Seasonality and January Effect Anomaly on the Ghana Stock Market

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Abstract: This paper examines whether the ‘January anomaly’ or any form of monthly seasonality exist in the Ghanaian stock market returns. The existence of any form of anomalous monthly return will be at odds with the foundation of the efficient market hypothesis. Investors and other market participants in such inefficient market can time the market to lock in arbitrage profits. The sample period of the study extends from 1st April, 1999 to 28th February 2014. However, the sample period is divided into two periods with the first sample period covering the dates from 1st April, 1999 to 2nd February, 2005 and representing periods in which the Ghana stock market was trading three times in a week. Whilst the second sample period spans from 3rd February, 2005 to 28th February, 2014 also representing the duration in which the exchange was trading five times in a week. The division within the sample period was to enable the study investigate the pattern of return for seasonality at the two distinctive periods. Employing the parsimonious GARCH, EGARCH and GJR models, the first period recorded no evidence of January effect or any other form of monthly seasonality. Investors trading in the first period should not consider market timing strategy due to monthly seasonality when forming portfolio of stocks. However, the second period documented significant anomalous positive returns in the months of January, April, May and June whilst the month of March and July also recorded statistically significant negative returns during the same period. Investors trading in the second period can exploit the prevailing market timing opportunity by buying in the months experiencing negative returns (buy low) and sell in the months recording positive returns (sell high). However, investors trading in the second period should exploit this opportunity with caution.

Keywords: Seasonality, January Effect Anomaly, GARCH, GJR, EGARCH, Ghana Stock Market
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1 INTRODUCTION

Ghana Stock Exchange was incorporated in July, 1989 and subsequently commenced trading in 1990. Since its inception, the stock market has witnessed an impressive growth in terms of the number of listed companies and the size of market capitalization. Ghana Stock Exchange commenced trading activities with only twelve (12) listed companies and government bonds. However, today, there are about thirty eight (38) listed companies in the stock exchange. The market capitalization for the first two years in operation was GH¢4.2 billion in 1992 and rose to GH¢47.35 billion in 2011. Market capitalization of listed securities at the end of December, 2013 was GH¢61.3 billion compared to the December, 2012 end figure of GH¢57.3 billion, an increase of about 6.8% (Ghana stock Exchange website). The exchange is therefore living up to its role as a source provider of funds for investment.

Despite the contributions offered to the economy of Ghana by the GSE, there is not much published research in the financial literature to investigate the efficiency of the market. In the light of this, the study tests the efficiency of the stock market by researching into the pattern of returns for the presence of monthly seasonal anomaly particularly, the January effect.

The January effect is a seasonal anomaly in finance where the average return for firms and industries is consistently and systematically higher in the month of January than any other months of the year. The existence of any kind of seasonal anomaly in stock returns will have important effects on investment strategies. Thus, prudent investors can capitalize on the anomaly to make abnormal returns. In essence, the presence of January effect is a symptom of stock market inefficiency and will invalidate the efficient market hypothesis.

Fama (1970) in the preposition of the Efficient Market Hypothesis argued that prices of securities reflect all available information in the market and thus stock returns follow a random walk. In this supposition, stock returns are unpredictable since prices fluctuate randomly through time. Current prices are fair and accurate and it should not be possible for investors to trade on information or historical price trends to make riskless profits. In essence, technical and fundamental analyses to beat the market are wasteful and fruitless.

By contrast, there are documented empirical evidences from other researchers to rebut this proposition. Famous amongst these, is calendar effect anomalies in financial
literature, namely, day of the week effects (weekend effect), holiday effect and turn of
the month effects (the January effect). Principally, these calendar effects suggest that
performance of firms in terms of return outputs exhibit a relatively abnormal pattern in
certain times of the day, week, month or year.

There are also momentum effects identified in stock, currency and commodity markets
which show that shares that have performed well in recent past continue to do so over
long period of time and losing stocks (bad performers) also continue to fall over long
period of time. In effect, prudent investors are able to take advantage of the presence of
momentum effect to make arbitrage profits. These occurrences are completely at odds
with the Efficient Market Hypothesis. Therefore, a test of seasonal anomaly in the
Ghana stock market is also a test of its efficiency.

This research topic is important because, since the introduction of seasonal anomaly
into financial literature by Michael S. Rozeff and William R. Kenny (1976) in their study
(Capital Market Seasonality), almost all the other studies on this topic have focused
primarily on the developed markets like; the U. S. A., the UK and Germany while
neglecting developing (emerging) markets particularly in Africa.

Until date, there is not much published research works in the financial literature which
investigates the presence of these seasonal anomalies by employing data from Ghana.
This thesis will bridge that gap and use data from an emerging economy (Ghana). The
experience of a newer economy will enrich the existing empirical financial literature.
Moreover, the need to test the efficiency of Ghana Stock Market is necessitated by the
spate at which the market is growing in terms of the number of listed companies and
the size of market capitalization. Therefore, a null hypothesis which states that returns
for all the months of the year are equal will be tested against the alternative which also
hypothesizes that return for at least one of the months in a year varies significantly
from all others. Although the emphasis of the paper is laid on discovering January
Effect on the Ghanaian stock market, any identified monthly seasonality will also be
reported.

The study will use the most current time series analysis techniques under the ARCH
family models to achieve the afore-mentioned objective. Hence, the standard GARCH,
Exponential GARCH (EGARCH) and Glosten Jagannathan and Runkle (GJR) models
will be used to that effect. The superiority of using the ARCH-family models stems from
their ability to account for common empirical observations in daily time series:
leptokurtosis due to time-varying volatility, skewness consequential to mean non-stationarity, volatility clustering and leverage effect. Therefore, the use of ARCH family model is necessitated by the presence of significant ARCH effect and autocorrelation in the return distribution. The return distribution also exhibits fat tailed characteristics which is positively skewed and also stationary.

The sections of this study are organized as follows: section two discusses history of the Ghanaian bourse, section three reviews theories, criticisms and previous literature on the topic, while section four contains the methodology part of the study and section five focuses on the data and its descriptive statistics for the study. The empirical results of this study are discussed in section six and the last section contains the summary and concluding part of the study.
2 HISTORY OF THE GHANA STOCK EXCHANGE

The plan to create a centralized stock market in Ghana started from 1968; however, the first major progress was made after the promulgation of the Stock Market Act of 1971 and the subsequent coming into being of the Accra Stock Market Limited (ASML) in the same year. Though the initiative looked promising, the ASML remained on paper for a considerable period of time due to the then existing unfavorable macroeconomic environment, chaotic political system and the lack of needed government support. Notwithstanding these initial drawbacks, corporate bodies conducted over-the-counter (OTC) share trading of some foreign-owned companies. The two most notable brokerage firms that conducted share trading over-the-counter are the National Trust Holding Company Ltd (NTHC) and National Stockbrokers Ltd.

In the 1980s, Ghana embarked on major structural economic and legal reforms to correct these irregularities and rigidities as measures to facilitate the establishment of an organized exchange, mainly under the auspices of International Monetary Fund (IMF) and World Bank. These corrective programs were instituted simultaneously with other financial reforms such as deregulation of interest rates, removal of credit controls and floating exchange rates. Moreover, capital controls were made flexible and trades were also liberalized. The urgent need for stock market in Ghana became pronounced and inevitable after these afore-mentioned massive structural system overhauls and also, following the divestiture of many of the under-performing state owned enterprises. As a result, in July 1989 a ten-member National Committee was commissioned with a singular task of furnishing a feasibility report for establishing a centralized stock market and the subsequent recommendations contained in the report brought forth the Ghana Stock Exchange (GSE) as a private company limited by guarantee under the Companies Code of 1963.

Although incorporation of the Ghana Stock Exchange (GSE) occurred in July, 1989, it received acknowledgment as an authorized Stock Exchange under the Stock Exchange Act of 1971 in October 1990 and also commenced trading in the same period. The GSE was officially launched in January, 1991 and subsequently in April 1994 a resolution was passed to change the status of the Exchange from private to a public company limited under the Company Code 1963.
Prospective companies who intend to list on the Ghanaian bourse are subject to meet certain criteria which include capital adequacy, spread of shares, number of years in operation, profitability and management efficiency. Before 2005, the market traded three times a week, thus; Monday, Wednesday and Friday lasting for two hours in each of the trading days and spanning between time periods of 10 am to 12 noon. Presently, GSE trades in ordinary shares and corporate bonds five times a week, from Monday to Friday. The open outcry system of trading is employed to conduct business on the exchange in lots of hundred shares with the exception of Anglo Gold Ashanti shares which trade in lot of ten shares and also trades over the counter market. GSE does not trade in derivatives such as options and futures. Though delivery in the market is centralized, it is not automated. The monetary authority of Ghana Stock Exchange is the Bank of Ghana whilst Securities and Exchange Commission regulates the activities of the exchange. There are several indices computed for the exchange made up S&P/IFCG Frontier Composite and S&P/IFCG Ghana which are two indices computed by Standard and Poor and also used for this study, the Databank Stock Index (DSI) which is also the oldest of all the indices. However, the main index is the GSE All Share Index.

Although the Ghanaian bourse is a newly emerging market with associated features of small size and low liquidity, it has performed creditably in terms of returns on investment thereby attracting various recognitions worldwide. In 2003, GSE was ranked third in the world behind Bulgaria and Brazil in a publication by Standard and Poor using price indices in United State Dollars on the top twenty five best performing stock markets in the world. Bulgaria and Brazil topped Ghana with 200.1% and 142.1% respectively, whilst Ghana placed third with 140.3%. Birinyi Associates, a research group based in United States graded Ghana Stock Exchange as the sixth best performing bourse in all emerging markets in 1994. GSE was also recognized as the best performing stock market in Africa and third best performing exchange in all emerging markets in 1998 based on capital appreciation by Standard Chartered Bank London Limited (Economic Commission of Africa, 1999). It was voted the best performing stock market at the closing of 2003 with annual return of 144% in dollar terms. The Ghana bourse experienced another impressive performance in 2013. The Composite Index increased by 78.81% becoming the second best performer in Africa behind Malawi. In US dollar ($) terms it increased by 55% second to Malawi in Africa. This outstanding 2013 performance was attributed largely to enhanced investor
awareness and improved operating results of the listed companies as well as a renewed investor confidence in the Ghanaian bourse and economy.

Since the introduction of the Ghanaian bourse, it has successfully played a vibrant role as a conduit in raising domestic and international capital through the issuance of initial public offerings (IPO’s). It has also served as market for corporations and government to raise substantial long-term capital through its link with the primary market. For instance, corporations were able to raise long-term capital to a tune of $125.8 million between 1991 and 1998 and a hopping sum of $13.38 billion was raised by government and other allied agencies in 2012. Despite the many successes and contributions offered by GSE, unstable microeconomic indicators continue to be a major impediment to its smooth progress and sustainability, and this challenge contributed enormously to the abysmal performance of the exchange in 2005. The adoption of an electronic trading system as well as surmounting other difficulties such as efficient information management and dissemination systems will be critical to overcome some of the major shortfalls of the exchange. (GSE Website)
3 THEORY AND PREVIOUS RESEARCH

This chapter will discuss the theories and previous researches on January effect. The presence of January effect in the market may imply that neither the random walk hypothesis nor the efficient market hypothesis holds.

3.1 Random Walk Hypothesis

Maurice Kendall (1953) studied the prices of the US commodity and the stock market in order to test for regularities in the price fluctuations. The result of the study discovered no such regular patterns; instead the study concluded that prices follow a random walk. According to the random walk theory propounded by Kendall, security price movements are independent of each other over time. The implication of this independence is that, historical stock prices cannot be used to forecast future innovation in prices.

The possibility to utilize historical price changes in order to predict future prices will imply the existence of arbitrages in the market. This risk-free investment will not be sustainable over a long period in an effective market since investors would push the prices to their true value. The import of this random walk hypothesis is that, it will not be possible for market participants to consistently lock in risk adjusted profits or outperform the market benchmark through trading only on information without bearing risk. The attempt of many rational investors in the market to compete to outperform the market results in the random fluctuation of prices (Brealey, Myer & Allen 2006: 333).

3.2 The Efficient Market Hypothesis

The efficient market hypothesis according to Fama (1970) is premised on the idea that security prices fully reflect all relevant available information in the market and that all participants in the market simultaneously have access to this information. This spontaneous and simultaneous assimilation of all information into prices at any point in time prevents investors from making risk free excess return by trading on only historical prices.

Fama (1970) made three cardinal distinctions on the type of market efficiency based on the relevant available information and the degree to which information is reflected in current prices. The different versions of market efficiency are the weak form, the semi-strong form and the strong form of market efficiency.
The weak form of market efficiency posits that one cannot use historical prices to predict future security price movements, since historical information is already assimilated into the prices. The import of the weak form of market efficiency is that trend analysis is fruitless.

However, in the case of market that exhibits the semi-strong form of efficiency, all publicly available information regarding the prospect of a firm is already reflected in the prices. The publicly available information includes historical price data, quality of management, balance sheet composition and others. The existence of semi-strong form of market efficiency also suggests that fundamental analysis is wasteful.

In addition, if the market shows strong-form market efficiency, not even insider information can be used to make risk free profits since all relevant information is fully reflected in the prices. The relevant information under the strong-form of market efficiency includes all historical prices, all publicly available information as well as all insider information. Many academicians, financial analysts and others view the strong-form of market efficiency as extreme and only likely to exist in theory but unlikely in practice. (Fama 1970, Brealey et al. 2006: 337, Bodie et al. 2009:348-349)

### 3.3 Calendar Anomalies

This section of the paper reviews some of the identified market calendar anomalies documented in various financial literatures. However, emphasis is laid on the monthly return anomaly popularly called January Effect.

The growing interest in studying various capital markets for their efficiency has persisted for more than three decades. This enthusiasm was generally influenced by the need to ascertain whether or not the returns generated on various capital markets follow a random walk and that the efficient market hypothesis holds. If this is the case, then there are no consistent patterns in return for savvy market participant to exploit for riskless opportunities and if there is a dependent structure in returns then the tendency for informed investors to make arbitrage profits increases.

Interestingly, calendar anomalies which signify significant deviations from market efficiency and the failure for the asset pricing model to hold during different calendar periods have been documented in both developed and emerging markets around the world, including U. K., U. S. A. and Finland. The calendar anomalies studied include the day of the week effect. The day of the week effect purports that significantly
different returns are generated on some days of the week than other days, mostly higher returns occur on Fridays and relatively lower returns are generated on Mondays. However, like all other calendar anomalies researched into in the financial arena, various conflicting results are documented on this anomaly. For instance, Flannery and Protopadakis (1988) documented an anomalous negative return for Mondays and positive Friday returns on different types of securities. Other researchers like Glenn (2003) also had a contradictory finding showing evidence of positive return generation on Mondays. Still, other evidence posits the observation of negative average return on Tuesdays (eg. Balaban (1995), while some other findings like, Gardeazabal and Rogulez (2004) records no day-of-the-week effect on the Spanish market.

Also, the holiday effect is one of the most pronounced calendar anomalies which have been studied for past few decades. The holiday effect connotes significant difference between stock returns of the days preceding or immediately after a public holiday and the rest of the working days of the week. This anomaly comes in two different dimensions, thus, the pre-holiday effect and the post-holiday effect. Lakonishok and Smidt (1988) studied the daily returns of Dow Jones Industrial Average (DJIA) and discovered a substantial pre-holiday effect for a considerable period of time. This study attracted other enthusiastic researchers to test other markets (see, Pettengill (1989), Ariel (1990), Kim and Park (1994) etc.). These researchers have proffered several explanations for the existence of this anomaly, many of which are centered on behavioral finance and on investors’ psychology (the optimism in investors in the days prior to public holidays contributes to the higher average returns while the low post-holiday returns are considered as reversion after the shocks).

In addition, the January effect is also one of the identified seasonal anomalies documented in financial literature. It occurs when the average returns on stock market tend to be systematically higher in the month of January than the rest of the months in a year. A vast amount of empirical findings documented in financial literature support the presence of January effect in some stock markets around the world. For instance, Keim (1983) and Roll (1983) find January effect in the US equity market. In addition to this finding, the studies also concluded that January effect is a small firm problem. A number of reasons have been advanced by different researchers and academicians to offer explanation for the existence of January effect in various financial markets. The most notable ones among these explanations of the January effect are presented below.
3.4 The Tax-loss-selling Hypothesis

The explanations proffered to explain the existence of January effect is that investors tend to sell bad investments at the end of the year to benefit from tax shield created by losses. Constantinides (1984) posits that, with no transaction costs investors should most favorably sell losing stocks to realize capital losses. Moreover, investors will defer selling until the cost of not selling exceeds the transaction costs. In effect, much of the tax-loss selling should happen in December. The increased sales of shares at the end of the year cause the security prices to decline at that time. In January, thus the beginning of the year, investors are willing to buy back their stocks. An increased demand for stocks at that time will push up the prices of stocks again.

Moreover, investors tend to postpone selling of shares that have increased in value to the beginning of the next year. These are found to be contributory factors to the observation that the month of January usually record significant excess return in many exchanges around the world. (D’Mello, Ferris & Hwang 2003)

The tax-loss selling hypothesis as a reason for the January effect is affirmed by some studies in financial literature. Poterba and Weisbemer (2001) studied the effect of changes in capital gain tax rules on January effect, and concluded that the turn-of-the-year return is positively related to the difference between short-term and long-term capital gain tax rates.

3.5 The Window-Dressing Hypothesis

According to the window dressing hypothesis, developed by Haugen and Lakonishok (1987) and Lakonishok et al. (1991), institutional managers normally take deliberate steps to make their portfolios look better in their account to boost their performance. This deliberate action is taken because institutional managers are evaluated and compensated based on their performance and investment philosophy. Mutual fund managers usually mix risky stocks (small cap) with large cap stocks (less risky) in their portfolio to enhance returns but sell them (risky stocks) before the end of the year in order to exclude them from reflecting in their end-year holdings. However, in the beginning of the subsequent year (in January), managers overturn the process by selling winners (large cap stocks) and low risk stocks while replacing them with past losers (risky stocks). This process window dresses the portfolio to look better in the annual reports. Although stakeholders are interested in both semi-annual and end-of-
the year report and as enforced per the Investment Company Act, 1940, the emphasis is mostly on the annual report.

The window dressing hypothesis has received attention in financial literature. Chevalier and Ellison (1997) model fund manager behavior based on incentives that are related to the amount that funds can attract from prospective investors. Potential investors normally evaluate the historical performance of different mutual funds before deciding on which ones to invest with. Managers therefore have incentive to beat the benchmark and if possible buy risky stocks and window dress them at the end of the year which likely result in January effect. (Lakonishok et al. 1991)

3.6 Information Hypothesis

The information hypothesis depends on the quantity of information available to different firms which result in varied returns and risk levels. Rozeff and Kenny (1976) suggest that, excess January returns are attributable to significant information releases in the first days of January. According to Barry and Brown (1984), firms with less information have higher risk than firms with adequate information though the systematic risk of the two firms may be the same. Therefore, if return generating model compensates for only beta risk whereas returns also depend on non-systematic risk, then the excess returns for firms with less information will be seen as abnormal returns. Because small firms have less information, abnormal return in January (January effect) is normally observed which are not captured by the return generating model.

3.7 Criticism

Like other theories, the January effect has also received its fair share of criticism. Lakonishok and Smidt (1988) presented three main criticisms against seasonal anomalies; the boredom factor, noise in stock returns and data snooping.

Concerning the boredom factor, the proponents argue that even though there are a lot of researches confirming the existence of efficiency in financial markets, they are likely not to be published. The reason is that, such studies do not provide any new information and only serve to confirm an already existing study.

Moreover, it argues that the failure to properly account for the noise levels in security returns usually result in misinterpretation of results. This makes one believe that there is an anomaly, when in fact it is simply a question of noise.
In addition, the argument on data snooping comes as a result of the dearth of financial data. The problem of data scarcity restricts many of the researchers and academicians in the financial arena to repeatedly test hypotheses on the same data. According to Lakonishok and Smidt (1988), “the best remedy for data snooping is new data” which may show that the market is efficient. The problem of data snooping can also be mitigated if data from other countries and markets with no or minimal correlation with the existing data sets are used for the study. Moreover, the use of different time periods from earlier studies on the same data set will be necessary to avoid data mining problem.
4 LITERATURE REVIEW

The study on seasonal anomalies or calendar effects in various stock markets has been conducted by numerous researchers. The documented seasonal anomalies in financial literature include; day of the week effects, turn of the month effects, turn of the year effects and holiday effect. However, the focus of this thesis is centered on turn of the month effect popularly referred in the academic literature as the January effect.

Most of the studies conducted into this area of research have presented findings to suggest that return in January is significantly different from returns in all other months of the year. For instance, Rozef and Kenney (1976) document significant positive returns for the month of January when an equally-weighted index of New York Stock Exchange from the United States equity market was examined for the period between 1904 and 1974. This seventy-year period examination recorded a mean monthly return of 3.5 percent for the month of January whilst the other months also recorded an approximate mean monthly return of 0.5 percent. Moreover, Gul'tekin and Gul'tekin (1983), Moller and Zilca (2008) discovered evidence to suggest that returns in January are significantly higher than returns recorded for the remaining months of the year when they surveyed stock market data from the United States. In addition, the following researchers have also come up with similar findings as above; Nassir and Mohammad (1987) and Balaban (1995), Ho (1999) using stock market data from Malaysia, Turkey and emerging Asian Pacific Stock Market respectively. In a more recent study, Fauntas and Segredakis (2002) studied Anthens Stock Exchange and documented the existence of January effect in the market. In addition, Haug and Hirschey (2006) studied the U. S market and concluded that January effect is a persistent small-cap problem. Gu (2002) discovered in his study that the January effect is declining in the U. S equity market.

Ayadi (1998) studied the stock return seasonality in low-income and emerging African markets using monthly indices for the Ghanaian bourse between the periods of 1991 to 1996, Nigerian Stock market indices spanning from 1984 to 1995 and the Zimbabwean stock market also for the periods of between 1987 to 1995. Ayadi employed Kruskal-Wallis and Friedman test in the study and the result rejected the presence of seasonality in returns for both Nigerian and Zimbabwean bourses whilst the Friedman test identified the existence of seasonality in returns for the GSE. Ayadi used the Wilcoxon- Mann-Whitney test and the dummy-variable regression in the same study which also buttressed the other result from the Kruskal-Wallis and Friedman tests,
thus, confirmed the presence of January effect in the Ghanaian stock market whilst rejecting the existence of January effect in both the Nigerian and Zimbabwean markets.

Also, contrary to the findings of Ayadi, a study conducted on the Nigerian stock market by Oqieva (2013) identified a consistent return pattern on the Nigerian bourse. Multiple ordinary least squared regression technique was adopted for the purposes of the study using Nigerian All Shares Price Index returns for sampled day periods from April, 2005 to September, 2010. The purposes of the study were in two folds, to test for the presence of day of the week effect and month of the year effect. The study reveals that Monday, Thursday and Friday are characterized with negative market returns while Tuesday and Wednesday returns are positive. The study suggests that savvy investors can make arbitrage profits by trading on Tuesdays and Wednesdays. Moreover, the monthly calendar test reveals that February, March, April, May and December were persistently characterized with negative market returns while January, August, September, October and November also experience positive market returns contrary to the earlier findings by Ayadi which disproved the presence of any form of calendar anomaly on the Nigerian stock market.

Similarly, Alagidede and Panagiotidis (2006) employed both daily and monthly stock data from the Ghana Stock Exchange (GSE) for the periods between 25th June, 1994 to 28th April, 2004 to investigate the calendar anomalies (day of the week and month of the year effects). The study used non-linear models from the GARCH family in a rolling framework to examine the role of asymmetries. The study found no evidence of January effect on the Ghanaian stock market. Instead, the study documented that returns in April are higher than the average monthly returns during the sample period. This study yet again contradicts the earlier finding by Ayadi who documents the presence of January effect on the Ghanaian bourse.

Whilst Alagidede and Panagiotidis (2006) use data from the databank stock index (DBI), the current study will use data from Ghana Stock Exchange computed by S&P Ghana BMI. Moreover, the current study uses monthly stock returns from 2nd April, 1999 to 18th February, 2014. In addition, the sample period will be divided into two sub-periods. The first sample period will cover the dates between 2nd April, 1999 to 2nd February, 2005. The division within the sample period is important because the first sample period captures the duration when the Ghanaian bourse was trading three times in a week. Also, within the 2005 period, the GSE experienced an all-time abysmal performance in terms of returns due to deteriorating macro and micro-economic
factors. The last sample period to be tested for return seasonality spans from 3rd February, 2005 to 18th February, 2014. The last period represents duration when the exchange was trading continuously for five day. The divisions within the sample period is to enable the study fully capture the different return behaviors and unique characteristic of stock return patterns during these two distinct periods.
5 METHODOLOGY

This section of the study describes the method used to test for seasonality (January effect) in the Ghanaian stock market. Brook and Burke (2003) suggested that GARCH (1, 1) model is adequate to account for all volatility clustering present in financial time series data. Moreover, Frimpong and Oteng-Abayie (2006), studying about modeling and forecasting volatility of returns on the Ghana stock exchange concluded that the GARCH (1, 1) model outperform the other models used.

Piesse and Hearn (2002) also recommended EGARCH model proposed by Nelson (1991) for use in African markets due to its accuracy to successfully capture asymmetric effect of both good and bad news. Moreover, Alagidede and Panagiotidis (2006) also used data from the Ghanaian stock market to investigate calendar anomaly and suggested that the best model to adequately explain the data is the Threshold Generalized Autoregressive Conditional Heteroscedascity (TGARCH). Bakaert and Harvey (1997) in the study of emerging market variability affirmed the potency of asymmetric GARCH models in accounting for stock return variability.

Based on the findings and suggestions from the afore-mentioned researchers, the parsimonious GARCH (1, 1) model will be used to capture the nature of variability of return in the various months of the year. Similarly, the EGARCH model as well as the GJR-GARCH models will be used to account for asymmetric effect (leverage effect) in the return series if any. Students t’ distribution will be used for the estimations to account for the non-normal and fat tailed characteristic of the financial time series data. The decision of the t-test as the favored choice is influenced by the fact that the population variance is not known and also the central limit theorem holds because of the large sample size used to conduct the test.

Using the models above, this paper hypothesizes (H₀) that there are no excess abnormal expected returns in the month of January. Thus, there is no January effect in the market and the expected returns are almost equal for each of the month in a year. Also, to be able to record excess returns for any of the months of the year, an additional null hypothesis stated as; no month of the year records a significantly different higher expected returns than all other months will be considered. Likewise, the alternative hypothesis (H₁) will be stated as expected return for at least one of the months is significantly unequal to others.
Mathematically, the null hypothesis is stated as

$$H_0: E(r_{jan}) = E(r_{feb}) = E(r_{mar}) = E(r_{apr}) = E(r_{may}) = E(r_{jun}) = E(r_{jul}) = E(r_{aug}) =
E(r_{sep}) = E(r_{oct}) = E(r_{nov}) = E(r_{dec})$$  (1)

Where, $E$ symbolizes expectation, $r$ denotes the return of the corresponding subscript month against the alternative hypothesis that at least one of the expected returns differs significantly from others. The null hypothesis will be rejected in favor of the alternative hypothesis if at least one of the coefficients is not equal and significant enough to have a differing impact on the mean equation. However, if expected returns are found to be the same for each month, then the difference between the estimated coefficients of $r_{jan}$ through $r_{dec}$ would be approximately zero and the null hypothesis is not rejected.

To test for the seasonal monthly and January effects in the Ghanaian bourse returns, the understated specification is proposed for the mean equation.

$$Return = c + \beta_1 D_{Feb} + \beta_2 D_{Mar} + \beta_3 D_{Apr} + \beta_4 D_{May} + \beta_5 D_{Jun} + \beta_6 D_{Jul} + \beta_7 D_{Aug} +
\beta_8 D_{Sep} + \beta_9 D_{Oct} + \beta_{10} D_{Nov} + \beta_{11} D_{Dec} + \gamma MA(1) + \epsilon_t$$  (2)

Where, $\beta_i$, $\beta_2$, $\ldots$, $\beta_{11}$ and $\gamma$ are parameters of the equations, $\epsilon_t$ is the disturbance term and $D_{Feb}$, $\ldots$, $D_{Dec}$ are monthly dummy variables such that $D_i = 1$, for the $i$th month and equal to zero otherwise.

Since non-trading and/or non-synchronous trading is a common feature of an emerging market, a moving average term, $MA(1)$, is introduced into the mean equation of all regression specifications to cope with any serial correlation that may have been induced by such tendency. The various statistical properties of the variance specifications used to conduct the tests are as presented below:

### 5.1 Autoregressive Conditional Heteroscedasticity (ARCH)

The ARCH model was developed by Engle (1986) and became a very useful tool for econometric modeling. It gives explanation to several of the important characteristics of financial asset returns, including; volatility clustering, where large changes in the return series tend to be accompanied by large changes and small changes by small changes for either signs for some period of time (Mandelbrot, 1963), leading to adjoining periods of volatility and tranquility in the stock market. Stock returns also display leptokurtosis, implying that returns distribution tend to be fat tailed (Fama,
1965). The test for the ARCH effect serves as a foundation for estimating GARCH-type models. Thus, the ARCH test serves as a diagnostic test to justify the application of GARCH-type models. The series is examined for ARCH effect at lag one.

The equation of the ARCH model is of the form

\[
\text{Return} = c + \beta_1 D_{Feb} + \beta_2 D_{Mar} + \beta_3 D_{Apr} + \beta_4 D_{May} + \beta_5 D_{Jun} + \beta_6 D_{Jul} + \beta_7 D_{Aug} + \beta_8 D_{Sep} + \beta_9 D_{Oct} + \beta_{10} D_{Nov} + \beta_{11} D_{Dec} + \epsilon_t
\]

\[h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2\]  

(3)  

Where equation (3) above is the conditional mean equation for the ARCH specification and equation (4) is the variance equation \((h_t)\). These conditions must hold for the conditional variance term \((h_t)\) to be positive, \(\alpha_0 \geq 0\) and \(\alpha_1 \geq 0\). The use of this ARCH model will only serve as a diagnostic check whilst the actual estimation and corresponding inferences will be done with the GARCH models because of the perceived statistical difficulties associated with the ARCH specification.

5.2 Generalised Autoregressive Conditional Heteroscedasticity (GARCH)

Bollerslev (1987) introduced GARCH \((1, 1)\) model as an extension to the ARCH model. This extension was purposed to streamline the application of ARCH model and to provide a good fit for financial time series data. GARCH model gives additional explanation to the distributional characteristics of asset returns and hence demonstrate a comparative supremacy over the ARCH model in terms of potency in modeling data and accuracy in forecasting. Among the statistical advantages of using the GARCH model is that, it is less likely to breach the non-negativity constraints imposed on it. Additionally, the GARCH model is parsimonious since lesser lags of the ARCH and the GARCH terms are required to be included in the model without compromising on its efficacy in modeling time series data. The GARCH model also includes a variable to account for the long run average level of the variance. Moreover, the GARCH specification allows the current conditional variance to be a function of past conditional variances thus allowing shocks to evolve over time. The mean equation for the GARCH \((1, 1)\) specification is as expressed below

\[
\text{Return} = c + \beta_1 D_{Feb} + \beta_2 D_{Mar} + \beta_3 D_{Apr} + \beta_4 D_{May} + \beta_5 D_{Jun} + \beta_6 D_{Jul} + \beta_7 D_{Aug} + \beta_8 D_{Sep} + \beta_9 D_{Oct} + \beta_{10} D_{Nov} + \beta_{11} D_{Dec} + \phi MA(1) + \epsilon_t
\]  

(5)
Where, D represents the dummy variable for the month specified in the subscript, c denotes the constant term which represents the return for January and $\varepsilon_t$ is the error term. The dummy variable is equal to one for the return of the month and zero otherwise (i.e., $D_{\text{Feb}} = 1$ for the month of February and zero for others). If c in the equation is found to be statistically significant and greater that the coefficient of any of the months, then it gives an impression of the existence of a January effect. Thus, January effect on the Ghanaian bourse will be adduced to exist if the positive coefficient of January is greater than all other monthly coefficients and also significant enough to impact on the mean equation. Likewise, monthly anomaly can be recorded for any of the months if coefficient of the said month is found positive and statistically significant to have a varied impact on the mean equation than the average of the mean coefficients of the other months.

The conditional variance of the GARCH (1, 1) specification is also expressed as

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1} \quad (6)$$

Where, $h_t$ represents the conditional variance term in period t and $\alpha_0$ is the mean which captures the weighted long-run variance. $\alpha_1$ represents the news coefficient and news about shock from the immediate previous periods taken as the lag of the squared error from the mean equation, $\varepsilon_{t-1}^2$. $\beta$ represents long-run persistence coefficient and $h_{t-1}$ is the forecast volatility at period $t - 1$ (GARCH term). Parameters $\alpha_0$ and $\alpha_1$ must be greater zero or equal to zero and coefficient $\beta$ should also be positive in order to satisfy the positivity (non-negativity) and invertibility of the conditional variance. The sum of the parameters $\alpha_1$ and $\beta$ is a measure of the persistence in volatility of the unexpected return and takes values between 0 and 1 to ensure a reversion to the mean. The more this sum approaches unity, the longer time it will take to revert to the mean following a shock and vice versa. On the other hand, if the sum of the parameters $\alpha_1$ and $\beta$ equals unity, it will suggest no reversion to the average mean and with each change in shock, a new level is attained. The GARCH (1, 1) refers to the presence of first-order GARCH term and first-order ARCH term.

The GARCH model does not account for asymmetry and non-linearity in the conditional variance estimation. Rather, the model enforces symmetric response to both positive and negative shocks of the same magnitude because it depends on the square of the past shocks and not on the absolute value. In reality however, it is
evidenced by Black (1976) and Christie (1982) that a negative shock to financial time series is likely to cause volatility to increase by more than a positive shock of equal magnitude. Based on the proposition by Black (1976) and Christie (1982), two asymmetric models are used to capture leverage effect in time series data in this paper.

5.3 GJR-GARCH Model

Glosten, Jagannathan and Runkle (1993) introduced the GJR-GARCH model which is an extension to the ordinary GARCH model but with an additional term to capture asymmetry. The conditional variance of GJR-GARCH model is as expressed as

\[
h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \varepsilon_{t-1} I_{t-1}
\]

(7)

Where, \( I_{t-1} = 1 \) if \( \varepsilon_{t-1} < 0 \) or \( I_{t-1} = 0 \) if otherwise. The GJR-GARCH model resembles the threshold GARCH (TGARCH) model proposed by Rabemananjara and Zakoian (1993) and Zakoian (1994). The import of this model is to account for leverage effect in the event that bad news has greater effect on volatility than good news of similar magnitude. For leverage effect to exist, the parameter \( \gamma \) is expected to be greater than zero (\( \gamma > 0 \)). The effect of positive shock will be captured by \( \alpha_1 \) whilst negative impact is accounted for by \( \alpha_1 + \gamma \). Also, the degree of persistence in the conditional variance is represented by \( \beta \).

The following conditions are necessary to ensure a positive conditional variance \( (h_t) \), \( \alpha_0 > 0, \alpha_1 > 0, \beta \geq 0 \) and \( \alpha_1 + \gamma \geq 0 \). The model will hold even if \( \gamma < 0 \), given that \( \alpha_1 + \gamma \geq 0 \). (Brooks, 2008:406). The degree of asymmetry is measured as \( (\alpha_1 + \gamma)/\alpha_1 \)

5.4 EGARCH Model

The Exponential GARCH introduced by Nelson (1991) includes a parameter in the conditional variance specification to account for leverage effect in volatility. The EGARCH also models the log of the conditional variance and therefore, even if the parameters are negative, the variance remains positive. The modeling of the log of the conditional variance obviates the artificial imposition of none negativity constraint on its specification contrary to the requirements under the GARCH specification. The variance of the EGARCH model is as expressed below

\[
\log(h_t) = \alpha_0 + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_1 \left| \frac{\mu_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\mu_{t-k}}{\sqrt{h_{t-k}}} \hspace{1cm} (8)
\]
Where, $\alpha_0$ the constant, $\beta_j$ is the coefficient of the lagged logarithmic conditional volatility which accounts for volatility persistence taken from the previous periods. $\gamma_k$ is the parameter to account for the possible sign-based asymmetric effect in volatility which captures the different impact of positive and negative news on volatility whilst parameter $\alpha_i$ accounts for an ARCH effect in the specification. For leverage effect to exist, the parameter $\alpha_i$ is expected to be positive while the sign effect parameter $\gamma_k$ is also expected to be negative. The significance of both parameters at any conventional level will indicate the presence of magnitude and sign effect in the model. The EGARCH model approaches a symmetric model in the case where the asymmetric parameter $\gamma_k = 0$. Also, a leverage effect can be adduced from the model if the asymmetric parameter $\gamma_k < 0$ and there is an evidence of differing impact of positive and negative shocks on volatility when the asymmetric parameter $\gamma_k \neq 0$. According to Brooks (2008:406), the EGARCH specification by design allows the oscillatory behavior of the conditional variance term. The degree of asymmetry in the EGARCH model is estimated by the relation $|1 - \gamma_k|/(1+\gamma_k)$

In an effort to determine which of the above mentioned variance specifications reasonably captures the return and volatility of the Ghanaian market, some diagnostic tests will be conducted on the residuals of the estimated models.

First, to ascertain whether the symmetric GARCH (1, 1) model is adequate to capture the properties of the distribution, a joint sign and size bias test introduced by Engle and Ng (1993) will be fitted to the residuals of the estimated models. The joint test is selected because Engle and Ng (1993) argue that the joint test is more powerful than the individual tests. A review of the basic news impact curve obtained from a GARCH (1, 1) model shows a symmetric response to volatility regardless of the sign. On the contrary, what is generally observed in financial time series; especially in stock market is that a negative shock causes greater volatility than a positive shock of the same magnitude. The import of this is that if the symmetric GARCH (1, 1) is employed as the volatility forecasting model, it will under-predict the volatility following a bad shock and over-predict the amount of volatility following a good shock. In addition, if large return shocks cause volatility than as implied by a quadratic function then the symmetric GARCH (1, 1) model under-predicts volatility after a large shock and over-predicts volatility following a small shock.
The Engle joint sign and size bias test will be conducted on the residuals of the estimated GARCH (1, 1) model. The joint test specification is expressed as

\[ z_{i,t}^2 = b_0 + b_1 s_{i,t-1} + b_2 s_{i,t-1} \varepsilon_{i,t-1} + b_3 (1 - s_{i,t-1}) \varepsilon_{i,t-1} + u_t \] (9)

Where, \( s_{i,t-1} \) is a dummy indicator that takes the value of 1 if \( z_{i,t} < 0 \) and zero otherwise. Also, \( u_t \) is an independent and identically distributed random variable and \( b_0 \) is an intercept term for the regression. The presence of sign bias is inferred from the significance or otherwise of \( b_1 \), and if \( s_{i,t-1} \) is used as a slope dummy variable, then negative sign bias is inferred based on the significance or otherwise of \( b_2 \). Also, defining \( b_2 s_{i,t-1} = 1 - s_{i,t-1} \) will pick up observations with positive innovations and the significance or otherwise of \( b_3 \) will indicate the presence or otherwise of positive sign bias. Therefore, whereas the significance of \( b_1 \) shows the presence of sign bias, meaning positive and negative shocks have dissimilar impacts on future volatility compared with the symmetric response imposed by the GARCH specification, the significance of \( b_2 \) and \( b_3 \) would indicate the presence of size bias which also implies that not only the sign but the magnitude of the shock is also essential. If sign and/or size bias is present in GARCH (1, 1) then the asymmetric models will be expected to perform well comparative to the symmetric GARCH (1, 1).

Moreover, to further test the adequateness of the symmetric GARCH model against the asymmetric models, a procedure to detect leverage effect in stock return volatility introduced by Enders (2004) will be fitted to the residuals of the GARCH model. The null in Enders’ method hypothesizes no leverage effect is tested by estimating this regression equation

\[ \varepsilon_{i,t}^2 = a_0 + a_1 \varepsilon_{t-1} + a_2 \varepsilon_{t-2} + a_3 \varepsilon_{t-3} + a_n \varepsilon_{t-n} \] (10)

The main idea underlying this procedure is that the squared residuals should not be correlated with the level of error terms in the absence of leverage effect. It follows therefore that, the null hypothesis \((H_0)\): \( a_1 = a_2 = a_3 = ... = a_n = 0 \) is tested with the joint F-statistic. If the p-value of the F-statistic is significant at 5% conventional level, then it can be concluded that there is asymmetric effect (leverage effect) which will render the use of symmetric GARCH model inappropriate and will favor the use of anyone of the asymmetric variance specifications.
Secondly, the standardized residuals from the estimated models are examined if they exhibit skewness and excess kurtosis. The idea behind this test is that, if the models are adequately specified, they should significantly reduce skewness and fisher kurtosis present in the standardized residuals. Thus, the Jarque-Bera test statistic should not reject the null of normal distribution of the standardized residuals.

Thirdly, an ARCH-LM test will be conducted on the models to examine whether their standardized residuals have ARCH effect. If a model is correctly specified and deemed to capture most of the stylized facts of the data, then the variance of standardized residuals should be homoscedastic by eliminating all heteroscedasticity in the variance.

In addition, both the Correlogram Q-Statistic and Correlogram Squared Residual of the estimated models will be examined at lag ten (10). The reason is that, a good model with the potency to capture most of the stylized facts of a series should significantly reduce dependence structure (autocorrelation) present in the first and second moments of the standardized residuals.

Lastly, other statistics of each estimated model such as the log likelihood ratio and the information criteria including both the Schwartz Information Criterion (SIC) and the Akaike Information Criterion will be compared across the models. Based on the diagnostic tests, a model that best fits the data will be selected and decision of the presence or otherwise of monthly seasonality will be made.
6 DATA

This chapter gives an overview of the data employed for the research work as well as the descriptive statistics of the data.

Daily closing price index computed by S&P Ghana BMI for all listed equities on the stock market is used. The data for Ghana BMI is obtained from Thompson Data Stream. The Ghana BMI is used for this study instead of the Ghana All Share Index which is the main index for the exchange because the latter does not have long frequency data required for this study. Also, monthly data is used because of the non-availability of daily or weekly data recorded for the exchange from the commencement of trading until 2005. The sample period of the study extends from 1st April, 1999 to 28th February 2014 with 181 total monthly observations. However, in order to examine seasonality at the two distinctive stages of the market, the data is divided into two sub-periods; with the first sample period covering the dates from 1st April, 1999 to 2nd February, 2005 with approximately 71 monthly observations and the last sample period spanning from 3rd February, 2005 to 28th February, 2014 also with 110 monthly observations. Monthly returns are thus generated using the continuously compounding formula as calculated below:

\[ R_t = \ln \left( \frac{p_t}{p_{t-1}} \right) \]  \hspace{1cm} (11)

Where, \( R_t \) is the logarithmic monthly return for month \( t \), \( p_t \) and \( p_{t-1} \) stand for the price at month \( t \) and the previous month’s price \( (t - 1) \) respectively.

The data used for this study is not adjusted for dividend payments since dividend payments on various listed stocks on the Ghanaian Stock Exchange are spread across the various months in a year. Thus, there is no over concentration of dividend payments in particular month(s) on the listed equities which could reasonably affect the results of the study. Moreover, according to Mills and Coutts (1995), the failure to adjust returns for dividends payments do not invalidate the results produced and this assertion by Mills and Coutts (1995) is the source of motivation for the refusal to adjust return for dividends among most studies testing seasonal anomalies in various markets around the world. Also, the Eviews program is used for all estimations in the paper.
6.1 Descriptive Statistics

This section contains the descriptive statistics and residual diagnostic tests for the monthly return series. The tests include the normality test, ARCH LM test, Autocorrelation test and Heteroscedasticity test. These diagnostic tests are necessary to ensure that the resultant estimates will be unbiased, correct and with a minimal standard error. These descriptive statistics and the residual diagnostic tests will suggest the adequateness of applying the ARCH-family models in the estimation. The statistical property of return series are as expressed below

6.2 Normality Test

According to the normality test as shown in table 1 below, the average monthly return of the series is 0.7% with a large difference between the maximum and the minimum return on the market. Return has a positive mean and a positive skewness indicating that return is skewed to the right. Return is leptokurtic with excess positive kurtosis of approximately 16 above the normal distribution and a corresponding high Jarque-Bera (J. B) statistic implying that return has a fat tail distribution. The null of normality is rejected at 1% level. The monthly standard deviation (12.11%) is also high indicating high variability in the Ghana BMI return series. The high monthly volatility is also an indication of the riskiness of investing in such and emerging African market. The sharp decline in the returns in 2005 could also explain the high volatility and outliers identified in the return series.

<table>
<thead>
<tr>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
<th>Min</th>
<th>St.dev</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.003</td>
<td>0.001</td>
<td>0.772</td>
<td>-0.735</td>
<td>0.121</td>
<td>19.009</td>
<td>0.185</td>
</tr>
</tbody>
</table>

**Jarque-Bera test for normality**

<table>
<thead>
<tr>
<th>Value</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1923.263</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*Note: Jarque-Bera test for the Ghanaian stock market return distribution between the periods of February, 1999 to February, 2014. A total of 180 monthly observations are used.*
6.3 ARCH LM Test

The ARCH LM test conducted on the residual found significant ARCH effect in the return series. The 1% significance level indicates that there is a dependence structure in the first and the higher moments which can be modeled with the ARCH family models. This is also supported by the high volatility and kurtosis in the return series. The presence of heteroscedasticity in variance informs the usage of an ARCH family model for volatility estimation and forecasting.

The summary of the test statistics for heteroscedasticity is seen in the Table 2 below

<table>
<thead>
<tr>
<th></th>
<th>F-statistic</th>
<th>Prob. F(1,177)</th>
<th>Prob. Chi-Square(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistic</td>
<td>48.67826</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Observed R-squared</td>
<td>38.60987</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Note: ARCH-LM test for the Ghanaian stock market return distribution between the periods of February, 1999 to February, 2014. A total of 180 monthly observations are used.

6.4 Autocorrelation Test

One obvious characteristic of an emerging market is the presence of thin trading (non-trading and non-synchronous trading) which introduces autocorrelation in a series that under normal circumstances would have been serially independent. Many academicians and researchers, for example Loc, Lanjouw and Lensink (2010) opine that thin trading usually result in the false conclusion that emerging markets are inefficient due to their propensity to introduce errors in the estimates. The Correlogram Q-Statistic is used to test the presence of serial dependence structure in the monthly return series. From the test Q statistics, the null of no serial correlation in the residuals is rejected. This result shows a significant serial dependence structure in the return series. The summary from the Autocorrelation test is shown in Table 3 below
### Table 3: Test for autocorrelation in return (Q-statistics)

<table>
<thead>
<tr>
<th>Autocorrelation</th>
<th>Partial Autocorrelation</th>
<th>Q-Statistics</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.202</td>
<td>-0.202</td>
<td>7.4950</td>
</tr>
<tr>
<td>2</td>
<td>0.087</td>
<td>0.048</td>
<td>8.8790</td>
</tr>
<tr>
<td>3</td>
<td>-0.003</td>
<td>0.187</td>
<td>13.197</td>
</tr>
<tr>
<td>4</td>
<td>-0.009</td>
<td>0.063</td>
<td>13.198</td>
</tr>
<tr>
<td>5</td>
<td>-0.009</td>
<td>-0.029</td>
<td>13.215</td>
</tr>
<tr>
<td>6</td>
<td>0.152</td>
<td>0.119</td>
<td>17.587</td>
</tr>
</tbody>
</table>

Note: Q-Statistics taken at lag six (6) for the Ghanaian stock return from February, 1999 to February, 2014.

#### 6.5 Unit Root Test

Stationary time series data is preferred for use in financial time series modeling and analysis to non-stationary data. The reason for this preference is that, if time series data is stationary, shocks to the system gradually die away as time evolves.

However, a unit root data is non-stationary since shocks to the system will have no tendency to revert to long-run deterministic paths. The variance of the non-stationary series is time-dependent and goes on to infinity as time progresses. The existence of unit root in time series modeling is counter-intuitive and undesirable since previous shocks are reasonably expected to have a decaying impact on current realizations as time progresses. (Brooks and Burke, 2003)

Test for stationarity is conducted on the monthly return series with the Augmented Dickey-Fuller unit root. The test rejects the presence of unit root in the series at 1% level. This is desirable since stationary data is required for the estimation. The unit root test result is as depicted in Table 4 below.
Table 4: Testing for unit root in return

Null Hypothesis: RETURN has a unit root

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller Test Statistic</th>
<th>T-Statistic</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>-16.2157</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
</table>

Note: Augmented Dickey-Fuller Unit root test for the Ghanaian stock return distribution for the sample periods from February, 1999 to February, 2014
7 EMPIRICAL RESULTS

This section of the paper summarizes the empirical results and the residual diagnostic tests for each model used in the study. To start with, the appropriate model that best captures the behavior of the distribution will be sought for. Residual diagnostic tests will be summarized and compared across the models for each period and the best model will be selected for determination. To this end, analysis of the empirical results will be divided into two to account for the first and the second period of the study respectively.

It is generally acknowledged that the GARCH-type models are appropriate to account for most of the stylized facts in financial time series data. Former studies have documented that a GARCH (1, 1) formulation captures the conditional volatility of returns very well while other researchers have favored either the EGARCH model or the GJR models because of their potency to capture asymmetry in return distribution. This paper employs all three afore-mentioned conditional variance specifications: the standard GARCH, EGARCH and the GJR models in order to evaluate the sensitivity of the results to employing different volatility specifications. Also, in an attempt to reduce serial correlation induced into the model due to non-synchronous trading commonly associated with emerging market data which Ghana stock market is a member of the category, the mean equation in all specifications and all periods includes a Moving Average (MA(1)) term.

7.1 ANALYSIS FOR THE FIRST PERIOD (April, 1999 to Feb, 2005)

Table 5 summarizes results of the different variance specifications for the Ghanaian bourse returns for the first period of the study spanning from 2\textsuperscript{nd} April, 1999 to 2\textsuperscript{nd} February, 2005. A cursory look at the bottom of this Table shows that GARCH (1, 1) model has the highest log-likelihood value as well as the lowest Schwarz and Akaike Information Criteria. This is followed closely by the EGARCH (1, 1) and GJR-GARCH (1, 1) respectively. In addition to the fact that the log-likelihood value as well as all the information criteria favors the standard GARCH (1, 1) as the best model, all other specification diagnostic tests also affirm that this model provides a better fit and captures most of the stylized facts of the market return distribution for the first period of the study. As a first diagnostic check, the Correlogram Q-Statistic from the estimation output for all three models displays evidence of serial correlation in the standardized residuals up to lag 10. The Q-Statistics are highly statistically significant at 1% level for the EGARCH and the GJR models, whilst the GARCH model is mostly
significant at 5% level. This results shows that there is a serial dependence in the mean of the return for which the models are failing to account for. Also, for the squared residuals up to lag 10, all models report no significant evidence of dependence structure. The import of this finding is that all three (3) variance specifications employed in this paper minimise volatility pooling as well as any inter-temporal autocorrelation in squares of standardized residuals. Moreover, the ARCH-LM (1) test statistics report no ARCH-effect in the standardized residuals for all three (3) models. This means all three models successfully modelled heteroscedasticity present in the distribution rendering the standardized residuals to be conditionally homoscedastic as expected from a well specified model. Furthermore, although the standardized residuals in none of the three (3) estimated models is normally distributed as reasonably expected from a well specified model, each of the three specifications performed well by reducing the value of skewness and the kurtosis in the standardized residuals.
Table 5: Summary statistics of Variance Specifications (period one)

\[
\text{Return} = c + \beta_1 D_{\text{Feb}} + \beta_2 D_{\text{Mar}} + \beta_3 D_{\text{Apr}} + \beta_4 D_{\text{May}} + \beta_5 D_{\text{Jun}} + \beta_6 D_{\text{Jul}} + \beta_7 D_{\text{Aug}} + \beta_8 D_{\text{Sep}} + \beta_9 D_{\text{Oct}} + \beta_{10} D_{\text{Nov}} + \beta_{11} D_{\text{Dec}} + \varnothing_{\text{MA}(1)} + \epsilon_t
\]

Mean Equation:

\[
\beta_{11} D_{\text{Dec}} + \varnothing_{\text{MA}(1)} + \epsilon_t
\]

Variance Specifications:

\[
h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1}
\]

GJR GARCH (1,1):

\[
h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1} + \gamma \epsilon_{t-1}^2 I_{t-1}
\]

EGARCH (1, 1):

\[
\log(h_t) = \alpha_0 + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \left| \frac{\mu_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^{k} \gamma_k \frac{\mu_{t-k}}{\sqrt{h_{t-k}}}
\]

<table>
<thead>
<tr>
<th>Month</th>
<th>GARCH (1,1)</th>
<th>EGARCH (1,1)</th>
<th>GJR (1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>-0.011 (-0.730)</td>
<td>-0.003 (-0.182)</td>
<td>0.028 (1.018)</td>
</tr>
<tr>
<td>February</td>
<td>0.006 (0.215)</td>
<td>-0.004 (-0.140)</td>
<td>0.049 (-1.945)</td>
</tr>
<tr>
<td>March</td>
<td>0.000 (0.001)</td>
<td>0.011 (0.492)</td>
<td>-0.010 (-0.286)</td>
</tr>
<tr>
<td>April</td>
<td>0.004 (0.176)</td>
<td>0.017 (0.833)</td>
<td>0.002 (0.072)</td>
</tr>
<tr>
<td>May</td>
<td>-0.013 (-0.606)</td>
<td>-0.003 (-0.129)</td>
<td>-0.025 (-0.653)</td>
</tr>
<tr>
<td>June</td>
<td>-0.005 (-0.249)</td>
<td>0.021 (1.030)</td>
<td>-0.019 (-0.519)</td>
</tr>
<tr>
<td>July</td>
<td>-0.005 (-0.269)</td>
<td>0.018 (0.859)</td>
<td>-0.019 (-0.469)</td>
</tr>
<tr>
<td>August</td>
<td>-0.012 (-0.577)</td>
<td>-0.002 (-0.068)</td>
<td>-0.023 (-0.575)</td>
</tr>
<tr>
<td>September</td>
<td>0.010 (0.434)</td>
<td>0.002 (0.002)</td>
<td>-0.027 (-0.301)</td>
</tr>
<tr>
<td>October</td>
<td>0.021 (0.948)</td>
<td>-0.002 (-0.109)</td>
<td>-0.045 (-1.019)</td>
</tr>
<tr>
<td>November</td>
<td>0.002 (0.071)</td>
<td>-0.010 (-0.417)</td>
<td>-0.036 (-0.967)</td>
</tr>
<tr>
<td>December</td>
<td>0.004 (0.251)</td>
<td>0.006 (0.302)</td>
<td>-0.040 (-1.266)</td>
</tr>
<tr>
<td>(\varnothing_{\text{MA}(1)})</td>
<td>0.311 (2.664***)</td>
<td>0.255 (1.771*)</td>
<td>0.316 (2.613***)</td>
</tr>
</tbody>
</table>

Variance Equation:

\[
\alpha_0 = 0.000(0.027)\quad -3.772 (-1.436)\quad 0.002 (0.712)
\]

\[
\alpha_1 = 13.367 (0.032)\quad 0.712 (0.826)\quad -0.066 (-0.204)
\]

\[
\beta = 0.823 (10.437***)\quad 0.359 (0.855)\quad 0.386 (0.470)
\]

Asymmetry (\(\gamma\)): .............. -0.542 (-0.914) 0.258 (0.628)

Log likelihood 115.641 115.515 114.165

SIC -2.237 -2.173 -2.135

AIC -2.779 -2.747 -2.797

Skewness -0.042 1.027 0.604

Kurtosis 16.432 7.570 5.219

Wald Test:

F-Statistics 0.390 0.470 0.818

F-Probability (0.954) (0.913) (0.622)

Note: Sampling is from April, 1999 to Feb, 2005 capturing the periods in which the Ghanaian bourse was trading three (3) times in a week. Numbers in parenthesis ( ) are Z-statistics, 1% significance level is denoted by (**), 5% significance by (**), and 10% significance level is also represented by (*). The ARCH parameter is denoted by \(\alpha_1\) while \(\beta\) represents the GARCH parameter.

One obvious limitation of GARCH model is its symmetric impact on volatility following both good and bad news. Therefore, to further check the appropriateness of using the standard GARCH model for the conditional volatility forecast, asymmetry in stock
market return volatility is examined to ensure that there is no dissimilar effect of positive and negative news on the structure of volatility. To this end, Engle and Ng (1993) joint sign and size bias test as well as Enders (2004) leverage effect tests are applied on the standardized error of GARCH (1,1) model. Table 6 below contains the summary of test statistics from the Engle and Ng joint test. The Table documents no sign bias in model since the probability value of sign bias test is statistically insignificant at any conventional level. This finding concludes that the estimated standard GARCH (1, 1) demonstrates a good ability to predict the impact of both good and bad shock on market volatility. Again, a p-value of 0.582 from the negative size bias test shows that there is no negative size bias in the Ghanaian bourse. The implication of this finding is that the fitted GARCH model adequately accounts for the impact of both large and small innovations. Moreover, the Engle and Ng test also rejects the null hypothesis that the positive shocks have different effect on future volatility with an insignificant p-value of 0.388. The conclusion here is that there is no positive size bias in the fitted GARCH (1, 1) model.

At the same time, the sample F-statistic for the null hypothesis is 0.573 and a probability value is 0.635 which emphatically concludes that there is no asymmetric effect in Ghanaian stock return behavior. In a nutshell, the joint test on the residuals from the standard GARCH (1, 1) model cannot reject the null of symmetry for the Ghanaian bourse. In other words, according to the Engle and Ng (1993) joint test fitted to standardized residuals of the estimated GARCH(1,1) model, the volatility of the Ghana stock market is symmetric and there is no asymmetric effect (leverage effect) in the stock return response to new information.

<table>
<thead>
<tr>
<th>Table 6: Test for Asymmetry (Engle and Ng 1993 test)-GARCH (1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>0.052</td>
</tr>
<tr>
<td>(0.133)</td>
</tr>
</tbody>
</table>

Notes: April, 1999 to Feb, 2005 Engle and Ng (1993) joint size and size bias test up to lag 1 for the GARCH(1, 1) specification, p-values are shown in parenthesis ( ), 1% significance level is denoted by (***) , 5% significance by (**), and 10% significance level is also represented by (*)
Again, to ascertain the veracity of the finding from Engle and Ng (1993) joint test, Enders (2004) method is applied. Table 7 below shows the summary statistics for regressing the squared standardized errors on its own lagged level of error terms from the fitted GARCH (1, 1) model. According to the Table 7, the joint F-statistic for the null hypothesis is 0.280 with a corresponding probability value of 0.890 indicating that there is no leverage effect in the volatility of the Ghanaian bourse. The implication of this is that, in the Ghanaian stock return data generating process the squared standardized error terms are not predictable on the basis of observed variables.

<table>
<thead>
<tr>
<th>Intercept</th>
<th>$\varepsilon_{t-1}$</th>
<th>$\varepsilon_{t-2}$</th>
<th>$\varepsilon_{t-3}$</th>
<th>$\varepsilon_{t-4}$</th>
<th>F-Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0463</td>
<td>-0.055</td>
<td>-0.086</td>
<td>0.041</td>
<td>-0.012</td>
<td>0.280</td>
</tr>
<tr>
<td>(0.037)</td>
<td>(0.611)</td>
<td>(0.432)</td>
<td>(0.704)</td>
<td>(0.915)</td>
<td>(0.890)</td>
</tr>
</tbody>
</table>

Notes: April, 1999 to Feb, 2005 Enders (2004) leverage effect test up to lag 4 for the GARCH (1, 1) specification, p-values are shown in parenthesis ( ), 1% significance level is denoted by (**), 5% significance by (***), and 10% significance level is also represented by (*)

This finding is also supported by the fact that none of the asymmetric parameters in both estimated asymmetric models (EGARCH and GJR) is statistically significant at any acceptable conventional level. The joint conclusion from afore-discussed findings is that there is no asymmetric effect in the Ghanaian stock market returns. It can therefore be concluded that investors in the market react symmetrically to both bad and good news. The variance equation of GARCH (1, 1) model is therefore the best model to be used since it is well specified and demonstrate a comparatively better ability to capture volatility in the Ghanaian stock market than the other two asymmetric models.

Since, most of the model diagnostic tests favor GARCH (1, 1) to capture most of the market movements during the first period, the presence of seasonal anomalies in the Ghanaian bourse will be based mainly on this model. To start with, the moving average (MA) coefficient in the mean equation from Table 5 is highly statistically significant. The significance of the MA (1) parameter indicates the presence of serial correlation in Ghana stock market return. To put it another way, even after the impact of non-synchronous trading is accounted for in the mean equation, the market still reveals inefficiency for the first period.
Also, the estimated $\alpha$ and $\beta$ parameters in the GARCH (1, 1) variance equation show a highly significant GARCH effect connoting a very high long-run persistence to shock but no ARCH effect (no volatility pooling in error term) or short run persistence to shock with $\alpha_1 + \beta > 1$. This finding ($\alpha_1 + \beta > 1$) suggests a non-stationarity in variance and therefore the unconditional variance will be undefined under this scenario. According to Brook and Burke (2003), “non-stationarity in variance does not have a strong theoretical motivation for its existence, as would be the case of non-stationarity in mean” although the conditional variance forecast will tend to infinity as the forecast horizon increases. The implication of non-stationarity in variance recorded in the Ghanaian stock market volatility is that a new level is attained with every change in price.

From Table 5, the mean equation displays the estimated value of the intercept and the coefficients of the monthly dummies. The intercept term determines the mean return for January whilst the coefficients of the dummy variables represent the corresponding mean return for the subscript month from February to December. The z-statistics are also shown in parentheses and they indicate the significance of the intercept at one percent, five percent and ten percent significance level. Also, the Wald statistic is also displayed in the Table. The Wald statistic determines the hypothesis that all months from January to December have identical mean values.

As apparent from Table 5, the mean monthly return for January is negative, but it is not statistically significant at any of the conventional levels. Also, the F-statistic from the Wald test which examines equality of the twelve months’ means is 0.390 with F-probability value of 0.954. This means that the null of no significant difference between the means of the various months cannot be rejected at any of the conventional levels. This result gives evidence that there is no January effect or any other type of monthly seasonality in the Ghanaian bourse from 2nd April, 1999 to 2nd February, 2005.

The import of this finding is that, there is the absence of any viable monthly information to exploit and therefore investors in the market should not take into account seasonal effect when forming their portfolio during that period.

7.2 ANALYSIS FOR THE SECOND PERIOD (Feb, 2005 to Feb, 2014)

Table 8 exhibits the summary statistics of the different volatility modeling specifications used to model the Ghanaian bourse return for the second period of the study (Feb, 2005 to Feb, 2014). Again, the bottom of the Table shows that GARCH (1, 1)
variance specification has the highest log-likelihood value and the lowest Schwarz and Akaike Information Criteria. The EGARCH and the GJR trails the performance of the standard GARCH (1, 1) in that order. Also, according to Correlogram Q- statistics taken at lag 10, GARCH (1, 1) only seconded the EGARCH model in their potency to eradicate dependence structure in the first moment of the standardized residuals at 5% percent significance level. The EGARCH model eradicated serial correlation in the error term from lag 3, the GARCH (1, 1) achieved it from lag 5 whilst GJR model maintained serial correlation in the standardized residuals at 1% significance level up to lag 10. This means that the EGARCH and the GARCH (1, 1) models accounted for most of the serial dependence structure in the mean of the distribution whilst GJR failed to account for most of the serial dependence in its mean. Also, from the squared correlogram statistic, all three models report no significant evidence of dependence structure in the squared residuals up to lag 10. The implication is that, all the three variance specifications have adequately accounted for volatility clustering as well as inter-temporal autocorrelation in squares of the standardized residual. In addition, the ARCH-LM (1) test reports no ARCH effect in the standardized residuals from all the variance specifications. The ability of the models to successfully account for all heteroscedasticity in volatility is a plus for all the models since the distribution of the error terms become homoscedastic. Moreover, one obvious expectation from a well-specified model is that the standardized residuals should be approximately normally distributed. However, none of the variance specifications was able to meet this target. Notwithstanding this shortfall, all the variance specifications adequately reduced the value of skewness and fisher kurtosis in the mean of the return distribution which is certainly a plus for all the models.
Table 8: Summary Statistics of Variance Specifications (Period two)

\[
\text{Return} = c + \beta_1 D_{Feb} + \beta_2 D_{Mar} + \beta_3 D_{Apr} + \beta_4 D_{May} + \beta_5 D_{Jun} + \beta_6 D_{Jul} + \beta_7 D_{Aug} + \beta_8 D_{Sep} + \beta_9 D_{Oct} + \beta_{10} D_{Nov} + \beta_{11} D_{Dec} + \varnothing MA(1) + \epsilon_t
\]

Mean Equation:

\[
h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1}
\]

Variance Specifications:

GARCH (1,1):

\[
h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1} + \gamma \epsilon_{t-1}^2 I_{t-1}
\]

GJR GARCH (1,1):

\[
h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1} + \gamma \epsilon_{t-1}^2 I_{t-1}
\]

EGARCH (1, 1):

\[
\log(h_t) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_1 \frac{|\epsilon_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{k=1}^{v} \gamma_k \frac{\epsilon_{t-k}}{\sqrt{h_{t-k}}}
\]

<table>
<thead>
<tr>
<th>Month</th>
<th>GARCH (1,1)</th>
<th>EGARCH (1,1)</th>
<th>GJR (1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>0.009 (7.285*** )</td>
<td>0.007 (1.109)</td>
<td>0.029 (0.195)</td>
</tr>
<tr>
<td>February</td>
<td>-0.007 (-0.716)</td>
<td>-0.005 (-0.643)</td>
<td>0.012 (0.442)</td>
</tr>
<tr>
<td>March</td>
<td>-0.011 (-2.180***)</td>
<td>-0.008 (-1.076)</td>
<td>0.022 (0.607)</td>
</tr>
<tr>
<td>April</td>
<td>0.048 (26.920*** )</td>
<td>0.044 (5.917*** )</td>
<td>0.031 (0.874)</td>
</tr>
<tr>
<td>May</td>
<td>0.006 (5.128***)</td>
<td>0.002 (0.320)</td>
<td>0.036 (1.110)</td>
</tr>
<tr>
<td>June</td>
<td>0.003 (2.708***)</td>
<td>0.002 (0.211)</td>
<td>0.008 (0.211)</td>
</tr>
<tr>
<td>July</td>
<td>-0.010 (-2.709***)</td>
<td>-0.010 (-1.193)</td>
<td>-0.036 (-0.992)</td>
</tr>
<tr>
<td>August</td>
<td>0.007 (0.928)</td>
<td>0.008 (0.910)</td>
<td>0.006 (0.171)</td>
</tr>
<tr>
<td>September</td>
<td>0.004 (0.567)</td>
<td>0.005 (0.504)</td>
<td>0.011 (0.309)</td>
</tr>
<tr>
<td>October</td>
<td>0.014 (1.112)</td>
<td>0.015 (1.315)</td>
<td>-0.003 (-0.078)</td>
</tr>
<tr>
<td>November</td>
<td>0.008 (1.090)</td>
<td>0.009 (0.652)</td>
<td>-0.009 (-0.009)</td>
</tr>
<tr>
<td>December</td>
<td>0.003 (1.071)</td>
<td>0.003 (0.380)</td>
<td>-0.023 (-0.696)</td>
</tr>
<tr>
<td>( \varnothing MA(1) )</td>
<td>0.309 (3.215*** )</td>
<td>0.283 (2.991*** )</td>
<td>0.329 (2.615*** )</td>
</tr>
</tbody>
</table>

Variance Equation:

\[
\alpha_0 = 0.000 (0.126) -1.176 (-3.471***) 0.002 (1.575) 0.006 (0.131) 7.306 (1.581) -0.084 (-0.845)
\]

\[
\alpha_1 = \frac{0.444 (3.213***)}{8.732 (7.263***)} 0.079 (0.694)
\]

\[
\gamma = \frac{-2.083 (-1.406)}{0.386 (3.105) 0.386 (1.305)}
\]

\[
\text{Log likelihood} = 196.733 190.282 167.343
\]

\[
\text{SIC} = -2.878 -2.717 -2.296
\]

\[
\text{AIC} = -3.298 -3.161 -2.740
\]

\[
\text{Skewness} = 1.590 1.421 0.118
\]

\[
\text{Kurtosis} = 9.003 7.939 6.294
\]

\[
\text{Wald Test} = 
\]

\[
\text{F- Statistics} = 1099.613 21.007 1.004
\]

\[
\text{F-Probability} = (0.000***)(0.000***)(0.449)
\]

Note: Sampling is from Feb, 2005 to Feb, 2014 capturing the periods in which the Ghanaian bourse was trading five (5) times in a week. Numbers in parenthesis ( ) are Z-statistics, 1% significance level is denoted by (**), 5% significance by (**), and 10% significance level is also represented by (*). The ARCH parameter is denoted by \( \alpha_1 \) whiles \( \beta \) represents the GARCH parameter.

From Table 8 and the discussed diagnostic tests, it can be concluded that the parsimonious GARCH (1, 1) is yet again the best model to be used to model volatility in the Ghanaian stock market for the second period. However, to completely justify its use, the Engle and Ng (1993) joint sign and size bias test as well as the Enders (2004)
procedure is applied to the estimated standardized residual of the GARCH output to test for asymmetry (leverage effect) in volatility.

Table 9 below summarizes the test statistics for Engle and Ng (1993) joint test. The table records no sign bias in the standard GARCH (1, 1) standardized residuals. The probability value of sign bias test is 0.988 which is statistically insignificant at any of the conventional levels. It is concluded that the estimated GARCH (1, 1) is capable of predicting the impact of both good and bad shock on volatility appropriately. Again, with a probability value of 0.371, the model can be considered to adequately account for both small and big innovations in volatility since the test records no statistically significant negative size bias in the Ghanaian market return. Engle and Ng (1993) joint test also rejects the presence of positive size bias in the model at an insignificant p-value of 0.265. Positive size therefore does not have different impact on future volatility.

Moreover, the probability value (0.542) of the sample F-statistic fails to reject the null hypothesis that there is no sign and size bias in the model. This concludes the observation that investors in the Ghanaian stock market do not overreact or underreact to positive or negative news arrival. Since the Engle and Ng (1993) test fails to reject the null of symmetric distribution of returns in the Ghanaian stock market, the parsimonious symmetric variance specification can be deemed adequate to model the market volatility.

<table>
<thead>
<tr>
<th>Intercept</th>
<th>Sign Bias Test</th>
<th>Negative Size Bias Test</th>
<th>Positive Size Bias Test</th>
<th>Joint Test F- Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.305196</td>
<td>-0.003</td>
<td>1.475</td>
<td>(-2.336)</td>
<td>0.721</td>
</tr>
<tr>
<td>(0.0291)</td>
<td>(0.988)</td>
<td>(0.371)</td>
<td>(0.265)</td>
<td>(0.542)</td>
</tr>
</tbody>
</table>

Notes: Feb, 2005 to Feb, 2014 Engle and Ng (1993) joint size and size bias test up to lag 1 for the GARCH (1, 1) specification, p-values are shown in parenthesis ( ), 1% significance level is denoted by (**), 5% significance by (**), and 10% significance level is also represented by (*)

Again, to confirm the adequateness of using the symmetric standard GARCH model, Enders (2004) procedure is applied to the standardized residuals of the estimated GARCH (1, 1) output. Table 10 displays the summary statistics for regressing the squared standardized residuals from the GARCH (1, 1) output on its own previous
levels. From the Table, the probability of join F-statistic is 0.466 and fails to reject the null hypothesis that there is no asymmetry in Ghanaian market returns.

Moreover, this singular conclusion from the Engle and Ng joint test as well as the Enders procedure to the effect that there is no leverage effect in the Ghanaian market return is also supported by the fact that none of the asymmetric parameters from the estimated EGARCH and GJR models is significant at any of the conventional levels. In conclusion, all the afore-discussed diagnostic checks show that the use of the standard GARCH (1, 1) model for volatility modeling in the Ghanaian stock market is appropriate and the best model.

**Table 10: Test for leverage effect (Enders method) – GARCH (1, 1)**

<table>
<thead>
<tr>
<th>Intercept</th>
<th>$\varepsilon_{t-1}$</th>
<th>$\varepsilon_{t-2}$</th>
<th>$\varepsilon_{t-3}$</th>
<th>$\varepsilon_{t-4}$</th>
<th>F-Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.046</td>
<td>0.045</td>
<td>0.208</td>
<td>0.160</td>
<td>0.019</td>
<td>0.902</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.760)</td>
<td>(0.136)</td>
<td>(0.249)</td>
<td>(0.893)</td>
<td>(0.466)</td>
</tr>
</tbody>
</table>

Notes: Feb, 2005 to Feb, 2014 Enders (2004) leverage effect test up to lag 4 for the GARCH (1, 1) specification, p-values are shown in parenthesis ( ), 1% significance level is denoted by (**), 5% significance by (**), and 10% significance level is also represented by (*)

Again, since most of the residual diagnostic tests conclude that the symmetric GARCH (1, 1) is the best variance specification to capture volatility in the Ghanaian stock market, the determination of the presence of any form of monthly seasonality will be inferred from this model. Table 8 above shows the summary statistics from the GARCH (1, 1) estimation output for the second period. From the Table, it is shown that the MA (1) parameter included in the mean equation is highly statistically significant at 1% level. The significance of the MA (1) parameter implies that the Ghanaian market exhibits signs of inefficiency due to the presence of serial correlation.

Furthermore, analysis of the variance output from the GARCH (1, 1) specification reveals the presence of a very high long-run persistence to shock (GARCH-effect) but an insignificant short-run persistence to shock (no volatility clustering). Again, the sum of the ARCH parameter and the GARCH parameter which measures the total persistence is greater than one ($\alpha_i + \beta >1$). This suggests that there is non-stationarity in variance and the unconditional variance is not defined.

From Table 8, the mean monthly return for January is positive and statistically significant at 1% significance level. Likewise, the coefficients of the mean returns for
April, May and June are all positive and significant at 1% level. A closer look at the monthly coefficients indicates that although January, May and June all have positive and significant mean returns; the month of April has the highest mean return. Again, February, March and July recorded negative monthly return during the period; however, the negative return recorded in February is not significant at any of the conventional levels. The negative mean return in March is statistically significant at 5% level whilst the negative mean return in the month of July is significant at 1% level. Moreover, the Wald test is used to check for the equality of the mean monthly coefficients. The probability value of the F-statistics is highly significant at 1% level and therefore, the null of equality of the mean monthly returns is rejected. This clearly buttresses the existence of monthly seasonality in the Ghanaian stock market returns. In a nutshell, it is concluded that there is a January, April, May and June effects in the Ghanaian stock market during the second period of the study since these months recorded positive and a highly statistically significant returns than the other months whilst March and July also experienced a statistically significant negative returns during the same period. Therefore, prudent investors should consider buying stocks (buy low) in the months of March and July where returns are low and sell them in the months of January, April, May and June when the returns are comparatively higher to take advantage of the presence of seasonal effect in the market during this period.
8 SUMMARY AND CONCLUSION

In this paper, January anomaly and other monthly return patterns have been examined in the Ghanaian stock market. The sample period under study was divided into two periods. The first period covered the duration when the Ghanaian market was trading only three times within a week and the second sample period also covered the duration when the exchange was trading for five days within a week. The main idea behind this division was to capture and compare the efficiency of the market at these two distinctive periods by examining the pattern of monthly return. The paper employed the logarithmic return of the Ghana BMI indices (dollar) from the stock market and different financial models were applied to examine same.

Also, in an attempt to select the best model to account for return and volatility in the Ghanaian stock market, the symmetric GARCH (1, 1) and two other asymmetric models (EGARCH and GJR) were estimated. The various statistical properties from the estimated models were examined and the standardized residuals were also checked for each model. The result from most of the statistical properties and residual diagnostics checks favored the standard GARCH (1, 1) as the best model to account for return and volatility attributes of the market for the periods under examination. This finding is consistent with the previous conclusion reached in a study conducted on the Ghanaian bourse by Frimpong and Oteng-Abayie (2006) which also concluded that the parsimonious GARCH (1, 1) model is the best specification to account for return and volatility in the market as there is no dissimilar reaction of investors towards good and bad news (no leverage effect) in the market.

Analysis of the dummies which represent the various months from the estimated GARCH (1, 1) model records no January effect or any other type of monthly anomaly for the first period. The Wald test applied to the estimated model also failed to reject the null hypothesis that the return coefficients for the various months are approximately equal. The policy implication of this finding is that investors trading in the market within this period should not consider monthly effects when forming their portfolio since there no information to exploit. However, the absence of any form of monthly anomaly in the market during this period does not necessarily imply that the market is efficient in its weak form. This assertion is informed by the fact that the moving average (MA (1)) parameter included in the mean equation is statistically significant, denoting the presence of serial correlation in the market.
On the contrary, the second period recorded significant anomalous positive returns in the months of January, April, May and June. These months serve as opportune periods for investors to sell stocks to benefit from excess abnormal returns. Moreover, the month of March and July also recorded significant negative returns during the same period. Savvy investors can buy stocks at low prices during those periods with negative returns and sell them for high arbitrage profits in the month of January, April, May and June when returns are very high. Again, investors in the market should exploit this opportunity with caution because of the significance of the moving average parameter. The existences of such market timing opportunities which are readily available to be exploited by prudent investors suggest that the Ghanaian stock market is not informationally efficient in accordance with the efficient market hypothesis.

Moreover, it should be emphasized that per the analysis from the pattern of return in the Ghana bourse, the question of whether the market is efficient is decided by specifying a particular time period. This is inferred from the fact that there are periods without monthly anomalous returns whilst there still exist periods with significant monthly abnormal returns. Variations in time periods as well as differences in the source of stock market data employed in various study on the Ghanaian bourse may be some of the reasons why there are conflicting conclusions on the efficiency or the presence of monthly anomaly on the Ghanaian stock market. Also, because of the mixed nature of the findings from this study, none of the reasons or theories proffered to explain the existence of month anomaly by earlier researchers can wholly be considered appropriate to support the pattern of stock return in the Ghanaian bourse.

Again, there exist an opportunity for improvement on this topic in future research work using the Ghanaian bourse as the case study area. In the first place, the study will be enhanced if the main index which is the Ghana All Share Index is used instead of the proxy indices such as the Ghana BMI and the Databank Indices which are commonly used in current and previous studies on the Ghanaian stock market. Prospective future researchers may have access to high frequency data and with enough time spans to use the Ghana All Share Index contrary to the present constraints imposed on the current and previous researchers on the market.

Also, it is possible for this study to be improved upon in future research work by using daily or weekly data instead of the monthly data used for this study. These high frequency data will be capable of capturing most of the dynamic structures inherent in the series as against the currently available monthly data used for this study.
REFERENCES


APPENDIX 1  WALD TEST FOR FIRST PERIOD MONTHLY COEFFICIENTS

The table below shows the summary statistics from Wald equality test for the first sample period. It fails to reject the equality of the various average monthly coefficients from April, 1999 to Feb, 2005. It supports the absence of any statistical significant anomalous return for that period.

<table>
<thead>
<tr>
<th>Test Statistic</th>
<th>Value</th>
<th>Degree of Freedom</th>
<th>Probability Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistic</td>
<td>0.390</td>
<td>(11, 54)</td>
<td>0.954</td>
</tr>
<tr>
<td>Chi-square</td>
<td>4.291</td>
<td>11</td>
<td>0.961</td>
</tr>
</tbody>
</table>
APPENDIX 2  WALD TEST FOR SECOND PERIOD MONTHLY COEFFICIENTS

The table below shows the summary statistics from Wald equality test for the second sample period. It rejects the null of equality of the various average monthly coefficients from February, 2005 to Feb, 2014. The highly statistical significance at 1% level supports the presence of anomalous return for some months within the sample period.

<table>
<thead>
<tr>
<th>Test Statistic</th>
<th>Value</th>
<th>Degree of Freedom</th>
<th>Probability Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistic</td>
<td>1099.613</td>
<td>(11, 92)</td>
<td>0.000</td>
</tr>
<tr>
<td>Chi-square</td>
<td>12095.74</td>
<td>11</td>
<td>0.000</td>
</tr>
</tbody>
</table>
APPENDIX 3  PATTERN OF RETURN DISTRIBUTION FOR ENTIRE STUDY PERIOD

Appendix 3 below is a pictorial display of the pattern of return distribution for the entire duration under study. It shows the movements of return (volatility) for the period.