THE EFFECTS OF HOLIDAYS ON THE GHANAIAN EQUITY MARKET

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ABSTRACT

This paper sought to determine if the Ghanaian equity market is a semi-strong efficient market by investigating whether or not the holiday effect exists by adopting an ARMAX (2, 2) - GARCH (1, 1) model with GL^{+} innovation. The results show that there are significant positive pre-holiday and post-holiday effects which may not be as a result of bearing higher levels of risk. This finding is important to investors to assist strategise better in order to take advantage of this calendar anomaly discovered on the Ghanaian equity market.

Keywords: *ARMAX, calendar anomalies, efficient market hypothesis, GARCH, GL^{+} innovation, holiday effect.*

JEL classification*:* C22 E37 G14

1. Introduction

Efficiency of the stock market is one of the fundamental concepts in finance that is used to explain and understand how the stock market functions. In his effort to explain the concept of efficiency, Fama (1970) proposed the Efficient Market Hypothesis (hereafter, EMH). It refers to the notion that capital markets are efficient and that these efficient markets follow the random walk theory, and past information cannot be used to predict the future. The EMH is categorised into three forms that are conditional to three types of information; strong-form efficiency, semi-strong efficiency and weak-form efficiency. Out of these three forms, the weak-form is believed to be the most acceptable due to the attention and weight it has drawn from the academic society (Jarett, 2010). The EMH states that it is extremely difficult and highly impossible to predict stock prices precisely because of the assumption that the market participants are rational, and the determination of the stock prices are as a consequence of the changes in demand and supply. The EMH has currently become one of the significant areas in financial literature, and as a result, there exists much research on this concept (Mlambo & Biekpe, 2007; Lee, Lee & Lee 2010; Jovanovic, Andreadakis & Schinckus, 2016; Jackson & Kremer, 2007; Hung, 2009).

Malkiel (2003) suggested that “a random walk is a term loosely used in the finance literature to characterise a price series where all subsequent price changes represent random departures from previous prices”. It further states that a time series consisting of changes in stock price does not depend on its past or historical values. Again, this theory suggests that because of the nature of stock prices to change randomly, it is highly not possible to predict the stock prices. It is prudent to note that when stock prices follow a random walk theory or model, it does not imply that the stock market with relatively rational investors is efficient (Malkiel, 2003).

However, with the discovery of calendar anomalies, the EMH has come under attack in the financial literature. Calendar anomalies are said to be the likelihood for returns of financial assets to display systematic patterns at certain times of the day, a particular day, a specific month (Alagidede & Panagiotidis, 2009; Brooks, 2008, p. 454). The discovery of these patterns has for the past three decades remained an area of increased interest for researchers since its existence has been discovered in most developed capital markets in the world. A study by Fields (1931) is considered as the first documentation of the existence of seasonalities. Fields (1931) analysed the weekend effect and showed that Saturdays tended to record higher returns than on Fridays and Mondays. After the study carried out by Fields (1931), many more anomalies have been discovered (Dodd & Gakhovich, 2011; Alagidede & Panagioditis, 2009; Mensah, Bokpin & Owusu-Antwi, 2016) and are used to test the efficiency of various stock markets. Some of such anomalies are the day-of-the-week (Alagidede & Panagioditis, 2009; Mensah et al., 2016), month-of-the-year (Alagidede & Panagioditis, 2009) and the holiday effect (Dodd & Gakhovich, 2011; Marrett & Worthington, 2009; Yuan & Gupta, 2014; Wassiuzaman, 2017 & 2018).

Marret and Worthington (2009) pointed out that the existence of calendar anomalies in the stock market returns is one of the consistent themes in the literature on market efficiency. The different studies together with their outcomes and explanations associated with the calendar anomalies make their study and examination even more crucial to all stakeholders in the financial industry. This has succinctly been emphasised by Jahfer (2015) and Lim, Ho and Dollery (2009) that the study of calendar anomalies is important to financial managers and investors, as well as, others who have a keen interest in developing a trading strategy that will lead to profit eventually. Hence, the most researched calendar anomalies in literature are the day-of-the-week and the month-of-the-year (Alagidede & Panagioditis, 2009; Mensah et al., 2016). Another of such calendar anomalies which has not received much attention is the holiday effect which is defined as "the tendency of stock market returns to exhibit significant higher returns before a holiday in comparison with the other normal trading days" (Ariel, 1990; Dodd & Gakhovich, 2011; Yuan & Gupta, 2014).

Generally, holiday effects in stock markets are said to occur when the returns on a day or few days (differ from studies to studies and could be a day or 5 days) before a holiday exhibit a pattern that is usually abnormally higher than the returns on other regular trading days. According to Pearce (1996) and Brockman and Michalyuk (1998), "the 'holiday effects' are one of the most mysterious and baffling of all the seasonal anomalies". A holiday is defined by Lakonishok and Smidt (1988) as a day when trading would normally have occurred but did not as a result of the holiday occurring. Studies on the holiday effect on the various stock market returns have been approached from various perspectives; in terms of specific holidays such as Ramadan effect, Halloween effect, Chinese Lunar New Year effect, religious and secular holiday effects, firm size effect, and industry level effects among others.

Huang, Shieh and Kao (2016) affirm that decision making by human beings always begins with behavioural finance. Behavioural finance has become a widely popular and relevant concept in financial literature. It has its roots firmly in the fields of psychology, economics, finance and sociology (Schindler, 2007; Huang, Shieh & Kao, 2016). Behavioural finance argues that behaviours and mood are among the many other factors that affect humans in the shaping of their investment preferences. There is no doubt that market participants have been exhibiting "irrational" attitudes as a matter of fact and this is arguably supported by Malkiel (2003) who is of the view that mistakes are bound to be made as a result of collective judgment of investors. This leads to the occurrence of pricing irregularities and prediction over some time and their persistence lasts for a short period. Again, Malkiel (2003) believes that the existence of a holiday effect is a violation of both the semi-strong and weak form of efficiency because of the patterns of returns around holidays. As a result, an investor either adopting the technical approach or the fundamental approach can earn abnormal returns, and this implies that in an efficient market no such anomaly should exist.

Early studies (Ariel, 1990; Pettengill, 1989; Lakonishok & Smidt, 1988; Kim & Park, 1994) show that holiday effect exists in developed countries and other studies including Alagidede (2013) indicate the presence of holiday effects in developing markets. For example, Yuan and Gupta (2014) examined the Chinese Lunar New Year (CLNY) holiday effect in major Asian stock markets: South Korea, Japan, Taiwan, China and Hong Kong as well as India for a period of 1st September 1990 to 28th March 2012. They used an ARMA (1,1) - GARCH (1,1) model to investigate the daily stock index returns for each market and concluded that in all the Asian stock markets a positively significant pre-Chinese Lunar New Year effect is observed. They also employed the ARMA-GARCH-in-mean (ARMA-GARCH-M) model to determine if the abnormal returns observed before the CLNY holiday was as a result of a reward for risk. From their findings, they observed that whereas the higher returns in other markets are caused by unknown factors as well as conditional risk, the higher returns in China were as a result of compensation for high risks levels. They argued that previous studies that ignored the distributional properties of the returns series and adopted the Ordinary Least Squares (OLS) dummy regression model did not acknowledge the reality of this property.

Alagidede (2013), on the other hand, investigated the presence of pre-holiday effects in six African countries and the implication on stock market efficiency by using OLS dummy regression model. By estimating a regression model and examining the significance of the mean and variance of the returns series, South Africa was the only country that showed significantly high pre-holiday returns. Alagidede (2013) opined that the discovery of a pre-holiday effect within the period of study could have been as a result of the closing effect which is usually characterised by high returns for observed financial assets at market closing and good mood usually exhibited by investors around holidays.

Contrary to previous studies such as Tonchev and Kim (2004) on the holiday effect in Central and Eastern European countries, Dodd and Gakhovich (2011) documented abnormal positive and significant post-holiday returns as well as the usual pre-holiday effect. Their paper applied OLS regression and found out that there was no single industry that was responsible for this effect. However, the Christmas and New Year holidays were the most common holidays which produced the highest and significant returns. They finally concluded that the diminishing trend of the pre-holiday effect observed was an indication of the improvement in the level of market efficiency of the countries considered over the period of the study.

Wasiuzzaman (2018) also performed a similar study as Yuan and Gupta (2014) where the study sought to find the relationship between Hajj pilgrimage on the Tadawull All-Shares Index (TASI) and other industrial indices of the Saudi stock market. She used ARMA (1,1) - GARCH (1,1) model from January 2010 to August 2014 and found that the Hajj period had a significant increase in volatility for all the indices except for that of the agricultural, petrochemical, food and retail sectors and an insignificant and negative impact on the mean return of all the sector indices and the TASI. However, Wasiuzzaman (2017) had established the fact that TASI of Saudi stock market exhibited a Hajj effect.

Various explanations have been attributed to the existence of holiday effects. First is the existing relationship between the holiday anomaly and other calendar anomalies. This is to say that holiday effect occurs as a result of other calendar anomalies such as the day-of-the-week effect or the month-of-the-year. Researchers such as Lakonishok and Smidt (1988), Ariel (1990) and Liano, Marchand and Huang (1992) used this explanation and concluded that the high returns observed on days preceding a holiday were not as a result of the occurrence and existence of the other calendar anomalies. Secondly, it has been established that holidays affect the mood, demeanour, attitude, and daily experiences of persons who observe them (Mehran, Meisami & Busenbark, 2012). It is believed that the euphoria which accompanies holidays, affects the mood and demeanour of most investors and make them act in ways that tend to affect the activities of the stock market. The euphoria that accompanies holidays is believed to eventually lead to short covering and a general and impulse buying pressure (Jacobs & Levy, 1988; Thaler, 1987; Lahav, Shavit & Benzion, 2016).

Wright and Bower (1992) are of the view that judgements of investors are likely to originate from their moods, whence a bad mood and a good mood could lead to pessimism and optimism respectively. Therefore, emotions and moods associated with the various holidays are believed to tend to exert influence on the decisions of investors and eventually their stock market attitudes. However, according to Keim (1989), Pettengill (1989) and Lahav, Shavit and Benzion (2016), the holiday effect discovered over the years was neither as a result of euphoria nor short-sellers as suggested by previous researchers but could be as a result of an effect of just the market closing which they termed the “closing effect”.

Overall, the holiday effect can be put into two forms; pre-holidays and post-holidays. The pre-holidays are days preceding holidays and post-holidays are days after holidays. However, the pre-holiday effect occurs when the returns of pre-holidays are significantly different from the other regular trading days, and the post-holiday effect occurs when the returns of post-holidays are also significantly different from the other trading days. Ariel (1990) and Dodd and Gakhovich (2011), believe that generally before a holiday, investors tend to close their short-selling positions before a holiday and reopen them after the holiday. This phenomenon tends to increase the pre-holiday returns and decrease post-holiday returns which lead to significant positive and significant negative returns respectively.

Most equity markets in Africa have relatively smaller sizes as compared to their counterparts in developed countries. Hence, the data set adopted in stock markets where the holiday effect was discovered in other parts of the world, cannot be used to explain the behaviour of investors on the Ghanaian stock market. This is because the variables used in such studies could have been influenced by distinct factors which are peculiar to their territories. Ghana, just like any other developing African market is characterised by illiquidity, higher volatility, low number of listed firms as well as thin trading which are unique to her environment and as such needs a unique study to focus on the holiday effect on the Ghanaian equity market.

A variety of studies on the efficiency of the Ghanaian equity market suggest that it is fully inefficient (Magnuson & Wydick, 2002; Appiah-Kusi & Menya, 2003; Simons & Laryea, 2006; Jefferis & Smith, 2005; Ntim, Opong, Danbolt & Dewotor, 2011, Mensah et al., 2016). The indication of this inefficiency serves as a perfect focal point for breeding of market anomalies. A market can become an efficient market if investors try to beat the market as a result of inefficiencies discovered (Malkiel, 2003). A further probe into the Ghanaian financial literature shows that majority of the studies conducted in the field of market efficiency employed the standard efficiency test such as the correlation test, run test, Augmented Dickey-Fuller test, random walk models, GARCH models (Magnuson & Wydick, 2002; Appiah-Kusi & Menya, 2003; Simons & Laryea, 2006; Jefferis & Smith, 2005; Ntim et al., 2011) amongst other tests and models. In the Ghanaian context, however, the existing works on calendar anomalies have concentrated mostly on the month-of-the-year effect and the day-of-the-week effect (Alagidede & Panagiotidis, 2009; Mensah et al., 2016).

In relation to the holiday effect, there have been various methods that have been employed by previous research papers. For instance, Pettengill (1989), Ariel (1990) and Kim and Park (1994) calculated the mean and variance of the daily returns as well as their respective t-statistics or chi-square to determine if there existed a difference in their average returns. Later studies such as Marrett and Worthington (2009), Alagidede (2013), Dodd and Gakhovich (2011) went a step further to estimate a simple Ordinary Least Square (OLS) dummy regression model to check the significance and equality of means. However, in their study Chien, Lee, and Wang (2002) pointed out that the OLS method might not have been a suitable approach for testing the seasonality in stock markets because of its empirically invalid assumptions (heteroscedasticity, non-normality and serial correlation). In effect, the use of OLS regression may result in questionable findings (Brooks, 2008, p. 386). According to Wasiuzzaman (2017) and Yuan and Gupta (2014), the ARMA (p, q) - GARCH (x, y) where $p, q, x, y \in \mathbb{Z}^{+}$ rather appears to be a better model than the OLS regression to test seasonalities since it has the capacity of treating autocorrelation and time-varying variance in the data (heteroscedasticity).

This paper is different from other existing papers on developing equity markets in three respects. First and foremost, extant researches that investigated the holiday effect did not adjust for thin-trading. This study adjusted the returns for thin-trading to remove any potential bias in its analysis. Again, the study used ARMAX-GARCH model to determine if the Ghanaian equity market had the holiday effect because it was capable of correcting for autocorrelation and heteroscedasticity in the data. Finally, the error terms assumed a GL^{+}innovation (Andoh, 2009 & 2010; Andoh, Mensah & Atsu, 2018) instead of the usual normal distribution imposed by other researchers. This is because most financial studies which used GARCH models and assumed normality test failed to appropriately model the leptokurtic nature of their distribution (tail of dithe stribution) (Nidhin & Chadran, 2013).

This paper focuses on holiday effect while examining the efficiency of the stock market through behavioural approach of investors to discover if there are abnormal returns as a result of a holiday occurring, using an ARMAX (p, q) - GARCH (1, 1) model, an extension of the ARMA (p, q) - GARCH (1, 1) model proposed by Wasiuzzaman (2017) and Yuan and Gupta (2014).

The rest of the paper is organised as follows: Section 2 focuses on a review of relevant literature. Section 3 highlights the methodology used in the analysis of the data. Section 4 provides an analysis and a discussion of the empirical results. Section 5 summarises and concludes the paper.

2. Methodology

2.1 Method of data analysis

The natural logarithm of the relative price was calculated for each day and a time series made up of continuously compounded returns was generated. A continuously compounded returns R_t time series (Brooks, 2008, p.7), is defined as inter-daily difference of the natural logarithm of the daily prices of the assets (P_t) and is given by:

$$R_t = log\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad (2.1)$$

where R_t is the continuous compounded return on day t, P_{t-1} is the closing market price in period $t-1$ (previous period), P_t is the closing market price in period t (current period) and log is the natural logarithm.

Thin trading is said to occur when stocks do not trade at every consecutive interval (Alkhazali, 2008). Emerging markets are on the whole described as having low liquidity, considerable high volatility, thin trading and perhaps investors that are less informed and have access not only to unreliable but also delayed information (Bekhaert, Erb, Harvey & Vishanta, 1998; Alkhazali, 2011; Yuan & Gupta, 2014). Hence, in testing the efficiency of the stock markets in these emerging markets, considering thin trading effects is imperative because it is usually considered as one of the major characteristics of such markets (Alkhazali, 2011). Most African equity markets have empirically documented pervasive thin trading (Appiah-Kusi & Menyah, 2003; Mlambo & Biekpe

2007; Kuttu, 2017) as such, the continuously compounded returns that are calculated for this study in equation (2.1) were adjusted for the thin trading effect with a methodical approach used by Kuttu (2017) and propounded by Miller, Muthuswamy and Whaley (1994). The following autoregressive model of order 1 (AR (1)) is used:

$$R_t = \alpha + \beta R_{t-1} + \varepsilon_t \tag{2.2}$$

where α is the constant term, R_{t-1} is lag of the returns of order 1 or the previous term of the returns, β is the parameter for the past term of the returns, and ε_t is the error term. The adjusted returns for thin trading are calculated by:

$$\hat{R}_t^{adj} = \frac{\hat{\varepsilon}_t}{1-\hat{\beta}} \tag{2.3}$$

The calculated $\hat{R}_t^{adj}$ is the adjusted for thin trading return at time t and it is hereafter represented as $\tilde{R}_t$.

These returns $\tilde{R}_t$ are then classified into pre-holiday returns, post-holiday returns and other normal trading days' returns. The average daily returns for n number of days preceding the holiday and after the holiday are determined.

2.2 Looking for a pattern using event study approach

Event studies, according to Sharpe, Alexander and Bailey (1999), are undertaken to see how returns react to an event or the release of information. This approach, in the end, is attempting to see if the returns are high or low, react rapidly or slowly or are just normal before the event. The event date for this study was defined as a date on which the holiday was declared and was observed during the period of study. Event studies essentially are usually employed to investigate the magnitude and relevance of a particular event on another event. The event window was extended to 8 days before and after the event date, in this case, the date of the holiday. That is, the event window for this study had 17 days (-8, -7, -6, -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6, 7, 8). Most researchers found the holiday effect on a day before and a day after a holiday (Ariel, 1990; Dodd & Gakhovich, 2011; Lakonishok & Smidt, 1988). However, there could be cases that these investors made preparations long before and in anticipation of the holiday or reacted oppositely after a holiday. Therefore, this allowed us to explore the timing of market reaction surrounding the observance of a holiday by investigating if there was any pattern in the returns of the stocks that could be as a result of a holiday occurring.

2.3 ARMAX (p, q) – GARCH (x. y) models

ARMA models incorporating GARCH-type innovations have been widely used to analyse particularly economic and financial time series data because of their stylised properties which include leptokurtic, volatility clustering and leverage effects (Makridakis & Hibon, 2000; Brooks, 2008, p. 380; Tolikas, 2011). The ARMA-GARCH models are basic and important because the theorems and methods obtained in these models form the basis for further inferences for more sophisticated models (Oh & Lee, 2017). The ARMA-GARCH model seems to be preferably better to adopt when testing for seasonalities than the OLS regression because ARMA-GARCH has the capacity of dealing with both autocorrelation and a time-varying variance in the dataset (Yuan & Gupta, 2014; Wasiuzzaman, 2017; Brooks, 2008, p. 386). One requirement that needs to be considered when using ARMA models is that the time series under consideration should be stationary. GARCH models have over the years received a considerable amount of attention from both the academic and other stakeholders since their discovery by Engle (1982), Bollerslev (1986) and Taylor (1986). These classes of models have in the past become important and have played a vital role in financial literature and most especially in the analysis of financial time series data particularly when it has to do with analysing and forecasting volatility (Angabini & Wasiuzzaman, 2011).

An extension of the ARMA model is the ARMAX model, which is an Autoregressive Moving Average (ARMA) model with exogenous input variables, X (Pickup, 2015, pp. 114-115). For this paper ,the exogenous variables are the dummy variables: preholiday and postholiday. This allowed us to determine whether the returns of the sub-periods (pre- and post-holidays) are statistically and significantly higher than the returns of the normal trading days. The ARMAX-GARCH model ,was estimated and modelled in the following form and assumed a GL^{+} innovation (Andoh, 2009; Yuan & Gupta, 2014; Wasiuzzaman, 2017 & 2018). To determine if there was a holiday effect in Ghana and to investigate which holidays celebrated led to a holiday effect, we used the following equations:

$$\tilde{R}_t = c + \beta_1 preholiday + \beta_2 postholiday + \omega_p \tilde{R}_{t-p} + \delta_q \varepsilon_{t-q} + \varepsilon_t \qquad (2.4)$$

$$\tilde{R}_t = c + \sum_{j=1}^{11} \beta_j preholiday_j + \sum_{j=12}^{22} \beta_j postholiday_j + \omega_p \tilde{R}_{t-p} + \delta_q \varepsilon_{t-q} + \varepsilon_t \qquad (2.5)$$

where $preholiday$ and $postholiday$ are dummy variables that represent 1 for all pre-holiday average returns and post-holiday average returns respectively and 0 otherwise, c is the average returns for normal trading days, $\beta_j, j = 1, \ldots, 22$ are the average returns coefficients for either pre-holidays and post-holidays for holiday j.

The innovations of ε_t are modelled as GARCH (x, y) given by:

$$\varepsilon_t = \sigma_t z_t , \qquad (2.6)$$

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{x} \omega_i \sigma_{t-i}^2 + \sum_{j=1}^{y} \rho_j z_{t-j}^2 \qquad (2.7)$$

$$\omega_0 > 0,\ \omega_i \geq 0, \rho_j \geq 0\ ,\ \omega_i + \rho_j < 1 \tag{2.8}$$

where σ_t^2 is the conditional variance based on the historical data, ω_i expresses how volatility responds to movements in the market (ARCH effects of the i^{th} order of the AR model) and ρ_j measures the persistence shocks caused by extreme values of the conditional variance (GARCH effects of the j^{th} MA model)).

According to Brooks (2008, p. 394), the GARCH (1, 1) is sufficient to capture all the volatility clustering in the data. Therefore, the study used the GARCH (1, 1) process to model the volatility present in the returns series data ($\tilde{R}_t$) and assumed it had a GL^+ innovation (see Andoh, 2010 & 2009; Andoh et al., 2018). The estimates of the parameters of the ARMAX-GARCH model were obtained via a maximum likelihood.

2.4 Parameter estimation

Let $f(\varepsilon, \theta)$ denote the joint density function for a vector of observations defined as:

$$\varepsilon = (\varepsilon_1, \varepsilon_2, \varepsilon_3, \dots, \varepsilon_n) \tag{2.9}$$

where θ is the parameter space.

For $\varepsilon = (\varepsilon_1, \varepsilon_2)$ the conditional probability function (or likelihood function) is:

$$f(\varepsilon_2 |\ \varepsilon_1) = \frac{f(\varepsilon_2, \varepsilon_1)}{f(\varepsilon_1)} \tag{2.10}$$

$$f(\varepsilon_1, \varepsilon_2) = f(\varepsilon_1). f(\varepsilon_2 |\ \varepsilon_1) \tag{2.11}$$

Therefore, by a repeated application of the definition of the conditional density function, we have for n number of observations, $\varepsilon = (\varepsilon_1, \varepsilon_2, \varepsilon_3, \dots, \varepsilon_n)$, the joint density function is given as:

$$f(\varepsilon|\theta) = \prod_{t=(x\vee y)+1}^{n} f(\varepsilon_t|F_{t-1}) \ . \ f(\varepsilon_{x\vee y}, \dots, \varepsilon_2, \varepsilon_1) \tag{2.12}$$

where $\mathrm{F}_{t-1} = (\varepsilon_{t-1}, \ \varepsilon_{t-2}, \varepsilon_{t-3}, \dots \dots \dots, \varepsilon_{t-(x\vee y)})$ and $n \gg x, n \gg y$.

The log-likelihood function is given as:

$$l(\varepsilon|\,\theta) = \sum_{t=(x\vee y)+1}^{n} \log(f(\varepsilon_t|\,F_{t-1})) + \log(\,f(\varepsilon_{x\vee y}, \dots, \varepsilon_2, \varepsilon_1)) \tag{2.13}$$

We use the following definition of Andoh (2009):

Definition: A random variable X has the GL^+ innovation (for short $GL^+\ (\mu, v^2, a, b)$) if its density function is given by:

$$f(X) \ = b\frac{\log a}{v}\frac{a^{-\frac{x-\mu}{v}}}{\left[1+a^{-\frac{x-\mu}{v}}\right]^{b+1}} \tag{2.14}$$

The following preposition from Andoh (2009) is needed: let $X\sim GL^+\ (\mu, v^2, a, b)$ and suppose that $Var\ (X) = \ \sigma^2$ and $E(X) = 0$. Then $\exists$ a unique $\tilde{a}\ \epsilon\ \mathcal{R}^+$such that

$$X\sim GL^+\left(\frac{-\sigma(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}, \sigma^2, \tilde{a}, b\right) \tag{2.15}$$

To use the GL^+ innovation for the ARMA-GARCH model, let $z_t\sim GL^+\left(\frac{-(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}, 1, \tilde{a}, b\right) =$ $SGL^+(b)$.

Hence, $f(\,\varepsilon_t|F_{t-1}) = \ GL^+\left(-\frac{\sigma_t(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}\ ,\ \sigma_t^2\ , \tilde{a}, b\right)$, where $\tilde{a} = \sqrt{\varphi'(b) + \varphi'(1)}$ and $SGL^+(b) = \ SGL^+\left(-\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}, 1, \tilde{a}, b\right)$.

The log-likelihood function $l(\varepsilon_t|\theta)$ is obtained as follows

$$\mathrm{L}(\varepsilon_t|\theta) = \log\left(\prod_{t=1}^{n}\left[b\log\tilde{a}\,\frac{\tilde{a}^{-\varepsilon_t-\left(\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}\right)}}{\left[1+\tilde{a}^{\varepsilon_t+\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}}\right]^{b+1}}\right]\right) + \log(f(\varepsilon_{p\vee q},\dots,\varepsilon_2,\varepsilon_1) \qquad (2.16)$$

$$= \sum_{t=1}^{n}\left[\log(b\log\tilde{a}) + \log\left(\frac{\tilde{a}^{-\varepsilon_t-\left(\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}\right)}}{\left[1+\tilde{a}^{\varepsilon_t+\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}}\right]^{b+1}}\right)\right] + \log(f(\varepsilon_{p\vee q},\dots,\varepsilon_2,\varepsilon_1) \qquad (2.17)$$

$$=\sum_{t=1}^{n}\left\{\log(b) + \log(\log\tilde{a}) + \log\left(\tilde{a}^{-\varepsilon_t-\left(\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}\right)}\right) - \log\left[\left[1+\tilde{a}^{-\varepsilon_t-\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}}\right]^{b+1}\right]\right\} + \log(f(\varepsilon_{p\vee q},\dots,\varepsilon_2,\varepsilon_1) \qquad (2.18)$$

$$= \sum_{t=1}^{n}\left\{\log(b) + \log(1) + \log(\log(\tilde{a})) + \left(-\varepsilon_t - \left(\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}\right)\right)\log(\tilde{a}) - (b+1)\log\left(1+\tilde{a}^{-\varepsilon_t-\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}}\right)\right\} + \log(f(\varepsilon_{p\vee q},\dots,\varepsilon_2,\varepsilon_1) \qquad (2.19)$$

Let $l_c = \log(f(\varepsilon_{p\vee q},\dots,\varepsilon_2,\varepsilon_1)$ however, there is no analytical form this term in equation 2.19. As $n\to\infty$, $l\to l_c$ is neglible (See Andoh, 2010). Therefore l_c is the conditional distribution of ε_t

given its past information F_{t-1}. The negative conditional distribution $(-l_c)$ of ε_t given its past information F_{t-1} and neglecting the constant in the log-likelihood function is:

$$= -\sum_{t=(x\vee y)+1}^{n}\left[-\log(b) + \left(\varepsilon_t + \left(\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}\right)\log(\tilde{a})\right) + (b+1)\log(1+\ \tilde{a}^{-\left(\varepsilon_{t+}\frac{(\varphi(b)-\varphi(1))}{\sqrt{\varphi'(b)+\varphi'(1)}}\right)}\right]$$

(2.20)

The values of the parameters are determined numerically by using Matlab R2017a.

2.5 Risk metrics

The VaR and the Expected Shortfall (ES) (ES is also referred to as the Conditional Value at Risk (CVAR)) were used to measure the risk associated with the holiday effect on the Ghanaian equity market. It is worth noting that the value of the CVaR risk measure is always higher than the value of the VaR risk measure, simply, because the former is larger than the later by the average excess of all losses exceeding VaR (Danielson, 2011, p. 87).

2.6 Data

This paper utilised mainly secondary data from the Ghana Stock Exchange (hereafter referred to as GSE) which primarily consists of daily closing prices of both the main financial index on the GSE; All Shares Index and the Ghana Stock Exchange Composite Index (hereafter referred to as GSE-CI). Currently, the total number of stocks listed on the GSE is approximately 43 as well as about 21 Licensed Dealing Members (LDM). The dataset for this study had a total of 2476 number of daily observations. The data used to carry out this empirical research was divided into three groups: pre-holiday days (105 observations), post-holiday days (105 observations) and other normal trading days (2266 observations). When identifying the existence of a holiday anomaly within the dataset used, the long period of daily historical data will help capture the various trends both within short and long periods because the larger the size of the data, the better estimates are believed to be.

The period of this study is from 3rd January 2007 to 30th December 2016; a 10-year period. The year 2007 was used because in 2006 the trading days changed from 3 days to 5 days while the year 2016 was the last full year that data could be obtained. This study used a more recent set of data for its analysis because changes and trends that have occurred in the past would have been documented. The same dataset was also used to examine the risk pattern around holidays.

The holidays to be considered are as follows: "New Year's Day, Independence Day, Good Friday, Easter Monday, May day, African Union day, Republic day, Eid-ul-Fitr, Eid-al-Adha, National Founder's day, Farmers' day, Christmas day and Boxing day". These holidays are public holidays as defined by the Holidays Act-2001 (Act 601), approved by the country's Ministry of Interior. However, there is no trading when any of the above falls on a week day due to the observance of the holiday. The dates of the holidays were collected from the Ministry of Interior website. However, for this paper, holidays such as "Good Friday" and "Easter Monday" are put together and referred to as Easter holiday while "Christmas day" and "Boxing day" are also considered Christmas holiday.

The pre-holidays are described as one or more number of days before a holiday. The post-holidays are also described as one or more number of days after a holiday. Normal trading days are any other trading around which no holiday occurs. However, trading on the Exchange takes place on all days except for days on which a holiday is observed. Hence, trading takes place on normal days, pre-holiday days and post-holiday days.

According to the descriptive statistics of the daily return series adjusted for thin trading as shown in Table 1, the normality is rejected, and the residual diagnostic test performed on the data indicated that the data is not well-behaved because it had the presence of heteroscedasticity, serial correlation and non-normality. However, the data was stationary.

(Insert Table 1 here)

3. Empirical results

3.1 Event study

Event date is defined in this study as the day on which the holiday occurred during the period of study. An event window around each holiday was centred such that there was the one day before and one day after a holiday event window, and 2^{nd} day before and 2^{nd} day after a holiday event window till the 8^{th} day before and 8^{th} day after a holiday event window. The creation of these different event windows was to enable the determination of any abnormal price reactions following shortly after or leading up to the occurrence and observance of a holiday. The estimation window was created for each defined event window. The data failed the normality test as shown in the descriptive statistics table; Table 1. The study, thus, focused more on the ARMAX-GARCH results because of the non-normality of the error terms in the data and the presence of heteroscedasticity and serial correlation. ARMA (2, 2) was used to run the estimation because it had the least information criteria value (shown in Appendix B) and based on the regression model stated in equation (2.4), the parameters of the ARMAX model was estimated and the results presented in Table 2.

(Insert Table 2 here)

A cursory look at Table 2 above shows abnormal returns for different days within the event window of interest. The regression results show that existing investors on the GSE have over the 10 years of the study exhibited diverse trading patterns with regards to the observance and celebration of a holiday. For instance, on the 8th day before a holiday, investors are seen to have engaged in substantially higher trading activities (average returns of about 13.59 per cent). Again, approximately 19.39 per cent was recorded on the 7th day before a holiday and represents the day on which the most trading activities occurred. However, from the 1st day to the 5th day before a holiday there was a major reduction of trading activities with some fluctuations between these days.

However, a closer analysis of this same table reveals that the GSE documented both pre-holiday and post-holiday effects because, for most of the days, the returns from pre-holidays or post-holidays are much higher than those of other normal trading days. These results could be an indication that on the whole, the GSE is informationally inefficient as suggested by Dodd and Gakhovich (2011). Pre-holiday effects occurred on the following windows; the 2nd day, the 7th day and the 8th day before a holiday because the other five windows either recorded lower returns (in comparison to returns of normal trading days) or had results that were not significant. Also, post-holiday effects occurred on all windows except on the 3rd day, 4th day, 6th day and 8th day after a holiday. It is worth noting that despite the significant results recorded in windows such as (+1 day), (-3 days, +3 days), (-4 days, +4 days) and (+5 days), there were neither pre-holiday effects nor post-holiday effects. This is because during these windows the average returns were lower than those of the normal trading days.

On the occasion where the average returns were positive, it implied that the market experienced greater returns. Conversely, the market underperforms when it recorded negative returns. Hence, the highest average return of 19.39 per cent for the period; pre-holiday days which occurred on the 7th day before a holiday may be due to the euphoria associated with holidays, meaning investors on the GSE currently tend to trade more on the 7th day before a holiday, in anticipation of the holiday as suggested by Gama and Vieira (2013). Again, the principle of demand and supply where excess demand leads to increase in price level may explain the phenomenon observed on the 5th day after a holiday and the post-holiday effects recorded the highest average returns of about 18.92 per cent. Another explanation for these observations may be as a result of buy-sell strategies as iterated by Meneu and Pardo (2004), where investors are just willing to buy before a holiday and buy after a holiday. These findings are not consistent with the findings of Ariel (1990) and Dodd and Gakhovich (2011) who found holiday effects occurring on one day before and one day after a holiday in the US and some selected Central and Eastern European countries respectively. These findings as discussed above were significant at 5 per cent significance level.

Comparing the returns for the 5th day and the 7th day (these days recorded the highest return as shown in Table 2), the 7th day had the least information criteria (AIC, HQIC and SBIC) which are an indication that it is the best model fit for this data set in this study. Hence, the holiday effect on the Ghanaian equity market occurs on the 7th day before and 7th day after a holiday. The pre-holiday effect discovered supports the results of Alagidede (2013), Ariel (1990) and Dodd and

Gakhovich (2011). Again, the positive post-holiday effect observed in the results was the same observation discovered by Dodd and Gakhovich (2011) which is a contradiction to studies by Ariel (1990) who opined that usually investors after a holiday open their short-selling positions which leads to lower and sometimes negative post-holiday returns. This implies that currently, investors on the GSE trade more on the 7th day before and the 7th day after a holiday. During this period the average returns before a holiday are about 19.39 per cent and 8.94 per cent after a holiday.

Finally, the significant pre- and post-holiday effects suggest that investors can take advantage of this anomaly and trade before or after a holiday on the GSE. For instance, on the (+7, -7) window the pre-holiday return is positively significant and about 969.50[1] times higher than the average return for normal trading days. The post-holiday returns are 447[2] times higher than the average returns for normal trading days.

3.2 Specific holiday

(Insert Table 3 here)

The results in Table 3 suggest that Farmers day holiday celebrated in Ghana is responsible for the pre-holiday effect observed in Table 3. Again, both the Farmers day holiday and the Workers day holiday are contributing to the post-holiday effects documented in Table 2. These results show that there is some evidence of the existence of abnormally high returns on the 7th day before Farmers' day of about 93.74 per cent and on the 7th day after both Farmers' day and Workers day of about

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[1]Based on results from Table 2, $\frac{preholiday\ return}{normal\ trading\ day\ return}$

[2] Based on results from Table 2, $\frac{postholiday\ return}{normal\ trading\ day\ return}$

46.15 per cent and 47.93 per cent respectively. Again, these returns are significantly different from zero at 95 per cent confidence level.

Generally, there seems to be insufficient evidence for individual holidays generating significant returns in this study. Out of the 11 holidays considered in this study only two exhibit significant results. Even holidays that are regarded as highly celebrated such as the New Year and Christmas holidays did not exhibit any significant results, contrary to Dodd and Gakhovich (2011).

The holiday effect on the GSE is further examined to substantiate if investors are influenced by strictly Ghanaian-specific observed holidays or non-Ghanaian specific holidays. Ghanaian holidays, for the purpose of this study, are holidays that are celebrated uniquely and only recognised in Ghana. They include the Independence Day, Republic day, Farmers' day and Founders day holidays. From the results on Table 4 A), both Ghana- specific holidays and Non-Ghanaian specific holidays contribute to the holiday effects observed in Table 2.

Again, the results from Table 4 B) show that there are significant and positive pre-holiday and post-holiday effects for Ghanaian holidays and only a positive and significant pre-holiday return for Non-Ghanaian holidays. However, the average return for days before Ghanaian holidays are greater than the other three categories, an indication that there are more trading activities in the market during such periods.

(Insert Table 4 here)

3.3 Risk measures

As opined by Andoh (2010) one interesting property of the GL^{+} innovation is the malleable nature of the skewness and shape parameters. This is important because of the empirical features of assets returns (such as leptokurtic- fatter tails). With the use of the GL^{+} innovation, one is able to choose the appropriate parameter that will appropriately represent the true nature of the distribution of the data and, this is done by adjusting at least one of the parameters and in this case the skewness parameter, b. The options for a suitable parameter b for this study were estimated and are shown in the Table 5.

(Insert Table 5 here)

In Table 5, the estimate for the level where the skewness, $b = 12.1$ is preferred because it has the closest values for the various levels of VaR at 5 per cent, 2.5 per cent and 1 per cent. Also, the non-negativity and stationarity assumptions were adhered to. Figure 1 shows 5 per cent VaR estimates (dashed lines) as well as the VaR exceedances (dotted lines) of the GARCH (1, 1) process $\sigma_t^2 = 0.1 + 0.23z_{t-1}^2 + 0.60\sigma_{t-1}^2$ with a GL^{+} innovation for the period 2007-2016. The exceedances (dotted line) are the times where the VaR exceeded the 5 per cent VaR levels.

The next section examined the VaR and CVaR for the various sub-periods: pre-holiday, post-holiday and normal trading days. The VaR at 5 per cent significance level for each period was calculated and compared amongst one another. The results are displayed in Table 6.

(Insert Table 6 here)

The results in Table 6 shows the Value-at-Risk (VaR), and the Conditional Value-at-Risk (CVaR) estimates at 5 per cent significance level for the sub-periods considered include the pre-holiday days, post-holiday days and the normal trading days. From the results, the risk measures for the normal trading days are higher than the other two sub-periods. Hence, in the worst 5 per cent of returns, an investor's average loss is approximately 8.43 per cent during post-holiday days on the GSE, and for an investor on the GSE, there is a 5 per cent chance to lose about 8.78 per cent of his or her return during pre-holiday days. This could be an indication that the high and abnormal returns observed in Table 5 above for the pre-holiday and post-holiday returns (in comparison to that of the normal trading days) could not be as a result of bearing higher risk as observed by Yuan and Gupta (2014) in China.

However, it could be as a result of other unknown factors as iterated by Yuan and Gupta (2014) as possible explanations for other countries where their risk measures were relatively lower.

(Insert Table 7 here)

From Table 7 it is observed that the risk levels associated with some of the holidays (Workers post and Farmers' pre) that had significant returns as observed in Table 3 are relatively lower. Workers post-holiday had a CVaR of approximately 0.541 per cent, and Farmers pre-holiday of about 0.694 per cent are comparatively lower than that of the other holidays considered in this study. These are indications that the significant results shown in Table 3 for both Farmers pre-holidays and Workers day holiday may be as a result of other factors such as mood or closing effect.

This notwithstanding, the Farmers post-holiday recorded the third highest CVaR of approximately 1.757 per cent after that of the Christmas pre-holidays (1.797%) and Normal trading days (62.19%). This value is an indication that the abnormally high returns observed in Table 3 for Farmers post-holiday may be as a result of their associated risk.

Generally, it is observed that all the holidays from both Table 8 and Table 9 have VaR and CVaR values below 5 per cent.

(Insert Table 8 and Table 9 here)

From Tables 8 and 9, it is generally observed that the risk levels associated with the returns of Ghana- specific holidays are relatively lower than that of the non-Ghana specific holidays. This again is an indication that the returns that contributed to the pre-holiday and post-holiday effects in Table 4 did not have their associated risk levels as a contributing factor.

A robustness test on the standardised residuals (z_t) and the squared standardised residuals $(z_t^2)$was performed and reported in Appendix C and shows there was no ARCH effect in the standardised residuals and squared standardised residuals. Whereas, there was no serial correlation in the squared standardised residuals, beyond the 7^{th} lag there was evidence of relatively little serial correlation in the standardised residuals. The two variables showed that they were not normally distributed but leptokurtic. This is a confirmation that the ARMAX-GARCH model is an appropriate model for the data used for the study.

4. Summary, Conclusion and Recommendations

4.1 Summary

The results suggest that there exist statistically significant positive pre-holiday effects and positive statistically significant post-holiday effects on the Ghanaian equity market. Furthermore, the study showed that the pre-holiday effects and post-holiday effects discovered occurred on the 7th trading day before and on the 7th trading day after a holiday. Significant pre- and post-holiday returns are implications that investors can take advantage by trading on the 7th trading day before and the 7th trading day after a holiday which means that there might be a possibility for investors to earn abnormal returns in these sub-periods.

Again, whereas, the 7th trading day before and the 7th trading day after the Farmers day holiday contributed significantly to the pre-holiday and post-holiday effects respectively, only the 7th trading day after the International Workers day (Labour day) holiday contributed significantly to the post-holiday effects. This suggests that on these days, the average returns on the GSE are abnormally higher than the returns on normal trading days indicating that on these days' investors tend to trade more.

4.2 Conclusion

The study revealed that the Ghana-specific holidays which are defined as holidays that are celebrated uniquely and only recognised in Ghana have pre- and post-holiday effects. The non-Ghana specific holidays which are holidays that are celebrated both locally and internationally, on the other hand, recorded only a pre-holiday effect. The results show that generally, only non-Ghanaian specific post-holiday returns are insignificant at 5 per cent. The highest average return was documented in the Ghana-specific pre-holiday days, followed by non-Ghana specific pre-holiday and the Ghana-specific post-holiday had the least average return. This shows that investors could take advantage of Ghana-specific pre-holiday days in terms of the holiday effect. Generally, investors are usually attracted to take on higher risks which usually come with higher returns. However, the results from the study show that the significant abnormal returns observed in both the pre- and post-holidays sub-periods were not serving as compensation to existing investors on the Ghana Stock Exchange for taking a higher level of risks because the risk measures for the normal trading days were higher than the other two sub-periods.

Also, the Farmers post-holiday returns amongst the other holidays considered recorded the second highest Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) estimates, whereas the other two holiday days (Farmers pre-holiday and Workers post-holiday) that recorded significant abnormal returns had relatively lower risks. These are indications that this could be the explanation for the abnormal returns observed during the Farmers post-holiday days and other factors such as mood, euphoria, closing effect could explain the Workers pre-holiday and Farmers pre-holiday abnormal returns. Again, the associated risk for non-Ghana specific pre-holiday days was the highest, and the lowest was recorded for the Ghana-specific pre-holiday days. Hence, investors could take advantage of the Ghana-specific pre-holiday days because the risk associated with these average returns are minimal.

Finally, the overall results showed that returns on the 7th day before International Workers day and the 7th day after either International Workers day or Farmers' day or both were abnormally higher and statistically significant. These results indicate that on Workers day and Farmers day the GSE experienced stronger investor reactions than on the other holidays, and therefore investors should trade on these days without necessarily worrying about their risk levels. The results also show that mood may not be the reason associated with the occurrence of the holiday effect since holidays such as Christmas, New Year and Easter had insignificant returns.

4.3 Recommendation and direction for further research

With the discovery of the holiday effect on the Ghanaian equity market and an eventual indication of the inefficiency of the market, investors on the GSE can make abnormal returns by taking advantage of this calendar anomaly. Again, with the indication of the inefficiency of the GSE, it is prudent for the regulatory bodies especially the Security and Exchange Commission (SEC) and the Ghana Stock Exchange (GSE) to formulate policies that are geared towards making the stock Exchange in Ghana efficient. These policies should encourage investors to take advantage of this anomaly because according to Malkiel (2003) a market can eventually become efficient if its inefficiencies are taking advantage of. This claim is supported by Philpot and Peterson (2011) who explained that particularly the day-of-the-week effect had gradually disappeared since 2003 and attributed it to the fact that investors had incorporated these patterns in their trading strategies with the widespread of its knowledge of existence.

4.4 Direction for further research

The number of years considered for this study was 10, this period compared to similar works done by Ariel (1990), Kim and Park (1994) and Dodd and Gakhovich (2011) could be referred to as a short period. There is, therefore, the need for further studies to consider larger observations by using hourly returns. It will be intriguing also to investigate the significance of the holiday effect by controlling for other market anomalies such as the month-of-the-year and day-of-the-week effects. This will determine if the holiday effect discovered is as result of other calendar anomalies. Additionally, investigating the holiday effect in relation to the following themes: firm size level, industry level, liquidity and its persistence over time will help determine which industry, firm size level experiences the holiday effect and if the holiday effect is persistent over time. Finally, investigating the spillover effects of public holidays in other nations such as Nigeria on the GSE will help know if holidays celebrated in other countries affect the way investors react on the GSE.

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APPENDICES

Appendix A

Table 1: Descriptive statistics of thin trading adjusted stock returns

	ADJUSTED RETURNS
Mean	-3.63E-17
Maximum	10.5070
Minimum	-11.3630
Std. Dev.	0.8380
Skewness	-0.7240
Kurtosis	40.3870
Jarque-Bera	144307.7000***
ARCH(p)	102.3330***
ADF	-12.3890***
Observations	2474.0000

Notes: *** denotes statistically significant at 1%, ADF denotes Augmented Dickey Fuller unit root test, ARCH(p) is the Engle (1982) test for ARCH with order p.

Data source: GSE, 2007-2016

Table 2: ARMAX regression results (pre- and post-holiday effects)

	DAY WINDOW							
VARIABLE	**±1**	**±2**	**±3**	**±4**	**±5**	**±6**	**±7**	**±8**
C	0.0002 (0)	-0.0003 (0)	-0.0007 (0)	0.0002 (0)	0.0011 (0)	0.0002 (0)	0.0002 (0)	0.0000 (0)
AR(2)	0.8411** (0.00106)	0.8426** (0.0009)	0.5406** (0.0073)	0.8022** (0.0011)	0.850** (0.0011)	0.8366** (0.0036)	0.8142** (0.0009)	0.8401** (0.0009)
PRE	-0.261** (0.0684)	0.0229** (0.0051)	-0.565** (0.0408)	-0.270** (0.0273)	-0.098** (0.0178)	0.0380 (0.0393)	0.1939** (0.0096)	0.1359** (0.0228)
POST	0.0562** (0.0233)	0.0363** (0.0051)	-0.098** (0.0120)	-0.030** (0.0093)	0.1892** (0.0089)	0.0762 (0.0089)	0.0894** (0.0098)	0.0104 (0.0173)
MA(2)	-0.711** (0.0014)	-0.714** (0.0012)	-0.376** (0.0075)	-0.664** (0.0013)	-0.728** (0.0015)	-0.707** (0.0015)	-0.695** (0.0013)	-0.714** (0.0013)
SEregression	0.8142	0.8143	0.8026	0.8093	0.8130	0.8141	0.8128	0.8138
Log Likelihood	-3.0E+03	-3.0E+03	-2.9E+03	-2.9E+03	-3.0E+03	-3.0E+03	-3.0E+03	-3.0E+03
AIC	-0.4090	-0.4089	-0.4379	-0.4211	-0.4120	-0.4094	-0.4126	-0.4101
HQC	-0.4047	-0.4047	-0.4336	-0.4168	-0.4078	-0.4051	-0.4083	0.4058
SBIC	-0.3972	-0.3972	-0.4261	-0.4094	-0.4003	-0.3977	-0.4009	-0.3983

Source: Authors' calculations, using MatlabR2017a.

Table 3: ARMAX regression results for specific holidays

Variables	Coefficient	Std. Error	*t* - Statistics
C	0.0003	0.0000	0.00
AR(2)	0.8215**	0.0039	211.2864
NYPRE	0.4894	1.1576	0.4228
NYPOST	-0.2677	1.4057	-0.1904
INDEPRE	0.2755	0.5114	0.5387
INDEPOST	0.1654	0.4033	0.4101
EASTERPRE	0.1589	0.8166	0.1946
EASTERPOST	0.1226	0.2949	0.4157
WORKERPRE	0.4393	0.2358	1.8627
WORKERPOST	0.4793**	0.2413	1.9864
AUPRE	0.5168	0.2978	1.7353
AUPOST	-0.0453	0.0957	-0.4736
REPUPRE	0.1753	0.1768	0.9916
REPUPOST	-0.025	0.0551	-0.4534
FITRPRE	0.1771	0.2055	0.8618
FITRPOST	-0.1375	0.8056	-0.1707
ADHAPRE	0.5874	0.4449	1.3202
ADHAPOST	-0.0221	0.0514	-0.4301
FARMERPRE	0.9374**	0.2223	4.2167
FARMERPOST	0.4615**	0.1044	4.4224
XMASPRE	0.0794	0.3298	0.2408
XMASPOST	0.0075	0.0283	0.2652
FOUNDERPRE	-0.1498	0.3531	-0.4242
FOUNDERPOST	-0.2566	0.2384	-1.0764
MA(2)	-0.6968**	0.0046	-151.9870

Notes: **- 5% Significance level

Source: Authors' calculations, using MatlabR2017a.

<u>Abbreviations:</u>

pre – pre-holiday effects, post – post- holiday effects.

nypre – New Year day pre, nypost – New Year day post, indepre – Independence day pre, indepost – Independence day post, aupre - African Union day pre, aupost – African Union day post, repupre – Republic day pre, repupost – Republic day post, fitrpre – Eid-il-Fitr pre, fitrpost – Eid-il-fitr post, adhapre – Eid-al-Adha pre, adhapost – Eid-al-Adha post, farmerpre – Farmers day pre, farmerpost – Farmers day post, xmaspre – Christmas day pre, xmaspost – Christmas day post, founderpre – Founder's day pre, founderpost – Founder's day post.

Table 4: ARMAX regression results for Ghana specific holidays and non-Ghana specific holidays

A) GENERAL

VARIABLES	COEFFICIENT	STD. ERROR	*t*-STATISTICS
C	0.0003	0.0000	0.0000
AR(2)	0.8216**	0.0011	772.2915
GH	0.1382**	0.0110	12.6017
NONGH	0.0571**	0.0127	4.4957
MA(2)	-0.6893**	0.0014	-480.0904

B) PRE AND POST

VARIABLES	COEFFICIENT	STD. ERROR	*t*-STATISTICS
C	0.0004	0.0000	0.0000
AR(2)	0.8192**	0.0011	743.9250
GHPRE	0.1817**	0.0232	7.8348
GHPOST	0.0793**	0.0204	3.8870
NONGHPRE	0.0860**	0.0110	7.8412
NONGHPOST	0.0213	0.0275	0.7744
MA(2)	-0.6857**	0.0014	-472.9686

Notes: **- 5% Significance level
NONGH- NON- GHANA SPECIFIC HOLIDAY
GH- GHANA SPECIFIC HOLIDAY

Source: Authors' calculations, using MatlabR2017a.

Table 5: VaR estimates for thin trading adjusted returns with possible asymmetry in the innovations

PARAMETERS	ω_0	ω_1	ρ_1
	0.1000	0.2300	0.6000
	LEVEL OF $\alpha\%$ VaR		
UNDERLYING DISTRIBUTION	0.0500	0.0250	0.0100
$SGL^{+}(0.5)$	0.0784	0.0574	0.0396
$SGL^{+}(0.9)$	0.0651	0.0440	0.0222
$SGL^{+}(5.1)$	0.0505	0.0255	0.0125
$SGL^{+}(10.1)$	0.0501	0.0246	0.0121
$SGL^{+}(11.1)$	0.0497	0.0246	0.0121
$SGL^{+}(12.1)$	0.0497	0.0246	0.0117

Note : SGL^{+} - Standardised GL^{+}

() are the parameter choice of the skewness (b)

Source: Authors' calculations, using MatlabR2017a.

Table 6: 5% VaR and 5% CVaR estimates for thin trading adjusted returns for the period 03.01.2007 to 30.12.2016 under the various categories.

	$Preholiday$	$Postholiday$	$Normal$
$VaR_{0.05}$	0.0858	0.0827	0.5755
$CVaR_{0.05}$	0.0878	0.0843	0.6220

Note: $CVaR_{0.05} = VaR_{0.05} + average(exceedances)$

Source: Authors' calculations.

Table 7: 5% VaR and 5% CVaR estimates for the adjusted for thin trading returns for the period 03.01.2007 to 30.12.2016 for the various holidays

Variables	$VaR_{0.05}$	$CVaR_{0.05}$
NYPRE	0.0156	0.0156
NYPOST	0.0096	0.0100
INDEPRE	0.0038	0.0038
INDEPOST	0.0037	0.0037
EASTERPRE	0.0038	0.0042
EASTERPOST	0.0069	0.0069
WORKERPRE	0.0062	0.0066
WORKERPOST	**0.0054**	**0.0054**
AUPRE	0.0052	0.0052
AUPOST	0.0090	0.0090
REPUPRE	0.0083	0.0083
REPUPOST	0.0072	0.0072
FITRPRE	0.0079	0.0083
FITRPOST	0.0054	0.0062
ADHAPRE	0.0089	0.0089
ADHAPOST	0.0055	0.0055
FARMERPRE	**0.0065**	**0.0069**
FARMERPOST	**0.0172**	**0.0176**
XMASPRE	0.0180	0.0180
XMASPOST	0.0111	0.0111
FOUNDERPRE	0.0039	0.0043
FOUNDERPOST	0.0040	0.0040
NORMAL	0.5755	0.6219

Source: Authors' calculations, using MatlabR2017a.

Table 8: 5% VaR and 5% CVaR estimates for Ghana-specific and non-Ghana specific holidays

	Ghana-specific holidays	Non-Ghana specific holidays
$VaR_{0.05}$	0.0536	0.1148
$CVaR_{0.05}$	0.0548	0.1173

Source: Authors' calculations, using MatlabR2017a.

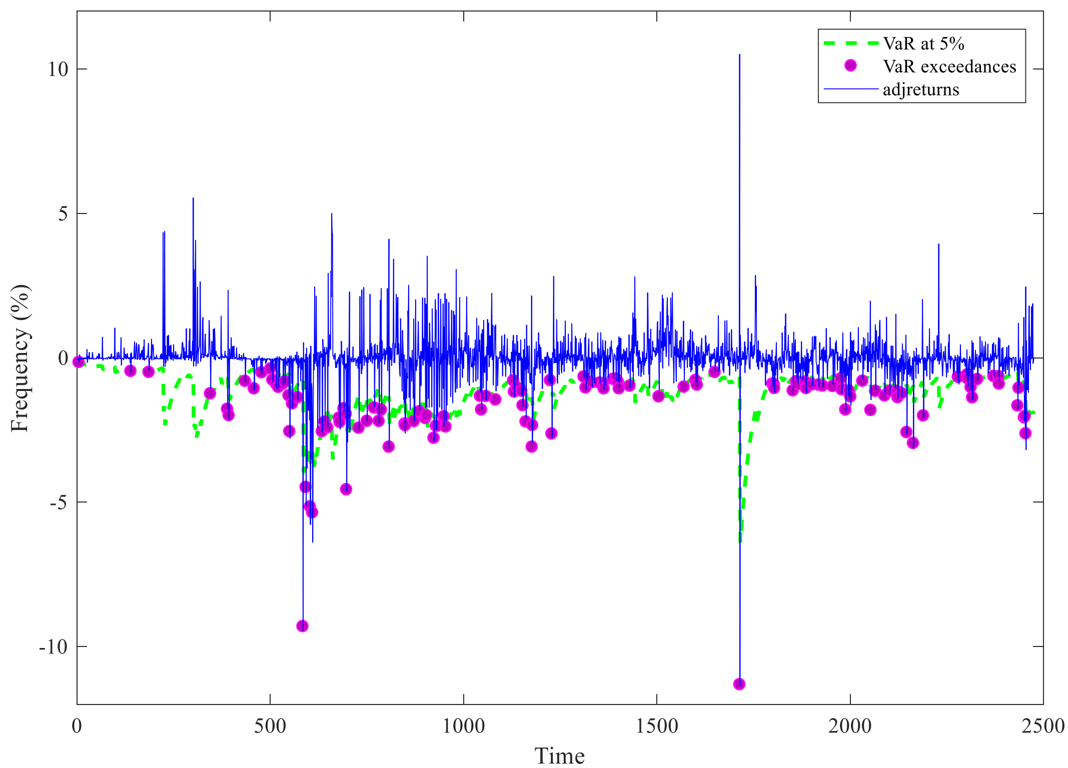
Table 9: 5% VaR and 5% CVaR estimates for pre- and post-holidays of Ghana-specific holidays and non-Ghana specific holidays

Variables	$VaR_{0.05}$	$CVaR_{0.05}$
GH. PRE	0.0223	0.0231
GH. POST	0.0318	0.0322
NON-GH. PRE	0.0606	0.0637
NON-GH. POST	0.0519	0.0532

Note: GH. –Ghana-specific, NON-GH- Non-Ghana specific.

Source: Authors' calculations, using MatlabR2017a.

Figure 1: Adjusted for thin trading returns, 5% VaR estimates and VaR exceedances estimates from 2007 to 2016.



Source: Authors' calculations, using MatlabR2017a.

Appendix B: Model specification for ARMAX model

To determine the order that will best fit the data in this study the information criteria was used. The results are shown in Table B.1 a) and Table B.1 b) below:

Table B.1: Model Specification for ARMAX (p, q) model.

Table B.1 a)

p	0	0	0	0	0	1	1	1	1	1
q	0	1	2	3	4	0	1	2	3	4
Adj T	2476	2476	2476	2476	2476	2475	2475	2475	2475	2475
T	2476	2476	2476	2476	2476	2476	2476	2476	2476	2476
K	2	2	2	2	2	2	2	2	2	2
AIC	-0.402	-0.402	-0.422	-0.405	-0.418	-0.402	-0.401	-0.422	-0.405	-0.418
HQC	-0.400	-0.398	-0.419	-0.414	-0.414	-0.398	-0.397	-0.418	-0.401	-0.413
SBIC	-0.395	-0.392	-0.413	-0.395	-0.408	0.392	-0.389	-0.410	-0.393	-0.406

Note: Adj T denotes the length of sample used for estimation after holdback adjustment, T represents the number of observations and K represents the number of exogenous variables.

Table B.1 b)

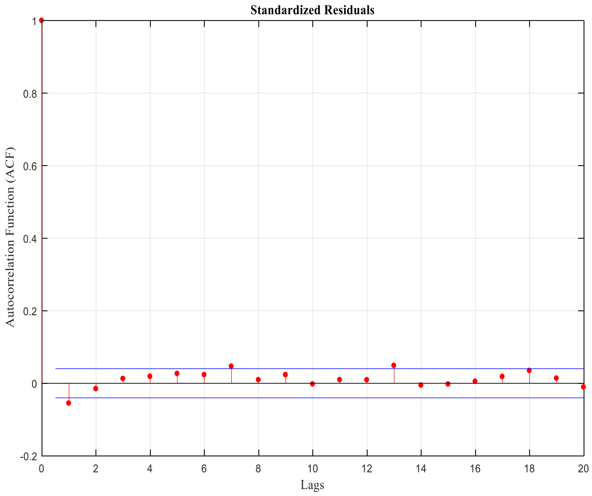
P	2	2	**2**	2	2	3	3	3	3	3
Q	0	1	**2**	3	4	0	1	2	3	4
Adj T	2474	2474	**2474**	2474	2474	2473	2473	2473	2473	2473
T	2476	2476	**2476**	2476	2476	2476	2476	2476	2476	2476
K	2	2	**2**	2	2	2	2	2	2	2
AIC	-0.429	-0.429	**-0.441**	-0.431	-0.436	-0.406	-0.406	-0.425	-0.408	-0.420
HQC	-0.426	-0.425	**-0.437**	-0.427	-0.432	-0.402	-0.402	-0.421	-0.403	-0.416
SBIC	-0.420	-0.417	**-0.429**	-0.420	-0.425	0.396	-0.394	-0.414	-0.396	-0.408

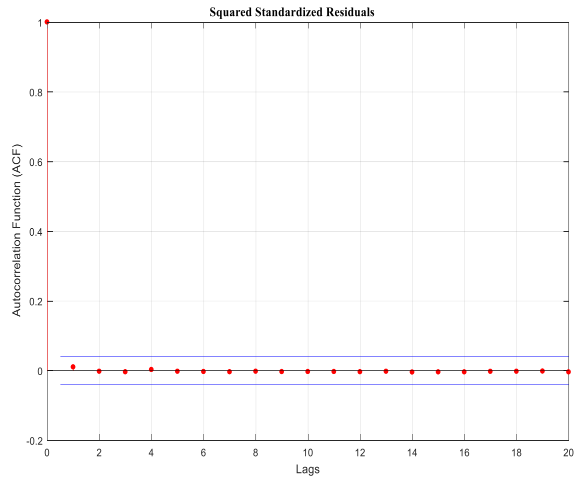
Source: Authors' calculations, using MatlabR2017a.

The Table B.1 a) and Table B.1 b) show the information criteria associated with the various orders (p, q) for the ARMAX model. For example, the order (1, 0) had an AIC value of -0.402, order (1, 4) had a SBIC value of -0.406 and order (3, 3) had an HQC value of -0.403. The order that best fits the data for the ARMAX model is order (2, 2) (the bolded values) because it recorded the lowest information criteria.

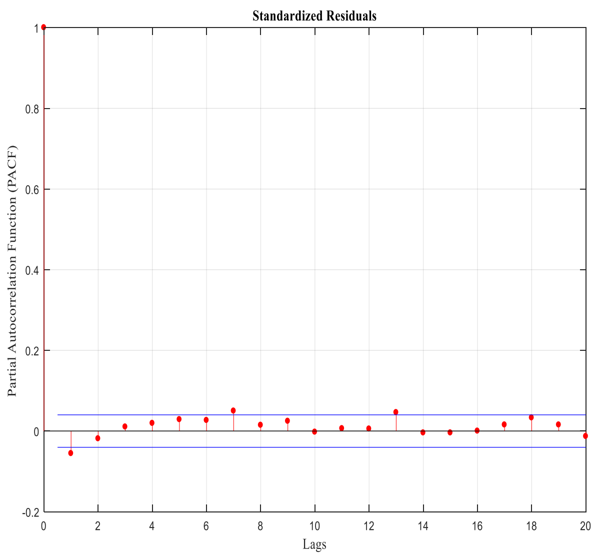
Appendix C: Robustness Test

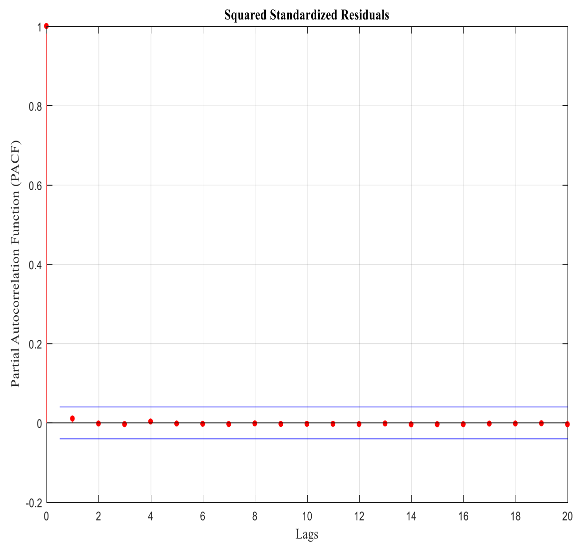
Autocorrelation Function (ACF)





Partial Autocorrelation Function (PACF)





Normality test

Variables	Stats.	Prob.*
z_t	0.1932	0.000
z_t^2	0.1247	0.000