722	0.0002*	0.0568
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0896	-0.0710	-0.0152	-0.0173	-0.045	1.8223	0.4171
	Stand. Error	0.0959	0.0919	0.2581	0.1590	0.0508	0.6477	0.1062
	z-Statistic	-0.9345	-0.7732	-0.0590	-0.1087	-0.893	2.8135	3.9267
	Probability	0.3500	0.4394	0.9530	0.9134	0.3715	0.0049*	0.0001*
CADOGAN		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	-0.1548	0.0593	-0.0501	-0.0351	0.0487	0.0094	0.0253
	Stand. Error	0.0754	0.0564	0.0296	0.0710	0.1737	0.0790	0.1346
	z-Statistic	-2.0513	1.0514	-1.6901	-0.4944	0.2804	0.1186	0.1877
	Probability	0.040**	0.2931	0.0910	0.6210	0.7792	0.9056	0.8511
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0617	0.0045	-0.0708	-0.0346	0.0378	-0.0421	1.0149
	Stand. Error	0.0259	0.1504	0.0191	0.0140	0.0666	0.0236	0.0305
	z-Statistic	2.3805	0.0297	-3.7186	-2.4794	0.5676	-1.7875	33.238
	Probability	0.017**	0.9763	0.0002*	0.013**	0.5703	0.0738	0.0000*
HERITAGE		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0656	0.0304	-0.0017	0.0247	-0.0041	-0.033	0.0076
	Stand. Error	0.0687	0.0571	0.0427	0.0415	0.0386	0.0508	0.0072
	z-Statistic	0.9558	0.5330	-0.0400	0.5950	-0.1073	-0.664	1.0497
	Probability	0.3392	0.5940	0.9681	0.5518	0.9146	0.5063	0.2938
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0365	-0.0331	0.0286	-0.0075	-0.050	-0.0984	0.9393
	Stand. Error	0.0585	0.0527	0.0509	0.0544	0.0884	0.0330	0.1496
	z-Statistic	0.6243	-0.6286	0.5606	-0.1372	-0.572	-2.9838	6.2772
	Probability	0.5325	0.5296	0.5751	0.8909	0.5669	0.0028*	0.0000*
KENTZ		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0206	0.0599	-0.0206	0.0813	0.0356	-0.014	0.0050
	Stand. Error	0.0477	0.0565	0.0545	0.0540	0.0294	0.0372	0.0359
	z-Statistic	0.4315	1.0602	-0.3777	1.5057	1.2116	-0.381	0.1390
	Probability	0.6661	0.2890	0.7057	0.1321	0.2257	0.7032	0.8895
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0408	0.0572	-0.0095	-0.0437	0.0198	-0.0811	0.6528
	Stand. Error	0.0502	0.0339	0.0289	0.0256	0.0396	0.0434	0.5402
	z-Statistic	0.8129	1.6846	-0.3266	-1.7107	0.5013	-1.8693	1.2085
	Probability	0.4163	0.0921	0.7439	0.0871	0.6162	0.0616	0.2269
EXILLON		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	-0.0268	0.0017	0.0429	-0.0890	0.0371	-0.038	0.0347
	Stand. Error	0.0805	0.0616	0.1061	0.0305	0.0392	0.0679	0.0613
	z-Statistic	-0.3325	0.0271	0.4042	-2.9158	0.9464	-0.560	0.5660
	Probability	0.7395	0.9784	0.6861	0.0035*	0.3439	0.5749	0.5714
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0080	0.0062	0.0316	0.1347	0.0109	-0.1521	1.1208
	Stand. Error	0.1441	0.0981	0.0611	0.0643	0.1198	0.0516	0.0523
	z-Statistic	-0.0556	0.0634	0.5175	2.0947	0.0907	-2.9461	21.430
	Probability	0.9556	0.9494	0.6048	0.036**	0.9278	0.0032*	0.0000*
ENQUEST		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0114	0.0291	-0.0084	-0.0345	0.0132	-0.037	-0.0883
	Stand. Error	0.0141	0.0242	0.0108	0.0091	0.0024	0.0023	0.0045
	z-Statistic	0.8054	1.2023	-0.7768	-3.7927	5.4497	-15.91	-19.461
	Probability	0.4206	0.2293	0.4373	0.0001*	0.0000*	0.0000*	0.0000*
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0528	0.0003	0.0298	0.0350	0.0163	2.6344	0.0041
	Stand. Error	0.0112	0.0018	0.0019	0.0039	0.0085	0.6869	0.0041
	z-Statistic	4.6996	0.1865	15.9163	9.0220	1.9049	3.8353	0.9832
	Probability	0.0000*	0.8521	0.0000*	0.0000*	0.0568	0.0001*	0.3255
ESSAR		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	-0.1503	-0.1401	0.0221	0.0012	0.0144	0.0002	-0.0428
	Stand. Error	0.0396	0.0505	0.0388	0.0501	0.0403	0.0177	0.0141
	z-Statistic	-3.7992	-2.7740	0.5702	0.0233	0.3569	0.0132	-3.0471
	Probability	0.0001*	0.0055*	0.5685	0.9814	0.7211	0.9894	0.0023*

		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0490	-0.0565	0.0751	0.0851	-0.079	2.1236	-0.0139
	Stand. Error	0.0164	0.0147	0.0267	0.0371	0.0259	0.8063	0.0450
	z-Statistic	-2.9768	-3.8532	2.8174	2.2900	-3.068	2.6337	-0.3095
	Probability	0.0029*	0.0001*	0.0048*	0.022**	0.0022*	0.0084*	0.7569
GENEL		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	-0.0407	0.0110	-0.0127	-0.0534	0.0170	0.0257	0.0039
	Stand. Error	0.0600	0.0471	0.0498	0.0429	0.0404	0.0592	0.0815
	z-Statistic	-0.6795	0.2340	-0.2549	-1.2450	0.4212	0.4342	0.0473
	Probability	0.4968	0.8150	0.7988	0.2131	0.6736	0.6641	0.9623
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.0413	-0.0344	0.0114	-0.0190	-0.045	-0.2309	1.1247
	Stand. Error	0.0374	0.0400	0.0402	0.0525	0.0330	0.1412	0.2198
	z-Statistic	1.1067	-0.8589	0.2838	-0.3621	-1.371	-1.6358	5.1167
	Probability	0.2684	0.3904	0.7766	0.7172	0.1702	0.1019	0.0000*
OPHIR		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	0.0230	-0.0415	0.1458	0.0652	0.0540	-0.007	-0.1005
	Stand. Error	0.1567	0.0945	0.0460	0.0466	0.0212	0.0991	0.0547
	z-Statistic	0.1468	-0.4389	3.1692	1.3980	2.5498	-0.073	-1.8364
	Probability	0.8833	0.6607	0.0015*	0.1621	0.010**	0.9413	0.0663
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	-0.0015	-0.0064	0.0219	-0.0729	-0.086	-0.1503	0.7220
	Stand. Error	0.1670	0.0670	0.1045	0.1073	0.0575	0.2047	0.7078
	z-Statistic	-0.0090	-0.0948	0.2096	-0.6794	-1.502	-0.7343	1.0200
	Probability	0.9929	0.9245	0.8340	0.4969	0.1329	0.4628	0.3077
RUSPETRO		**January**	**February**	**March**	**April**	**May**	**June**	**July**
	Coefficient	-0.1070	-0.2810	-0.2630	0.1984	-0.0823	-0.016	-0.2666
	Stand. Error	0.7381	0.2822	0.0910	0.0763	0.0228	0.0763	0.1252
	z-Statistic	-0.1450	-0.9958	-2.8899	2.6021	-3.6067	-0.214	-2.1299
	Probability	0.8847	0.3193	0.0039*	0.0093*	0.0003*	0.8302	0.033**
		August	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Alpha1**	**Beta1**
	Coefficient	0.1169	-0.1531	0.1573	-0.0742	-0.090	-0.2006	0.7203
	Stand. Error	1.3228	0.1807	0.0906	0.1203	0.2388	0.0913	0.3857
	z-Statistic	0.0884	-0.8474	1.7373	-0.6165	-0.379	-2.1972	1.8675
	Probability	0.9296	0.3968	0.0823	0.5376	0.7040	0.028**	0.0618

NOTE: * and ** denote level of significance at 1% and 5% respectively. The coefficients are deemed to be significant if their z-Statistic's value is greater than its critical value or if probability value is less than 0.01 and 0.05. Probability values are used for interpretation in this case. Alpha1 stands for ARCH term while Beta1 represents GARCH term in the variance equation of the GARCH (1,1).

Source: Author (2015)

The results in Table 8.3 show the monthly effect of January through December on the stock returns of the UK oil and gas companies and some related FTSE indices. Most of the monthly coefficients in the oil and gas companies were found to be insignificant at both 1% and 5% significance level except in oil companies that were listed on the Exchange recently (2010 to date). The results from the FTSE indices differ. January, May and November coefficients were found to be highly significant at 1% level in FTSE All Share and FTSE 100 indices. It shows the presence of January effect; a finding which has been famous in the literature. End-of-the-year activities such as Christmas and New Year holidays are part of the reasons for January effects. May effects were also not a surprise. In the UK, tax year begins from 6 April and ends 5 April in the following year. For that reason, most of the companies that are operating in the UK prefer to use a financial year that corresponds with tax year for easy tax assessment. November effect could be due to the actions or inactions of investors to gain from the December anomaly. The stock returns of oil and gas companies were found to be insensitive to January effects except in Fortune Oil, Hunting and Aminex. May coefficient was also significant in FTSE UK Oil and Gas index returns. Seasonal effects as a result of winter and summer periods due to changes in energy usage have not been found in any of the key FTSE Oil and Gas indices. The significance of coefficients in Enquest, Essar Energy, Ophir Energy and Ruspetro were suspected to be due to short time series of stock returns as companies were listed on the Exchange in recent times.

8.4 Findings

The results generated from our seasonality analysis of the day-of-the-week and monthly effects have not shown any evidence of these calendar anomalies in London-quoted oil and gas stocks and in a few FTSE share indices investigated. Based on these findings, and with all other factors held constant, we cannot reject the Efficient Market Hypothesis. This outcome coincides with that of Steeley (2001) who noted the disappearance of the weekend effect in the UK market except if the data is partitioned along the direction of the market. Chang et al (1993) have also discovered the disappearance of a day-of-the-week-effect in the most recent data of the United States investigated.

Our methodology is also similar to that of Guidi (2010) who examined for the existence of a day-of-the-week effect in the Italian stock market using the Generalised ARCH (GARCH) model in the regression and found no evidence of the DOTW effect in the market's stock returns.

8.5 Conclusion

In this chapter, we have attempted to contribute to the existing studies on whether calendar anomalies have any effect to the pricing of stocks. The seasonality analysis is considered as another tool that can provide further evidence to our investigation of the market efficiency of the oil and gas sector and some FTSE share indices. Our investigation on London-quoted oil and gas stocks and some FTSE share indices which employed various statistical tools could not provide any statistical evidence to reject the Efficient Market Hypothesis in the UK oil and gas sector in the London stock exchange.

CHAPTER 9

VOLATILITY PROCESSES, ESTIMATION AND FORECASTING

9.1 Introduction

The uncertainty in capital markets will be manageable for effective investment strategies and decisions if the causes behind the stock market volatility are well understood. The interest in the volatility in the markets has increased among researchers as a result of the failure of conventional models in explaining the dynamics of stock prices. Engle (1982) and Bollerslev (1986) improved the earlier forecasting models by focusing more on the volatility of stock returns. Stylized facts of the volatility of stock returns are used to test market efficiency in the light of the Efficient Market Hypothesis. Volatility asymmetry, clustering, persistence and a positive risk premium are the most commonly stylised facts of volatility used in assessing the information efficiency of a market, (Iyiegbuniwe et al., 2012). Volatility asymmetry, also known as the 'leverage effect', and describes the existence of a high volatility in a security due to negative performance of the overall market and vice versa. Volatility clustering suggests the need for Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Models. It is a situation where a high volatility is followed by high volatility and low volatility followed by low volatility with either positive or negative signs (Mandelbrot, 1963). Clustering signals the existence of conditional heteroscedasticity in the time series of stock returns which are contrary to the assumption of homoscedasticity mostly adopted by conventional models. GARCH models are designed by Bollerslev (1986) to address issues in time series modelling where conventional models are regarded as inappropriate. Volatility persistence is another stylized fact of volatility where the past or present volatility has a substantial effect on the expected volatility.

To analyse the price behaviour of the UK oil and gas stocks, conditional volatility is to be assessed in the subsequent sections of this chapter. Here, volatility is assumed to be the variability of future returns based on the information of the variability of past returns or any other known information. Engle (1982) introduced an autoregressive conditional heteroscedasticity (ARCH) model, designed to measure whether a series of stock returns is characterised by the existence of conditional heteroscedasticity (time-varying volatility). Stochastic volatility is based on the assumption that volatility follows a random walk. Continuous-time models are used to study the pattern of changes in this volatility over time which is one of the objectives of this research. There are also parametric and implied types of volatility. Parametric volatility of returns is based solely on the assumption that stock prices follow a Geometric Brownian Motion (GBM) and the volatility is calculated as a parameter represented by a standard deviation of a compounded returns at any given period of time. Implied volatility is a measure of the variability in returns calculated from an option price. However, this study will not consider volatility as a parameter guided by the GBM assumptions due to the unrealistic nature of the assumptions and implied volatility due to a lack of data availability on options.

It is noted that the results of the calculations of conditional, stochastic and realized volatility of a given series at any time cannot be the same due to different assumptions of the underlying models. Nevertheless, this will not affect the desire of the researcher to find a volatility stylized fact in the returns of the UK oil and gas sector in comparison to that of the FTSE All Share index. An important aspect of volatility modelling is forecasting future stock returns. Engle and Patton (2001) reported that such forecasts are used for many financial activities including risk management, derivative pricing and hedging, investment decisions, market making, market timing, portfolio management and options trading.

9.2 Review of Literature on Market Volatility

9.2.1 Conditional Volatility

The notion of conditional volatility evolved from the assumption of the conditional density function $f(y_t / y_{t-1})$ where today's value y_t depends on past value or information y_{t-1}, represented as $E(y_t / y_{t-1})$ with an estimated variance of $V(y_t / y_{t-1})$, stressing the dependence of the conditional variance on past information. Degiannakis et al. (2014) have described conditional volatility as a standard deviation of any asset return that depends on past available information to investors. The mathematical representation of conditional variance can be shown as $(y_t|I_{t-1}) \equiv V_{t-1}(y_t) \equiv \sigma^2{}_t$, where I_{t-1} represents the set of information available to investors at the time of investment decision. As investors are interested in the relationship between risk and return of their investments, risk measures such as variance and standard deviation play an important role in investment evaluation by market participants. On this point, scholars such as Sharpe (1964) and Black and Scholes (1972) developed various theoretical asset pricing models that incorporate risk measures. A risk was specifically perceived as changes in the variance of an asset's returns, even though Kraus and Litzenberger (1976) argued that risk cannot only be seen as a function of variance. Due to the increase in financial and economic crises over time, many studies have been conducted on the volatility of asset returns. The extent of volatility transmission among different stock exchanges and its link to global financial crises have also been examined.

Taylor and Poon (1992) examined the relationship between stock returns and volatility in the United Kingdom. The test of their examination was conducted on daily, weekly, fortnightly, and monthly returns of the FTSE All Share index in order to assess the role of different forms of data frequency on the relationship between stock returns and volatility. The coefficients of volatility or variance of stock returns derived are found to be positively correlated with expected stock returns, although the estimates of the coefficients are not statistically significant.

Mougoue and Whyte (1996) investigated the relationship between stock returns and volatility in French and German stock exchanges. Stock returns in the two exchanges were discovered to have a significant relationship with volatility to the extent that stock returns can be estimated or explained by volatility models.

Baillie and DeGennaro (1990) employed various models to examine the relationship between stock mean returns and volatility. The data were monthly values of the weighted stock returns index obtained from the Centre for

Research in Security Price (CRSP) in the United States. The findings suggested no significant empirical evidence to establish a strong relationship between stock returns and volatility. The scholars concluded that investors consider other measures of risk more important than the variance of stock returns.

Researchers also examined the relationship between conditional volatility and other economic variables. Morelli (2002) used UK data to explore the relationship between conditional volatility of stock market returns by the FTSE All Share Index and conditional volatility of macroeconomic variables such as industrial production, money supply, inflation, foreign exchange rate and real retail sales variables. Empirical results showed a significant relationship between the volatility of stock market returns and the UK macroeconomic variables when the variables are modelled at the same time using a Vector Auto Regression (VAR) estimation to forecast the volatility of the FTSE All Share index. However, when considering the individual macroeconomic variables such as inflation as explanatory variables to analyse the stock market volatility, no relation was discovered whatsoever.

Cai et al (2006) conducted a research study on the association between individual country stock market volatility and global stock market volatility. The scholars used the Morgan Stanley Capital International (MSCI)'s World Stock Market Index to represent world stock markets and twenty-two (22) emerging markets indices at the individual country level. The coefficients of beta generated indicate a significant relationship.

The discovery of an Autoregressive Conditional Heteroscedasticity (ARCH) effect in the behaviour of stock returns by Engle (1982) has motivated the study of stock market volatility and statistical adjustments of the ARCH models into various forms.

9.2.1.1 Autoregressive Conditional Heteroscedasticity (ARCH) Models

The development of these models resulted from a significant number of studies showing that most of the assumptions of traditional econometric models were unrealistic. Engle (1982) proposed that the assumption of homoscedasticity can be avoided by the introduction of more realistic models leading to the development of autoregressive conditional heteroscedasticity (ARCH) models. ARCH models are designed with zero mean, an absence of serial correlation and changing variances that are dependent or conditional on past information. The various extensions of the model were designed as a measure of time-varying conditional variances in a second or higher order moments. The measure was to provide a superior alternative to the use of only first order period variances or co-variances that have conditional zero dependence on past information in assessing the volatility or uncertainty in the movement of asset prices. Since the introduction of ARCH models, many researchers have adopted numerous extensions to the new models to explain the dynamics of assets pricing. However, existing studies have pointed out several areas that need further research.

Engle (1982) was the first scholar to test for the existence of an ARCH effect on time series data. The test was conducted on United Kingdom inflation data over the sample period of 1958 to 1977 and the residuals or disturbances from the more complex regression indicated an effect of missing variables in the estimated model. The conclusion derived was that a conventional regression model is not adequate to explain the variance of UK inflation. The existence of an ARCH effect in the series signifies that their variance is more defined by the effect of past information introduced into the model as an exogenous variable. The heteroskedasticity assumption in the ARCH model means conditional variances are not constant but vary widely with changes in information. McNees (1979, p. 52) as reported by Engle (1982) supported the assertion by making an inference that the "inherent uncertainty or randomness associated with different forecast periods seems to vary widely over time". Discussions around the innovation of new models with conditional variances continue to attract the attention of researchers.

Engle and Bollerslev (1986) reviewed the studies conducted using both ARCH and generalized ARCH models. The interesting point in their review was the use of a simple model as a benchmark for testing the new models. Clearly, the inadequacy of the conventional econometric models in assessing risk and uncertainties were highlighted. One of the limitations of a simple model such as $Y_t = \gamma Y_{t-1} + \varepsilon_t$ (where Y_t is price today, Y_{t-1} is price yesterday, γ is coefficient (always less than 1) and ε_t is the disturbance or residual deemed to be independent and identically distributed (iid)) is the formulation that made ε_t (regarded as the risk) in the model to remain constant. This is proven mathematically as follows:

$Y_t = \gamma Y_{t-1} + \varepsilon_t$, where the mean and variance for the disturbance ε_t is $E(\varepsilon_t) = 0$ and $V(\varepsilon_t) = \sigma^2$ respectively. In this case, the conditional mean for Y_{t+1} will be $E_t(Y_{t+1}) = \gamma Y_t$, dependent on γ which represents an information set and certainly a random variable. From that point, the variance and conditional variance of

Y_{t+1} will be $V(Y_{t+1}) = \sigma^2/(1-\sigma^2)$ and $V_t(Y_{t+1}) = E_t[Y_{t+1} - E_t(Y_{t+1})]^2 = \sigma^2$ respectively. Both the variance and conditional variance will remain constant if γ is between 0 and 1. These notations show a defiance to the randomly changing information set.

Engle and Bollerslev (1986) tested the superiority of ARCH models on weekly exchange rate data of the US dollar/Swiss Franc ranging from July, 1973 to August, 1985. It was achieved by the assumption of conditional variance dependence on randomly changing information set which is by the existence of heteroskedasticity provision in the model. These discoveries were important because even the higher order ARCH/GARCH models applied on the entire series did not indicate any failure in the model specification and hence are deemed to be more fit in assessing risks and uncertainties in the movement of asset prices. However, the data set used by the scholars was the same as that examined by Diebold and Nerlove (1985), and therefore any inaccuracies in the data would equally be transmitted.

Wolff (1988) reasoned that the coefficients of an ARCH model are similar to the coefficients of a traditional random walk model by highlighting that every ARCH term in a model can be transformed to ordinary random coefficients. The scholar concluded that the behaviour of conditional variance was the same in both ARCH and traditional random models.

Lamoureux and Lastrapes (1990) supported the view of Engle (1982) on the existence of Autoregressive Conditional Heteroscedasticity in stock returns. Trading volume was used in the variance equation of ARCH as an explanatory variable, and the power of the explanatory variable in the equation was found to be significant. Having considered changes in trading volume as a flow of information to the investors, it was concluded that the variance of stock returns is time dependence which conforms to the assumptions of ARCH specifications.

Yildirim (2013) provided empirical evidence confirming the assumptions of the ARCH specification by emphasizing that, due to the exhibition of second order dependence by stock returns, linear white noise processes cannot be used in modelling the time series of stock returns. It was discovered that forecasts by ARCH models are more accurate compared to traditional or other asset pricing models.

However, the Autoregressive Conditional Heteroscedasticity (ARCH) models are considered to have a limitation because current conditional variance is modelled as a function of past errors or information only and holding unconditional variance as constant without including past conditional variance in the equation. Bollerslev (1986) generalized the ARCH model by adding past conditional variance into ARCH equation.

9.2.1.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Models

Bollerslev (1986) introduced the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model as an extension of the ARCH model. He explained this as similar to the extension of the Autoregressive (AR) model to an Autoregressive Moving Average (ARMA) model. In the new process, the conditional variance is a function of past error or information and lagged conditional variance which allows for more flexibility in the lag structure of the model. Both the lagged past error and past conditional variance can easily be adjusted to required lags and the process is recognized as GARCH (p,q) where 'p' represents the lagged error term and 'q' is the lagged conditional variance term. Empirical parameters of the GARCH model are explained in the subsequent sections.

Bollerslev (1987) tested the validity of the GARCH model on speculative prices and rates of return of the US dollar against the British pound and the German Deutschmark in the New York foreign exchange market. For the fact that price-change (y_t) series are uncorrelated over time and characterized by volatile periods, the simple GARCH (1,1) model was found to be an accurate fit to explain the series.

Ashley and Patterson (2010) have tested the specification of the GARCH (1,1) process on daily stock returns using a new evaluation technique developed by the authors. The new model evaluation technique is a combination of various tests designed to assess the non-linearity of stock market returns based on which the GARCH processes are developed. The findings suggested that, out of all the ARCH/GARCH family models considered in the study, only the GARCH (1,1) model was found to be viable for daily stock return.

Efimova and Serletis (2014) investigated the empirical properties of energy market volatility using both univariate and multivariate GARCH estimation models. The volatility of oil, natural gas and electricity prices was examined where volatility spill overs and interactions between the individual prices were equally assessed using trivariate BEKK and Dynamic Conditional Correlation (DCC) models. The performances of different models employed in the study were also measured. GARCH models showed effectiveness in measuring the short-run volatility of the energy prices investigated because the models address short-term inconsistencies of volatility. The statistical results or estimates generated from both univariate and multivariate models applied are not widely different. However, it was discovered that univariate models have a high power of forecasting ability while multivariate models preserve information or data since first differencing was ignored and the models have the ability to assess interactions between variables. Co-integration, interactions and volatility spill overs were discovered in energy prices with the oil price having more influence followed by natural gas and electricity prices in that order.

Bonilla and Sepulveda (2011) applied various GARCH models on the stock returns of thirteen (13) emerging markets to test for the adequacy of the models. The underlying processes of these returns were not captured by the GARCH model or any of its extensions. The scholars concluded that, while GARCH models are relevant in developed markets, they may not be appropriate to model emerging markets stock returns especially because of the non-existence of long term ARCH effects in the series.

9.2.2 Realised Volatility

Realised or historical volatility is another form of measuring and determining present or future volatility. In the same process as in other forms of volatility, realised volatility is used to estimate the statistical characteristics of past volatility and in many cases to forecast future volatility. Mathematically, realised volatility can be derived by calculating the sum of the squared intraday stock returns for a given day.

Andersen et al (2001) explained the empirical distribution of realised volatility using the individual stocks in the Dow Jones industrial average index. The findings from their research characterised the distribution of realised volatility as having variance and covariance being rightly skewed. Temporary dependence and long memory processes were also observed in the realised volatility and correlations.

Andersen et al (2003) modelled and forecasted spot market foreign exchange rates for the Deutschemark/Dollar and the Yen/Dollar using long-memory Gaussian vector autoregression of the realised volatility from high frequency of intraday returns. The forecasts showed more predictive power than traditional or more conventional ARCH and GARCH models.

Areal and Taylor (2002) estimated the realised volatility of future prices of the FTSE 100 Share index and its distribution was discovered to be lognormal while the series of the realised volatility being positively autocorrelated in the long run.

The forecasting value of realised or historic volatility was examined by Koopman et al. (2005) using the S&P 100 stock index. The findings suggested more predictive power of forecast by realised volatility models compared to stochastic and ordinary GARCH models.

Thomakos and Wang (2003) examined the characteristics of realised volatility in the futures markets using intraday returns from four futures contracts over a period of five (5) years. Their findings are similar to the findings of Andersen et al. (2001). Standard deviations and correlations exhibit long memory process, with returns being serially uncorrelated. The distribution of the past variances is found to be leptokurtic with skewness more diverted to the right.

Christensen and Prabhala (1998) investigated the relationship existing between implied and realised volatility. They found that forecasting using implied volatility had more predictive power than realised volatility. The conclusion was also made that implied volatility can also be used to forecast future realised data. The findings are contrary to previous studies that had concluded about the insignificance of implied volatility. The difference between the previous and current findings was attributed to the use of long-term non-overlapping data by Christensen and Prabhala (1998).

9.2.3 Stochastic Volatility

The concept of stochastic volatility is another estimation of time series variance based on the notion that variances are products of random process derived from a stochastic time series. In other words, the standard deviation of stock returns is believed to be changing with a change in time. Stochastic volatility is mostly used by experts in option pricing.

Abanto-valle et al. (2011) examined the relationship between returns and its stochastic volatility using the Bayesian approach. The data set used was found to be characterized by a strong leverage effect. The empirical results generated confirmed the hypothesis that investors require high returns for unexpected variances or stochastic volatility.

Omori et al. (2007) have also employed the Bayesian approach to estimate the stochastic volatility of Japanese stock return data. The stochastic volatility models developed explain the behaviour of stock returns volatility better than other competing volatility models.

Kim et al. (1998) conducted an empirical study to compare stochastic volatility estimation models with the conventional GARCH models. The stochastic volatility was estimated using Simulation-based techniques instead of the Bayesian-based techniques employed by most researchers. Stochastic volatility was found to be more accurate and superior in measuring volatility than the conventional GARCH models.

Sandmann and Koopman (1998) used the Monte Carlo maximum likelihood approach to estimate the stochastic volatility of the Standard and Poor (S&P)'s 500 stock return series. The estimates are found to be more accurate estimators compared to other conventional specifications of stochastic volatility.

9.2.4 Asymmetric Volatility

The extensive literature on the asymmetric volatility of stock returns indicates the extent of its acceptance in the area of finance by scholars. The majority of the studies conducted on whether the volatility of stock returns has asymmetric characteristics have concluded that asymmetric volatility is the best description of stock return volatility. Researchers also discovered that forecasting volatility with asymmetric models delivers more forecasting accuracy than other conventional models such as GARCH (1,1). The notion of asymmetry in volatility lies in the argument that negative news resulted in higher fluctuation or a decrease in stock returns than any positive news of the same magnitude.

Campbell and Hentschel (1992) constructed a model from the conventional symmetric GARCH to account for the volatility feedback effect in stock returns. The scholars reported that the resulting model was an asymmetric GARCH model that captured about fifty percent (50%) of the skewness and excess kurtosis of the stock returns. The volatility feedback effect represents the 'no news is good news' slogan and the model fit of the stock return data investigated more than any other model. The findings include the discovery of around 1% stock return volatility under normal conditions which rose to about

25% in the 1930s due to the economic depression and 13% in 1987 as a result of the stock market crash.

Bekaert and Wu (2000) also believe that stock market volatility is asymmetric. In their study, they have investigated asymmetric volatility at the individual firm and overall market levels with a strong emphasis on the leverage effect and volatility feedback effect. The former was rejected under a riskless debt assumption for a market portfolio but accepted at the firm level. A volatility feedback effect was found to be present at both firm and market portfolio level. In 2001, as co-author of Bekaert and Wu (2000)'s article, Guojun Wu, constructed a model using a simulated method of moments that incorporated the leverage effect and the volatility feedback effect. Wu (2001) discovered that the leverage and the volatility feedback effects are key variables in the explanation of stock market asymmetric volatility.

Mele (2007) explained that the reason why stock market volatility is high during bad times (economic and financial crisis) than good times (economic and financial stability) is the fact that the entire economic environment is frequently affected by shocks similar to those affecting stock returns.

Leeves (2007) employed three asymmetric volatility models of GJR, NGARCH, and AGARCH to investigate the behaviour of Indonesian stock market volatility during the Asian crisis. Significant ARCH and GARCH terms were observed over the entire period of study with asymmetric signs more obvious over the period of the crisis.

A similar study of Leeves (2007) was conducted by Zhang and Li (2008) on the Chinese stock market. A rolling sample windows method was used to study the asymmetric behaviour of the market. It was found that the market tended to overreact to any information that resulted to negative returns of a stock.

In an effort to provide more empirical evidence that can explain the negative asymmetric return-volatility relation, Hibbert et al. (2008) undertook a different approach on the S&P 500 index by justifying or linking their empirical result to investors' attitude using extrapolation bias concepts. Contrary to the findings of many scholars, Hibbert et al. (2008) discovered that both the leverage effect and the volatility feedback effect are insignificant variables to explain the volatility of the S&P 500 index. The behaviour or attitude of investors was found to be consistent with their empirical findings.

The asymmetry in the United States stock market volatility was equally examined by Ederington and Guan (2010) using the GJR (or TGARCH) and exponential GARCH (or EGARCH) models on the S&P 500 index and the Chicago Board Option Exchange's indices. Strong empirical evidence was gathered to support the asymmetry of volatility in US stock returns.

Hammoudeh et al. (2010) investigated the impact of global, country, and industry level variables on the volatility of US stock returns of twenty seven (27) sectors for both short and long run time frames. In this case, the impact of developments in the oil and gas sector and the Morgan Stanley Capital International world markets index were found to be distinctive on the volatility of the sector's equity prices. Changes in oil prices resulted in a decrease in volatility while MSCI's changes caused an increase in volatility. The perception of negative or positive news depends on the attitude of investors and market participants.

Asymmetric volatility spillover in different stock markets has also been investigated by a significant number of researchers. Reyes (2001) employed bivariate EGARCH to examine asymmetric volatility spillover among stock indices in the Tokyo stock exchange. Volatility spillover was found from indices of large companies to small companies in Japan but not in the reverse case.

Karunanayake and Valadkhani (2011) investigated volatility transmission or spillover between the four countries of Australia, United Kingdom, United States, and Singapore using multivariate GARCH (MGARCH) models. Negative innovations in all the markets are found to account for a higher increase in volatilities and co-volatilities than positive innovations. Volatility spill over was found to emanate from the US market to the other markets and not vice-versa.

9.2.5 Volatility and Efficient Market Hypothesis (EMH)

Shiller (1981) stated that many scholars had attempted to use measures of stock return variance or volatility to provide evidence of the market efficiency hypothesis. In most of the cases, the existence of high volatility or rapidly changing variance of stock returns was seen as evidence to justify a random walk process which presumes an inability to predict stock prices or make abnormal gains. However, the results from the empirical tests conducted by

Shiller (1981) failed to support the random walk hypothesis, probably due to the nature of data used in the study or the fact that the market is not rational as stated by the scholar.

Harvey and Whaley (1992) tested and rejected the hypothesis that stock market volatility cannot be predicted. The parameters or coefficients in the estimation models used suggest predictability in the volatility of stock returns. Harvey and Whaley (1992) argued that despite the accuracy of the volatility forecast in their study, abnormal returns cannot be acquired. Hence, it was concluded that the dynamics of volatility are consistent with the Efficient Market Hypothesis.

Omet et al. (2002) examined volatility in the Jordanian stock market and its conformity with the assumptions of market efficiency. High persistent volatility clustering was found in the market returns using the GARCH (1,1) model. The Efficient Market Hypothesis was strongly rejected by the empirical results of the study. The inconsistency of the market conforms to the findings of various scholars in respect of studies on emerging stock markets.

Szafarz (2012) argued that the relationship between the concept of market efficiency and volatility depends on the composition of the market traders and their investment horizons. If fundamentalists dominate the market, which has a few speculators, the action of the former to 'buy and hold' stock for long period would create illiquidity in the market, and then, there would be a high volatility due to the tension created. However, behavioural models are against this argument because it is believed that, in a market characterised by various speculators, fundamentalists restore confidence to the belief that the share price would revert to its fundamental value in the long run. Szafarz (2012) opined that market volatility reduces with an increase in the number of speculators operating in the market.

9.2.6 Volatility Forecasting and VaR Measures

The forecasting of a volatility of stock returns became prominent after the acceptance of numerous volatility models by financial analysts and scholars. The accuracy of such models is tested through forecasting by usually measuring the forecast errors generated from various forecasting evaluation statistics. The concern of investors with the volatility of returns in respect of their investment portfolios has also contributed to more effort by finance experts to predict the future volatility for efficient investment strategies.

Liu and Hung (2010) forecasted the volatility of the Standard and Poor (S&P) 100 stock index using various specifications of GARCH type models under different error distribution assumptions in order to determine the best model for forecasting. The asymmetry GARCH models, specifically GJR-GARCH and EGARCH produced low forecast errors from the out-of-sample forecast which indicates high predictive power. The asymmetric GARCH models are found to be better than symmetric GARCH models under any assumption of the error distribution. The Threshold or GJR-GARCH model appeared to be the best model for volatility forecasting.

The volatility of the S&P 500 index was also modelled and forecasted by Srinivasan (2001) using simple GARCH (1,1), Exponential GARCH (1,1), and Threshold GARCH (1,1) models. Based on the out-of-sample forecast results and the forecast evaluation statistics, the symmetric GARCH models perform better than the asymmetric GARCH models. The findings of Srinivasan (2011) are contrary to the findings of many researchers who discovered more predictive power in asymmetric models (Liu and Hung, 2010; Harrison and Moore, 2012; Engle and Ng, 1993).

Harrison and Moore (2012) tested the predictive power of twelve forms of GARCH models ranging from simple to complex models in forecasting the volatility of Central and East European (CEE) stock markets. Six forecast evaluation statistics were used to measure the performance of the models. Results have shown that asymmetric GARCH models are superior to the symmetric GARCH models in volatility forecasting.

It was also emphasized that the value-at-risk (VaR) policies or measures are likely to improve with an efficient forecast of volatility, (Tripathy and Abdul Rahman, 2013). Tripathy and Abdul Rahman (2013) tested the fit of the three error distributions of GARCH model namely, the Normal Error Distribution, Student's t Distribution and Generalized Error Distribution. GARCH (1,1) under Generalised Error Distribution (GED) produced a more accurate forecast with the lowest value of forecast error statistics compared to the other distributions.

9.2.7 Summary of Literature and Research Objectives

Stock market analysts and participants are always in search for answers to stock market puzzles. Conventional models are believed to have weaknesses in explaining the dynamics of stock returns. The findings of Engle (1982) have led to the discovery of new statistical features of stock returns. Time-varying variance or conditional heteroscedasticity was found to be present in many financial data time series and thus scholars used models that are built on the assumption of conditional heteroscedasticity to explain the behaviour of stock returns particularly in relation to changing variance or volatility. In that course, various forms of volatility such as stochastic, realised, implied and conditional volatility have been empirically tested for significance in explaining the pricing behaviour of stock markets. However, an absolute solution to the asset pricing puzzle has not been provided. More studies are being undertaken to capture all the characteristics of stock markets for effective asset pricing and investment strategies.

This study will attempt to analyse the volatility of the UK oil and gas sector. The volatility modelling and forecasting processes will involve conditional volatility using various forms of ARCH and GARCH models.

9.3 Volatility Processes and Estimation on the FTSE Market and Oil and Gas Indices

The volatility processes undertaken for estimation are presented in stages in the following sub-sections. Section 9.4 will present the volatility forecast from the estimation models employed in this section.

9.3.1 Volatility Modelling of FTSE All Share and Oil and Gas Indices Return Series

Table 9.1 shows the series of the Financial Times Stock Exchange (FTSE) indices of the London Stock Exchange assessed in this chapter. Volatility estimations are made from the returns of the series highlighted below using various forms of Autoregressive Conditional Heteroskedasticity (ARCH) models. The returns of the series are defined and calculated as in previous chapters.

Table 9.1 – FTSE UK Oil and Gas and FTSE All-Share Indices Series

S/N	Indices	Range of Prices	Series in Years	Observations
1.	FTSE UK Oil & Gas	31 Dec 1993 to 31 Dec 2012	19	4956
2.	FTSE All Share	31 Dec 1992 to 31 Dec 2012	20	5217

Source: Author (2015)

All series under study were subjected to a stationarity test in chapter 4 of this study and convincingly the returns are confirmed to be stationary.

9.3.2 Test for ARCH Effect in the Residuals of the FTSE Indices Return Series from Simple Regression Model

The residuals of the returns from a simple regression model are also examined to establish whether there is the existence of conditional heteroskedasticity for effective ARCH modelling. The examination was conducted by modelling the return series into a simple regression (mean equation) model and the residuals generated were plotted graphically for observation. The residuals were further subjected to the ARCH Test and the null hypothesis of 'there is no ARCH effect in the series' was used to confirm the behaviour of the residuals.

The equation of the simple regression model is given as:

$$'Y_t = \beta_0 + \beta_1 Y_{t-1} + \varepsilon_t'$$

Where; Y_t = today's return,

β_0 = constant/intercept,

β_1 = coefficient of the equation,

Y_{t-1}= one day lagged return, and

ε_t = residual, disturbance or error term.

In this case, the residual (ε_t) is the subject of examination. The model was estimated, and results are depicted as follows:

Table 9.2 – Simple Regression Model on FTSE UK Oil and Gas Index Returns

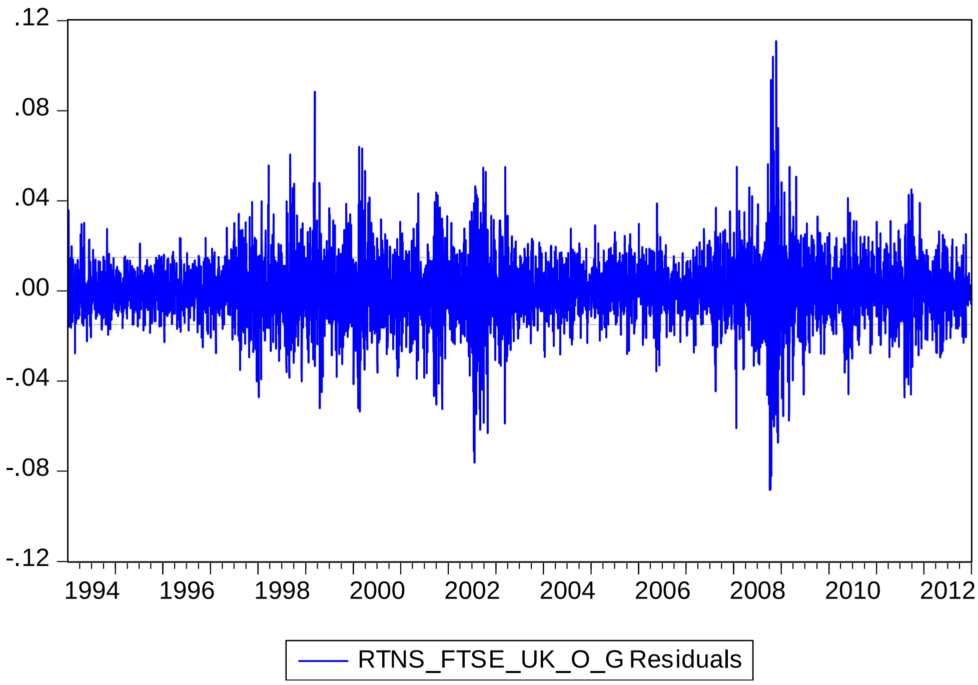
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000244	0.000211	1.153137	0.2489
One lagged Return	0.001949	0.014209	0.137200	0.8909
Diagnostic tests				
R-squared	0.000004	Mean dependent var	0.000244	
Adjusted R-squared	-0.000198	S.D. dependent var	0.014882	
S.E. of regression	0.014884	Akaike info criterion	-5.576716	
Sum squared resid	1.097190	Schwarz criterion	-5.574089	
Log likelihood	13818.31	Hannan-Quinn criter.	-5.575795	
F-statistic	0.018824	Durbin-Watson stat	1.999549	
Prob(F-statistic)	0.890878			

Source: Author (2015)

Table 9.2 shows the result from the regression model applied to the return series of FTSE UK oil and gas index. The t-statistics of 1.15 for constant and 0.13 for Y_{t-1} are insignificant as shown by the p-values. R^2 value of 0.000004 does not indicate any tight fitness in the model. The null hypothesis in this model is H_0: $\rho = 0$ ($\beta_1 = 0$), meaning that 'there is no significant linear correlation in the series'. The p-value from our result is greater than 5%, and the null hypothesis is to be accepted. In other words, there is no significant linear correlation in the series. However, the regression model was purposely applied to find out whether the residuals generated are heteroskedastic or homoscedastic in nature. To accomplish that, the residuals are plotted graphically, and observation was made as shown below.

Graphical presentation of residuals is as follows:

Figure 9.1 - Residuals of FTSE UK Oil & Gas Index Returns from Simple Regression Model



Source: Author (2015)

From the graph, it can be established that from 1994 to 1996 low volatility is followed by low volatility while from 1997 to 2003 high volatility is followed by high volatility. This feature indicates the presence of conditional heteroskedasticity. The variance and standard deviation of the error term (residuals) are not constant.

To confirm the existence of conditional heteroskedasticity in the residuals, an ARCH test was conducted with the null hypothesis that 'there is no ARCH effect in the series.'

Table 9.3 – ARCH Test on the Residuals of Simple Regression Model for FTSE UK Oil & Gas Index Returns

Heteroscedasticity Test: ARCH				
F-statistic	420.8822	Prob. F(1,4952)		0.0000
Obs*R-squared	388.0693	Prob. Chi-Square(1)		0.0000
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000159	8.27E-06	19.27096	0.0000
Residual^2 (-1)	0.279887	0.013643	20.51541	0.0000
Diagnostic tests				
R-squared	0.078335	Mean dependent var.		0.000221
Adjusted R-squared	0.078148	S.D. dependent var.		0.000565
S.E. of regression	0.000542	Akaike info criterion		-12.20184
Sum squared resid	0.001455	Schwarz criterion		-12.19922
Log likelihood	30225.97	Hannan-Quinn criter.		-12.20092
F-statistic	420.8822	Durbin-Watson stat.		2.123427
Prob(F-statistic)	0.000000			

Source: Author (2015)

The p-value (Prob. Chi-Square (1)) of the 'Observed R-squared' from Table 9.3 is significant at 5% level and the null hypothesis (there is no ARCH effect in the series) is rejected.

The existence of conditional heteroskedasticity or ARCH effect shows that the return series of the FTSE UK oil and gas index can be represented or modelled in ARCH family models.

Table 9.4 - Simple Regression Model on FTSE All Share Index Returns

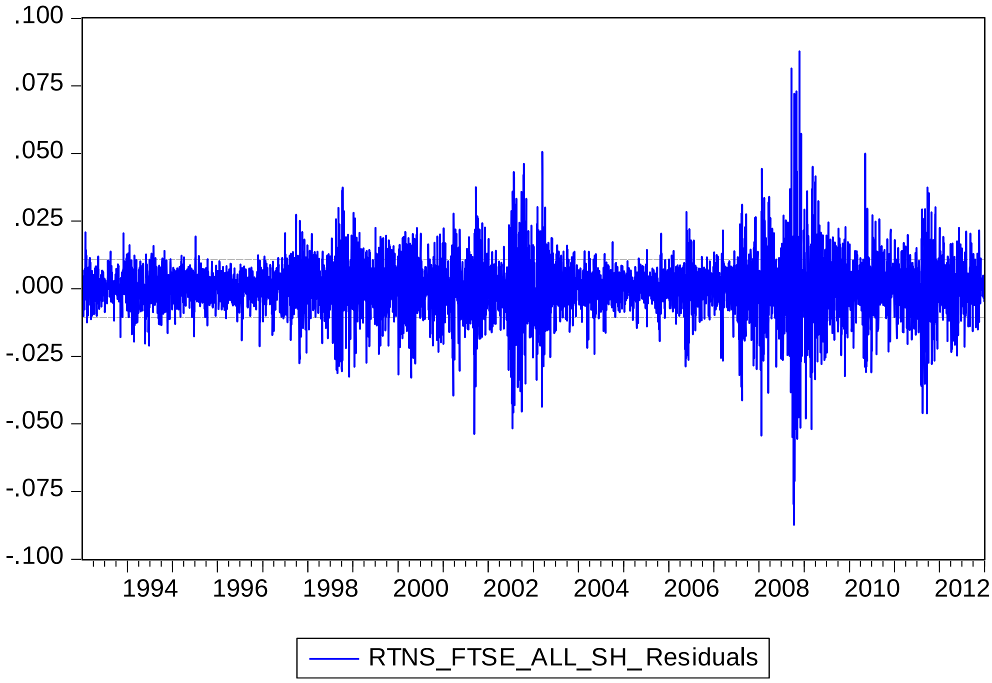
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000158	0.000149	1.054738	0.2916
One lagged Return	-0.003907	0.013849	-0.282150	0.7778
Diagnostic tests				
R-squared	0.000015	Mean dependent var.		0.000157
Adjusted R-squared	-0.000177	S.D. dependent var.		0.010792
S.E. of regression	0.010793	Akaike info criterion		-6.219515
Sum squared resid	0.607336	Schwarz criterion		-6.217000
Log likelihood	16222.50	Hannan-Quinn criter.		-6.218635
F-statistic	0.079609	Durbin-Watson stat.		2.000202
Prob(F-statistic)	0.777840			

Source: Author (2015)

Table 9.4 shows the result from the regression model applied to the return series of the FTSE UK All Share index. The t-statistics of 1.05 for constant and -0.28 for Y_{t-1} are insignificant as shown by the p-values. R^2 value of 0.000015 does not indicate any tight fitness in the model. The null hypothesis in this model H_0: $\rho = 0$ ($\beta_1 = 0$) (there is no significant linear correlation in the series) cannot be rejected and, therefore, is accepted at 0.7778. The regression model was purposely applied to find whether the residuals generated are heteroskedastic or homoscedastic in nature. To accomplish that, the residuals are plotted graphically, and observation was made as shown below.

Graphical presentation of residuals is as follows:

Figure 9.2 - Residuals of FTSE All Share Index Returns from Simple Regression Model



Source: Author (2015)

The graph in Figure 9.2 depicted the existence of conditional heteroskedasticity. Low volatilities are followed by low volatilities (of either signs) from 1992 to 1997, and 2003 to 2007 while high volatilities are also followed by high volatilities (of either signs) from 1998 to 2002 and 2008 to 2012.

To confirm the existence of conditional heteroskedasticity in the residuals, an ARCH test was conducted. The null hypothesis that 'there is no ARCH effect in the series' was also tested for significance using 5% level of significance.

Table 9.5 – ARCH Test on the Residuals of Simple Regression Model for FTSE All Share Index Returns

Heteroscedasticity Test: ARCH				
F-statistic	283.6065	Prob. F(1,4952)		0.0000
Obs*R-squared	269.0766	Prob. Chi-Square(1)		0.0000
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	9.00E-05	4.89E-06	18.39322	0.0000
Residual^2 (-1)	0.227150	0.013488	16.84062	0.0000
Diagnostic tests				
R-squared	0.051597	Mean dependent var.		0.000116
Adjusted R-squared	0.051415	S.D. dependent var.		0.000344
S.E. of regression	0.000335	Akaike info criterion		-13.16663
Sum squared resid	0.000584	Schwarz criterion		-13.16411
Log likelihood	34333.98	Hannan-Quinn criter.		-13.16575
F-statistic	283.6065	Durbin-Watson stat.		2.115135
Prob(F-statistic)	0.000000			

Source: Author (2015)

The p-value (Prob. Chi-Square (1)) of the 'Observed R-squared' from Table 9.5 is significant at 5% level and the null hypothesis (there is no ARCH effect in the series) is rejected.

The existence of conditional heteroskedasticity or ARCH effect shows that the return series of the FTSE All Share index can be represented or modelled in ARCH family models.

9.3.3 Estimation using ARCH (1) and GARCH (1,1) Models

9.3.3.1 ARCH (1) Model

The Autoregressive Conditional Heteroskedasticity (ARCH (q)) model was developed by Engle (1982) by including a conditional variance in an autoregressive process. The simplest form of ARCH (q) is seen by researchers as ARCH (1) and it is the first order autoregressive conditional heteroskedasticity derived from one lag squared residual on a condition that the distribution of a future value or return is conditional on previous values or returns where the mean is constant with time-changing variance. The present volatility is determined by previous volatility which is conditional on past information represented by one lagged squared residual (ε^2_{t-1}) referred to as 'ARCH term'. The present volatility or variance (h_t) is calculated in the ARCH (1) process as:

$$h_t = \omega + \alpha_1 \varepsilon^2{}_{t-1} + \ \ldots..\alpha_q \varepsilon^2{}_{t-q} + u_t$$

Where $\omega > 0$, $\alpha \geq 0$, and summation of all α_i is less than 1.

Bollerslev (1986) extended the ARCH (1) model into the Generalized ARCH (GARCH) by introducing one lagged variance (h_{t-1}) referred to as the 'GARCH term'. The volatility or variance equation in the GARCH (1,1) model has one 'ARCH term' of the ARCH (1) process and one 'GARCH term' as introduced by Bollerslev.

9.3.3.2 GARCH (1,1) Model

The Generalised Autoregressive Conditional Heteroskedasticity (GARCH)(p,q) model is an extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model. The simplest form of the GARCH (p,q) model is GARCH (1,1) which has two equations similar to every ARCH model. It is important to note that every ARCH model has two equations of mean and variance. The mean equation in the model is used for the extraction of the residuals to be used in the estimation of the variance equation. The equations are explained below.

a- Mean Equation

b- Variance Equation

The mean equation is given by:

$$Y_t = a + \beta_1 X_t + u_t$$

Where,

Y_t = Oil and gas stock/index returns as dependent variables

a = Constant

β_1 = Parameters

X_t = Explanatory or independent variable (Y_{t-1})

u_t = Disturbance or residuals

The variance equation is given by:

$$\sigma^2{}_t = \omega + \alpha\sigma^2{}_{t-1} + \beta\varepsilon^2{}_{t-1}$$

Where in this study;

$\sigma^2{}_t$ = Variance

ω = Constant term

σ^2_{t-1}= One lagged period variance (GARCH term)

e^2_{t-1} = Squared one lagged period residuals (ARCH term)

The ARCH and GARCH models are not based on the conventional econometric assumption of stationarity where the mean, variance and covariance are viewed as constant. The assumption of Classical Linear Regression Model (CLRM) that the variance is constant has been referred to as homoscedasticity. Scholars have observed that homoscedasticity cannot be attained in the series of stock returns. In other words, the variance and covariance of stock returns are found to be changing over time (heteroscedasticity). Therefore, the only condition for the application of GARCH models on stock return series is the existence of conditional heteroskedasticity not stationarity. Many researchers have concluded that the best of the GARCH models is its first order specification (GARCH 1,1) based on the view that the first lag of conditional variance is enough to capture the volatility clustering in the data. Hansen and Lunde (2005) had compared the power of 330 ARCH-type models in explaining the conditional variance of exchange rate and stock return data. The scholars discovered no evidence suggesting that more sophisticated models can outperform the GARCH (1,1). Taylor (2005) also described the GARCH (1,1) specification as the most popular in modelling the volatility of daily stock returns. Therefore, it is strongly argued that the first order lags (1,1) of GARCH model have similar forecasting power with higher order specifications as shown in Appendix 8.

Appendix 8 shows the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) diagnostic results of GARCH (1,1), (2,2), (3,3), (4,4). From the results, it can be confirmed that GARCH (1,1) has similar accuracy to forecast future volatility when compared with higher order specifications.

The model is also evaluated under the assumptions of three error distributions (Normal Gaussian Distribution, Student's t with fixed parameters and Generalized Error Distribution (GED) with fixed parameters) to achieve the best model standing or position. The three distributions suggest that previous day information, previous day volatility and external factors can all affect today's volatility. In other words, the coefficients for the ARCH term, the GARCH term, and any exogenous factors might be significant in the model.

In testing the model under the three distributions, the following null hypotheses will be tested in respect of the residuals computed from the models.

- i- There is no serial correlation in the residuals.
- ii- There is no ARCH effect in the residuals, and
- iii- Residuals are normally distributed.

The first null hypothesis of 'there is no serial correlation in the residuals' will be tested for significance using the 'correlogram square residuals test'. The second null hypothesis of 'there is no ARCH effect in the residuals' will be tested for significance using the 'ARCH test'. The third null hypothesis of 'residuals are normally distributed' will be tested using the 'Jacque bera statistic'. Acceptance or rejection of the null hypotheses will be based on 5% significance level.

If the estimate of GARCH (1,1) complies with the assumptions of any of the three distributions at the same time accepting the above null hypotheses in respect of the residuals generated, the GARCH (1,1) will be the best fit under that distribution. In this study, the series of the UK oil and gas sector and FTSE All Share index will be modelled in GARCH (1,1) under all the three distributions in order to find the best fit distribution for the model and thus:

(a) GARCH (1,1) model under the assumptions of Normal Gaussian Distribution:

Table 9.6 – GARCH (1,1) Model on the FTSE UK Oil and Gas Index Returns under the Normal Gaussian Distribution

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000475	0.000165	2.876885	0.0040
One lagged Return	0.020280	0.014709	1.378704	0.1680
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.76E-06	3.69E-07	4.766301	0.0000
Residual(-1)^2	0.066237	0.004890	13.54623	0.0000
GARCH(-1)	0.925475	0.005392	171.6236	0.0000
Diagnostic tests				
R-squared	-0.000584	Mean dependent var.	0.000244	
Adjusted R-squared	-0.000786	S.D. dependent var.	0.014882	
S.E. of regression	0.014888	Akaike info criterion	-5.859531	
Sum squared resid	1.097834	Schwarz criterion	-5.852964	
Log likelihood	14521.99	Hannan-Quinn criter.	-5.857229	
Durbin-Watson stat	2.033707			

Source: Author (2015)

Convergence was achieved after ten (10) iterations in estimating GARCH (1,1) model. Thus, the model can be expressed from the above Table 9.6 as follows:

$$Y_t = \underset{(2.87)}{0.000475} + \underset{(1.37)}{0.0202}Y_{t-1} + u_t$$

$$h_t = \underset{(4.76)}{0.00000176} + \underset{(171.62)}{0.925}h_{t-1} + \underset{(13.54)}{0.0662}u^2_{t-1}$$

The first segment of the Table 9.6 represents the mean equation while the second segment represents the variance from the error of the mean equation in the first segment. The 'RESID(-1)^2' from Table 9.6 is 'e^2_{t-1} or u^2_{t-1}' in the GARCH (1,1) model referred to as the ARCH term and its p-value is 0.0000 which is significant because it is less than 5%. Next to 'RESID(-1)^2' in the table is 'GARCH (-1)' referred to as the GARCH term and its p-value is also 0.0000 which is significant because it is less than 5%. This is proven by the z-statistics of 4.76, 171.62 and 13.54 of the model which are all significant.

Concisely, modelling GARCH (1,1) on the returns of the FTSE UK Oil and Gas index complies with the assumption of Normal Gaussian distribution which indicates that both the ARCH and GARCH terms are significant.

However, prior to making any conclusion the serial correlation, ARCH effect and normality of the residuals derived from the model in Table 9.6 must be assessed using the following null hypotheses:

H_o1 – There is no serial correlation in the residuals

Table 9.6.1 – Correlogram Square Residual Test on the Garch (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Normal Gaussian Distribution

Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
| |	| |	1	0.012	0.012	0.6882	0.407
| |	| |	2	0.023	0.023	3.2303	0.199
| |	| |	3	0.004	0.003	3.3067	0.347
| |	| |	4	0.007	0.006	3.5357	0.472
| |	| |	5	0.039	0.039	11.239	0.047
| |	| |	6	0.016	0.015	12.477	0.052
| |	| |	7	-0.010	-0.012	12.927	0.074
| |	| |	8	-0.018	-0.018	14.479	0.070
| |	| |	9	-0.018	-0.018	16.067	0.066
| |	| |	10	0.017	0.017	17.545	0.063

Source: Author (2015)

The residuals from the GARCH (1,1) model on the FTSE UK Oil and Gas Index returns under the assumptions of Normal Gaussian distribution were tested for serial correlation using correlogram square residual test. The test was conducted on 10 lags of the series, and the results are depicted in Table 9.6.1 showing the autocorrelation, partial autocorrelation, Q-statistics and probability (p-value) of every lag. The autocorrelation and partial autocorrelation show very small absolute values throughout the 10 lags indicating weak association among the values in the series. More evidence of the absence of correlation was provided by the p-values of the 10 lags which are all greater than 5% except lag 5 (0.047) and as a result of which the null hypothesis cannot be rejected. In other words, the null hypothesis that 'there is no serial correlation in the residuals' is accepted because the p-values are not less than 5%.

H_o2 – There is no ARCH effect in the residuals

Table 9.6.2 – ARCH LM Test on the Garch (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Normal Gaussian Distribution

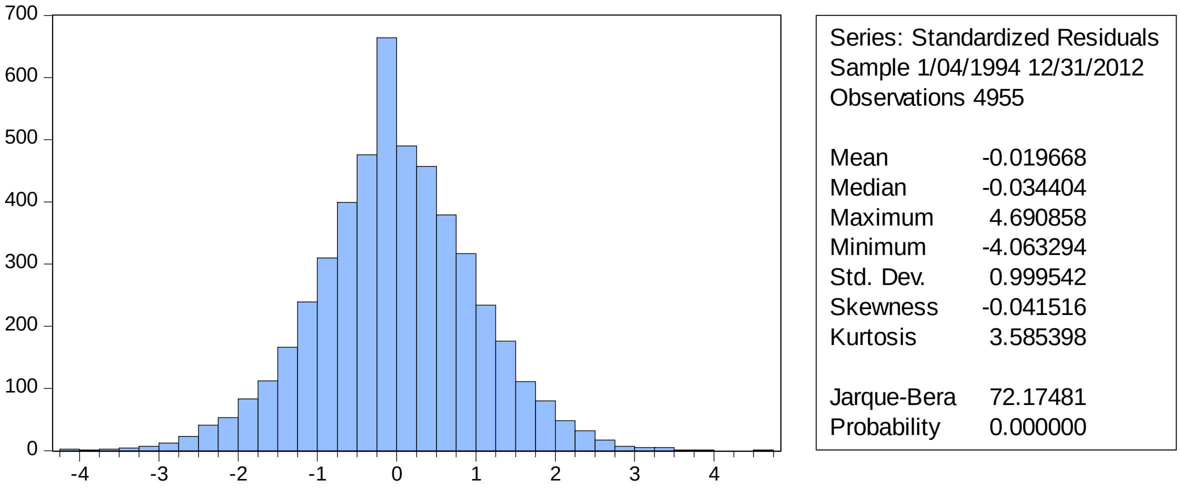
Heteroscedasticity Test: ARCH				
F-statistic	0.687438	Prob. F(1,4952)		0.4071
Obs*R-squared	0.687620	Prob. Chi-Square(1)		0.4070
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.987516	0.026900	36.71072	0.0000
WGT_Residual^2(-1)	0.011782	0.014210	0.829119	0.4071
Diagnostic tests				
R-squared	0.000139	Mean dependent var.		0.999290
Adjusted R-squared	-0.000063	S.D. dependent var.		1.607941
S.E. of regression	1.607991	Akaike info criterion		3.788252
Sum squared resid	12804.07	Schwarz criterion		3.790880
Log likelihood	-9381.501	Hannan-Quinn criter.		3.789174
F-statistic	0.687438	Durbin-Watson stat.		2.000443
Prob(F-statistic)	0.407077			

Source: Author (2015)

The probability (chi-square(1)) of the observed R-square in the table is to be used based on a 5% significance level to reject or accept the null hypothesis of the ARCH effect. In this result, the p-value is 0.4070 which is more than 5% and the rule is that the null hypothesis cannot be rejected unless the p-value is less than 5%. This means that the residuals from GARCH (1,1) of the FTSE UK Oil and Gas Index returns have no ARCH effect. This is a good sign for the model because of the compliance with its assumption.

H_O3 – Residuals are normally distributed

Figure 9.6.1- Histogram - Normality Test (Jacque-Bera) on the GARCH (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Normal Gaussian Distribution



Source: Author (2015)

The assumption for the best fit GARCH (1,1) model is for the residuals to be normally distributed, which is the acceptance of the null hypothesis when the p-value is greater than 5%. However, the results from the GARCH (1,1) model of the FTSE UK Oil and Gas Index returns under Normal Gaussian distribution indicate the p-value from the Jacque-Bera to be 0.0000 which is less than 5% and thus highly significant to reject the null hypothesis. Hence, the residuals are not normally distributed.

Table 9.7 GARCH (1,1) Model on the FTSE All Share Index Returns under the Normal Gaussian Distribution

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000456	0.000106	4.313822	0.0000
One lagged Return	0.017404	0.015102	1.152471	0.2491
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	8.53E-07	1.40E-07	6.076577	0.0000
Residual(-1)^2	0.086404	0.005850	14.77090	0.0000
GARCH(-1)	0.906669	0.006001	151.0761	0.0000
Diagnostic tests				
R-squared	-0.001219	Mean dependent var.	0.000157	
Adjusted R-squared	-0.001411	S.D. dependent var.	0.010792	
S.E. of regression	0.010799	Akaike info criterion	-6.644726	
Sum squared resid	0.608086	Schwarz criterion	-6.638439	
Log likelihood	17334.45	Hannan-Quinn criter.	-6.642527	
Durbin-Watson stat	2.039555			

Source: Author (2015)

Convergence was achieved after eleven (11) iterations in estimating GARCH (1,1) model. Thus, the model can be expressed as follows:

$$Y_t = \underset{(4.31)}{0.000456} + \underset{(1.15)}{0.0174}Y_{t-1} + u_t$$

$$h_t = \underset{(6.07)}{0.000000853} + \underset{(151.07)}{0.9066}h_{t-1} + \underset{(14.77)}{0.0864}u^2_{t-1}$$

The first segment of Table 9.7 represents the mean equation while the second segment represents the conditional variance from the error term series generated from the mean equation in the first segment. The 'RESID(-1)^2' from Table 9.7 is 'e^2_{t-1} or u^2_{t-1}' in the GARCH (1,1) model referred to as ARCH term and its p-value is 0.0000 which is significant because it is less than 5%. Next to 'RESID(-1)^2' in the table is 'GARCH (-1)' referred to as GARCH term and its p-value is also 0.0000 which is significant because it is less than 5%.

This is proven by the z-statistics of 6.07, 151.07 and 14.77 of the model which are all significant.

Succinctly, modelling GARCH (1,1) on the FTSE All Share index returns complies with the assumption of Normal Gaussian distribution which indicates that both the ARCH and GARCH terms are significant.

However, prior to making any conclusion the correlation, ARCH effect and normality of the residuals derived from the model in Table 9.7 must be assessed using the following null hypotheses:

H_o1 – There is no serial correlation in the residuals

Table 9.7.1 Correlogram Square Residual Test on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Normal Gaussian Distribution

Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
| |	| |	1	-0.014	-0.014	0.9783	0.323
| |	| |	2	0.012	0.012	1.7595	0.415
| |	| |	3	0.026	0.026	5.1890	0.158
| |	| |	4	0.011	0.012	5.8613	0.210
| |	| |	5	0.008	0.008	6.1924	0.288
| |	| |	6	0.009	0.009	6.6543	0.354
| |	| |	7	-0.001	-0.001	6.6579	0.465
| |	| |	8	0.019	0.018	8.5932	0.378
| |	| |	9	-0.014	-0.014	9.6325	0.381
| |	| |	10	-0.004	-0.005	9.7062	0.467

Source: Author (2015)

The residuals from the GARCH (1,1) model on the FTSE All Share Index returns under the assumptions of Normal Gaussian distribution were tested for serial correlation using the correlogram square residual test. The test was conducted on 10 lags of the series, and the results are depicted in Table 9.7.1 showing the autocorrelation, partial autocorrelation, Q-statistics and probability (p-value) of every lag. In this particular case, the p-values of all the 10 lags generated are more than 5%. Since the p-values are more than 5%, the null hypothesis that 'there is no serial correlation in the residuals' is to be accepted. In other words, there is no serial correlation in the residuals.

H_o2 – There is no ARCH effect in the residuals

Table 9.7.2 – ARCH LM Test on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Normal Gaussian Distribution

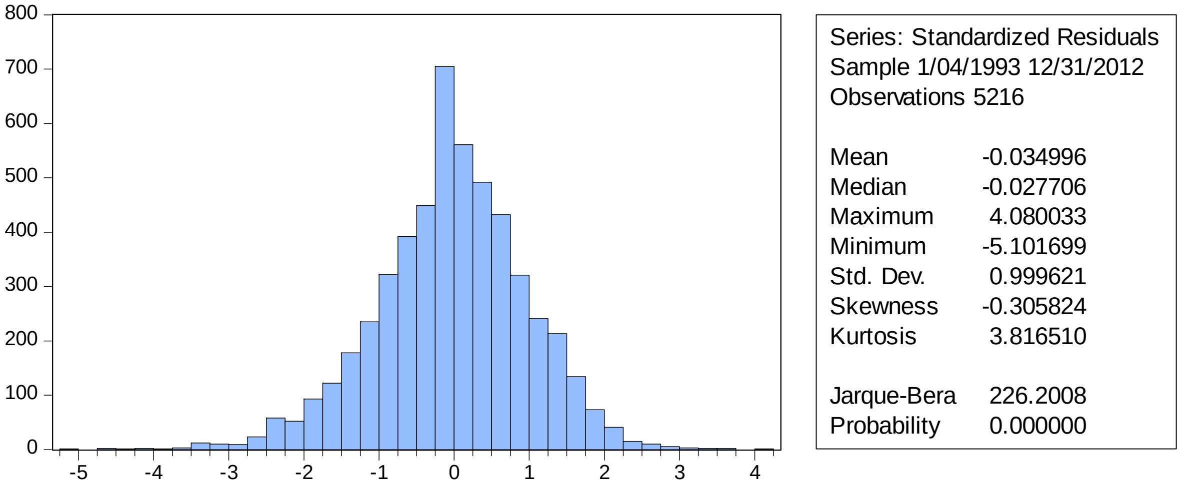
Heteroscedasticity Test: ARCH				
F-statistic	0.977386	Prob. F(1,4952)		0.3229
Obs*R-squared	0.977578	Prob. Chi-Square(1)		0.3228
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.013921	0.027209	37.26460	0.0000
WGT_Residual^2(-1)	-0.013691	0.013849	-0.988628	0.3229
Diagnostic tests				
R-squared	0.000187	Mean dependent var.		1.000226
Adjusted R-squared	-0.000004	S.D. dependent var.		1.691120
S.E. of regression	1.691124	Akaike info criterion		3.889047
Sum squared resid	14908.65	Schwarz criterion		3.891562
Log likelihood	-10138.69	Hannan-Quinn criter.		3.889927
F-statistic	0.977386	Durbin-Watson stat.		1.999671
Prob(F-statistic)	0.322891			

Source: Author (2015)

To check for the existence of the ARCH effect in the residuals from the results of the GARCH (1,1) model under Normal Gaussian distribution of the FTSE All Share index returns, the ARCH test was conducted and the results are portrayed in Table 9.7.2 above. The probability (chi-square (1)) of the observed R-square in the table is to be used based on 5% significance level to reject or accept the null hypothesis. In this result, the p-value is 0.3228 which is more than 5%, and according to the rule, the null hypothesis cannot be rejected unless if the p-value is lower than 5%. This means that the residuals from GARCH (1,1) of the FTSE All Share index returns has no arch effect since the null hypothesis is accepted. This is a positive sign for the model because of the compliance with its assumption.

H_o3 – Residuals are normally distributed

Figure 9.7.1 - Histogram - Normality Test (Jacque-Bera) on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Normal Gaussian Distribution



Source: Author

In Figure 9.7.1 the results of the Jarque-Bera statistic was used to determine the rejection or acceptance of the null hypothesis based on a significance level of 5%. The null hypothesis stated that the 'residuals are normally distributed' and is to be rejected if the p-value is less than 5% and accepted if it is greater than 5%. The assumption for the best fit GARCH (1,1) model is for the residuals to be normally distributed, which is the acceptance of the null hypothesis when the p-value is greater than 5%. However, the results from the GARCH (1,1) model of the FTSE All Share index returns under Normal Gaussian distribution indicate the p-value from the Jacque-Bera statistic to be 0.0000 which is less than 5% and thus highly significant to reject the null hypothesis. Hence, the residuals are not normally distributed.

(b) GARCH (1,1) model under the assumptions of Student's t with fixed parameter (df) at 10

Table 9.8 - GARCH (1,1) Model on the FTSE UK Oil and Gas Index Returns under the Student's t with fixed parameter (df) at 10

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000463	0.000162	2.861366	0.0042
One lagged Return	0.019315	0.014576	1.325131	0.1851
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.97E-06	4.95E-07	3.973521	0.0001
Residual(-1)^2	0.069846	0.006956	10.04156	0.0000
GARCH(-1)	0.921582	0.007475	123.2858	0.0000
Diagnostic tests				
R-squared	-0.000523	Mean dependent var.	0.000244	
Adjusted R-squared	-0.000725	S.D. dependent var.	0.014882	
S.E. of regression	0.014887	Akaike info criterion	-5.870620	
Sum squared resid	1.097767	Schwarz criterion	-5.864053	
Log likelihood	14549.46	Hannan-Quinn criter.	-5.868318	
Durbin-Watson stat.	2.031938			

Source: Author (2015)

Table 9.8 represents the results of the FTSE UK Oil and Gas index returns using the GARCH (1,1) model under the distribution of student's t with fixed df. The mean and variance equations can be expressed from the table as:

$$Y_t = 0.000463 + 0.0193Y_{t-1} + u_t$$
$$\quad\quad (2.86) \quad\quad (1.32)$$

$$h_t = 0.00000197 + 0.9215h_{t-1} + 0.0698u^2_{t-1}$$
$$\quad\quad (3.97) \quad\quad (123.28) \quad\quad (10.04)$$

Both the ARCH term (RESID(-1)^2 or $0.0698u^2_{t-1}$) and GARCH term (GARCH (-1) or $0.9215h_{t-1}$) in the variance equation (second segment of the table) are significant because their p-values are less than 0.05 (5%). This is also confirmed by the significance level of the variables' z-statistics, which stands at 10.04 and 123.28 for the ARCH and GARCH terms respectively. This result satisfies the assumption of student's t with fixed parameter distribution.

However, prior to making any conclusion, the correlation, ARCH effect and normality of the residuals derived from the model in Table 9.8 must be assessed using the following null hypothesis:

H_o1 – There is no serial correlation in the residuals

Table 9.8.1 Correlogram Square Residual Test on the GARCH (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Student's t with fixed parameter (df) at 10

Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
| |	| |	1	0.009	0.009	0.4040	0.525
| |	| |	2	0.020	0.020	2.4634	0.292
| |	| |	3	0.002	0.001	2.4781	0.479
| |	| |	4	0.005	0.004	2.5833	0.630
| |	| |	5	0.038	0.037	9.5748	0.088
| |	| |	6	0.014	0.013	10.541	0.104
| |	| |	7	-0.011	-0.013	11.139	0.133
| |	| |	8	-0.019	-0.019	12.876	0.116
| |	| |	9	-0.019	-0.018	14.649	0.101
| |	| |	10	0.017	0.016	16.021	0.099

Source: Author (2015)

The residuals from the GARCH (1,1) model on the FTSE UK Oil and Gas index under the assumptions of student's t with fixed parameter (df) at 10 were tested for serial correlation using the correlogram square residual test. The test was conducted on 10 lags of the series, and the results are depicted in Table 9.8.1 showing the autocorrelation, partial autocorrelation, Q-statistics and probability (p-value) of every lag. The autocorrelation and partial autocorrelation show very small absolute values throughout the 10 lags indicating a weak association among the values in the series. More evidence of the absence of correlation was provided by the p-values of the 10 lags which are all greater than 5%, as a result of which the null hypothesis cannot be rejected. In other words, the null hypothesis that 'there is no serial correlation in the residuals' is accepted because the p-values are not less than 5%.

H_o2 – There is no ARCH effect in the residuals

Table 9.8.2 ARCH LM Test on the GARCH (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Student's t with fixed parameter (df) at 10

Heteroscedasticity Test: ARCH				
F-statistic	0.403534	Prob. F(1,4952)		0.5253
Obs*R-squared	0.403665	Prob. Chi-Square(1)		0.5252
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.980906	0.026659	36.79410	0.0000
WGT_Residual^2(-1)	0.009027	0.014210	0.635244	0.5253
Diagnostic tests				
R-squared	0.000081	Mean dependent var.		0.989842
Adjusted R-squared	-0.000120	S.D. dependent var.		1.593812
S.E. of regression	1.593908	Akaike info criterion		3.770658
Sum squared resid	12580.77	Schwarz criterion		3.773286
Log likelihood	-9337.921	Hannan-Quinn criter.		3.771580
F-statistic	0.403534	Durbin-Watson stat.		2.000278
Prob(F-statistic)	0.525299			

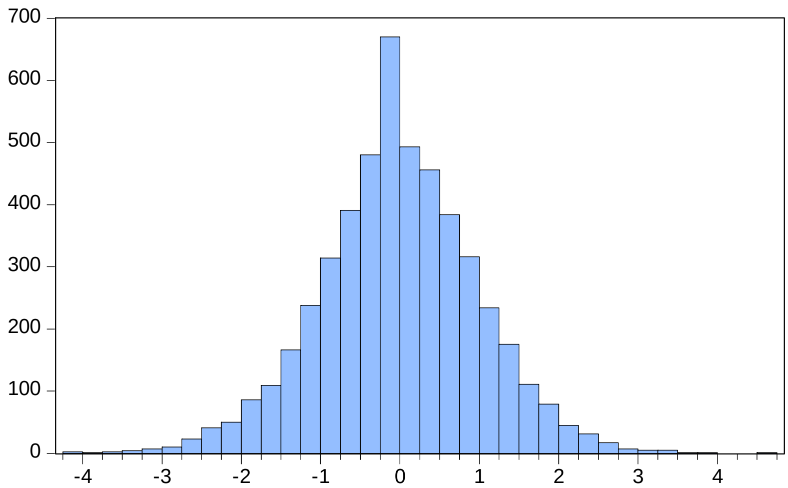
Source: Author (2015)

Similar to the ARCH test carried out under Normal Gaussian distribution, the test for the existence of an ARCH effect in the residuals from the GARCH (1,1) model under student's t with fixed parameter (df) at 10 of the FTSE UK Oil and

Gas index returns was also conducted and results are portrayed in Table 9.8.2 above. The probability (chi-square(1)) of the observed R-square in the table is to be used based on a 5% significance level to reject or accept the null hypothesis. In this result, the p-value is 0.5252 which is more than 5%, and the rule is that the null hypothesis cannot be rejected unless if the p-value is less than 5%. This means that the residuals from GARCH (1,1) of the FTSE UK Oil and Gas index returns has no ARCH effect. This is a positive sign for the model because of the compliance with its assumption.

H_O3 – Residuals are normally distributed

Figure – 9.8.1 - Histogram - Normality Test (Jacque-Bera) on the GARCH (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Student's t with fixed parameter (df) at 10



Series: Standardized Residuals	
Sample 1/04/1994 12/31/2012	
Observations 4955	
Mean	-0.018501
Median	-0.032584
Maximum	4.652145
Minimum	-4.023176
Std. Dev.	0.994827
Skewness	-0.040538
Kurtosis	3.589089
Jarque-Bera	73.00357
Probability	0.000000

Source: Author (2015)

In Figure 9.8.1 the results of the Jarque-Bera statistic was used to determine the rejection or acceptance of the null hypothesis based on a significance level of 5%. The null hypothesis that 'residuals are normally distributed' is to be rejected if the p-value is less than 5% and accepted if the p-value is greater than 5%. The assumption for the best fit GARCH (1,1) model is for the residuals to be normally distributed, which gives the acceptance of the null hypothesis when the p-value is greater than 5%. However, the results from the GARCH (1,1) model of the FTSE UK Oil and Gas index returns under the student's t with fixed parameter (df) at 10 indicate the p-value from the Jacque-Bera statistic to be 0.0000 which is less than 5% and thus highly significant to reject the null hypothesis. Hence, the residuals are not normally distributed.

Table 9.9 GARCH (1,1) Model on the FTSE All Share Index Returns under the Student's t with fixed parameter (df) at 10

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000537	0.000102	5.271556	0.0000
One lagged Return	0.015011	0.014828	1.012382	0.3114
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	7.48E-07	1.75E-07	4.281480	0.0000
Residual(-1)^2	0.084286	0.007654	11.01252	0.0000
GARCH(-1)	0.910275	0.007554	120.4971	0.0000
Diagnostic tests				
R-squared	-0.001595	Mean dependent var.	0.000157	
Adjusted R-squared	-0.001787	S.D. dependent var.	0.010792	
S.E. of regression	0.010801	Akaike info criterion	-6.661715	
Sum squared resid	0.608314	Schwarz criterion	-6.655427	
Log likelihood	17378.75	Hannan-Quinn criter.	-6.659516	
Durbin-Watson stat.	2.034005			

Source: Author (2015)

Table 9.9 represents the results of the FTSE All Share index returns using the GARCH (1,1) model under the assumptions of student's t with fixed df. The mean and variance equations can be expressed from the table as:

$$Y_t = \underset{(5.27)}{0.000537} + \underset{(1.01)}{0.0150}Y_{t-1} + u_t$$

$$h_t = 0.0000007 + 0.9102h_{t-1} + 0.0842u^2_{t-1}$$
$$(4.28) \quad (120.49) \quad (11.01)$$

Both the ARCH term (RESID(-1)^2 or $0.0842u^2_{t-1}$) and the GARCH term (GARCH (-1) or $0.9102h_{t-1}$) in the variance equation (second segment of the table) are significant because their p-values are less than 0.05 (5%). This is also confirmed by the significance level of the variables' z-statistics, which stands at 11.01 and 120.49 for the ARCH and GARCH terms respectively. This satisfies the assumption of the student's t with fixed parameter distribution.

However, prior to making any conclusion, the correlation, ARCH effect and normality of the residuals derived from the model in Table 9.9 must be assessed using the following null hypothesis:

H_o1 – There is no serial correlation in the residuals

Table 9.9.1 - Correlogram Square Residual Test on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Student's t with fixed parameter (df) at 10

Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
| |	| |	1	-0.011	-0.011	0.6821	0.409
| |	| |	2	0.013	0.013	1.6262	0.443
| |	| |	3	0.026	0.027	5.2343	0.155
| |	| |	4	0.012	0.012	5.9936	0.200
| |	| |	5	0.009	0.008	6.3733	0.272
| |	| |	6	0.010	0.009	6.8808	0.332
| |	| |	7	0.000	-0.000	6.8810	0.441
| |	| |	8	0.019	0.018	8.7377	0.365
| |	| |	9	-0.014	-0.014	9.7068	0.375
| |	| |	10	-0.003	-0.004	9.7607	0.462

Source: Author (2015)

The residuals from the GARCH (1,1) model of the FTSE All Share index returns under the assumptions of student's t with fixed parameter (df) at 10 were tested for serial correlation using the correlogram square residual test. The test was conducted on 10 lags of the series, and the results are depicted in Table 9.9.1 showing the autocorrelation, partial autocorrelation, Q-statistics and probability (p-value) of every lag. The p-values of all the 10 lags are greater than 5% which prevent the rejection of null hypothesis and therefore it can be concluded that there is no serial correlation in the residuals.

H_o2 – There is no ARCH effect in the residuals

Table 9.9.2 ARCH LM Test on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Student's t with fixed parameter (df) at 10

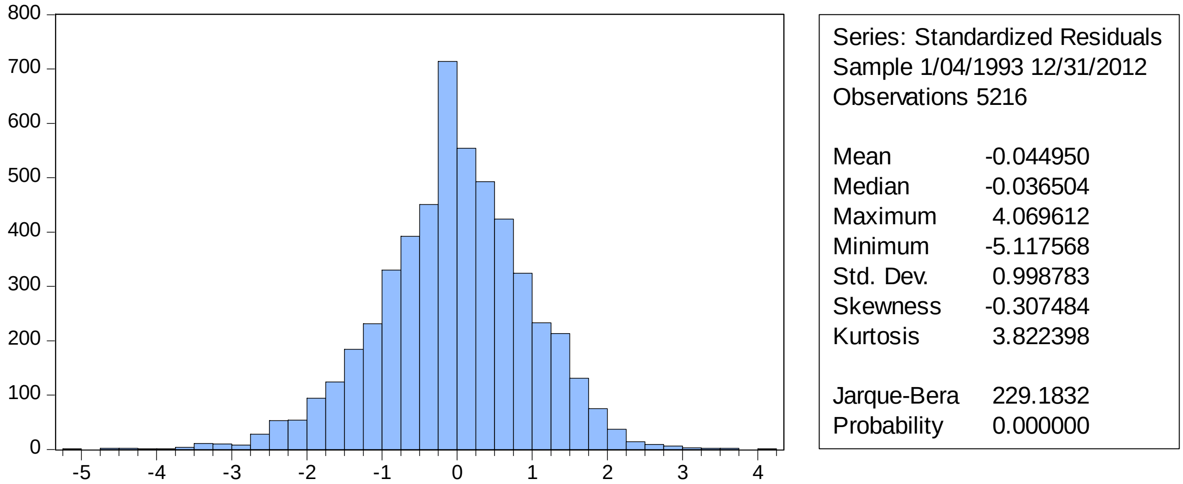
Heteroscedasticity Test: ARCH				
F-statistic	0.681360	Prob. F(1,4952)		0.4092
Obs*R-squared	0.681532	Prob. Chi-Square(1)		0.4091
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.010779	0.027245	37.09924	0.0000
WGT_Residual^2(-1)	-0.011432	0.013849	-0.825445	0.4092
Diagnostic tests				
R-squared	0.000131	Mean dependent var.		0.999354
Adjusted R-squared	-0.000061	S.D. dependent var.		1.694646
S.E. of regression	1.694698	Akaike info criterion		3.893270
Sum squared resid	14971.75	Schwarz criterion		3.895785
Log likelihood	-10149.70	Hannan-Quinn criter.		3.894150
F-statistic	0.681360	Durbin-Watson stat.		1.999695
Prob(F-statistic)	0.409157			

Source: Author (2015)

Similar to the ARCH test carried under Normal Gaussian distribution, the test for the existence of an ARCH effect in the residuals from the GARCH (1,1) model under student's t with fixed parameter (df) at 10 of the FTSE All Share index returns was also conducted and the results are portrayed in Table 9.9.2 above. The probability (chi-square(1)) of the observed R-square in the table is to be used based on a 5% significance level to reject or accept the null hypothesis. In this result, the p-value is 0.4091 which is more than 5% and the rule is that the null hypothesis cannot be rejected unless the p-value is less than 5%. The results show that the residuals from GARCH (1,1) of the FTSE All Share index returns has no ARCH effect. It is a positive sign for the model because of the compliance with its assumption.

H_O3 – Residuals are normally distributed

Figure – 9.9.1 Histogram - Normality Test (Jacque-Bera) on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Student's t with fixed parameter (df) at 10



Source: Author (2015)

In Figure 9.9.1 the results of the Jarque-Bera statistic was used to determine the rejection or acceptance of the null hypothesis based on a significance level of 5%. The null hypothesis that 'residuals are normally distributed' is to be rejected if the p-value is less than 5% and accepted if the p-value is greater than 5%. The assumption for the best fit GARCH (1,1) model is for the residuals to be normally distributed, which is the acceptance of the null hypothesis when the p-value is greater than 5%. However, the results from the GARCH (1,1) model of the FTSE All Share index returns under student's t with fixed parameter (df) at 10 indicate the p-value from the Jacque-Bera statistic to be 0.0000 which is less than 5%, and thus highly significant, allowing rejection of the null hypothesis. Hence, the residuals are not normally distributed.

(c) GARCH (1,1) model under the assumptions of Generalized Error Distribution (GED) with fixed parameter at 1.5

Table 9.10 GARCH (1,1) Model on the FTSE UK Oil and Gas Index Returns under the Generalized Error Distribution (GED) with fixed parameter at 1.5

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000382	0.000159	2.407044	0.0161
One lagged Return	0.018131	0.014291	1.268662	0.2046
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.84E-06	4.99E-07	3.682574	0.0002
Residual(-1)^2	0.068268	0.006906	9.885546	0.0000
GARCH(-1)	0.923411	0.007477	123.5023	0.0000
Diagnostic tests				
R-squared	-0.000350	Mean dependent var.	0.000244	
Adjusted R-squared	-0.000552	S.D. dependent var.	0.014882	
S.E. of regression	0.014886	Akaike info criterion	-5.875454	
Sum squared resid	1.097578	Schwarz criterion	-5.868886	
Log likelihood	14561.44	Hannan-Quinn criter.	-5.873151	
Durbin-Watson stat.	2.029970			

Source: Author (2015)

The results of the FTSE UK Oil and Gas index returns using the GARCH (1,1) model under the assumptions of Generalized Error Distribution are shown in Table 9.10. Mean and variance equations from the table are expressed below:

$$Y_t = \underset{(2.40)}{0.00038} + \underset{(1.26)}{0.0181}Y_{t-1} + u_t$$

$$h_t = 0.00000184 + 0.9234h_{t-1} + 0.0682u^2_{t-1}$$
$$(3.68) \qquad (123.50) \qquad (9.88)$$

Both the ARCH term (RESID(-1)^2 or $0.0682u^2_{t-1}$) and the GARCH term (GARCH (-1) or $0.9234h_{t-1}$) in the variance equation (second segment of the table) are significant because their p-values are less than 0.05 (5%). This is also confirmed by the significance level of the variables' z-statistics, which stands at 9.88 and 123.50 for the ARCH and GARCH terms respectively. This satisfies the assumption of Generalized Error Distribution (GED).

However, prior to making any conclusion, the correlation, ARCH effect and normality of the residuals derived from the model in Table 9.10 must be assessed using the following null hypotheses:

H_o1 – There is no serial correlation in the residuals

Table 9.10.1 - Correlogram Square Residual Test on the GARCH (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Generalized Error Distribution (GED) with fixed parameter at 1.5

Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
| |	| |	1	0.010	0.010	0.4911	0.483
| |	| |	2	0.021	0.021	2.6525	0.265
| |	| |	3	0.002	0.002	2.6802	0.444
| |	| |	4	0.005	0.005	2.8229	0.588
| |	| |	5	0.038	0.038	9.9453	0.077
| |	| |	6	0.015	0.014	11.019	0.088
| |	| |	7	-0.011	-0.013	11.586	0.115
| |	| |	8	-0.019	-0.019	13.338	0.101
| |	| |	9	-0.019	-0.018	15.068	0.089
| |	| |	10	0.017	0.017	16.490	0.086

Source: Author (2015)

The residuals from the Garch (1,1) model on the FTSE UK Oil and Gas index returns under the assumptions of Generalized Error Distribution (GED) with fixed parameter at 1.5 were tested for serial correlation using the correlogram square residual test. The test was conducted on 10 lags of the series and the results are depicted in Table 9.10.1 showing the autocorrelation, partial autocorrelation, Q-statistics and probability (p-value) of every lag. The autocorrelation and partial autocorrelation show very small absolute values throughout the 10 lags indicating a weak association among the values in the series. More evidence of the absence of correlation was provided by the p-values of the 10 lags which are all greater than 5%, as a result of which the null hypothesis cannot be rejected. In other words, the null hypothesis that 'there is no serial correlation in the residuals' is accepted.

H_o2 – There is no ARCH effect in the residuals

Table 9.10.2 ARCH LM Test on the GARCH (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Generalized Error Distribution (GED) with fixed parameter at 1.5

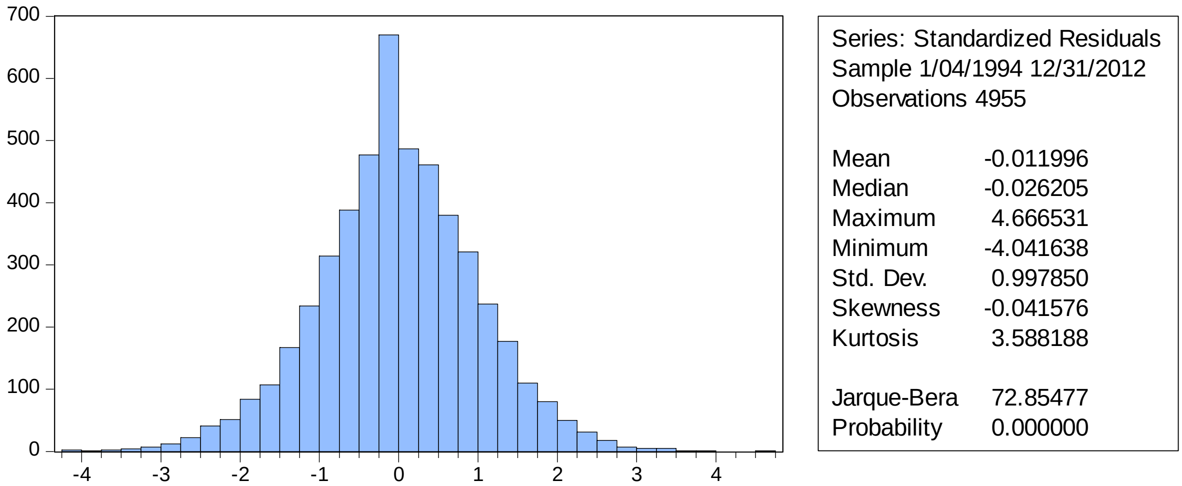
Heteroscedasticity Test: ARCH				
F-statistic	0.490545	Prob. F(1,4952)		0.4837
Obs*R-squared	0.490695	Prob. Chi-Square(1)		0.4836
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.985758	0.026810	36.76873	0.0000
WGT_Residual^2(-1)	0.009953	0.014210	0.700389	0.4837
Diagnostic tests				
R-squared	0.000099	Mean dependent var.		0.995669
Adjusted R-squared	-0.000103	S.D. dependent var.		1.602670
S.E. of regression	1.602753	Akaike info criterion		3.781726
Sum squared resid	12720.78	Schwarz criterion		3.784353
Log likelihood	-9365.334	Hannan-Quinn criter.		3.782647
F-statistic	0.490545	Durbin-Watson stat.		2.000327
Prob(F-statistic)	0.483717			

Source: Author (2015)

On the same note with the ARCH test carried under Normal Gaussian and Student's t with parameter distributions, the test for the existence of an ARCH effect in the residuals from the GARCH (1,1) model under Generalized Error Distribution (GED)with fixed parameter at 1.5 of the FTSE UK Oil and Gas index returns was also conducted and the results are portrayed in Table 9.10.2 above. The probability (chi-square (1)) of the observed R-square in the table is to be used based on a 5% significance level to reject or accept the null hypothesis. In this result, the p-value is 0.4836 which is more than 5% and the rule is that the null hypothesis cannot be rejected unless the p-value is less than 5%. This means that the residuals from GARCH (1,1) of the FTSE UK Oil and Gas index returns has no ARCH effect. This is a positive sign for the model because of the compliance with its assumption.

H_o3 – Residuals are normally distributed

Figure 9.10.1 Histogram - Normality Test (Jacque-Bera) on the GARCH (1,1) Model of the FTSE UK Oil and Gas Index Returns under the Generalized Error Distribution (GED) with fixed parameter (df) at 1.5



Source: Author (2015)

In Figure 9.10.1 the results of the Jarque-Bera statistic were used to determine the rejection or acceptance of the null hypothesis based on a significance level of 5%. The null hypothesis that 'residuals are normally distributed' is to be rejected if the p-value is less than 5% and accepted if the p-value is greater than 5%. The assumption for the best fit GARCH (1,1) model is for the residuals to be normally distributed, which allows the acceptance of the null hypothesis when the p-value is greater than 5%. However, the results from the GARCH (1,1) model of the FTSE UK Oil and Gas index returns under Generalized Error Distribution (GED) with fixed parameter (df) at 1.5 indicate the p-value from the Jacque-Bera statistic to be 0.0000 which is less than 5% and thus highly significant, allowing rejection of the null hypothesis. Hence, the residuals are not normally distributed.

Table 9.11 GARCH (1,1) Model on the FTSE All Share Index Returns under the Generalized Error Distribution (GED) with fixed parameter at 1.5

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000491	0.000100	4.893056	0.0000
One lagged Return	0.012572	0.014452	0.869941	0.3843
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	8.15E-07	1.86E-07	4.387932	0.0000
Residual(-1)^2	0.085333	0.007903	10.79783	0.0000
GARCH(-1)	0.908153	0.007963	114.0448	0.0000
Diagnostic tests				
R-squared	-0.001224	Mean dependent var.	0.000157	
Adjusted R-squared	-0.001416	S.D. dependent var.	0.010792	
S.E. of regression	0.010799	Akaike info criterion	-6.665010	
Sum squared resid	0.608089	Schwarz criterion	-6.658722	
Log likelihood	17387.35	Hannan-Quinn criter.	-6.662811	
Durbin-Watson stat.	2.029905			

Source: Author (2015)

The results of the FTSE All Share index returns using the GARCH (1,1) model under the assumptions of Generalized Error Distribution are shown in Table 9.11. Mean and variance equations from the table are expressed below:

$$Y_t = \underset{(4.89)}{0.000491} + \underset{(0.86)}{0.0125} Y_{t-1} + u_t$$

$$h_t = \underset{(4.38)}{0.0000008} + \underset{(114.04)}{0.9081} h_{t-1} + \underset{(10.79)}{0.0853} u^2_{t-1}$$

Both the ARCH term (RESID(-1)^2 or $0.0853u^2_{t-1}$) and GARCH term (GARCH (-1) or $0.9081h_{t-1}$) in the variance equation (second segment of the table) are significant because their p-values are less than 0.05 (5%). This is also confirmed by the significance level of the variables' z-statistics, which stands at 10.79 and 114.04 for the arch and garch terms respectively. This satisfies the assumption of Generalized Error Distribution (GED).

However, prior to making any conclusion, the correlation, ARCH effect and normality of the residuals derived from the model in Table 9.11 must be assessed using the following null hypotheses:

H_o1 – There is no serial correlation in the residuals

Table 9.11.1 - Correlogram Square Residual Test on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Generalized Error Distribution (GED) with fixed parameter at 1.5

Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
| |	| |	1	-0.013	-0.013	0.8372	0.360
| |	| |	2	0.013	0.013	1.7128	0.425
| |	| |	3	0.026	0.026	5.2342	0.155
| |	| |	4	0.012	0.012	5.9364	0.204
| |	| |	5	0.008	0.008	6.2730	0.281
| |	| |	6	0.010	0.009	6.7761	0.342
| |	| |	7	-0.000	-0.001	6.7765	0.453
| |	| |	8	0.019	0.018	8.7053	0.368
| |	| |	9	-0.014	-0.014	9.7204	0.374
| |	| |	10	-0.004	-0.005	9.7860	0.459

Source: Author (2015)

The residuals from the GARCH (1,1) model on the FTSE All Share index returns under the assumptions of Generalized Error Distribution (GED) were tested for serial correlation using the correlogram square residual test. The test was conducted on 10 lags of the series and the results are depicted in Table 9.11.1 showing the autocorrelation, partial autocorrelation, Q-statistics and probability (p-value) of every lag. In this particular case, the p-values of all the 10 lags are greater than 5%, as a result of which the null hypothesis of no serial correlation in the residuals is accepted.

H_o2 – There is no ARCH effect in the residuals

Table 9.11.2 ARCH LM Test on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Generalized Error Distribution (GED) with fixed parameter at 1.5

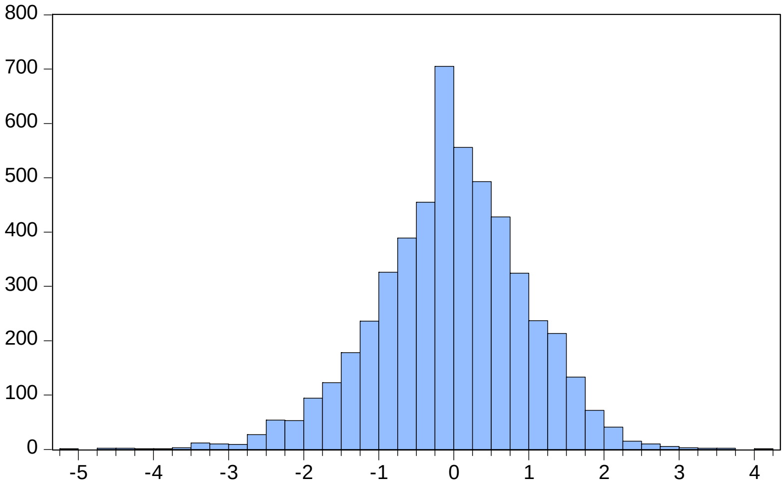
Heteroscedasticity Test: ARCH				
F-statistic	0.836329	Prob. F(1,4952)		0.3605
Obs*R-squared	0.836515	Prob. Chi-Square(1)		0.3604
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.013558	0.027249	37.19614	0.0000
WGT_Residual^2(-1)	-0.012665	0.013849	-0.914510	0.3605
Diagnostic tests				
R-squared	0.000160	Mean dependent var.		1.000880
Adjusted R-squared	-0.000031	S.D. dependent var.		1.694087
S.E. of regression	1.694113	Akaike info criterion		3.892580
Sum squared resid	14961.41	Schwarz criterion		3.895095
Log likelihood	-10147.90	Hannan-Quinn criter.		3.893459
F-statistic	0.836329	Durbin-Watson stat.		1.999676
Prob(F-statistic)	0.360491			

Source: Author (2015)

On the same note with the ARCH test carried under Normal Gaussian and Student’s t with parameter distributions, the test for the existence of an ARCH effect in the residuals from the GARCH (1,1) model under Generalized Error Distribution (GED)with fixed parameter at 1.5 of the FTSE All Share index returns was also conducted and the results are portrayed in Table 9.11.2 above. The probability (chi-square (1)) of the observed R-square in the table is to be used based on a 5% significance level to reject or accept the null hypothesis. In this result, the p-value is 0.3604 which is more than 5%, and the rule is that the null hypothesis cannot be rejected unless the p-value is less than 5%. This means that the residuals from GARCH (1,1) of the FTSE All Share index returns has no ARCH effect. This is a positive sign for the model because of the compliance with its assumption.

H_O3 – Residuals are normally distributed

Figure 9.11.1 Histogram - Normality Test (Jacque-Bera) on the GARCH (1,1) Model of the FTSE All Share Index Returns under the Generalized Error Distribution (GED) with fixed parameter (df) at 1.5



Series: Standardized Residuals	
Sample 1/04/1993 12/31/2012	
Observations 5216	
Mean	-0.039201
Median	-0.031884
Maximum	4.074796
Minimum	-5.108294
Std. Dev.	0.999791
Skewness	-0.307847
Kurtosis	3.817909
Jarque-Bera	227.7774
Probability	0.000000

Source: Author (2015)

In Figure 9.11.1 the results of the Jarque-Bera statistic was used to determine the rejection or acceptance of the null hypothesis based on a significance level of 5%. The null hypothesis that 'residuals are normally distributed' is to be rejected if p-value is less than 5% and accepted if the p-value is greater than 5%. The assumption for the best fit GARCH (1,1) model is for the residuals to be normally distributed, which allows acceptance of the null hypothesis when the p-value is greater than 5%. However, the results from the GARCH (1,1) model of the FTSE All Share index returns under Generalized Error Distribution (GED) with fixed parameter (df) at 1.5 indicate the p-value from the Jacque-Bera statistic to be 0.0000 which is less than 5% and thus highly significant, allowing rejection of the null hypothesis. Hence, the residuals are not normally distributed.

9.3.3.3 Findings

To appropriately model the volatility of the UK oil and gas sector share indices in comparison to the volatility of the overall market indices of the London stock exchange, the GARCH (1,1) model was selected and applied on the FTSE UK Oil and Gas and FTSE All Share indices. The GARCH (1,1) was decided by testing for compliance of the series with the assumptions of three main distributions of Normal Gaussian, student's t with fixed parameter and Generalized Error with fixed parameter. The three distributions mainly assume that both the ARCH and GARCH terms in the variance equation of GARCH (1,1) are significant enough to influence or dictate the volatility of any series subjected to the GARCH (1,1) model. However, the residuals of the series subjected to the GARCH (1,1) model are expected to be non-serially correlated, with an absence of ARCH effects and normally distributed for the postulation of Arch and GARCH terms significance in the model to be effective. In that direction, all series under study were modelled in GARCH (1,1) under the three different distributions mentioned earlier. Examination conducted has led to inferences as discussed in subsequent paragraphs.

FTSE UK Oil and Gas index returns is one of the two index series under consideration in this chapter. The index comprises oil and gas producing companies and oil equipment and services companies. It has 4956 observations generated from a 19 years period between 31 December, 1993 and 31 December, 2012. The returns are shown to be stationary based on the stationarity test conducted in Chapter 6. When the series was modelled in simple regression, the residuals depict the existence of conditional heteroskedasticity or volatility clustering, which motivated the application of the GARCH (1,1) model. The results from further modelling of the series into GARCH (1,1) under Normal Gaussian Distribution, student's t with fixed parameter at 10 and Generalized Error Distribution with fixed parameter at 1.5 have all shown similar characteristics. The residuals from the model have indicated the non-existence of serial correlation when tested using the correlogram square residual test as presented in Table 9.6.1. Similarly, the results presented in Table 9.6.2 portrayed that the residuals have no ARCH effect after the ARCH test was conducted. These two inferences are positive for the effectiveness of GARCH (1,1) in explaining and forecasting the volatility of the series. The last hypothesis that residuals have a normal distribution was tested using the Normality test of Jacque-bera, but the residuals are not normally distributed which violated the underlying assumption of the GARCH (1,1) model. Nevertheless, the normality distribution hypothesis is deemed to be a weak assumption and has been ignored by many researchers. Conclusively, the volatility of the FTSE UK oil and gas index returns can be explained by the GARCH (1,1) model under any of the three distributions (Normal Gaussian, Student's t with fixed parameter at 10 and Generalized Error Distribution with fixed parameter at 1.5). Akaike and Schwarz Information Criteria are considered appropriate for homoscedastic linear models such as linear regression, autoregressive moving average and kernel models and hence have not been used as criteria for model selection in this chapter. Under this circumstance, the GARCH (1,1) model under Normal Gaussian distribution is considered for selection to model the volatility of the FTSE UK oil and gas index returns. Results as presented in Table 9.6 have shown the variance equation of the GARCH (1,1) model under Normal Gaussian distribution as '$h_t = 0.000000176 + 0.925h_{t-1} + 0.0662u^2_{t-1}$' and both ARCH ($0.0662u^2_{t-1}$) and GARCH ($0.925h_{t-1}$) terms are highly significant with p-values of 0.0000 each. The significance is also supported by high z-statistics of 171.62 for the GARCH term and 13.54 for the ARCH term. In other words, the volatility of the returns of the FTSE UK Oil and Gas index is highly affected by its past information (ARCH term) and its past volatility trend (GARCH term). This suggests that volatility in the share returns of the FTSE UK oil and gas companies is determined by the internal shocks from the companies. Based on the facts presented, application of superior GARCH models in the study of the FTSE UK Oil and Gas index returns are to be considered under Normal Gaussian Distribution, except in section 9.4 where all the models will be used in order to select the most appropriate in volatility forecasting.

To compare the behaviour of the oil and gas sector with that of the entire market (LSE), the FTSE All Share index was selected as another variable for examination. It comprises all the companies listed on the LSE and 20 years series with 5217 observations generated from the period between 31 December, 1992 and 31 December, 2012. The returns are assumed to be stationary based on the stationary test conducted in Chapter 6 and, when the series was modelled in simple regression, the residuals depicted the existence of conditional heteroskedasticity or volatility clustering, which motivated the application of the GARCH (1,1) model. The results from further modelling of the series into GARCH (1,1) under Normal Gaussian distribution have shown compliance with the assumptions of non-serial correlation and non-existence of arch effect in the residuals (Table 9.7.1 and 9.7.2). However, the null hypothesis of normal distribution has been strongly rejected (Figure 9.7.1).

The results from GARCH (1,1) under student's t with fixed parameter at 10 also accepted the null hypotheses of non-serial correlation and non-existence of ARCH effect and as a result and similar to other distributions the hypothesis of normal distribution was rejected, (see Tables 9.9.1, 9.9.2, and Figure 9.9.1). Results from GARCH (1,1) under Generalized Error distribution with fixed parameter at 1.5 indicated the non-existence of serial correlation (Table 9.11.1) and non-existence of ARCH effect (Table 9.11.2) in the residuals. Figure 9.11.1 confirmed that the residuals are not normally distributed. Hence, all the models for the FTSE All share index returns are desirable from which only GARCH (1,1) under the Normal Gaussian distribution is to be selected for the study. Conclusively, the volatility of the FTSE All share index returns can be explained by the GARCH (1,1) model under the assumption of Normal Gaussian distribution. The results presented in Table 9.7 (GARCH (1,1) under Normal Gaussian distribution) showed a variance equation as '$h_t = 0.0000000853 + 0.9066h_{t-1} + 0.0864u^2_{t-1}$' in which both arch ($0.0864u^2_{t-1}$) and garch ($0.9066h_{t-1}$) terms are highly significant with p-values of 0.0000 each. The significance is also supported by high z-statistics of 151.07 for the GARCH term and 14.77 for the ARCH term. In other words, the volatility of the returns of the FTSE All Share index is highly affected by its previous period squared residual (past values of shocks) referred as the ARCH term and its previous day variance or volatility referred as the GARCH term. This proposes that volatility in the share returns of the oil and gas sector has the same characteristics with that of the entire market (London stock exchange). Also, the volatility in their returns is determined by internal factors or shocks from the respective companies. Based on the facts presented, application of GARCH models in the study of the FTSE All share index is to be considered under

Normal Gaussian Distribution. Furthermore, Liu and Hung (2010) suggested that the GARCH (1,1) model with normal distribution is preferred to more complex error distribution assumptions. However, all models will be applied in volatility forecasting to select the most accurate.

9.3.4 Asymmetric Volatility Model

The phenomenon of asymmetric volatility is another contentious topic in the field of finance. Some scholars believe that the volatility of equity markets is always asymmetrical while others have the opposite opinion. It is, therefore, important to investigate the asymmetric characteristics of the LSE oil and gas sector and the entire market. A model developed as an extension of GARCH is employed for the investigation.

9.3.4.1 Threshold ARCH (TARCH) (1,1,1) Model

Threshold GARCH or GJR-GARCH, commonly referred to as the Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model, is an asymmetric volatility model developed by Glosten, Jagannathan and Runkle (1993) to measure the impact of both positive (good news) and negative (bad news) announcements (innovations) on volatility. According to the TARCH model, positive innovation at present (time‘t’) has an impact on future (time‘t+1’) volatility that is equal to α times the residual squared (α x ε^2), while a negative innovation at present (time‘t’) has an impact on future (time‘t+1’) volatility that is equal to $(\alpha+\gamma)$ times the residual squared ($(\alpha+\gamma)$ x ε^2). If the parameter γ is positive, then the impact of negative innovation on volatility is higher than that of positive innovation. The parameter γ being positive also signifies the presence of the leverage effect. The TARCH model is given by the following formula:

$$\sigma^2_t = \omega + \beta\sigma^2_{t-1} + \alpha\varepsilon^2_{t-1} + \gamma\varepsilon^2_{t-1} S_{t-1}$$

Where; S_{t-1} represents additional information in the previous period, while ε^2_{t-1} represents past information as squared residuals. $S_{t-1} = 1$, if $\varepsilon_{t-1} < 0$ (negative information) and $S_{t-1} = 0$, if $\varepsilon_{t-1} \geq 0$ (positive information).

Good news = $\varepsilon_{t-1} > 0$ and its impact on volatility is (α x ε^2), while bad news = $\varepsilon_{t-1} < 0$, and its impact on volatility is (($\alpha + \gamma$) x ε^2). If $\gamma_t > 0$, the impact of bad news on volatility would be higher than the impact of good news on volatility. If $\gamma_t \neq 0$, the impact of news on volatility will be asymmetric. A leverage effect could exist if bad news causes high negative volatility that reduces the equity value of a firm in the market. The effect happens when the proportion of leverage increases as a result of a decrease in equity value.

It has been discovered from the previous section of this chapter that past information (ARCH term) of previous returns affects the present volatility of today's or future returns. In this line of thought, the study explored the extent of past information's influence on volatility by splitting the information into good and bad news, and measuring the impact of each news on the volatility using Threshold GARCH (TARCH, 1,1,1).

Table 9.12 TARCH (1,1,1) Model on FTSE UK Oil and Gas Index Returns under the Normal Gaussian Distribution

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000265	0.000166	1.595684	0.1106
One lagged Return	0.020262	0.014641	1.383926	0.1664
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	2.09E-06	3.69E-07	5.667341	0.0000
Residual(-1)^2	0.032703	0.005424	6.028957	0.0000
Residual(1)^2*(Residual(-1)<0)	0.058324	0.008145	7.160959	0.0000
GARCH(-1)	0.927541	0.005613	165.2360	0.0000
Diagnostic tests				
R-squared	-0.000335	Mean dependent var.	0.000244	
Adjusted R-squared	-0.000537	S.D. dependent var.	0.014882	
S.E. of regression	0.014886	Akaike info criterion	-5.866943	
Sum squared resid	1.097561	Schwarz criterion	-5.859062	
Log likelihood	14541.35	Hannan-Quinn criter.	-5.864179	
Durbin-Watson stat.	2.034177			

Source: Author (2015)

The interpretation of the results shown in Table 9.12 has indicated the existence of additional information (S_{t-1}) presented as' Residual(-1)^2*(Residual(-1)<0)' on the table. The impact of this information (bad news) on volatility is measured by testing the null hypothesis that states '$S_{t-1} = 0$' in respect of 'Residual(-1)^2*(Residual(-1)<0)'. A 5% significance level was used to reject or accept the null hypothesis. A p-value of less than 5% allows the null hypothesis to be rejected so accepting the alternative hypothesis that states '$S_{t-1} \neq 0$'. The p-value of Residual(-1)^2*(Residual(-1)<0) is 0.0000, which is less than 5% and deemed highly significant to reject the null hypothesis and accept the alternative hypothesis that confirms the existence and asymmetric impact of additional information (bad news) on volatility. It is to be recalled that if the coefficient of ($\varepsilon^2_{t-1}\ S_{t-1}$) which is ($\gamma$), is greater than 0, then the impact of bad news on volatility would inevitably be higher than the impact of good news since ($(\alpha + \gamma)$ x ε^2). In particular for the volatility of FTSE UK Oil and Gas index returns, past information is classified into good and bad news and the impact of bad news on volatility is higher than that of good news which increases the chances of leverage effect. The extent of the leverage effect as a result of asymmetric volatility could be investigated in further research.

The TARCH (1,1,1) model applied under Normal Gaussian Distribution had been subjected to a diagnostic test and the residuals generated have complied with the assumptions of non-serial correlation and non-existence of arch effect by accepting the null hypotheses that states 'there is no serial correlation' and 'there is no ARCH effect'. The assumption of normality distribution has not been satisfied because the null hypothesis of 'residuals are normally distributed' has been rejected. Many researchers have ignored the postulation that residuals should be normally distributed in the application of the ARCH models.

Table 9.13 TARCH (1,1,1) Model on FTSE All Share Index Returns under the Normal Gaussian distribution

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000214	0.000106	2.015655	0.0438
One lagged Return	0.021078	0.014944	1.410502	0.1584
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.07E-06	1.20E-07	8.978917	0.0000
Residual(-1)^2	0.009087	0.006413	1.417026	0.1565
Residual(1)^2*(Residual(-1)<0)	0.110498	0.008170	13.52512	0.0000
GARCH(-1)	0.922031	0.005767	159.8784	0.0000
Diagnostic tests				
R-squared	-0.000640	Mean dependent var.	0.000157	
Adjusted R-squared	-0.000832	S.D. dependent var.	0.010792	
S.E. of regression	0.010796	Akaike info criterion	-6.667385	
Sum squared resid	0.607734	Schwarz criterion	-6.659840	
Log likelihood	17394.54	Hannan-Quinn criter.	-6.664746	
Durbin-Watson stat.	2.048133			

Source: Author (2015)

Similar to the results in Table 9.12, those shown in Table 9.13 have also indicated the existence of additional information (S_{t-1}) presented as 'Residual(-1)^2*(Residual(-1)<0)' on the table. The impact of this information (bad news) on volatility is measured by testing the null hypothesis that states '$S_{t-1} = 0$' in respect of 'Residual(-1)^2*(Residual(-1)<0)'. A 5% significance level was used to reject or accept the null hypothesis. A p-value of less than 5% allows the null hypothesis to be rejected, so accepting the alternative hypothesis that states '$S_{t-1} \neq 0$'. The p-value of Residual(-1)^2*(Residual(-1)<0) is 0.0000, which is less than 5% and deemed highly significant to reject the null hypothesis and accept the alternative hypothesis that confirms the existence and asymmetric impact of additional information (bad news) on volatility. It is to be recalled that if the coefficient of ($\varepsilon^2_{t-1} S_{t-1}$) which is ($\gamma$), is greater than 0, then the impact of bad news on volatility would inevitably be higher than the impact of good news since (($\alpha + \gamma$) x ε^2). Therefore, the volatility of the FTSE All Share index is more affected by the impact of bad news than good news. It is also possible for the leverage effect to increase as a result of a decrease in equity value due to a persistent shock from the bad news. The extent of the leverage effect as a result of asymmetric volatility could be investigated in further research.

9.3.4.2 Findings

The coefficients of '$\varepsilon^2_{t-1}S_{t-1}$' or 'Residual(-1)^2*(Residual(-1)<0)' representing additional information (bad news) or (γ) in the variance equation from the results in both Table 9.12 and 9.13 are greater than '0' at 0.058324 and 0.110498 respectively. It is a clear indication that the impact of bad news (($\alpha + \gamma$) x ε^2) would be higher than that of good news (α x ε^2).

The volatility in the returns of both the FTSE Oil and Gas and the FTSE All Share indices can be affected more significantly by the bad news than good news. The extent is 0.058324 in addition to any information that is not regarded as bad news by the market in the case of the oil and gas sector and 0.110498 in the case of the entire market represented by the FTSE All Share index. This shows that the entire market is more vulnerable to bad news than the oil and gas sector. The results generated confirmed the presence of a leverage effect.

9.3.5 Variance Regressor (Brent Crude Oil Price) and GARCH (1,1) Model

Variance regressors are exogenous variables introduced into the variance equation of the GARCH (1,1) model to examine the impact of external factors on the volatility of a return series. The adjusted variance equation estimates both the internal shocks (ARCH and GARCH terms) and the external shocks (regressors) associated with the volatility of a series. Section 9.3.3 of this chapter analysed volatility by applying the GARCH (1,1) model on the FTSE All Share and UK Oil and Gas indices without any consideration for the role of external factors. Thus, only internal shocks are examined. In this section, the return series from the UK Brent crude oil price is presented as a variance regressor in the GARCH (1,1) variance equation.

9.3.5.1 Brent Crude Oil Price (log changes) as Exogenous Variable in GARCH (1,1) Model

The UK Brent crude oil price is the leading global benchmark price for Atlantic basin crude oil. Two-third (2/3) of the entire world's traded crude oil is priced using the UK Brent Crude oil price. Other prices such as the Dubai Crude, the Oman Crude, the West Texas Intermediate and the OPEC Reference Basket are used as benchmark prices. The trading activities by market players in various futures and swaps markets also determine the international price of Brent Crude. However, the spot market has been the earliest formal market existing since the 1980s that determines the Brent crude oil price and is referred to as 'Dated Brent'. To avoid the complexities of forward markets, the spot market price (Dated Brent) has been earmarked for this study. The prices are downloaded from Datastream for the equivalent periods of the UK Oil and

Gas stock series examined. Such prices are converted to a return series using the formula;

$r_t = \log(P_t) - \log(P_{t-1})$.

The adjusted variance equation from the GARCH (1,1) model is given as:

$$\sigma^2_t = \omega + \beta\sigma^2_{t-1} + \alpha\varepsilon^2_{t-1} + \gamma \log(BCOP_t - BCOP_{t-1})$$

Where: ω = constant, σ^2_{t-1} = GARCH term, ε^2_{t-1} = ARCH term, BCOP = Brent Crude Oil Price, and β_1 to β_4 are the coefficients.

Table 9.14 Dated Brent Crude Oil Price (log changes) as Exogenous Variable in GARCH (1,1) Model on the FTSE UK Oil and Gas Index Returns under the Normal Gaussian Distribution

Conditional mean equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	0.000491	0.000167	2.939323	0.0033
One lagged Return	0.019768	0.014722	1.342778	0.1793
Conditional variance equation				
Model Variables	Coefficients	Standard Error	t-Statistic	Probability
Constant	1.79E-06	3.71E-07	4.817274	0.0000
Residual(-1)^2	0.065958	0.004879	13.51928	0.0000
GARCH(-1)	0.925729	0.005387	171.8452	0.0000
Rtns_Dated_Brent	-4.29E-05	4.35E-05	-0.984835	0.3247
Diagnostic tests				
R-squared	-0.000600	Mean dependent var.	0.000244	
Adjusted R-squared	-0.000802	S.D. dependent var.	0.014882	
S.E. of regression	0.014888	Akaike info criterion	-5.859305	
Sum squared resid	1.097852	Schwarz criterion	-5.851424	
Log likelihood	14522.43	Hannan-Quinn criter.	-5.856542	
Durbin-Watson stat.	2.032670			

Source: Author (2015)

Table 9.14 presents the results of the revised GARCH (1,1) model for the oil and gas sector after including the log price changes of Dated Brent Crude Oil as an exogenous variable or variance regressor in order to assess the impact of the changes on the volatility of the oil and gas sector. Thus, the variance equation from the new model is expressed as:

$$h_t = 0.0000017 + 0.9257h_{t-1} + 0.0659u^2_{t-1} + (-0.0000429)log\Delta BCOP$$
$$(4.81) \quad (171.84) \quad (13.51) \quad (-0.984)$$

The p-value of the Dated Brent Crude price return coefficient was found to be 0.3247, which indicates insignificance in the variance equation since the value is significantly greater than the 5% significance level.

9.3.5.2 Findings

The last section shows that the volatility of the FTSE Oil and Gas index is not influenced by changes in the price of dated Brent crude oil. In other words, the volatility in the dated Brent crude oil price is not transmitted to the volatility of the oil and gas index. The absence of volatility spill over between the spot market dated Brent price and the FTSE oil sector could be explained by many factors such as hedging strategies, the long term investment horizon of projects and the diversified product mix of many companies in the sector. In a study conducted by Antonios and Foster (1992), the relationship between Brent spot and futures market price volatility was investigated using GARCH models and it was discovered that the nature of Brent spot price volatility had changed after the introduction of various forms of Brent forward prices. They were categorical in describing that the Brent crude oil spot price ceases to be important to market participants from the time when its risks can be hedged by various instruments such as Brent forward and swap contracts. In this case, the findings of Antonios and Foster (1992) have coincided with our findings in which the volatility of Brent crude spot price does not have any impact on the volatility of the FTSE oil and gas sector.

9.4 Volatility Forecasting

The specification or fitness of an estimated equation model can be tested by looking at the accuracy of its forecasts. In this section, the models formulated in the previous sections are used in forecasting and various forecasting evaluation techniques are equally employed to measure their fitness and performance.

9.4.1 Forecasting using GARCH (1,1) Model

A dynamic forecast method is employed in forecasting because the equations of the models constructed are characterized by an autoregressive process of one order (AR (1)). The research data sample under consideration ranges between 1994 and 2012 for the FTSE Oil and Gas index, and 1993 to 2012 for the FTSE All Share index. Model estimation for forecasting would cover the period of 1994 to 2009 for the FTSE Oil and Gas index and of 1993 to 2009 for the FTSE All Share index. An out-of-sample forecast would be conducted for three years from 2010 to 2012 in respect of all the indices. Forecast results are compared with actual results and variances are to be measured by forecasting performance evaluation statistics.

Forecasting performance evaluation statistics employed are the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percent Error (MAPE) and the Theil Inequality Coefficient (TIC). The Theil

Inequality Coefficient also consists of three additional measures of Bias Proportion, Variance Proportion and Covariance Proportion. The following formulae give the statistics:

RMSE = $\sqrt{\sum_{t=T+1}^{T+h}(\hat{y}_t - y_t)^2 / h}$

MAE = $\sum_{t=T+1}^{T+h} |\hat{y}_t - y_t| / h$

MAPE = $100 \sum_{t=T+1}^{T+h} \left|\frac{\hat{y}_t - y_t}{y_t}\right| / h$

TIC = $\frac{\sqrt{\sum_{t=T+1}^{T+h}(\hat{y}_t - y_t)^2 / h}}{\frac{\sqrt{\sum_{t=T+1}^{T+h}\hat{y}_t^2}}{h} + \frac{\sqrt{\sum_{t=T+1}^{T+h}y_t^2}}{h}}$

Where; forecast sample = T+1, T+2,………T+ h, actual value = y_t , forecasted value = $\hat{y}_t$, both values are assumed to be in period 't'. RMSE simply measures the differences between all the forecast statistical variables or values and that of the actual values. MAE measures the average of the absolute errors recorded between the forecast and the actual values. MAPE presents MAE in percentage terms and seen as a measure of inaccuracy. TIC is also referred to as 'U' and it measures or compares estimated and forecasted values. If U=0, there is a perfect forecast. If U=1, the predictive power is worst.

TIC has three (3) additional statistics as:

Bias Proportion = $\frac{(\left(\frac{\sum \hat{y}_t}{h}\right) - \bar{y})^2}{\sum(\hat{y}_t - y_t)^2 / h}$

Variance Proportion = $\frac{(s_{\bar{y}} - s_y)^2}{\sum(\hat{y}_t - y_t)^2 / h}$

Covariance Proportion = $\frac{2(1-r)s_{\hat{y}}\, s_y}{\sum(\hat{y}_t - y_t)^2 / h}$

Bias proportion measures the difference between the forecast and the mean of the actual values. Variance proportion as the name implies measures the difference in variance and, lastly, the covariance proportion measures the balance of errors that have not been captured by Bias and Variance proportions. The summation of the three (3) statistics is usually equal to 1.

In general, the lower is the value of any forecast evaluation statistic, the more accurate is the forecast. Results from our forecasts are shown in the subsequent tables below.

Table 9.15 Volatility Forecast using GARCH (1,1) Model on the FTSE UK Oil and Gas Index Returns

	Normal Gaussian Distribution	Students 't' with Fixed Parameter at 10	Generalized Error Distribution (GED) with Fixed Parameter at 1.5
Root Mean Squared Error	0.013085	0.013085	0.013081
Mean Absolute Error	0.009763	0.009762	0.009757
Mean Absolute Percent Error	111.6001	111.0725	108.2710
Theil Inequality Coefficient:	0.961424	0.962520	0.968445
Bias Proportion	0.002227	0.002112	0.001546
Variance Proportion	0.997706	0.997820	0.998402
Covariance Proportion	0.000067	0.000068	0.000052

Source: Author (2015)

Table 9.15 presents the forecast performance evaluation statistics and judgement is to be made based on whether the value of the statistic is low or high. A high value of the parameters indicates a high error in the forecast while a low value signifies a low error and hence a superior forecast. The forecast based on the GARCH (1,1) model under Generalized Error Distribution resulted in lower Root Mean Squared Error (RMSE), Mean Absolute Error

(MAE), Mean Absolute Percent Error (MAPE), bias proportion and covariance proportions at 0.013081, 0.009757, 108.2710, 0.001546 and 0.000052 respectively as compared to the other models . However, the difference in value is insignificant in all the statistics among the three respective distributions. Although, the forecasting errors between the models are meagre, the best fit model to forecast the conditional volatility of the FTSE Oil and Gas index can be deemed to be GARCH (1,1) under Generalized Error Distribution with fixed parameter (df) at 1.5 because of its lower forecasting errors.

Table 9.16 Volatility Forecast using GARCH (1,1) Model on the FTSE All Share Index Returns

	Normal Gaussian Distribution	Students 't' with Fixed Parameter at 10	Generalized Error Distribution (GED) with Fixed Parameter at 1.5
Root Mean Squared Error	0.010781	0.010784	0.010782
Mean Absolute Error	0.007810	0.007815	0.007812
Mean Absolute Percent Error	128.0794	135.0266	131.6306
Theil Inequality Coefficient:	0.959413	0.952107	0.955644
Bias Proportion	0.000849	0.001400	0.001115
Variance Proportion	0.998926	0.998409	0.998704
Covariance Proportion	0.000225	0.000191	0.000181

Source: Author (2015)

Table 9.16 shows the forecast performance evaluation statistics as similar to the method employed in interpreting the results stated in Table 9.15. Judgement is to be made based on whether the value of the statistic is low or high. A high value of the parameters indicates a high error in the forecast while a low value signifies a low error and hence a superior forecast. In this case, forecasting the market stock return volatility of the London stock exchange can best be achieved under GARCH (1,1) model under Normal

Distribution because of its low values for RMSE, MAE, MAPE, and bias proportion at 0.010781, 0.007810, 128.0794 and 0.000849 respectively. The difference in the values of the error statistics between the three distributions is also not significant. Although, the forecasting errors between the models are meagre, the best fit model to forecast the conditional volatility of the FTSE All Share index can be deemed to be GARCH (1,1) under Normal Distribution contrary to the findings that suggest that the GARCH (1,1) model under Generalized Error Distribution (GED) with Fixed Parameter at 1.5 is the best fit model for forecasting the stock return volatility of FTSE Oil and Gas sector.

9.4.2 Forecasting using Threshold ARCH (TARCH) (1,1,1) Model

The Threshold-ARCH model was introduced into the GARCH (1,1) model as suggested by Glosten, Jagannathan and Runkle (1993) to assess the impact of negative innovation on the volatility of stock returns of the FTSE market and oil and gas sector as shown in the previous sections. The findings show a significant impact of negative news on estimated volatility than positive news. To test the viability of the models used in the estimation process, an out-of-sample forecast will be conducted to assess their predictive power by comparing the values of generated forecast performance evaluation statistics with that of the simple GARCH (1,1) models.

Results from the forecast using an asymmetric model of three (3) different distributions are shown in the following tables below.

Table 9.17 Volatility Forecast using Threshold ARCH (TARCH) (1,1,1) Model on the FTSE UK Oil and Gas Index Returns

	Normal Gaussian Distribution	Students 't' with Fixed Parameter at 10	Generalized Error Distribution (GED) with Fixed Parameter at 1.5
Root Mean Squared Error	0.013078	0.013078	0.013076
Mean Absolute Error	0.009752	0.009752	0.009749
Mean Absolute Percent Error	105.5699	105.6441	103.6671
Theil Inequality Coefficient:	0.974425	0.974258	0.978726
Bias Proportion	0.001072	0.001084	0.000789
Variance Proportion	0.998885	0.998872	0.999179
Covariance Proportion	0.000043	0.000044	0.000032

Source: Author (2015)

Table 9.17 shows the forecast evaluation statistics from the forecasted volatility of the FTSE Oil and Gas index using asymmetric volatility models. The model estimated under the assumption of Generalized Error Distribution recorded lower RMSE, MAE, MAPE, Bias Proportion and Covariance Proportion at 0.013076, 0.009749, 103.6671, 0.000789 and 0.000032 respectively. Similar to the results from the simple GARCH (1,1) model without consideration for asymmetry, the model under Generalized Error Distribution (GED) with Fixed Parameter at 1.5 proved to be the best model for forecasting.

In comparing the entire forecast evaluation statistics using an asymmetric volatility model (Table 9.17) with that from a simple volatility model (Table 9.15), the asymmetric volatility or Threshold GARCH model recorded lowest values which signifies higher predictive power. Our results support the findings of Harrison and Moore (2012) who tested the predictive power of twelve (12) forms of the GARCH models and discovered superior predictive power in the asymmetric form of the GARCH models. In a cognate study, Liu and Hung

(2010) also confirmed that volatility asymmetric models such as the Threshold GARCH, EGARCH and PGARCH models have higher forecasting accuracy compared to simple GARCH models.

Table 9.18 Volatility Forecast using Threshold ARCH (TARCH) (1,1,1) Model on the FTSE All Share Index Returns

	Normal Gaussian Distribution	Students 't' with Fixed Parameter at 10	Generalized Error Distribution (GED) with Fixed Parameter at 1.5
Root Mean Squared Error	0.010777	0.010778	0.010778
Mean Absolute Error	0.007800	0.007806	0.007804
Mean Absolute Percent Error	111.6031	120.5579	118.5863
Theil Inequality Coefficient:	0.977903	0.967669	0.969894
Bias Proportion	0.000082	0.000401	0.000310
Variance Proportion	0.999609	0.999365	0.999479
Covariance Proportion	0.000309	0.000234	0.000211

Source: Author (2015)

Table 9.18 presents the forecast evaluation statistics from the forecasted volatility of the FTSE All Share index using asymmetric volatility models. The model estimated under Normal Distribution recorded lower RMSE, MAE, MAPE and Bias Proportion at 0.010777, 0.007800, 111.6031 and 0.000082 respectively. This is similar to the results from the simple GARCH (1,1) model without consideration for asymmetry in which the best fit model for forecasting the volatility of the FTSE All Share index was found to be under Normal Distribution.

In comparing the entire forecast evaluation statistics from the forecast using the asymmetric volatility model (Table 9.18) with that from a simple volatility model (Table 9.16), the asymmetric volatility or Threshold GARCH model recorded the lowest values which signifies higher predictive power. See also the findings of Harrison and Moore (2012); and Liu and Hung (2010).

9.4.3 Findings

The GARCH (1,1) model with Generalized Error Distribution was found to have more forecasting power than the assumptions of normal and student's t distributions in forecasting both the FTSE Oil and Gas and the FTSE All Share indices. This complies with the findings of Varma (1999) in which the GARCH (1,1) model with Generalized Error Distribution was reported to have a superior predictive power in forecasting the volatility of the Indian Stock Exchange. As reported earlier, the difference in the error statistics between the three (3) distributions is not significant and therefore no further statistical test such as Diebold and Mariano (DM) has been employed to measure the significance of the difference.

It was also noted that an asymmetric GARCH model referred to as Threshold-GARCH or TARCH has lower forecast error statistics indicating more accuracy in forecasting compared to that from the symmetric GARCH model in forecasting both the FTSE Oil and Gas and FTSE All Share indices. The results confirmed the findings of Liu and Hung (2010), Abdul Rahman and Tripathy (2013) and Banerjee and Sarkar (2006). Studies by scholars such as Srinivasan (2011) and Gokcan (2000) have contradictory findings that symmetric GARCH models are better in forecasting than asymmetric GARCH models, even though empirical evidence has not been provided. Scholars such as Ng and McAleer (2004) believe that the performance of any type of the

GARCH models depends on the data set used. Several of the proponents of the superiority of the asymmetric GARCH model in forecasting tested various forms of asymmetric GARCH models such as Exponential GARCH (EGARCH), Threshold-GARCH (TARCH), and Power-ARCH (PARCH) models. Alberg et al (2008) concluded that EGARCH under skewed student's t distribution performs better than other asymmetric GARCH models in forecasting. Najand (2003) also affirmed that EGARCH is the best forecasting model compared to other asymmetric volatility models. Liu and Hung (2010) opined that Threshold-GARCH (TARCH) asymmetric volatility models are the best in forecasting before EGARCH and PARCH models.

9.5 Summary and Conclusions

ARCH and GARCH models have been employed to model the FTSE Oil and Gas index and the FTSE All Share index based on the behaviour of the series' residuals or error terms from a simple regression which suggested conformity with an underlying assumption of the models. It is clear from the residuals plotted from the mean equation of the UK oil and gas index that there is the existence of conditional heteroskedasticity which advocated a stylized fact of volatility clustering in the series. The FTSE All Share index has also shown similar characteristics of volatility clustering.

The GARCH (1,1) model consisting of one ARCH term (e^2_{t-1}) representing previous day squared residuals (past information) and one GARCH term (h_{t-1}) representing the volatility or fluctuation of the previous day was adopted to find the current or today's volatility and the active variables that determine it.

Other external variables were not included in the model at this stage. At the same time, higher order GARCH models were also not considered.

To select the best fit GARCH (1,1) for the series under study, the model was estimated under three (3) different distributions (Normal Gaussian distribution, Student's t with fixed parameter and Generalized Error distributions) where both ARCH and GARCH terms are shown to be significant. In other words, past information and fluctuation can affect or determine current volatility. The GARCH (1,1) estimates were subjected to further examination in order to determine the best distribution by generating and testing its residuals for conformity with the assumptions of non-serial correlation, non-existence of Arch effect and normal distribution. In that respect, three null hypotheses (there is no serial correlation in the residuals, there is no ARCH effect in the residuals and the residuals are normally distributed) were formulated and tested for significance using the correlogram square test, the ARCH test and the Jacque bera statistic. Based on those criteria, the best model under appropriate distribution was selected for volatility modelling and forecasting. Details of results and findings from the analyses were discussed in the previous sections of this chapter.

The FTSE UK Oil and Gas index was analysed to identify its volatility behaviour and characteristics. The results from GARCH (1,1) under the three different distributions have all shown similar attributes. It was concluded that GARCH (1,1) was the best fit under any of the three distributions. Hence, Normal Gaussian distribution has been selected for the GARCH modelling of the UK oil and gas index throughout this study. Inferences made suggested that the volatility of the UK oil and gas sector is affected by the previous day's return information and volatility which can influence present or future volatility.

The FTSE All share index also showed similar characteristics in terms of the best fit GARCH (1,1) model which suggests a significance of parameters in all the distributions. In other words, both ARCH and GARCH terms in the variance equation of the model are significant in determining the volatility of the FTSE All share index returns.

The assumption of asymmetric volatility was also tested on the indices to assess the impact of the same magnitude of negative and positive news on volatility using the Threshold-GARCH model. The results confirmed that the impact of negative news on volatility is higher than that of positive news. Thus, the presence of a leverage effect is equally confirmed. It was also discovered that the asymmetric shock is higher in the FTSE All Share index than in the FTSE Oil and Gas index, which means that the entire market is more vulnerable to negative innovation.

The Brent crude oil price from the spot market was also used as a variance regressor or exogenous variable in the symmetric volatility model of GARCH (1,1) to assess the existence of any volatility spill over from the spot price of Brent crude oil. Surprisingly, the results showed no signs of the effect of the Brent crude price shocks or volatility on the volatility of FTSE Oil and Gas sector. The absence of volatility spill over was attributed to the behaviour of investors and portfolio managers in mitigating risks by using the forward market of Brent crude oil price. The long-term investment horizon of projects and the diversified product mix of many companies in the sector have also been seen as risk mitigating factors that prevent volatility spillover.

The accuracy of both symmetric and asymmetric GARCH models employed was tested via forecasting performance. In symmetric GARCH (1,1) models, it was discovered that the GARCH (1,1) model under Generalized Error Distribution with fixed parameter has more predictive power compared to the other distribution assumptions. Threshold-GARCH represents the asymmetric volatility model employed, and it proved to be more powerful than symmetric models in forecasting.

Investors and portfolio managers can assess the volatility of the FTSE Oil and Gas sector and the entire market as represented by FTSE All Share index using various forms of the GARCH models since the changes in prices have been characterized by volatility clustering and the existence of conditional heteroscedasticity. The effect of exogenous variables can also be incorporated into the models to measure the extent of volatility spill over between variables. In forecasting, asymmetric GARCH models should be employed because of the presence of a leverage effect and their low forecasting evaluation statistics. The entire process would enhance the understanding of risks associated with oil and gas stocks and the entire market, thus improving pricing and risk management efficiencies that lead to superior investment strategies.

The forecast errors recorded have shown that volatility cannot be accurately predicted. If the stock market volatility is unpredictable, then the future returns of the market cannot also be predicted. Hence, it was concluded that the dynamics of volatility are consistent with that of the efficient market hypothesis.

CHAPTER 10

ASSET PRICING MODELLING IN THE UK OIL AND GAS SECTOR

10.1 Introduction

One of the biggest challenges in the field of finance is how to effectively model the risk and return of financial securities. Researchers have formulated various asset pricing models that tend to explain the determinants of asset prices or returns. Markowitz's (1952) mean-variance analysis of portfolio returns was one of the earliest attempts in this regard. Sharpe (1964), Lintner (1965), and Mossin (1966) developed a single factor model commonly known as the Capital Asset Pricing Model (CAPM). The main assumption in this model is that asset return is determined by an asset's systematic risk since unsystematic risks of individual assets can be eliminated by diversification in an efficient portfolio. The main criticism of the CAPM is its failure to consider size, value and momentum aspects of different securities. These anomalies have resulted in modifications to the single factor model. Multi-factor asset pricing models such as that of Fama and French's (1993) three factor model and Fama, French and Carhart's (1997) four-factor asset pricing models have been developed to consider more relevant factors in the determination of an asset's price. In recent years, the impact of other commodity prices such as international oil prices have also been incorporated into multi-factor asset pricing models to find the best explanation of a stock's price dynamics.

In this study we aim to investigate the determinants of asset pricing in the UK oil and gas stocks quoted on the London stock exchange. We plan to adopt a multi-factor asset pricing model of Fama-French-Carhart (1997) augmented with an oil price represented by the OPEC Basket Price.

10.2 Review of Literature on Asset Pricing Models

10.2.1 Capital Asset Pricing Model (CAPM)

The initial proposition of the Capital Asset Pricing Model (CAPM) was derived from the works of Sharpe (1964) and Lintner (1965) as an extension of Markowitz's mean-variance analysis model. The model was built on the assumption of perfect market condition, existence and easy accessibility of a riskless asset, hitch-free portfolio formation and diversification of individual asset's risk (unsystematic risk). It was simply argued that an asset price at a given period is the function of a risk free asset return and market risk premium determined by beta (systematic risk). Mossin (1966) confirmed the assertion of Sharpe (1964) that, if investors are rational in a market, the individual risk of assets can be eliminated by diversification and movement to any desired point on the capital market line. However, the model suffered various criticisms from scholars who discovered anomalies in terms of overstatement or understatement of actual asset prices. The criticism of the model started emanating from scholars such as Black (1972) who argued that the assumption of the availability of a riskless asset in the investment opportunities of investors is flawed. The perfect market assumption was also criticised due to short sales restrictions and varying borrowing costs for investment in different assets. Ross (1977) also found that institutional restrictions on short sales which could be due to bankruptcy terms and the presence of financial intermediaries who may introduce barriers such as cost of transaction or brokerage commission will affect the validity of a simple single factor as used in the CAPM. Avramov and Chordia (2006) have also reported that the work of Basu (1977), Banz (1980), Jegadeesh (1990) and the relatively recent study of Fama and French (1993) following the discovery of CAPM have all criticised the assumptions of the CAPM based on which the asset's return hypothesis was formed. The scholars suggest that asset returns are not only determined by market risk but also by other factors such as a firm's size and book-to-market ratio. Despite all the criticisms, many practitioners have continued to apply the CAPM due to its simplicity. Levy (2010) argued that it is still valid and titled his journal article as "The CAPM is Alive and Well: A Review and Synthesis".

Black (1972) presented more tests of the CAPM avoiding some of its unrealistic assumptions in order to explore the nature of security returns in a different way. In the additional tests provided, the expected return of a single security (R_i) used as a dependent variable in the traditional CAPM was substituted by a proxy or an aggregate of a large number of securities (R_K) since the market risk factor represents the entire securities in the market. The results generated from the adjusted model suggest that the expected return of an asset is not based on systematic risk alone and therefore strongly reject the hypothesis of the CAPM.

Bartholdy and Peare (2005) have also tested the validity of the CAPM on Standard and Poor's composite index and Morgan Stanley's World Market Capital index by using different time frames, data frequencies and equal-weighted index instead of the commonly used value-weighted indices. The results of the test showed significant or best estimates in five (5) years monthly data and the equal-weighted index. Nevertheless, the general performance of the CAPM was weak even in the best form of data because only 3% of the changes in stock returns are accounted for by the model.

Bornholt (2007) tried to improve the CAPM by employing a reward beta to replace the original beta of the model (CAPM) that is based on a mean-variance assumption and given by $(\beta_{i,m} = Cov\,(R_i, R_m)/Var\,(R_m))$. The reward beta which is a substitute for the CAPM beta is based on the mean-risk assumption given by the ratio of a security's risk premium to the market risk premium as $(\beta_{i,m} = E[R_i - r_f]/E[R_m - r_f])$ since the mean-variance assumptions seem to be unrealistic. The extended CAPM with the reward beta was found to be more significant and effective than the original CAPM by the results of the out of sample forecast.

Dalgin et al (2012) tested the validity of the CAPM on the Istanbul stock exchange, Turkey using the methodology adopted by Fama and MacBeth (1973) over the period between 1989 and 2008. The period consists of both stability and high volatility regimes. In all the periods the CAPM was found to be invalid. Bilgin and Basti (2014) also confirmed the invalidity of the asset pricing model for the Istanbul stock exchange.

Soumare et al (2013) applied the CAPM to the Bourse Regionale des Valeurs Mobilieres (BRVM), a regional stock market in West Africa serving eight (8) countries of Benin, Burkina Faso, Guinea Bissau, Cote d'Ivoire, Mali, Niger, Senegal and Togo for the period between 2001 and 2008. CAPM was found to be relevant in eleven out of the twenty-eight stocks selected for the study. It showed that the CAPM was outrightly rejected as an effective asset pricing model in most of the stocks.

10.2.2 Fama-French's Three Factor Asset Pricing Model

Fama and French (1993) proposed a three factor asset pricing model. This became one of the most prominent multi-factor pricing models designed to overcome some of the limitations of the CAPM. Fama and French (1993) built the model to consider additional portfolios or components of systematic risk. This included a firm-size level factor referred to as 'Small minus Big' or the SMB factor where stocks with low market values are formed into a portfolio and those with high market values into a different portfolio. The difference between the returns from the two portfolios is tested for significance as a risk factor to find whether the size of firm has an impact on stock returns. The scholars also suggested the inclusion of another risk factor to assess the impact of a firm's value in terms of book-to-market value referred to as the 'High minus Low (HML)' factor. Firms that have low book-to-market value are seen as growing firms combined into a single portfolio while firms that have high book-to-market value are regarded as value firms and formed into a different portfolio. The assertion that the stock returns from investment in growing firms are higher than that from value companies can also be tested by incorporating the returns differential of the two portfolios into the model. The three factors considered by Fama and French (1993) in their model are a beta proxy for market risk, SMB and HML factors. Similar to CAPM, many scholars have tested the validity of this model on several stocks and stock exchanges.

In some cases, the individual risk factors are also tested separately as predictors of stock returns.

Pontiff and Schall (1998) have reported that the book-to-market ratio of the US Dow Jones Industrial Average (DJIA) index is capable of predicting market return and excess return of small companies. The study concluded that book-to-market ratios contain important information that is relevant in forecasting future returns.

Gaunt (2004) tested the validity of the Fama-French three factor asset pricing model in the Australian stock market using a 1981-2000 time period. The study found strong evidence for the significance of firm's size and book-to-market ratios effects as determinants or explanatory variables of returns.

Bartholdy and Peare (2005) have also tested the validity of Fama-French's three factor model on Standard and Poor's composite index and Morgan Stanley's World Market Capital index by using different time frames, data frequencies, and equal-weighted index instead of the commonly used value-weighted indices. The results were significant in five years monthly data and the equal-weighted index. Nevertheless, the general performance of the three factor model was poor even in the best form of data because only 5% of the changes in stock returns are accounted for by the model. The study tested both the CAPM and Fama-French three factor model on the same data and the Fama and French multi factor model was found to be superior to the CAPM with a very small difference that may not be seen as significant.

Lawrence et al (2007) conducted a study that compared the original CAPM, the three-moment CAPM and the Fama-French three factor pricing models using Fama and French's twenty five portfolios data. The three-moment CAPM was developed by Kraus and Litzenberger (1976) who adjusted the assumption of the existence of an unconditional risk free asset with that of a conditional risk free asset on the skewness of the return distribution and the co-skewness between the individual stock return distribution and the market portfolio return distribution. The findings of the study suggest that the Fama and French three factor model is more powerful in explaining stock returns than the original CAPM and the three-moment CAPM. The adjusted R^2 of the three-moment CAPM was found to be higher than that of the original CAPM.

The robustness of Fama and French's three factor model was also examined in the Indian stock exchange by Sehgal and Balakrishnan (2013). The methodology used was similar to the one employed by Fama and French (1993) particularly in the formation of the portfolios. The findings of the research show Fama and French's three factor asset pricing model as superior in explaining stock returns when compared to the traditional CAPM.

Soumare et al (2013) also applied the Fama and French three-factor model to the Bourse Regionale des Valeurs Mobilieres (BRVM) for the period between 2001 and 2008. Fama and French's three-factor model was found to be relevant in ten out of the twenty-eight (28) stocks selected for the study. Therefore, Fama and French's three-factor model was rejected as an effective asset pricing model in most of the stocks.

10.2.3 Fama-French-Cahart's Four Factor Asset Pricing Model

Carhart (1997) suggested the importance of a firm's recent performance in asset pricing. This strategy aims to capitalize on the continuance of existing trends in the market. In other words, investors should take a long position in an asset which has shown an upward trending price or sell a security that has been on a downward trend. The basic idea is that, once a trend is established, it is more likely to continue in that direction than to move against the trend. A momentum factor was not considered in Fama and French three factor model. In order to improve the multi-factor model, Carhart's proposition was merged with that of Fama and French's original model. Fama–French-Carhart's four factor model was formulated with an additional risk factor of momentum. The difference between the returns from the portfolio of weak performing (value loss) stocks and portfolio of strong performing (value gain) stocks is tested for significance in the determination of stock returns.

Fama-French-Carhart's four factor model has been tested by researchers in various countries. Chen and Fang (2009) have tested the Fama-French-Carhart's four factor model in seven markets of the Pacific Basin (Japan, South Korea, Singapore, Thailand, Indonesia, Malaysia, and Hong Kong) by making a comparison between the CAPM, FF-three factor, and FF-Carhart's four factor models. The study was to determine whether the multi-factor models will outperform the single factor model in countries outside the US. The findings showed the power of multi-factor risk components in asset pricing over the single factor model except for Carhart's momentum factor which was not found to be significant.

Alternatives to Fama-French-Carhart's four factor model were formulated and tested in the UK by Gregory et al (2013). The adjustments were made in reference to the most recent suggestions in the literature of value weighting and disintegration of the various risk factors. The results from the comprehensive analysis adopted have not shown any difference or improvement in explaining returns in UK stocks.

In the emerging markets, Al-Mwalla (2012) tested the significance of the multi-factor asset pricing models on the Amman Stock Exchange (ASE) of Jordan and the results showed Fama and French's three factor model to be superior to the four factor model.

10.2.4 International Oil Price Risk Exposure in Asset Valuation

The multi-factor asset pricing models have also been used by researchers to assess the impact of commodity prices on stock returns of firms presumed to have association with that commodity. Oil price risk exposure is one of the most tested in the literature because of the pervasive nature of oil prices.

Faff and Brailsford (1999) investigated the impact of oil price on the entire Australian stock market between the period 1983 and 1996 using a two- factor asset pricing model (Beta plus the oil price risk factor). The results generated from the model showed the oil price risk factor as being more significant than the market factor. The oil price risk factor's significance was found to be positive in the oil and gas industry and negative in paper and packaging and transport industries. Few firms were found to have transferred most of the oil price risk to customers or managed it with hedging.

The relationship between oil shocks and oil and gas stock returns of Central and Eastern Europe (CEE) markets (Czech Republic, Hungary, Poland, Romania, Slovenia, and Austria) was examined by Mohanty et al (2010) using a two-factor model similar to the one used by Faff and Brailsford (1999). Contrary to the findings of Faff and Brailsford (1999), Mohanty et al (2010) found no significant relationship between oil prices and stock returns over the period of the study between 1998 and 2010. Similarly, there was no significant relationship found between oil prices and the oil and gas sector of the CEE stock exchanges under study.

Mohanty and Nandha (2011) estimated the oil price risk exposure of the US oil and gas sector using Fama-French-Carhart's four factor asset pricing model. The model was expanded by an additional risk factor of the monthly changes in oil price (West Texas Intermediate (WTI)). The coefficients of the independent variables were significant indicating that all the risk factors of systematic, size, book-to-market values and fluctuation in oil price explained changes in the US oil and gas stock returns. However, the impact of oil price fluctuation varies over time, firm type and also industry subsectors (exploration, equipment services and integrated oil and gas). The risk exposure was found to be higher in exploration and oil equipment services companies. In addition, periods of economic crisis and oil market instability are also found to have resulted in high oil price risk exposure in the US oil and gas stock returns. The findings comply with that of Manning (1991) who found changes in oil price to have a significant influence on UK oil and gas stocks.

Scholars such as Elyasiani et al (2011) examined the association between oil price and stock returns using GARCH (1,1) which is a different technique from the conventional multi-factor pricing model. Elyasiani et al (2011) assessed the changes in oil prices and the stock return volatilities of thirteen (13) US industries. The GARCH (1,1) coefficients indicated a significant impact of the changes in oil price on nine (9) of the thirteen (13) industries which coincided with the majority of the findings from the multi-factor asset pricing models.

Fama-French-Carhart's four factor model augmented with changes in the oil price as a risk factor was applied to the US travel and leisure industry by Mohanty et al (2014). Oil risk exposure was found to be negative in most of the cases and to vary considerably over gambling, hotels, airlines, restaurants, recreational services, travel and tourism. The impact of the oil price was found to be more significant on airlines, restaurants and bars and recreational services. The global economic crisis between 2007 and 2009 has contributed to the high oil price risk exposure of the US airline industry.

10.2.5 Summary of Literature and Research Objectives

The Capital Asset Pricing Model (CAPM) has been one of the most prominent asset pricing models according to the finance literature despite its proclaimed limitations. It remains useful because of its simplicity. Multi-factor models that have been designed to overcome the limitations of the CAPM are basically the extension of the single factor CAPM. Fama-French's three factor and Fama-French-Carhart's four factor models are the multi-factor asset pricing models mostly adopted for asset pricing by both academics and practitioners. Commodity prices such as international oil price have also been augmented as additional risk factors into the asset pricing models by researchers.

We employ Fama-French-Carhart's four factor model augmented with the OPEC Basket Price on the UK oil and gas sector in order to explore the determinants of the stock returns and oil price risk exposure of London-quoted oil and gas companies.

10.3 The Application of Multi Factors on the Oil and Gas Stocks Quoted on the London Stock Exchange

In this section, the four factor model of Fama-French-Carhart augmented with the log changes of the OPEC oil basket price is tested on oil and gas companies quoted on the London stock exchange. The model derives its roots from the capital asset pricing model (CAPM) developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM model is given by:

$$R_{it} - R_{ft} = \alpha_{i0} + \beta_{im}(R_{mt} - R_{ft})$$

Where:

R_{it} = Individual asset (stock) returns

R_{ft} = Risk free rate of return (Treasury bill rate)

$R_{it} - R_{ft}$ = Individual asset (stock) excess return

β_{im} = Coefficient representing market risk (systematic risk or volatility)

R_{mt} = Overall market return

$R_{mt} - R_{ft}$ = Market excess return (risk premium)

α_{i0} = Constant replacing the risk free rate

The Fama-French three factor model included additional risk factors of size of firms and book-to-market values in addition to CAPM's beta. The model is specified as:

$$R_{it} - R_{ft} = \alpha_{i0} + \beta_{im}(R_{mt} - R_{ft}) + \beta_1 SMB_t + \beta_2 HML_t$$

Where:

SMB_t = Small Minus Big (Difference between the small and large stock portfolios based on market capitalisation)

HML_t = High Minus Low (Difference between portfolios having high and low book-to-market ratios)

The model was designed to capture the size effect (SMB) of firms as well as the effect of firms with high or low book-to-market values. Carhart (1997) joined Fama and French to expand the earlier three-factor model with an additional factor of momentum. Fama-French-Carhart's (1997) four factor asset pricing model has introduced another dimension of asset valuation using momentum. The model is given as:

$$R_{it} - R_{ft} = \alpha_{i0} + \beta_{im}(R_{mt} - R_{ft}) + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 Mom_t$$

Where:

Mom_t = Momentum factor (assumption that price is more likely to be moving in the same direction without change).

Although, the Fama-French-Carhart (1997) multifactor model was considered to allow for the most common macroeconomic variables such as the expected GDP growth, default risk and inflation (Liew and Vasalou, 2000; He and Ng, 1994; Kelly, 2003), the impact of commodity price risk in the asset pricing model has been ignored as suggested by Mohanty and Nandha (2011). In order to consider the effect of commodity price risk on stock returns, researchers such as Faff and Brailsford (1999), Mohanty and Nandha (2011), and Martinez, et al (2014) have incorporated the fluctuation of oil prices (oil price risk) into the asset pricing models to assess its impact on asset pricing or valuation.

Mohanty and Nandha (2011) have estimated the oil price and interest rate risk exposures of the United States oil and gas sector using Fama-French-Carhart's four-factor asset pricing model incorporating the West Texas Intermediate (WTI) oil price and the 10-year U.S. Treasury bond yield as an interest rate factor.

In this research, we applied the same methodology employed by Mohanty and Nandha (2011) to investigate the power or effect of the risk factors in Fama-French-Carhart's four factor model and the augmented OPEC oil basket price in the asset pricing of oil and gas companies on the London stock exchange. Considering that interest rates (Official Bank Rate) have been constant at 0.5% for over five years since March 2009 (Bank of England, 2014), an interest rate risk factor exposure is not included in our model as augmented by Mohanty and Nandha (2011).

Our model is the Fama-French-Carhart (1997) four factor model augmented with the oil price (OPEC Basket Price) which can be written and interpreted as follows:

$$R_{it} - R_{ft} = \alpha_{i0} + \beta_{im}\left(R_{mt} - R_{ft}\right) + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 Mom_t + \beta_{ioil} R_t OilPrice + \varepsilon_{it}$$

Where:

R_{it} = Individual asset (stock) monthly returns of oil and gas companies quoted on the London stock exchange

R_{ft} = Risk free rate of return (UK Treasury bill rate adjusted to a monthly rate)

$R_{it} - R_{ft}$ = Individual asset (stock) monthly excess returns

β_{im} = Coefficient representing market risk (systematic risk or volatility) of the London stock exchange

R_{mt} = Overall market monthly returns represented by FTSE All Share Index

$R_{mt} - R_{ft}$ = Market monthly excess return (risk premium)

SMB_t = Small Minus Big (Difference between the small and large stock portfolio returns based on companies' market values)

HML_t = High Minus Low (Difference between the high and low stock portfolio returns based on companies' book-to-market values)

Mom_t = Momentum factor (assumption that price is more likely to be moving in the same direction without change)

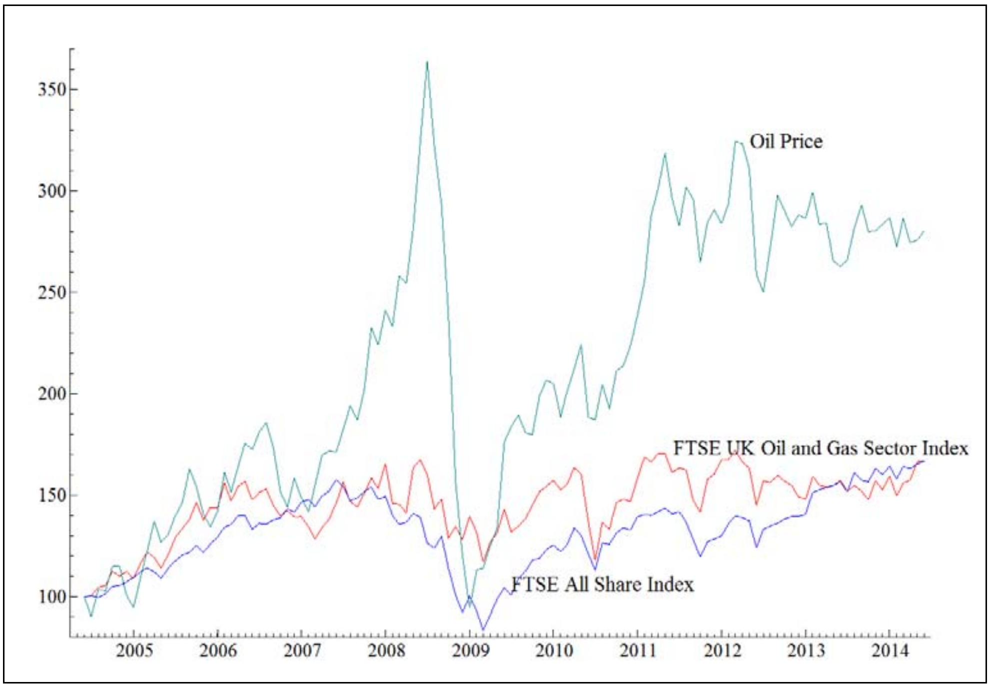
$R_t OilPrice$ = Log changes of the OPEC oil basket price

ε_{it} = Error term

This study will use the monthly return series of the FTSE All Share index representing the entire market of the London stock exchange, the UK Treasury bill rate as the risk free rate of return, oil and gas stocks quoted on the main market of the London stock exchange and the OPEC oil basket price.

We also present the pictorial relationship of the movement or fluctuation between the oil and gas sector index, market index and oil price over the period June, 2004 to June, 2014 in Figure 1 below.

Figure 10.1 Graphical Presentation of the Stock Market (FTSE All Share) Index, Oil and Gas Sector Index and OPEC Oil Basket Price Monthly Series



(Rebased: June 2004 = 100)

Source: Author (2015)

Figure 10.1 shows the relative trend of the key parameters of the study; as the oil price, oil and gas sector, and the United Kingdom stock market index. The series are rebased to '100' at the same starting point of June, 2004 to June, 2014 in order to make effective comparative analysis. The oil price as represented by the OPEC basket price in US dollars per barrel is shown to be the most volatile series when compared to the market and oil sector indices. The shock or fall of the oil price between 2008 and 2009 was significant and thus could possibly be attributed to the effect of the economic crisis in 2007. The oil price recovered to its position before the drastic fall in 2010 through 2014. The FTSE All Share and FTSE UK Oil and Gas Sector indices move in a similar direction and the series are more stable over the period than the oil price. The design of our asset pricing model will enable us to assess whether the observed high volatility in the OPEC basket price has any impact on the valuation or pricing of oil and gas stocks quoted on the London stock exchange.

We begin our analysis by showing a summary of the descriptive statistics of the oil and gas stock monthly returns between June, 2004 and June 2014 in Table 10.1 below.

Table 10.1 Summary Descriptive Statistics for the Oil and Gas Stocks' Monthly Returns between June, 2004 and June, 2014

Company Name	Obs.	Mean	Maximum	Minimum	Std. dev.
Amec	120	0.012766	0.162899	-0.310585	0.080125
Aminex	120	-0.02126	0.701412	-0.622354	0.19546
BG Group	120	0.010832	0.13378	-0.235747	0.066244
BP	120	0.000387	0.230829	-0.291454	0.070889
Cairn Energy	120	0.004306	0.290535	-0.335134	0.109774
Dragon Oil	120	0.021621	0.396349	-0.559018	0.127809
Fortune Oil	120	0.008931	0.534469	-0.263417	0.124032
Hunting	120	0.01501	0.225417	-0.325663	0.093079
JKX Oil and Gas	120	-0.00234	0.414654	-0.527556	0.139149
Premier Oil	120	0.009749	0.412132	-0.355972	0.105385
Royal Dutch Shell 'B'	120	0.004826	0.160582	-0.172987	0.061583
Soco International	120	0.014059	0.32824	-0.317513	0.107926
Tullow Oil	120	0.01726	0.322918	-0.238736	0.095042
Wood Group (John)	120	0.014116	0.236646	-0.384793	0.097701
Afren	110	0.009354	0.758152	-0.539637	0.17869
Hardy Oil and Gas	107	-0.00542	0.500657	-0.604941	0.167706
Royal Dutch Shell 'A'	106	0.002663	0.135738	-0.18002	0.060756
Petrofac	104	0.017776	0.232556	-0.351711	0.097714
Lamprell	91	-0.00062	0.351486	-1.291484	0.224319
Salamander Energy	90	-0.00365	0.351844	-0.415931	0.129016
Endeavor Intl. Corp	77	-0.01943	0.470004	-0.784323	0.198645
Kentz	75	0.023017	0.276728	-0.381855	0.101159
Heritage Oil	74	0.005565	0.435366	-0.34998	0.145388
Cadogan Petroleum	71	-0.04181	0.662842	-0.960093	0.250211
Exillon Energy	53	-0.00474	0.426667	-0.470239	0.1754
Enquest	49	0.007236	0.197826	-0.212076	0.07946
Essar Energy	49	-0.03502	0.366318	-0.388305	0.143093
Genel Energy	35	0.001573	0.114496	-0.174941	0.07469
Ophir Energy	34	0.006262	0.385758	-0.25223	0.113268
Ruspetro	28	-0.07243	0.416894	-0.702537	0.239229

Source: Author (2015)

Table 10.1 shows the number of observations, mean, maximum, minimum and standard deviation of every oil stock of the thirty identified. Fourteen of the companies had complete data over the period of study, while the remaining sixteen companies had incomplete data due to their date of listing being beyond June, 2004. Twenty stocks were found to have positive mean monthly returns while ten stocks have negative monthly returns. Standard deviations were seen to be within the same range for all the oil and gas companies under study.

10.3.1 Correlations between Risk Factors considered in the Asset Pricing Model

Correlation analysis was also conducted on the independent variables (risk factors) of market excess return, log changes in oil price, SMB, HML and momentum factors in order to ensure the absence of multi-colinearity before the estimation of multivariate regression model. The result of the correlation analysis is shown in Table 10.2 below.

Table 10.2 Correlation between Asset Pricing Model Independent Variables (Risk Factors)

	$(R_{mt} - R_{ft})$	SMB_t	HML_t	Mom_t	$\Delta OilPrice_t$
$(R_{mt} - R_{ft})$	**1.000000**	0.035143	-0.072742	-0.010599	0.356722
SMB_t	0.035143	**1.000000**	0.300600	-0.425127	0.342677
HML_t	-0.072742	0.300600	**1.000000**	-0.089216	-0.140262
Mom_t	-0.010599	-0.425127	-0.089216	**1.000000**	-0.389493
$\Delta OilPrice_t$	0.356722	0.342677	-0.140262	-0.389493	**1.000000**

Source: Author (2015)

The correlation coefficients depicted in Table 10.2 shows the level of correlation between the independent variables listed above. None of the coefficients was found to be above 0.50 and the highest was between SMB and momentum factors at 0.425127. Researchers have used up to 0.8 thresholds in previous studies to determine the existence of correlation between independent variables.

10.3.2 Fama-French-Carhart's Four Factor Asset Pricing Model Augmented with International Oil Price

We estimate our multivariate regression model based on the theory of Fama-French-Carhart's (1997) four factor asset pricing model. Table 10.3 shows coefficients of the risk factors considered in the model. Residual diagnostics measure the statistical accuracy of the model and model fitness statistics.

Table 10.3 Fama-French-Carhart's Four Factor Asset Pricing Model Augmented with International Oil Price

Company Name	Intercept (α_{i0})	Market ($\beta_{i,m}$)	SMB (β_1)	HMB (β_2)	Mom (β_3)	Oil Price ($\beta_{i,oil}$)	Residual Diagnostics: Serial Corr. Test Breusch-Godfrey	Residual Diagnostics: Normality Test Jacque-bera	Residual Diagnostics: Heteroskedasticity Test Breusch-Pagan Godfrey	Model Fitness: Adj.R^2	Model Fitness: F-Statistic (Prob)
Amec	0.004708	0.8709***	-0.063743	-0.17818*	0.004511	0.257***	0.050681	3.46326	7.887485	0.4237	[0.0000]
	(0.60784)	(6.27885)	(-0.5871)	(-1.688)	(0.0388)	(3.48855)	[0.975]	[0.176996]	[0.1625]		
	[0.5445]	[0.0000]	[0.5583]	[0.0941]	[0.9691]	[0.0007]					
Aminex	0.000368	1.013***	1.2049***	0.6524**	-0.32007	0.18377	0.22393	1.2963	1.638845	0.3387	[0.0000]
	(0.018171)	(2.796291)	(4.248385)	(2.366334)	(-1.0537)	(0.95473)	[0.8941]	[0.523013]	[0.8965]		
	[0.9855]	[0.0061]	[0.0000]	[0.0197]	[0.2942]	[0.3417]					
BG Group	0.000212	0.7144***	-0.06392	-0.10577	0.089525	0.195***	2.858216	37.3643	8.208176	0.3771	[0.0000]
	(0.031912)	(6.007491)	(-0.68679)	(-1.16891)	(0.8981)	(3.1029)	[0.2395]	[0.0000]	[0.1451]		
	[0.9746]	[0.0000]	[0.4936]	[0.2449]	[0.371]	[0.0024]					
BP	-0.0102	0.9755***	-0.306***	0.3619***	0.107797	0.210***	0.024612	37.1327	17.29035	0.5392	[0.0000]
	(-1.66331)	(8.881667)	(-3.56457)	(4.330878)	(1.1708)	(3.6059)	[0.9878]	[0.0000]	[0.004]		
	[0.099]	[0.0000]	[0.0005]	[0.0000]	[0.2441]	[0.0005]					
Cairn Energy	-0.01218	1.1630***	-0.13683	-0.23626	0.147722	0.283***	1.354905	8.11829	18.6315	0.3514	[0.0000]
	(-1.08221)	(5.770427)	(-0.8674)	(-1.54057)	(0.8744)	(2.6499)	[0.5079]	[0.017264]	[0.0023]		
	[0.2814]	[0.0000]	[0.3875]	[0.1262]	[0.3837]	[0.0092]					
Dragon Oil	0.008951	1.1746***	0.266272	0.236616	0.167181	0.429***	6.972744	43.3169	12.44088	0.3533	[0.0000]
	(0.683747)	(5.010548)	(1.451274)	(1.326567)	(0.8508)	(3.4460)	[0.0306]	[0.0000]	[0.0292]		
	[0.4955]	[0.0000]	[0.1494]	[0.1873]	[0.3966]	[0.0008]					
Fortune Oil	-0.00353	0.7770***	0.9864***	-0.27087	0.290784	0.0004	3.528489	41.6416	7.634254	0.2428	[0.000001]
	(-0.25624)	(3.154222)	(5.11568)	(-1.445)	(1.4081)	(0.00306)	[0.1713]	[0.0000]	[0.1776]		
	[0.7982]	[0.0021]	[0.0000]	[0.1512]	[0.1618]	[0.9976]					
Hunting	0.014986	1.2221***	0.22117*	-0.2327**	-0.13843	0.1811**	1.241503	2.010425	4.495211	0.5182	[0.0000]
	(1.823003)	(8.30241)	(1.919687)	(-2.07752)	(-1.121)	(2.3163)	[0.5375]	[0.365967]	[0.4805]		
	[0.0709]	[0.0000]	[0.0574]	[0.04]	[0.2642]	[0.0223]					
JKX Oil and Gas	-0.01254	1.0966***	0.6235***	-0.4792**	0.105667	0.199563	1.10718	26.20191	28.48466	0.2606	[0.0000]
	(-0.82381)	(4.023214)	(2.922814)	(-2.31086)	(0.4624)	(1.3783)	[0.5749]	[0.000002]	[0.0000]		
	[0.4118]	[0.0001]	[0.0042]	[0.0226]	[0.6446]	[0.1708]					

Premier Oil	-0.0175	1.2662***	0.24000*	-0.11033	0.453***	0.257***	0.19037	7.918631	7.252863	0.4287	[0.0000]
	(-1.72382)	(6.96417)	(1.686588)	(-0.7975)	(2.9743)	(2.67036)	[0.9092]	[0.019076]	[0.2025]		
	[0.0875]	[0.0000]	[0.0944]	[0.4268]	[0.0036]	[0.0087]					
Royal Dutch Shell 'B'	-0.00757	0.8446***	-0.303***	0.2917***	0.14698*	0.189***	2.534959	5.003789	10.42384	0.5570	[0.0000]
	(-1.44828)	(9.022547)	(-4.14497)	(4.096582)	(1.8733)	(3.8121)	[0.2815]	[0.08193]	[0.0641]		
	[0.1503]	[0.0000]	[0.0001]	[0.0001]	[0.0636]	[0.0002]					
Soco International	0.0014	0.48548**	0.45888**	-0.26402	0.205179	0.153471	4.827487	11.49932	5.434437	0.1213	[0.001311]
	(0.108763)	(2.106073)	(2.54356)	(-1.50532)	(1.0619)	(1.2535)	[0.0895]	[0.003184]	[0.3652]		
	[0.9136]	[0.0374]	[0.0123]	[0.135]	[0.2905]	[0.2126]					
Tullow Oil	-0.00512	0.8514***	-0.13511	-0.22952*	0.28646*	0.309***	1.867153	9.589463	11.03639	0.3433	[0.0000]
	(-0.52315)	(4.858704)	(-0.98511)	(-1.7213)	(1.9502)	(3.3277)	[0.3931]	[0.008273]	[0.0507]		
	[0.6019]	[0.0000]	[0.3267]	[0.0879]	[0.0536]	[0.0012]					
Wood Group (John)	0.002659	1.0782***	0.031961	-0.359***	0.01891	0.449***	3.557231	0.756262	2.261099	0.6385	[0.0000]
	(0.355144)	(8.041247)	(0.304535)	(-3.51925)	(0.1682)	(6.3149)	[0.1689]	[0.685141]	[0.812]		
	[0.7231]	[0.0000]	[0.7613]	[0.0006]	[0.8667]	[0.0000]					
Afren	-0.00824	1.7689***	1.0627***	0.058504	0.395358	0.553***	2.919304	23.20388	10.88641	0.5218	[0.0000]
	(-0.49384)	(6.174666)	(4.451077)	(0.260361)	(1.5253)	(3.42497)	[0.2323]	[0.000009]	[0.0537]		
	[0.6225]	[0.0000]	[0.0000]	[0.7951]	[0.1302]	[0.0009]					
Hardy Oil and Gas	0.007093	0.7813**	1.3888***	-0.882***	-0.2555	-0.03837	3.864797	28.94402	14.51513	0.3326	[0.0000]
	(0.376218)	(2.455529)	(5.182996)	(-3.54166)	(-0.876)	(-0.2126)	[0.1448]	[0.000001]	[0.0126]		
	[0.7075]	[0.0158]	[0.0000]	[0.0006]	[0.3826]	[0.832]					
Royal Dutch Shell 'A'	-0.00151	0.8548***	-0.365***	0.3031***	0.174***	-0.00151	0.280506	3.294782	11.23334	0.6132	[0.0000]
	(-0.40414)	(9.7636)	(-5.22327)	(4.391968)	(3.6285)	(-0.4041)	[0.8691]	[0.192552]	[0.0241]		
	[0.687]	[0.0000]	[0.0000]	[0.0000]	[0.0004]	[0.687]					
Petrofac	0.014689	0.8882***	0.068707	-0.742***	-0.16279	0.2212**	1.060235	0.047889	14.46819	0.5616	[0.0000]
	(1.61261)	(5.875438)	(0.503672)	(-6.13423)	(-1.0999)	(2.54741)	[0.5885]	[0.97634]	[0.0129]		
	[0.1100]	[0.0000]	[0.6156]	[0.0000]	[0.2741]	[0.0124]					
Lamprell	-0.00899	2.4260***	1.2124***	-0.18613	0.318757	0.4503*	4.9225	328.1955	11.75326	0.4832	[0.0000]
	(-0.36613)	(6.276601)	(3.233552)	(-0.56748)	(0.8176)	(1.9163)	[0.0853]	[0.0000]	[0.0383]		
	[0.7152]	[0.0000]	[0.0017]	[0.5719]	[0.4158]	[0.0587]					
Salamander Energy	-0.00874	1.1100***	0.218873	-0.08796	0.059292	0.3143**	1.877643	5.846015	3.650366	0.2965	[0.000002]
	(-0.52473)	(4.265347)	(0.868524)	(-0.39908)	(0.2252)	(1.9882)	[0.3911]	[0.053772]	[0.6008]		
	[0.6012]	[0.0001]	[0.3876]	[0.6908]	[0.8223]	[0.05]					
Endeavor Intl. Corp	-0.01786	-0.02632	1.0094**	-0.882**	0.042072	-0.10558	4.188136	58.888	5.176868	0.0451	[0.141534]
	(-0.55682)	(-0.05422)	(2.009739)	(-2.17976)	(0.0841)	(-0.3541)	[0.1232]	[0.0000]	[0.3947]		
	[0.5794]	[0.9569]	[0.0483]	[0.0326]	[0.9332]	[0.7243]					

Kentz	0.011558	0.5893***	0.5078**	-0.2958*	0.257912	0.3236**	7.475821	0.889148	8.170642	0.3829	[0.0000]
	(0.819272)	(2.917749)	(2.458247)	(-1.75931)	(1.1912)	(2.6118)	[0.0238]	[0.641097]	[0.1471]		
	[0.4155]	[0.0048]	[0.0165]	[0.083]	[0.2376]	[0.011]					
Heritage Oil	-0.0384	0.6836**	0.471474	-0.380854	0.8247**	0.324665	1.065912	5.273877	3.247406	0.1724	[0.002854]
	(-1.61954)	(2.033682)	(1.358843)	(-1.36072)	(2.2872)	(1.5668)	[0.5869]	[0.07158]	[0.6619]		
	[0.1100]	[0.0459]	[0.1787]	[0.1781]	[0.0253]	[0.1218]					
Cadogan Petroleum	0.040719	-0.04391	0.735189	1.5819***	-0.9541*	0.60792*	1.97363	8.363614	18.44997	0.3584	[0.000002]
	(1.127758)	(-0.0809)	(1.381641)	(3.688267)	(-1.7384)	(1.8330)	[0.3728]	[0.015271]	[0.0024]		
	[0.2636]	[0.9358]	[0.1718]	[0.0005]	[0.0869]	[0.0714]					
Exillon Energy	0.004932	1.61464**	1.2656**	0.306836	-0.05066	0.290511	0.867496	6.464637	5.279673	0.2644	[0.00138]
	(0.141567)	(2.413147)	(2.414737)	(0.629148)	(-0.083)	(0.6859)	[0.6481]	[0.039466]	[0.3827]		
	[0.888]	[0.0198]	[0.0197]	[0.5323]	[0.9336]	[0.4961]					
Enquest	0.002839	0.9749***	0.37639*	-0.5163**	-0.07933	0.173631	0.342277	0.820288	4.984507	0.4146	[0.000027]
	(0.189239)	(3.452335)	(1.733506)	(-2.58479)	(-0.311)	(0.9594)	[0.8427]	[0.663555]	[0.4178]		
	[0.8508]	[0.0013]	[0.0902]	[0.0132]	[0.7573]	[0.3427]					
Essar Energy	0.024428	1.000906	-0.52956	-0.33751	-1.465**	-0.39081	4.053082	0.481151	4.251234	0.1278	[0.051951]
	(0.740854)	(1.612703)	(-1.1098)	(-0.76884)	(-2.6142)	(-0.9826)	[0.1318]	[0.786175]	[0.5138]		
	[0.4628]	[0.1141]	[0.2733]	[0.4462]	[0.0123]	[0.3313]					
Genel Energy	0.010049	0.596562	0.062383	0.31032	-0.1195	0.271647	0.715605	0.457461	3.182345	0.1361	[0.097874]
	(0.486355)	(1.534062)	(0.223043)	(1.261624)	(-0.354)	(0.97452)	[0.6992]	[0.795543]	[0.6719]		
	[0.6304]	[0.1359]	[0.8251]	[0.2171]	[0.7256]	[0.3379]					
Ophir Energy	0.017088	0.298536	0.319371	-0.6854*	-0.30479	0.190355	1.170693	2.90887	5.699019	0.0256	[0.346868]
	(0.511497)	(0.443792)	(0.706427)	(-1.72481)	(-0.558)	(0.39664)	[0.5569]	[0.233532]	[0.3366]		
	[0.613]	[0.6606]	[0.4858]	[0.0956]	[0.5808]	[0.6946]					
Ruspetro	0.035416	1.02724	3.2418***	-2.602***	-1.8375*	-0.78695	2.080072	0.549894	6.52957	0.4382	[0.002639]
	(0.644792)	(0.793495)	(3.503988)	(-3.65849)	(-1.9857)	(-0.9290)	[0.3534]	[0.759613]	[0.258]		
	[0.5257]	[0.436]	[0.002]	[0.0014]	[0.0597]	[0.3629]					

(***), (**), and (*) attached to coefficients indicate statistical significance at 0.01, 0.05, and 0.10 level respectively which is also used for the rejection or acceptance of null hypotheses.

Source: Author (2015)

Diagnostic tests and model fitness statistics are also shown in Table 10.3 above in addition to the model coefficients. The Breusch-Godfrey test was used to test whether the residuals are serially correlated by rejecting or accepting the null hypothesis; the residuals are not serially correlated. The Jacque-bera statistic test was used to test the normality of residuals by accepting or rejecting the null hypothesis; the residuals are normally distributed. The existence of heteroskedasticity in the residuals was tested using the Breusch-Pagan Godfrey test to accept or reject the null hypothesis: there is ARCH effect in the residuals. Model assumptions are deemed to be valid if the null hypotheses stated with regard to the residuals are accepted using an appropriate significance level (0.05 level in this study). The results have shown that both the observed Breusch-Godfrey statistic and its respective probability (p-value) are insignificant to reject the null hypotheses that the residuals are not serially correlated in all the stock series except in Kentz where the p-value was found to be significant at 0.0238. The serial correlation test is considered as the most important residual diagnostic test by various researchers and as a result of which we can consider our models to be statistically fit. In normality tests, the Jacque-bera statistics and its p-values were also found to be insignificant in fifteen stocks to reject the null hypothesis that the residuals are normally distributed. Despite the view of some scholars that normality assumption is the weakest among the model validity assumptions, our test accepted the normality distribution in the residuals of fifty percent of our models. The check of constant variance in the residuals of our models was conducted by the Breusch-Pagan Godfrey heteroskedasticity test and results have suggested the acceptance of the null hypothesis that there is no ARCH effect in the residuals in twenty one out of the thirty models. Based on these results, we consider our models statistically fit to present valid inferences.

Further tests of model fitness were reported by the adjusted R-square and F-statistic (probability) tests. The Adjusted R^2 in the majority of the models were found to be in the average range (neither too small nor too high). The F-statistic's probabilities were strongly significant even at 0.01 levels to reject the combined null hypotheses that the model coefficients are equal to zero $(\beta_{im} = 0,\ \beta_1 = 0,\ \beta_2 = 0,\ \beta_3 = 0, and\ \beta_{i,oil} = 0)$ which is a positive sign that the independent variables are significant in the model. In other words, the coefficients of the independent variables are not equal to zero $(\beta_{im} \neq 0,\ \beta_1 \neq 0,$ $\beta_2 \neq 0,\ \beta_3 \neq 0, and\ \beta_{i,oil} \neq 0)$. The model fitness tests support our findings from the residual diagnostic tests which suggest the statistical accuracy of our models.

The interpretation of the coefficients from the multivariate regression model estimated in Table 10.3 shows systematic risk to be highly significant at 0.01 level and 0.05 level (Soco, Hardy, Heritage, and Exillon stocks) in the Endeavor International Corporation, Essar Energy, Genel Energy, Ophir Energy and Ruspetro stocks where the systematic risk was found to be insignificant. The behaviour of the market factor in the majority of the stocks could suggest the relevance of the Capital Asset Pricing Model (CAPM) in the valuation of oil and gas companies.

Size factor was found to be the second most significant variable following the market factor in the pricing of the oil and gas stocks on the London stock exchange. The coefficients recorded demonstrate strong significance even at 0.01 level in ten stocks, 0.05 level in four stocks and 0.10 level in two stocks.

The oil price as represented by the OPEC Basket Price was found to be the third most important or significant variable following the market factor and the SMB factor. The changes in oil price was found significant at 0.01 level in ten (10) stocks, at 0.05 level in four (4) stocks and at 0.10 level in two (2) stocks.

HMB and momentum factors have less impact on the pricing or valuation of oil and gas stocks. HMB factor was found significant at 0.01 level in eight (8) stocks which increased to thirteen (13) stocks at 0.05 significance level. The momentum factor was statistically insignificant in most of the models.

10.4 Summary of Findings

Firstly, we discovered from graphical observations that the oil price (OPEC Basket Price) is more volatile than FTSE All Share and FTSE UK Oil and Gas sector indices over the period between June 2004 and June 2014 especially around 2008 to 2009 which could be explained by the impact of the global economic crisis. However, the volatility has not been seen to strongly affect the asset pricing of the oil and gas stocks because, among the five independent variables used in our model, the oil price was found to be the third most significant variable following the market and SMB factors. Mohanty and Nandha (2011) showed a similar relationship in respect of the US equity market (S&P 500), the US oil and gas sector and the oil price (West Texas

Intermediate (WTI)). The relationship between the three variables was observed to have almost the same pattern over the period of the study.

Secondly, the market factor was found to be significant in almost all the oil and gas stocks. The finding demonstrates the importance of systematic risk in the determination of the excess return of the individual stocks. It also justifies the relevance of the Capital Asset Pricing Model (CAPM) despite its criticisms. Similar to our findings, various scholars have tested the validity of the CAPM on a large number of different stocks and confirm its validity using the significance of the market factor.

Thirdly, the 'Small minus Big' or 'SMB' factor was found to be significant in seventeen (17) stocks at the significance levels of 0.01 (10 stocks), 0.05 (4 stocks) and 0.10 (3 stocks). The finding indicates that the construction of portfolios by buying stocks of small firms and selling stocks of large firms could have significant impact in the oil and gas portfolios in the London stock exchange. The SMB factor was found to be more relevant in the model than the HML (value) factor which is also similar to the findings of Chen and Fang (2009).

Fourthly, we discovered that the 'High minus Low' or 'HML' was also significant but not at the same level as the market and SMB factors.

Fifthly, we tested the significance of a momentum factor as in Fama-French-Carhart's model and found that momentum is not as significant as other factors in our model. Cheng and Fang (2009) also found the momentum factor to be insignificant in the stock returns of the Pacific Basin markets.

Lastly, our results suggest that the volatility in oil price is highly significant in the asset pricing of oil and gas stocks. We found that, among the risk factors in our model, only the market and SMB factors are more significant than the log changes in oil price. The log changes in oil price was found to be significant in sixteen oil and gas stocks at different levels of significance, that is, 0.01 (10 stocks), 0.05 (4 stocks) and 0.01 (2 stocks). Our finding is similar to those of Moya-Martinez et al (2014), Faff and Brailsford (1999) and Mohanty and Nandha (2011). Though, Moya-Martinez et al (2014) and Mohanty and Nandha (2011) have found variation in the level of oil price risk exposure over time which was attributed to the fluctuation in the oil market and the global economic crisis among other factors.

10.5 Conclusion

Market risk (systematic risk), firm's size represented by the 'SMB' factor and book-to-market value represented by the 'HML' factor are all relevant factors in explaining the returns of London-quoted oil and gas companies. Carhart's momentum factor was found to be insignificant. The OPEC Basket Price was added into the multi-factor model because of its diversity as the weighted average of oil prices of countries that are members of the Organisation of the Petroleum Exporting Countries (OPEC) and also deemed as an important benchmark for the international oil price. The results generated from our model signify the importance of the oil price as a risk factor in the valuation of oil stocks.

CHAPTER 11

SUMMARY, CONCLUSION AND RECOMMENDATIONS

11.1 Summary and Conclusion

This section summarises the findings from the empirical investigation conducted to explore the price dynamics of oil and gas stocks quoted on the London Stock Exchange. Specifically, information efficiency, volatility behaviour and asset pricing models were examined. We also plan to review the research objectives, questions and hypotheses that were formulated as a pathway to achieving the aim of the study.

The first objective of the study was to examine the nature of weak form market efficiency in the London-quoted oil and gas companies and explore the relevance of technical trading rules. A comparative analysis was also to be made between the results from the entire stock market, the oil industry of the main market and the relevant stocks on the Alternative Investment Market (AIM). To accomplish that, both parametric and non-parametric tests of randomness were conducted on all the series (oil stocks and five FTSE indices) under study and their results used in rejecting or accepting the Random Walk Hypothesis. The results generated by the autocorrelation function and Q-Statistic tests provide evidence of serial correlation in the entire FTSE share indices and sixteen other individual oil and gas companies out of the total number of thirty companies under study. In other words, the FTSE All Share index, the FTSE Oil and Gas Share index, and other major oil stocks show persistence in returns. A non-parametric runs test was employed to overcome the strong assumption of normal distribution of daily stock returns by parametric tests. The Runs test results show that the FTSE All Share, FTSE 100, and FTSE UK Oil and Gas Producers share indices change sign and this is not statistically different from a random series. These results were found to be contrary to the results of the Ljung-Box Q-Statistic tests. Nevertheless, the Runs test results on FTSE UK Oil and Gas and FTSE AIM SS Oil and Gas indices including eight other individual oil stocks were found to be consistent with that of the autocorrelation function and Q-Statistic results. Conventional statistical tools such as the autocorrelation function used in testing the random walk and weak form market efficiency hypotheses have been criticised because the absence of serial correlation cannot exclusively suggest market efficiency. To overcome that, we have employed advanced tools such as the variance ratio test and the BDS test in the study. According to the variance ratio test results, the null hypothesis of random walk (VR=1) has been accepted in most of the series that are considered for investigation in this study. In simple terms, the results advocate that the oil and gas sector and the main indices of the London stock exchange fluctuate randomly. The BDS test was also employed because of its power to detect whether the structure of the series is linear or non-linear in addition to randomness assessment. The residuals from a linear model of ARMA (1,1) were tested for randomness in order to assess the effectiveness of the model in capturing the linearity of the series. The results rejected the null hypothesis of white noise in all the residuals generated which is an indication that the series are not linear since linear models could not capture all the statistical properties of the series. On the same note, the random walk hypothesis was rejected in all the series due to the existence of serial correlation in the residuals of the series.

Technical trading rules were employed to assess the possibility of making abnormal returns by trading on technical strategies designed to exploit serial correlation found in the stock series under investigation. Our findings suggested that the simple trading rules cannot provide above normal returns after considering the brokerage cost associated with every transaction. We also employed the moving average trading rules in a similar way employed by Brock et al (1992) to assess whether our findings are going to be different. However, despite the application of 10 different combinations of moving average trading rules, the t-statistics were not significant enough to reject the null hypothesis that the returns from the trading rule are equal to that from a buy and hold strategy. In other words, we have to accept the null hypothesis that the returns generated from the moving average trading rule are not different from the returns of a buy and hold investment strategy. To confirm the authenticity of our results, we tested whether the return series generated by the moving average trading rule are stationary or not. The test of unit root hypothesis on the return series generated by the moving average (10) trading rule had confirmed the existence of stationarity and therefore authenticate the use of constant statistical properties such as the mean to assess the power of the trading rule. We also tested the assertion of Milionis and Papanagiotou (2008) that shorter moving average trading rules perform more effectively than longer moving average trading rules. We confirmed that assertion in some of our stock series and equally rejected it in a few others. We have not gone further to investigate the variation in performance among the different ranges of the moving averages. All of these results indicate weak form efficiency in the overall market and especially in the oil and gas sector.

The second objective of the study was to examine the behaviour of the London-quoted oil and gas stocks during different time periods by conducting a seasonality analysis (days-of-the-week effect). The results generated from our analysis of the day-of-the-week effect have not shown any evidence of calendar related anomalies in the majority of the oil and gas stocks and the FTSE share indices investigated. Based on this finding, and with all other factors held constant, we cannot reject the Efficient Market Hypothesis.

The third objective of the study was to conduct an analysis of volatility modelling and forecasting in the oil and gas stocks on the London Stock Exchange. This involved modelling conditional volatility using various forms of ARCH and GARCH models. ARCH and GARCH models were used to model the daily returns of the FTSE Oil and Gas index and the FTSE All Share index. The modelling was based on the behaviour of the series' residuals from simple regression to comply with the underlying assumption of the models. The residuals plotted from the mean equation of the UK oil and gas index confirmed the existence of conditional heteroskedasticity in the series. The FTSE All Share index also showed similar characteristics of volatility clustering. The GARCH (1,1) model was adopted to find today's volatility and the active factors that determine it. Three null hypotheses (there is no serial correlation in the residuals, there is no ARCH effect in the residuals and the residuals are normally distributed) were formulated and tested for significance using the correlogram square test, the ARCH test and Jacque bera statistic test. Based on this criteria, the most effective model under appropriate distribution was selected for volatility modelling and forecasting. The results from GARCH (1,1) under the three different distributions have all shown similar attributes. It was concluded that GARCH (1,1) could be best fit under any of the three distributions. Hence, Normal Gaussian distribution has been selected for the GARCH modelling of the UK oil and gas index throughout this study. Inferences made suggested that the volatility of the UK oil and gas sector is affected by the previous day's return information and volatility which can influence present or future volatility. In comparison to the volatility behaviour of the UK oil and gas sector, the FTSE All Share index showed similar characteristics in terms of the best fit GARCH (1,1) model which suggests significance of the parameters in all the distributions. In other words, both ARCH and GARCH terms in the variance equation of the models are significant in determining the volatility of the FTSE All Share index returns.

The assumption of asymmetric volatility was also tested on the indices to assess the impact of the same magnitude of negative and positive news on volatility using the Threshold-GARCH model. The results confirmed that the impact of negative news on volatility is higher than that of positive news and thus the presence of a leverage effect is equally confirmed. It was also discovered that the asymmetric shock is higher on the FTSE All Share index than on the FTSE Oil and Gas sector, which means that the entire market is more vulnerable to negative innovations. The Brent crude spot oil price was also used as a variance regressor or exogenous variable in the symmetric volatility model of GARCH (1,1) to assess the existence of any volatility spill over from the spot price of Brent crude oil. Surprisingly, the results showed no signs of the effect of the Brent crude price shocks on the volatility of the FTSE Oil and Gas sector possibly due to hedging, a long-term investment horizon and product mix strategies. The accuracy of both symmetric and asymmetric

GARCH models employed was tested via forecasting. In symmetric GARCH (1,1) models, it was discovered that GARCH (1,1) model under Generalized Error Distribution with fixed parameter has more predictive power compared to the other distribution assumptions. Threshold-GARCH represents the asymmetric volatility model employed and in forecasting it proved to be more powerful than the symmetric models.

The last objective of the study was to investigate the predictive capability of a multi-factor asset pricing model augmented with an international oil price. It was noted from graphical observations that the oil price (OPEC Basket Price) was more volatile than the FTSE All Share and FTSE UK Oil and Gas sector indices. From the period between June 2004 and June 2014, the volatility was higher around 2008 to 2009 which could be due to the impact of the global economic crisis. However, shocks in the oil price have not been traced to the oil and gas stock returns as shown by the results of the asset pricing model. In the model, the market factor was found to be the most significant along with SMB and HML factors. The momentum factor was not found to be significant.

In the light of seeking for further empirical evidence, we had also tested the formulated hypotheses of the study. The first null hypothesis that 'market prices of oil and gas companies quoted on the London stock exchange do not move according to Random Walk and Efficient Market Hypotheses' was not out rightly rejected in all cases. Despite the presence of persistence in returns, the application of technical trading rules helped to establish that investors cannot earn abnormal returns after considering the transaction costs. The second null hypothesis that 'volatility behaviour or patterns of London-quoted oil and gas stock returns cannot be an indication of future returns' was rejected. Our results have clearly indicated that the pattern of volatility (risk) can be forecasted. The third null hypothesis that 'asset pricing dynamics of London-quoted oil and gas companies do not follow the propositions of the capital asset pricing model and other multifactor pricing models' was also rejected. The rejection was because our results show the significance of risk and other factors used in the various models.

11.2 Recommendations

Based on the findings of our investigation, we observed that the oil and gas indices are less volatile than individual stocks. It will, therefore, be easier to model and forecast the FTSE UK Oil and Gas, and FTSE UK Oil and Gas Producers indices than individual stock returns. Risk-averse investors are advised to invest in the sector indices rather than individual stocks for more control of their risks and returns.

Oil companies with longer existence on a stock exchange such as the BG Group Plc, BP Plc, Royal Dutch Shell 'B' Plc, and Wood Group Plc offer more consistent returns compared to newly listed companies such as Hardy Oil and Gas Plc, Salamander Plc and Ruspetro Plc.

The simple technical trading rules like trading and filter rules or moving average based rules would not be very helpful for active portfolio management. Investors will have to look at the fundamentals and long-term investment horizons for more effective risk-adjusted returns.

Investors and portfolio managers can assess the volatility of FTSE Oil and Gas sector and the entire market represented by FTSE All Share index using various forms of GARCH models. That was because the changes in their prices have been characterized by the volatility clustering and the existence of conditional heteroscedasticity. The effect of exogenous variables can also be incorporated into the models to measure the extent of volatility spill over between variables. In forecasting, asymmetric GARCH models should be employed because of the presence of a leverage effect and their low forecasting evaluation statistics. The entire process would enhance the understanding of risks associated with oil and gas stocks and the entire market, thus improving pricing and risk management efficiencies that lead to improved investment strategies.

In the oil and gas sector, there is an advantage of using a multifactor asset pricing model instead of a single factor capital asset pricing model because of the significance of the size effect, the book-to-market ratio and the oil price as additional factors. The analysis of the last three years' data shows that a momentum based strategy would not yield significant returns in the oil and gas sector.

11.3 Further Research

The statistical theories adopted in this research are not without limitations to practical applicability. The limitations are mostly as a result of the diverse characteristics of data which in some instances violate the underlying assumptions of a given statistical model. Financial time series are typically known to exhibit statistical properties such as heavy tails and extreme values (outliers). Statistical modelling and forecasting of financial time series should be undertaken using models that recognise the unique nature of the data. Of recent, there was the development of generalised dynamic conditional score models that have the capability of capturing outliers and changes in scale and location of observations over time. Generalised Least Squares (GLS) models were also developed to overcome the existence of autocorrelation and heteroscedasticity found in financial time series. Such models should be the focal point of scholars in modelling the financial time series for appropriate risk assessment and investment decisions. Furthermore, the criticisms of statistical modelling, especially after the financial crisis in 2007 to 2008 has necessitated the need for change. Scholars argue whether mathematical notations can continue to be used in the explanation of dynamic financial variables. In that regard, we suggest that the philosophical approach of behavioural finance should also be considered in addition to conventional statistical models when modelling and forecasting financial time series.

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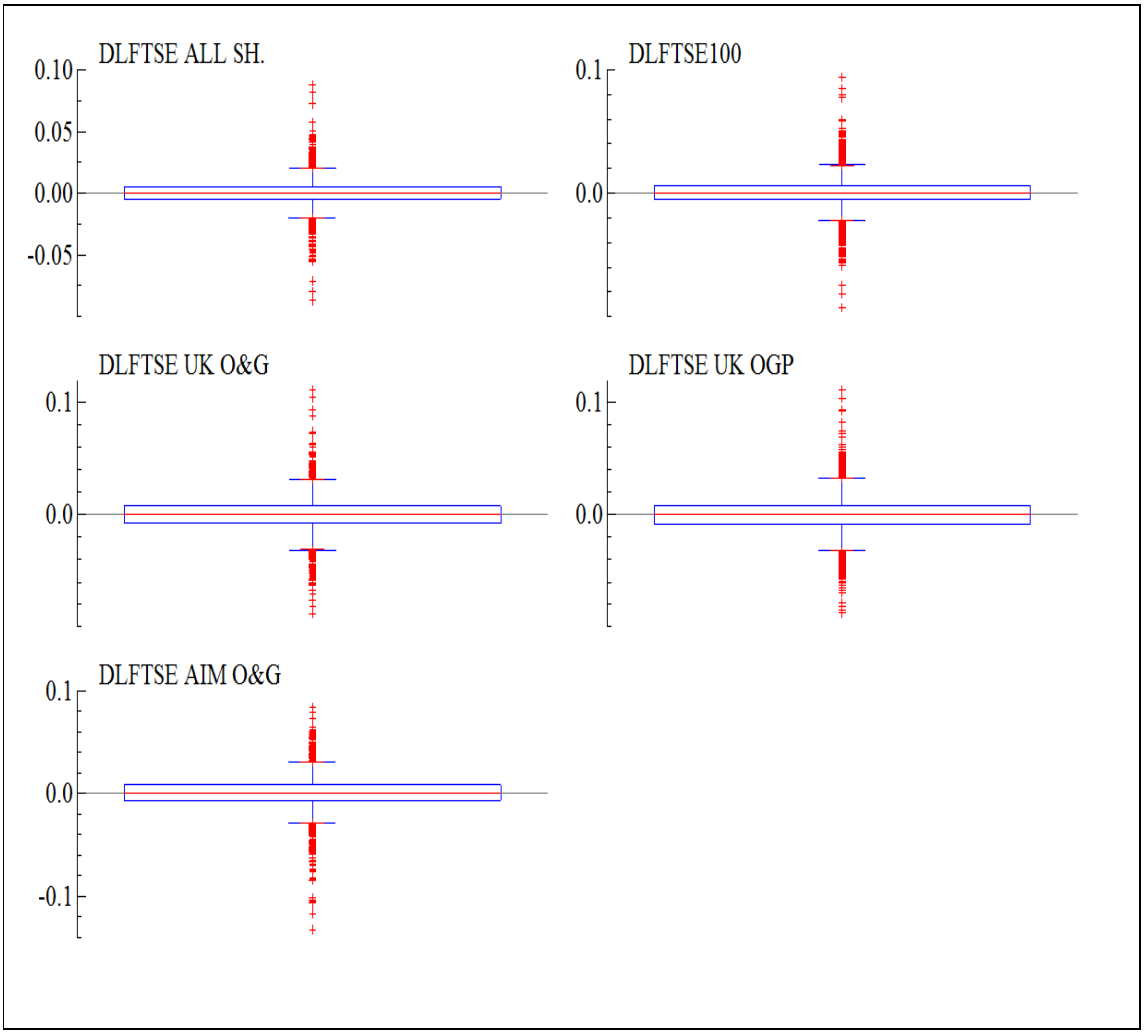
APPENDICES

Appendix 1 Box Plot of Indices' Return Series under Study

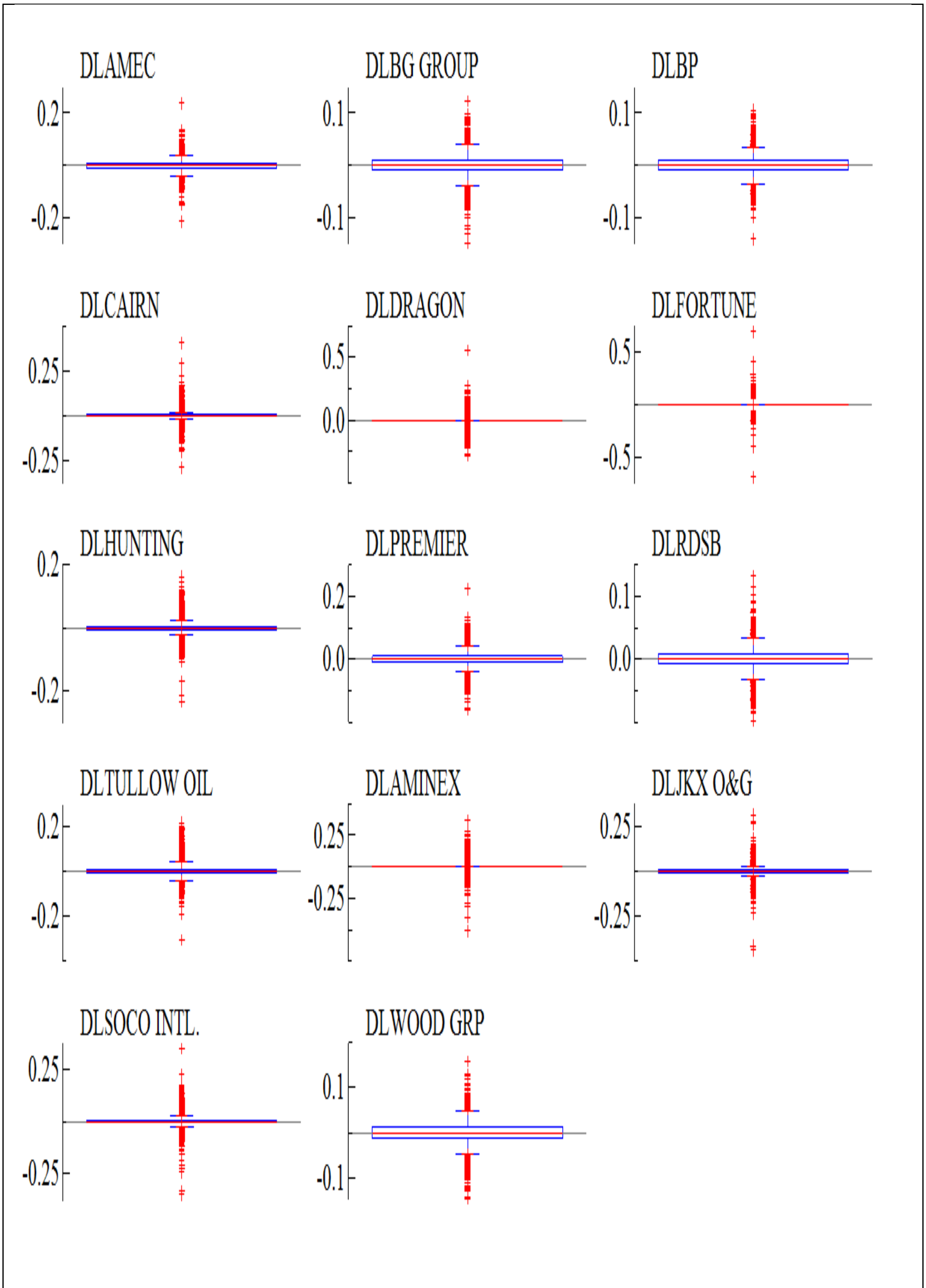
Table 6.5.1 – Box Plot of Indices' Return Series under Study



Source: Author (2015)

Appendix 2 Box Plot of Stock Returns of Companies with More Than 10 Years Series under study

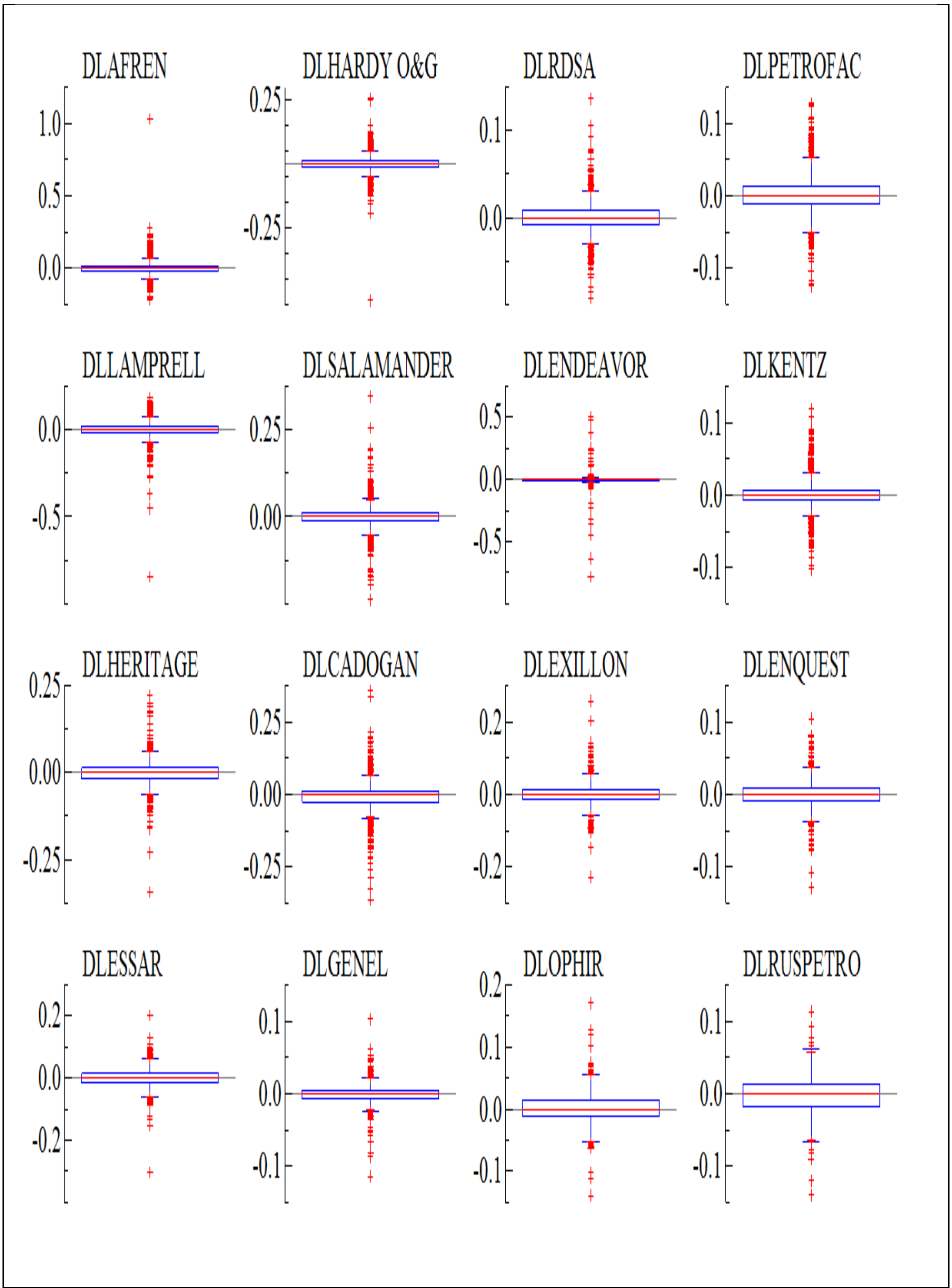
Table 6.5.2 – Box Plot of Stock Returns of Companies with More Than 10 Years Series under Study



Source: Author (2015)

Appendix 3 Box Plot of Stock Returns of Companies with Less Than 10 Years Series under Study

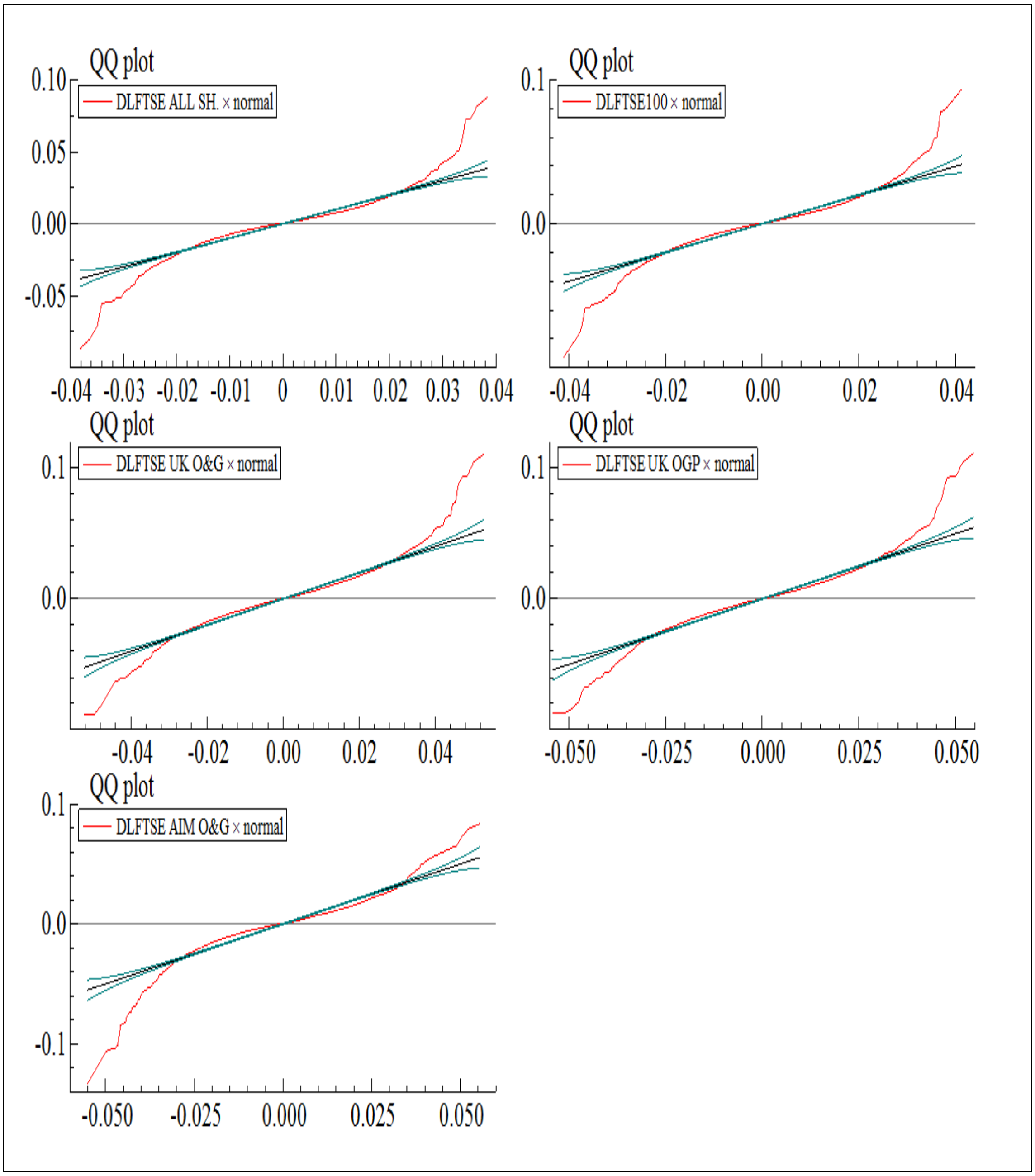
Table 6.5.3 – Box Plot of Stock Returns of Companies with Less Than 10 Years Series under Study



Source: Author (2015)

Appendix 4 Quantile-Quantile (Q-Q) Plot of Indexes' Return Series under Study

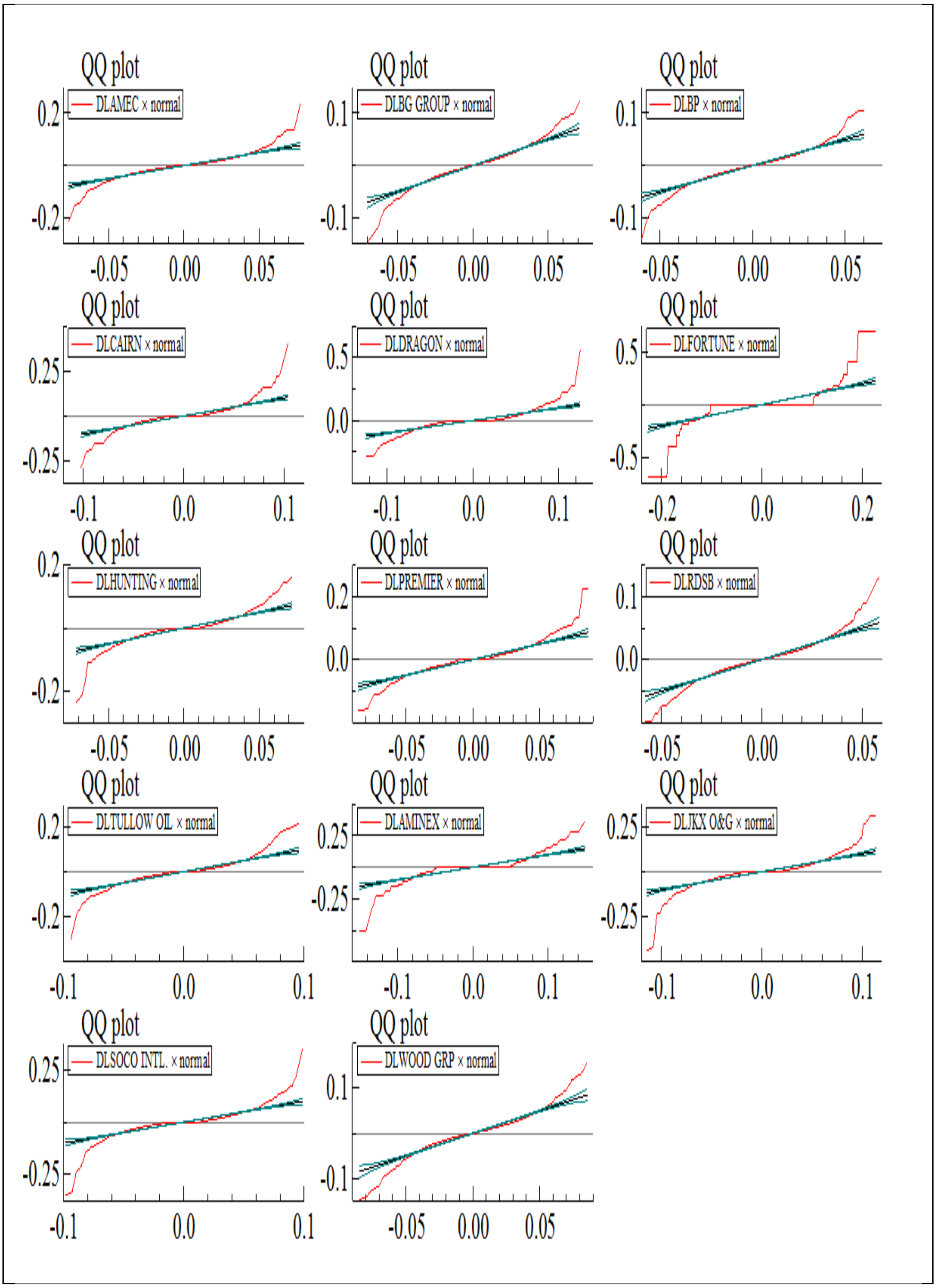
Table 6.6.1 – Quantile-Quantile (Q-Q) Plot of Indexes' Return Series under Study



Source: Author (2015)

Appendix 5 Quantile-Quantile (Q-Q) Plot of Companies with More Than 10 Years Series under Study

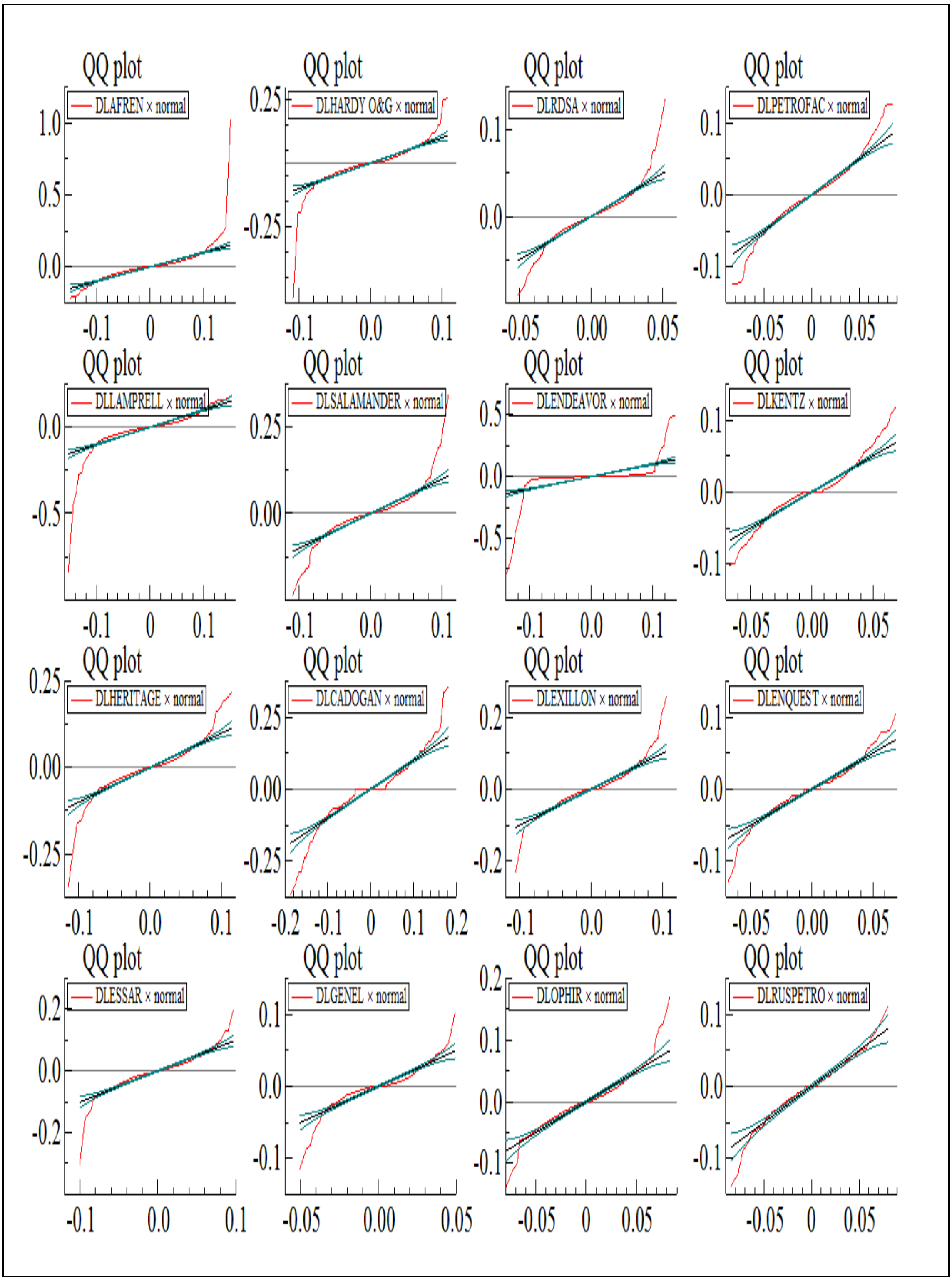
Table 6.6.2 – Quantile-Quantile (Q-Q) Plot of Companies with More Than 10 Years Series under Study



Source: Author (2015)

Appendix 6 Quantile-Quantile (Q-Q) Plot of Companies with Less Than 10 Years Series under Study

Table 6.6.3 – Quantile-Quantile (Q-Q) Plot of Companies with Less Than 10 Years Series under Study



Source: Author (2015)

Appendix 7 Autocorrelation Coefficient Band using 95% Level of Confidence Interval

Table 7.1.4 Autocorrelation Coefficient Band using 95% Level of Confidence Interval

	Obs (N)	95% Level of Confidence Interval $(\pm 1.96 \times \frac{1}{\sqrt{N}})$
FTSE All Share	5217	0.027
FTSE 100	5217	0.027
FTSE UK O&G	4956	0.028
FTSE UK O&G Prod.	4956	0.028
FTSE AIM SS O&G	3131	0.035
FTSE All Share	5217	0.027
Amec Plc	5217	0.027
BG Group Plc	5217	0.027
BP Plc	5217	0.027
Cairn Energy	5217	0.027
Dragon Oil	5217	0.027
Fortune Oil	5217	0.027
Hunting Plc	5217	0.027
Premier Oil	5217	0.027
Royal Dutch Shell B	5217	0.027
Tullow Oil Plc	5217	0.027
Aminex Plc	4563	0.029
JKX O&G	4559	0.029
Soco Intl.	4068	0.030
Wood Group (John)	2764	0.037
Afren Plc	2036	0.043
Hardy Oil & Gas Plc	1975	0.044
Royal Dutch Shell A	1943	0.044
Petrofac Ltd	1890	0.045
Lamprell Plc	1624	0.048
Salamander Energy	1588	0.049
Endeavor Intl.	1316	0.054
Kentz Corp.	1280	0.055
Heritage Oil	1241	0.055
Cadogan Petroleum	1184	0.057
Exillon Energy	793	0.069
Enquest	715	0.073
Essar Energy	695	0.074
Genel Energy Plc	402	0.098
Ophir Energy	387	0.099
Ruspetro Plc	248	0.124

Source: Author (2015)

Appendix 8 Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) Diagnostic Results of GARCH (1,1), (2,2), (3,3), (4,4) on the FTSE UK Oil and Gas and FTSE All Share Indices Returns

FTSE UK Oil and Gas Index		
GARCH Specification	AIC	SIC
(1,1)	-5.859531	-5.852964
(2,2)	-5.858734	-5.849540
(3,3)	-5.861261	-5.849440
(4,4)	-5.860325	-5.845877
FTSE All Share Index		
GARCH Specification	AIC	SIC
(1,1)	-6.644726	-6.638439
(2,2)	-6.644775	-6.635972
(3,3)	-6.645308	-6.633989
(4,4)	-6.644624	-6.630790

Source: Author (2015)