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# CALENDAR ANOMALIES IN THE GHANA STOCK EXCHANGE

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Abstract

This paper investigates two calendar anomalies in an emerging African market. Both the day of the week and month of the year effects are examined for Ghana. The latter is an interesting case because i) it operates for only three days per week during the sample period and ii) the increased focus that African stock markets have received lately from both academics and practitioners. Non-linear models from the GARCH family are used in a rolling framework to investigate the role of asymmetries and assess the effects of policy and institutional changes. Contrary to a January return pattern in most markets, an April effect is found for Ghana. The day of the week effect with asymmetric volatility provides a superior performance than the benchmark linear paradigm. This seasonality though disappears when rolling regression techniques are employed (time-varying asymmetric GARCH).

Keywords: Calendar Anomalies, Non-Linearity, Market Efficiency, Asymmetric Volatility, Rolling windows.

JEL Classification: C22, C52, G10

## I. Introduction

A vast literature on the existence of patterns in stock returns commonly known as calendar anomalies (effects) has been developed over the last three decades. Calendar anomalies refer to the tendency of financial asset returns to display systematic patterns at certain times of the day, week, month or year.

These patterns have been attributed to an array of factors— tax-loss selling hypothesis, settlement procedures, negative information releases, and bid-ask-spread biases among others. The most common of these anomalies are the month of the year and day of the week effects. On a face value, seasonalities contradict the efficient market hypothesis and cast a considerable amount of doubt on asset pricing models. The January effect postulates that stock returns in January are higher than other months of the year; Rozeff and Kinney (1976), Gultekin and Gultekin (1983), Keim and Stambaugh (1984), Kato and Shallheim (1985) confirm the existence of the January effect. The day of the week effect holds that stocks exhibit significantly lower returns over the period between Friday's close and Monday's close (see Gibbons and Hess 1981, Mills and Coutts 1995, Al-Loughani and Chappell 2001).

Previous research on anomalies has concentrated exclusively on developed economies. The few existing studies in developing economies pay little attention to the emerging equity markets of Africa. To the best of our knowledge there is no known published study on calendar effects in the Ghana Stock Exchange. To the extent that patterns in stock returns are now accepted 'stylised facts' in both developed and emerging economies, this study is fundamentally different for a number of reasons (a) it investigates two prominent anomalies—month of the year and day of the week effects in the Ghana stock market. This serves not only as the first attempt at modelling seasonality but also wishes to provide an econometric framework which subsequent studies could use; (b) the data under study is unique because during the sample period the market trades three days a week— Mondays, Wednesdays and Fridays; (c) new techniques are employed i.e. time-varying GARCH models (rolling regressions) to uncover the dynamics and shed more light on the various anomalies.

The conclusions of this study are:

i) January return is not higher than other months of the year. Instead, returns in April are significantly over and above average monthly returns during the sample period. The April return pattern is due to the submission of company reports in late March, which causes higher April returns.

ii) Significant patterns in daily stock returns, with Monday's recording lower average returns than other days of the week. However, contrary to the usual linear specifications in the literature, a threshold GARCH yield better results. In a rolling framework the latter fails to provide support for the existence of seasonalities. This reinforces the argument in favour of EMH and the sceptics approach for the existence of seasonalities[1].

The rest of the study is organised as follows; section two briefly examines the literature on both day of the week and month of the year effects in global stock markets. Section three concentrates on the background of the Ghana stock market, its institutional characteristics and performance over the years; section four looks at the methodology while the fifth section explores the data set. Empirical results are presented in the penultimate section while the last section concludes.

**II. Literature**

One of the areas of academic and practitioner research in financial economics that has generated the most excitement and attracted the most attention over the past three decades concerns persistent cross sectional and time series patterns that have been documented in equity markets worldwide. The most prominent of these anomalies are the weekend or day of the week effect where Monday's returns are much lower than other days of the week and the January or month of the year effect, where returns are much higher during the

[1] This conclusion is a strong one and remains tentative until further evidence report otherwise. Given that the GSE is still an infant market, weak form efficiency may be untenable. Indeed the existence of anomalies does not in all cases imply market inefficiency. Similarly, the absence of anomalies cannot be taken on *prima facie* to mean market efficiency.

month of January than any other months[2](see table 1 for a summary of selected literature).

Rozeff and Kinney (1976) first examined the January pattern using New York Stock Exchange (NYSE) stocks for the period 1904 to 1974 and find that average return for the month of January was 3.48% compared to only 0.42% for the other months. Keim (1983) employ the same data set for the period 1963-79 and find that nearly 50% of the average magnitude of risk-adjusted premium of small firms relative to large firms is due to the January abnormal returns. Further, more than 50% of the January premium is attributable to large abnormal returns during the first week of trading in the year. Kato and Shallheim (1985) examined excess returns in January and the relationship between size and the January effect for the Tokyo Stock Exchange. They find no relationship between size and return in non-January months. However, they find excess returns in January and a strong relationship between return and size, with the smallest firms returning 8% and the largest 7%. Keim and Stambaugh (1984) study the January return anomaly in the bond market between 1926-1978. They find that, on average, only in January do low quality bonds give an extra return. Fama (1991) reports the results of the S&P 500 for

[2] There has been a considerable explosion in the anomalies literature in all stock markets. For the US see Fama (1965), Cross (1973), French (1980), Lakonishok and Levi (1982), Rozeff and Kiney (1976), Keim (1983); For UK see Reinganum and Shapiro (1987), Thoebald and Price (1984), Board and Sutcliffe (1988), Mills and Coutts (1995); for Greece see Alexakis and Xanthakis (1998); for international evidence, see Gultekin and Gultekin (1983), Jaffe and Westerfield (1985) ,Fountas and Segredakis (2002).

the period 1941-1981. In this period, small stocks averaged a return of 8.06% in January. Large stocks managed a return of 1.342%.

Outside the UK and US, substantial January return pattern has been uncovered. Boudreaux (1995) employed the Global stock indices (indexes reported by the Morgan Stanley Capital International) to investigate the monthly seasonality in seven countries. The results indicate a positive monthly effect for Denmark, Germany and Norway stock markets. A significant negative effect was found in Singapore/Malaysia. Further investigation indicated that the monthly effect is either confounded or manifested by the January effect. Using parametric and nonparametric techniques, Gultekin and Gultekin (1983) examined the January return patterns for 17 developed economies and find much higher returns in January than non-January months in all the countries. Returns are bigger especially for the non-US markets. However, in UK an April effect is present, and with the exception of Australia the January anomaly coincides with turn of the year.

A number of reasons have been advanced for the month of the year and January effect, typically including but not limited to the tax loss selling hypothesis, the small firm effect (size effect), insider trading/information release hypothesis, omitted risk factors and data snooping (See Choudhry 2001 for further discussion).

For most of the western economies, (U.S.A., U.K., Canada) empirical results have shown that on Mondays the market has statistically significant negative returns while Fridays returns are significantly positive and higher. In other markets such as Japan, Australia, Singapore, Turkey and France, the highest negative returns appear on Tuesdays. Gibbons and Hess (1981) examined this effect on the New York Stock Exchange (NYSE) from 1962 to 1978 and found that Mondays return was a negative (-33.5%) on annualized basis. They also report a large positive return on Wednesdays and Fridays. Athanassakos and Robinson (1994) examine daily index return data from the Toronto Stock Exchange and conclude the results show significant negative Monday returns and insignificant positive Tuesday returns. The average returns on Friday in the Canadian market were found to be greater than the average return on all other days of the week. Mills and Coutts (1995) used FTSE indices between January 1986 and October 1992 and established that calendar effects exist in the FTSE 100, Mid 250 and 350 indices, and certain of the accompanying industry baskets for the period under consideration. Recently, Tsiakas (2005) demonstrated that there is a higher number of statistically significant calendar effects in volatility than in expected returns using daily returns from ten international stock indices.

The reasons for the day of the week effect have been attributed to the fact that usually the most unfavourable news appear during the weekend. This affects investors negatively causing them to sell on the coming Monday. The sale of stocks increases supply giving the consequence of negative returns on shares. In addition many analysts believe that investor psychology plays a role in causing this anomaly. Since Monday is regarded as the beginning of the working week, most investors consider it as the worse day and feel pessimistic whereas they are optimistic about Friday because it is the end of the working week.

The existence of these anomalies, if indeed they exist, cast a considerable doubt on the validity of the Capital Asset Pricing Model, and hence, market efficiency. However, it must be emphasized that even if these anomalies are persistent in their occurrence and magnitude, the cost of implementing any potential trading rules may be prohibitive due to illiquidity and round trip transactions cost, thus leaving the efficient market hypothesis unscathed. The literature for both anomalies is summarized in Table 1.

Table 1: Summary of Calendar Anomalies

| Anomaly Tested | Methodology/or data | Empirical Results | Paper |
|---|---|---|---|
| January/ Month of the year effect | Random walk. Equally-weighted index of NYSE 1904-1974. | Average return for the month of January 3.48% compared to only 0.42% for the other months. | Rozeff and Kinney (1976). |
| | FTSE 100, Mid 250, and 350 indices 1986-1992 | calendar effects exist in the FTSE 100, Mid 250 and 350 indices | Mills and Coutts (1995). |
| | Closing values of 17 countries including the New York Stock Exchange | Higher returns occur in January than non-January months, especially for non US markets. April effect in UK. | International evidence, Gultekin and Gultekin (1983). |
| | pre-World War One data for Germany, US and UK via GJR | January effect and the month of the year effect on the UK and the US returns but not in German returns. | Choudhry (2001) |
| | Daily closing prices of the Hang Seng Index from 1985 to 1997 | evidence of January effect in the Hang Seng index | Cheung and Coutts (1999). |
| | Weekly and monthly data on stock index returns from 18 emerging stock markets | Seasonal effects exist in all 18 markets albeit weak in Jordan, Pakistan, Taiwan and Venezuela. Overall, there is no January effect | International evidence, Fountas and Segredakis (2002). |
| Day of the week effect | S&P 500 Composite Index returns for the period 1962–1978 | Negative returns recorded for Mondays while other days of the week are significantly positive | Gibbons and Hess (1981). |
| | Daily closing values of Kuwaiti stock price index from 1993 to 1997.GARCH (1, 1) | existence of the day-of-the-week effect in the Kuwait Stock Exchange | Al-Loughani and Chappell (2001). |
| | Daily closing prices in UK, Japan, Canada and Australia, | Negative mean Monday return and positive mean Friday or Saturday return. | International evidence, Jaffe and Westerfield (1985). |
| | Daily S&P 500 returns. GARCH[PAR-PIGARCH] | Positive(negative) autocorrelation is found in returns on Monday(Tuesday) | Franses and Paap(2000) |
| | daily stock index returns from 19 countries. GJR model used. | predictable time varying daily volatility in all markets among which eight also exhibit a significant leverage effect. | International evidence. Balaban et al (2001) |
| | Daily return data from 10 stock markets using periodic volatility, bootstrapping and hypothesis testing. | Size and statistical significance found in day of the week, month of the year and holiday seasonal effects. At least 20% more of these are significant in volatility than in expected returns | International evidence, Tsiakas (2005) |

Source: author's survey (2006)

## III. Ghana Stock Market

Attempts to establish a stock exchange in Ghana dates back to 1968; however, it was not until the promulgation of the Stock Market Act of 1971, that led to the establishment of the Accra Stock Market Limited (ASML) in the same year. Although a sparkling idea, the ASML remained on paper and never took off. Unfavourable macroeconomic environment, political instability and lack of government support undermined the viability of the experiment. In spite of these early set backs, corporate bodies traded shares through the National Trust Holding Company Ltd (NTHC) and National Stockbrokers Ltd, now Merban Stockbrokers Ltd, two brokerage firms that did over-the-counter (OTC) trading in shares of some foreign-owned companies.

In the 1980s, Ghana underwent major structural reforms to correct massive distortions and rigidities in the economy, mostly under the surveillance of the IMF and World Bank. The recovery programme was mounted simultaneously with other financial reforms including but not limited to deregulation of interest rates, removal of credit controls, and floating of exchange rates. In addition, capital controls were partly relaxed, and trade, liberalised. The need for stock market in Ghana became inevitable after the financial liberalisation and the divestiture of a host of state owned enterprises whose performance had been nothing to write home about. Consequently, in 1989 a report on the feasibility for a stock market was commissioned and the recommendations contained in the report gave birth to the Ghana Stock Exchange (GSE).

The GSE commenced operations with three brokerage firms (currently 14) and 11 listed companies. The number of listed companies increased to 13 in 1991; 19 in 1995 and currently stands at 29 (S&P 2005). The increase in the number of listings has also reflected in market capitalisation. At the end of 2004, market capitalisation stood at US$ 2,644 million. Annual turnover ratio hovered around 3.2% in 2004, from an all-time high of 6.5% in 1998. Ghana's share of frontier market capitalisation is 2.2% (See S&P 2005). The main index is the GSE All Share Index[3].

The instruments traded are ordinary shares and corporate bonds. Trading in ordinary shares and corporate bonds now takes place five times a week, from Monday to Friday[4]. Trading in Anglo Gold Ashanti shares however take place over the counter. Trading on the floor of the exchange is the open outcry system and is done in lots of 100 shares with the exception of Anglo Gold Ashanti shares, which trade in lot of 10 shares. Delivery is centralised but not automated. There are no derivatives. The monetary authority of the GSE is the Bank of Ghana while the main regulator is the Securities and Exchange Commission.

[3] Standards and Poor also compute two indices, S&P/IFCG Frontier Composite and S&P/IFCG Ghana. The Databank Stock Index (DSI) is the oldest of all the indices.
[4] Before 2005, the market traded three times a week, i.e. Monday, Wednesday and Friday for a period of two hours i.e. 10 am to 12 noon. The Databank Stock Index (DSI) which we use in this study essentially covers the period.

The performance of the Ghanaian bourse has been very impressive in recent times. A publication of the top 25 performing stock markets in the world for 2003 by Standard and Poor using price indices in $US dollars ranked Ghana third, only after Bulgaria and Brazil. Bulgaria and Brazil were placed ahead of Ghana with 200.1% and 142.1% respectively, and Ghana placed third with 140.3%.[5] Ghana was the world's best performing stock market in 2003. The Ghana bourse, with a U.S. dollar return of 144%, outpaced 61 markets around the world surveyed by Databank Financial Services, Ltd.[6].

The GSE has played a vibrant role in raising domestic and international capital through the issue of initial public offerings (IPO’s). The GSE has also provided a good platform for corporations to raise long-term capital to the tune of about $125.8 million from 1991 to 1998. However, unstable macroeconomic performance continues to be a major hurdle. For the whole of 2005, the GSE All Share Index remained disappointingly low. The most critical challenge for the GSE is to eliminate existing impediments to institutional development. These include a wider dissemination of information, and the implementation of robust electronic trading system.

[5] Source: www.ghanaweb.com, Business News, 29 June 2004.
[6] Databank Group Research, Accra

## IV. Methodology

A conventional way of modelling stock return seasonality is by estimating the basic model in {1} and {2}

$$R_t = \phi_1 D_{1t} + \phi_3 D_{3t} + \phi_5 D_{5t} + \eta_i R_{t-1} + \varepsilon_t \qquad \{1\}$$

$$R_t = \xi + \sum_{i=2}^{12} \phi_i D_{it} + \varepsilon_t \qquad \{2\}$$

$$\varepsilon_t | \varphi_{t-1} \sim N\,(0, h_t) \qquad \{3\}$$

$$h_t = \omega + \alpha \varepsilon^2_{t-1} + \beta h_{t-1} \qquad \{4\}$$

where $R_t$ is the continuously compounded daily (monthly) index returns. The autoregressive term in {1} account for statistically significant but economically minor autocorrelation and correct for possible nonsynchronous trading; $\phi_1$, $\phi_3$ and $\phi_5$ are parameters, $\varepsilon_t$ is an error term and $D_1$, $D_3$ and $D_5$ are dummy variables for Monday, Wednesday and Friday[7] (i.e. $D_1$=1 if *t* is Monday and zero otherwise).

Equations {1} and {2} have been the standard methodology in the anomalies literature. However, financial asset returns exhibit certain stylised facts (volatility clustering and leptokurtosis) that linear models are unable to explain. Modelling time varying asset returns volatility in financial markets has been achieved through (generalised) autoregressive conditional

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[7] $D_{2t} = 1$ if month *t* is February and zero otherwise; $D_{3t} = 1$ if month *t* is March and zero otherwise and so forth.

heteroscedasticity models (GARCH) due to Engel (1982) and Bollerslev (1986) and including various extensions (see Bollerslev, Chou and Kroner 1992 for comprehensive reviews on theory and application of GARCH models). Equation {4} is therefore fit into daily returns to model the conditional variance in the Ghanaian data. The conditional variance, $h_t$, must be nonnegative and positive, hence, restrictions of $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$ are sufficient conditions to ensure $h_t > 0$. The ARCH term, $\alpha$, indicates the short run persistence of shocks, while the GARCH term, $\beta$, represents the contribution of shocks to long run persistence.

The GARCH model assumes that positive and negative shocks have the same effect on volatility because it depends on the square of the previous shocks. In practice, financial asset returns respond differently to positive and negative innovations. It has been argued that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude (See Black 1976 and Christie 1982). Two asymmetric GARCH models are employed. Glosten, Jagannathan and Runkle (1993) GJR for short introduced the Threshold GARCH (TGARCH):

$$h_t = \omega + \alpha \varepsilon^2_{t-1} + \gamma \varepsilon^2_{t-1} I_{t-1} + \beta h_{t-1} \qquad \{5\}$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, or zero otherwise. For leverage effect $\gamma > 0$. For $h_t > 0$, the following restrictions on the models parameters must hold; $\omega \geq 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \gamma \geq 0$.

The Exponential GARCH due to Nelson (1991) has the following structure,

$$\ln(h_t) = \omega + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\ln(h_{t-1}) \qquad \{6\}$$

The EGARCH has several advantages. Since the conditional variance is modelled in logs, then even if the parameters are negative, $h_t$ will be positive. There is thus no need to artificially impose non-negative constraints on the model parameters. Again asymmetries are allowed since if the relationship between volatility and returns is negative, $\gamma$ will be negative. All the estimation is carried out using quasi maximum likelihood estimates (QMLE). Bollerslev and Wooldridge (1992) stress that QMLE is generally consistent, has normal limiting distribution and provides asymptotic standard errors that are valid under non-normality. In this study both the normal and the student's t-distribution were employed.

**V. Data**

The Databank Stock Index (DSI)[8] was the first major share index on the Ghana Stock Exchange and its computation began on 12 November 1990. The index is composed of all the listed equities. This research makes use of daily closing prices of the period 15 June 1994 to 28 April 2004, giving a total of 1508 observations after holidays have been excluded. The monthly observations run from 30 June 1994 to 28 April 2004, giving 120 data points.

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[8] The authors would like to thank Ken Ofori-Atta and Daniel O. Tetteh of Databank for making available the data employed in this paper.

The data is not adjusted for dividends, because the vast majority of empirical studies concerned with calendar anomalies have employed non-dividend adjusted returns, since the exclusion of dividend payments do not invalidate the results of the study, (see Mills and Coutts 1995), and thus do not impact on the statistical significance of the results.

The DSI is not a value weighted index and the overwhelming majority of the stocks are thinly traded. Another interesting feature is the fact that the Ghana Stock Exchange opens three days in a week— Monday, Wednesday and Friday. There are no market crashes, although periods of economic instability exist.

## VI. Empirical Results

### (a) Month of the Year and January Effect[9]

Results for the month of the year and January effect after estimating equation {2} are

$$\underset{[1.512]}{R_t=0.0184D_{1t}}+\underset{[1.918]}{0.0435^{*}D_{2t}}+\underset{[2.012]}{0.0627^{**}D_{3t}}+\underset{[2.55]}{0.0821^{**}D_{4t}}\underset{[-0.21]}{-0.048D_{5t}}+\underset{[1.12]}{0.0193D_{6t}}$$

$$+\underset{[1.76]}{0.0249^{*}D_{7t}}+\underset{[0.85]}{0.0131D_{8t}}+\underset{[0.15]}{0.0027D_{9t}}+\underset{[0.68]}{0.0113D_{10t}}+\underset{[1.10]}{0.0175D_{11t}}+\underset{[1.13]}{0.0171D_{12t}}+\varepsilon_t$$

$R^2 = 0.1417$ *F-Stat:* 4.3027(0.0001) ARCH LM(10)=1.8133(0.0571)

[9] Test statistics are reported in [ ]. *, ** denotes significance at the 10% and 5% respectively.

Mean monthly returns are significant in February, March, April and July. The highest monthly returns are reported in April, approximately 8%. March records 6.3% while February and July report 4.4% and 2.5% respectively. Contrary to evidence from global stock markets that monthly returns tend to be higher in January than other months, we cannot confirm this for Ghana. Instead, an April effect is found, similar to the finding of Gultekin and Gultekin (1983) for UK. The *F*-test rejects the null hypothesis that all of the regression coefficients are zero and there is no evidence for the presence of ARCH effects.

The non-existent January effect in Ghana could be attributed to the reporting time in the GSE. Publicly listed companies in Ghana are expected to submit annual reports three months into the new financial year. With March as the deadline for all companies to announce their reports, excessive build up occur thereby translating into the high April return.

From a macroeconomic perspective, Ghana has consistently run double digit inflation during the sample period with attendant effect on equity prices. The most plausible case here is that with the high prevailing rates of inflation positive results announced in the end of March, translates into significant price gains in April.

**(b) Day of the Week Effect**

Table 2 displays the results of the day of the week effect from various models from 15 June 1990 to 28 April 2004. Table 3 shows various diagnostic tools. Estimates of the rolling windows are reported in figures 1 to 4.

The OLS estimates of {1} reject the null of no day of the week effect. All test statistics are very significant at 5% for Monday and 1% for Wednesday and Friday. Mean daily returns during the estimation period on Mondays are also lower than other days of the week (0.1% on Mondays as opposed to 0.18% and 0.19% on Wednesdays and Fridays respectively). These results are therefore supported by previous studies that investigated the day of the week effect, notably Gibbons and Hess (1981) for US, Mills and Coutts (1995), Arsad and Coutts (1997) for UK. Given these patterns, a plausible investment strategy would be to buy low on Mondays and sell high on Fridays. However, there is need for caution because since the discovery of anomalies in the literature, there is no evidence of anyone profiting from them. Further, illiquidity and round trip transactions cost sets an upper bound to the use of profitable trading rules.

A discovery of the day of the week effect could be attributed to market inefficiency, because if the market pricing mechanism works well, all arbitrage opportunities should disappear upon discovery. With the Ghana stock exchange still at its embryonic stages of development with respect to information processing and pricing mechanism, this could well represent the case. However, the day of the week effect is now a stylized fact in even the developed markets and thus market inefficiency cannot possibly explain this phenomenon well in Ghana. Another research avenue is to hypothesize that anomalies disappear after correcting for autocorrelation, heteroscedasticity and data snooping biases.

Also, there is increasing evidence that stock returns exhibit volatility clustering and leptokurtosis, features linear models such as {1} are unable to explain. Secondly, asymmetric shocks exist in financial asset returns (Black 1976). Finally, if the linear framework could explain the dynamics of the data then the residuals should be IID (Independently and Identically Distributed) (Test Specification Theorem, see Brock and Dechert 1988). The IID assumption was examined through the application of the BDS test proposed by Brock et al. (1996). The results are presented in Table 2 (employing the Kočenta 2001 approach) and Table 3 (under OLS). The IID null is rejected in all cases ($p$-value of 0). As a result the benchmark linear framework has to be rejected.

Three GARCH models were employed: GARCH, EGARCH and TGARCH (with both normal and student's $t$-distribution, see Table 2). Their standardised residuals were saved and the BDS test statistic was calculated in each case (Table 4). The AR (1) is significant in all cases. The estimated GARCH term $\beta$ is always significantly positive; 0.7732, 0.928, 0.848 in the

GARCH, EGARCH and TGARCH respectively. As is typical of GARCH model estimates for financial asset returns data, the sum of the coefficients on the lagged squared error and lagged conditional variance is very close to unity (though less than one) in all three cases. This implies that shocks to the conditional variance will be highly persistent. In a forecasting domain, a large sum of these coefficients will imply that a large positive or a large negative return will lead future forecasts of the variance to be high for a protracted period.

The asymmetry term $\gamma$ is significant in TGARCH but not EGARCH. We can thus document significant leverage effect via TGARCH, indicating negative news in the Ghana stock market causes volatility to rise by more than positive news of the same magnitude. This is estimated to be about 0.12%.

The GARCH and EGARCH posit significant returns on Wednesdays and Fridays while TGARCH confirms that there are significant seasonalities throughout, with lower returns on Mondays and higher returns on Fridays. The TGARCH results are thus in consonance with the linear estimates, indicating the Ghana stock market starts low on Monday and ends high on Friday's. These latter results are however more robust than the linear estimates. The Ljung-Box Q-statistic on the standardized (normalized) squared residuals on all the volatility models does not find any model misspecification. For GARCHQ (*10*)=*0.994*(1.00); EGARCH Q(*10*)=*0.4414*(1.00) and TGARCH Q(*10*)= *0.3997*(1.00), with *p*-values in parenthesis. Thus the volatility equations are adequate at the 5% level. Further analysis shows that the Lagrange multiplier test gives LM(10)=0.981(0.998), LM(10)=0.4387(0.999) and LM(10)=0.3977(0.999) for GARCH, EGARCH and TGARCH respectively. Therefore there is no serial correlation or conditional heteroscedasticity in the standardized residuals of the fitted models[10].

The BDS test statistic is employed as a tool for model selection. The results are shown in Tables 3 and 4. The BDS test for IID random variables rejects the assumption of linearity for residuals $\varepsilon_t$ of OLS and the standardized (normalized) residuals $\varepsilon_t |h_t^{1/2}$ of GARCH and EGARCH, but not the TGARCH model (the *p*-values in the last column are all above 0.05). Additionally, the Engle and Ng (1993) test for asymmetry was carried out (see Table 5). The sign bias, negative and positive size bias and the join test confirms the presence of asymmetries in the data. Overall, the evidence suggests that the best model is the threshold generalised autoregressive conditional heteroscedasticity (TGARCH) model. The TGARCH performs better in terms of i) information criteria, ii) BDS and iii) the log likelihood function value.

**(c) Anomalies in Rolling Windows**

Changes in the month of the year and day of the week effects are examined via rolling regressions. The OLS coefficients on D1-D12 and D1-D5 for the monthly and weekly dummies respectively are plotted in figures 1 and 2. The

[10] This contrasts sharply with the linear model with LM(10)=98.033(0.000)

first estimate uses observations 1-50 and step size of 1; 67 for each coefficient for the month of the year. The variation in the coefficients confirms the lack of stability in any month of the year effects. After initial divergence, coefficient estimates in the latter half of the sample for January, February, March, April, August and December tend to converge. The reverse is true for July. For the day of the week, wide error bands indicate divergence and instability for linear estimates of the coefficients.

In Figure 3, we employ a rolling window for the TGARCH[11]. This reveals changes as the rolling window approaches the end of our sample. Higher estimates of all coefficients are observed in the first period of our sample and these are progressively becoming very close to zero. The latter implies that seasonality disappears if only recent information is used to estimate the preferred TGARCH model. As a result the rolling window analysis does not allow us to reject the hypothesis that the estimated day of the week coefficients are zero.

## VII. Conclusions

Two calendar anomalies were investigated in this research. Our overall estimates indicate the absence of January but the presence of an April effect. Mean April returns are estimated to be about 8%. This is higher than all other

[11] Rolling regression using QMLE is computationally expensive and convergence is not guaranteed. As a result we had to resort to windows of 1000 observations that gave us 507 estimates of each coefficient for both the mean and the variance specification.

months of the year and is attributed to the submission of company reports in March which creates significant build up at March ending. However, the latter disappears if only recent information is used (employing a rolling window).

Employing linear and nonlinear, symmetric and asymmetric volatility estimates we document day of the week effects in the Ghana stock market. The novelty of this finding rests on employing TGARCH and rolling estimates for both linear and nonlinear specifications that better explains the behaviour of daily index returns in Ghana. In a time varying Asymmetric GARCH framework we fail to find support for the existence of the day of the week.

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Table 2: Estimated Model: Day of the Week Effect 1990-2004

| | ESTIMATED MODELS | | | |
|---|---|---|---|---|
| | **OLS** | **GARCH** | **EGARCH** | **GJR-GARCH** |
| Monday | 0.0011**(2.41) | 0.00025 (0.56) | -0.0004 (-1.46) | 0.00055*(1.679) |
| Wednesday | 0.0018***(3.96) | 0.0015*** (3.63) | 0.00129*** (3.24) | 0.0016***(3.277) |
| Friday | 0.00187***(4.07) | 0.00139*** (4.75) | 0.00118***(5.29) | 0.0015***(3.569) |
| $\eta$ | 0.211***(8.36) | 0.275***(6.89) | 0.157***(5.46) | 0.211***(5.88) |
| $\omega$ | | 1.02E05***(13.7) | -0.00049***(17.9) | 6.95E-06(1.564) |
| $\alpha$ | | 0.144***(8.54) | 0.0109*** (16.15) | 0.141***(2.559) |
| $\beta$ | | 0.7732*** (45.16) | 0.928*** (18.34) | 0.848*** (17.06) |
| $\gamma$ | | | 0.1094(1.2806) | -0.128(-2.11) |
| S.E. of regression | 0.01019 | 0.0102 | 0.01029 | 0.0102 |
| Adj $R^2$ | 0.04407 | 0.0354 | 0.02662 | 0.04009 |
| AIC | -6.3297 | -6.6288 | -6.6439 | -6.653 |
| SBC | -6.3152 | -6.6041 | -6.6156 | -6.624 |
| F-test | 23.657 (0.000) | 10.064 (0.000) | 6.8004 (0.000) | 9.7832 (0.000) |
| $LBQ^2(10)$ | | 0.9947 (1.000) | 0.4414 (1.000) | 0.3997 (1.000) |
| LM(10) | 98.033 (0.000) | 0.981 (0.998) | 0.4387 (0.999) | 0.3977 (0.999) |
| LL | 4771.69 | 4998.5 | 5011.2 | 5017.8 |

Notes: test statistics reported in parenthesis. **, *** denotes significance at 5% and 1% respectively. AIC and SBC refer to Akaike and Schwarz information criterion LBQ is the Ljung-Box test on squared standardized residuals LM is Lagrange multiplier and LL is the log likelihood function value.

**Table 3: Computed BDS Statistics for the residuals of the linear model**

| | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_5$ | $\beta_6$ | $\beta_7$ | $\beta_8$ | $\beta_9$ | $\beta_{10}$ |
|---|---|---|---|---|---|---|---|---|---|
| | **0.8** | **1.124** | **1.4333** | **1.739** | **2.023** | **2.305** | **2.579** | **2.854** | 3.131 |

Notes: All the computed test statistics from the Kočenda (2001) framework using the optimal range of (0.60 $\sigma$ , 1.90 $\sigma$ ) and a bootstrap sample of 2500 independently drawn from the empirical distribution of the linear model, were rejected at the 1% significance level. The beta coefficients indicate the dimensions. These computations were done using K2K software.[12].

[12] The novelty of Kočenda (2001) and Kočenda and Briatka (2005) rests on an alternative way of selecting the range through integration across correlation integral, thereby avoiding arbitrary selection of epsilon, which has long been a weakness of Brock et all (1996) approach. The BDS statistic is by $\beta_m = \dfrac{\sum_\varepsilon \left(\ln(\varepsilon) - \overline{\ln(\varepsilon)}\right) * \left(\ln(C_{m,T(\varepsilon)}) - \overline{\ln(C_{m,T(\varepsilon)})}\right)}{\sum_\varepsilon \left(\ln(\varepsilon) - \overline{\ln(\varepsilon)}\right)^2}$, where $\beta_m$ is the slope coefficient, calculated from the least squares regression $\ln\left(C_{m,T(\varepsilon_i)}\right) = \alpha_m + \beta_m \ln(\varepsilon_i) + u_i$ *i=1,…., n,* where $\ln(\varepsilon)$ is the logarithm of the proximity parameter, $\ln(C_{m,T(\varepsilon)})$ is the logarithm of the same correlation integral, *m* is the embedding dimension while bars on variables denote the mean of their counterparts without bars. See Kočenda (2001) and Kočenda and Briatka (2005) for further discussion.

Table 4: Diagnostic Checks

| | OLS | GARCH | EGARCH | TGARCH |
|---|---|---|---|---|
| BDS:Bootstrap | | | | |
| 2 | 0.000 | 0.000 | 0.000 | 0.234 |
| 3 | 0.000 | 0.000 | 0.000 | 0.114 |
| 4 | 0.000 | 0.000 | 0.000 | 0.148 |
| 5 | 0.000 | 0.000 | 0.020 | 0.362 |
| BDS: Asymptotic | | | | |
| 2 | 0.000 | 0.000 | 0.042 | 0.2513 |
| 3 | 0.000 | 0.000 | 0.004 | 0.1237 |
| 4 | 0.000 | 0.000 | 0.001 | 0.1614 |
| 5 | 0.000 | 0.000 | 0.003 | 0.3899 |

Notes: Only *p*-values of BDS test statistic are reported.

Table 5. Test for Asymmetry

| Sign Bias | Positive Size bias | Negative bias | Joint test |
|---|---|---|---|
| -0.564(-1.311) | 0.199(0.457) | -0.0418(-0.156) | 2.3014[0.512] |

Notes: p-values are shown in [ ] and t-statistics in ( ) parenthesis.

SB: $z_t^{\,2} = \alpha + bS_t^{-} + e_t$ i)

PSB: $z_t^{\,2} = \alpha + bS_t^{-}\varepsilon_{t-1} + e_t$ ii)

NSB: $z_t^{\,2} = \alpha + b(1 - S_t^{-})\varepsilon_{t-1} + e_t$ iii)

Joint test: $z_t^{\,2} = \alpha + b_1 S_t^{-} + b_2 S_t^{-}\varepsilon_{t-1} + b_3(1 - S_t^{-})\varepsilon_{t-1} + e_t$ iv)

The Engle and Ng (1993) are based on the news impact curve implied by the particular GARCH model used. The premise is that if the volatility process is correctly specified, then the squared standardized residuals should not be predicted on the basis of observed variables. These tests are (a) the sign bias test (b) the negative size bias (c) the positive size bias, and (d) the joint test. Our test is performed on the residuals of the symmetric GARCH model in table 4 and are based on equations (i) to (iv), where $\varepsilon_t$ is the error term under the null, $S_t^{-}$ is a dummy variable that takes the value of one when $\varepsilon_{t-1} < 0$ and zero otherwise (and vice versa for $S_t^{+}$).

Figure 1: Rolling Estimates of the linear model (initial sample of 50 observations and step size of 1; 67 observations for each coefficient)

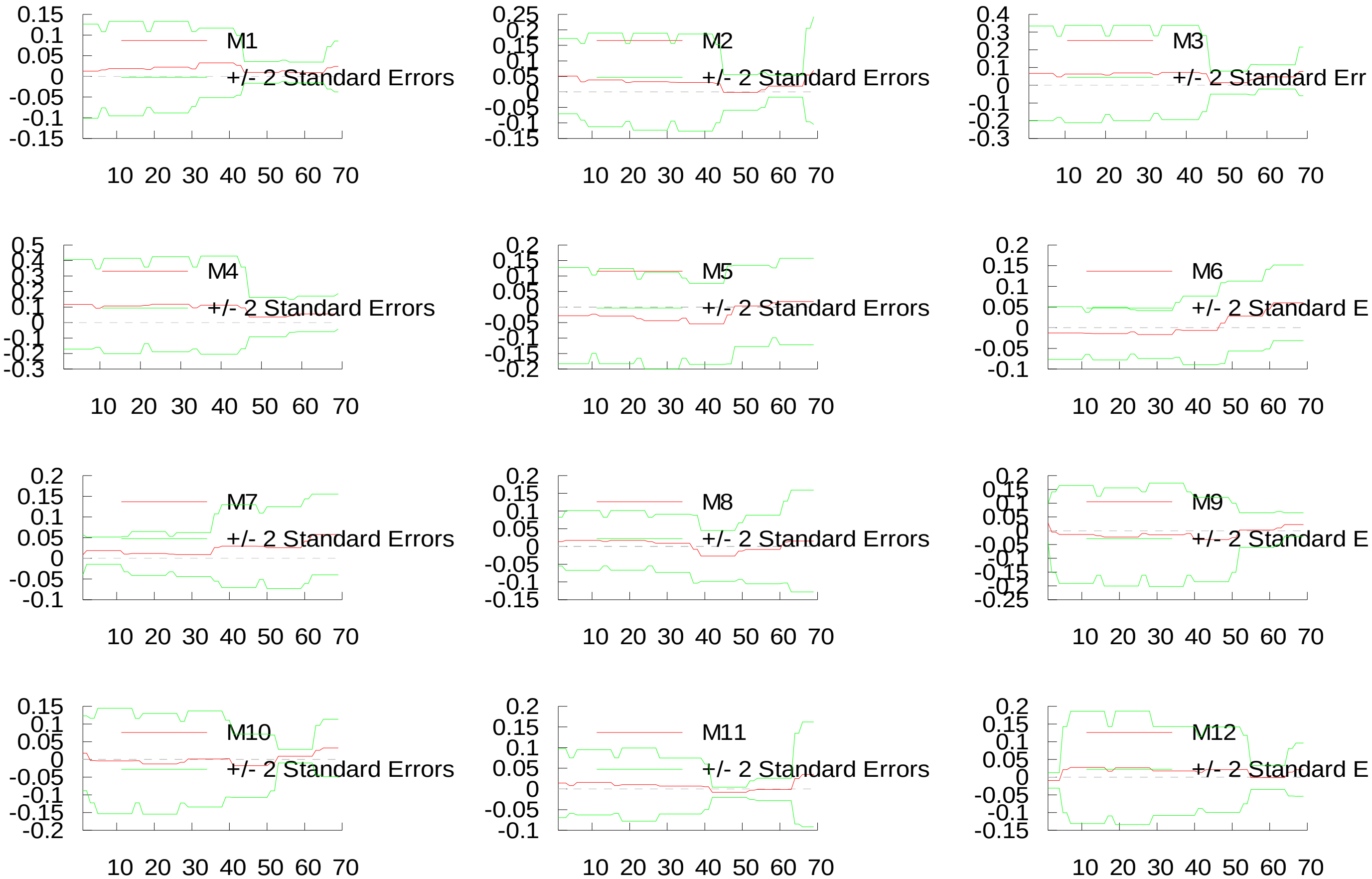

Figure 2: Rolling Estimates of the linear model (initial sample of 1000 observations and step size of 1; 507 observations for each coefficient)

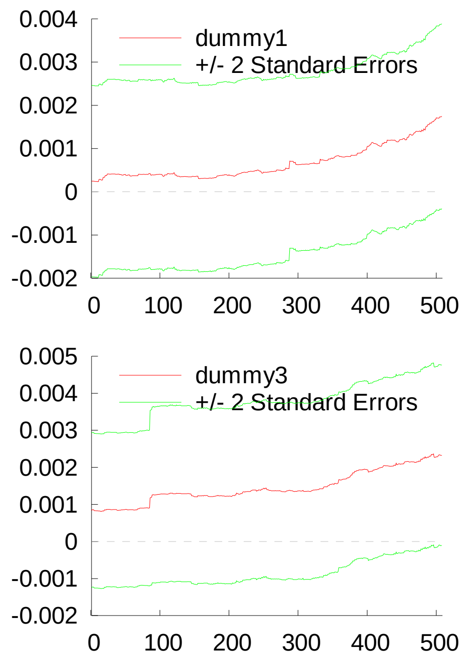

Figure 3: Rolling Estimates of the coefficients of the TGARCH model (initial sample of 1000 observations and step size of 1; 507 observations for each coefficient)

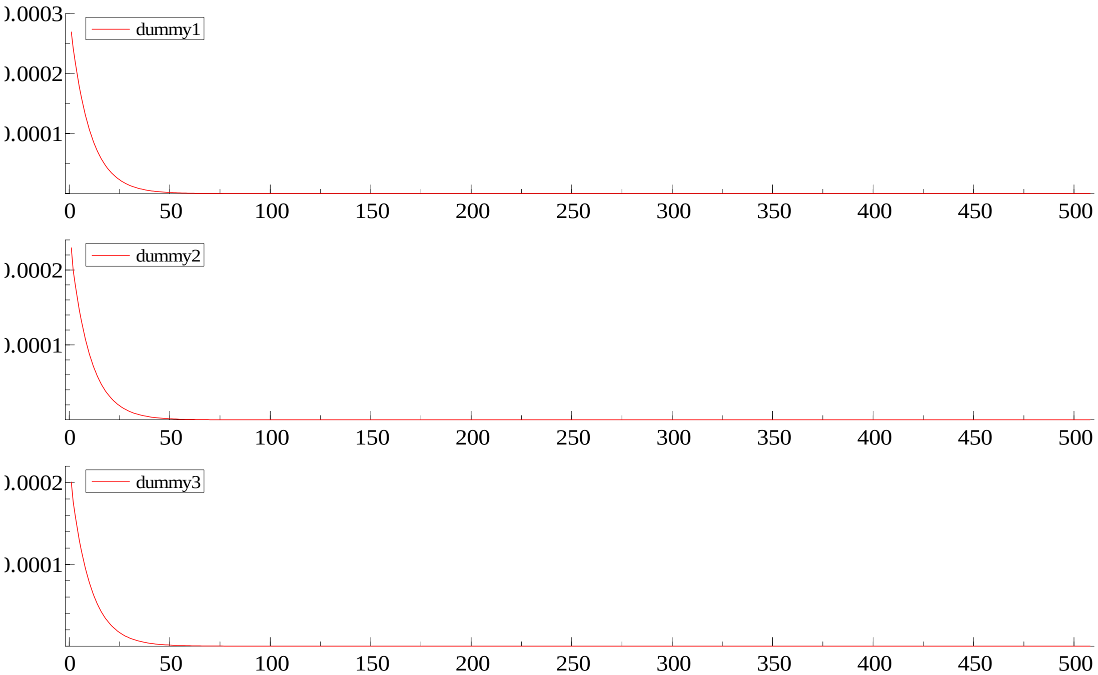

Figure 4: Rolling Estimates of the conditional variance coefficients of the TGARCH model (initial sample of 1000 observations and step size of 1; 507 observations for each coefficient)